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ABSTRACT

Estimating the Green Wage Premium*

To address climate change concerns, Japan is accelerating the greening of its economy. In this paper we analyze the characteristics of the workers that are contributing to the green transition and estimate the so-called green wage premium. Using propriety data from a recent worker-level survey for Japan, we provide a continuous measure of the degree to which a job can be considered green and document how green jobs are different from non-green jobs by sector, occupation and different demographics. Our structural model estimates of a green wage premium show that the hourly wage of green workers is 7.3% higher on average than non-green workers. A 10% increase in the green intensity of a job is shown to increase average hourly wages by 0.8%. Decomposition results suggest that the explainable part of the wage premium is largely due to task differences, gender disparities (in lower percentiles), and occupation. The unexplained part of the green wage premium are found mainly in high-paying green jobs where certain characteristics appear to be better rewarded, possibly driven by supply and demand imbalances.

JEL Classification: Q50, Q52, J24, J31

Keywords: employment, green jobs, green transition, climate change, wage gap, Japan

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1 Introduction

In October 2020, the former Japanese Prime Minister Suga declared that Japan will reduce greenhouse gas emissions to net zero by 2050. In December 2020, the government developed its 'Green Growth Strategy' which selected 14 sectors as new green industries including new energy, electricity, resource management, and the transportation sector. Several funds were also created to promote ecological related businesses and to support eco-innovation. The government estimates that the policy will increase GDP by 2 trillion USD and create 18 million jobs by 2050. Outside of Japan, the European Green Deal and the Inflation Reduction Act (IRA) in the United States (US) also include claims that these initiatives will lead to the creation of jobs primarily in green sectors of the economy.[1]

Green growth initiatives are predicted to reshape not only the operational structure of companies and industries but also profoundly transform how firms organize and manage their workforce. New green job opportunities are being created and many existing roles are incorporating the skills required to integrate green and low-carbon technologies into existing production processes. The result is that the labor market is also undergoing a green transition which is changing the future of work in ways that are not yet fully understood. Despite the increasing rhetoric about how the green transition should lead to the creation of cleaner, higher quality, and better paid jobs, little is known about the characteristics of green workers, how green workers are distributed across the economy and the wage differences between green workers and non-green workers. This gap in the literature highlights the need for research to help policymakers understand the impact of green transition initiatives on the workforce (ILO 2013), where there may be future skill shortages and to what extent the green transition is on course to be socially just (Mabon et al. 2022, UNDP 2022, Galanis et al. 2024).

The purpose of this paper is to present a picture of Japan's recent green job landscape and to provide the first estimates of a green wage premium using worker-level data. To this end, we employ novel and representative data based on a survey of Japanese workers conducted by Toshihiro Okubo (Keio University) and the Nippon Institute for Research Advancement (NIRA). As part of the survey design, we incorporated a dedicated module assessing the green activities performed by workers in their primary jobs, as well as the amount of time devoted to these activities. The survey has been run ten times since March 2020 with participants usually included in multiple waves. To the best of our knowledge, no survey of this nature for a major developed country has previously included green-job-specific questions. The answers mean we were able to define what constitutes a green job in a new way and to capture the green intensity of a job based on the time spent on green activities.[2]

More specially, the contribution of the paper is three-fold. First, because we have individual worker survey responses we are able, for the first time in the green jobs literature, to examine the characteristics of those workers currently employed in green, non-green

[1]For details the Green Growth Strategy through achieving carbon neutrality in 2050 in Japan see `https://www.meti.go.jp/english/policy/energy_environment/global_warming/ggs2050/index.html`. Details of the European Green Deal can be found at `https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en` and the US IRA is described at `https://www.whitehouse.gov/cleanenergy/inflation-reduction-act-guidebook/`.

[2]The questions included in the survey are described in detail in Section 3.

and more intensively green jobs including age, gender, education, sector, occupation, and region. Second, employing a structural model to address potential selection biases, we estimate the green wage premium by considering not only whether there is a wage differential between workers in green and non-green jobs but also whether jobs with higher green intensity are associated with higher wages. The comprehensive nature of the survey means we are able to control not only for the standard variables typically included in wage equations mentioned above but also for job task-related variables and individual personality traits. Third, after applying a DiNardo-Fortin-Lenieux (DFL) adjustment to the wage distribution (DiNardo et al. 1996), we take a Firpo-Fortin-Lemieux (FFL) decomposition approach (Firpo et al. 2007) to understand better how the wage gap between green and non-green jobs is derived from differences in traits (wage structure effect) and which observable factors contribute to the green wage premium (compositional effect).

In addition to the main question which is whether there is a wage premium for workers in green jobs and whether it increases with the green intensity of the job our empirical approach allows us to address three other distinct questions. First, whether the green wage premium varies by skill level? It is evident that green jobs require a range of different skills and education. Some green jobs undoubtedly require higher technical skills and scientific knowledge (e.g. engineers, scientists, and technicians who work in the development and implementation of green technologies). Indeed, Consoli et al. (2016) argue that green jobs tend to be characterized by a higher degree of advanced cognitive and interpersonal skills compared to non-green jobs and that such jobs were also found to require more formal education, work experience, and on-the-job training. However, other green jobs may require less specialized skills and knowledge (e.g. installers and maintainers of solar panels or wind turbines). For lower-skilled green jobs, the wage premium may be less pronounced due to a larger available labor pool and less specialized training requirements. However, even these jobs might offer a premium compared to similar non-green jobs due to policy support and green sector growth more broadly. For example, Muro et al. (2019) show that around 50% of workers in the clean energy sector have no more than a high school diploma, yet they earn higher wages than similarly-educated workers in other sectors. Similar results were found by Vona et al. (2019), who shows that the wage premium is higher for low-skilled manual green occupations (8%) compared to high-skilled green occupation (2%).

Second, and subject to considerable debate, is whether the green transition will be a socially just transition (UNDP 2022, Galanis et al. 2024). Historical evidence on labor demand shocks (e.g., globalization and skill-biased technological change) indicates that economic transitions often have a limited yet long-term negative impact on employment, with disproportionate welfare losses concentrated among vulnerable groups—particularly women and older workers (Autor et al. 2003, Autor & Dorn 2013). Although existing studies have shown that green jobs tend to be male-dominated (Peters 2014, Muro et al. 2019) there has been no analysis of the wage gap between females in green jobs earn and their counterparts in non-green jobs and whether female green workers have a higher or lower hourly wage than male green workers. Card et al. (2016), Zhang et al. (2021) and He et al. (2023) argue that females can face greater barriers to employment and career advancement and hence need to demonstrate superior work performance to receive the same recognition, opportunities, and compensation as males. Furthermore, males might negotiate salaries more aggressively or effectively than females, a factor that could also hold for workers in green jobs. Third, and also related to a just green transition discussion is to ask whether new green opportunities are available to all age groups. Although Muro et al. (2019) show that the clean energy economy workforce is older, to the best of our knowledge, there have been no empirical studies examining the difference in the green wage premium by age and whether the wage premium is impacted by the green intensity of the job. Because green jobs are often in new and emerging technologies, older workers may lack the knowledge and skills required or be less adaptable to rapidly changing technologies such that there may be no wage premium for older cohorts.

