Working Towards an Environmentally Sustainable and Equitable Future? New Evidence on Green Jobs from Linked Administrative Data in the UK

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Abstract:

Given the urgency to transition to net-zero, there is a need for a robust evidence-base to support an environmentally sustainable and equitable changeover. However, intelligence on green jobs and their impact on different groups is lacking. This study examines the dynamics of green jobs, leveraging a novel linked dataset that combines detailed occupational, industry, demographic and pay information from 2011 to 2018. By employing both cross-sectional and panel estimation techniques, we provide a wide-ranging analysis of employment in green occupations. The results indicate that individuals are more likely to work in green occupations if they are white, male, fulltime, not in a trade union and work for a small or foreign owned business. There is a pay premium for working in green occupations, which reduces gender and ethnic pay gaps. However, conditional on working in a green occupation, gender and ethnic pay gaps persist. This implies that to have a fair and just transition to net-zero, policy interventions are required to address the dual inequality of opportunity and pay.

Keywords:

fair and just; green jobs; inequality; multivariate quantitative methods; net zero; pay gap

1. Introduction

The climate crisis and environmental emergency is potentially the greatest challenge faced by the global community. International governments have set ambitious plans to transform to a net zero economy, with the UK targeting 2050 (BEIS, 2021).

"Green jobs" are at the core of this transition and will have an important role in both developing and delivering environmental management strategies that promote sustainable economic development and cleaner production. At the same time, this evolution provides an opportunity to address embedded labour market inequalities to support a fair and just transition.

To support a fair and just transition to net zero, government and businesses need to develop policy and strategy which is based on a robust and reliable evidence base, but which at present is lacking (Skidmore, 2022). Outside of the US, the financial returns of working in a green job are under-researched. This creates a social and environmental cost, as it limits the incentive for individuals to transition to green employment. Green jobs have the potential to serve as a catalyst for social equity, but little is known about how the transition is impacting different groups.

This article uses England and Wales as a case study to explore green jobs by exploring the following research questions:

[1] What are the characteristics of those that work in green jobs?
[2] How do job and employer characteristics affect the likelihood of being in a green job?
[3] Can working in a green job go some way to offsetting the gender and ethnic pay gap?
[4] To what extent are gender and ethnic pay gaps embedded within green jobs?

New knowledge is presented about the attributes of those who work in green occupations and the firms who are most likely to employ those individuals. The research uses a novel linked administrative dataset based on high quality, employer provided earnings information to estimate the economic benefit of working in a green occupation. For the first time, the large-scale employer-employee dataset allows for the control of individual, job and employer characteristics. The research adds to the international literature of pay in green jobs, estimating a positive pay premium for those working in green jobs. The results show that those working in green jobs are less likely to be represented by collective agreements (e.g. trade union membership), but those that do, receive a pay premium. Finally, the research provides an original contribution revealing that working in a green occupation can offset some of the inter-occupation pay gap, while revealing that the pay gap within green occupations persist. The study emphasises the need for inequalities to be captured by theory that attempts to understand and conceptualise the uptake of green jobs, while also making a practical contribution by providing evidence-based policy recommendations.

2. Theory

2.1 Green jobs: definition and measurement

The theoretical foundation of the green economy covers a variety of concepts, which includes environmental economics and ecological economics. Much of the focus has been on renewable energy, resource efficiency, low carbon technologies, circular economy and cleaner production. However, given the diverse nature of the green economy, the measurement of green jobs has been challenging and has varied based on the criteria used to define it.

There is currently no international consensus as how to define and measure a green job, (Bowen et al, 2018; Sulich 2020). Rodriguez (2019) reports the task as under permanent construction with no bounded content and meaning. Van der Ree (2019) argues that green jobs can be viewed from two perspectives, through the lens of final output or through the production process.

There are several different approaches that can be used to explore green jobs, these include looking at jobs within green industries; jobs within businesses operating in a green way; and/or green jobs within businesses or industries of any kind. Theoretically, these different approaches can generate vastly different estimates of green jobs. This lack of consistency has impacted on the breadth and depth of research into green jobs, while making it difficult to compare the results between studies and across borders.

In response to recommendations in the UK's Green Jobs Taskforce report (2021), and to create a consistent data collection framework within the UK, the Office for National Statistics (ONS) have recently published their revised definition of a green job:

> "Employment in an activity that contributes to protecting or restoring the environment, including those that mitigate or adapt to climate change." (ONS, 2023a, p.3)

The definition was arrived at following a wide-ranging consultation and substantial stakeholder engagement. ONS have produced experimental estimates based on this agreed definition, providing estimates for three approaches: industry-based, occupation-based, and firm-based (ONS, 2024). In a separate publication, ONS also provide estimates of the size of the UK's Low Carbon and Renewable Energy Economy (LCREE).

In the UK, as data will be collected using this consistent definition, comparisons between studies will become more meaningful. However, when analysing internationally and using UK historic data series, other approaches are still required.

One such approach is to apply the definitions developed by the O*NET green tasks development project (2010), who began investigating the impact of "green economy" and its effect on green employment. As such, the approach used in this study is to apply the definitions developed by the O*NET green tasks development project (2010). O*NET define the "green economy" as:

> "economic activity related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emission, increasing the efficiency of energy use, recycling materials, and developing renewable sources of energy." (p.3)

This led to identifying 12 green economic sectors, which were home to 138 directly green occupations.

2.2 Green jobs: industrial transition

Much has been written about the green industrial restructuring, with Zachmann, et al., (2018) emphasising the need for a just transition, focussing on the distributional effects for workers in terms of both sector and place. In order to better understand the industrial transition to the green economy, researchers have applied several different methodological approaches. Quantitatively one approach that has been applied is to use computable generable equilibrium models (e.g. Maxim and Zander, 2020). These models can be useful in aiding the understanding of how an economy adjusts to changes in policy, technology, and other external factors. Others have developed input-output models, which are particularly useful when exploring the relationships between different industries of the economies (e.g. Bagheri et al., 2018; Garrett-Peltier). Multivariate analysis has also been used by several researchers (e.g. Aldieri et al., 2019; Ciocirlan, 2023; Pinzone et al., 2019; Unay-Gailhard and Bojnec, 2019), as it can help in providing a more nuanced understanding of the relationships between various factors affecting green jobs. This study builds on this multivariate approach, being particularly helpful when exploring issues of inequality, enabling an exploration of the diverse and interconnected factors that influence green jobs.

