Working Towards a Greener Britain: Who, Where and for Whose Benefit?

Abstract:

Given the urgency of the transition to net-zero, there is a need for a robust evidence base to support green policy interventions. Intelligence in relation to green jobs, however, is partial and fragmented, partially due to the lack of an international consensus on definition. This paper contributes to addressing this knowledge gap, by exploring green employment in England and Wales.

For the first time, we use multivariate analysis to account for the firm in an analysis of green employment across different groups. Using a high quality, large-scale, employer informed micro-dataset (Annual Survey of Hours and Earnings linked to Census 2011), we find that male, white, fulltime, and individuals working for small, and foreign owned companies are more likely to work in green occupations. There is also a substantial pay premium for those that do. The pay premium is not equally distributed, with Asian and Asian British workers fairing comparatively less well. Our results suggest that to have a fair and just transition, interventions may be required to address the dual inequality of opportunity and pay experienced by some minority groups in relation to green employment.

Applying Holland's Theory of Career Choice, our study is also the first to use a large-scale dataset to investigate whether personal behaviours and green employment choices are consistent. To do so, we explored whether an individuals' travel to work behaviour is aligned with their choice of occupation. Preliminary results suggest that they may not be, but these findings require further investigation ahead of full publication.

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1. Motivation and research questions

1.1 Introduction

The climate crisis and environmental emergency is potentially the greatest current global challenge. In response, the UK government has set ambitious plans to transform to be a net zero economy by 2050 (BEIS, 2021). Green jobs will be at the core of this transition, but for government to put policies in place to support such a fundamental transition, they require a robust and reliable evidence base, which at present is lacking (Skidmore, 2022).

Over the past twenty years, the topic of green jobs has grown in attention, which has resulted in a diverse and substantial number of published papers internationally (Stanef-Puică et. al, 2022). However, studying green jobs presents several challenges, reflecting the complexity of the field which intersects environmental concerns, economic development, policy, and social dynamics.

1.2 Green jobs

Green jobs are often linked with concepts such as sustainable development (Rutkowska, 2020), the green economy (Lee, 2019), the circular economy (Bassi and Guidolin, 2021), energy (UNEP, 2008), economic development, and employment (Song, 2021).

The theoretical foundation of the green economy covers a variety of concepts which includes environmental economics, and ecological economics. What appears to unite these concepts and theories appears to be the focus on achieving a balance between economic growth and environmental sustainability. Much of the focus has been on renewable energy, resource efficiency, and low carbon technologies. 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 what constitutes a 'green job'.

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. This continuum makes creating a consistent and reliable evidence base challenging. This lack of clarity 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.

However, 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. The definition was arrived at following a wide-ranging consultation and substantial stakeholder engagement Their definition is as follows:

> "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)

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 employment. O*NET defined 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 them identifying 12 green economic sectors, 138 green enhanced skills and green new and emerging occupations, as well as occupations that, although not "directly green", experienced growth through increased demand for their products and services. As such, O*NET classified any occupation affected by greening as a green job.

The O*NET database contains a rich set of variables that describe work and worker characteristics, including skill requirements. with green task markers included in the O*NET data for the first time in 2011. 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.

Other additional challenges facing researchers who work in this field include the availability and quality of data, the rapidly evolving nature of the sector, changing economic and political priorities, global versus local perspective, and complexity and interdisciplinarity nature of green jobs research (Stanef-Puică et. al, 2022; Sulich 2020). As such, addressing these challenges requires a multi-faceted approach, involving collaboration across disciplines, sectors, and regions, as well as the development of innovative methodologies and data collection strategies.

Internationally, most work conducted on green employment/green jobs focuses on job creation and losses, the move towards low carbon or greener economies, or overall jobs outcomes from policies to encourage this transition (Bradley et al., 2023 in press).

Few studies analyse important topics such as the pay premium for green jobs, and if so focus on the aggregate level rather than focusing on more nuanced and detailed characteristics relating to those employed in green jobs. Much of the work has been focussed on the US economy. Vona (2019) (and earlier work Vona 2018) in their US study estimate that green employment tends to be highly skilled and commands a wage premium of 4% and is geographically concentrated. This said, not all current and future green jobs will be highly skilled; for example, in the case of installing heat networks many jobs will be created by the need to 'dig up' streets to install the network etc. Bowen et al (2018) also conduct some analysis of pay premium/wage differentials for the US. Kim and Jeong (2016) conduct a small amount of wage analysis for the USA specifically in relation to electricity sector restructuring. Antoni et al (2015) look at the wage premium in relation to renewable energy related jobs in Germany and a pay premium for renewable energy establishments compared to their sector peers.

In the UK, Sissons (2018) conducts a quantitative regression analysis of large datasets for the UK to understand the links between sector of employment and poverty outcomes and extends the analysis to assess family characteristics and labour market experiences jointly. The study is not focused on green jobs and provides no insights specifically in relation to green jobs. The study does however indicate that in a changing economy, patterns of sectoral growth and decline impact associated poverty outcomes, which suggests that the transition and structural changes towards green economy will likely have impacts (good or bad) on people's incomes.

Researchers have applied several different qualitative and quantitative methodological approaches to understand green jobs. For example, quantitatively one approach that has been applied is to use Computable Generable Equilibrium models (e.g. Bouzaher et al., 2015; Kolsuz and Yeldan, 2017; Maxim and Zander, 2020). These models can be useful in aiding understanding 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, 2017; MarkaKi, et al., 2013). Multivariate analysis has also been used by several researchers (e.g. Antoni et al., 2015; Kim et al., 2019; Yoo and Heshmati, 2019), as it can aid in providing a more nuanced understanding of the relationships between various factors affecting green jobs. Multivariate analysis is particularly helpful when exploring the diverse and interconnected factors that influence green jobs.

1.3 Green jobs research in the UK

The lack of green jobs research has in some part been due to the lack of large scale, longitudinal and reliable labour market 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.

The value of the task and occupation-based approach is that it captures those in occupations not classified within green industries and sectors. This therefore broadens the definition of green jobs beyond those just working in green industries. The main limitation of this approach, 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 (ONS 2022a).

Notwithstanding the validity of these assumptions, a further challenge is that the data must also then be mapped from US to UK via occupation code using international occupation classification. This is potentially problematic as it presents an opportunity for mismatching. Such a task and occupation-based approach, however, is a worthwhile endeavour, as it can capture "greening" within occupations, reflecting changes over time of activity for each occupation.

At an aggregate level, the US sector share of green jobs, has been applied to the UK to calculate the proportion of green jobs by sector. The initial results from Robins et al. (2016) indicate that about one-fifth of jobs in the UK, involve skills that could either experience demand growth or demand reduction in the transition to Net Zero

There have been two notable studies that have used the O*NET data in some detail to explore green jobs in the UK economy. ONS combine O*NET data with the Annual Population Survey, and the Annual Survey of Hours of Earnings (ASHE) (ONS, 2023b) to estimate the amount of time spent doing green tasks. Results were reported at the aggregate level for the UK and its constituent nations. This innovative approach used information on the importance and relevance of task to provide aggregate estimates of time spent green jobs. However, results 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.

Valero et al (2021) combined the O*NET data with the Labour Force Survey (LFS) to provide a more disaggregated view of green jobs, utilising the distinction between occupation categories provided by the O*NET database. The O*NET database identifies three occupation categories according to the effect the transition to a sustainable economy has on occupations. These are Green New and Emerging (GN&E), Green Enhanced Skills (GES) and Green Increased Demand (GID). Valero et al (2021) report that GN&E are new occupations that have been created in the move to a sustainable economy (e.g. wind energy engineers); GES identifies occupations where tasks, skills and knowledge requirements has significantly altered due to the transition to a sustainable economy (e.g.

construction engineer undertaking energy efficient retro fitting); while GID are occupations which are in greater demand due to the transition to a greener economy, but there are no significant changes to the tasks or worker requirements (e.g. industrial production managers). The strength of this approach is that it enables an analysis of jobs that are both directly (GN&E plus GES) and indirectly green (GID).

A limitation of the Valero study, however, is that it uses LFS data. This relies on voluntary participation, covering approximately 75,000 individuals from 35,000 households and is based on self-reported information which is subject to rounding and recall bias. The current study uses higher quality ASHE data, which is based on a much larger mandatory employer survey, greater sample (180,000), using payroll data and therefore directly furthers the evidence base in the UK. In addition, academic knowledge is furthered as for the first time, to the authors knowledge, the analysis takes the firm into account when making estimates of pay premiums. It further provides novel findings as it explores the effect of green employment on different ethnic groups, while exploring other nuanced, detailed characteristics including household and foreign ownership.