We chose Japan as our country of analysis for four reasons. First, Japan's push for greater reliance on renewable energy and the associated creation of green jobs has received significant government support. As of 2020, the renewable energy sector employed approximately 236,266 workers, with solar photovoltaic systems accounting for 93.1% of the total employment in this sector (ILO 2022). Such trend aligns with Japan's broader environmental strategy, as reflected in its performance in the 2022 Environmental Performance Index (EPI) where Japan ranked 25th out of 180 countries (ILO 2022). Second, the commitment to sustainability is further underscored by Japan's renewable energy output, which reached 197,851 GWh in 2020, following a steady annual growth rate of 3.6% since 2000 (ILO 2022). Hydropower comprised 44.2% of this production, indicating a diversified approach to green energy utilization (ILO 2022). Third, Japan's green transition is part of a broader strategy to enhance environmental health and mitigate climate change, which are critical given the country's vulnerability to climate related natural disasters (typhoons, landslides and flooding) and its dense urban populations.[3] Finally, Japan is a developed country with high quality data and a survey in which we were given the unique opportunity to include our own green activity questions which would be challenging for countries in the EU and the US.

To briefly summarize our results, we find that green jobs tend to be associated with higher levels of education and professional qualifications, are male dominated, and on average occupied by older workers (although on average younger workers have the most green intensive jobs). More generally, the green intensity index of a given job tends to increase with education and decrease with age. Green workers are most often found in the Managerial and Professions and Technicians occupational groups, although managerial roles tend to have lower average green intensity indices, while occupations associated with professions and technicians have higher green intensity indices. The highest percentage of green workers is found in the Manufacturing sector while the sectors with the highest green intensity index tend to be in the relatively high polluting sectors, such as 'Electricity, gas and water supply' and 'Mining and construction'.

In terms of wage premiums, we find that there is a wage premium for workers in green jobs and that the premium increases with the green intensity of the job. More specifically, the hourly pay of green workers is 7.3% higher than non-green workers on average, and if the green intensity of a job increases by 10% this leads to a roughly 0.8% increase in average hourly wage. The green wage premium differs by skill-level, gender, and age. Our FFL decomposition results reveal that the wage structure effect is particularly strong at the upper end of the wage distribution suggesting that in higher-paying jobs, the labor

[3] For a discussion on Japan's energy transition and its estimated impact on employment see Nagatomo et al. (2021), Kuriyama & Abe (2021) and Ju et al. (2022).

market tends to reward similar observable characteristics (such as tasks, education, experience) in green jobs differently to non-green jobs. By decomposing the composition effect, we find that the explained wage gap between green and non-green jobs is primarily driven by task differences, gender disparities (in lower percentiles), and occupation types, while factors like education and tenure play relatively smaller, yet consistent roles.

The remainder of the paper is organized as follows: Section 2 reviews the literature. Section 3 presents the data and highlights key stylized facts. In Section 4, we analyze and discuss the results, while Section 5 investigates the possible mechanism underlying our findings. Section 6 concludes.

2 Defining a green job and a green wage premium

2.1 Defining a green job

This section provides a brief overview of the somewhat convoluted history of the measurement of so-called green jobs. Despite a growing literature, defining what constitutes a green job or the extent to which existing jobs are green or becoming greener over time remains work in progress. In this section we highlight the main developments and show how the survey based approach presented in this paper contributes to the measurement literature.

The most widely used definition of a green job comes from a report 'Green Jobs: Towards Sustainable Work in a Low-Carbon World' by the UNEP/IL/ITUC, 2008. In this report, green jobs are generally defined as decent jobs that contribute to preserving or restoring the environment, and are not restricted to a specific industry or occupation (UNEP/ILO/ICTU 2008). Green jobs can therefore be found in traditional sectors such as manufacturing and construction, or in new emerging green sectors such as renewable energy and electric transportation. To meet the increasing demand for statistics on green jobs, in 2013 the ILO initiated efforts to define a green job and provide conceptual guidelines for gathering the statistics needed for the production of internationally harmonized and comparable data (ILO 2013). The proposal was that green jobs should be decent and produce environmental goods and services (green output) and use green technologies (green processes). The ILO definition is a combination of two approaches: (1) the Green product approach, to identify green products and services and the corresponding jobs within firms engaged in producing such goods and services, and (2) the Green process approach, to identify environmentally friendly production processes and the associated jobs within firms that use these green production methods.

Early studies, predominantly in European countries, focused on estimating the number of workers employed in green or so-called eco-industries. The most widely used measurement of what constitutes an eco-industry was developed by Eurostat (2009) building on work from the OECD who in 1999 proposed the concept of Environmental Goods and Services Sectors (EGSS) and argued that the number of workers in EGSS was a crucial green growth indicator for tracking progress towards a more environmentally sustainable economy (OECD 2011). The EGSS consists of a heterogeneous set of producers of goods and services who's activities include (a) protection of the environment and (b) management of natural resources (Eurostat 2009).[4] Since 2015, the approach of the UK's Office for National Statistics (ONS) is to measure employment in what they call Low Carbon and Renewable Energy Economy (LCREE) sectors although it excludes some activities that might be considered green but are not low carbon such as recycling and the protection of biodiversity.[5]

In the first US study, the Pew Charitable Trust in their report 'The Clean Energy Economy Repowering Jobs Businesses and Investments Across America', provided a list of SIC codes they believed captured the extent of the clean energy economy in the US. Yi & Liu (2015) used these SIC codes to examine the regional breakdown of green jobs in the China. A more recent unofficial US study by Georgeson & Maslin (2019) employed a data triangulation approach using different sources and multiple types of data to estimate the scale of employment in the Low Carbon and Environmental Goods and Services Sector. Analysis at the sector level, however, have been criticized for using definitions that are either too broad or are focused only on selected industries (ILO 2013). The argument is that this may lead to an over estimation of the number of green jobs as firms often produce multiple goods and services only some of which may be green. The problem is that current industrial classifications and product codes are not detailed enough to distinguish between green products and non-green products within individual sectors. Sector-level analysis also misses those jobs in firms classified as belonging to a non-green sector but operate using green production processes.

To address concerns with sector-level analysis, researchers turned to occupation-level measures, building on the work of Dierdorff et al. (2009, 2011). These authors define three distinct categories of green occupations based on the O*NET database. The first two categories are considered direct measures of green jobs, while the third is viewed as indirect, a distinction noted in existing studies (e.g., Consoli et al. 2016, Vona et al. 2018, 2019). The first direct category comprises Green New and Emerging (NGE) occupations that are a direct result of a greening economy. The second direct category is Green Enhanced Skills (GES) occupations which includes those occupations that require the acquisition of new skills or the modification of existing skills to enable the worker to adapt to the evolving demands of a greener economy. The third category is defined as jobs consisting of Green Increased Demand (GID) occupations and refers to those jobs that experience an increase in demand as a result of the transition towards a greener economy and can be thought of as an indirect measure.[6]

A benefit of using the O*NET classification is that it allows researchers to match

[4]The EGSS is embedded in the System of Environmental and Economic Accounting (SEEA) Central Framework, and provides estimates of employment by Classifications of Environmental Protection Activities (CEPA) and Resource Management Activities (CReMA). Although a broad definition it excludes activities such as nuclear power.