Studies on wage effects of green employment tend to focus on the US economy. For example, Vona et al. (2019) estimate that US green employment tends to be highly skilled and commands a wage premium of 4%. Bowen et al. (2018) applied the O*NET data to the US labour market and estimated that around 20% of jobs were either directly or indirectly green. They reported simple wage averages to show that green jobs, which were either new or emerging, were higher paid, regardless of skill level. Kim and Jeong (2016) conducted an analysis in relation to the electricity sector in the US and its relationship to greenhouse gas efficiency and the employment reallocation. They reported a positive feedback relationship between employment and wages. Outside of the US, Antoni et al. (2015) estimated a wage premium in relation to renewable energy related jobs in Germany. Their results showed that renewable energy establishments pay considerably more than non-renewable.

The lack of green jobs wage research has in some part been due to the lack of high-quality, large scale and longitudinal data on which to base such studies. In the UK, however, given the challenges of identifying "green jobs" in the UK's large scale labour market surveys, one approach has been to use the US O*NET data to identify green occupations and green tasks. This requires the linking of US occupation classifications with UK occupation classifications.

There have been two notable studies that have used the O*NET data in some detail to explore green jobs in the UK economy. In one study, ONS combine O*NET data with the Annual Population Survey, and the Annual Survey of Hours of Earnings (ASHE) to estimate the amount of time spent doing green tasks (Martin and Monahan, 2022). This innovative approach used information on the importance and relevance of task to provide aggregate estimates of time spent green jobs.

The authors highlight that a strength of this task and occupation-based approach is that it is a broad measure, capturing those in occupations not classed within green industries and sectors. The authors, however, point to potential issues including assuming that tasks undertaken within occupations are the same within the US and UK; the potential for mis-mapping from US to UK occupation codes; and the potential to overlook variations within occupations, where factors like the firm, industry, or specific job role can influence the amount of time spent on green tasks. This study differentiates itself as results from the ONS study were confined to estimates of time spent on green tasks, with results reported just at the national and sector level, with no reference to the characteristics of those employees and employers involved with green tasks, and no reference to pay.

A further UK based study was Valero et al. (2021) which combines the O*NET data with the UK's Labour Force Survey (LFS) to provide a disaggregated view of green jobs and an estimate of pay. This study extends this approach through its application to the higher quality ASHE data[1], which is based on a much larger mandatory employer survey, giving a greater sample (1% of those in employment – circa 180,000). The ASHE data also uses accurate employer payroll data, rather than self-reported information in the LFS, which is subject to rounding and recall bias. In addition, by linking the O*NET, ASHE and Census 2011 datasets, this study is able to take firm characteristics into account for the first time when making estimates of pay premiums. It further provides novel findings as it explores the effect of green employment on ethnic groups, while exploring other nuanced, detailed individual

[1] ASHE has much larger sample size than the LFS, is a mandatory survey filled in by employees which is linked to employer, it includes high quality hourly pay and working time information, and combined with Census 2011, allows for a rich set of individual and household characteristics to be explored for the very first time in relation to green and brown jobs.

and company characteristics such as whether an individual is covered by collective bargaining, or whether the company is in foreign ownership.

3. Material and Methods

3.1 Data

The main data sources for the analysis are ASHE, ASHE linked to Census 2011, and O*NET. ASHE is an employee-employer dataset, it allows for characteristics of the firm to be accounted for within the analysis. Having wage and hours data is a significant improvement from the self-reported estimates available in the LFS data, as ASHE reports precise earnings reported directly by the employer from payroll data. Self-selection bias is limited as employers are mandatorily required to supply this data in response to a statutory request from the UK's National Statistics Authority. As gender is already accounted for in the ASHE dataset, in order to maximise sample sizes, gender breakdowns are calculated using ASHE data only.

However, an additional benefit is derived by linking the payroll-based ASHE to the 2011 Census of England and Wales. This allows for a rich set of personal and family characteristics for employees from the Census to be added to the accurate components of pay and employer identification coming from the ASHE. After linking the Census to ASHE, the database contains around 0.5 percent of the population of employees in England and Wales in 2011, albeit there is attrition in the match rate as this linkage is applied to ASHE data over time[2].

The ethnicity breakdowns are calculated using ASHE linked to Census estimates. As such, in 2011 180,000 ASHE only observations are reduced to 121,000 observations when matched with Census. By 2018, the number of ASHE Census 2011 observations are reduced to 76,000 reflecting the attrition over the seven-year period, combined with the fact that joiners and leavers of the ASHE survey since 2011 are excluded from the linked dataset. The authors note that this could be a potential source of sample bias, if either the match rate, attrition rate and/or profile of those joining/leaving is not random.

This matching, however, enables a detailed look at the demographic characteristics of those individuals working in green jobs, enabling first estimates to be made of any pay premiums or penalties incurred by different groups working in green jobs in the UK.

Our analysis benefits from the fact that the wage estimates are based on high quality employer payroll data. Using the O*NET data allows us to assess whether these vary according to different types of green occupations. Thus, this research provides the most comprehensive picture of green jobs in England and Wales, providing new evidence which can support the creation of more effective strategies to foster the growth of sustainable industries and incentivise the creation of green jobs.

We report estimates from the ASHE and ASHE-Census data. ASHE theoretically covers the whole of the UK, but fieldwork for Northern Ireland is conducted separately and is therefore not included here. The ASHE linked with the Census 2011 data only includes estimates for England and Wales, and therefore any estimates reported using this data source will exclude Scotland.

[2] This results from a match rate between ASHE and Census of 74% in 2011, which reduces to approximately 48% in 2018 – see Forth et al. (2022) for further information on the linking process.

The analysis and classification of green jobs at the task and occupational level in existing literature predominantly relies on the framework developed by the O*NET system in the United States. The O*NET database facilitates the classification of occupations based on the environmental relevance of their associated tasks, utilising a broad definition of green jobs across 12 sectors identified as significantly impacted by decarbonization efforts. O*NET designates any occupation influenced by the greening process as a green job. In line with this methodology (see Valero et al., 2021) an occupation based, bottom-up approach is used to identifying green jobs in the UK.

The value of the task and occupation-based approach is that it captures green employment across sectors. This, therefore, broadens the definition of green jobs beyond those just working in green industries. The main limitation of this study, however, is that it makes the key assumption that tasks undertaken within occupations are the same in the UK and US, and that those occupations considered green in the US are also considered green in the UK.

O*NET uses a concept of the “green economy”[3] and “greening of occupations”[4], which informs the development of the three green occupational categories which are used in this analysis – Green New and Emerging (GN&E), Green Enhanced Skills (GES) and Green Increased Demand (GID). For the two directly green categories (GN&E and GES), O*NET provides a green task statement; GID does not directly have any green tasks as they relate to increased demand due to the greening of the economy. Given the indirect nature of these type of green jobs, to distinguish the findings, the analysis includes results for all categories, separating out directly and indirectly green occupations.