The choices that individuals make when selecting employment been prevalent in the human resources and psychology literature for many years. For example, Holland's Codes, which is ever-present in vocational guidance settings, represent a theory of career choice (1973). It proposes that people and work environments can be classified into six types: Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C). According to Holland's theory, individual career satisfaction is based on the fit or congruence between the career personality and the environment of the work, which is known as person-environment fit (Zainudin et al. (2020). To the authors knowledge, these issues have not been explored in relation to green employment. As such, for the first time, this study explores this issue exploring whether there is congruence between an individual's behaviour, in terms of method of commute, and their chosen green occupation.

1.4 Research gap

Our study extends the approach taken by Valero et al (2021) to improve the evidence base by applying ASHE microdata linked to Census 2011 (ONS, 2023c)[1]. Other studies have applied this dataset to improve the evidence base in other areas. For example, Phan et. al, (2022) used the ASHE linked to Census 2011 dataset in their analysis of ethic pay gaps, across the pay distribution n while controlling for firm effects. While Forth et al., (2023a and 2023b) used the dataset to explore the experience of low paid workers in Britain and the impact of Rising Minimum Wages on labour mobility.

The specific research questions we will address are as follows:

- Who works in green occupations?
- Where do these individuals work?
- Is their choice reflected in their commuting behaviours?
- What is the wage premium/penalty for those working in green occupations?

[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.

Some suggest that as we move towards net zero all jobs will be green, however until we reach that position the transition is likely to have far reaching and unequal impacts, which may vary across the short, medium, and long-term (Stern and Rydge, 2012). As identified, many studies have focussed on net job creation, (Blyth et al., 2014; Montt et al., 2018) and their effects over these different timeframes (Popp et al., 2020). Others have focussed on exogenous shocks and in particular how changes to environmental policies have affected employment. The evidence here appears mixed, with some suggesting that changes to environmental policies can have negative or negligible employment effects (Walker, 2011, Martin et al. 2014), albeit when considered against wider social benefits, they are likely to outweigh any such costs (Deschênes, 2018). Others have focussed more on the need for a just transition, focussing on the distributional effects for workers in terms of both sector and place (Zachman, G et al., 2018).

We contribute to the literature on green jobs by investigating the characteristics of those who work in green occupations, the type of green work that they do, the distribution effects across sectors, regions, and communities with protected characteristics; we also consider how these have changed over time. Our estimates show that males and white workers are disproportionately represented in green occupations.

We provide new knowledge about the attributes of those firms who employ individuals working in green occupations. We provide the first UK estimates of the additional economic benefit of working in a green occupation, and explore if those benefits are shared equally across different groups. Our results show that even after controlling for individual, firm, sector and regional effects, there appears to be a 18.7% premium for working in green occupations. We also provide some novel preliminary findings which links together individuals' 'green' behaviours, in terms of mode of transport taken to commute to work, to their chosen occupation, whether green or brown. Our analysis shows that the behaviours of those working in green occupation in terms of travel to work, do not necessarily align, albeit these estimates do not consider distance to travel to work, given that detailed geographic information has been excluded from the dataset due to data owners concerns around potential for disclosure – data is only available at the local authority level.

2. Data and empirical approach

2.1 Data

The main data sources for our analysis are O*NET, ASHE and ASHE linked to Census. In line with the methodology employed by Valero et al (2021) we use an occupation based, bottom-up approach to identifying green jobs. To do this, we use the US O*NET data to map US green tasks and occupations to UK occupations.

O*NET use a concept of the "green economy"[2] and "greening of occupations"[3], which was used to inform the development of the three green occupational categories – GN&E, GES and GID – used in this analysis. To facilitate an examination of how specific occupational greening might occur, a list of 12 green economy sectors were researched (for a full discussion on the O*NET methodology, please

[2] 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)
[3] 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)

refer to Dierdorff et al., 2009). In total there were 204 green occupations identified at the O*NET 7-digit level, and classified to GN&E, GES and/or GID. For the two directly green categories (GN&E and GES) O*NET provide 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.

The mapping was completed via the "LMI for All" crosswalk, which is freely available at the UK's Department for Education's online portal (LMI For All, 2019). The mapping is complex, resulting in multiple matches between US and UK sectors. As such, two approaches were taken. Initially we create a binary definition of a green occupation, where a UK occupation is considered green if at least one of the US occupations matched to the UK occupation code was green – we call this variable "green_occ".

These estimates, however, are top end estimates of green jobs and as such a weighted measure was constructed to produce a continuous estimate of green occupations (weighted_green_occ). In line with Dickerson and Morris (2019) weights were created to account for the US employment share of all matched occupations to each UK occupation – in this study, this s applied at the two digit level. In additional to avoid double counting of US O*NET occupations being matched to multiple UK occupations, in line with methodology employed 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

As well as applying this method to green occupations, we are also able to calculate continuous measures for the direct measures of green occupations (green tasks, GID and GN&E) as well as the indirect measure (GID).

The O*NET data is matched to the ASHE occupational data using the 2010 UK standard Occupational Classification at the four-digit level. The ASHE data is based on a sample of 1% of the Great British working population of employees, approximately 180,000 people in each year. However, recent analysis in relation to attrition bias in ASHE, has identify that the achieved sample is closer to 0.7% (circa 130,000) (Stokes et al., 2021). For a full review of the ASHE-Census dataset, please refer to Appendix A in Phan et. al, 2022)

As ASHE is an employee-employer dataset, it allows for characteristics of the firm to be accounted for within the analysis. Wage and hours data is a significantly improvement from the self-reported estimates available in the LFS data – ASHE reports precise earnings reported directly by the employer from payroll data. Self-selection bias is limited as employers are mandatory required to supply this data in response to a statutory request from the UK's National Statistics Authority. To maximise sample sizes, gender breakdowns are calculated using ASHE data only.

An additional benefit is derived by linking 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. After linking 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[4].

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 is 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. 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, allowing us to provide first estimates of any pay premiums or penalties incurred by different groups working in green jobs in the UK. In addition, 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 estimate for just England and Wales, and therefore any estimates reported using this data source will exclude Scotland.

2.3 Empirical approach

Given the limited understanding of green employment in the UK, initially we map employment by green occupation. We provide descriptive statistics for various aspects of green jobs, segmented by job type, gender, ethnicity, sector, and region. ASHE is an extensive survey capturing earnings and hours worked, when we combine with the comprehensive demographic information from the Census, we can explore nuances of the green job market. This combination enabled us to explore disparities and trends within this sector effectively. We initially focus on 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. We compare these results to 2018, the latest data on which ASHE linked to Census 2011 data is available, albeit acknowledging that there is attrition to the ASHE linked to Census dataset over the period, while new entrants to the labour market will not be picked up during this period.

For the first time we provide insight into the link between 'green behaviour;' and `green employment`, by exploring data in relation to mode of travel to work. Our analysis contributes to the understanding of the distribution and characteristics of green jobs, highlighting the intersection of environmental sustainability with socio-economic factors.

The descriptive analysis is followed by a multivariate analysis to identify factors associated with employment in green occupations for individual *i* in 2018. First, we use a common logistic regression specification illustrated below to examine the probability of an individual working in a green occupation based on the various independent variables.

[4] 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.

$$\log\left(\frac{p}{1-p}\right)_i = \beta X_i + \beta Z_i + \beta \mathrm{F}_i + \beta S_i + \beta X_i + u_i$$

Where:

- p is the probability of an individual working in a green occupation (green_occ).
- $\log\left(\frac{p}{1-p}\right)$ is the natural logarithm of the odds ratio of working in a green occupation.

The vector X includes individual characteristics (e.g. age, gender, education, ethnicity) while job characteristics (e.g. job type, tenure) are captured in vector Z. The set of firm characteristics (e.g. company size and foreign ownership) are captured in vector F, while S and R capture sector and regional effects respectively. A full list of all variables used in the regression is included in Appendix 1.

To account for the fact that observations within the same occupation group may be correlated, this model (and all subsequently reported models) are estimated by clustering the standard errors by occupation.

