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Profiling Green Jobs and Workers in South Africa

An Occupational Tasks Approach

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Abstract

To adequately prepare the labor force for the green economy, policy makers and workers require a detailed understanding of the nature of green jobs. This study profiles green jobs in the South African labor market. It uses labor force survey data and applies an occupational task-based approach to identify current green occupations and associated jobs, count them, and profile their workers and wages. The findings show that 5.5 to 32 percent of South Africa's jobs can be labeled as "green," where the former estimate uses a strict definition and the latter uses a broad definition. The share of strictly green jobs has not changed over the past eight years. While 65 percent of strictly green occupations can be classified as high (skill) occupations, only 55 percent of workers are in these occupations, reflecting numerous employment opportunities in mid-level and elementary green occupations. Strictly green occupations tend to be male-dominated and held by prime-age (25–44) workers with post-secondary school. However, the profile of those in the greenest of the green occupations shows that they are older (age 45–65) workers and Black Africans with lower than completed high school education. Policies to prepare South Africans to engage in the green economy include developing a strategy to teach new and existing workers to use green technologies; targeting green occupations in youth development programs; making a concerted effort to support women in science, technology, engineering, and mathematics; helping low-skilled green workers to organize and improve their work conditions; and continuing to collect and analyze data for better tracking South Africa's progress in becoming a green labor force.

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Profiling Green Jobs and Workers in South Africa: An Occupational Tasks Approach

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1 Introduction

Like many parts of the world, South Africa is experiencing deteriorating climate conditions. Rising temperatures, droughts and water shortages have become the new normal (Republic of South Africa 2021; Arndt, Gabriel, Hartley, Strzepek, and Thomas 2021; World Bank Group 2022; Engelbrecht et al. 2015). These weather events are destroying and disrupting communities and livelihoods.[4] At the same time, South Africa's high reliance on coal for its energy needs may be contributing to the climate crisis. Global pressure to move away from carbon-based energy is a challenge in a labor market where the mining industry directly and indirectly creates thousands of jobs (Maseko 2021; Makgetla and Patel 2021; Makgetla 2021) even as aggregate employment rates have been on the decline and unemployment has been on the rise since 2008 (StatsSA 2022; Maseko 2021; World Bank Group 2018).[5]

The South African government is committed to growing its economy and creating jobs through environmentally friendly strategies (Inglesi-Lotz 2021, DEA 2011, NPC 2011). The National Development Plan of 2011 envisions the green economy – which can be characterized as industries and outputs that do not create significant environmental risks[6] – as an avenue for job creation and a pathway to alleviate the challenges of high levels of poverty and inequality by promoting an "environmentally sustainable, climate change resilient, low-carbon and just society" (NPC 2011). The education and skills sectors are preparing to train workers for green jobs, which can be defined as jobs that aim to reduce the human-induced negative impact on the environment and climate change.[7]

Research supports the view that the transition to a green economy could be a job-creator in South Africa (World Bank Group 2022; PCC 2021; Merven et al. 2019, Maia et al. 2011, Rutovitz 2010), though these studies do not directly measure green jobs. Instead, they use an "output approach" (Granata and Posadas 2024), where they select industrial sectors that are directly linked to energy, natural resources, or waste pollution and estimate job growth scenarios based on how the industries are expected to grow. The estimates range from 149,000 (Rutovitz 2010) to nearly 500,000 (Maia et al. 2011) new jobs over the next few decades. While these studies give rough orders of magnitudes of the future number of jobs

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[4] For example, during the severe 2018 water crisis in the Western Cape, two-thirds of tourism businesses reported being adversely affected (World Bank Group 2022).

[5] Employment rates in South Africa have been on the decline and aggregate unemployment has been on the rise since the 2007-2008 global financial crisis, exacerbated by the recent Coronavirus (COVID-19) pandemic. In the first quarter of 2022, the unemployment rate stood at 34.5 percent (StatsSA 2022) for the working age population but was much higher for young people (63.9 percent for those aged 15-24 years). Of 10.2 million youth aged 15-24 years, 37 percent were not in employment, education nor training (NEET) in the first quarter of 2022 (StatsSA 2022).

[6] Specifically, the NPC adopts the UNEP definition of the green economy which is "...a system of economic activities related to the production, distribution and consumption of goods and services that result in improved human well-being over the long term, while not exposing future generations to significant environmental risks and ecological scarcities".

[7] There is no consensus in the literature as to the concise definition of green jobs, making the process of measuring green jobs complex. There is however a convergence on the concept that green jobs are those that aim to reduce the human-induced negative impact on the environment and climate change, as defined by UNEP and the ILO (Stanef-Puică et al. 2022).

in climate-related industries,[8] they do not tell us about the nature of green jobs today, wages earned, or who works in those jobs.

A recent international literature uses a more systematic approach to identify and characterize green jobs. These studies use an occupational task approach, where they label an occupation – and the jobs within – as green based on how green the tasks within an occupation are, rather than the industry that houses a job (Granata and Posadas 2024; Vona et al. 2019; Consoli et al. 2016; Vona et al. 2018). The occupational tasks approach has been widely applied in labor economics to analyze how technological change has affected skills, wages and job polarization over time (Autor et al. 2003; Acemoglu and Autor 2011; Goos et al. 2014; Cunningham et al. 2022).[9] We can use the same logic to understand how a shift to a green economy may affect jobs. Using the occupational task approach allows for greenness of an occupation to be defined according to the number of tasks relating to environmental sustainability that are typically carried out in that occupation (Vona et al. 2019). The advantage of the occupational task approach is that one can identify green jobs in any industry, even those not directly engaged in environmentally sensitive industries.

This paper aims to fill the gap in the South African literature by using South African household survey data and applying an occupational task-based approach to characterize green jobs and workers in South Africa. Inspired by Granata and Posadas (2024), we define two sets of green jobs: strict and broad. Recognizing that occupations are groupings of jobs with similar tasks, we first identify "strictly green jobs," as those in occupations that require at least one task that is directly linked to the environment. We then broaden our definition to include occupations with job tasks that could reduce human-induced environmental risks, if they used green technology or processes[10] and refer to the larger set of jobs as "broadly green jobs". Notably, strictly green jobs are a subset of broadly green jobs. We then take stock of occupations that can be classified as strictly and broadly green in the current South African economy and, using regression analysis, profile the related jobs and workers. The paper does not forecast the number of new jobs or occupations that will arise from the transition to a

[8] These studies may over-estimate the number of green jobs since not all workers in these sectors are involved in green activities. On the other hand, they underestimate green jobs because they do not consider other sectors where workers might be carrying out tasks that reduce the human-induced negative impact on the environment and climate change.

[9] In this literature, it is useful to distinguish between tasks and skills. A task is defined as a unit of work activity that produces output (goods and services). A skill is defined as a worker's endowment of capabilities for performing various tasks (Acemoglu and Autor 2011). Workers with similar skills can perform different tasks depending on the technology available to them and the production function.[10] These jobs could be carried out using green or non-green technologies or processes. For example, workers in agriculture could use traditional methods (non-green technologies) or could practice sustainable farming (green technology). Since we do not have information about the take-up of green technologies within occupations, we assume that those occupations where green technologies or processes could be used do indeed use them. This gives us an upper-bound of broadly green jobs in South Africa.

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green economy.[11]

We find that a substantial number of South African jobs and a broad range of workers can be classified as green. We estimate that 5.5 percent of South Africa's jobs can be strictly defined as green while 32 percent can be defined as broadly green.[12] This maps to 46 strictly green occupations and 137 broadly green occupations, from a list of 428 occupations. The green jobs estimates are within the range of other countries. While 65 percent of strictly green occupations in the South African labor market require highly skilled workers, resulting in a wage premium for those employed in these occupations, they employ only 55 percent of workers in strictly green jobs. Instead, a smaller share of mid-level and elementary occupations are responsible for 45 percent of total (strictly) green employment. While the share of strictly green jobs has barely changed over the past eight years, there was an increase in the share of broadly green jobs between 2013 and 2014. Consistent with international literature, relative to the general labor force, the average workers in strictly green occupations tend to be male, of prime working age (25-44) and have some type of tertiary qualification.

This exercise contributes to the literature in several ways. First, it provides a benchmark against which to measure South Africa's evolution of green jobs on average and among traditionally excluded groups. Second, it offers guidance on how to prepare today's South Africans for today's green jobs. Third, it joins a small literature using the occupational task approach (Granata and Posadas 2024; Vona et al. 2019; Consoli et al. 2016; Vona et al. 2018) and illustrates how to utilize the methodology for a country-specific analysis.

The rest of this paper is organized as follows. Section 2 describes the data and methodology while Section 3 shares a descriptive analysis. In Section 4 we present and discuss regression results. Section 5 concludes and offers five policy messages for a more inclusive and successful green labor force and economy.

2 Data

We use the Post-Apartheid Labour Market Series (PALMS) dataset (Kerr et al. 2019). PALMS is constructed from several South African Labour Force Surveys for the years 1993-2019,[13] curated and harmonized by DataFirst at the University of Cape Town. We extract the Quarterly Labour Force Survey (QLFS) 2012-2019 data from the PALMS dataset for our analysis. The QLFS is a nationally representative household survey collected by the national statistical agency Statistics South Africa (Stats SA) since 2008. It includes data on the labor market activities of individuals aged 15 years and older who live in South Africa. Each survey samples approximately 33,000 dwelling units based on about 3,324 Primary Sampling Units (PSUs). For each quarter of the QLFS, a quarter of the sampled dwellings are rotated out of

[11] Examples of studies that make projections about employment due to the transition to a greener South African economy include Rutovitz (2010), Maia et al. (2011) and Merven et al. (2019).

[12] As of 2019, there were approximately 16.4 million jobs in South Africa.

[13] The PALMS dataset includes the 1993 Project for Statistics on Living Standards and Development (PSLSD), the annual October Household Surveys (1994-1999), the biannual Labour Force Surveys (2000-2007) and the Quarterly Labour Force Surveys (2008-2019). We only use the QLFS 2012-2019 in this analysis.

the sample and replaced by new dwellings from the same PSU or the next PSU on the list.

PALMS is well suited for this paper's analysis. It includes occupational information up to the four-digit level and uses the South Africa Standard Classification of Occupations (SASCO) from 2003 (Statistics South Africa 2003). SASCO 2003 is based on the International Standard Classification of Occupations of 1988 (ISCO-88).[14] To ensure comparability, DataFirst has gone to great lengths to harmonize the PALMS dataset in terms of variable names over time. Additionally, the data set comes with re-calibrated weights using a cross entropy (CE) approach (Branson and Wittenberg 2014) to ensure continuity and comparability between surveys over time.

