The Full Returns to Low Wage Jobs *

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Abstract

Research has shown that minimum wages, which play a particularly important role in the Low Pay Sector, have had a strong positive effect on earnings and have been successful in reducing earnings inequality. But to understand the full extent of labour market inequality in the Low Pay Sector, we need data on both earnings and the amenities experienced by workers. We use data on subjective wellbeing in a large sample of UK workers to calculate the value of amenities in low-paid occupations and industries, and construct a measure of "full earnings" for workers in this sector. We find that earnings inequality is lower in the Low Pay Sector than in the rest of the economy, but also show that taking data on amenities into account leads to an estimate of labour-market inequality that is 100% higher in low-paid occupations and 41% higher in low-paid industries, and that these figures cannot be explained away by individual selection. Looking at groups that have been historically disadvantaged in the labour market, we find that women, young people, and ethnic minorities have particularly poor outcomes according to our measure of "full earnings".

Keywords: Low Pay Sector; Wages; Non-pecuniary Benefits; Inequality.

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Executive Summary

Twenty years after the introduction of the national minimum wage, research has shown that minimum wages have had a strong positive effect on earnings and have been successful in reducing earnings inequality in the UK. But to fully understand the impact of the minimum wage on low-paid workers we need to take into account labour-market outcomes that go beyond wages and unemployment. The aim of this report is to provide the Low Pay Commission with an analysis of the UK low-pay sector in which we measure both wages and non-wage benefits, show how the two are correlated, and establish whether labour-market inequality in the low-pay sector is underestimated when looking at data on earnings alone.

This type of analysis has been difficult to perform previously. To understand movements in workers' welfare, we require information not only on wages, but also on all non-wage benefits and how much these are valued by workers. However, workers' non-wage benefits are often unobservable or, if observable, measured with error. And even if we can measure non-wage benefits accurately, we lack information on how important they are to workers. We propose to bypass these limitations via an innovative approach, as set out in Clark et al. (2021): we capture the job amenities that matter to workers and account for the different values that they may put on them by outsourcing the task to the workers themselves. To do so, we will make use of information on the subjective wellbeing of workers, and specifically on their life satisfaction. The worker's level of life satisfaction (net of that associated with wages) reveals the value of their job's non-wage benefits. Using data on both earnings and our estimate of non-wage benefits, we construct a measure of "full-earnings" for workers in the Low Pay Sector.

To identify workers in the low-pay sector, we make use of the industry and occupational classification developed by the Low pay Commission, at the 4-digit level. Following this classification, our analysis will include 86 low-paid occupations and 176 low-paid industries. Our analysis makes use of two large UK surveys, namely the Annual Population Survey and Understanding Society. The benefit of the former is its large sample size which allows for highly dis-aggregated analyses across occupations and industries in the Low Pay Sector. The advantage of the latter is its panel dimension, which allows us to track individuals over time and address issues regarding selection into the Low Pay Sector and into different occupations and industries.

In the results section of this report we provide an analysis of both the wages and non-wage benefits of UK workers in low-pay sectors, allowing for a fuller description of their position in the labour market. We will perform this analysis in both the cross-section and in the panel, and show how our conclusions change when we control for worker-specific fixed effects. Second, we repeat the above analysis for groups of low-paid workers with protected characteristics. We consider men and women separately, as well as different ethnic groups. We also focus on young people, and we provide some evidence on the geographical variation in both wages and non-wage benefits.

The main findings in this report are the following:

- Wages and amenities in the low-pay sector are related in the same way as in the rest of the UK economy, and in line with the previous work of Clark et al. (2021): there is no evidence that workers in the low-pay sector are compensated by better amenities, and even within the low-pay sector there is more inequality in labour-market outcomes than earnings alone would suggest. Full labour-market inequality is 100% higher in low-paid occupations and 41% higher in low-paid industries when amenities are taken into account.

- Earnings inequality in the low-pay sector is lower than that found for the whole economy, consistent with the minimum wage compressing the bottom of the earnings distribution. On the other hand, the amenities inequality in the low-pay sector is very similar to that experienced by workers in the rest of the economy.

- Robustness checks using panel data indicate that this inequality cannot be entirely explained by the selection of workers into these types of jobs, and is at best a lower bound on the full level of labour-market inequality experienced by workers in the low-paid sector.

- Our analysis indicates that retail and manufacturing jobs have very low levels of amenities, as reported by the workers themselves. On the other hand, less-routine jobs and work that requires more outdoor activity both have higher than average amenities.

- Women, young people, and ethnic minorities have both lower earnings and lower amenities as compared to the reference group. This indicates that the gender, ethnic and age gap in the Low Pay Sector is even larger than the incomes of these groups alone would suggest.

- While men and women in the low-paid sector experience similar dispersion in both earnings and amenities, young workers and members of ethnic minorities experience significant inequality that is almost entirely driven by inequality in non-pecuniary outcomes.

- We have found that the amenities that people in the Low Pay Sector Experience are particularly low in London and in the South of England, and that the regional variation in earnings maps poorly into the regional variation in terms of full earnings.

- Last, we considered whether our findings are sensitive to the introduction of the National Living Wage in 2016. We found no evidence that this policy change significantly affected labour-market inequality in the low-pay sector, either in terms of earnings or amenities.

1 Introduction and Background

Twenty years after the introduction of the national minimum wage, research has shown that minimum wages have had a strong positive effect on earnings, and have been successful in reducing earnings inequality in the UK (Cooper et al., 2020). But to fully understand the impact of the minimum wage on low-paid workers we need to take into account labour-market outcomes that go beyond wages and unemployment. Research has increasingly underlined that many workers care deeply about the non-pecuniary aspects of their work, and as such prefer to take their labour-market rewards partly in monetary and partly in non-monetary form. We here propose an analysis of the UK low-pay sector in which we are able to measure both wages and non-wage benefits, show how the two are correlated, and establish whether labour-market inequality in the low-pay sector is underestimated when looking at data on earnings alone.

We know only little about the relationship between wages and non-wage benefits in the low-paid sector. A report from the Low Pay Commission[1] discusses anecdotal evidence that firms may have effected adjustments following the introduction of the minimum wage, including via lower non-wage benefits. The growing number of flexible zero-hours contracts in the past few years could be just one of many such non-wage adjustments. One specific adjustment found in the US, in Clemens et al. (2018), is that higher minimum wages reduced the likelihood that workers receive employer-sponsored health insurance. But despite the importance of taking both wages and non-wage benefits into account, research on this topic has to date only been limited.

To understand movements in workers' welfare, we require information not only on wages, but also on all non-wage benefits and how much these are valued by workers. This will allow us to calculate a full value for the return to workers on the labour market. However, one major impediment to measuring the levels (or changes) in workers' non-wage benefits is that these are often unobservable or, if observable, measured with error. And even if we can measure non-wage benefits accurately, we lack information on how important they are to workers. Without understanding the importance that people assign to these benefits we cannot make statements on how much these are valued on the labour market. We propose to bypass these limitations via an innovative approach, as set out in Clark et al. (2021): we capture the job amenities that matter to workers and account for the different values that they may put on them by outsourcing the task to the workers themselves. To do so, we will make use of information on the subjective wellbeing of workers, and specifically on their life satisfaction. The worker's level of subjective wellbeing (net of that associated with wages) reveals the value of their job's non-wage benefits.

Clark et al. (2021) find that non-wage benefits and wages are positively correlated in the UK labour market as a whole, so that higher-paying jobs offer better amenities while workers in lower-paid occupations have worse-than-average benefits. The total inequality in the UK labour market, when taking both wages and non-wage benefits into account, is calculated to be one-third higher than data on wages alone would suggest.

Extrapolating from the positive correlation in Clark et al. (2021) for the whole labour market, a rise in minimum wages may then not produce worse non-wage benefits. However, we do not currently know whether this extrapolation is appropriate: the wages-amenity relationship may work differently in the low-pay sector, so that higher minimum wages may end up doing only little to reduce overall labour-market inequality. As low-paid workers are more likely to be younger, women, and ethnic minorities, establishing how wages and non-wage benefits are related in this sector also helps inform us about the evolution of gender, ethnic and other types of labour-market inequality.

[1] $https://www.gov.uk/government/publications/20-years-of-the-national-minimum-wage$

We propose to apply this new method of measurement to the low-pay sector in the UK, to provide new information on how wages and non-wage benefits are related in low-pay sectors. First, we will provide a new analysis of both the wages and non-wage benefits of UK workers in low-pay sectors, allowing a fuller description of their position in the labour market. Second, we will repeat the above analysis for groups of low-paid workers with protected characteristics. We will consider men and women separately, as well as different ethnic groups. We will also focus on young people. Currently, only workers aged 25 and older are eligible for the National Living Wage (NLW). However, given the government's target to expand this measure to workers aged 23 and over from April 2021, and to workers aged 21 and over by 2024, this analysis by age is relevant. We will also provide evidence on the geographical variation in both wages and non-wage benefits. We believe that, in the context of the levelling-up agenda, this analysis of spatial differences will be of great interest to policy makers, by showcasing the role that the experiences of workers in low-pay sectors play in different parts of the country. Finally, we will appeal to the time dimension of our data. We consider the policy reform of the introduction of the NLW in 2016, and ask whether this exogenous rise in wages changed the way in which wages and non-wage benefits are related.