In order to account for the "greenness" of the individuals' job, we then replace the dependent variable with a weighted variable to estimate the following model.

$$Y_i = \beta X_i + \beta Z_i + \beta \mathrm{F}_i + \beta S_i + \beta X_i + u_i$$

- Y_i represents the greenness score of the individual's occupation.

This allows for more nuanced analysis and tests the robustness of the original specification. We rerun the multivariate model using the same independent variables. This time however, as well as estimating how the various characteristics influence an individual's engagement in green activities within their occupation, we also break this down to look directly and indirectly at green activities. As such, we also include the indirect measure of green occupation (GID) and three direct measure (green tasks, and its two constituent parts broken down individually - GN&E and GES).

Finally, we use clustered OLS regressions to explore whether there is a pay premium, or pay penalty for working in a green occupation, and to what extent this can be explained by the different characteristics. The initial model estimated is as follows:

$$\log Y_i = \beta 0 + \beta 1$$

- $\log Y$ represents the log of basic hourly pay.
- β1 is the coefficient for the greenness of the occupation.

We use a stepwise approach and progressively adding individual, firm, sector, and regional controls to assess the impact of each group of characteristics on the dependent variable and to understanding how the inclusion of different variables changes the model's explanatory power and the coefficients of other variables.

3. Results

The results section begins by providing descriptive statistics on the characterises of who works in green occupations, detailing the sectors and regions that they work in and how this has changed over time (between 2011 and 2018). We then present information on pay gaps, by gender and ethnicity, before presenting some preliminary results exploring whether individuals' choice to work in green occupations is also reflected in their behaviour. We do this by looking at their mode of commuting. Finally, we use multivariate analysis to explore these issues in further detail.

3.1 Descriptive analysis

Table 1 presents the estimates of green jobs using two approaches for the years 2011 to 2018. The first and second column of results (Max) record our top end estimates of employment in green occupations (i.e. considered green if at least one of its matched O*NET occupations was green). Table 1 shows there was little growth, albeit, nearly a third of the workforce being seen as green.

The following rows, break the information down to those occupations which were directly green and those which were indirectly green - given the mapping structure of this data, some occupations were classified to more than one type of green job. Of the jobs which were directly green, just over 14% of all jobs were GN&E and approximately 20% GES. The estimates fell slightly over the period, while it was estimated that the share of indirectly green jobs (GID) rose over this period to just under 20% in 2018.

We then apply a weighted estimate across all the US O*Net occupation mapped to UK occupations, while also taking into account any double counting of UK occupations – this is our preferred measure. This creates a measure of greenness (values range from 0 to 1 for each occupation). These more conservative estimates are presented in the third and fourth column of results. They indicate that approximately 16% of all occupations are green. Of those directly green occupations, 4.3% are green new and emerging occupations and 6.1% are in relation to green enhanced skills. It I estimated that 6.1% are indirectly green. Our weighted-mean approach is in line with estimates of Bowen et al. (2018) and Valero et al (2021) who estimated an overall share of the green employment being 19% for the US economy and 17% for the UK economy (using LFS data).

Table 1: Share of green employment

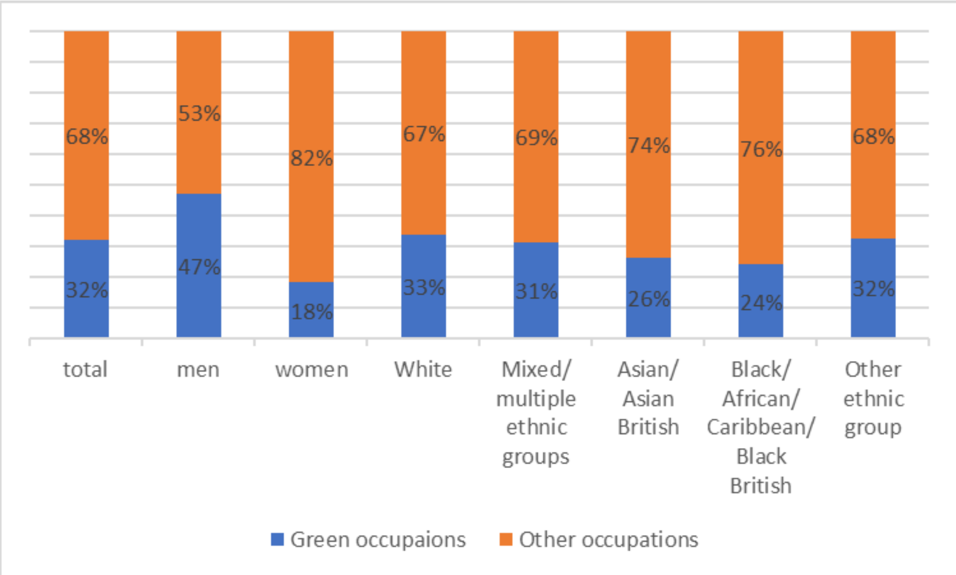
		Max		Average	
		(1) 2011	(2) 2018	(3) 2011	(4) 2018
	Green occupations	31.8%	31.9%	15.9%	15.9%
Directly green:	Green new and emerging	14.3%	14.2%	4.3%	4.3%
	Green enhanced skills	20.1%	19.7%	6.1%	6.1%
Indirectly green:	Green Increased demand	18.9%	19.3%	6.2%	6.2%

Source: O*NET and ONS (ASHE)

Using our binary measure of green jobs, we then look at the distribution across different groups. Figure 1 records the average proportion of green jobs to total jobs by group and reveals that in 2018, nearly 70% of all green occupations were filled by men, this compares to 52% of all employment (ONS, 2023d). In terms of ethnicity, 93% of all green occupations are undertaken by white workers, while they account for just 80% of the working age population (Gov.UK, 2023a).

Well Figure 1 clearly illustrates the difference between men and women in green and other types of occupations. In terms of ethnicity the difference appears less pronounced, however it is of note that Black/African/Caribbean/Black British are clearly underrepresented, conditional on already being employed. Given that employment rates for this group are below that for white counterparts – 69% compared to 77% (Gov.UK, 2023b), the disadvantage in terms of employment in green occupations is compounded. Given the enhanced opportunities green employment can offer to individuals as we transform 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 the underrepresented communities across gender and ethnic groups. It also suggesting there is a need for further research to explore the spread of green jobs across other groups, such as by socioeconomic status (e.g. income deciles), education levels and skill level.

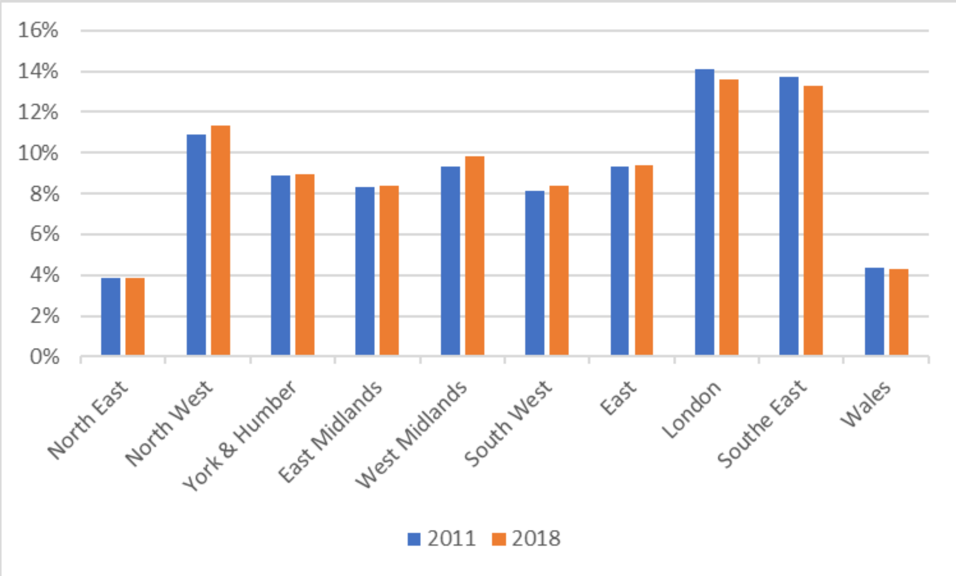
Figure 1: Share of green employment by gender and ethnicity (2018)



Source: O*NET and ONS (ASHE and ASHE linked to Census 2011)

Figure 2 presents the regional breakdown of green occupations by NUTS1 regions. Over a quarter of all green jobs were based in London and the Sout East combined, with each region accounting for over 13% of green occupations nationally. Between 2011 and 2018 the proportion of green occupational employment grew sharpest in the West Midlands, increasing by nearly 0.5 percentage points. Given the West Midlands strong industrial base, this likely reflects the transitioning towards green technologies, such as clean manufacturing and green automotive (like electric vehicle production). London and the South-East witnessed the sharpest decline, 0.6 and 0.4 percentage points respectively. This may partially reflect higher cost of living and operating businesses in these area, discouraging investment in green projects which can be capital-intensive and have longer payback periods. In London, it may also reflect the fact that the economy is heavily skewed towards the financial service sector, which has seen not seen as much green job growth.