For this study, we restrict our analysis to the period 2012-2019. Data are available for more recent years but to avoid contaminating the results with the effects of the COVID-19 pandemic, we exclude data collected in 2020 or after. We pool data from the four quarters of each year resulting in 32 quarters (waves) of data.[15] The pooling of the data over the 8 years gives a sample size that will allow analysis at the 4-digit SASCO level. Using these data, we profile the labor force working in green occupations by age, gender, location, skill, and education level.

2.1 Methodology to Generate the List of Green Occupations

We adopt the occupational task approach and use Dierdorff et al. (2009) to adapt our definition of green jobs to reference occupational tasks. Specifically, we define strictly green jobs as occupations that require tasks that have environmental impacts. We define broadly green jobs as occupations that are strictly green or occupations with tasks that could have environmental impacts if green technology is used. Some of these jobs benefit from the green revolution, such as miners of lithium for electric car batteries. Others are negatively affected, such as coal miners and those working in coal-fired plants. We include both in our analysis.

While many studies in various countries use tasks information from the US Occupational Information Network (O*NET) inventory and its associated Green Economy Program (GEP) (Consoli et al. 2016; Vona et al. 2019, 2018) to measure green jobs, we find these data are not appropriate for our analysis for several reasons. The O*NET is a US cross-sectional database with detailed information about work context, tasks, activities and skills at the occupational level.[16] The O*NET Green Economy program (GEP) identifies 12 industries that should be impacted by the greening of the economy and an associated list of occupations and

[14] International Standard Classification of Occupations 1988 (ISCO-88) is a four-level hierarchically structured system that allows all jobs in the world to be classified into unit groups based on their similarity in terms of the skill level and skill specialization required for the jobs. The most aggregated level is the one-digit code (10 major groups), followed by the two-digit code (28 sub-major groups), the three-digit code (116 minor groups) and the most detailed level of the classification is the four-digit code (390 groups). The SASCO includes an additional 39 occupations, reflecting uniquely South African labor markets.

[15] To ensure there is no double counting of individuals, we divide the survey weights by the number of quarters.

[16] The O*NET is the primary source of occupational information in the United States. The data are collected through industry expert interviews and surveys of representative samples of workers. https://www.onetonline.org/

green tasks used therein.[17] This data set, while quite rich, faces three primary shortcomings in our context. First, it may not be applicable to countries outside the US, especially middle-income and developing nations since production methods and technology may differ across economies or the required task profiles to realize those occupations may differ. Second, the GEP data were collected before 2009 while green technologies have evolved rapidly in the past 14 years. Additionally, it only considers jobs in 12 industries. Third, researchers report significant measurement error (Vona et al. 2019; Granata and Posadas 2024) when transforming 8-digit O*NET SOC codes to 4-digit ISCO codes.

Other studies have developed a methodology using text analysis of occupational tasks data to identify green jobs. Janser (2018) applied text analysis to a German occupational tasks database (BERUFENET) to identify green jobs in Germany. Granata and Posadas (2024) applied this method to ISCO occupational descriptions to profile green jobs in Indonesia.

Given that currently there is no occupational tasks database for South Africa, and the limitations of the O*NET GEP, we follow Granata and Posadas (2024) who apply a text analysis methodology to the ISCO-08 (developed in 2008) to identify occupations that perform green tasks. Granata and Posadas (2024) create a dictionary of green terms that are used to build a green occupation database. The dictionary of green terms is basically a collection of terms (words, roots, or expressions) that are commonly found in environmental economics literature. To make their list as comprehensive as possible, they draw green terms from various databases.[18] They reviewed more than 70 references to fine-tune the list. The final green terms dictionary includes 347 green terms, of which 308 are considered strict green because they are directly linked to the green economy. Another 39 terms are added to generate the broad green list of terms. These terms are not explicitly linked to environmental sustainability and climate change, but they could become directly linked if green technology or practices are adopted. These are added to the database to capture tasks that could be green. For example, the statement "land use" might not be directly linked to the green economy, but if greener technologies and practices are adopted in land use then this statement would be linked to the green economy. Any green terms clusters (a grouping of similar terms) can include only strict green terms, only terms that could be green that are used for the broad green definition, both, or neither. That said, the strict green list of terms is a subset of the broad green list of terms. Table 1 shows a sample of terms in the dictionary.

[17] To build the GEP, the O*NET team reviewed the literature and identified 12 green sectors. Work activities identified as green included those that reduce the use of fossil fuels, decrease pollution and greenhouse gas emissions, increase the efficiency of energy usage, have to do with recycling materials and developing and adapting renewable sources of energy (Dierdorff et al. 2009). To identify green tasks within occupations and develop a definition of green jobs, the United States Department of Labor conducted representative surveys of job incumbents and interviewed industry experts. This information has been integrated into the United States standard occupations classification (SOC) and can be matched with labor force surveys.

[18] Including the O*NET GEP, Burning Glass Technologies (BG) green list, US Bureau of Labor Statistics (BLS), GTP survey, IAB Janser (2018) list, UN Environmental GS, and the European Skills, Competences, Qualifications and Occupations (ESCO) skills taxonomy.

Table 1: An excerpt from the dictionary of green terms

Green terms clusters	Strict green terms	Additional terms on the broad green terms list
Agriculture, forestry, and fish production	Biochar, precision irrigation	Agri, Crop
Environmental Knowledge	Biotechno, geophysics	energy engineer, wood science
Environmental Regulations and Compliance	environmental law, environmental liabil	
Greenhouse Gas Reduction	emissions analyz, emissions inspect	
Low-carbon mobility	electric vehicles, transportation efficiency	motor buses, passenger train
Low-polluting construction	green building, sustainable materials	lighter materials, lightweight construction
Natural Resource Conservation	Deforestation, drought	land use, reforest
Recycling and reuse of waste and materials	waste management, waste reduction	Disposal
Clean Energy	alternative energy, alternative fuel	
Common terms	climate change, global warming	
Energy efficiency	detect hot spots, efficiency heat	
Dictionary total (451 terms)	**308**	**39**

Source: Granata and Posadas (2024)

After compiling the green dictionary, Granata and Posadas (2024) apply text analysis to all occupations in the four-digit ISCO-08 occupational taxonomy to calculate a green task intensity score for each occupation. The ISCO-08 database provides a description of each occupation at the four-digital level, including tasks carried out in the occupation. For each occupation (*i*), the text analysis identifies the number of tasks in the ISCO-08 occupation description that match green terms in the dictionary. Following Vona (2021), the count is used to calculate a greenness score (*Green Task Intensity - GTI*) for each occupation, which is the number of green tasks divided by the total number of tasks in each occupation:

$$GreenTaskIntensity_i = \frac{\#Greentasks_i}{\#Totaltasks_i} \quad (1)$$

Granata and Posadas (2024) calculate two measures of greenness for each occupation: GTI-strict and GTI-broad. The strict measure includes tasks that are matched to strict green terms in the dictionary. The broad measure includes tasks that are matched to either strict or the broad green terms, as defined in the green dictionary. An occupation may include only strict green terms, only the terms added when the green terms definition is broadened, both, or neither. The GTI-strict and GTI-broad are equal for occupations that do not include at least one of the 39 broad green terms. The GTI-strict will have a smaller value than the GTI-broad for occupations with tasks that match at least one of the 39 broad green terms. The GTI-strict will equal 0 if there are no tasks from the strict green terms list. The GTI-broad will equal 0 if there are no tasks from the GTI-broad list (which includes the GTI-strict list).[19]

[19] In other words, GTI-strict ≥ 0 and GTI-broad ≥ 0 and GTI-strict ≤ GTI-broad.

We further adjust the green dictionary so that it reflects the South African context. We reviewed the South African literature and policy reports for occupations that are expected to reduce the human-induced negative impact on the environment and climate change. We found discussion of industries that will adapt due to the greening of the economy - energy generation, resource efficiency, emissions control, and natural resource management – and industries that are most vulnerable to job loss –mining, petrochemical, electricity, agriculture, and tourism sectors (PCC 2021; ILO 2018; McLean 2018; Montmasson-Clair 2012; Maia et al. 2011; Rutovitz 2010; Nhamo 2010). None of these studies, however, takes an occupational approach, i.e., looks at the actual activities or tasks individuals do in jobs that could affect the human-induced impact on the environment. The only list of green occupations that we found was compiled by the Department of Higher Education and Training (DHET) through their organizing framework for occupations (OFO).[20] We use the DHET list to adjust the Granata and Posadas (2024) green dictionary.

We follow a three-step process to adapt the green dictionary for the South African context and connect it to the PALMS database. First, we adjusted a few terms in the green dictionary based on the DHET list of green occupations: *heat pump*, *biotechno*, *chemistry*, *geograph* and *geophysics.* These were in the Granata and Posadas (2024) green dictionary but were not identified as strict green terms. However, they should be classified as strict in the South African context since the OFO list includes occupations with those root terms: geophysicist, biotechnologist, geophysical technician, and heat pump installer (DHET 2013). After this adjustment, we ended up with 321 strict green terms and 37 additional terms for the broad green list. Second, we use the South Africa-adjusted green dictionary and follow the method used by Vona (2019) to calculate the GTI scores for each occupation as per Equation 1. Third, to merge the GTI scores to PALMS, we used crosswalks to transform the ISCO-08 occupation codes to the ISCO-88 codes used in the PALMS.

Finally, we define an occupation – and the jobs within it – as green based on its calculated GTI. An occupation is defined as green if it has a GTI greater than zero. All the jobs corresponding to that occupation are assigned the same GTI and the same greenness status. We generate a list of strictly green occupations, which are those occupations with a GTI-strict value that is a positive number. The broadly green occupation list are those occupations with a GTI-broad value that is greater than zero.

We primarily use the strictly green occupations for our analysis, as the list of GTI-strict terms more concisely identifies jobs with tasks that are currently engaged in the green economy. But we present and discuss the results for both strictly and broadly green occupations, understanding that the results emerging from the analysis of strictly green jobs can be taken as the lower bound of green employment and broadly green jobs taken as the upper bound of green employment.

[20] The OFO is DHET's tool for identifying, reporting, and monitoring scarce and critical skills. This list cannot be easily mapped to household survey data because the structure of the occupation code differs from that of ISCO-88 (DHET 2013). For example, the OFO only has 8 one-digit ISCO occupations because major code 7 and 8 have been combined, making it hard to disentangle crafts and related trades and machine operators.