2 Data

To measure full earnings, we require not only data on earnings from work but also a means of calculating the monetary value of the non-pecuniary aspects of different low-pay sector jobs. We will establish the latter from the relationship between a summary measure of well-being (life satisfaction) and dis-aggregated low-paid occupations and industries, holding labour earnings and some exogenous individual characteristics constant.

To identify workers in the low-pay sector, we make use of the industry and occupational classification developed by the Low pay Commission[2]. This measure of low-paid occupations and industries is very dis-aggregated, at the 4-digit level, using the SOC2010 classification for occupations and the SIC2007 classification for industries. Following this classification, our analysis will include 86 low-paid occupations and 176 low-paid industries. We note here that our analysis of the low-paid sector is not equivalent to an analysis of workers who directly benefit from the minimum wage. We instead look at sectors that will have a disproportionately large share of workers who are low-paid. In separate analyses we will also check how our results change if we only look at those individuals who are towards the bottom of the earnings distribution within these low-pay occupations or industries.

Our main source of data is the Annual Population Survey (APS)[3], a large representative repeated cross-section survey of the UK population. The APS started in 2004, and its main purpose is to provide information on important social and socio-economic variables at local levels, including questions on a wide range of labour-market outcomes, as well as housing, ethnicity, religion, health, and education. The APS uses data from the Labour Force Survey (LFS), giving it the largest coverage of any UK household survey. We make use of all the APS waves that collect data on the variables that are required for our analysis (2013-2019).

Our sample consists of respondents aged 18 to 65 who are in full-time employment. We apply this latter restriction as the earnings distribution has a different significance for full and part-time workers. We also exclude the self-employed, as both the earnings and non-pecuniary amenities of this group are to a large extent within their control. Finally, we drop those respondents whose reported hourly wage

[2] https://www.gov.uk/government/publications/low-pay-commission-report-2020

[3] More information about the APS can be found at https://www.ons.gov.uk/.

is in the bottom 1% of the distribution of earnings. Our final sample of respondents who work in the low-pay sector contains information on 66,864 full-time employees in low-paid occupations and 74,256 in low-paid industries.

Our key outcome variable is life satisfaction. Following the OECD Guidelines, we use life satisfaction as a summary measure of overall individual well-being. Since 2011, the UK Office for National Statistics (ONS) has asked APS respondents four personal wellbeing questions and the answers to these are considered to be official national statistics. The first of these wellbeing questions refers to life satisfaction. Respondents are asked "Overall, how satisfied are you with your life nowadays?", with answers on an 11-point scale (0 corresponding to "not at all satisfied" and 10 to "completely satisfied").

Earnings are measured by the logarithm of real hourly earnings. Hourly earnings in the APS are a derived variable, based on responses to gross weekly earnings and to usual hours of work and paid overtime. The APS also contains information on individual demographics and employment-related variables. With respect to the former, our empirical analysis will focus on gender, age, and ethnicity. Gender is a dummy variable taking on the value "1" for women and "0" for men, age enters as a quadratic in the empirical analysis, and there are 11 ethnicity categories.

One limitation of the Annual Population Survey is that it is a cross-section, so that the same individuals cannot be followed over time. We thus complement our cross-sectional analysis with the analysis of panel data from Understanding Society (US).[4] This survey started in 2009, and interviews around 40,000 households per year. We will here make use of all ten currently-available waves of Understanding Society.

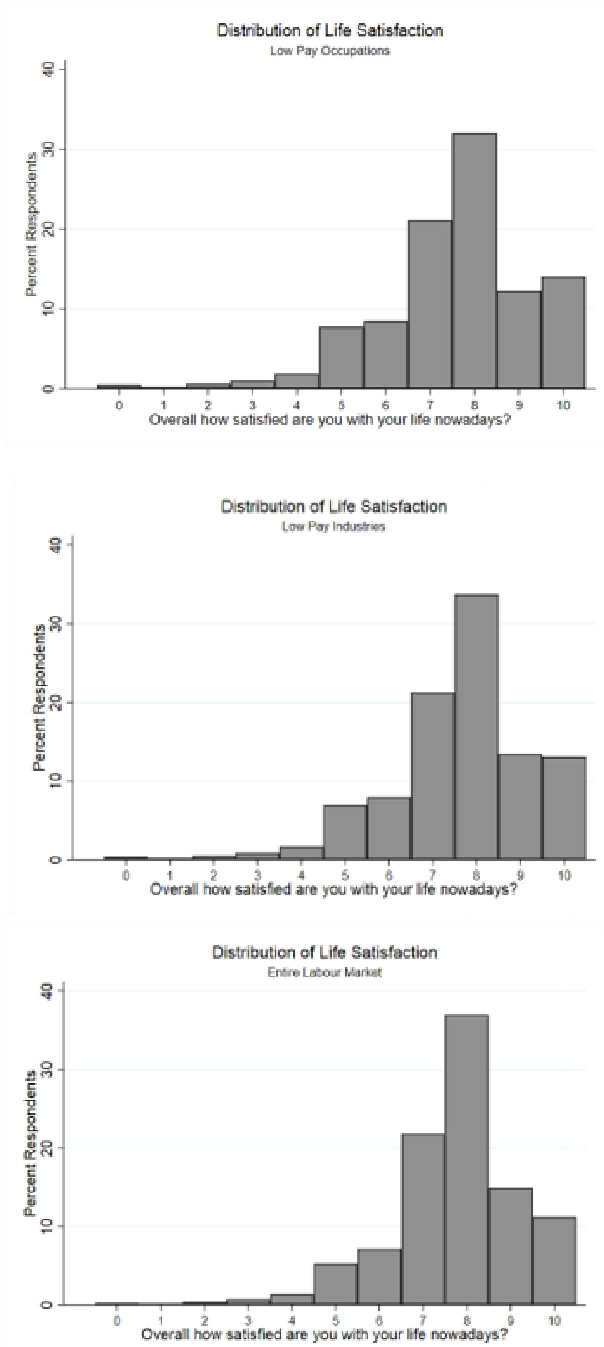
In Understanding Society, life satisfaction is coded on a 7-point scale where an answer of 1 corresponds to "completely dissatisfied" and an answer of 7 to "completely satisfied".[5] To help the interpretation of the empirical results here to those obtained from the APS, we re-scale this measure of life satisfaction such that it is also measured on an 11-point scale. The US survey also includes information on gender, age, and ethnicity, as well as on occupation and industry, using the same 4-digit classifications as in the APS. The logarithm of hourly earnings is calculated from individual monthly labour earnings and hours worked, including paid hours of overtime work.

Figure 1 below shows how the distribution of Life Satisfaction in low-pay occupations and industries compares to that in the entire Labour Market. The distribution of life satisfaction according to both low-pay definitions is very similar, but both differ notably from the distribution in the whole UK labour market. There is more mass to the left of the distribution in the low-pay sector, so that the workers in this sector are less likely to be satisfied with their lives.

[4]More information about Understanding Society can be found at https://www.understandingsociety.ac.uk/.

[5]Understanding Society also includes a measure of job satisfaction. However, for the purpose of this analysis, we have chosen to focus on life satisfaction, as opposed to job satisfaction. This is because life satisfaction matters to individuals when they make choices over their lives (such as picking an occupation or an industry), not the satisfaction felt in only one domain of their lives. Clark et al. (2021) use job satisfaction as a robustness check and find that their results for the whole economy are robust and stronger when using this measure instead.

Figure 1: The Distribution of Life Satisfaction in the Low-Pay Sector and the Whole Labour Market



Source: Annual Population Survey (2013-2019).
Notes: These are histograms plotting the distribution of life satisfaction measured on an 11-point scale, where 0 corresponds to “not at all satisfied” and 10 correspond to “completely satisfied”. The first panel plots life satisfaction in 86 low-paid occupations, and the second panel life satisfaction in 176 low-paid industries. The last panel plots life satisfaction in the whole UK labour market. In all three panels, the sample is restricted to respondents aged 18 to 65 who are in full-time employment.

3 Method

Our approach builds on that in Clark et al. (2021) and allows us to measure the non-wage benefits received by low-paid workers, in the absence of detailed administrative data on amenities. To do so, we use data on subjective well-being to create a measure of non-wage benefits across occupations (or industries) in low-paid sectors. The advantage of this approach is that it allows us to quantify the importance that workers in low-paid sectors assign to non-wage benefits, and work around the long-standing measurement limitations associated with this domain of research.