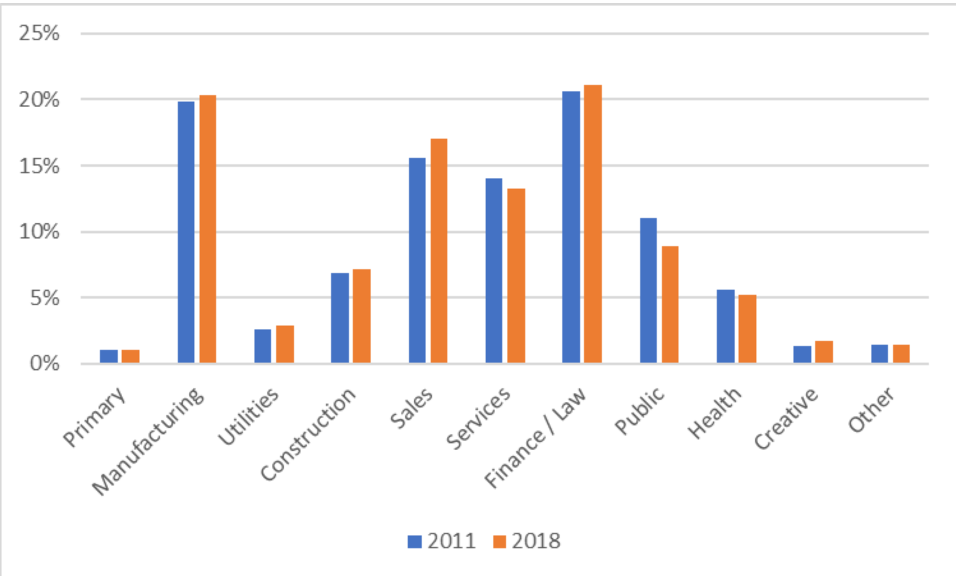
Figure 2: Regional share of green occupational employment (2011 and 2018)



Source: O*NET and ONS (ASHE)

The sector breakdown of employment in green occupations is presented in Figure 3. It shows that Finance/Law and Manufacturing were the two largest providers of green occupations, each contributing approximately 20% of all green occupations – over 40% in total. Although starting from a low base, the creative industries recorded the highest sector growth rate in terms of the proportion of green occupations compared to all other occupations, witnessing nearly a 30% increase. The public sector accounted for 11% of all green employment, but experienced the greatest reverse in the proportion of green occupations compared with all other occupations, falling by nearly 20%. This may indicate that austerity and public sector cuts are being felt more heavily green occupations.

Figure 3: Sector share of employment by green occupation (2011 and 2018)



Source: O*NET and ONS (ASHE)

In terms of pay structure, the initial analysis (excluding ethnic breakdowns) uses ASHE data only, to exploit the benefits of the greater sample size. Table 2 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 exceeds average wage for all employment (£12.04). However, the gender breakdown reveals that women working in green occupations receive nearly 10% less per hour than their male counterparts working in in green occupations. This gap in gender pay for green occupations is broadly reflective of the estimates for the full economy (ONS, 2022b)

Table 2: Hourly average earnings by gender (2018, median pay)

	Occupations		
	Green	Other	Total
Male	£14.38	£12.33	£13.39
Female	£13.06	£10.53	£10.99
Total	£14.00	£11.14	£12.04

Source: O*NET and ONS (ASHE)

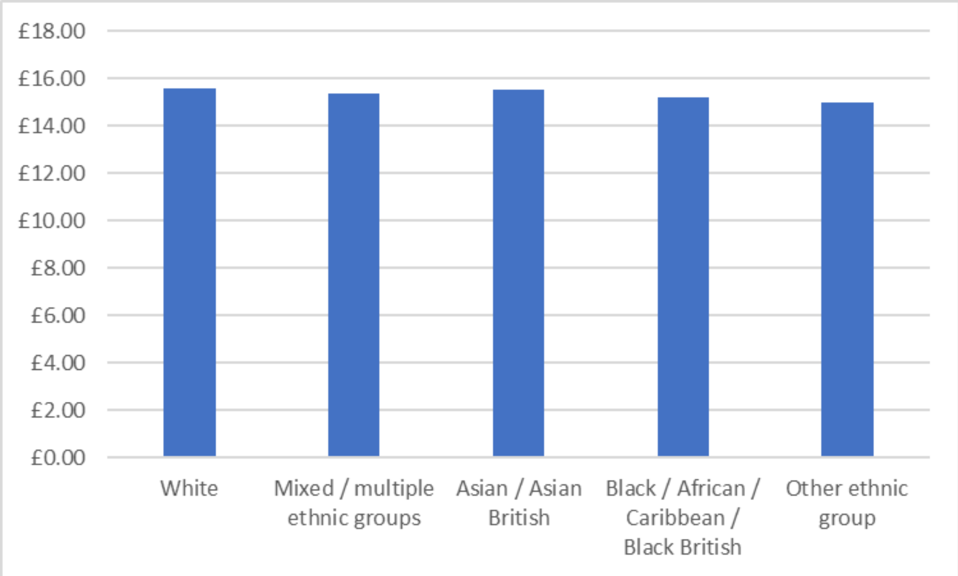
Additional breakdowns on pay by region, sector and age pay profiles are included in Appendix 2, but excluded here for brevity. These breakdowns show that in terms of median pay, unsurprisingly there is an additional pay premium for those working in green occupations in Lonon (£18.92), while earnings were highest for the 36-45 category (£15.73). This aligns with prior knowledge on earnings profiles, was earnings have a non-linear age function, partially due to cohort effects (i.e. high earners leaving employment earlier in their working life). However, of more interest is the additional premiums experienced by those working in the utilities sector (£15.74 per hour). This, at least in some part, may reflect an increase in investment in green technologies and renewable energy sources, which require new, specialised roles to manage and maintain these technologies and resources.

There are likely to be several contributing factors to any such pay premiums, which are explored in some detail in the multivariate analysis presented. However, one striking difference is the structure of the job, particularly in terms of average hours worked. Given that fulltime jobs are generally better paid that part-time roles (ONS, 2022b), part of the difference may be explained by the fact that those working in green occupations, on average work seven hours longer a week than those working in other occupations (see Appendix 3 for more detail).

By combining the ASHE data with the Census 2011 data, we are also able to look at 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 to increase to £15.54 per hour, from £14.00 per hour for the the full ASHE sample. As such, comparisons of ethic wages are with respect to the heighted average for this subset (£15.54 per hour).

Figure 4 shows that there is a pay gap for each of the four ethnic groups specified, ranging from just 0.2% for Asian/Asian British workers to 3.8% for 'other ethic groups' than the other four specified. While the negative gap appears small with Asian / Asian British, although not directly comparable, this is considerable reversal to the findings reported in Phan (et al., 2022) when exploring pay gaps for the whole labour market. In their study they found that individuals with Indian and Chinese ethnicities recorded positive median pay gaps compared to white workers of around 7% and 12% respectively.

Figure 4: Hourly average pay, by ethnicity (2018, median)



Source 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. All 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. Again, there may be many factors at work here, and these issues are explored in more detail in the multivariate analysis.

The linked ASHE-Census 2011 data also allows us to explore the link between green work and green behaviours. For the first time this study uses large scale national statistical data, to explore Holland's Theory of Career Choice in relation to green jobs. As such, we investigate whether environmental behaviours mirror occupational choices through presentation information on modes of travel to work by those working in green occupations. Counterintuitively, Table 3 shows that those working in other occupations are more likely to use public transport than those working in green occupations.