Once the green occupations in the US are identified from the US O*NET dataset, they are then mapped to the UK via an occupation code using international occupation classification. Annual updates capture "greening" within occupations, reflecting changes over time of activity for each occupation. In total, ONET-SOC at the 8-digit level identifies over 200 green occupations. The occupational classification system used in the UK Annual Survey of Hours and Earnings (ASHE) is the UK Standard Occupational Classification (UK SOC) 2010, which contains 369 occupations at the four-digit level.

We employ a direct crosswalk between the ONET-SOC (8-digit) and UK SOC systems, developed by the 'LMI for All' data portal and funded by the UK Department for Education (LMI For All, 2019). The mapping is complex, resulting in multiple matches between US and UK occupations. The classification is represented as a binary variable, where 0 indicates non-green and 1 indicates green. This approach results in a broad classification of greenness, as UK occupation codes are more aggregated compared to the detailed O*NET occupations they are mapped to. Consequently, whole occupational categories in the UK may be classified as green even if only a single sub-category is considered green in O*NET. These estimates are therefore considered a maximum.

In order to address this potential limitation, a revised weighted continuous measure is also constructed to provide a more cautious estimate of green jobs. In line with Dickerson and Morris (2019), weights were created to account for the US employment share of all matched occupations to

[3] The green economy encompasses the economic activity related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy. (p.3)

[4] The “greening” of occupations refers to the extent to which green economy activities and technologies increase the demand for existing occupations, shape the work and worker requirements needed for occupational performance, or generate unique work and worker requirements. (p.4)

each UK occupation at the two-digit level. In addition, to avoid double counting of US O*NET occupations being matched to multiple UK occupations, and in line with methodology employed by Valero et al (2021), we further weight the estimates using the UK employment share of those occupations.

An example of this approach is follows:

- A UK occupation (OCC1) has three US occupations attached to it, one of which is green. The US green occupation accounts for 20% of the employment from the three US occupations matched to the UK occupation.
  - OCC1 initial weighted = 1 * 0.2
- The US green occupation is mapped to two UK occupations (OCC1 and OCC2). The employment share between OCC1 and OCC2 is 40% and 60% respectively.
  - Therefore, the final estimate for OCC1 = 0.2 * 0.4 = 0.08

In the regression analysis, both binary and continuous measures of greenness are used to test the robustness of the results. However, the preferred measure reported in the main study uses the continuous variable.

The O*NET data is matched to the ASHE occupational data using the 2010 UK standard Occupational Classification at the four-digit level and then linked to the payroll-based ASHE to the 2011 Census of England and Wales. As such, this allows for a rich set of personal and family characteristics for employees from the Census to be added to the accurate components of pay and employer identification coming from the ASHE.

3.2 Calculation

The data begins in 2011 as this was the first year for which O*NET data is available and the year that the ASHE data was initially linked to Census 2011. ASHE linked to Census 2011 data is available each year until 2018, with the descriptive analysis being based on the latest year (2018).

Cross sectional analysis is also applied to the latest data (2018) to exploit the individuals' (fixed and semi-fixed) characteristics, which are added by linking to the Census data. In this study gender is used as a fixed binary category which does not change overtime, a limitation imposed due to data restrictions.

A fixed effect model is used for the full panel (2011-2018), addressing issues of endogeneity by accounting for all time-invariant characteristics of the individuals (e.g. ability). This approach allows for a focus on the net effect of the variables that change over time.

For robustness, two different measures of green occupations (i.e. binary or continuous but bounded between 0 and 1) are used to estimate several cross sectional and panel models (e.g. Ordinary Least Squares, Censored Tobit, Logit). The preferred specification uses the continuous measure of green jobs, as the binary approach is likely to overestimate green employment.

In the simplest form, the (cross-sectional) model is estimated as:

$$Y_i = \beta X_i + \beta Z_i + \beta F_i + \beta S_i + \beta R_i + \beta I_i + \epsilon_i \qquad (1)$$

Where Y_i is a marker of an individual working in a green occupation. When using the continuous measure, it can be conceptualised as representing either the greenness of the occupation, or a weighted probability of working in a green occupation.

The dependent variable is replaced with its constituent parts (GN&E, GES and GID) to explore the effects for different types of green occupations. The vector X includes individual characteristics, while job characteristics are captured in vector Z. The set of firm characteristics are captured in vector F, while S, R and I capture sector, region and Interaction terms respectively. To account for the fact that observations within the same occupation group may be correlated, all models are estimated by clustering the standard errors by occupation. A list of variables used in the regression is included in Appendix A.

In the cross-sectional analysis of likelihood of working in a green occupation, a censored Tobit model is used in order to account for the fact that the dependent variable is bounded between 0 and 1. To estimate the panel fixed effects model of working in a green job, the preferred specification uses a Logit Fractional Response Model (FRM). To estimate the FRM, the bounded estimates of 0 and 1 are transformed to 0.0001 and 0.9999 respectively. The benefit of using the Logit model is that it accounts for unobserved heterogeneity across individuals, ensuring that the predicted values remain within the bounded interval, and is intuitive in its interpretation. The Logit model estimated is as follows:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right)_i = \alpha_i + \gamma_{it}\beta + \epsilon_{it} \qquad (2)$$

In the model, $\log\left(\frac{p_{it}}{1-p_{it}}\right)$ is the natural logarithm of the probability of individual *i* working in a green occupation at time t. and γ_{it} is a vector of explanatory variables.

For the pay premium regressions, log of real hourly wage is the dependent variable (Y). A continuous measure of green occupations is used to explore whether there is a pay premium or pay penalty for working in a green occupation. A stepwise approach is used, adding various vectors of controls (i.e. individual, job, firm, sector, region and interactions). The initial (cross-sectional) model estimated is as follows:

$$logY_i = \alpha_i + G_i\beta 1 + \epsilon_i \qquad (3)$$

$logY_i$ represents the log of real basic hourly pay. β1 is the coefficient for the greenness of the occupation.

Following this, the model is rerun for just those individuals working in green occupations, in order to gain a better understanding of how certain characteristics impact on pay for those working in green jobs. Again, both the cross section and panel estimations are used.