We use the industry and occupational classification developed by the Low Pay Commission[6] to identify the low-paying sectors of the labour market. We begin our analysis by asking how individual wellbeing is related to personal characteristics, earnings, and occupation or industry. We estimate the following equation for the low-paid occupations in the UK labour market, according to the Low pay Commission classification:

$$W_{ij} = \alpha_0 + \alpha_1 X_i + \alpha_2 LogEarnings_i + \sum_j \alpha_3^j Occupation_{ij} + \tau_t + \varepsilon_{ij} \tag{1}$$

where W_{ij} is the life satisfaction of the i^{th} individual in the j^{th} low-paid occupation, X_i is a vector of exogenous control variables (a quadratic in age, and sex and ethnicity dummies), and $LogEarnings_i$ is the logarithm of respondent hourly pay. [7] There is also a dummy variable for each occupation j, and the α_3^j coefficients in the equation above capture the non-pecuniary advantage of each of these j occupations. Amenities are thus not measured directly, but are instead reflected by the average wellbeing in each low-pay occupation once we have removed the effects of wages and personal characteristics. To help with the interpretation of the estimated coefficients on the occupation dummies, and avoid having to interpret each α_3^j relative to some baseline occupation, we follow Krueger and Summers (1988) and express the occupation coefficients as deviations from an employment-share-weighted mean. Last, τ_t is a wave fixed effect and ε_{ij} a normally-distributed error term.

We take an analogous approach at the industry level (as the low-pay sector can be defined at either the industry or occupational level):

$$W_{ik} = \beta_0 + \beta_1 X_i + \beta_2 LogEarnings_i + \sum_j \beta_3^k Industry_{ik} + \tau_t + \nu_{ik} \tag{2}$$

Here the β_3^k coefficients will capture the non-pecuniary advantage of each industry k. The remaining coefficients have the same interpretation as in Equation (1), and we include the same set of controls.

The coefficients of interest (α_3^j and β_3^k) will be used to create an overview of the level of non-wage benefits across occupations and industries in the low-pay sector. The standard deviation of this vector of coefficients will show how unequal these amenities are in low-paying jobs. We can therefore establish both the level and dispersion of amenities *between* occupations and industries in the low-pay sector.

We can use the estimation results above to evaluate the interpersonal dispersion of full earnings

[6] $https://www.gov.uk/government/publications/low-pay-commission-report-2020$.

[7] We here use earnings, as opposed to hours worked or job security as they are central to our methodology of estimating the amenities in each occupation or industry. Specifically, the coefficient on earnings allows us to assign a monetary value ot the non-pecuniary aspects of jobs.

between occupations, to understand the full level of labour-market inequality. We do so by combining each respondent's logarithm of hourly earnings with the monetary value of the non-pecuniary advantages of the occupation in which they work. We thus re-write Equation (1) as:

$$W_{ij} = \alpha_0 + \alpha_1 X_i + \alpha_2 FullEarnings_{ij} + \tau_t + \varepsilon_{ij} \tag{3}$$

where full earnings is given by:

$$FullEarnings_{ij} = (LogEarnings_i + \sum_j \frac{\alpha_3^j}{\alpha_2} Occupation_{ij}) \tag{4}$$

In Equation (4), the full earnings of a worker are composed of a monetary element and a term capturing the non-pecuniary aspect of low-paying occupations. The former is $LogEarnings_i$ and the latter is the coefficient α_3^j for each occupation j, transformed into monetary terms when divided by α_2. A similar exercise can be carried out across industries, using Equation (2).

However, this exercise cannot capture the degree of inequality *within* a particular occupation or industry. This is important, as not all people working in low-paying occupations and industries will themselves benefit from minimum wages. For example, those working in management or executive positions will still earn substantially higher wages than their lower-paid colleagues. We analyse this intra-occupation and intra-industry variation by estimating Equations (1) and (2) separately for different parts of the earnings distribution in each low-paying occupation and industry. We here pay particular attention to those workers at the bottom of the wage distribution, as they are the most likely to be directly affected by the minimum wage.

Our second objective is to investigate how different vulnerable sub-groups fare in terms of their non-wage benefits *between* low-paying occupations and industries. We will measure the *between* difference by estimating Equations (1) and (2) separately for men and women, for people of different ethnic backgrounds, and by age group.

One limitation of using the APS is its cross-sectional nature, which does not allow us to observe the same workers over time. This may imply that our estimates are vulnerable to bias stemming from the unobserved characteristics of workers who select into specific occupations and industries or, more generally, into the low-paid sector. By observing the same workers over time, we can control for individual fixed effects that remove all individual-specific time-invariant unobserved variation (such as differences in ability), address selection, and reduce the possibility of bias in our estimates. Specifically, we will re-estimate Equations (1) and (2) including an individual-specific fixed-effect ϕ_i, and will compare our vectors of coefficients on occupations or industries in the low-pay sector estimated this way to the vectors α_3^j and β_3^k above.

Our third and last objective refers to the time dimension of our data. Specifically, we can carry out a before-after analysis to identify the effect of the introduction of the National Living Wage in 2016. This will allow us establish the short- and medium-run consequences of this policy change in the low-paid sector. We will do so by allowing our estimates for the non-wage benefits in low-paying occupations and industries to vary over time. A comparison of these estimates before and after the policy change (net of a general time-trend) will help us to provide a more causal interpretation of the effect of minimum wages.

4 Full Labour Market Inequality in the Low-Pay Sector

Table 1 presents the estimation results for Equation (1), showing how individual life satisfaction is correlated with exogenous personal characteristics and with earnings, where earnings is given by the logarithm of hourly pay. The first column estimates Equation (1) for the 86 occupations in the low-paid sector, while the results in column 2 are for the 176 industries in the low-pay sector. As noted above, the occupation and industry coefficients are expressed as deviations from an employment-share-weighted mean.[8] This regression explains about 3% of the variation in life satisfaction. This rather low R^2 figure reflects both our small set of right-hand variables and the fact that we analyse a more homogeneous group: adults aged 18 to 65 in full-time employment.

Table 1: An Equation of Predicted Life Satisfaction

	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.226***	0.292***
	(0.025)	(0.017)
Female	0.081***	0.050***
	(0.021)	(0.017)
Age	-0.058***	-0.045***
	(0.005)	(0.005)
Age-squared/100	0.063***	0.048***
	(0.006)	(0.006)
Occupation fixed effects	Yes	No
Industry fixed effects	No	Yes
Wave fixed effects	Yes	Yes
R-squared	0.03	0.03
N	66,864	74,256
SD dependent	1.711	1.632

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regression in Column 1 controls for 86 low-pay occupations, at the 4-digit level. The regression in Column 2 controls for 176 low-pay industries, at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

The estimated coefficients on the logarithm of earnings is 0.226 for occupations and 0.292 for industries. This is a fairly standard type of figure in the literature. It implies that doubling hourly earnings would increase life satisfaction by 0.158 and 0.204 points respectively, on the 11-point scale (as doubling earnings causes log earnings to rise by 0.7). These figures correspond to 0.09 and 0.13 of a standard deviation of life satisfaction. Women report higher life satisfaction than do men in the APS data (this is also

[8] One potential issue with this approach is that the standard errors on the occupation and industry dummies may be downward-biased in small samples. Haisken-DeNew and Schmidt (1997) show that this is not a concern in large samples, where the standard errors are virtually equivalent to those estimated by dropping a reference category. Our analysis sample here is close to their definition of a large sample and, as expected, the standard errors using the two methods are very similar.

a common finding), although the estimated coefficient is not large. The estimated relationship between life satisfaction and age is U-shaped in the APS data, as is very often found in the empirical subjective well-being literature. In Table A6 in the Appendix we run our analysis on those workers who are employed, but not in the low-pay sector as defined by the Low Pay Commission. Comparing these estimates to those in Table 1, we can see that workers in the low-pay sector are not substantially different to those in the rest of the economy in terms of the estimated coefficients. In particular, earnings attract similar estimated coefficients for the two groups.

The estimated coefficients on the 86 occupation dummies and 176 industries dummies in Table 1 capture the non-pecuniary aspects of work. For occupations, we divide these coefficients by the coefficient on the logarithm of earnings α_2: the resulting coefficient $\frac{\alpha_3^j}{\alpha_2}$ measures the non-pecuniary values of the different occupations in units of log earnings. We run a similar exercise for our regression involving low-paid industries.