2.2 Limitations to the Methodology to Generate the List of Green Jobs

There are some shortcomings to this method. First, Granata and Posadas (2024) observe that the GTI may underestimate the level of greenness of an occupation as the ISCO-88 does not present a comprehensive list of tasks for every job in an occupational category, but rather a description of what the occupation involves for the majority of jobs. Second, emerging occupations, some of which are associated to the greening of the economy, may be under the residual occupation code "Not elsewhere classified" and may not be captured since the task description of these residual occupations tend to be quite general (Granata and Posadas 2024). Third, the ISCO descriptions of occupations are static and therefore we might fail to capture new and emerging green tasks overtime. Lastly, it is possible that the text analysis methodology underestimates the share of green tasks in managerial occupations because administrative tasks such as policy makers who form clean energy and environmental policies are not emphasized.[21]

2.3 Analytical Methodology

We use standard econometric techniques to understand the factors associated with being in a green job, being in a greener job, and earnings in green jobs.

2.3.1 Factors associated with being in a green job

To understand the factors related to being in a green job, we estimate a logit model of the probability of being in a green job as specified in equation 2.

$$\Pr(Y = 1 \mid X) = F(\beta_0 + \beta_i X_i + \alpha_p + \eta_l + \delta_t + \theta_s + \varepsilon_i) \quad (2)$$

Y is a binary dependent variable equal to one if the respondent is in a green job (GTI >0) and zero otherwise. We use the strictly green job definition for the first round of estimates and the broadly green job definition for a second round of estimates. F is the logit function link while the individual characteristics (age, race, gender, education level) are represented by X_i. α_p is a location dummy for urban residence, η_l is a vector of province dummies and δ_t are quarter of year dummies. θ_s is a vector of industry dummies. ε_i is the error term. Our sample includes working-age individuals (age 15-65) who are employed.

To create the variables, we adapt some variables in the PALMS data. We convert the continuous education variable into a four-category variable:[22] 1=less than grade 12 (those without a high school qualification), 2=matric (complete high school), 3=other tertiary (those with more than a high school qualification but less than university), and 4=degree (those with a university degree). For the age variable, we construct 5 categories from a continuous age variable as follows: age 15-24, age 25-34, age 35-44, age 45-54 and age 55-65. Gender is defined as a binary variable (1=female, 0=male). For ethnicity group or race,[23] we use the

[21] This final caveat underlies one of the key differences between the text analysis and O*NET tags a much larger share of managerial jobs as green, as compared to the text analysis.

[22] As we used categorical variables to show green employment by education and age categories in the descriptives sector, for consistency, we maintain the same categories for the regressions. The South African literature (Branson and Leibbrandt 2013) has also found that the relationship between education and labor market outcomes is convex and for this reason it is more informative to use education categories.

[23] Race is included in the regression analysis because it remains an important determinant of labor

categories currently used by Statistics South Africa i.e., African, Coloured, Indian/Asian and White while the location variable is a dummy with urban=1 and rural=0. The province vector is a 9-category variable of the nine provinces in South Africa namely, Western Cape, Eastern Cape, Northern Cape, Free State, KwaZulu-Natal, Northwest, Gauteng, Limpopo, Mpumalanga. Industry dummies represent each of the nine one-digit groups i.e., agriculture, mining, manufacturing, utilities, construction, trade, transport, finance, and community services or other private household enterprises.

2.3.2 *Factors associated with being in a greener occupation*

Restricting the sample to only those in a strictly green job, we estimate an ordinary least square (OLS) model of the factors associated with being in a greener occupation, as captured by the GTI, as per equation (3).

$$\ln Y_i = X_i'\beta + \alpha_p + \eta_l + \delta_t + \theta_s + \varepsilon_i \tag{3}$$

lnY_i is the log of the continuous measure of strictly green task intensity (GTI-strict) in $occupation_i$ and X_i are individual characteristics gender, age, race, and level of education. Location, province, location, industry of employment and time dummies are represented by α_p, η_l, θ_s and δ_t respectively.

2.3.3 *Do green jobs pay higher wages?*

To understand whether there is a wage premium as a result of being in a green job, we estimate the commonly used wage regression model (Mincer 1974). We augment this regression model with industry dummies and our variable of interest, a binary variable of whether an individual is in a green job, as specified in equation 4.

$$\ln W_i = X_i'\beta + D_i'\gamma + \alpha_p + \eta_l + \delta_t + \theta_s + \rho_C + \varepsilon_i \tag{4}$$

lnW_i is the log monthly wage of individual *i*, X_i are individual characteristics (age, race, gender, education level). The binary variable D_i takes a value of 1 if the individual *i* is in an occupation that has a positive share of green tasks (GTI-strict), and 0 otherwise. We estimate equation (4) again using the GTI-broad to indicate green jobs. The location, province, industry and time dummies are denoted by α_p, η_l, θ_s and δ_t respectively, and ε_i is the error term.

We estimate two models, where the control variables differ across models. The first model only includes the variable of interest D_i and controls for province and time dummies. In the second model, we add controls for gender, age, education, and race (X_i), as well as α_p (location) and ρ_C (vector of nine occupation dummies). Our sample includes working-age individuals (age 15-65) who are employed and report positive earnings.

We create a variable to proxy for how skill intensive an occupation is, which we use in the descriptives section. The three skill categories follow SASCO 2003 and ISCO-88 classification as

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market outcomes and people's livelihoods even decades after the demise of apartheid. During apartheid, discrimination was institutionalized with policies such as *the Bantu education act* and *the job reservation act* ensuring that Black (Coloured, Indian and African) South Africans received inferior education and could not access professional occupations.

detailed in Table 2. High (skill) level occupations include managers, professionals and technicians. Mid (skill) level occupations include clerks, services, crafts and machine operators. Elementary (skill) level are elementary occupations, including domestic workers.

Table 2: Skill levels in SASCO 2003 and ISCO-88 major code (one digit) occupations

Code	Major group	Skill level	Equivalent education
1	Legislators, senior officials, and managers	*	*
2	Professionals	4	Postgraduate
3	Technicians and associate professionals	3	College/tech degree
4	Clerks	2	Complete high school
5	Service workers and shop/market sales workers	2	Complete high school
6	Skilled agricultural and fishery workers	2	Complete high school
7	Craft and related trades workers	2	Complete high school
8	Plant and machinery operators and assemblers	2	Complete high school
9	Elementary occupations	1	Primary/no schooling

Note: Major code 0 (Armed forces with 20 four-digit occupations) is not included in this table and is also excluded from our sample. The *asterisks mean that there is no skill reference for this occupation. In this paper we combine this occupation with professionals and technicians therefore assuming a skill level of 3 and 4. Source: SASCO 2003

3 Description of Green Jobs in the South African Labor Market

3.1 Which Occupations Are Green?

In this section, we provide a description of green jobs using both the strict and broad definitions of green tasks. Using the strict[24] definition of green tasks, we find that 46 out of 428 occupations in ISCO-88 can be classified as strictly green, meaning that their strict-GTI is greater than zero.[25] When using the broad definition of green tasks, we count 137 occupations can be classified as broadly green; the additional 91 occupations are those that do not include any strictly green tasks but do include tasks on the broad green tasks list. See Tables A1 and A2 in the Appendix for the full lists of strictly green and broadly green occupations.

[24] The strict definition of green tasks is measured by the total number of strictly defined green tasks in a 4-digit occupation divided by the total number of tasks in that occupation. A job is classified as green if it has a green task intensity (GTI) greater than zero, meaning it has at least one strictly defined green task.

[25] Our original list had 47 strictly green occupations, including ISCO code 5169 (protective services not elsewhere classified) with a GTI of 10 percent. We chose to shift this occupation to the list of broadly defined green occupations. While this occupation contains jobs such as park rangers and wardens that would be classified as green (park rangers are classified as green in the DHET (2013) OFO skills list), the majority of the workers in this occupation are security officers whose tasks cannot be classified as strictly green. Because this occupation accounts for a very large share of jobs (over 500,000 employees), removing it from the strictly green occupations list reduced the share of strictly green employment in South Africa from 9 percent to 5.5 percent.

Table 3: An extract of the 20 4-digit strictly green occupations with the highest green task intensity (GTI) and the total employment in each

ISCO	Occupational Title	GTI-Strict	n
9161	Garbage collectors	79.2	61023
2112	Meteorologists	77.8	463
2211	Biologists, botanists, zoologists and related professionals	75.0	3603
2114	Geologists and geophysicists	58.3	3048
2210	Scientist	50.0	1581
8163	Incinerator, water-treatment and related plant operators	50.0	22455
3222	Sanitarians	45.0	5058
9321	Assembling laborers	41.7	2803
3119	Physical and engineering science technicians not elsewhere classified	40.0	3112
2149	Architects, engineers and related professionals not elsewhere classified	36.7	6971
2213	Agronomists and related professionals	33.3	6101
3213	Farming and forestry advisers	33.3	3831
5161	Fire-fighters	33.3	19234
7134	Insulation workers	33.3	275
2142	Civil engineers	28.6	15455
2113	Chemists	25.0	1109
7132	Floor layers and tile setters	25.0	34631
7231	Motor vehicle mechanics and fitters	22.9	201292
3112	Civil engineering technicians	22.2	10641
6141	Forestry workers and loggers	20.0	12121

Notes: Own calculations using PALMSv3.3. Note: the 1-digit code for each occupation is simply the first digit in the 4-digit span. The 2-digit code is simply the first 2-digits in the 4-digit span.

Strictly green (4-digit) occupations are a mix of high-level, mid-level, and elementary jobs. The occupation with the highest green task intensity is the elementary occupation of garbage collectors (code 9161) with a GTI of 79.2 (Table 3). This means that 79 percent of tasks in this occupation's description include terms from the strictly green list. The high GTI for garbage collectors is attributable to the terms *"recycling"* and *"collecting recyclable materials or items"* in the occupational tasks description, all derivations of the green dictionary term *"recycl12"*. This root term appears in most tasks for this occupation.[26] The next two greenest occupations require high skills. Meteorologists (code 2112) and biologists and related professionals (code 2211) have GTIs of 77.8 and 75.0 respectively; both are classified as high-level occupations.