The comparisons over time show that the choice to use public transport has fallen for both groups during this period, but at a faster rate for those working in green occupations. This resulted in a smaller percentage of workers in green occupations choosing to use public transport when they have a car at their disposal. These results will be informed by many other factors, such as proximity to work, location of work (e.g. rural and urban) and make no account for electric car ownership, but are worthy of further examination. As such, we expect to further explored this issue in subsequent drafts, and encourage the use of similar large-scale datasets to examine behaviours underpinning green employment.

Table 3: Travel to work by public transport and car or van availability, by green and other occupations

	2011		2018	
	No of obs.	Percent	No of obs.	Percent
Green Occupations				
Public transport user: Household has 1 or more car(s) or van(s)	3,785	9.9%	2,242	8.9%

Public transport user: Household has no cars or vans	1,340	3.5%	825	3.3%
Not a public transport user	33,072	86.6%	22,046	87.8%
Other occupations				
Public transport user: Household has 1 or more car(s) or van(s)	9,031	10.9%	5,229	10.2%
Public transport user: Household has no cars or vans	4,013	4.9%	2,279	4.4%
Not a public transport user	69,606	84.2%	43,805	85.4%

Source O*NET and ONS (ASHE Linked to Census 2011)

3.2 Empirical results

To further investigate the characteristics of those who are employed in green occupations we turn to the regression analysis outlined in Section 2.3. The first set of results are shown in Table 4, which presents coefficients relating to the individual and firm characteristics, while controlling for various other individual, firm sector and regional effects - other coefficients have been excluded for brevity but will be presented in the full version of the paper. All models are clustered by occupation, which means that the standard errors of the coefficients are adjusted to account for the fact that observations within the same occupation may be correlated. This is important for accurate inference, as it affects the calculation of p-values and confidence intervals.

The results in column 1 are from a logistic regression with the dependent variable being binary, indicating whether an individual is in a green occupation or not. 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 (these have been calculated but not reported here). There is a positive association between being male and being in a green occupation. Odds of being in a green occupation are 1.93 times higher for males compared to females, assuming all other variables in the model are held constant.

When looking at ethnicity, white is the reference group. The model reports odds of being in a green occupation are 20% lower for Asian workers being in a green occupation compared to white worker. It is important to note that this is a comparative statement and does not imply any causation.

In terms of education, degree was the reference category. The results report that Individuals with an apprenticeship qualification are over twice as likely to be in a green occupation than those with a degree. This suggests a strong positive association between having an apprenticeship and being in a green occupation. This may reflect the technical nature of some of these roles.

As first highlighted in the descriptive analysis, our model suggests that part-time workers are less likely to be in a green occupation compared to full-time workers – approximately 40% les likely. Those that work in smaller companies are more likely to work in green occupations than those that work in larger companies. This likelihood increases (from 1.4 to 1.6 to 1.9 times) as the company size falls from large (50-249 employees) to medium (10-49 employees) to small employers (0-9 employees. It is also worthy of note that those that work for foreign owned companies are 1.3 time more likely to work in green occupations.

Models 2-6 use an Ordinary Least Squares (OLS) regression where the dependent variable is continuous, ranging from 0 to 1, and reflects the likelihood or intensity of being in a green occupation. As such, we can interpret the coefficients as the expected change in likelihood, or intensity of being in a green occupation, for a one-unit increase in the independent variable, holding all other variables constant.

The results are broadly supportive of that reported for the logistic regression. For example, being male, having an apprenticeship, working in smaller sized enterprises and working for foreign owned business all have positive coefficients, which are significant in most specifications. This indicates that as these factors increase the likelihood or intensity of being in a green occupation also increases. For example, column 2 suggest that a male worker has a 9% increase in the probability of being in a green occupation, or greener occupation compared to female workers, assuming all other factors are held constant.

It is noticeable, however, that some of the negative coefficients in the probability model (model 1), and in the OLS models which capture directly green jobs (model 2-5), generally have the same coefficient signs, albeit they may not be significant. Results for some variables in model 6, which is run solely on indirectly green jobs, reveal different relationships. For example, model 6, which is the only model in which Asian workers are more likely to be employed in (indirectly) green occupations compared to white workers. The same is true for hourly paid employees compared to salaried. These indirectly green jobs do not require any new knowledge or enhanced skills, and are therefore likely to be relatively lower paid.

Table 4: Selected coefficients of characteristics of workers in green jobs (2018)

	Logistic		OLS				
	(1) Green Occupation		(2) Green Occupation	(3) Green Task	(4) Green enhanced skills	(5) Green new and emerging	(6) Green in demand
Male	0.660***		0.090***	0.044**	0.024	0.021***	0.052**
Ethnicity (Ref. white)							
Mixed / multiple ethnic groups	0.087		0.006	-0.003	-0.013	0.005	0.011
Asian / Asian British	-0.202**		-0.029**	-0.031***	-0.024**	-0.013***	0.004
Black /Africal / Caribbean / Black Briti	-0.208		-0.012	-0.025***	-0.019***	-0.012***	0.016
Other Ethnick Group	0.080		-0.008	-0.030	-0.025	-0.005	0.018
Born outside the UK	-0.045		-0.014	-0.025***	-0.016**	-0.013***	0.013
Qualification (Ref. Degree)							
None	0.227		0.021	-0.010	0.011	-0.024	0.037
Level 1	0.122		0.015	-0.011	0.004	-0.014	0.031**
Level 2	0.170		0.015	-0.009	0.002	-0.010	0.028***
Apprenticeship	0.705***		0.057***	0.019	0.010	0.013	0.049***
Level 3	0.201*		0.020	0.007	0.006	0.006	0.017***
Other vocational	0.317*		0.036	-0.002	0.014	-0.018**	0.045**
Marital status (Ref. married)							
Single	0.005		-0.013	-0.013	-0.008	-0.007	0.000
Part-time marker	-0.499**		-0.009	0.020	0.022	-0.004	-0.026**
Experience marker	-0.528***		-0.007	0.004	0.006	-0.001	-0.009
Hourly paid marker	-0.474***		-0.045*	-0.043***	-0.021**	-0.037***	0.004
Enterprise size (Ref. 250+ employees)							
0-9	0.644*		0.133	0.110	0.079	0.036	0.027
10-49	0.477***		0.054***	0.038***	0.036***	0.014	0.011
50-249	0.394***		0.045***	0.025***	0.026***	0.004	0.015*
Foreign ownership marker	0.281***		0.031**	0.003	0.000	0.006	0.026**
Additional controls							
Personal charactoristics	Y		Y	Y	Y	Y	Y
Job charactoristics	Y		Y	Y	Y	Y	Y
Industry and sector controls	Y		Y	Y	Y	Y	Y
Regional dummies	Y		Y	Y	Y	Y	Y
*p<0.01; **p<0.005; *** p<0.001							
Number of obs.	34,720		34,722	34,722	34,722	34,722	34,722
Wald chi2(42)	329.5	F(43, 358)	6.99	2.36	2.12	1.51	4.06
Prob > chi2	0	Prob > F	0	0	0.0001	0.0247	0
Pseudo R2	0.17	R-squared	0.1925	0.1542	0.1105	0.1051	0.1079
Std. err. adjusted for 359 clusters in occ10 - all models		Root MSE	0.28364	0.22477	0.17173	0.15851	0.18034

Source O*NET and ONS (ASHE Linked to Census 2011)

Following the analysis on the characteristics of those working in green occupations, we then moved on to explore the pay implications of doing so. Table 5 reports the estimated pay premium of working in green occupations. We use an OLS stepwise regression where the logarithm of hourly pay is the dependent variable. This approach has been employed to understand how the inclusion of different sets of characteristics (i.e. individual, job, employer, and sector and region) affects the model and the interpretation of coefficients.

The models start with just the green occupation variable, which is a continuous specification between 0 and 1 and represents the greenness of the occupation. The model indicates the 'unadjusted' effect of being in a green occupation on hourly pay. On average, being in a green occupation is associated with an approximately 34% higher hourly pay compared to non-green occupations. This suggests that jobs classified as more environmentally sustainable or 'green' tend to offer higher pay than jobs that are not classified as such. This result could be interpreted as 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.

Individual characteristics (e.g. age, education, gender etc.) are added to the model, which reduces the premium to working in a green job to approximately 22%. This also considerably improves the explanatory power of the model, with the R-squared jumping from 3% to 30%. The importance of having a degree in relation to increased earning is shown by the negative and significant coeffects of all other forms of education. While having very good health, no disability being married and having a dependent child are all positive contributors to higher pay.