[5]For details on the LCREE survey from the ONS see: `https://www.ons.gov.uk/economy/environmentalaccounts/methodologies/lowcarbonandrenewableenergyeconomylcreesurveyqmi`.

[6]As O*NET does not provide green task statements for GID occupations they tend to be excluded from O*NET based green job studies. To illustrate what we mean by direct and indirect green occupations, jobs in the the sector '51-8012.00 Power Distributors and Dispatchers' are classified under the GID category which means it is an indirect green occupation. O*NET does not fully capture those occupations that are intensively using green technologies, such as smart grids, which enhance operations and integrate renewable energy sources such as solar and wind into the electricity system.

O*NET green occupations with other datasets using occupation crosswalks. Studies of the US labor market usually match O*NET data with the OES to produce annual employment and wage estimates for approximately 830 occupations by US State, metropolitan/non-metropolitan areas, and sectors (e.g., Peters 2014, Consoli et al. 2016, Vona et al. 2018, Bowen et al. 2018, Vona et al. 2019). Other studies have applied the O*NET green occupation definitions to European countries by matching US SOC code with International Standard Classification of Occupations (ISCO) and then linking this data with data from EU country or European Labor Force Surveys which provide information on the characteristics of individuals working in different occupations which can be aggregated to give summary statistics by age, gender, education, and income (e.g., Sofroniou & Anderson 2021, Bluedorn et al. 2023, Elliott et al. 2024). So while O*NET definitions allow the researcher to measure how green a given occupation is by making a distinction between green and non-green tasks, one drawback is that European country studies struggle to overcome measure error concerns inherent in the use a cross-walk from the US O*NET-SOC classification (6-digit) to the ISCO (4-digit). A second concern is that these studies still apply occupation definitions to workers even though workers in the same occupation may have a different balance of green tasks within their working day depending on the firm they work for and the firm's sector (Vona 2021, Scholl et al. 2023).[7]

An emerging literature that engages with the need to work at a more disaggregated level uses online job postings. For example, Curtis & Marinescu (2023) identify clean energy jobs through text analysis of job titles and descriptions to highlight changes in the demand for green skills (mainly in renewable energy sectors like wind and solar). Similarly, Saussay et al. (2022), Sato et al. (2023), Ehlinger & Stephany (2023) combine a list of skills from online job vacancy data with low-carbon related words to identify green jobs. Job postings data can provide an estimate of the wages on offer that broadly reflects the demand for green workers but necessarily excludes those already employed in a green jobs. As pointed out by Kureková et al. (2015) and Fabo et al. (2022), research using data from online job portals, while promising, also needs to carefully consider issues related to representativeness, consistency, and accuracy.

In this paper we provide a missing piece of the green jobs jigsaw by combining elements from the sector and occupational approaches described above. More specifically, we use a survey that asks workers (1) standard questions about their individual characteristics and income and (2) questions regarding the extent to which their current job involves green job activities which are specific to that worker's personal circumstances. By contributing to the survey design, we ensured that the necessary data were collected to provide a unique perspective on green jobs—to understand who green workers are, how green their job is (intensity) but also, for the first time, to estimate the green wage premium. Our approach does not have cross-walk or aggregation measurement concerns and is based on currently employed workers who, as part of the survey, provide actual income and hours worked data. This greatly simplifies the analysis while addressing pre-

[7] Using the Dutch economy as an example, Elliott et al. (2024) provide a detailed description of how best to overcome the various crosswalk issues by applying appropriate weights to accurately reflect the relative size and significance of each occupation in different classification systems when transitioning from O*NET to the European ISCO classification. Note also that despite the rapidly changing clean technology sector and the changing nature of employment, the O*NET classification of green tasks and green occupations has not been updated since 2012. Updates can be found on the O*NET website: `https://www.onetcenter.org/dictionary/28.0/excel/appendix_updates.html`.

vious measurement concerns.

2.2 Defining a green wage premium

As highlighted in the previous section, the limited number of studies using worker-level data in the green jobs literature means that little is known about the fundamentals such as the age, gender and skill levels associated with green workers. Moreover, even less research has investigated the existence and magnitude of a green wage premium, as well as the factors that contribute to it. Nevertheless, a small body of related research exists, which is discussed below.

The demand and supply of labor are continuously evolving due to technological and structural change including the impact of different green transition policies (Fierro et al. 2022, Leblebicioğlu & Weinberger 2021). In a perfectly competitive market, each worker should be paid a wage equivalent to the marginal product of labor. In turn, a worker's productivity depends on their capabilities, specifically, the tasks they are able to complete (i.e., their skills). However, scarcity also plays a role. The fewer the number of workers who can perform a particular task, the greater the wages those workers can demand (Autor 2014). For example, when demand for workers with certain skills increases a skill premium can appear (at least temporarily). By the same reasoning, if the demand for these green skills is greater than the supply, the result will be, at least in the short-term, a green wage premium.

On the demand side, the last decade has seen those sectors associated with green jobs expanding rapidly. A study in Australia, Annandale et al. (2004) show that employment in green businesses grew much faster than the general business sector, and that green hires were not in response to regulations or to maintain profits but to build firms' sustainable development practices. A similar result has been found in Horbach & Janser (2016), who observed that the environmental sector is characterized by disproportionately high employment growth and that innovation and industry agglomeration foster employment growth in establishments within the environmental sector. Conversely, establishments without green products and services show a smaller increase in employment, even if they are also innovative (Horbach & Janser 2016). In a similar study, Elliott et al. (2024) use a linked employer-employee administrative dataset for the Netherlands and show that while eco-innovation does not affect overall employment, eco-product innovation results in an increase in green employment, which primarily stems from a compositional shift, with a small but significant rise in the number of green workers and a reduction in the number of non-green workers.

Despite the perceived benefit from hiring green workers, according to ManpowerGroup (2023), many firms who are developing environmental, social and governance (ESG) strategies are reporting not having the talent needed to implement their ESG plans. Similarly, the 'Global Green Skills Report 2023' by LinkedIn (2023) demonstrated a significant disparity between the demand and supply of green skills pointing out that the demand for jobs requiring green skills has surged, with job postings for such roles increasing by a median of 22.4% between 2022 and 2023 while the availability of workers with these skills has not kept pace, with only a median increase of 12.3% in green talent across the surveyed countries (LinkedIn 2023). Growing demand for green skills is further underscored by the fact that the median LinkedIn hiring rate for workers with at least one green skill is 29% higher than the workforce average, indicating a market preference for individuals with these capabilities (LinkedIn 2023). As the demand for green skills outpaces the supply, the economic value of workers with these skills is likely to increase, which should be reflected in their wages. In related work, Yadav et al. (2017) argue that firms that prioritize environmental sustainability will develop a competitive advantage, which allows them to offer higher wages and benefits to attract and retain workers with green skills.

While the case for a green wage premium may appear to be a strong one, any premium may be offset for two reasons. First, the observation that workers in green industries or occupations may have strong environmental values and put these values ahead of monetary gain. One of the few studies that does exist is Krueger et al. (2022) who show for Swedish firms that workers earn approximately 9% less when they work in firms that operate in more sustainable sectors. They argue that this is because some workers, especially high skilled workers, may be willing to accept lower wages in exchange for working in an environmentally friendly industry or occupation that aligns with their personal values and beliefs. Second, Marinescu et al. (2021) highlight that labor market concentration can lead to wage suppression in certain industries. This phenomenon might be reflected in green sectors if they are sufficiently concentrated and can exert market power over wages, potentially offsetting any positive wage premium associated working in a green job.