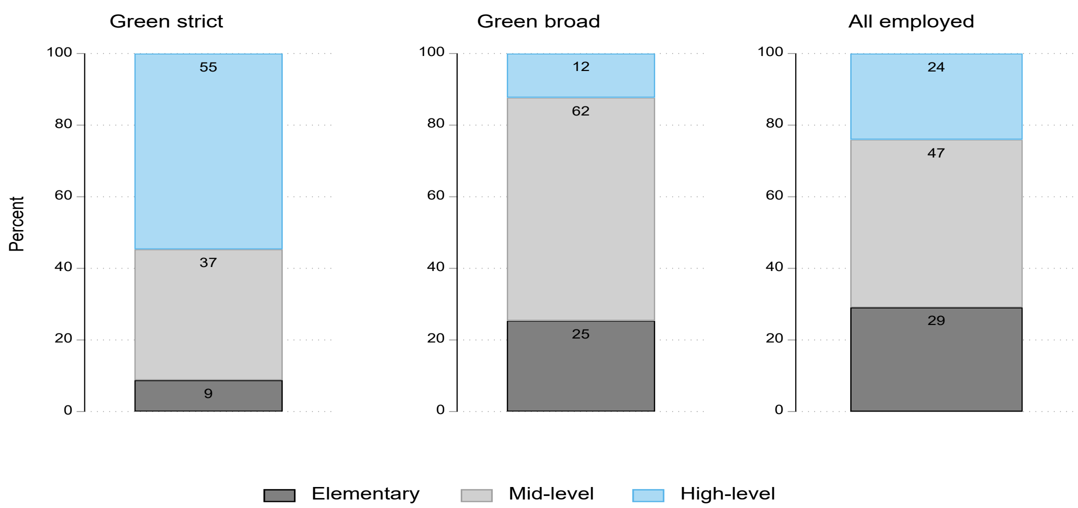
The majority of strictly green occupations are high-level, though a disproportionate share of

[26] Recall that the GTI score is calculated using ISCO-08 which is a newer version of occupation classification to ISCO-88. Our data PALMS is based on ISCO-88 and the occupation Garbage collectors, ISCO-88 code 9161 maps to two ISCO-08 occupations. Garbage recyclers and collectors (code 9611) where 3 out of 4 tasks in this occupation are green with a GTI score of 75 and Refuse sorters (code 9612) where 5 out 6 tasks are green with a GTI score of 83. The GTI score for ISCO-88 code 9161 (Garbage collectors) is then 79, the average of the two which is what we report in the paper.

strictly green jobs are mid-level or elementary occupations. High-level strictly green occupations – defined as those with a 1-digit ISCO code of 1-3 – are 65 percent of the sample but high-skilled green jobs (jobs are the number of people working in an occupation) are only 55 percent of the sample (Figure 1). This mismatch is due to a larger number of South Africans working in mid-level (ISCO 1-digit code of 4-8) or elementary (ISCO 1-digit code of 9) strictly green occupations. For example, an estimated 61,000 work as garbage collectors (elementary occupation) and 201,000 are employed as motor vehicle and mechanics fitters (mid-level occupation). This is in contrast with only about 3,600 employed as biologists and related professionals and about 3,000 geologists and geophysicists, all classified as high-level occupations. That said, a much higher proportion of strictly green jobs are in high-level occupations (55 percent) as compared to the share of high-level occupations in the general labor market (24 percent) (Figure 1). The greater share of high-level green occupations reflects findings from similar studies in the global north (Consoli et al. 2016; Vona et al. 2019; Bowen, Kuralbayeva, and Tipoe 2018).

The greenest South African occupations are disproportionately classified as elementary or mid-level. Of the 20 strictly greenest occupations, 85 percent of the jobs are in mid-level or elementary occupations (1-digit codes 5,6,7,8, and 9 in Table 3), though they only represent 8 of the top 20 occupations with the highest strictly green GTI scores (Table 3).

Figure 1: Green jobs and all jobs, by skill intensity of the occupation



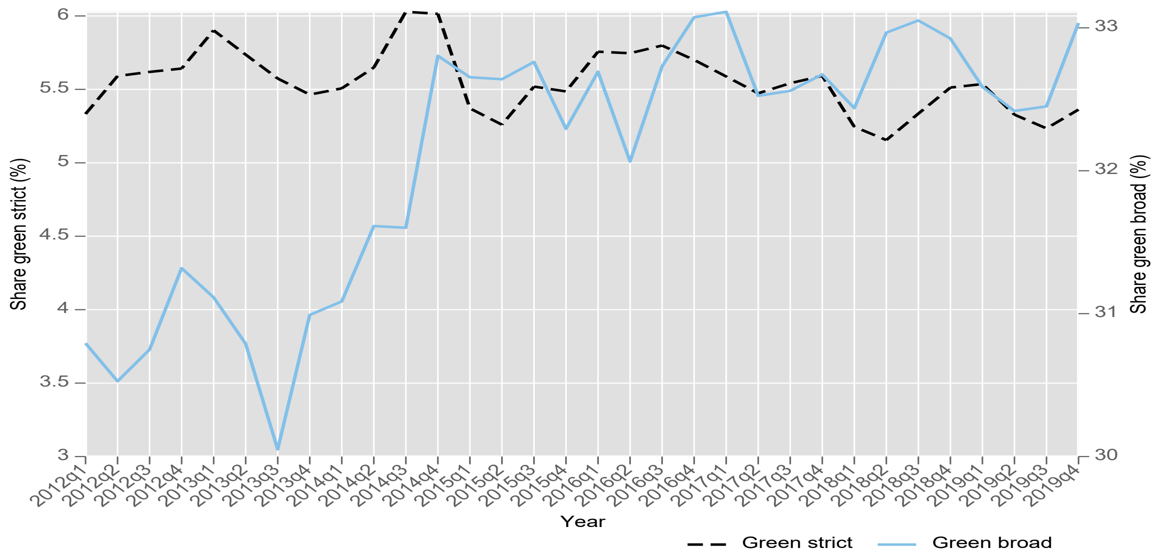
Source: authors' calculations using PALMS. Note: strictly green jobs are those with at least one task on the strictly green task list. Broadly green jobs are those with at least one task that is on the broad green task lists (which includes the strictly green tasks).

Broadly green jobs are more prevalent in mid-level and elementary occupations. Once the definition of green tasks is expanded to include broad green tasks, 88 percent of jobs are in mid-level and elementary occupations. For example, if we allow that occupations under code 7 – such as extraction and building trades (code 71), metal machinery and related trades (code 72) and precision, handicraft and craft trades (code 73) – may adopt green technologies, they would be considered green. A much lower share of broadly green jobs (12 percent) can be classified as high-level occupations, as compared to the overall labor market (24 percent). Thus, while strictly green occupations are highly skilled and concentrated in high-level occupations, there is potential for more employment in mid-level and elementary occupations if green technology and processes are more widely adopted to stem the impact of humans on the environment.

3.2 How Prevalent Are Green Jobs in South Africa?

The 46 occupations that can be classified as strictly green account for about 5.5 percent of total employment in the South African labor market that employs 16.4 million people. This share has barely moved over the period 2012-2019 with only a small increase in 2014 (Figure 2). The lack of increase in the strictly green jobs trend could be an indication of a slow implementation of green economy practices. Or it may be a casualty of the data since the task description of occupations is static. In other words, jobs may have adopted technology or processes that require tasks in the strictly green list of the green dictionary, but these tasks may not be reflected in the ISCO-88 occupational task descriptions. Further, strictly green jobs may have added more green tasks over time, but greening within a job is not captured in our data.

Figure 2: Green employment over time (2012-2019)



Source: authors' calculations using PALMS.

Expanding the definition to capture broadly green jobs, the share of broadly green employment is nearly 33 percent in 2019, up from 31 percent in 2012. A look at employment trends over time shows that there was a visible upward shift in 2013-2014 as a result of an increase in employment in a few mid-level and elementary occupations, specifically extraction and building trades (ISCO code 71), metal machinery and related metal trades (code 72), laborers in agriculture (code 92) and laborers in mining and construction (codes 93). These occupations, especially extraction and building trades and metal machinery and related metal trades, include many broadly green 4-digit ISCO occupations. The increase in broadly green jobs is temporally aligned with the Renewable Energy Independent Power Producer Programme (REIP4) that offered incentives to firms to invest in green energy production. The program was introduced in 2011, active in 2013 and 2014, and slowed down after 2014, mirroring the potential green jobs trend in Figure 2.[27]

The share of green jobs in the South African labor market greatly differs by gender with only 3 percent of working South African women being in strictly green occupations, compared to 8 percent of men. When using the broad definition of green jobs, 14 percent of women are in broadly green jobs compared to 47 percent of men. As we discuss below, the gender difference in the share of green jobs is linked to the persistent gender occupational segregation in the labor market.

The South Africa estimates are within the range of estimates from other countries. Granata and Posadas (2024), whose methodology we use in this paper, report 2.3 percent green employment for Indonesia.[28] Similarly, Doan et al (2022) find that 3.6 percent of Vietnamese jobs can be classified as strictly green while 41 percent are broadly green. Using the O*NET definition of green occupations and a continuous measure of green jobs, Vona et al. (2019) estimate the share of green jobs in the US to be between 2-3 percent over the period 2006-2014. Using a binary definition of green jobs which allowed for a broader set of green occupations, Consoli et al. (2016) report that between 9.8 and 12.3 percent of U.S. workers were in green employment in the period 2011-2012. In another study from the U.S, Bowen et al. (2018) estimate that 10.3 percent of all employment in the US were in "directly green" occupations while "indirectly green" occupations made up another 9.1 percent of all employment. Valero et al. (2021) estimate the share of green employment in the UK to be between 17 percent and 39 percent in 2019. The higher share of green jobs for the UK as compared to other countries is partly due to data challenges when cross-walking between the O*NET which uses the US 8-digit standard occupational classification and the UK labor force surveys which is based on the 4-digit ISCO-08 classification.