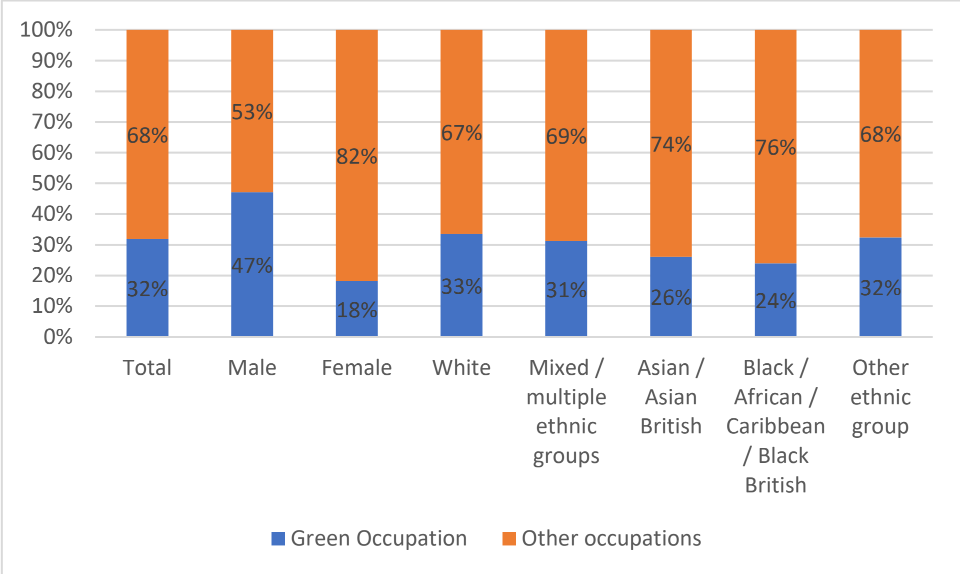
4. Results and Discussions

4.1 Descriptive analysis

4.1.1 Green occupations

Figure 1 uses the binary measure of green jobs and reveals that 32% of occupations were classed as being green in 2018. Albeit when the (preferred) continuous measure is used approximately 16% of all occupations are green. These estimates are in line with those of Bowen et al. (2018) and Valero et al. (2021) who estimated an overall share of the green employment being 19% in the US and 17% in the UK (using LFS data) respectively.

Figure 1: Share of green employment by gender and ethnicity (2018)



Source: Authors calculations based on O*NET and ONS

The gender breakdown reveals that 68% of all green occupations were filled by men, this compares to 52% of all employment (ONS, 2023). Green occupations accounted for one in three occupations for white workers, whereas this dropped to less than one in four for black and black British workers. Since employment rates for this group are below that for white counterparts – 69% compared to 77% (Gov.UK, 2023) - the green occupation employment disadvantage is compounded.

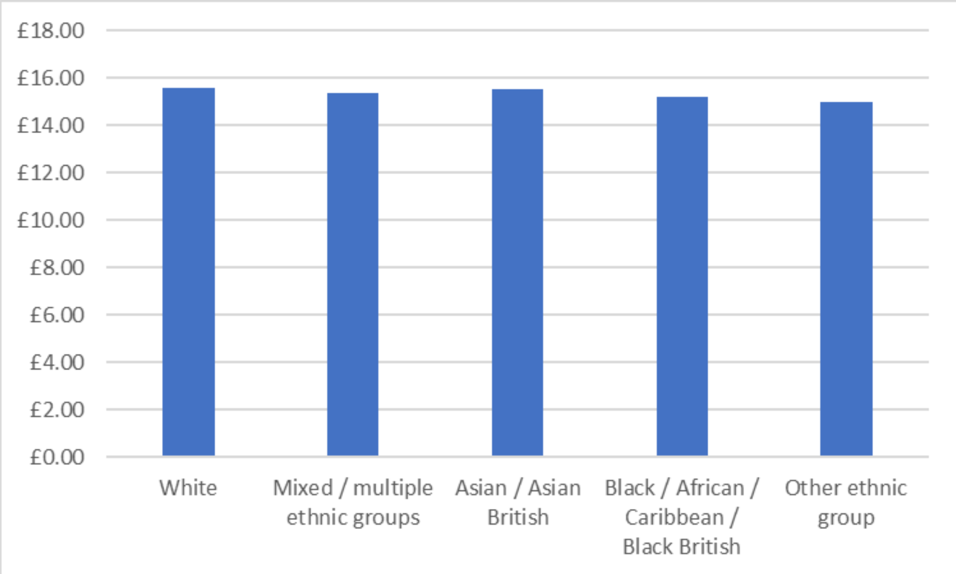
Given the enhanced opportunities green employment can offer to individuals as society transforms to a net zero economy, it is somewhat concerning that the inequalities embedded in the wider labour market are further pronounced in green occupations. As such, this indicates a need for policy interventions to help address some of the inequalities by incentivising both employers and employees to encourage growth in green occupational employment from underrepresented communities across gender and ethnic groups.

4.1.2 Pay

To exploit the benefits of the greater sample size, pay analysis is presented using ASHE data only. The exception to this is the ethnicity analysis which is only possible using the ASHE linked to Census 2011 dataset. The analysis shows that in 2018 the median wage of those working in green occupations was £14.00 per hour, compared to just £11.14 for those working in all other occupations. The average hourly wage for both men and women working in green occupations exceed the average wage for all employment. However, the gender breakdown reveals that women working in green occupations receive nearly 10% less per hour than their male counterparts. This gap in gender pay for green occupations is broadly reflective of the estimates for the full economy (ONS, 2022)

By combining the ASHE data with the Census 2011 data, it is possible to examine the breakdown of pay by ethnic group. Due to the reduced sample size, this results in the median wage for those working in green occupations in this sub-sample increasing to £15.54 per hour, from £14.00 per hour for the full ASHE sample. As such, comparisons of ethic wages are with respect to this revised average for ASHE-Census (£15.54 per hour). Figure 2 shows that black and black British and other ethnic groups earn 2.1% and 3.8% less than white workers respectively.

Figure 2: Median of hourly pay, by ethnicity (2018)



Source: Authors calculations based on O*NET and ONS (ASHE linked to Census 2011)

The negative pay gap for ethnic workers working in green occupations further compounds the inequality experienced in terms of working in a green occupation. Some ethnic groups seem to face a double disadvantage when it comes to green occupational employment. Not only are they less likely to be employed in a green occupation than their white counterpart, but they are also likely to face a pay penalty compared to their white counterpart, conditioned on already working in a green occupation. There may be many factors at work here, and these issues are explored in more detail in the multivariate analysis.

4.2 Empirical estimation

To further investigate the characteristics of those who are employed in green occupations, the regression approach outlined in Section 3 is applied. Only a selection of the variables of interests are reported[5]. For example, although education is controlled for in all models, and a significant determinant of both green employment and pay, it is omitted from all tables presented as it was not deemed to be part of the main narrative.