Nevertheless, existing studies increasingly support the existence of a green wage premium. A report by Muro et al. (2019) show that the wages of US workers in clean energy sectors exceed the national average hourly wage by 8 to 19%. Vona et al. (2019) also provides evidence that green jobs in the US pay on average 4% more than skill comparable non-green occupations. Using job posting data also for the US, Curtis & Marinescu (2023) showed that solar and wind related jobs pay around 21% more than average. While Sato et al. (2023) found evidence of a wage premium of up to 15% for low-carbon jobs in the early 2010s using job postings data although they also noted that this premium has been declining in recent years. A falling wage premium could be attributed to more individuals retraining and an increase in green skill-related education and training opportunities provided by universities and firms.

3 Empirical strategy

3.1 Data

The primary data used in this research are obtained from a survey on Japanese workers called the 'Questionnaire Survey on the Effects of the Spread of COVID-19 on Telework-based Work Styles, Lifestyle, and Awareness,' (Okubo-NIRA Telework Survey), conducted by the Nippon Institute for Research Advancement (NIRA) and Toshihiro Okubo (Keio University). See Okubo (2022*a*,*b*), Okubo & Nippon Institute for Research

Advancement (2020a,b,c, 2021a,b,c 2022a,b) for details.[8]

The survey adopts a representative stratified random sampling strategy. The sample is stratified into five regions over Japan and six age groups for each gender (hence 12 age groups per region). The number of samples for 60 region–age groups is determined by population ratios. The Labor Force Survey (Ministry of Internal Affairs and Telecommunication) is employed as the sampling unit. The respondents to the survey are workers living in Japan and has been run periodically since March 2020 (which coincides with the early period of COVID-19 pandemic, i.e. before the first state of emergency in Japan). First, for each group, all respondents that had previously joined the survey at least once were asked to join the survey again. If some respondents do not join again then new respondents are invited until the sample in each group is complete. Hence, new individuals join each wave.[9]

Our paper focuses on the fifth wave of the survey, conducted in September 4th to 22nd 2021. The sample size is 10,644 of which 8,455 respondents were in a previous wave of the survey. In addition to the standard questions, at the request of the authors the respondents in the fifth wave were also asked a series of questions related to activities at work that can be considered green. The respondents provided information on gender, age, annual income, occupation, industry, residential prefecture, employment status, university degree, job tenure, qualifications, and some PIIAC questions.[10] There are also other wave-specific questions from the sixth and seventh waves on social capital and parents' main occupation that we used to create our instrumental variables.

The green job specific questions asked whether the respondents job can be considered green and what proportion of their workday they spend on green job activities on average. The survey questionnaire uses the BLS green jobs definition so that workers are identified as green if they respond that as part of their job they: (1) produce green goods or provide green services or (2) use environmentally friendly production processes and practices.[11]

More specifically, the questionnaire includes the following questions:

Q1. Does your job qualify as a green job? Please answer for each of the green job categories below either 'Applicable', 'Part of the work is applicable', or 'Not applicable'.

(1). Compliance with environmental regulations, education and training, and enhancing public awareness.

[8] The surveys were conducted online by Nikkei Research Co and are conducted in Japanese with the original questions translated from English by the authors for inclusion in the survey. The questionnaire is available at `https://www.nira.or.jp/paper/report012110_pre.pdf`.

[9] See Okubo (2022) for details on the sampling procedure. As of May 2024, the panel data consists of ten waves. The sample sizes in the first to the ninth waves are 10,516, 12,138, 10,523, 9,796, 10,644, 10,113, 10,595, 9,804, 9,779, and 10,726, respectively.

[10] The Program for the International Assessment of Adult Competencies (PIAAC) is an initiative focused on evaluating and analyzing the skills of adults. See `https://www.oecd.org/skills/piaac/`. For a link to a report using the broader data see `https://nira.or.jp/paper/data/2022/26.html`.

[11] We acknowledge the potential biases associated with self-reported data which is an inherent challenge in survey-based research for which there is no perfect solution. Hence, we apply a range of strategies from the survey's initial design to its execution to minimize any potential bias which we describe in more detail in the survey section of Appendix A.

(2). Recycling and reuse, reduction of greenhouse gases, reduction and elimination of pollution.

(3). Conservation of natural resources (including organic agriculture, sustainable forestry, land management, soil, water, wildlife protection, and rainwater management).

(4). Improving energy efficiency.

(5). Energy generation from renewable resources.

Once the respondent has completed Q1, they are then asked to approximate the amount of time they spend on activities associated with the text presented in question 1 which can be broadly thought of as the time spent on green activities.

Q2. Please indicate the percentage of your total working time that is spent on green activities in increments of 10 from 0 to 100.

Answer: %.

This answer to Q2, which is a percentage, is then used to construct an index of the green intensity of an individual's job that we call the KEOO index and is defined as the proportion of an individual's total working time that is dedicated to the green job activities described above. For example, if an individual spends 50% of their time on activities 1 and 3 their green intensity index will be 0.5. Compared to other greenness indices, the KEOO index is simple to measure and understand.[12]

3.2 Stylized facts

We begin with a series of stylized facts to illustrate the characteristics most clearly associated with green workers or put simply, we answer the question 'who are the green workers?' We classify the individual responses into five different categories based on the amount of time they spend on green job activities. For illustrative purposes, we categorize green jobs as very dark green if workers spend more than 30% of their working hours on green job activities (i.e., a KEOO index greater than 0.3), dark green if workers spent less than or equal to 30% but greater than 20% of their work hours on green job activities (i.e., a KEOO index between 0.2 and 0.3), light green if workers spent less than or equal to 20% but greater than 10% of their work hours on green job activities (i.e., a KEOO index between 0.1 and 0.2), and finally very light green if workers spent less than or equal to 10% but greater than zero of their work hours on green job activities (i.e., a KEOO index of less than 0.1).[13]

[12] Unlike task-based measures that weight tasks by importance, the KEOO index is derived from self-evaluation of the relative importance of green job activities within total activities. As a sense check we compare our KEOO index and O*NET based task-based measures at a broad occupational level. To make the comparison we manually matched our occupations (38 categories) to the ISCO at the 2-digit level (42 categories with the military occupation group excluded). The crosswalk between the occupations of our classification and ISCO is available upon request. Using the task-based measure as outlined in Elliott et al. (2024), we calculated the simple average greenness at 2-digit ISCO occupation level. The correlation between our measure and the O*NET task-based greenness index is 0.68, which is significant at the 1% level.