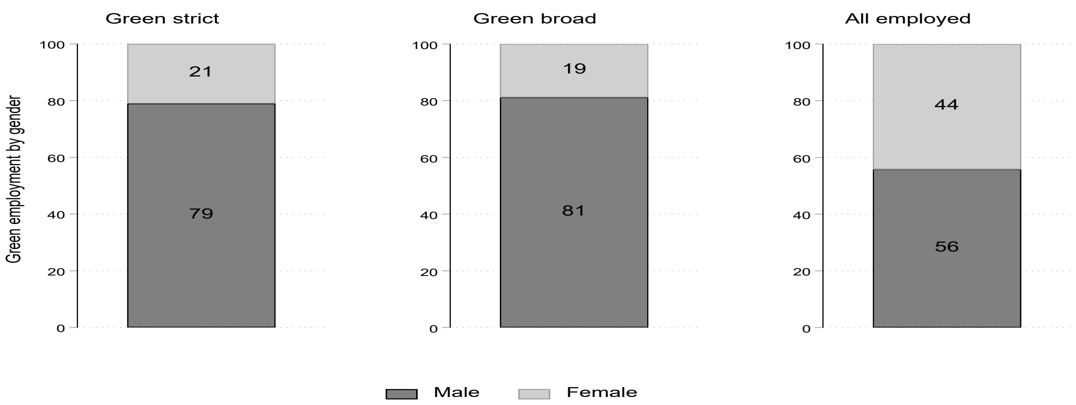
[27] Introduced in 2011, the REIP4 used a competitive procurement program to increase electricity generation through renewable energy sources. Investing companies needed 40 percent local ownership, leading to increased partnerships between foreign and South African companies, including knowledge and skill sharing and green jobs (ILO 2018). The increase in the demand for solar PVs may have increased the demand for solar panel installers and assemblers, explaining the increase in potentially green jobs between 2013 and 2014. However, the stalling of the REIP4 initiative after 2014 meant that investment in renewable energy technology also stalled corresponding to the flattening of the trend.

[28] Although we use the same methodology as Posadas and Granata (2024), there are a few reasons that could explain the differences in the estimated share of green jobs in South Africa and Indonesia. First, the Granata and Posadas (2024) analysis excludes agricultural occupations while we include the agricultural occupations in the sample. Second, it is possible that the South African economy differs from the Indonesian economy both in structure and in the profile of workers. For example, the mining sector, which will be substantially affected by the green transition, contributes to a significant share of employment in the South African economy and for this reason, our green occupations list includes occupations such as mining managers and mining engineers, occupations which are not included in Granata and Posadas' (2024) green occupations list.

3.4 Who Works in Green Occupations?

Consistent with international literature (Vona 2021; Valero et al. 2021, Doan 2022), we find that regardless of the definition (strict or broad), men are over-represented in green jobs. While women account for 44 percent of all workers, only 21 percent of strictly green jobs are held by women compared to 79 percent held by men (Figure 3). Women account for an even smaller share of broadly green jobs (19 percent). The underrepresentation of women in green jobs stems from gendered occupational segregation in the labor market, such that men and women sort into different occupations. Of the 20 occupations in Table 2, only three have a female share of more than 50 percent,[29] all of which employ a relatively small share of workers. The two-digit ISCO level occupations with the greatest number of four-digit green occupations are physical, mathematical, and engineering professionals (code 21) where the female share is only 22 percent. In contrast, office clerks (code 41) have zero GTI (strict or broad) though 70 percent of people working in the occupation are women. The green occupations where women are well represented, such as life science and health professionals (code 22), employ a relatively small proportion of South Africans.[30]

Figure 3: Share employed in green occupations by gender



Source: authors' calculations using PALMS

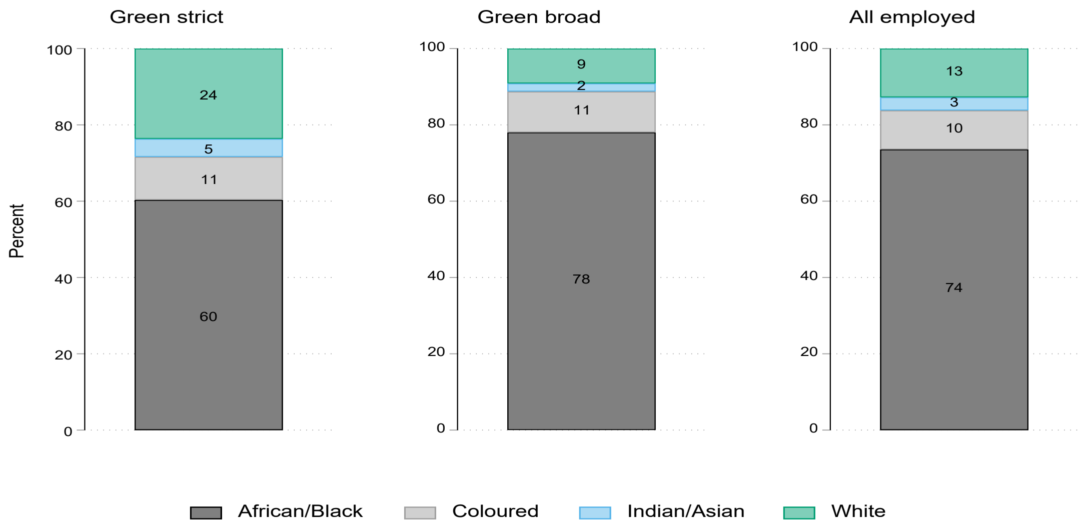
A disproportionate share of white South Africans hold strictly green jobs as compared to the general employed population. As we have shown above, strictly green occupations are concentrated among highly skilled occupations. The continued gaps in educational attainment inherited from the apartheid era mean that white South Africans are better prepared for strictly green occupations. While Black South Africans dominate green and all jobs due to their high population share in South Africa, they are 60 percent of strictly green jobs but 74 percent of the working population. Instead, white workers hold 24 percent of strictly green jobs as compared to 13 percent of all jobs in the general labor market. There is little difference in representation between strictly green and non-green of the other racial or ethnic groups. The gaps by race between broadly green jobs and the general labor market are much narrower. White South Africans hold 9 percent of broadly green jobs while Black South Africans hold 78

[29] Meteorologists (2112), biologists (2211) and chemists (2113).

[30] For example, while the female share in the life science and health professionals is above 60 percent, this occupation only employs 3 percent of all women and 0.9 percent of all men (Mosomi et al. 2020).

percent of the jobs, as compared to 13 percent and 74 percent, respectively, for the general labor market (Figure 4).

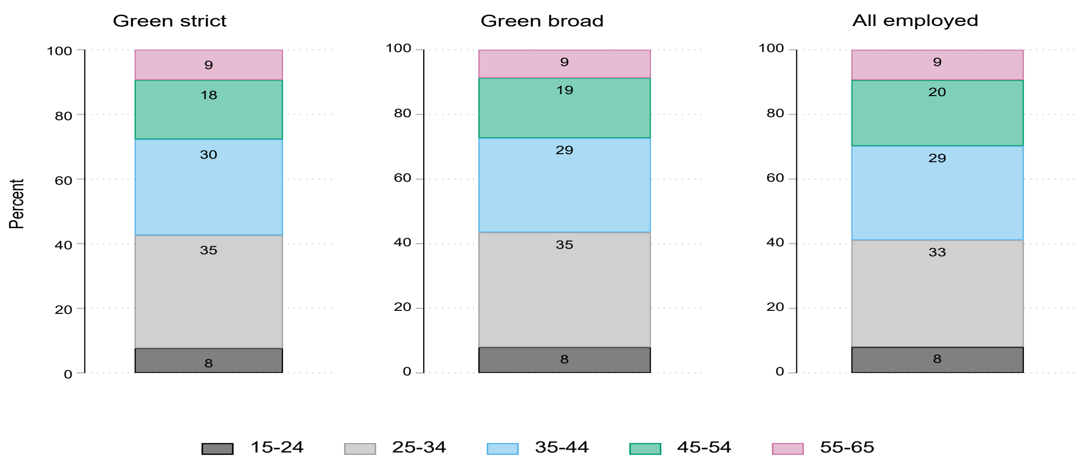
Figure 4: Share employed in green occupations by race



Source: authors' calculations using PALMS

The distribution of green jobs by age reflects the overall labor market. Strictly green jobs are most prevalent within the 25-34 (35 percent) and 35-44 (30 percent) age groups (Figure 5), as compared to 62 percent of all jobs belonging to the prime working age group (25-44). When considering both the strict and broad definitions of green jobs, the 25-34 age group has a slightly higher propensity for green jobs than for all jobs, by a few percentage points (Figure 5). The older (55-65) and youngest (15-24) age groups hold 9 percent and 8 percent of all jobs, strictly green jobs, and broadly green jobs.

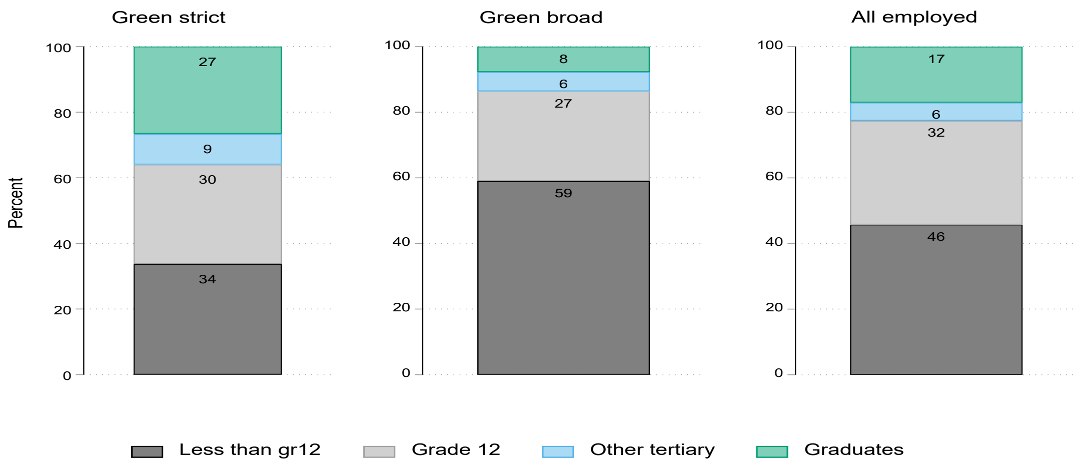
Figure 5: Share employed in green occupations by age



Source: authors' calculations using PALMS

Compared to the general labor market, individuals with some tertiary level qualifications are overrepresented in strictly green jobs while individuals with high school or less are overrepresented in broadly green jobs. Of all workers in strictly green jobs, an estimated 27 percent are university graduates and 9 percent have a post high school qualification (principally a technical or vocational school certificate). This contrasts with only 17 percent of workers with university degrees and 6 percent with post-secondary qualifications in the general labor market. Still, the largest share of strictly green jobs is held by those with a high school or lower qualification (64 percent). This is because, as discussed above, while the majority of strictly green occupations are high skilled, more people are employed in mid-level and low skill elementary jobs in the South African labor market. A high share (59 percent) of the workers in broadly green jobs have less than a high school qualification, while only 8 percent of broadly green jobs belong to university graduates. This is consistent with the above discussion that broadly green occupations include many lower skilled occupations (Figure 6).[31]