4.2.1 Green occupation

The empirical analysis of green jobs enables us to answer the following research questions:

[1] What are the characteristics of those that work in green jobs?
[2] How do job and employer characteristics affect the likelihood of being in a green job?

The first set of results shown in Table 1 are estimated using a censored probit regression. Columns 1 and 5 estimate the likelihood/intensity of working in any type of green occupations, while models

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[5] The full models are available by application from the corresponding author (damian2.whittard@uwe.ac.uk)

presented in columns 2-4 explore the drivers of different types of green occupations (i.e. directly green (columns 2 and 3) and indirectly green (column 4)).

Table 1: Selected coefficients of characteristics of workers in green occupations – cross sectional censored Tobit regressions

	(1) Green Occupation	(2) Green Enhanced Skills	(3) Green New and Emerging	(4) Green in Demand	(5) Green Occupation & Female interaction
Female	-0.275***	-0.161**	-0.179***	-0.198***	0.002
Age	0.009*	0.006	0.006	0.001	0.011*
Age-squared	-0.097*	-0.057	-0.070	-0.008	-0.084
Ethnicity (ref. white)					
Asian/Asian British	-0.088*	-0.112***	-0.090**	0.016	-0.086
Black/Black British	-0.064	-0.133***	-0.116***	0.059	-0.021
Married	0.028*	0.035***	0.026*	-0.003	0.036*
Pre-school child	0.027	0.005	0.026*	0.010	0.038*
Public Transport User	-0.066*	-0.076**	-0.075***	-0.016	-0.090**
Basic paid hours	0.008**	0.007	0.002	0.003	0.006
Experience	-0.000	-0.003	-0.000	0.002	0.000
Experience-squared	0.006	0.067*	0.074*	-0.085*	-0.056
Part-time	-0.186**	-0.138**	-0.236***	-0.088	-0.173*
Hourly paid	-0.193**	-0.173***	-0.294***	-0.002	-0.120
Enterprise size (ref 250+)					
0-9	0.293*	0.192**	0.131	0.179**	0.351**
10-49	0.138**	0.117***	0.073*	0.045	0.149***
50-249	0.114***	0.089**	0.041*	0.056*	0.111***
Collective agreement	0.037	-0.022	-0.057**	0.103**	0.125**
Foreign owned	0.085***	0.021	0.056***	0.071***	0.073***
Female interaction					
& age					0.006
& age-squared					-0.171**
& Apprenticeship					-0.222*
& pre-school child					-0.068*
& primary school child					-0.086**
& senior school child					-0.090***
& construction					-0.409**
Additional controls	Y	Y	Y	Y	Y
Observations	34009	34009	34009	34009	34009
Clustered by occupation	359	359	359	359	359
Pseudo R-Squared	0.14	0.13	0.17	0.14	0.15
AIC	50458	32376	27329	33151	49488
BIC	50888	32807	27759	33581	50365

* p<0.10 ** p<0.05 *** p<0.01

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

The coefficient for females in models 1 to 4 is negative and significant at the 1% level. This suggests that females are less likely to be employed in green occupations. Female interaction terms are then introduced in model 5 to explore the relationship further. By doing so, the female coefficient becomes positive but is insignificant, supporting the suggestion of an underlying complexity. In line with the social role theory and broader literature on the gender pay gap, the interactive model reveals that female employment opportunities are negatively affected by factors including child responsibilities, sector specific challenges (i.e. construction), and job types (i.e. apprenticeships). Age is also important as the results suggest that women's employment in green occupations increases at a marginally quicker rate than men, but also declines at a faster rate (i.e. age squared[6]).

The childcare interaction term is particularly informative. Men having a dependent child has a positive impact on the likelihood of working in green occupation, but for women this makes it less likely. This outcome suggests that childcare responsibilities maybe a significant barrier to employment in green jobs for women. Female domestic responsibilities can affect job choice, availability to work in certain conditions or schedules, or even the type of job considered. As such, in an attempt to increase the proportion of women in green jobs, organisations may wish to adopt supportive childcare policies and practices. This might include flexible working conditions, childcare support, or targeted recruitment strategies to overcome these barriers.

The results also highlight that Asian and Black minority ethic groups are less likely to be employed in a green occupation, particularly in directly green occupations (columns 2-3). There is theoretical and empirical support that this may in some part be driven by discrimination. For example, field experiments have shown that racial discrimination in hiring continues to persist in the British labour market (Heath & Di Stasio, 2019). However, given that the lack of opportunity is only in relation to 'directly' green jobs, this may provide some empirical support in support of social role theory. Social role theory indicates that cultural norms can impact the types of jobs and career paths that are deemed appropriate for different ethnic groups. Further work is required to explore the results in more detail, but it suggests policies aimed at addressing societal expectations and creating supportive work environments may help in overcoming the barriers to green employment experienced by some ethnic groups.

There are several other personal characteristics and job characteristics that negatively affect the chances of working in a green occupation. Of note is the structural effects and potential lack of flexibility around green occupations, which can have indirect discriminatory effects (e.g. gender). For example, those working part-time and being paid hourly, are less likely to be employed in green occupations.

Also of interest is that those that use public transport are less likely to work in green occupations. This is somewhat counter intuitive as one would expect that those working in green occupations may be more environmentally driven and therefore prone to take public transport. The result, however, does not account for location of employment and distance travel to work. This is a potentially interesting finding and worthy of further investigation but is beyond the scope of this study.

Also of note is that working for small and medium sized companies, and/or one that is foreign owned is positively correlated with working in a green occupation. This might imply that smaller and/or foreign owned business are more able to be flexible, innovative, or otherwise more inclined to integrate green practices into their operations.

To benefit from the full power of the 2011-2018 dataset, the analysis is repeated using a Logit Panel Fixed Effect, Fractional Response Model. Results of particular interest are reported in Table 2.

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[6] In order to aid the presentation of the table, age-squared in the model is calculated as age^2/1000. This has the effect of increasing the size of the age-squared coefficient.