[13] The thresholds are determined by the distribution of the KEOO index based on those that have a percentage greater than zero. A KEOO index value of 0.3 corresponds to the 75th percentile of the

As shown in Table 1, our sample consists of 10,348 respondents, out of which 3,188 can be considered green workers based on their replies to Q1. In terms of the different types of green activity, the distribution is relatively even and individuals can engage in one or more of the activities as part of their working day. The activities with the largest number of positive responses are Environmental Compliance, Education/Training, Raising social awareness with 2,745 responses and Recycling/Reuse, Reduction of GHGs, Reduction/Elimination of pollution with 2,179 responses. In terms of our green job classifications, very light green jobs represent that largest green job category with 1,514 workers while the second largest is very dark green jobs with 731 workers. Using categories shows that the majority of jobs are very light or light green. The majority of workers (7,160) are therefore working in non-green jobs. Note that very dark green is highly correlated with green activity 5 "Energy generated from renewable resources", while very light green is more correlated with green activity 1 "Environmental compliance".[14]

Table 2 compares the demographic characteristics of green and non-green workers and the associated KEOO index for each group. Overall, as shown in the top row, the average KEOO index value is 0.08. The average KEOO index value for individuals who engage in at least some green activities shown in row 2 (30.8% of the sample) is 0.24. Assuming a seven hour work day this means the average green worker spends 1.75 hours a day working on green activities. The relatively low average KEOO index indicates that the time spent on green activities is limited for most jobs, which is consistent with previous studies based on O*NET defined green tasks that find that most green jobs are only slightly green (e.g., Peters 2014, Bowen et al. 2018, Vona et al. 2019).

Looking at different group characteristics we find the average KEOO index for females is lower (almost half) that for males (0.06 VS 0.09), and females are significantly under-represented in green jobs (31.5%) compared to non-green jobs (50.1%). Males on the other hand are more likely to undertake some green activities as part of their job (68.5%). In other results we find that there is a higher proportion of workers in green jobs than non-green jobs for the age group 20-29 (17.5% vs 14.2%), the age group 50-64 (31.5% vs 28.1%) suggesting a possible polarization in the distribution of green jobs by age group. The KEOO index results also show that, on average, workers in the older age groups have jobs with a lower degree of green intensity suggesting that younger workers have more intensive green jobs.

In terms of education, we find that with the exception of junior high school education or below, the average KEOO index increases with the level of education up to masters level and is suggestive of a degree of concentration of green jobs in high and very low skilled sectors. Workers with a master degree have the highest average KEOO index of 0.13 while workers in green jobs are more likely to hold a university degree and above or hold some sort of job related qualification compared to those in non-green jobs. We find

distribution; 0.2 for the 50th percentile, and 0.1 for the 25th percentile.

[14]Table B1 of Appendix B shows that 54.8% of the sample are regular workers, 32% non-regular workers (part-time, temporary, or contract workers) and the others are self-employed workers or similar. According to the Ministry of Internal Affairs and Communication (MIC) of Japan, non-regular workers accounted for 36.7% of all employees (excluding executives) in 2021 (Robinson et al. 2022). Hence, our sample distribution is close to the proportion of regular, non-regular, and other workers in the broader population in Japan, which has seen a dramatic increase in non-regular jobs in recent years (Esteban-Pretel & Fujimoto 2020). Table B2 in the Appendix B provides summary statistics for the whole sample.

Table 1: Green job categories

Job categories	**Sub-categories**	**Number of workers**	**Percentages**
Total jobs		10,348	-
Green jobs		3,188	30.8%
Non green jobs		7,160	69.2%
Green activity 1	Compliance with environmental regulations, education and training, and enhancing public awareness	2,745	26.5%
Green activity 2	Recycling and reuse, reduction of greenhouse gases, reduction and elimination of pollution	2,179	21.1%
Green activity 3	Conservation of natural resources	1,585	15.3%
Green activity 4	Improving energy efficiency	1,761	17.0%
Green activity 5	Energy generation from renewable resources	1,478	14.3%
Very dark green jobs	$Time > 30\%$	731	7.1%
Dark green jobs	$20\% < Time \leq 30\%$	401	3.9%
Light green jobs	$10\% < Time \leq 20\%$	542	5.2%
Very light green jobs	$Time <= 10\%$	1,514	14.6%
Non green jobs	Time = 0	7,160	69.2%

Note: Green jobs are classified according to the distribution in our green job sample. Categories are defined by the following percentiles and their corresponding greenness values: Very dark green jobs with a KEOO index above 0.3 (above the 75th percentile); Dark green jobs with KEOO index between 0.2 and 0.3 (above the 50th percentile but up to and including the 75th percentile); Light green jobs with a KEOO index between 0.1 and 0.2 (above the 25th percentile but up to and including the 50th percentile); Very light green jobs with a KEOO index less than 0.1 (up to and including the 25th percentile).

61.2% of green workers hold a university degree and above versus 46.3% for non-green workers, and 67% of green workers hold a work-related qualification compared to 44% for non-green workers.

Table 2: Demographic characteristics of jobs

	All (%)	KEOO index	Green job (%)	Non-green job (%)
Whole sample	100	0.08	30.8	69.2
Green sample	-	0.24	100	0
Female	44.4	0.06	31.5	50.1
Male	55.6	0.09	68.5	49.9
Age				
20-29	15.3	0.12	17.5	14.2
30-39	18.2	0.08	16.6	19
40-49	24.3	0.06	21.2	25.7
50-64	29.1	0.07	31.5	28.1
>64	13.1	0.06	13.2	13
Education				
Junior high school & below	1.7	0.08	1.3	1.8
High school	26.2	0.06	20.3	28.9
Junior college & technical college	21.4	0.06	17.8	23
Undergraduate	43.9	0.09	50.7	40.9
Master	5.4	0.13	8.7	4.2
Doctor	1.4	0.12	1.9	1.2
Qualified	51.1	0.11	67	44
Occupational groups				
Managers	9.3	0.12	16.6	6.1
Professions & technicians	25	0.10	29.4	23
Clerks	27.4	0.07	23.8	29
Sales workers	7.2	0.06	6.1	7.7
Service workers	12.4	0.06	9.3	13.7
Security workers	1	0.06	0.9	1.1
Agriculture, forestry & fisheries	0.4	0.11	0.5	0.4
Production project workers	3.8	0.05	2.8	4.2
Transport & machine operators	0.9	0.06	0.7	1
Construction & mining workers	0.6	0.10	0.6	0.5
Workers in transportation cleaning & packaging	2.4	0.06	1.6	2.7
Others	9.7	0.07	7.9	10.5
Industry groups				
Agriculture, forestry & fishing	1.1	0.12	1.4	1
Mining, construction	5.7	0.10	7.5	5
Manufacturing	16.7	0.09	19.4	15.5
Wholesale & retail trade	12.2	0.06	10.5	12.9
Accommodation & food serving	3.4	0.05	2.2	3.9
Financial institutions	6.7	0.08	7.3	6.5
Transportation	4.8	0.07	4.0	5.1
Information research	3.2	0.09	3.4	3.1
Information & communication	4.2	0.09	4.6	4
Electricity, gas & water supply	1.6	0.21	3.1	0.9

Medical care & welfare	10.9	0.06	8.7	11.9
Education & Training support	5.5	0.07	5.9	5.3
Other service activities	18.6	0.07	16.3	19.6
Public affairs	5	0.08	5.6	4.8
Others	0.4	0.02	0.2	0.5
N	10,348	10,348	3,188	7,160

Note: Within this table, the term 'All' refers to the entire sample, inclusive of both green and non-green job categories. The 'KEOO Index' is calculated from answers to questions where respondents indicate the proportion of time dedicated to green activities on an average working day ranging from 0 to 1. 'Green job' means jobs that involve at least one green activity, i.e. with KEOO index greater than zero; and 'Non-green job' are those workers that do not allocate any time to green activities, indicated by a KEOO index of zero.