Table 2 presents information on the standard deviation of earnings, the non-pecuniary job rewards (α_3^j and β_3^k), the non-pecuniary job rewards adjusted in monetary terms ($\frac{\alpha_3^j}{\alpha_2}$ and $\frac{\beta_3^k}{\beta_2}$), and full earnings (the sum of earnings and the non-pecuniary rewards). Table 2 shows that in the low-pay sector, the distribution of rewards on the labour market is substantially larger once we take their non-pecuniary elements into account. This is easily seen by comparing the interpersonal dispersion in earnings (0.38 and 0.49 respectively) to the interpersonal dispersion in full earnings (0.76 and 0.69 respectively). In other words, full labour-market inequality is 100% higher in low-paid occupations and 41% higher in low-paid industries when amenities are taken into account.

Table 2: Important Standard Deviations

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD	0.38	0.14	0.62	0.76
Sample Size	66,864			
Industries				
SD	0.49	0.15	0.51	0.69
Sample Size	74,256			

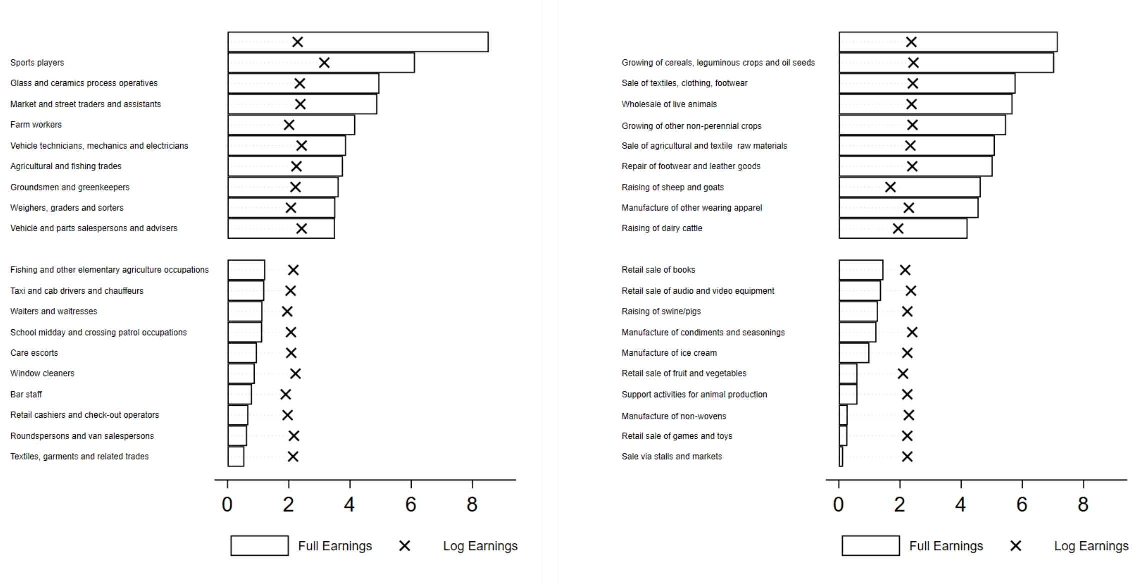
Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. These standard deviations are based on the regressions in Table 1, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table 1) and industries (column 2, Table 1). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table 1). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table 2 shows that in the low-pay sector in the UK there is somewhat larger dispersion in amenities (0.62 and 0.51 respectively) than in earnings (0.38 and 0.49). In Table A7 in the Appendix we carry out the same exercise for the non-low pay sector. The results there indicate that while earnings dispersion is larger for the non-low pay sector, the dispersion of amenities is not different from that experienced by workers in the low-pay sector. While this smaller earnings inequality in the low-pay sector is likely a direct consequence of the minimum wage, which is known to have reduced earnings inequality over the past 20 years, we find no evidence that workers in low-pay sectors face greater inequality in non-monetary rewards as a consequence of this policy. In an additional robustness check presented in Tables

A8 and A9 in the Appendix, we can also include part-time workers in our analysis of the low-pay sector. While this increases our sample size significantly, we do not find that our main results change if part-time workers are included in the analysis.

Figure 2 below plots the top and bottom 10 occupations and industries in the low-pay sector, according to our measure of full earnings. In these figures, we rank individual occupations and industries in the low-pay sector in terms of full earnings, and compare this ranking to that obtained using only information on hourly earnings.

Figure 2: Best and Worst Low-paid Occupations (Left Panel) and Industries (Right Panel), according to Full Earnings



Source: Annual Population Survey (2013-2019).

To avoid choosing an arbitrary baseline, the non-pecuniary aspects of each occupation and industry are expressed in terms of deviations from the sample mean. Full earnings, which are the sum of hourly earnings and the monetary value of the non-pecuniary amenities in that occupation, are depicted by the horizontal bars; hourly earnings are represented by the black crosses. The gap between hourly and full earnings corresponds to the monetary value of non-pecuniary amenities in that occupation or industry. A black cross that is to the right of the bar then indicates a below-average value of amenities in that occupation or industry.

Overall, we find a positive correlation between earnings and full earnings, such that better paying occupations also tend to have better amenities and vice-versa. This is in line with the findings in Clark et al. (2021), who perform this exercise for the whole UK economy. In the case of industries, this pattern is less clear. While both the levels of earnings and of amenities are lower than across the entire labour market, our findings for the low-pay sector confirm that there is no evidence of compensating differentials for workers in these types of jobs either. This reflects our finding in Table 2 that accounting for amenities increases the standard deviation of rewards on the labour market.

In terms of the type of jobs that are best and worst for workers, some clear patterns emerge. Workers in retail and manufacturing jobs have poor average amenities, and as a result lower levels of life satisfaction than their earnings alone would suggest. On the other hand, jobs that involve outdoor work and less-repetitive tasks tend to have high levels of amenities and, consequently, produce higher levels of life satisfaction for the employees there. While people in typical agricultural jobs and who work outdoors may also report higher life satisfaction due to living in lower-cost areas, the coefficients that we estimate on occupations and industries relate to the life-satisfaction residual specific to these jobs, net of earnings. As such, geographic differences in the cost of living are unlikely to play a large part. However, in Appendix Tables A13 and A14 we also show that our main results presented in Tables 1 and 2 are robust to including an extensive set of area dummies, at the Local Authority District level, which are likely to pick up much of any cost-of-living differences.

One limitation of the Annual Population Survey is its cross-sectional nature, which does not allow us to address the selection of individuals into different occupations or industries. To address this concern and analyze the extent to which our results are biased, we make use of Understanding Society data. We use the panel dimension of this data and add individual fixed effects to Equation (1) above. This approach will remove all time-invariant unobserved individual characteristics, and minimize the extent to which our results are biased by, for example, selection based on ability or fixed preferences for work. For comparison purposes, we adjust the 7-point scale measure of life satisfaction in Understanding Society to be on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 corresponds to "completely satisfied".

Table 3 below first replicates the cross-sectional analysis from Table 1 in column 1 (for low-paid occupations) and column 2 (for low-paid industries). The last two columns then exploit the panel dimension of the data by adding individual fixed effects to Equation (1) for low-paid occupations (column 3) and industries (column 4). In line with our previous findings, and consistent with Clark et al. (2021), the coefficients from the panel estimations are much smaller.

Table 3: An Equation of Predicted Life Satisfaction in the cross-section (columns 1 and 2) and in the panel (columns 3 and 4)

	Life Satisfaction (0-10)	Life Satisfaction (0-10)	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.372***	0.446***	0.106	0.062***
	(0.090)	(0.052)	(0.112)	(0.006)
Female	0.031	0.035		
	(0.099)	(0.057)		
Age	-0.074***	-0.065***		
	(0.021)	(0.014)		
Age-squared/100	0.082***	0.075***		
	(0.026)	(0.018)		
Occupation fixed effects	Yes	No	Yes	No
Industry fixed effects	No	Yes	No	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	No	No	Yes	Yes
R-squared	0.04	0.04	<0.01	<0.01
N	10,209	25,696	10,159	25,227

Source: Understanding Society (2009-2019) ;
Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regressions in Columns 1 and 2 are cross-sections, and those in Columns 3 and 4 are panel with

*individual fixed effects. The regressions in Columns 1 and 3 control for 86 low-pay occupation dummies, at the 4-digit level, and those in Columns 2 and 4 control for 186 low-pay industry dummies, again at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table 4 below summarises labour-market inequality in the low-pay sector, estimated from Understanding Society data. The first panel carries out this exercise for low-paid occupations and the second panel for low-paid industries. In the cross-section, the dispersion in earnings is very similar to that from the Annual Population Survey analysis. However, the dispersion in amenities is somewhat larger using Understanding Society data, as compared to the APS results in Table 2. This may partly reflect the smaller sample sizes in Understanding Society, as well as a somewhat different time-span for the analysis. In the panel analysis of Understanding Society, we find that the inequality of amenities is much larger when individual fixed effects are added to Equation (1). This is the case for both low-paid occupations and low-paid industries, and suggests that our cross-sectional estimates may be a lower bound on the full labour-market inequality experienced by workers in the low-pay sector. The extremely large standard deviations for Full Earnings in the panel results reflect the very small income coefficients in the last two columns of Table 3.