In step 3 we add a number of controls for aspects of the job such as full-time/part-time status and whether paid hourly. These are individually negatively significant, indicating that if you work part-time and are hourly paid, you are likely to be paid less. The inclusion of these controls further improve the fit of the model which increases to 35% and reduces the 'green occupations' premium to around 19%.

In step 4 we include controls for the employer (e.g. firm size, foreign ownership), many of which are significant. For example, our results suggest that wages are approximately 4% higher for individuals working in foreign owned companies, assuming all other variables in the model are held constant. Their inclusion further improves the overall fit of the model, capturing 39% f the overall variation.

Finally, we move to our preferred specification which controls for sector and regional dummies. This only slightly improves the fit of the model, which now explains 40% of the variation. In this specification, although somewhat reduced from the original 'unadjusted' estimate, it appears that there is a considerable pay premium to working in a green occupation (circa 19%), even after controlling for numerous observable factors.

Table 5: Selected coefficients Stepwise OLS regression on the pay premium and the greenness of jobs (2018)

	(1) Base model	(2) Individual controls	(3) Job controls	(4) Employer controls	(5) Sector and region
Green Job	0.335***	0.216***	0.185***	0.195***	0.187***
age		0.030***	0.028***	0.030***	0.030***
age squared		0.000***	0.000***	0.000***	0.000***
Male		0.184***	0.163***	0.172***	0.167***
Ethnicity (Ref. white)					
Asian/Asian British		-0.037*	-0.030	-0.071***	-0.075***
Black/African/Caribbean/Black British		-0.042**	-0.041**	-0.051**	-0.059***
Qualifications (Ref. degree)					
No qualifications		-0.605***	-0.517***	-0.498***	-0.501***
Level 1 (e.g. upto 4 GCSEa)		-0.498***	-0.438***	-0.431***	-0.434***
Level 2 (e.g. over 5 GCSEs)		-0.440***	-0.393***	-0.377***	-0.380***
Apprenticeship		-0.424***	-0.366***	-0.341***	-0.345***
Level 3 (e.g. 2+ A-Levels)		-0.360***	-0.332***	-0.304***	-0.306***
Other vocational		-0.519***	-0.445***	-0.409***	-0.412***
Health (Ref. Very good health)					
Good health		-0.055***	-0.049***	-0.055***	-0.056***
Fair Health		-0.095***	-0.089***	-0.092***	-0.092***
Bad health		-0.095***	-0.094***	-0.149***	-0.146***
Disability (Ref. none)					
Daily activities limited a little		-0.041***	-0.035***	-0.025**	-0.024**
Marital status (Ref. married)					
Single		-0.053***	-0.059***	-0.076***	-0.077***
Dependent child indicator		0.097***	0.065***	0.058***	0.058***
Basic paid hours worked		0.001	-0.010***	-0.012***	-0.012***
Part-time marker			-0.296***	-0.340***	-0.337***
Paid hourly marker			-0.186***	-0.216***	-0.215***
Foreign Ownership marker				0.047***	0.042***
Firm size and other charactoristics				Y	Y
Industry and secyor					Y
Regional dummies					Y
_cons	2.535***	2.203***	2.750***	2.786***	2.770***
*p<0.01; **p<0.005, ***<0.001					
Std. err. adjusted for 359 clusters in occ10 - all models					
Number of obs =	178,408	76,141	76,141	34,722	34,722
F(43, 358) =	8.57	36.92	57.10	86.36	95.51
Prob > F =	0.0036	0.0000	0.0000	0.0000	0.0000
R-squared =	0.0328	0.2963	0.3531	0.3943	0.4001
Root MSE =	0.5064	0.4276	0.4100	0.4025	0.4006

Source O*NET and ONS (ASHE Linked to Census 2011)

4. Conclusion

In this paper, we explore the characteristics of employment in green occupations and the potential impact working in such occupations can have on pay. We use both descriptive statistics and multivariate analysis to understand who works in green occupations, and in which sector and regions they work. We find 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. White workers are disproportionately overrepresented in green occupations, with ethnic groups appearing dually disadvantaged in terms of both being underrepresented in green employment, while also facing a pay penalty compared to white workers, conditional on working in a green occupation.

For the first time we also use large scale national datasets to apply Holland's Theory of Career Choice, to investigate whether personal behaviours and choice of green employment are consistent. On average, early indications are that there is limited empirical support for this, but further research is required.

We use a stepwise regression approach to estimate whether there is a pay premium or penalty for working in green occupations. We estimate an unadjusted pay premium of 34%, which reduces to a still considerable 19% when other characteristics are controlled for.

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 in the UK. 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. We acknowledge the main challenge with this methodology is that it assumes the same task and occupational structure between US and UK economy. As such, given this limitation, we recommend that the results should be treated with caution and should be used to convey a sense of proportion of any such relationship, rather than be interpreted as a precise estimate.

However, given the pay premium result is robust across the various specifications, this 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 UK's 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. However, further research should be undertaken to demonstrate the benefit to the demand side (employer), by completing productivity studies in relation to green employment.

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, they are paid less. Further research is needed to explore the mechanisms through which this occurs and policies put into place to mitigate this.

The preliminary findings in relation to a potential mismatch between employer commuting behaviours and choice of occupation, is also worthy of further study. Linking ASHE with Census 2021 should provide an opportunity to further explore the behavioural aspects in more detail. Finally, given the rich home and workplace location information available in the dataset, this provides an opportunity to further explore regional variation, potentially through a multilevel modelling approach which can better account for regional differences in economic, social, and environmental factors that influence the prevalence and nature of green occupations.

5. References

Antoni, M., Janser M., Lehmer, F. (2015) The hidden winners of renewable energy promotion: Insights into sector-specific wage differentials. *Energy Policy*, 86, 595–613. http://dx.doi.org/10.1016/j.enpol.2015.07.027

Bagheri M., Guevara Z., Alikarami M., Kennedy C.A., Doluweera G. (2018). Green growth planning: A multi-factor energy input-output analysis of the Canadian economy. *Energy Economics*, 74, 708-720. https://doi.org/10.1016/j.eneco.2018.07.015

BEIS (2021) *Net Zero Strategy: Build Back Greener.* London: Her Majesty's Stationery Office

Bouzaher A., Sahin, S., Yeldan E. (2015) How to go green: a general equilibrium investigation of environmental policies for sustained growth with an application to Turkey's economy. *Lett Spat Resour Sci*, 8, 49–76. DOI 10.1007/s12076-014-0124-0

Bowen, A., K. Kuralbayeva and E. L. Tipoe (2018) Characterising green employment: the impacts of 'greening' on workforce composition. *Energy Economics*, 72: 263-275.

Department for Education (2019) *LMI for All* – available at www.lmiforall.org.uk

Dickerson, A. and Morris, D., 2019. The changing demand for skills in the UK. *Centre for Vocational Education Research, Research Paper*, 20.

Dierdorff EC, Norton JJ, Drewes DW, Kroustalis CM, Rivkin D, Lewis P (2009) *Greening of the World of Work: Implications for O*NET-SOC and New and Emerging Occupations.* Report prepared for U.S. Department of Labor, Employment and Training Administration, Office of Workforce Investment, Division of Workforce System Support, Washington, DC.

Forth, J., Phan, V., Ritchie, F., Whittard, D., Stokes, L., Bryson, A., and Singlvaleton, C. (2022) *ASHE – Census 2011 Data Linkage User Guide for Drop 2 of the ASHE-Census 2011 Dataset*. Bristol: Wage and Employmnet Dynamics Project

Gov.UK (2023a) *Working Age Poulation.* London

Gov.UK (2023b) *Employmnet.* London

Green Jobs Taskforce (2021) *Report to Governmnet, Industry and the Skills Sector.* London

Garrett-Peltier, H. (2017) *Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model*. Economic Modelling 61, 439–447.

Holland, J.L., (1973) Making career choices: A theory of careers. *Englewood Cliffs, NJ*.

Kim, A., Kim, Y., Han, K. 2019. A Cross Level Investigation on the Linkage Between Job Satisfaction and Voluntary Workplace Green Behavior. *Journal of Business Ethics*, 159, 1199–1214. https://doi.org/10.1007/s10551-018-3776-7

Kolsuz, G. Yeldan A.E. (2017) Economics of climate change and green employment: A general equilibrium investigation for Turkey. *Renewable and Sustainable Energy Reviews,* 70, 1240 – 1250.