The occupational groups with the highest KEOO indices are Managers, Professions and technicians, and Agriculture, forestry, and fisheries. Similarly, we find that Managers constitute a significantly larger proportion within the occupational distribution of green jobs relative to non-green jobs (16.6% vs 6.1%). Closely behind is the Professions and technicians occupational group, which also exhibits a higher shares of green jobs compared to non-green jobs (29.4% vs 23%). The industry with the highest KEOO index is Electricity, gas and water supply with a KEOO index of 0.21 followed by the Agriculture, forestry and fishing industry, and the Mining and construction industry. While the industries with the highest percentage of green workers are Manufacturing which accounts for 19.4% of green workers and Other service activities with 16.3%.

The next stage is to compare the characteristics by our four categories of green job. The results are presented in Table 3. The first two rows of Table 3 present the distribution of males and females across the different green job categories and shows that male workers dominate all green categories with the highest representation in Light green jobs at 72.5%, while female are under-represented in all green jobs categories with their highest representation in Very dark green jobs at 34.2%. Looking into possible polarization in the distribution of green jobs by age group found in Table 2, Table 3 shows that younger individuals (aged 20-29) are more prevalent in Very dark green jobs, while older age groups, particularly those aged 50-64, dominate in the Light and Very light green job categories. In terms of education, the data indicates that green jobs, regardless of their intensity, are predominantly held by workers with an undergraduate education. The Qualified row, which captures those with a professional qualification or certification, shows that as jobs become less green, the proportion of workers with job-related qualifications decreases.

In terms of occupations, there is a distinction between the green intensity between Managers and Professions and technicians with Manager roles tending to be in the less intense green categories (Light and Very light) and Professions and technicians more likely to be associated with the more intense green categories (Dark and Very dark). Turning to industry groups, Table 2 shows that Manufacturing has the highest percentage of green workers. However, Table 3 reveals that within the green job categories, the majority of Manufacturing workers are primarily classified under Light green jobs. This indicates that while Manufacturing has a significant number of green jobs, the intensity levels show they tend to be in the Light green category where 10 - 20% of a workers time is spent on green job activities.

Table 3: Demographic characteristics of green jobs categories

	Very dark green job (%)	Dark green job (%)	Light green job (%)	Very light green job (%)
Female	34.2	30.2	27.5	32
Male	65.8	69.8	72.5	68
Age				
20-29	30.4	21.5	14.6	11.3
30-39	22.8	21.4	16.4	12.4
40-49	19.3	23.4	21.2	21.6
50-64	20.8	24.4	32.5	38.1
>64	6.7	9.2	15.3	16.6
Education				
Junior high school & below	1.9	1.2	0.9	1.1
High school	19.5	20.7	20.5	20.5
Junior college & technical college	17.9	16	15.3	19.1
Undergraduate	49.4	50.6	54.1	50.1
Master	8.8	9	8.7	7.3
Doctor	2.5	2.5	0.6	2
Qualified	74.6	72.1	65.9	62.4
Occupational groups				
Managers	11.4	14.7	18.6	18.9
Professions & technicians	34.5	34.4	29.7	25.4
Clerks	22.7	22	22	25.4
Sales workers	4.9	6	6.5	6.5
Service workers	8.6	9	10	9.5
Security workers	1	0.3	1.1	0.9
Agriculture, forestry & fisheries	0.6	0.5	1.1	0.3
Production project workers	2.5	1.5	2.4	3.4
Transport & machine operators	0.7	1.0	0.4	0.7
Construction & mining workers	0.8	0.3	0.6	0.6
Workers in transportation cleaning & packaging	2.2	1.3	1.9	1.4
Others	10.3	9.2	5.9	7.1
Industry groups				
Agriculture, forestry & fishing	2	1.3	1.7	1.1
Mining, construction	8	10.5	7.9	6.3
Manufacturing	19.2	18.5	23.1	18.4
Wholesale & retail trade	7.8	11.7	10.7	11.4
Accommodation & food serving	1.9	2.7	2.6	2.1
Financial institutions	6.3	6.7	6.6	8.1
Transportation	4.9	3.5	2.4	4.3
Information research	4	2.5	3.5	3.4
Information & communication	5.3	5.7	3.7	4.4
Electricity, gas & water supply	4.8	4	3.3	1.9
Medical care & welfare	9.6	8.7	6.5	9
Education/Training support	4.1	5.2	5.4	7.1
Other service activities	17.1	14.5	16.4	16.3
Public affairs	5.2	4.5	6.1	5.9
Others	0	0	0.2	0.3
N	731	401	542	1,514

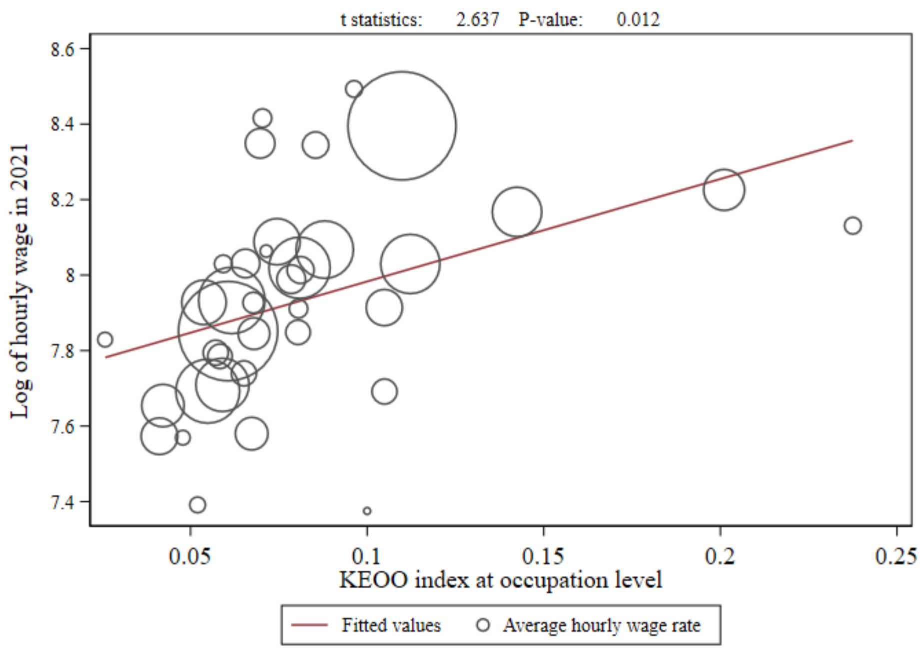
Note: Based on the distribution of our green job sample, green jobs are categorized into four distinct groups. These groups are delineated by specific percentiles and their associated greenness values: Very dark green jobs with a KEOO index above 0.3 (above the 75th percentile); Dark green jobs with a KEOO index between 0.2 and 0.3 (above the 50th percentile but up to and including the 75th percentile); Light green jobs with a KEOO index between 0.1 and 0.2 (above the 25th percentile but up to and including the 50th percentile); Very light green jobs with a KEOO index less than 0.1 (up to and including the 25th percentile).