Table 4: Important Standard Deviations using Understanding Society

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD (cross-section)	0.41	0.35	0.94	1.04
Sample Size	10,209			
SD (panel)	0.41	0.81	7.63	7.64
Sample Size	10,159			
Industries				
SD (cross-section)	0.52	0.34	0.77	0.92
Sample size	25,696			
SD (panel)	0.52	0.79	12.73	17.75
Sample size	25,227			

Source: Understanding Society (2009-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. These standard deviations are based on the regressions in Table 3, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and 3 and industries in column 2 and 4). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (columns 1 and 3, Table 3) and industries (columns 2 and 4, Table 3). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table 3). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in equation (1) above.

These small income coefficients reinforce concerns about our sample size in Understanding Society: our identification hinges on an only very small number of movers across the small cells resulting from the analysis of highly dis-aggregated occupations and industries. It is entirely possible that these movers are not a random sub-sample of low-pay workers, and outliers could play a significant role in these panel results. In a number of robustness checks in the Appendix we attempt to address these small-sample issues. In Table A11 we drop occupations with cell sizes in the bottom decile of the whole distribution, and in Table A12 we aggregate, where possible, low-pay occupations and industries to the 3-digit level. In line with the concerns outlined above, the dispersion in the panel analysis is lower in these robustness checks, but still remains larger than in the cross-section. Given the data limitations in Understanding Society, we therefore interpret these estimates with caution.

5 Heterogeneous Effects Across Disadvantaged Groups

In this section we consider how the labour-market inequality observed in the low-paid sector differs for members of disadvantaged groups and for those workers who are at the bottom of the earnings distribution.

To formally analyse how earnings and amenities differ across these groups, we follow the method used in Clark et al. (2021) and decompose the effect of different demographics on full earnings into their effect on (i) earnings and (ii) the non-pecuniary amenities in each occupation. We estimate the following three equations:

$$LogEarnings_{ik} = \gamma_0 + \gamma_1 X_i + \tau_t + \nu_{ij} \tag{5}$$

$$(\alpha_3^j/\alpha_2)_{ik} = \delta_0 + \delta_1 X_i + \tau_t + \upsilon_{ij} \tag{6}$$

$$FullEarnings_{ik} = \beta_0 + \beta_1 X_i + \tau_t + \eta_{ij} \tag{7}$$

where the coefficient vectors in Equations (5) and (6) by design sum up to the coefficients in Equation (7), so that $\gamma_1 + \delta_1 = \beta_1$ for all demographics in the vector of controls X_i, namely gender, age, and ethnicity.

Table 5.1 shows the results from estimating Equations (5) to (7) for low-paid occupations, while those in Table 5.2 refer to low-paid industries. For interpretation reasons, the estimated coefficients for the age and ethnicity categories in these two tables are calculated as deviations from the sample average.

The results show that women in the low-pay sector earn significantly less than their male counterparts, both across occupations and across industries. Furthermore, in column 2 women also experience worse amenities than do men, such that the full gender gap is significantly larger than data on earnings alone would suggest. We estimate the full gender gap to be at least twice as large as that in the earnings data, both using the occupational and industrial definitions of the low-pay sector.

Tables 5.1 and 5.2 show that younger workers are at a particular disadvantage in terms of earnings, although there is a partial degree of compensation in terms of amenities across industries. In low-paid occupations, both earnings and amenities peak between the ages 36 and 45, but the labour market inequality in both earnings and amenities falls thereafter. Similar patterns are observed in low-paid industries, although there is significantly less variation in terms of amenities.

Finally, non-white respondents earn much less than their white counterparts, and in many cases they are also penalised in terms of amenities. Again, these patterns are more pronounced across occupations but remain consistently sizable across industries. Particularly striking results are found for Bangladeshi and Black respondents, for whom the full-earnings penalty is many times lower than their earnings alone would suggest.

Table 5.1: Variation Across Low-Paying Occupations

	Log Earnings	Non-Pecuniary Aspects	Full Earnings
Female	-0.115***	-0.167***	-0.281***
	(0.004)	(0.007)	(0.008)
Age			
18-24	-0.163***	-0.044***	-0.207***
	(0.005)	(0.009)	(0.011)
25-35	0.018***	0.027***	0.045***
	(0.003)	(0.006)	(0.007)
36-45	0.067***	0.033***	0.101***
	(0.004)	(0.005)	(0.008)
46-55	0.067***	-0.001	0.066***
	(0.003)	(0.005	(0.007)
56-65	0.043***	-0.029***	0.013
	(0.004)	(0.007)	(0.008)
Ethnicity			
White	0.013***	0.016***	0.029***
	(0.001)	(0.002)	(0.002)
White Irish	0.102***	0.017	0.119
	(0.003)	(0.066)	(0.076)
Other White	-0.032***	0.003	-0.029***
	(0.005)	(0.009)	(0.011)
Mixed	0.038	-0.070	-0.032
	(0.024)	(0.047)	(0.058)
Indian	-0.033**	-0.062***	-0.094***
	(0.015)	(0.019)	(0.026)
Pakistani	-0.092***	-0.161***	-0.252***
	(0.017)	(0.025)	(0.031)
Bangladeshi	-0.099***	-0.246***	-0.345***
	(0.029)	(0.038)	(0.048)
Chinese	-0.089**	-0.137**	-0.226***
	(0.039)	(0.058)	(0.075)
Other Asian	-0.082***	-0.114***	-0.195***
	(0.021)	(0.024)	(0.033)
Black	-0.032***	-0.122***	-0.154***
	(0.010)	(0.017)	(0.022)
Other	-0.067***	-0.040*	-0.106***
	(0.014)	(0.022)	(0.027)
Occupation fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
R-squared	0.10	0.02	0.06

N	66,864	66,864	66,864

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Log Earnings is the logarithm of hourly earnings. Non-pecuniary aspects in Column 2 are estimated from Equation (1) and divided by the coefficient on earnings such that they are expressed in monetary terms. These coefficients capture the non-pecuniary aspects in each occupations/industries. Full Earnings in Column 3 are calculated as explained in Equation (1) above. To ease the interpretation of coefficients, the reference categories for age and ethnicity are the sample averages. The regressions control for 86 low-pay occupations at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table 5.2: Variation Across Low-Paying Industries

	Log Earnings	Non-Pecuniary Aspects	Full Earnings
Female	-0.118***	-0.117***	-0.235***
	(0.004)	(0.005)	(0.007)
Age			
18-24	-0.287***	0.018**	-0.269***
	(0.006)	(0.007)	(0.009)
25-35	-0.024***	0.011***	-0.013**
	(0.003)	(0.004)	(0.005)
36-45	0.116***	-0.005	0.111***
	(0.004)	(0.005)	(0.006)
46-55	0.134***	-0.016***	0.117***
	(0.004)	(0.005)	(0.006)
56-65	0.072***	-0.019***	0.053***
	(0.005)	(0.006)	(0.008)
Ethnicity			
White	0.022***	0.003**	0.025***
	(0.001)	(0.001)	(0.002)
White Irish	0.168***	-0.047	0.120**
	(0.029)	(0.033)	(0.047)
Other White	-0.054***	0.043***	-0.010
	(0.006)	(0.008)	(0.010)
Mixed	0.022	-0.060***	-0.038
	(0.025)	(0.022)	(0.037)
Indian	-0.056***	0.003	-0.053**
	(0.017)	(0.015)	(0.023)
Pakistani	-0.170***	-0.037**	-0.207***
	(0.019)	(0.018)	(0.027)
Bangladeshi	-0.175***	-0.152***	-0.327***
	(0.032)	(0.024)	(0.037)
Chinese	-0.128***	0.015	-0.114**
	(0.040)	(0.037)	(0.058)
Other Asian	-0.151***	-0.050***	-0.201***
	(0.020)	(0.037)	(0.017)
Black	-0.098***	-0.106***	-0.204***

	(0.012)	(0.011)	(0.017)
Other	-0.119***	-0.041**	-0.160***
	(0.016)	(0.019)	(0.027)
Industry fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
R-squared	0.22	0.03	0.10
N	71,835	71,835	71,835

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Log Earnings is the logarithm of hourly earnings. Non-pecuniary aspects in Column 2 are estimated from Equation (1) and divided by the coefficient on earnings such that they are expressed in monetary terms. These coefficients capture the non-pecuniary aspects in each occupations/industries. Full Earnings in Column 3 are calculated as explained in Equation (1) above. To ease the interpretation of coefficients, the reference categories for age and ethnicity are the sample averages. The regressions control for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

In the reminder of this section we consider how labour-market inequality in the low-pay sector differs for disadvantaged groups and for those at the bottom of the income distribution within the low-paid sector. Tables 6, 7, 8 and 9 present the standard deviations discussed above for workers who are are in the bottom quartile of the income distribution in the low-paid sector, for men and women, for young and older workers, and for white and non-white respondents. Tables A1, A2, A3 and A4 in the Appendix show the associated regressions of Equation (1) for each of these sub-categories. We however emphasise that the samples here are relatively small, leading to more imprecise estimates in these heterogeneity analyses than for the whole sample.