Figure 6: Share employed in green occupations by education level



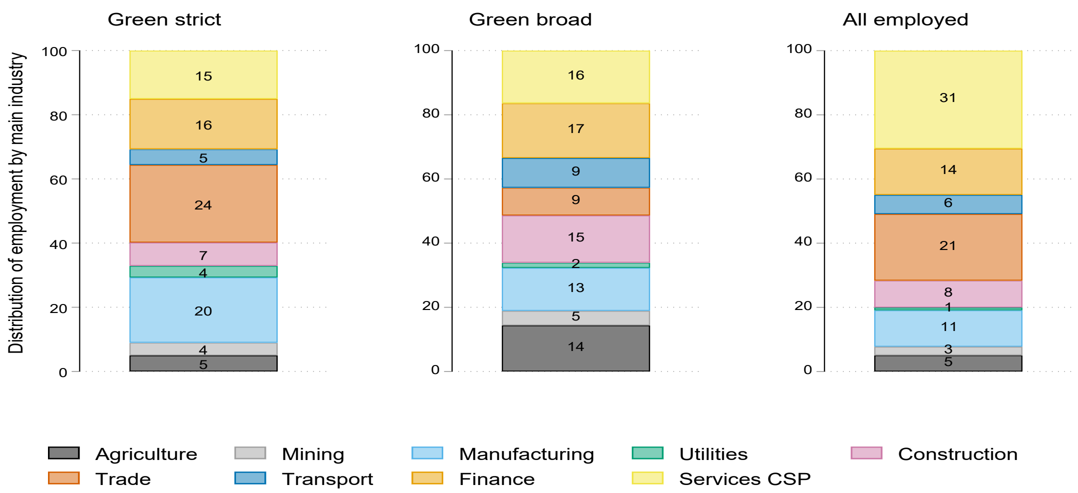
Source: authors' calculations using PALMS

The industries with the highest shares of green jobs are manufacturing, trade, and finance but compared to the general employed population, manufacturing, utilities, and finance sector jobs are over-represented among green jobs (Figure 7). The green jobs in the utility industry are those related to electricity, gas and waste collection and purification. The finance sector enables others to develop and use green technologies, including research and development, renting of machinery and other business activities, computer and related services and financial intermediaries. While finance might not seem like a directly green occupation, other studies have found that it is a sector that records a significant share of green jobs (Valero et al. 2021). This reinforces the idea that quantifying green jobs through the occupational lens allows one to capture green jobs in industries that might not be thought

[31] Doan et al. (2022) find that, on average, green jobs in Viet Nam require higher qualifications than non-green jobs.

of as green.[32]

Figure 7: Share employed in green occupations by Industry



Source: authors' calculations using PALMS

4 Regression Results

Conditional correlations allow us to understand the nuance in the patterns observed in the comparison of means.

4.1 Factors Associated with Being in a Green Job

Regardless of the definition used (strictly or broadly green jobs) women are less likely to be in green jobs (Table 4). Women are 5 percent less likely than men to be in strictly green jobs and 25 percent to 31 percent less likely than men to hold broadly green jobs. The conditional results reflect the clustering of broadly green jobs in typically male dominated occupations.

Workers aged 25-44 are the most likely to be in strictly and broadly green jobs. The conditional correlates for the age dummy variables are not stable for strictly green jobs, with statistical significance changing based on the set of control variables. The estimated correlation for the two oldest categories is negative, though with a very small value, reflecting the unconditional correlations. The estimates for the broadly green jobs are consistent across age groups, with all age cohorts being more likely to work in a green job as compared to the youngest age group. This result is consistent with the unconditional estimates in the descriptive section.

More educated workers are more likely to be in strictly green jobs while high school dropouts are most likely to hold broadly green jobs. This reflects the unconditional correlations, where workers with more than a high school (matric) education were over-represented among strictly green workers. The results for broadly green jobs also follow the conditional correlations since the category includes several populous mid-skilled and elementary

[32] Doan et al. (2022) find that green jobs in Viet Nam are concentrated in utilities (electricity, gas, water), mining and quarrying, and market services.

occupations (Table 2), that are aligned with lower levels of education.

Table 4: The probability of being in a green job in 2019

Model	Pr(strictly green job)		Pr(broadly green job)	
Marginal effects	dy/dx	dy/dx	dy/dx	dy/dx
Female	-0.060***	-0.053***	-0.314***	-0.250***
	(0.001)	(0.001)	(0.001)	(0.001)
base=age 15-24				
25-34	0.005***	0.005***	0.042***	0.033***
	(0.001)	(0.001)	(0.002)	(0.002)
35-44	0.001	0.004***	0.037***	0.031***
	(0.001)	(0.001)	(0.002)	(0.002)
45-54	-0.005***	-0.001	0.010***	0.013***
	(0.001)	(0.001)	(0.003)	(0.002)
55-65	-0.003**	0.000	0.008***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
base=less than matric				
Matric	0.007***	0.007***	-0.105***	-0.074***
	(0.001)	(0.001)	(0.001)	(0.001)
Other tertiary	0.036***	0.036***	-0.054***	-0.039***
	(0.001)	(0.001)	(0.003)	(0.003)
Degree	0.034***	0.042***	-0.233***	-0.198***
	(0.001)	(0.001)	(0.002)	(0.002)
base=black/African				
Coloured	0.022***	0.018***	0.012***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.002)
Indian	0.014***	0.007***	-0.097***	-0.079***
	(0.002)	(0.002)	(0.004)	(0.004)
White	0.033***	0.028***	-0.007***	-0.040***
	(0.001)	(0.001)	(0.002)	(0.002)
Urban	0.011***	0.011***	-0.086***	-0.021***
	(0.001)	(0.001)	(0.002)	(0.002)
Industry dummies	No	Yes	No	Yes
Observations	609,628	609,472	609,628	609,472

Standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1

Logit estimate (equation 2), reporting marginal effects. The dependent variable takes a value of 1 if the observation reports a strictly (columns 1 and 2) or broadly (columns 3 and 4) green job (GTI-strict > 0). Survey weights applied in all regressions. Sample includes employed individuals aged 15-65. All columns include survey quarter dummies, province dummies. Source PALMS V3.3.

Black Africans are least likely to be in strictly green jobs, even when controlling for education level, but most likely to hold broadly green jobs. This may be expected due to the disproportionately high share of high-level jobs in strictly green occupations, where Black Africans are under-represented due to the persistent occupational segregation by race in the

South African labor market (Gradín 2019).[33] In contrast, Black male workers are overrepresented in manual occupations such as machine plant operators and assemblers, which are classified as broadly green jobs and are numerous.

Relative to rural workers, urban workers are more likely to be in strictly defined green jobs while rural workers are more likely to be in broadly green jobs. The results for strictly green jobs do not change when industry dummies are added to the regression. This may reflect the more urban nature of strictly green jobs, in professional fields as well as public services. However, the point estimate for broadly green jobs decreases, while remaining negative, suggesting that manufacturing industries, which are broadly green jobs, may be partly driving the results.

4.2 Which Green Workers Are in the Greenest Jobs?

When restricting the sample to only those working in strictly green occupations,[34] results show that not only are women less likely to be in strictly green jobs (Table 4), but they are also less likely to be in the greenest jobs (Table 5). Women are 8.2 percent less likely to be in the greenest jobs. The coefficient estimate remains negative when controlling for industry.

Relative to the youngest age group, older individuals are more likely to be in the greenest jobs. The coefficients are positive and statistically significant for the oldest age groups (age 45-54 and 55-65) with the oldest age group being 8.5 percent more likely to be in the greenest jobs as compared to the youngest age group (15-24). Thus, while the oldest age groups were the least likely to be in green jobs, those who do end up in green jobs are in the greenest.

Individuals with less than complete high school education are more likely to be in the greenest jobs (Table 5), even though they were less likely to be in green jobs as compared to other age groups (Table 4). Every education group is 30 percent less likely than workers without completed high school to be in the greenest jobs. This result stems from the fact that while most green jobs are high skilled, some low-skill, high employment occupations, such as garbage collectors and motor vehicle mechanics and fitters have high GTI scores, resulting in the greenest jobs belonging to those with lower than grade 12 level of education (see Figure 6).

Individuals from the African subpopulation are more likely to be in the greenest of the green jobs. All other population groups are on average less likely to be in the greenest jobs, even when controlling for education level, industry, and urban residence. Once controlling for industry, the gap reduces, but remains negative. So, while Black Africans are less likely to work in a strictly green job, when they do have that job, it is greener.

Urban workers are more likely to work in the greenest of the strictly green jobs. Individuals working in the urban areas are 15 percent more likely to be in the greenest jobs. This seems to reflect the industrial distribution across locations, though. When controlling for industry, the

[33] The legacy of apartheid labor market policies such as the *job reservation act* and the *Bantu education act* is still reflected in the present labor market, with Black South Africans being underrepresented in professional occupations and in institutions of higher learning and overrepresented in elementary occupations.

[34] We do not do this exercise for potentially green jobs since the broad green definition includes tasks that could become green (hence the green task intensity (GTI_broad)), but this transition is far from certain.

correlation disappears.

Table 5: Characteristics of those in a green job

Model	OLS, y=ln(GTI)	
Female	-0.082***	-0.060***
	(0.014)	(0.014)
base=age 15-24		
25-34	0.002	0.018
	(0.020)	(0.019)
35-44	0.020	0.020
	(0.020)	(0.019)
45-54	0.046**	0.046**
	(0.022)	(0.020)
55-65	0.084***	0.084***
	(0.024)	(0.023)
base=less than matric		
Matric	-0.344***	-0.307***
	(0.013)	(0.012)
Other tertiary	-0.449***	-0.418***
	(0.019)	(0.018)
Degree	-0.475***	-0.399***
	(0.015)	(0.015)
base=black/African		
Coloured	-0.146***	-0.067***
	(0.019)	(0.017)
Indian	-0.289***	-0.178***
	(0.026)	(0.025)
White	-0.369***	-0.188***
	(0.015)	(0.014)
Urban	0.155***	0.008
	(0.016)	(0.014)
Constant	2.944***	3.390***
	(0.040)	(0.041)
Industry dummies	No	Yes
Observations	31,638	31,637
R-squared	0.131	0.273
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

OLS estimates, as per equation (3). The dependent variable is ln(GTI-strict). Sample includes employed individuals aged 15-65 who work in strictly green occupations. All models include survey quarter dummies and province dummies. Model 1 excludes industry dummies while model 2 is the full sample of those in strictly defined green jobs. Survey weights applied in all regressions. Source PALMS V3.3.