Turning to income, we now present some stylized facts regarding hourly wage rates.[15] Figure 1 presents a scatterplot with a fitted line to capture the relationship between the log of average hourly wages and the degree of greenness across occupations. The KEOO index is measured as an occupational-level index that ranges between 0 and 1, with a higher number indicating a higher percentage of time, on average, recorded by individuals working in that occupation being spent on green activities. The size of each bubble is proportional to number of green workers in each occupation. A simple visual inspection suggests positive relationship between occupational greenness and average wages. However, to better understand the relationship between the green intensity of a job and wages we need to use regression analysis.

Table 4 captures the differences in hourly wages by skill level, gender, and age group and presents a breakdown of earnings for all jobs, non-green jobs, green jobs, very dark, dark, light, and very light green jobs. The results show that high-skill workers consistently earn higher wages than low-skill workers across all jobs, non-green and green. Comparing high-skill and low-skill workers within green job types reveals that in Very Dark Green Jobs and Dark Green Jobs, high-skill workers actually earn less than low-skill workers on average. However, in Light Green Jobs and Very Light Green Jobs, the typical pattern resumes, with high-skill workers earning more than their low-skill counterparts.

[15]Our data consists of annual income (in JPY) reported by respondents in 2021. Due to missing values our regression sample is slightly smaller. There are three working hour variables in the data which are average hours worked per day at the usual workplace during three periods: (1) The first week of September 2021; (2) the period when the Olympics were held in Japan (July 23 - August 8, 2021); and (3) early July 2021, both for regular and teleworking days. To generate the hourly wage rate, we assume that the average Japanese worker has 16 public national holidays, an average of 10 vacation days, and $52 * 2 = 104$ weekend days, giving us a total of 235 working days in the average year. Given the average number of working hours per day, we can calculate the hourly wage rate by dividing the annual income by the product of the total working days and the average working hours per day. By doing so, we can ensure that the calculated hourly wage rate accurately reflects the diverse working conditions and schedules of all respondents and provides a precise measure of hourly income for both regular and non-regular workers. See Appendix B for details.

Figure 1: KEOO index and wages at occupation level



Note: Log of hourly wage rate (in JYP) and the KEOO indices are averaged for each of the 38 NIRA occupational categories. The area of each circle corresponds to the number of green workers in each occupation. Data source from Okubo-NIRA Telework Survey.

Table 4: Average hourly wage for different job categories, in Japanese Yen (JPY) and U.S. Dollars (USD)

Category	**All Jobs**	**Non-green Jobs**	**Green Jobs**	**Very Dark Green Jobs**	**Dark Green Jobs**	**Light Green Jobs**	**Very Light Green Jobs**
High skill	4,232	3,899	4,815	6,189	4,887	4,807	4,223
	(29.6)	(27.3)	(33.7)	(43.3)	(34.2)	(33.6)	(29.6)
Low skill	3,558	3,153	4,769	6,964	5,463	4,729	3,677
	(24.9)	(22.1)	(33.4)	(48.8)	(38.2)	(33.1)	(25.7)
Male	4,309	3,908	4,960	6,326	5,335	4,902	4,330
	(30.2)	(27.4)	(34.7)	(44.3)	(37.3)	(34.3)	(30.3)
Female	3,393	3,112	4,412	6,826	4,537	4,453	3,270
	(23.8)	(21.8)	(30.9)	(47.8)	(31.8)	(31.2)	(22.9)
Young worker	3,965	3,386	5,338	6,901	5,631	5,236	3,933
	(27.8)	(23.7)	(37.4)	(48.3)	(39.4)	(36.7)	(27.5)
Old worker	3,883	3,630	4,414	5,806	4,523	4,501	4,048
	(27.2)	(25.4)	(30.9)	(40.6)	(31.7)	(31.5)	(28.3)

Note: Data source from Okubo-NIRA Telework Survey. The values in this table are presented in Japanese Yen (JPY), with the equivalent values in U.S. Dollars (USD) shown in parentheses. The given exchange rate used for conversion is 1 JPY = 0.007 USD. High skill refers to those who have a university degree or above, while low skill refers to those without a university degree; Younger workers are defined as individuals below the age of 45, and older workers are those who are over 45 years old.

Second, the wage disparity between genders is evident across almost all job categories. Overall, male workers consistently earn more than female workers in all job types, with male workers earning a higher average hourly wage of JPY 4,309 (USD 30.2) compared to JPY 3,393 (USD 23.8) for female workers in all jobs. The wage gap persists across both non-green and green jobs, with males in green jobs earning JPY 4,960 (USD 34.7) compared to JPY 4,412 (USD 30.9) for females. Interestingly, in Very Dark Green Jobs, female workers surpass male workers, earning JPY 6,826 (USD 47.8) compared to JPY 6,326 (USD 44.3). However, in all other green job categories, male workers consistently earn more than their female counterparts, reflecting a persistent gender wage gap across most green job categories.

Finally, examining hourly wage trends across different age groups, younger workers earn slightly more than older workers in both green and non-green jobs. Younger workers have an average wage of JPY 3,965 (USD 27.8) across all jobs, compared to JPY 3,883 (USD 27.2) for older workers. The wage gap becomes more pronounced in green jobs, where younger workers earn JPY 5,338 (USD 37.4), significantly higher than older workers who earn JPY 4,414 (USD 30.9). This trend continues in very dark, dark and light green jobs, with younger workers earning more in each category. However, in the very light green job category, older workers earn slightly more than younger workers.

It is also worth noting that wages in green jobs are consistently higher than those in non-green jobs across all characteristic categories. Among the various green job categories, very dark green jobs command the highest average wages, indicating that these roles, perhaps due to their specialized nature or critical importance within the green economy, offer superior compensation.

3.3 Estimating a green wage premium

To investigate whether there is a green wage premium, we estimate the following wage equation:

$$ln\omega_i = \beta_0 + \beta_1 Green_i + \beta_2 X_i + \gamma + u_i \tag{1}$$

Where $ln\omega_i$ is the log hourly wage of the worker i (in JYP), $Green_i$ is an indicator of green jobs, X_i is a vector of control variables for the worker i, including gender, education, tenure, and other demographic characteristics. γ is a vector of dummies that captures fixed effects of prefecture, industry, and occupation. In this context, $Green_i$ can either be a dummy variable taking value of 1 if an individual's job involves at least one green task from Q1 described earlier, or a continuous variable between 0 to 1 which captures the amount of time a worker spends on green activities (KEOO index). The green intensity measure is only estimated within the sample of green jobs.

Our key interest lies in the coefficient β_1. When $Green_i$ is a dummy variable, β_1 captures the wage premium associated with being employed in a green job compared to a non-green job. When $Green_i$ is a continuous measure of green intensity, β_1 reflects the wage premium associated with an increase in the KEOO index (green intensity). A positive β_1 would indicate that, on average, workers in green jobs earn higher wages than when they work in non-green jobs, and as the degree of greenness increases (as measured by the KEOO index), the wage premium increases.