Table 6: Important Standard Deviations for those in the bottom 25% of the earnings distribution

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD	0.34	0.24	2.98	3.00
Sample size	15,366			
Industries				
SD	0.35	0.25	27.92	27.92
Sample size	16,855			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment who are in the bottom 25% of the earnings distribution. These standard deviations are based on the regressions in Table A1, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table A1) and industries (column 2, Table A1). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A1). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table 6 shows that, compared to the whole of the low-pay sector (see Table 2), workers at the bottom of the earnings distribution experience less earnings inequality but greater inequality in amenities. The lower inequality of earnings is again consistent with a positive effect of the minimum wage in reducing earnings dispersion, and confirms that these effects are largest for those who are the most likely to benefit from this policy. On the other hand, the greater dispersion of amenities for the lowest-paid workers may suggest that employers reduce non-pecuniary aspects in response to the minimum wage.

Table 7 looks at the labour-market inequality experienced by men and women in the low-pay sector. Despite the fact that women have both lower earnings and worse amenities, leading to much lower full earnings (see Tables 5.1 and 5.2), the inequality of both earnings and amenities is remarkably similar by sex. In other words, women experience worse labour-market outcomes than do men, but a similar distribution of these measures. Nonetheless, the fact that the value of amenities relative to earnings is larger for women than for men leads to somewhat greater inequality of full earnings across both low-paid occupations and low-paid sectors.

Table 7: Important Standard Deviations for men and women

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD Men	0.38	0.17	0.53	0.69
Sample size	34,508			
SD Women	0.37	0.16	1.53	1.60
Sample size	32,356			
Industries				
SD Men	0.50	0.19 0.53	0.72	
Sample size	36,064			
SD Women	0.47	0.16	0.77	0.87
Sample size	38,192			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for men and women separately. These standard deviations are based on the regressions in Table A2, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table A2) and industries (column 2, Table A2). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A2). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Tables 8 and 9 analyse labour-market inequality for young workers (18-24) and for ethnic minorities, as compared to their older or white counterparts. A rather bleak picture emerges for both of these groups of workers, who have historically been disadvantaged in the labour market. While earnings inequality alone varies little in Tables 8 and 9, young workers and ethnic minorities face a large dispersion in terms of the amenities that they experience in the low-paid sector. This inequality in amenities, coupled with the fact that both young workers and ethnic minorities appear to value non-pecuniary aspects more than earnings, leads them to experience substantial inequality in full earnings. As these groups have long been both disadvantaged in the labour market and over-represented in the low pay sector, these findings further emphasise the importance of understanding and addressing the underlying causes of this inequality.

Table 8: Important Standard Deviations for the young (18-24) and the older (25-65)

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD Young	0.38	0.29	2.07	2.13
Sample size	6,426			
SD Older	0.37	0.12	0.47	0.63
Sample size	60,438			
Industries				
SD Young	0.39	0.29	1.36	1.44
Sample size	5,897			
SD Older	0.49	0.16	0.51	0.68
Sample size	68,359			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for young and old respondents separately. These standard deviations are based on the regressions in Table A3, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table A1) and industries (column 2, Table A3). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A3). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table 9: Important Standard Deviations for white and non-white respondents

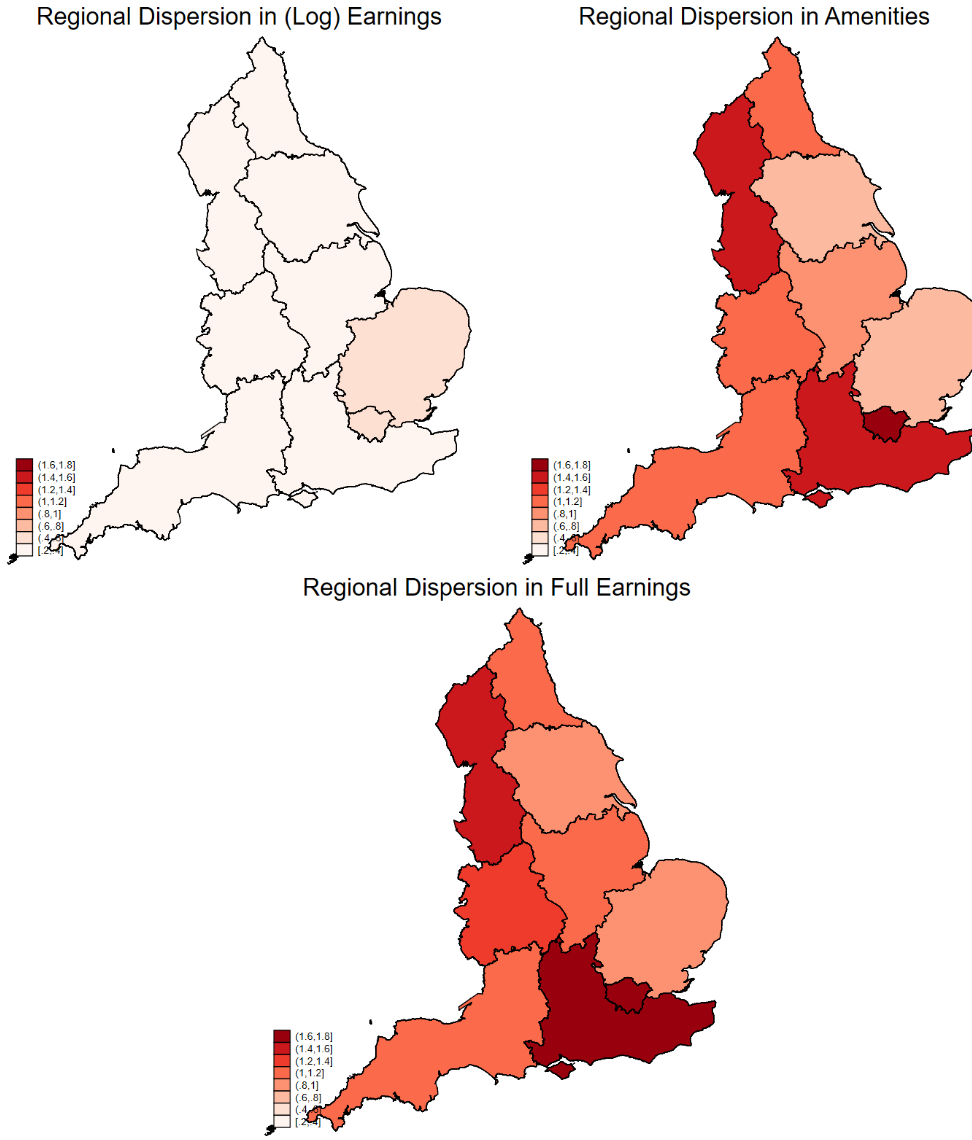
	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD White	0.38	0.14	0.57	0.73
Sample size	60,061			
SD Non-White	0.38	0.28	4.15	4.16
Sample size	6,803			
Industries				
SD White	0.49	0.16	0.50	0.69
Sample size	66,863			
SD Non-white	0.49	0.30	1.67	1.68
Sample size	7,393			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for white and non-white respondents separately. These standard deviations are based on the regressions in Table A3, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table A1) and industries (column 2, Table A3). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A3). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Finally, in the light of the levelling-up agenda and the sustained interest in spatial inequality, we estimate Equation (1) across regions and calculate the associated dispersion in amenities and full earnings.

The three maps below illustrate these dispersion figures for England, plotting the figures for intra-regional inequality in (1) earnings, (2) amenities (translated into monetary terms), and (3) full earnings in low-paid occupations. The full set of numbers for the UK, as well as the corresponding figures for low-paid industries, can be found in Appendix Table A5.

Figure 3: Intra-Regional Dispersion in Labour Market Earnings, Amenities and Full Earnings, in Low Paid Occupations



Source: Annual Population Survey (2013-2019).

London and the East of England record the largest dispersion in earnings, although overall earnings inequality is rather modest across England suggesting that the introduction of the minimum wage has been successful in tackling large intra-regional differences in wages in the Low Pay Sector. However, differences between regions are much more pronounced when amenities inequality is taken into account. London has by far the largest dispersion in the amenities that people in the Low Pay Sector experience, followed by the South East and the North West. Consequently, the bottom panel of Figure 3 shows that these regions also experience the highest Full Earnings dispersion.

Overall, we conclude that simply looking at intra-regional earnings inequality produces a relatively uniform portrait across England. However, taking data on amenities into account changes this conclusion substantially, as large regional differences are documented, with London and the South East of England recording striking levels of inequality in terms of the amenities that workers in the Low Pay Sector experience.