Table 2: Selected coefficients of characteristics of workers in green occupations – panel fixed effects, logit fractional response model (2011-2018)

	(1)	(2)	(3)	(4)
	Green Occupation	Green Enhanced Skills	Green New and Emerging	Green in Demand
Age	0.054***	0.088***	0.084***	0.016***
Age-squared	-0.540***	-0.835***	-0.949***	-0.138***
Basic paid hours	0.017***	0.023***	0.003***	0.010***
Experience	-0.006***	0.002*	0.014***	-0.016***
Experience-squared	0.227***	0.017	0.081**	0.229***
Part-time	-0.659***	-0.866***	-1.232***	-0.468***
Hourly paid	-0.417***	-0.685***	-1.152***	0.192***
Enterprise size (ref 250+ employees)				
0-9	0.228***	0.139*	-0.099	0.383***
10-49	0.235***	0.396***	0.107***	0.079***
50-249	0.203***	0.311***	0.066***	0.095***
Collective agreement	0.167***	-0.113***	-0.227***	0.496***
Foreign owned enterprise	0.122***	0.080***	0.114***	0.093***
Additional controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y
Observations	652128	652128	652128	652128
AIC	494928	248750	201106	307728
BIC	495303	249126	201482	308103

* p<0.10 ** p<0.05 *** p<0.01

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

The coefficients in a logistic regression model represent the log odds, which can be converted into odds ratios by taking the exponential of the coefficients. Table 2 reveals that as individuals become older, they are more likely to work in a green occupation, but this effect is not linear and diminishes with age. The panel confirms that those working in more flexible employment are considerably less likely to work in green occupations – a potential form of indirect discrimination. Taking the exponential of the coefficient reveals that those working part-time and hourly paid are 48% and 34% less likely to be employed in a green job respectively.

The panel confirms that those working in SMEs and/or working for a foreign owned company are all more likely to work in a green occupation. If promoting green jobs is a policy goal, this might suggest that targeting SMEs for grants, tax incentives, or regulatory support may enhance their capacity for sustaining or increasing their green initiatives. To promote a fair transition, these efforts may be linked to measures which promote the creation of inclusive environments. It also suggests that further investigation is needed into the reasons smaller businesses have greener occupations, which could be due to agility, less bureaucracy, and/or closer ties with local communities and environmental issues.

Of note is that having some form of collective agreement, which can be viewed as a proxy indicator for trade union membership, is negatively associated with working in a directly green occupation (column 2 and 3), but positively associated with working in an indirectly green occupation (column 4). This could in some part be influenced by a combination of factors including that the directly green jobs are in new and emerging sectors, predominately based in small and medium size companies, and workers in green occupations may see themselves as professional or skilled labour, all of which would have typically lower rates on collectivism and unionisation. This may be partially offset through targeting awareness and education campaigns of the benefits of union membership to those working in green occupations.

4.2.2 Pay penalty or pay premium for working in a green occupation

Following the analysis of the characteristics of those working in green occupations, the exploration then shifts to the pay implications of these roles. This enables us to answer the following two research questions:

[3] Can working in a green job go some way to offsetting the gender and ethnic pay gap?
[4] To what extent are gender and ethnic pay gaps embedded within green jobs?

Table 3 reports a wage regression in order to estimate the pay premium of working in green occupations. An OLS stepwise regression is used where the log of real hourly pay is the dependent variable.

Table 3: Selected coefficients of pay premium and the greenness of jobs – stepwise OLS cross section regression (2018)

	(1) Basic	(2) Individual	(3) Job & Employer	(4) Sector & Region	(5) Interaction & Linear Lasso
Green occupation	0.333***	0.212***	0.193***	0.170***	0.152**
Female		-0.183***	-0.170***	-0.153***	-0.030
Age		0.021***	0.020***	0.019***	0.025***
Age-squared		-0.241***	-0.222***	-0.220***	-0.279***
Ethnicity (reg. white)					
Mixed/multiple ethnic groups		0.022	-0.009	-0.045*	-0.068
Asian/Asian British		-0.053**	-0.083***	-0.118***	-0.142***
Black/Black British		-0.066***	-0.072***	-0.147***	-0.177***
Other		-0.041	-0.045	-0.078**	-0.076*
Additional controls		Y	Y	Y	Y
Observations	174512	73252	33906	33882	33882
Clustered by occupation	367	367	359	359	359
Adj. R-Squared	0.03	0.31	0.40	0.44	0.45
AIC	257801	81800	33907	31494	31243
BIC	257821	82020	34169	31924	32162

* p<0.10 ** p<0.05 *** p<0.01

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

Given the dependent variable is in log form, the exponentiate of the coefficient is calculated and reported due to its ease of interpretation. The model indicates the unadjusted effect of being in a green occupation on hourly pay. The exponential of the coefficient (0.333) suggests that without controlling for other confounding factors, on average being in a green occupation is associated with an approximately 39% higher hourly pay compared to non-green occupations. This initial estimate infers that there is an economic incentive, or premium associated with green jobs, possibly reflecting the higher demand for such jobs, the specialised skills required, or a combination of other factors.

To explore this premium further, individual characteristics (e.g. age, education, gender etc.) are introduced to the model (column 2), which considerably improves the explanatory power of the model. After exponentiating the coefficients, it reveals that the premium of working in a green job reduces to approximately 24% when controlling for other factors (coefficient 0.212).

Model 5 is the preferred specification as it includes confounders as selected by the Lasso analysis, has the highest adjusted R-squared, and records the lowest AIC/BIC scores. In this model the green occupational pay premium is reduced to 16% (exponent of 0.152). Of special note in this model is the introduction of the interaction term of working in a green occupation and being female. The result suggests that being female and working in a green occupation goes someway to offsetting the gender pay gap with males, albeit caution should be taken when interpreting this result given the female and green occupation & female coefficients are not statistically significant.

The 16% pay premium for working in a green occupation is still somewhat higher than in previous studies (e.g. Vona et al., 2018; Valero et al., 2021), and therefore in Table 4 the full panel is used to generate more precise estimates. Some additional interactions terms are also incorporated to enable the inclusion of some of the non-time varying variables from the Census (e.g. gender, ethnicity) with time varying characteristics (e.g. green occupation). By doing so, it is possible to develop a deeper understanding of how effects can vary across groups within the panel data framework.

Table 4: Selected coefficients of pay premium and the greenness of jobs – stepwise OLS panel fixed effects regression (2011 - 2018)

	(1) Base model	(2) Individual	(3) Job & Employer	(4) Sector & Region	(5) Interaction & Lasso Linear
Green Occupational Marker	0.096***	0.076***	0.063***	0.060***	0.041***
Age		0.091***	0.084***	0.083***	0.072***
Age-squared		-0.873***	-0.773***	-0.761***	-0.659***
Green occupation & Female					0.028***
Green occupation & Black/Black British					0.035*
Green occupation & Other					0.066*
Additional controls					
Fixed Effects	Y	Y	Y	Y	Y
Observations	1398000	1375696	648007	647443	313228
Adj. R-Squared overall	0.04	0.09	0.12	0.13	0.09
AIC	-615232	-776163	-484441	-487227	-260197
BIC	-615208	-776078	-484281	-486840	-259728

* p<0.10 ** p<0.05 *** p<0.01

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

The fixed effects model generates more plausible estimates of the pay premium of working in a green job. This ranges from 10% in the raw model (1) to 4% in the final model (5) – this is in line with estimates of US green employment wage premium (Vona et al., 2018). Of particular interest in Table 6 are the positive coefficients for the interaction terms of green occupations and females, and green occupations with black and other minority ethnic groups. This suggests that working in green occupations can potentially offset some of the pay gaps these groups generally experience in the labour market.