Lee, T.; van der Heijden, J. (2019) Does the Knowledge Economy Advance the Green Economy? An Evaluation of Green Jobs in the 100 Largest Metropolitan Regions in the United States. *Energy Environ*, *30*, 141–155.

Markaki M., Belegri-Roboli, A., Michaelides P., Mirasgedis S., .Lalas, D.P. (2013) The impact of clean energy investments on the Greek economy: An input–output analysis (2010–2020). *Energy Policy*, 57, 263–275. http://dx.doi.org/10.1016/j.enpol.2013.01.047

Maxim M.R., and Zander K. 2020. Green tax reform and employment double dividend in Australia should Australia follow Europe's footsteps? A CGE analysis. Margin—*The Journal of Applied Economic Research*, 14, 4, 454–472.

O*NET (2010) *O*NET Green Task Development Project* available at www.onetcenter.org/reports/GreenTask.html

Office for National Statistics (2022a) *Research into "green jobs": time spent doing green tasks, UK: 1997 to 2019.* Newport

Office for National Statistics (2022b) *Gender pay gap in the UK: 2022.* Newport

Office for National Statistics (2023a*) "Green jobs" update, current and upcoming work*: March 2023. Newport

Office for National Statistics (2023b) *ONS SRS Metadata Catalogue, dataset, Annual Survey of Hours and Earnings linked to 2011 Census - England and Wales*., https://doi.org/10.57906/80f7-te97

Office for National Statistics (2023c) *ONS SRS Metadata Catalogue, dataset, Annual Survey of Hours and Earnings Longitudinal – UK.* Released 11 May, https://doi.org/10.57906/nz2h-kc10

Office for National Statistics (2023d) A02 SA: Employment, unemployment and economic inactivity for people aged 16 and over and aged from 16 to 64 (seasonally adjusted).

Phan, V., Singleton, C., Bryson, A., Forth, J., Ritchie, R., Stokes, L. and Whittard, D. (2022) Accounting for Firms in Ethnicity Wage Gaps throughout the Earnings. *IZA Institute of Labour Economics Discusion Paper*

Robins N, Gouldson A, Irwin W, Sudmant A (2019*) Investing in a Just Transition in the UK: How investors can integrate social impact, place-based financing into climate strategies.* London: Grantham Research Institute on Climate Change, the Environment.

Rutkowska, M.; Sulich, A. (2020) Green Jobs on the Background of Industry 4.0. *Procedia Comput. Sci.*, *176*, 1231–1240

Rodríguez, J.L. (2019) The Promotion of Both Decent and Green Jobs through Cooperatives. *Boletín Asoc. Int. Derecho Coop. 54*, 115–129

Sissons, P., Green, A.E., Lee, N. 2018. Linking the Sectoral Employment Structure and Household Poverty in the United Kingdom. *Work Employment and Society*, 32, 6, 1078–1098. https://doi.org/10.1177/0950017017722939

Skidmore, C., (2022). *Mission Zero: Independent Review of the UK Government's Approach to Delivering Net Zero.* London

Song, K.; Kim, H.; Cha, J.; Lee, T. (2021) Matching and Mismatching of Green Jobs: A Big Data Analysis of Job Recruiting and Searching. *Sustainability*, *13*, 4074.

Stanef-Puică, M.R., Badea, L., Șerban-Oprescu, G.L., Șerban-Oprescu, A.T., Frâncu, L.G. and Crețu, A., (2022) Green Jobs—A literature review. *International Journal of Environmental Research and Public Health*, *19*(13), p.7998.

Stokes, L; Forth, J; Ritchie, F; Singleton, C; Phan, V; Bryson, A; Whittard, D; McKenzie, A (2021) *Methodology Paper: Weighting for employer non-response in ASHE*. Bristol: Wage and Employmnet Dynamics Project

Sulich, A.; Rutkowska, M.; Popławski, Ł. (2020) Green Jobs, Definitional Issues, and the Employment of Young People: An Analysis of Three European Union Countries. *J. Environ. Manag. 262*, 110314.

United Nations Environment Programme (2008) *Green Jobs: Towards Decent Work in a Sustainable, Low-Carbon World*: Washington, DC, USA, 2008.

Valero, A., Li, J., Muller, S., Riom, C., Nguyen-Tien, V., and Draca M. (2021) Are 'green' jobs good jobs? How lessons from the experience to-date can inform labour market transitions of the future. London: *Granthan Research Institute on Climate Change and the Environment*

Vona. F., 2018. Job losses and political acceptability of climate policies: why the 'job-killing' argument is so persistent and how to overturn it. *Climate Policy,* 19, 4, 524-532. DOI: 10.1080/14693062.2018.1532871

Vona, F., Marin, G., Consoli, D. 2018. Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014. *Journal of Economic Geography,* 19, 5, 1021–1048. https://doi.org/10.1093/jeg/lby038

Vona, F. 2019. Job losses and political acceptability of climate policies: why the 'job-killing' argument is so persistent and how to overturn it. *Climate Policy,* 19, 4, 524-532. DOI: 10.1080/14693062.2018.1532871

Yoo, S., Heshmati, A. (2019) The Effects of Environmental Regulations on the Manufacturing Industry's Performance: A Comparison of Green and Non-Green Sectors in Korea. *Energies*, 12, 2296. doi:10.3390/en12122296

Zachmann, G., Fredriksson, G. and Claeys, G., (2018) The distributional effects of climate policies. *Bruegel Blueprint Series*, *28*, p.2018.

Zainudin, Z.N., Rong, L.W., Nor, A.M., Yusop, Y.M. and Othman, W.N.W., (2020) The relationship of holland theory in career decision making: A systematic review of literature. *Journal of critical reviews*, *7*(9), pp.884-892.

6. Appendix

6.1 Appendix 1: List of variables used in the ASHE and ASHE-Census 2011 dataset

Variable	Description	Variable name
Basic hourly wage	Basic hourly pay is a continuous variable, calculated by the ratio of the basic weekly earnings to the total number of basic weekly paid hours (Unit: £)	bpay/bhr
Age	Employee's age (years)	age
age squared	Employee's age (years) squared	age_squared
Male	Dummy variable indicating wether the employee is male	sex
Ethnicity	Employees ethnicity - white, mixed/multiple ethnic groups; Asian/Asian British; Black/Africam/Caribean/Black Britich; Other Ethnic Groups	aggethpuk111
Born outside the UK	Dummy variable to indicate wether the individual was born out side the UK	aggcobpuk113
Qualifications	Self reported level of highest qualification, listed as no qualification; level1; Level2; Apprenticeship; Level 3; Level 4: Other viocational	hlqpuk11
Health	Dummy varaible for self reported health varaible using a five point scale of very good health; good health; fair health; bad health; and very bad health	health
Disability	Self reported variable to identify if diability interfers with daya to day activities - reported as not at all; to a limited extent; and to a lot	disability
Marital status (Ref. married)	Dummy variable - nine point marker indicating the marital status of the individual covers single; married; divorced; widowed; legally registered in a same sex civil partnership; seperated but still legally in a same sex civil partnership; disolved same sex civil partnership; surviving partner of asame sex civil partnership	marstat
Dependent child	Dummy varaiable to indicate whether the indivudal is responsible for a dependent child	dchpuk11
Basic paid hours worked	Basic weekly paid hours worked = basic pay*100 / hourly rate of pay	bhr
Parttime marker	Dummy varaiable to indicate wether the job is part time	fulltime
Experience	A dummy variable to indicate wether the current main job is the longest job the individual has on record - the marker is derived from the empsta varaiable	main_job_tenure
Paid hourly marker	Dummy varaiable to indicate whether the individual was hourly paid	hourly_paid
Firm size band	The number of people working in the firm ny size band 0-9; 10-49; 50-249 and 250+	emp_size_band
Collective agreement	Dummy marker to indicate wether the individual is subject to a collective bargaining agreement or not.	coll_agt
Foreign Ownership	Dummy marker to indicate wether the individual works for a company which is foreign owned	for_own
Sector	Dummy marker to identify wether the individual works for a firm in the public, private or unclassified sector	pubpriv
Industry	Industry as measured by five digit sic07	sic07
Region	Governmnet office region of workplace - NUTS 1 regions of UK	region
Green Occupation (binary variable)	Dummy variable to identify UK occupations which match to one or more of the US green occupations idenmtified via the O*NET project. The main occupation varaible is further dissagrgated to include green task; green new and emerging; green enhanced skills and green in demand derivative varaiable	max_green_occ max_green_task max_GN&E max_GES max_GID
Green occupation (continuous variable)	Continuous varaiable which weights the occupation data to identify the greeness of the occupation. It does this by using a first weighting factor to account for the proprtion of US green and non-green occupations matched to a single UK occupation, weighted by the size of the US labour force. A second weighting factor is applied to account for any double counting where multiple UK occupations are matched to a single US occupation.	wght_mean_green_occ wght_mean_green_task wght_mean_GN&E wght_mean_GES wght_mean_GID