6 Introduction of the National Living Wage

Our third and last objective appeals to the time dimension of our data. The introduction of the National Living Wage in 2016 led to higher wages. This policy change provides us with a natural experiment from which we can see how an exogeneous increase in earnings relates to changes in the amenities that workers experience in the low-pay sector.

Using the Annual Population Survey, we carry out a before-after analysis to identify the effect of the National Living Wage, following its introduction in 2016. This will allow us to establish the short- and medium-run consequences of this policy change in the low-pay sector. We will do so by allowing our estimates for non-wage benefits in low-paying occupations and industries to vary over time. We thus estimate Equation (1) separately before and after the introduction of the National Living Wave, and so allow the coefficients on both earnings and amenities (the well-being residual in each low-paid occupation and industry, net of the effect of earnings and demographics) to differ between these two periods. The comparison of the estimates before and after the policy change (net of a general time-trend) will help us provide a more causal interpretation of the effect of minimum wages.

Table 10 below shows how the dispersion in earnings and amenities differs before and after the introduction of the National Living Wage, both across low-paid occupations and industries.

Table 10: Important standard deviations before (2011-2015) and after (2016-2019) the introduction of the National Living Wage

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD before NLW	0.38	0.16	0.71	0.84
Sample size	33,919			
SD after NLW	0.38	0.17	0.71	0.83
Sample size	32,945			
Industries				
SD before NLW	0.49	0.18	0.59	0.76
Sample size	37,346			
SD after NLW	0.48	0.17	0.60	0.75
Sample size	36,910			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. The standard deviation of Log Earnings is calculated at the respondent level, in each sample, before and after the introduction of the NLW. The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations and industries before and after the introduction of the NLW. These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings. The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained above and by estimating Equation (1) before and after the introduction of the NLW.

The main conclusion is that the introduction of the National Living Wage did not materially affect the labour-market inequality experienced by workers in the low-pay sector: both the dispersion in earnings and the dispersion in amenities are remarkably stable across these two periods. In Table A10 in the Appendix we replicate this analysis for those workers who are in the bottom 25% of the earnings distribution, who were more likely to be directly impacted by changes to the National Living Wage. We continue to find that the introduction of the National Living wage had little effect on the observed inequality of earnings and amenities in the low-pay sector. We do note, however, that our findings relate to only a relatively short time period (2016-2019) over which any changes can be observed, and employers may require some time to adjust.

7 Recommendations and Conclusions

In this policy report, we have argued that to fully understand the impact of the minimum wage on low-paid workers it is necessary to take into account labour-market outcomes beyond wages and employment. We have here considered the non-pecuniary aspects of jobs, and shown how these are related to earnings in 86 low-paid occupations and 176 low-paid industries.

Our main finding is that wages and amenities in the low-pay sector are related in the same way as in the rest of the UK economy. In line with the findings in Clark et al. (2021), we find a positive correlation between earnings and amenities. In other words, there is no evidence that workers in the low-pay sector are compensated with better amenities. According to our analysis, even within the low-pay sector there is more inequality in labour-market outcomes than earnings alone would suggest.

However, the sources of inequality in the low-pay sector are different to those for the whole UK economy. While the amenities inequality in the low-pay sector is very similar to that experienced by workers in the rest of the economy, the earnings inequality there is lower than that found for the whole economy, consistent with the minimum wage compressing the bottom of the earnings distribution. Robustness checks using panel data indicate that this inequality cannot be entirely explained by the selection of workers into these types of jobs, and is at best a lower bound on the full level of labour-market inequality experienced by workers in the low-pay sector.

In terms of the types of jobs that are particularly good or particularly bad for the wellbeing of low-paid workers, our descriptive analysis indicates that retail and manufacturing jobs come with very low levels of amenities, as reported by the workers themselves. On the contrary, less-routine jobs and work that requires more outdoor activities both have higher than average amenities, such that the full earnings of workers in these jobs are higher than their earnings alone would suggest.

As for the whole economy, we have found that members of disadvantaged groups have particularly poor outcomes in the low-pay sector. Women, young people, and ethnic minorities have both lower earnings and lower amenities. This indicates that the gender, ethnic and age gap in the labour market is even larger than the incomes of these groups alone would suggest. In terms of the inequality experienced by these groups, the picture is particularly bleak for young workers and ethnic minorities. While men and women in the low-paid sector experience similar dispersion in both earnings and amenities, young workers and members of ethnic minorities experience significant inequality which is almost entirely driven by inequality in non-pecuniary outcomes.

With the levelling-up agenda in mind, we have also considered how labour-market inequality in the low-paid sector differs across regions in England. The dispersion in amenities is particularly severe in London and in the South of England, and the regional variation in earnings dispersion maps only poorly onto the regional variation in terms of full-earnings dispersion.

Last, we considered whether our findings are sensitive to the introduction of the National Living Wage in 2016. There is no evidence that this policy change significantly affected labour-market inequality in the low-pay sector, either in terms of earnings or amenities. However, we do note that the time span of our analysis is relatively short. Furthermore, the fact that we are analysing the response in the low-pay sector overall, as opposed to the specific workers who were directly affected by this change may make it more difficult for our empirical analysis to pick up relatively small changes in labour-market inequality in this context.

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Appendix

Table A1: An Equation of Predicted Life Satisfaction for those in the bottom 25% of the earnings distribution

	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.081	-0.009
	(0.058)	(0.053)
Female	0.199***	0.148***
	(0.046)	(0.039)
Age	-0.060***	-0.040***
	(0.010)	(0.009)
Age-squared/100	0.064***	0.040***
	(0.012)	(0.012)
Occupation fixed effects	Yes	No
Industry fixed effects	No	Yes
Wave fixed effects	Yes	Yes
R-squared	0.04	0.04
N	15,366	16,855
SD dependent	1.88	1.84

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regression in Column 1 controls for 86 low-pay occupations at the 4-digit level. The regression in Column 2 controls for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment, who are in the bottom 25% of the earnings distribution. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A2: An Equation of Predicted Life Satisfaction for men and women

	Life Satisfaction (0-10) Men	Life Satisfaction (0-10) Men	Life Satisfaction (0-10) Women	Life Satisfaction (0-10) Women
Log Earnings	0.313***	0.351***	0.104***	0.210***
	(0.034)	(0.023)	(0.036)	(0.025)
Age	-0.073***	-0.055***	-0.039***	-0.032***
	(0.007)	(0.007)	(0.007)	(0.007)
Age-squared/100	0.082***	0.060***	0.039***	0.031***
	(0.008)	(0.008)	(0.009)	(0.008)
Occupation fixed effects	Yes	No	Yes	No
Industry fixed effects	No	Yes	No	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
R-squared	0.03	0.04	0.02	0.02
N	34,508	36,064	32,356	38,192
SD dependent	1.66	1.57	1.77	1.69

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions, run separately for men and women. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regressions in Columns 1 and 3 control for 86 low-pay occupations at the 4-digit level. The regressions in Columns 2 and 4 control for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A3: An Equation of Predicted Life Satisfaction for the young (18-24) and the older (25-65)

	Life Satisfaction (0-10) Less than 25	Life Satisfaction (0-10) Less than 25	Life Satisfaction (0-10) 25 or older	Life Satisfaction (0-10) 25 or older
Log Earnings	0.141***	0.215***	0.260***	0.308***
	(0.068)	(0.065)	(0.026)	(0.017)
Female	0.065	0.065	0.088***	0.054***
	(0.056)	(0.053)	(0.022)	(0.017)
Age	-0.690**	-0.345	-0.058***	-0.060***
	(0.320)	(0.331)	(0.007)	(0.006)
Age-squared/100	1.496*	0.640	0.063***	0.063***
	(0.747)	(0.772)	(0.008)	(0.007)
Occupation fixed effects	Yes	No	Yes	No
Industry fixed effects	No	Yes	No	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
R-squared	0.06	0.06	0.02	0.03
N	6,426	5,897	60,438	68,359
SD dependent	1.53	1.49	1.73	1.64

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions, ran separately for young (18-24) and older respondents (25-65). Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regressions in Columns 1 and 3 control for 86 low-pay occupations at the 4-digit level. The regressions in Columns 2 and 4 control for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A4: An Equation of Predicted Life Satisfaction for white and non-white respondents