4.2.3 Pay in green occupations

To further explore the experience of different groups, a cross-sectional model is run for those that work just in green occupations. As such, the results presented in Table 5 now allow for a direct comparison of individuals and groups who work just in green occupations.

Table 5: Selected coefficients on pay of GREEN JOBS – stepwise OLS cross section regression (2018)

	(1) Individual	(2) Job & Employer	(3) Sector & Region	(4) Interactions
Female	-0.181***	-0.171***	-0.148***	-0.329
Ethnicity (ref. white)				
Asian/Asian British	-0.101***	-0.113***	-0.152***	-0.159***
Black/Black British	-0.124***	-0.093***	-0.177***	-0.211***
Married	0.066***	0.068***	0.072***	0.086***
Dependent child (ref. none)				
Senior school child	0.023***	0.030***	0.032***	0.041***
Enterprise size (ref 250+)				
0-9		-0.128**	-0.093	-0.094
10-49		-0.048***	-0.063***	-0.079***
Manufacturing			0.151***	0.199***
Finance/Law			0.132***	0.176***
Female interactions:				
& Married				-0.052**
& Dependent - senior school child				-0.043**
Enterprise size (ref 250+)				
& 0-9				-0.209**
& 10-49				0.078*
& Manufacturing				-0.129**
& Finance/Law				-0.089*
Additional controls	Y	Y	Y	Y
Observations	24601	14364	14353	14353
Clustered by occupation	142	141	141	141
Adj. R-Squared	0.25	0.33	0.38	0.39
AIC	29169	15221	14114	14098
BIC	29355	15448	14493	14870

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

The cross-sectional analysis reveals that the same pay inequalities (gender and ethnicity) present in the wider labour market are still present when looking solely at green occupational employment.

To uncover nuanced patterns of gender inequality, several terms are interacted with being female. The results presented in Table 5 suggest there is an effect over and above the additive effect of the two terms independently. Of note is the negative effect domestic responsibilities seem to have on female pay in green occupations (i.e. female and married; female and dependent child). There are also increased disadvantages for females working for small companies (0-9) and in specific sectors (manufacturing and finance/law).

It is noteworthy that when comparing intra-occupational pay gaps for green occupations (Table 5) with the results for non-green occupations (Table 6), it becomes evident that both the gender pay gap and ethnic pay gap is less pronounced in green occupations relative to non-green occupations.

Table 6: Selected coefficients on pay of NON_GREEN JOBS – stepwise OLS cross section regression (2018)

	(1) Individual	(2) Job & Employer	(3) Sector & Region	(4) Interactions
Female	-0.190***	-0.177***	-0.161***	0.018
Ethnicity (ref. white)				
Asian/Asian British	-0.040	-0.069***	-0.102***	-0.149***
Black/Black British	-0.047	-0.066**	-0.135***	-0.175***
Additional controls	Y	Y	Y	Y
Observations	48651	19542	19529	19529
Clustered by occupation	225	218	218	218
Adj. R-Squared	0.31	0.40	0.45	0.45
AIC	52705	18791	17408	17167
BIC	52907	19027	17802	17979

* p<0.10 ** p<0.05 *** p<0.01

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

This implies that working in a green occupation can go someway to addressing the gender and ethnic pay gap overall, but the gap still exists, conditional on working in a green occupation.

Given the findings of the study, this suggests that inequalities experienced in the wider labour market also appear within green occupations. This implies that unless action is taken quickly, these inequalities may become entrenched, reinforcing the divide and ultimately limiting personal commitment to greening of the economy and threaten the transition to net-zero.

A panel fixed effect model is then used to explore some of these effects in more detail.

Table 7: Pay green jobs (2011-2018): panel fixed effects - green jobs

	(1) Individual	(2) Job and Employer	(3) Sector & Region	(4) Interaction & Lasso linear
Age	0.093***	0.087***	0.086***	0.083***
Age-squared	-0.873***	-0.795***	-0.785***	-0.762***
Basic paid hours	-0.007***	-0.009***	-0.009***	-0.011***
Experience	0.007***	0.005***	0.005***	0.005***
Experience-squared	-0.115***	-0.090***	-0.086***	-0.070***
Part-time		-0.055***	-0.052***	-0.053***
Hourly paid		-0.008***	-0.006***	-0.008***
Enterprise size (ref.250+)				
0-9		-0.055***	-0.050***	-0.031
10-49		-0.042***	-0.046***	-0.039***
50-249		-0.015***	-0.018***	-0.025***
Collective agreement		0.009***	0.006***	0.006***
Foreign owned enterprise		0.019***	0.014***	0.015***
Sector (ref.Public Sector)				
Primary			0.095***	0.105***
Manufacturing			0.066***	0.089***
Utilities			0.095***	0.093***
Construction			0.060***	0.068***
Sales			0.010	0.026*
Services			0.029***	0.043***
Health			-0.023*	-0.030
Female Interactions:				
& age				-0.029***
& age_squared				0.292***
& Basic paid hours				0.002***
& Time in job squared				-0.070**
& Manufacturing				-0.093***
& Construction				-0.056*
& Sales				-0.074***
& Services				-0.050**
Additional controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y
Constant	0.662***	0.871***	0.896***	1.187***
Observations	441358	245553	245340	124937
Adj. R-Squared overall	0.09	0.10	0.11	0.08
AIC	-403873	-260635	-261576	-134090
BIC	-403807	-260499	-261232	-133408

Source: Authors calculations based on O*NET and ONS (ASHE Linked to Census 2011)

The results confirmed that individual, job, employer, sector and region effects were all important in understanding pay for green occupations. Having a collective agreement (proxy for union membership) adds between 0.6 and 0.9% to log of hourly pay, confirming the benefit of working in a green occupation and being covered by a collective pay agreement. Model (4) introduces female interaction terms.

Model 4 shows that pay increases with age (8.6% per year initially – coefficient 0.083) but the relationship is not linear and reduces over time. However, for females the rate of increase is lower initially, but declines at a slower rate. There are also some sector effects of note. For example, working in the manufacturing sector is associated with an 9.3% increase in pay (coefficient 0.089) compared to working in the public sector. However, the negative coefficient for females working in the manufacturing sector indicates that the pay advantage of working in a green occupation is not only absent for females, but marginally reversed. The same is true for sales and services, while for construction the pay premium is considerably diminished for females.