4.3 Is There a Wage Premium for Being in a Green Job?

There is a wage premium to green jobs. Table 6 presents regression results as per equation 4. Model 1, where we only include a strictly green job dummy, dummy variables for location and province, and time fixed effects, shows that those in a strictly green job earn nearly 43 percent higher wages than those who are in jobs without any green tasks. When adding the full set of demographic, industry, and occupation controls, which are often correlated with wages, the green premium is still a positive and statistically significant 2.7 percent.[35]

If we include the broad definition of a green job, the wage premium disappears. The coefficient on *green_broad* is negative. Workers in broadly green jobs earn 14.9 percent less than those in non-green jobs. The gap narrows to 9.9 percent when including the full set of demographic, occupation, and industry controls. This follows from the descriptive section where we showed that once we expand the definition of a green job to include broadly green occupations, mid-level and elementary occupations (1-digit ISCO codes 7, 8, and 9) are more heavily weighted in the broadly green sample relative to the non-green sample.

Table 6: Wage regression, using the strict and broad definition of green jobs

Models	Strictly Green Jobs		Broadly Green Jobs	
Variables	Baseline	Full	Baseline	Full
green_strict (green_broad)	0.432***	0.027***	-0.149***	-0.099***
	(0.011)	(0.010)	(0.005)	(0.005)
Female		-0.263***		-0.281***
		(0.004)		(0.004)
Age		0.032***		0.032***
		(0.001)		(0.001)
Age2		-0.000***		-0.000***
		(0.000)		(0.000)
base=less than matric				
Matric		0.287***		0.283***
		(0.005)		(0.005)
Other tertiary		0.480***		0.479***
		(0.009)		(0.009)
Degree		0.821***		0.811***
		(0.009)		(0.009)
base=black/African				
Coloured		0.054***		0.054***
		(0.007)		(0.007)
Indian		0.110***		0.108***
		(0.015)		(0.015)
White		0.270***		0.271***
		(0.008)		(0.008)
Urban	0.478***	0.200***	0.466***	0.198***
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	8.117***	7.234***	8.201***	7.287***
	(0.012)	(0.038)	(0.012)	(0.038)
Observations	419,148	415,553	419,148	415,553
R-squared	0.070	0.345	0.067	0.346
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

[35] Doan et al. (2022) carry out a similar conditional estimate and do not find a wage premium for green jobs relative to non-green jobs.

OLS estimates, as per equation (4). Dependent variable is ln(earnings). Sample includes employed individuals aged 15-65. Income bracket weights applied. The 'baseline' columns control for survey quarter dummies and 9 province dummies. The 'Full' columns add demographic characteristics (gender, age, education, and race), 9 main industry dummies, a location dummy and 9 main occupation dummies to the variables in the baseline model. Source: PALMS v3.3 data. Our variable of interest is the variable *green_strict* which is a binary variable equal to one if an individual is in a green job.

5 Conclusion and Policy Directions

This paper aims to profile green jobs in the South African labor market. We utilize the PALMS labor force survey data 2012-2019 and apply an occupational task-based approach to identify green jobs, count them, and profile the workers and the wages for green jobs. Through the process, we adapt a green terms dictionary to be relevant for the South African labor market.

We find that 5.5 percent of South Africa's jobs can be classified as strictly green, while 32 percent can be classified as broadly green. The share of strictly green jobs is in the range of estimates from other countries, spanning 2.3 percent in Indonesia to 39 percent in the UK. South Africa's share of strictly green jobs has barely changed over the last 10 years, while broadly green jobs are slowly increasing. This may be a statistical anomaly driven by the limitations in our data that do not allow us to update the task content of jobs as they evolve. Alternatively, it may be a signal that strictly green job growth is stagnant in the South African economy, even as broadly defined green sectors are growing. This brings into question if today's green policies are sufficiently transformational to shift the South African economy, and its labor force, to greener jobs.

While 65 percent of South Africa's strictly green occupations can be classified as high-level, only 55 percent of green workers are in those jobs. South Africa has a higher number of strictly green occupations among high-level occupations (e.g., science and engineering professionals and technicians) than among mid-level and elementary occupations. Those working in these jobs enjoy a significant wage premium. However, elementary and mid-level strictly green occupations employ a disproportionately larger share of people in South Africa than high-level strictly green jobs do. In short, a narrow set of occupations have the potential to sweep up large numbers of typically excluded workers as the economy greens.

The green economy offers jobs across the socio-economic spectrum in South Africa. While studies from the global north find that green jobs are concentrated in professional and managerial jobs (Vona 2021; Consoli et al. 2016; Bowen et al. 2018; Valero et al. 2021), our results, especially under the broad definition of green jobs, show that there is an opportunity for green jobs in mid-level and elementary occupations. Similar results emerge in the middle-income country of Viet Nam (Doan et al 2022). This is a significant finding for an economy such as South Africa that has a large low-skilled workforce and high rates of unemployment among more vulnerable groups.

The profile of green job workers illustrates exclusion of some groups, but inclusion of others. Most strictly green occupations are dominated by older males, a fact that reflects persistent gendered occupational segregation and high levels of youth unemployment. Green occupations are concentrated in engineering and mathematical professional occupations or mid-level and elementary skill blue collar jobs where women are underrepresented. Women in professional occupations are concentrated in teaching, health professions and office clerks, all of which have a very low (or zero) GTI. Younger individuals (15-24) are also less likely to be in green jobs. However, workers in the greenest of the green occupations are those who tend to be most excluded from the general labor market: Black African workers with lower than matric qualifications. We attribute this result to the fact that the few mid-level and elementary occupations that can be classified as strictly green (e.g., refuse and garbage collectors), exhibit some of the highest GTIs and are responsible for a large share of employment.

Five policy areas emerge from the analysis. First, as the green economy grows, there will be a need to upskill the current work force and prepare the incoming work force with skills used in strictly and broadly green occupations. The 2022 critical skills list identifies 101 occupations that cannot be filled by South Africans; 40 are on our strictly green list, pointing to the current scarcity of local skills to fill (mostly) high-level green jobs.[36] Even more worrisome is that while most of the skills required for a green economy could be delivered by some slight adjustments to the education system, it is not happening on the required scale (Duncan 2023). A skills development strategy to carry out the tasks defined in the green jobs identified in this paper can create some order and efficiency in the scattered and ad hoc current offering of green skills programs (ILO 2019). It can be used to incentivize universities to expand curriculum that aligns with the green occupations identified in this paper to build the missing cohort of scientists and managers needed to spur the green revolution. It can also be a means for expanding and organizing the TVET system to prepare workers in mid-level occupations, particularly for broadly green jobs. Partnerships with the private training sector, which is already active in providing short courses in a range of green-related technologies, will allow for a rapid expansion of training opportunities to engage less-skilled youth in green occupations (Duncan 2023). Even workers in elementary occupations will need to upskill and reskill as new technologies and industries come on the market. This group is best served through practical, short courses provided through municipalities or other local private sector players.

Second, the low prevalence of youth in green jobs suggests a need to proactively engage youth to view green jobs as a viable job opportunity. Three types of interventions can bring more youth to green jobs. First, career counseling programs, such as the SkillCraft career guidance portal on SAYouth.mobi, can present green occupations as career options and guide youth toward training programs to prepare to enter these fields. Second, scholarships for TVET study can be earmarked for green occupations. Third, the Presidential Youth Employment Initiative, Extended Public Works Program, and other programs that provide youth a first job experience can expand their offering of strictly or broadly green jobs.

Third, women's under-representation in green jobs needs to be addressed before they are left out of the green transition. Girls can be encouraged to engage in STEM fields, as is shown through computer programming clubs in high schools (Yabas et al 2022), scholarships for girls entering STEM fields in TVET or university, and career guidance that provides earnings information (among other) for STEM careers. Publicly recognizing and celebrating successful women in STEM or mentorship programs between female STEM students or young women in the STEM workforce with established women in STEM fields can help newcomers navigate the male world of green jobs. A societal shift in mindset – that STEM is for girls and women – through public campaigns has been successful in other countries (Hill et al 2010).

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[36] Department of Home Affairs. 2022. *Government Gazette (Vol. 680) #45860 of February 2022.* Republic of South Africa.

Fourth, elementary strictly green jobs are home to many excluded workers that play a vital role in the green economy value chain but may be even more productive through organization. For example, waste pickers in South Africa are beginning to organize by registering with municipal authorities, organizing their work streams to increase the value added, and gaining some worker rights. As the green economy expands, such organized groups of workers may play a stronger role (Medina 2008).

Finally, as South Africa moves toward a green economy, it will be even more important to understand and track the impact on jobs. This paper used proxies to estimate the number and profile of green jobs in South Africa. But better measures will be needed. This highlights the need to develop detailed and regularly updated occupation-task databases, such as through web scrapes or other big data sources. It will also require academia-industry collaboration to more succinctly define the South African skill profile needed in emerging green jobs, as well as profiling those occupations that will disappear through the transition and related necessary reskilling.