6.2 Appendix 2: Median pay, by region, sector and age-band

Appendix 2a: Hourly average pay, by region (NUTS 1)							
		2011			2018		
Region		Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
NE	Median	9.45	11.66	10.08	10.43	13.08	11.24
NW	Median	9.46	12.02	10.16	10.66	13.24	11.5
Yorks	Median	9.36	11.84	10.09	10.43	12.65	11.24
EM	Median	9.33	11.41	10.1	10.23	12.5	11.12
WM	Median	9.38	11.79	10.13	10.54	13.13	11.46
SW	Median	9.47	11.85	10.16	10.65	13.37	11.55
East	Median	9.74	12.66	10.65	10.83	13.89	11.82
Lond	Median	13.38	17.38	14.78	14.02	18.92	15.59
SE	Median	10.09	13.53	11.18	11.35	14.79	12.37
Wales	Median	9.33	11.89	9.98	10.44	12.59	11.11
Scot	Median	*	*	*	11.5	14.15	12.35
Unknown	Median	*	*	*	10.23	16.11	11.73
Total	Median	10	12.77	10.9	11.14	14	12.04
* Denotes removed for disclosure purposes							

Appendix 2b: Hourly average pay, by sector							
		2011			2018		
		Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
primary	Median	8.93	13.23	10.51	10	13.29	11.34
manuf	Median	10.66	12.83	12.14	12.24	14.26	13.6
utilities	Median	12.89	14.22	13.81	14.91	15.79	15.49
construction	Median	10.75	13.14	12.3	12.65	14.68	14.06
sales	Median	7.65	10.1	8.2	9.19	11.74	9.87
services	Median	8.4	13.16	10	9.26	14.08	10.69
fin/law	Median	10.6	14.28	11.86	12.05	15.36	13.25
public	Median	12.71	13.79	12.95	14.11	15.27	14.37
health	Median	11.09	12.11	11.15	11.74	13.3	11.96
creative	Median	8.53	10.16	8.88	9.5	11.38	9.94
other	Median	8.53	11.88	9.23	9.67	13.6	10
Total	Median	10	12.77	10.9	11.14	14	12.04

Appendix 2c: Hourly average pay, by age-band							
		2011			2018		
		Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
25 and under	Median	7.22	8.54	7.51	8.64	9.96	8.93
26-35	Median	10.91	12.57	11.52	11.78	13.63	12.49
36-45	Median	11.53	14.38	12.57	13	15.73	14.02
46-55	Median	10.92	14.25	12.07	12.02	15.64	13.25
56-65	Median	9.87	12.7	10.78	10.92	14.48	11.93
66 and over	Median	8	10.25	8.33	9.75	12.29	10.15
Total	Median	10	12.77	10.9	11.14	14	12.04

6.3 Appendix 3: Median pay, by region, sector and age-band

Appendix 3a: Average basic weekly working hours, by gender (mean)						
	2011			2018		
Gender	Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
Male	33.26	37.28	35.13	33.09	37.57	35.2
Female	26.79	31.89	27.73	27	33	28
Total	29.23	35.66	31.27	29.16	36.18	31.39

Table 3b: Average basic weekly working hours, by ethnicity (mean)						
	2011			2018		
	Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
White	29.41	36.01	31.54	30	37	32
Mixed/multiple ethnic groups	28.12	34.27	29.77	30.77	35.9	32.37
Asian/Asian British	29.68	34.63	30.98	31.16	35.59	32.31
Black/African/Caribbean/Black British	29.63	34.37	30.68	31.15	36.38	32.4
Other ethnic group	29.94	35.55	31.57	32.26	36.34	33.58
Total	29.42	35.9	31.47	30.17	36.5	32.25

Appendix 3c: Average baic weekly working hours, by region (NUTS 1)						
	2011			2018		
Region	Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
NE	29.12	35.41	31.04	29.16	36.02	31.27
NW	29.26	35.63	31.24	29.23	36.13	31.42
Yorks	28.88	36	31	28.62	36.26	31.17
EM	29.06	35.83	31.57	28.52	36.52	31.43
WM	28.78	35.86	31.13	29.29	36.4	31.76
SW	28.19	35.5	30.38	27.9	36.1	30.42
East	28.66	36.04	31.03	28.51	36.38	31.04
Lond	31.12	35.68	32.53	31.18	36.1	32.65
SE	28.79	35.72	30.94	28.88	36	31.11
Wales	29.02	36	31.13	28.91	36.45	31.15
Scot	*	*	*	29.04	35.72	31.06
Unknown	*	*	*	31.17	37.2	33.01
Total	29.23	35.66	31.27	29.16	36.18	31.39
* Denotes removed for disclosure purposes						

Appendix 3d: Average basic weekly working hours, by sector (mean)						
	2011			2018		
	Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
primary	32.29	37.57	34.9	32.22	38.16	34.93
manuf	34.89	37.43	36.64	34.66	37.68	36.77
utilities	35.6	36.6	36.29	35.97	37.8	37.25
construction	33.17	39.02	37.03	31.72	38.86	36.33
sales	27.09	34.55	29.26	27.39	35.98	30.23
services	30.51	36.9	32.68	29.38	37.33	31.83
fin/law	30.82	34.99	32.42	30.65	35.35	32.46
public	28.07	33.52	28.97	28.17	33.52	29.01
health	29.47	32.19	29.83	29.91	32.62	30.21
creative	25.47	33.08	27.34	23.39	33.27	25.87
other	26.72	33.89	28.43	25.29	33.54	26.95
Total	29.23	35.66	31.27	29.16	36.18	31.39

Appendix 3e: Average basic weekly working hours, by age-band (mean)						
	2011			2018		
	Other occupation	Green ocupation	Total	Other occupation	Green ocupation	Total
25 and under	25.8	33.91	27.86	25.76	34.96	28.15
26-35	31.29	35.85	32.83	31.24	36.5	33.05
36-45	30.07	36.12	32.1	30.24	36.48	32.32
46-55	30.24	36.38	32.25	30.31	36.87	32.45
56-65	28.01	35.3	30.35	27.86	35.92	30.41
66 and over	18.76	26.91	20.43	18.99	28.62	21.43
Total	29.23	35.66	31.27	29.16	36.18	31.39

6.4 Appendix 4: Median pay, by region, sector and age-band

Appendix 4: Method of travel to work, by green and other occupations

	2011		2018	
	No. of obs.	Percent	No. of obs.	Percent
Green occupations				
Work mainly at or from home	760	2.0%	430	2%
Underground, metro, light rail, tram	1,132	3.0%	591	2%
Train	2,196	5.8%	1,264	5%
Bus, minibus or coach	1,797	4.7%	1,212	5%
Taxi	60	0.2%	49	0%
Motorcycle, scooter or moped	478	1.3%	342	1%
Driving a car or van	25,540	67.3%	16,840	68%
Passenger in a car or van	1,926	5.1%	1,300	5%
Bicycle	1,360	3.6%	962	4%
On foot	2,571	6.8%	1,825	7%
Other method of travel to work	112	0.3%	66	0%
Total	37,932	100.0%	24,881	100%
Other occupations				
Work mainly at or from home	1,312	1.6%	760	2%
Underground, metro, light rail, tram	2,287	2.8%	1,213	2%
Train	3,925	4.8%	2,192	4%
Bus, minibus or coach	6,832	8.4%	4,103	8%
Taxi	279	0.3%	149	0%
Motorcycle, scooter or moped	602	0.7%	335	1%
Driving a car or van	48,868	59.9%	31,093	61%
Passenger in a car or van	4,188	5.1%	2,594	5%
Bicycle	2,455	3.0%	1,567	3%
On foot	10,577	13.0%	6,563	13%
Other method of travel to work	193	0.2%	109	0%
Total	81,518	100.0%	50,678	100%

Source O*NET and ONS (ASHE)