The findings highlight potential gender inequalities in green occupational employment which are increased by age and in terms of sector-specific pay. This suggests that further research may be required to investigate the underlying causes of these disparities and develop strategies to address them. Such analysis is important for understanding how the transition to net zero and growth in green jobs can affect the gender pay gap. The focus on sectors may be particularly important as pay equity may not exist between genders, necessitating targeted interventions.

5. Conclusion

Given the challenges in identifying green jobs in large scale national datasets, this is the first time that such a detailed analysis has been conducted on high quality, employer payroll data which enables an exploration of both the characteristics of the individual and firms involved in green employment and explores the effect green employment has on pay gaps.

This was made possible, by matching US O*NET data on green occupations to the newly created ASHE linked to Census 2011 dataset for England and Wales. The main challenge with this methodology is that it assumes the same task and occupational structure between US and UK economy. As such, the results should therefore be used to convey a sense of proportion of any such relationship, rather than be interpreted as a precise estimate.

This article explores the characteristics of employment in green occupations and the potential impact these roles can have on pay. It uses descriptive statistics and multivariate analysis to understand who works in green occupations. The analysis reveals that males are much more likely to be employed in green occupations, as are salaried workers, fulltime employees, those working in smaller business, and for foreign owned companies. Those working in green jobs are less likely to be represented by collective agreements, but those that are receive a pay premium. Male and white workers are disproportionately overrepresented in green occupations, while females and some ethnic groups appear dually disadvantaged in terms of both being underrepresented in green employment and facing a pay penalty compared to male/white workers when they work in green occupations.

A stepwise regression approach is used to estimate whether there is a pay premium or penalty for working in green occupations. Using a panel fixed effect model, an unadjusted pay premium of 10% is estimated, which reduces to a 4% when other characteristics are controlled for. This estimate is meaningful as it is generated using high quality wage information provided by the employer, is estimated using panel data over a period of eight years and is in line with Vona et al.'s (2018) study of green jobs in the US local labour market. The fact that the pay premium result is also robust across the various specifications, suggests there is a strong correlation between higher pay and working in a green occupation. This is an important finding which could help accelerate the transition to net zero if it can be used to incentivise the supply side of the equation (i.e. labour) to upskill, search out and secure green employment, given the financial rewards for doing so.

The identification of a pay premium in green occupations suggests that these jobs are not only vital for environmental sustainability, but are also becoming economically sustainable and desirable. This can help shift public perception of green jobs from being "alternative" or "niche" roles to mainstream career paths that offer competitive or even superior compensation. For policymakers, this finding can justify more robust support and investment in the green economy, leveraging economic incentives to meet environmental goals. Moreover, for businesses, it emphasises the importance of aligning business practices with sustainability goals to attract talent and capital in an increasingly eco-conscious market environment. The lack of clarity on what constitutes a green job, however, which will result in at least some businesses/individuals not knowing that they offer/work in green employment, will limit such an effect. As such, this suggests that there is a need for greater clarity in definitions and collection of green job data internationally.

The greening of the economy offers the potential for a more inclusive and just transition. That said, of particular concern to policy makers should be the dual inequality that green occupational employment appears to engender. Not only are female and ethnic groups underrepresented in green employment, when they are employed in green jobs, they are paid less than their counterparts. Further research is needed to explore the mechanisms through which this occurs, and policies put into place to mitigate this. Given that some green sectors may be concentrated in areas, it would also be useful to further explore spatial issues and their influence on inequality.

Equality is at the heart of a just transition towards sustainable development. As such, this study highlights the importance of extending and deepening the understanding of gender and ethnicity and ensuring its incorporation into theory that attempts to understand and conceptualise the transition to a green economy and green jobs.

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Appendices

Appendix A

Table A1: List of variables used in the ASHE and ASHE-Census 2011 dataset

Variable	Categories	ASHE-Census
Basic hourly wage	Continuous variable calculated by the ratio of basic weekly earning to the total number of basic weekly paid hours	bpay/bhr
Female	Dummy variable	sex
Age Age-squared	Continuous variable with squared value	age age_squared
Ethnicity	Categorical variable (white; mixed/multiple ethnic groups; Asian/Asian British; Black/African/ Caribbean/ Black British; Other ethnic group	aggethpuk11
Education	Categorical variable: Self-reported level of highest qualification. Grouped into five categories - no qualification, up to A-level, apprenticeship, Other/vocational qualification, degree or above)	hlqpuk11
Marital status	Dummy variable (1for those married or in a registered same-sex civil partnership)	marstat
Born outside UK	Dummy variable	aggcobpuk113
Health – Fair to very bad	Dummy variable (0,1) for self-reported health created from a five-point scale of very good health, good health, fair health, bad health and very bad health	health
Dependent child	Categorical variable to indicate whether the individual is responsible for a dependent child – four categories include no dependent child in family; pre-school age (0-4); primary school (5-11) or senior school (12-18)	dpcefamuk11
Public transport user	Dummy variable whether individual is a public transport user	ptranspuk11
Disability	Dummy variable for those who report a disability that interferes with their day-to-day activity	disability
Basic paid hours	Basic weekly paid hours worked	bhr

Experience Experience-squared	Continuous variable and squared term. Time in job calculated by year of observation, minus employment start year plus one	empstart_y
Part-time job	Dummy variable to indicate whether job is part-time	fulltime
Hourly paid	Dummy variable to indicate whether the individual was hourly paid	hourly_paid
Size of employer	Categorical variable for the employer size band. Four categories of 0-9, 10-49, 50 to 249 and 250 and over.	emp_size_band
Collective agreement	Dummy variable to indicate whether the individual is subject to a collective bargaining agreement	coll_agt
Foreign owned enterprise	Dummy variable to indicate whether the individual works for a foreign owned company	for_own
Sector	Categorical variable -11 industrial sectors	sector
Region	Categorical variable – government office region at workplace (NUTS1: North East, North West, Yorkshire, East Midlands, West Midlands, South West, East, London, South East, Wales)	region
Variable	Categories	O*NET/ LMI Crosswalk
Green Occupation (Binary Variable)	Dummy variable to identify UK occupations which match to one or more of the US green occupations identified via the O*NET project. The main variable is further disaggregated to created derived variable markers for green tasks; green new and emerging; green enhanced skills; and green in demand	max_green_occ max_green_task max_GN&E max_GES max_GID
Green Occupation continuous variable)	Continuous variable which weights occupation date to identify probability or greenness of occupation.	wght_mean_green_occ wght_mean_green_task wght_mean_GN&E wght_mean_GES wght_mean_GID