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Table A1: Strictly Green Occupations

ISCO code	Occupational title	GTI strict	Total employ
1221	Production and operations departmen managers in agriculture, hunting, forestry and fishing	4,17	9 464
1222	Production and operations department managers in manufacturing	9,17	47 087
1311	General managers in agriculture, hunting, forestry and fishing	2,83	21 310
1312	General managers in manufacturing	9,17	11 751
2112	Meteorologists	77,78	463
2113	Chemists	25,00	1 109
2114	Geologists and geophysicists	58,33	3 048
2141	Architects, town and traffic planners	16,67	12 629
2142	Civil engineers	28,57	15 455
2147	Mining engineers, metallurgists and related professionals	11,11	4 388
2149	Architects, engineers and related professionals not elsewhere classified	36,67	6 971
2159	Physical sciences technologists	11,11	342
2190	Physical, mathematical and engineering science professionals not elsewhere classified	11,11	76
2210	Scientist	50,00	1 581
2211	Biologists, botanists, zoologists and related professionals	75,00	3 603
2212	Pharmacologists, pathologists and related professionals	16,67	2 097
2213	Agronomists and related professionals	33,33	6 101
2412	Personnel and careers professionals	16,67	54 620
3111	Chemical and physical science technicians	16,67	21 817
3112	Civil engineering technicians	22,22	10 641
3114	Electronics and telecommunications engineering technicians	7,14	69 608
3117	Mining and metallurgical technicians	12,50	3 383
3119	Physical and engineering science technicians not elsewhere classified	40,00	3 112
3151	Building and fire inspectors	11,11	4 398
3152	Safety, health and quality inspectors	16,68	101 189
3211	Life science technicians	5,00	8 159
3212	Agronomy and forestry technicians	16,25	1 617
3213	Farming and forestry advisers	33,33	3 831
3222	Sanitarians	45,00	5 058
3471	Decorators and commercial designers	2,22	46 105
5161	Fire-fighters	33,33	19 234
6141	Forestry workers and loggers	20,00	12 121
6142	Charcoal burners and related workers	20,00	36
6151	Aquatic-life cultivation workers	11,11	317
6152	Inland and coastal waters fishery workers	4,17	3 322
7132	Floor layers and tile setters	25,00	34 631
7134	Insulation workers	33,33	275
7216	Underwater workers	8,33	278
7231	Motor vehicle mechanics and fitters	22,92	201 292
8161	Power-production plant operators	16,67	6 335
8162	Steam-engine and boiler operators	16,67	2 024
8163	Incinerator, water-treatment and related plant operators	50,00	22 455
8232	Plastic-products machine operators	7,14	19 367
9153	Vending-machine money collectors, meter readers and related workers	14,29	13 288
9161	Garbage collectors	79,17	61 023
9321	Assembling laborers	41,67	2 803
	Total		879 818

Source: authors' calculations using PALMS v3.3 data. Employment totals of less than 3000 individuals are estimated from small cells (few observations of less than 100 in an occupation) therefore these totals should be interpreted with caution.

Table A2: Broadly green jobs complete list

No	ISCO-88 code	Occupational Title	GTI-Potential	Total employed
1	1221	Production and operations department managers in agriculture, hunting, forestry and fishing	69.23	9464
2	1222	Production and operations department managers in manufacturing	9.17	47087
3	1311	General managers in agriculture, hunting, forestry and fishing	47.35	21310
4	1312	General managers in manufacturing	9.17	11751
5	2112	Meteorologists	88.89	463
6	2113	Chemists	25.00	1109
7	2114	Geologists and geophysicists	58.33	3048
8	2141	Architects, town and traffic planners	20.83	12629
9	2142	Civil engineers	57.14	15455
10	2144	Electronics and telecommunications engineers	13.39	3882
11	2145	Mechanical engineers	14.29	16116
12	2147	Mining engineers, metallurgists and related professionals	11.11	4388
13	2149	Architects, engineers and related professionals not elsewhere classified	36.67	6971
14	2159	Physical sciences technologists	11.11	342
15	2190	Physical, mathematical and engineering science professionals not elsewhere classified	11.11	76
16	2210	Scientist	62.50	1581
17	2211	Biologists, botanists, zoologists and related professionals	81.25	3603
18	2212	Pharmacologists, pathologists and related professionals	20.83	2097
19	2213	Agronomists and related professionals	100.00	6101
20	2222	Dentists	8.33	6237
21	2412	Personnel and careers professionals	20.00	54620
22	3111	Chemical and physical science technicians	16.67	21817
23	3112	Civil engineering technicians	33.33	10641
24	3113	Electrical engineering technicians	33.33	31598
25	3114	Electronics and telecommunications engineering technicians	24.29	69608
26	3115	Mechanical engineering technicians	12.50	25245
27	3116	Chemical engineering technicians	20.00	1434
28	3117	Mining and metallurgical technicians	25.00	3383
29	3118	Draughtspersons	37.50	13400
30	3119	Physical and engineering science technicians not elsewhere classified	40.00	3112
31	3132	Broadcasting and telecommunications equipment operators	10.00	4759
32	3141	Ships' engineers	40.00	135
33	3142	Ships' deck officers and pilots	12.50	692
34	3145	Air traffic safety technicians	25.00	192
35	3151	Building and fire inspectors	16.67	4398
36	3152	Safety, health and quality inspectors	29.91	101189
37	3211	Life science technicians	5.00	8159
38	3212	Agronomy and forestry technicians	75.00	1617
39	3213	Farming and forestry advisers	100.00	3831
40	3222	Sanitarians	55.00	5058
41	3241	Traditional medicine practitioners	8.33	42474
42	3471	Decorators and commercial designers	2.22	46105
43	4223	Telephone switchboard operators	10.00	70541
44	5112	Transport conductors	10.00	1800

45	5161	Fire-fighters	33.33	19234
46	5169	Protective services workers not elsewhere classified	10.00	573030
47	6111	Field crop and vegetable growers	81.82	12789
48	6112	Tree and shrub crop growers	81.82	4138
49	6113	Gardeners, horticultural and nursery growers	38.38	5994
50	6114	Mixed-crop growers	63.64	763
51	6121	Dairy and livestock producers	15.38	10186
52	6122	Poultry producers	16.67	1805
53	6123	Apiarists and sericulturists	66.67	171
54	6130	Market-oriented crop and animal producers	50.00	3678
55	6141	Forestry workers and loggers	80.00	12121
56	6142	Charcoal burners and related workers	80.00	36
57	6151	Aquatic-life cultivation workers	44.44	317
58	6152	Inland and coastal waters fishery workers	22.50	3322
59	6153	Deep-sea fishery workers	12.50	1086
60	6154	Hunters and trappers	20.00	423
61	6210	Subsistence agricultural and fishery workers	15.82	61
62	6211	Subsistence farmers	28.57	10009
63	7111	Miners and quarry workers	5.56	63534
64	7112	Shotfirers and blasters	9.09	5355
65	7113	Stone splitters, cutters and carvers	14.29	6045
66	7114	Diamond drivers	14.29	147
67	7121	Builders, traditional materials	14.29	779
68	7122	Bricklayers and stonemasons	23.81	243612
69	7123	Concrete placers, concrete finishers and related workers	20.00	31728
70	7124	Carpenters and joiners	60.00	98070
71	7129	Building frame and related trades workers not elsewhere classified	4.76	83473
72	7132	Floor layers and tile setters	25.00	34631
73	7134	Insulation workers	33.33	275
74	7136	Plumbers and pipe fitters	20.00	122045
75	7137	Building and related electricians	25.00	143051
76	7211	Metal moulders and coremakers	14.29	1598
77	7212	Welders and flamecutters	12.50	117626
78	7213	Sheet-metal workers	42.86	87238
79	7214	Structural-metal preparers and erectors	16.67	18192
80	7215	Riggers and cable splicers	50.00	1808
81	7216	Underwater workers	25.00	278
82	7221	Blacksmiths, hammer-smiths and forging-press workers	14.29	519
83	7222	Tool-makers and related workers	36.36	8080
84	7224	Metal wheel-grinders, polishers and tool sharpeners	14.29	13649
85	7231	Motor vehicle mechanics and fitters	37.50	201292
86	7232	Aircraft engine mechanics and fitters	40.00	2176
87	7233	Agricultural- or industrial-machinery mechanics and fitters	41.07	90254
88	7241	Electrical mechanics and fitters	57.14	41065
89	7242	Electronics fitters	45.24	16256
90	7243	Electronics mechanics and servicers	45.24	26238
91	7244	Telegraph and telephone installers and servicers	57.14	4349
92	7245	Electrical line installers, repairers and cable jointers	45.24	10459

93	7311	Precision-instrument makers and repairers	17.50	2495
94	7312	Musical instrument makers and tuners	9.09	445
95	7313	Jewellery and precious-metal workers	9.09	4074
96	7341	Compositors, typesetters and related workers	5.56	14108
97	7345	Bookbinders and related workers	14.29	1540
98	7346	Silk-screen, block and textile printers	11.11	1181
99	7414	Fruit, vegetable and related preservers	20.00	1357
100	7415	Food and beverage tasters and graders	20.00	2461
101	7422	Cabinet-makers and related workers	16.67	9409
102	7423	Woodworking-machine setters and setter-operators	16.67	748
103	7432	Weavers, knitters and related workers	3.85	3363
104	7433	Tailors, dressmakers and hatters	18.18	30299
105	7434	Furriers and related workers	18.18	104
106	7436	Sewers, embroiderers and related workers	8.33	24965
107	7437	Upholsterers and related workers	16.67	12899
108	7442	Shoe-makers and related workers	38.46	16347
109	8111	Mining-plant operators	5.56	31888
110	8112	Mineral-ore- and stone-processing-plant operators	10.00	19001
111	8113	Well drillers and borers and related workers	10.00	312
112	8161	Power-production plant operators	16.67	6335
113	8162	Steam-engine and boiler operators	16.67	2024
114	8163	Incinerator, water-treatment and related plant operators	50.00	22455
115	8212	Cement and other mineral products machine operators	10.00	7565
116	8231	Rubber-products machine operators	8.33	9003
117	8232	Plastic-products machine operators	14.29	19367
118	8240	Wood-products machine operators	8.33	3087
119	8251	Printing-machine operators	5.56	15614
120	8252	Bookbinding-machine operators	7.14	713
121	8262	Weaving- and knitting-machine operators	3.85	4268
122	8264	Bleaching-, dyeing- and cleaning-machine operators	3.70	4182
123	8265	Fur- and leather-preparing-machine operators	4.55	699
124	8311	Locomotive-engine drivers	20.00	24423
125	8320	Driver, taxi	28.57	188508
126	8322	Car, taxi and van drivers	12.50	147914
127	8323	Bus and tram drivers	28.57	34886
128	8324	Heavy truck and lorry drivers	33.33	250167
129	8331	Motorised farm and forestry plant operators	62.50	51772
130	9141	Building caretakers	25.00	34029
131	9153	Vending-machine money collectors, meter readers and related workers	14.29	13288
132	9161	Garbage collectors	87.50	61023
133	9162	Sweepers and related laborers	26.19	193167
134	9211	Farm-hands and laborers	21.75	957792
135	9212	Forestry laborers	87.50	31848
136	9321	Assembling laborers	50.00	2803
137	9332	Drivers of animal-drawn vehicles and machinery	11.11	37
	Total			**5096474**

Source: authors' calculations using PALMS v3.3 data. Employment totals of less than 3000 individuals are estimated from small cells (few observations of less than 100 in an occupation) therefore these totals should be interpreted with caution.