	Life Satisfaction (0-10) White	Life Satisfaction (0-10) White	Life Satisfaction (0-10) Non-White	Life Satisfaction (0-10) Non-White
Log Earnings	0.254***	0.310***	0.067	0.182***
	(0.026)	(0.018)	(0.086)	(0.059)
Female	0.101***	0.061***	-0.005	0.012
	(0.022)	(0.018)	(0.066)	(0.056)
Age	-0.061***	-0.047***	-0.039*	-0.038**
	(0.005)	(0.005)	(0.017)	(0.017)
Age-squared/100	0.066***	0.050***	0.044**	0.044**
	(0.006)	(0.006)	(0.021)	(0.021)
Occupation fixed effects	Yes	No	Yes	No
Industry fixed effects	No	Yes	No	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
R-squared	0.02	0.03	0.05	0.06
N	60,061	66,863	6,803	7,393
SD dependent	1.69	1.61	1.89	1,81

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions, run separately for those of white ethnicity and those of another ethnicity. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regressions in Columns 1 and 3 control for 86 low-pay occupations at the 4-digit level. The regressions in Columns 2 and 4 control for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A5: Important Standard Deviations across UK Regions

	Earnings	Amenities (Unadj.)	Amenities (Adj.)	Full Earnings	N
Occupations					
North East	0.37	0.26	1.07	1.12	4,805
North West	0.36	0.27	1.41	1.49	7,111
Merseyside	0.39	0.45	4.23	4.29	1,753
Yorkshire & Humberside	0.36	0.27	0.72	0.81	6,258
East Midlands	0.38	0.29	0.95	1.05	4,009
West Midlands	0.38	0.30	1.13	1.21	5,153
Eastern	0.40	0.28	0.74	0.88	4,207
London	0.42	0.26	1.65	1.72	4,462
South East	0.39	0.29	1.56	1.66	6,867
South West	0.37	0.26	1.05	1.11	5,461
Wales	0.38	0.23	0.81	0.90	7,211
Scotland	0.37	0.27	1.83	1.90	9,567
Industries					
North East	0.46	0.31	0.94	1.05	4,874
North West	0.47	0.30	0.76	0.88	7,519
Merseyside	0.49	0.47	1.69	1.76	1,922
Yorkshire & Humberside	0.46	0.34	0.94	1.03	6,718
East Midlands	0.49	0.36	1.04	1.12	4,175
West Midlands	0.49	0.34	0.98	1.10	5,370
Eastern	0.51	0.38	2.06	1.17	4,859
London	0.54	0.25	1.31	1.39	5,883
South East	0.54	0.29	0.98	1.15	8,370
South West	0.47	0.31	0.90	0.98	6,208
Wales	0.46	0.25	0.96	1.05	7,914
Scotland	0.45	0.27	0.99	1.08	10,444

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time. The standard deviation of Log Earnings is calculated at the respondent level, in each region. The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations and industries, by estimating Equation (1) for each region. These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings. The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained above and by estimating Equation (1) for each region.

Table A6: An Equation of Predicted Life Satisfaction in the Non-Low Pay Sector

	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.207***	0.243***
	(0.009)	(0.008)
Female	0.052***	0.043***
	(0.009)	(0.009)
Age	-0.054***	-0.051***
	(0.003)	(0.003)
Age-squared/100	0.053***	0.051***
	(0.003)	(0.003)
Occupation fixed effects	Yes	No
Industry fixed effects	No	Yes
Wave fixed effects	Yes	Yes
R-squared	0.02	0.03
N	215,378	215,108

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regression in Column 1 controls for 283 non low-pay occupations at the 4-digit level. The regression in Column 2 controls for 430 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A7: Important Standard Deviations in the Non-Low Pay Sector

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD	0.52	0.13	0.61	0.83
Sample Size	215,378			
Industries				
SD	0.52	0.12	0.49	0.68
Sample Size	215,108			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. These standard deviations are based on the regressions in Table 1, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (columns 1 Table A6) and industries (columns 2 Table A6). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A6). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table A8: An Equation of Predicted Life Satisfaction including Part-Time Workers

	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.191***	0.267***
	(0.018)	(0.014)
Female	0.145***	0.099***
	(0.016)	(0.014)
Age	-0.066***	-0.054***
	(0.003)	(0.003)
Age-squared/100	0.075***	0.060***
	(0.004)	(0.004)
Occupation fixed effects	Yes	No
Industry fixed effects	No	Yes
Wave fixed effects	Yes	Yes
R-squared	0.02	0.02
N	123,417	125,317

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regression in Column 1 controls for 86 non low-pay occupations at the 4-digit level. The regression in Column 2 controls for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A9: Important Standard Deviations including Part-Time Workers

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD	0.38	0.13	0.66	0.80
Sample Size	123,417			
Industries				
SD	0.48	0.13	0.49	0.69
Sample Size	125,317			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. These standard deviations are based on the regressions in Table 3, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (columns 1 Table A8) and industries (columns 2 Table A8). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A8). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table A10: Important standard deviations before (2011-2015) and after (2016-2019) the introduction of the National Living Wage

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD before NLW	0.33	0.28	4.41	4.42
Sample size	7,714			
SD after NLW	0.36	0.30	2.51	2.53
Sample size	7,696			
Industries				
SD before NLW	0.33	0.33	9.04	9.04
Sample size	8,838			
SD after NLW	0.36	0.29	8.78	8.81
Sample size	8,406			

Source: Annual Population Survey (2013-2019);
Notes:These figures are calculated for respondents aged 18 to 65 in full-time, whose earnings fall in the bottom 25% in the low-pay sector. The standard deviation of Log Earnings is calculated at the respondent level, in each sample, before and after the introduction of the NLW. The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations and industries before and after the introduction of the NLW. These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings. The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained above and by estimating Equation (1) before and after the introduction of the NLW.

Table A11: Important Standard Deviations using Understanding Society (Restricted Sample)

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD (cross-section)	0.41	0.24	0.64	0.78
Sample Size	9,202			
SD (panel)	0.41	0.64	9.31	9.30
Sample Size	8,912			
Industries				
SD (cross-section)	0.52	0.26	0.56	0.76
Sample size	23,135			
SD (panel)	0.52	0.62	6.30	6.33
Sample size	23,135			

Source: Understanding Society (2009-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment, excluding the bottom 10% of low paid occupations and industries in terms of size. The standard deviation of Log Earnings is calculated at the respondent level. The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations and industries from a regression of Equation (1) on this restricted sample. These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings. The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table A12: Important Standard Deviations using Understanding Society (Aggregated Sample)

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD (cross-section)	0.41	0.20	0.53	0.68
Sample Size	10,209			
SD (panel)	0.41	0.46	8.60	8.61
Sample Size	10,209			
Industries				
SD (cross-section)	0.52	0.20	0.46	0.70
Sample size	25,696			
SD (panel)	0.52	0.59	8.89	8.93
Sample size	25,615			

Source: Understanding Society (2009-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment, by aggregating low paid occupations and industries at the 3-digit level. The standard deviation of Log Earnings is calculated at the respondent level. The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations and industries from a regression of Equation (1) on this restricted sample. These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings. The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.

Table A13: An Equation of Predicted Life Satisfaction with Area Fixed Effects

	Life Satisfaction (0-10)	Life Satisfaction (0-10)
Log Earnings	0.272***	0.306***
	(0.027)	(0.020)
Exogenous demographics	Yes	Yes
Occupation fixed effects	Yes	No
Industry fixed effects	No	Yes
Area fixed effects	Yes	Yes
Wave fixed effects	Yes	Yes
R-squared	0.04	0.04
N	57,296	58,850
SD dependent	1.721	1.653

Source: Annual Population Survey (2013-2019);
*Notes: These are OLS regressions. Life Satisfaction in measured on an 11-point scale, where 0 corresponds to "not at all satisfied" and 10 correspond to "completely satisfied". Log Earnings is the logarithm of hourly earnings. The regression in Column 1 controls for 86 low-pay occupations at the 4-digit level. The regression in Column 2 controls for 176 low-pay industries at the 4-digit level. The sample is restricted to respondents aged 18 to 65 in full-time employment. Heteroscedasticity-robust standard errors appear in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.*

Table A14: Important Standard Deviations with Area Fixed Effects

	Earnings	Amenities (unadjusted)	Amenities (adjusted)	Full Earnings
Occupations				
SD	0.38	0.14	0.50	0.66
Sample Size	57,296			
Industries				
SD	0.48	0.15	0.48	0.68
Sample Size	58,850			

Source: Annual Population Survey (2013-2019);
Notes: These figures are calculated for respondents aged 18 to 65 in full-time employment. These standard deviations are based on the regressions in Table 1, in the following way. The standard deviation of Log Earnings is calculated at the respondent level, in each sample (occupations in column 1 and industries in column 2). The standard deviation of non-pecuniary aspects in calculated by looking at the distribution of the coefficients on occupations (column 1, Table A14) and industries (column 2, Table A14). These coefficients capture the non-pecuniary aspects in each occupations/industries, and are translated into monetary terms by dividing each coefficient by the coefficient on Log Earnings (see Table A14). The standard deviation of Full Earnings is calculated by looking at the distribution of Full Earnings, calculated as explained in Equation (1) above.