Equation (1), however may not be an unbiased estimate of the impact of job type on hourly wages. One key concern is omitted variable bias, where unobserved factors such as individual characteristics or job attributes could simultaneously influence both wages and the likelihood of engaging in green employment. In addition, there is a risk of reverse causality, as wages might influence a worker's decision to pursue employment in a green job. More specifically, policies designed to promote green transitions, such as tax incentives or subsidies for firms that adopt environmental practices may create a more attractive job market. This in turn may encourage sorting of the most able workers to more productive firms that are likely to pay higher wages that also invest more in the green transition.

To mitigate omitted variable bias, we control for a set of individual and job-related characteristics. Specifically, we control for measures of task intensity including Abstract, Routine, and Manual tasks, to account for variations in task requirements and their potential impact on wages. This ensures that the wage effect attributed to green jobs is not confounded by differences in job complexity. In addition, we incorporate the Big Five personality traits, including Extroversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. Personality traits may indirectly shape preferences for green jobs, and these traits can also influence wage levels (Bowles et al. 2001*a*, Rice & Robone 2022).

To address the potential endogeneity concern associated reverse causality, we implement a Endogenous Treatment Effect model (ETM) which estimates the average treatment effect (ATE) from observational data when the treatment assignment (those employed in a green job) is correlated with the potential outcome (hourly wage). To control for the endogeneity of the treatment assignment, the ETM uses a control-function approach, which controls for endogeneity by including the residuals from the treatment assignment model as a regressor in the model for the potential outcome (Wooldridge 2010). The control function approach adjusts for the correlation between the error term and the explanatory variable, making the coefficient estimates unbiased and consistent. However, if there is no endogeneity, a Rubin causal model estimator (Rubin 1974) is preferred as it provides more efficient standard errors (Cameron & Trivedi 2020).

The potential outcomes Y ($ln\omega_{1i}$ and $ln\omega_{0i}$) of a treatment dummy ($GreenJob$= 1, 0) are assumed to depend upon observable variables X and unobservables. Therefore, the first step is to estimate a treatment assignment model that estimates the determinants of an individual's employment in a green job. More specifically, the Treatment assignment model can be expressed as follows:

$$\text{GreenJob}_i = E(\text{GreenJob}_i|Z_i) + \nu_i \tag{2}$$

where Z_i is a vector of variables that may affect an individual's choice of a green job and includes all of the exogenous variables from the continuous equation. Moreover, we include a set of exclusion restrictions to help identification using a 'control function' approach (Wooldridge 2015).

The first exclusion restriction is the moral test score (non-cognitive score) by father's birthplace at prefecture level. Our dataset contains information on the birthplace (prefecture level) of both parents. The data source for the moral score variable is the Educational Survey on Soldiers in the Conscription System conducted by the Ministry of Education in Japan in 1941. This survey included educational exams that all males aged 20 were required to take as part of Japan's conscription system. The exam covered various subjects, including language, science, and moral education. The non-cognitive score specifically refers to prefecture-level average scores on the moral section of this exam, which included questions related to civic virtues such as kindness, respect for elders, and hard work, many of which were influenced by Taoist principles.[16]

Japan consists of 47 prefectures with heterogeneous cultures, exhibiting substantial geographic variation in both cognitive and non-cognitive skills. This path-dependence can be traced back to the Edo period, when education and governance were highly decentralized, fostering regional differences in values, conformity, and educational approaches (Okubo et al. 2017). These social norms likely shaped the upbringing and value systems passed down through generations, influencing present-day attitudes toward green jobs, which emphasize environmental responsibility and social welfare. The pre-war moral test score is exogenous to the individual wage outcomes of the children, as it was measured long before current labor market dynamics. Since this score reflects historical moral education rather than individual characteristics, it provides a valid excluded restriction for addressing endogeneity in the wage equation.

The second type of exclusion restriction is the parental occupational KEOO indices. The data contains information on the occupation of both parents so by calculating the average KEOO index for each parent by occupation, we obtain the mother's and father's KEOO indices. An overall parent's occupational green intensity index is obtained by calculating the average KEOO index for each parent by occupation. The green intensity of a parent's occupation indicates their environmental awareness and a value system centered around sustainability. Parents who prioritize environmental sustainability are likely to instill these values in their children, influencing them to pursue green careers. Given the large literature documenting parental influence on occupational choices can affect wages (Hellerstein & Morrill 2011, Long & Ferrie 2013, Keijer et al. 2016, Doepke & Zilibotti 2017, Lo Bello & Morchio 2022), it is important to ascertain the green intensity of parent's occupation is primarily a reflection of value systems and environmental awareness. This distinction is important because while parental influence on occupational choices can affect wages, the green intensity of an occupation is primarily a reflection of value systems and not necessarily earnings potential. Indeed, in the period when the worker's parents were choosing their occupations, the labor market conditions in Japan would have been significantly different. Even for the youngest workers in our sample, little priority would have given to the green economy and low-carbon initiatives, and hence their parents are unlikely to have received a green wage premium. Therefore, environmental values, inherited through a family socialization process, may shape a child's career preferences towards environmentally sustainable jobs without directly impacting their earnings potential.[17]

[16] For more details about this survey, see Kiyokawa (1992), Shimamura (2002) and Nishihira (2013).

[17] Unfortunately, we do not observe parental hourly wages. However, when we include the average

In the second stage, the continuous equation estimates the factors that affect an individual's wage outcome. There are two regimes in the continuous equation: Regime 1 for green jobs, and regime 0 for non-green jobs.

$$\text{Regime 1:} \qquad \ln(\omega_{1i}) = E(\ln(\omega_{1i})|X_i) + \epsilon_{1i} \tag{3}$$

$$\text{Regime 2:} \qquad \ln(\omega_{0i}) = E(\ln(\omega_{0i})|X_i) + \epsilon_{0i} \tag{4}$$

where X_i represents a vector of covariates, such as education, tenure, and gender while $\epsilon_{1i}, \epsilon_{0i}$ are error terms in regime 1 and 0, respectively, which are subject to:

$$E(\epsilon_{ji}|X_i, Z_i) = E(\epsilon_{ji}|X_i) = 0 \text{ for } j \in \{0, 1\} \tag{5}$$

to ensure error terms are independent of covariates; and

$$E(\epsilon_{ji}|\text{GreenJob}_i) \neq 0 \text{ for } j \in \{0, 1\} \tag{6}$$

states that the unobservables in the potential-outcome equations are correlated to treatment status. Equation (6) = 0 indicates that there is no correlation between the treatment and outcome unobservable and that Rubin causal model estimators are obtained instead.

4 Results

4.1 Reduced form results

In this section we use reduced form regression analysis to ask whether there is a green wage premium in Japan and if there is, what is the magnitude and whether the premium increases with the green intensity of the job. The baseline results shown in Table 5 are based on simple OLS estimations of a standard wage equation that incorporate a dummy variable to indicate whether a worker is in a green job or not.[18]

The main findings from the baseline OLS results presented in Table 5 is the positive relationship between the green job dummy and the log of hourly wages. Adding more

occupational wage of the parents, the impact on the parental greenness (KEOO index) coefficient is minimal and hence our main results are unchanged.

[18] Our initial sample size comprised of 10,348 respondents of which 30.81% were considered to be in a green job. Estimating the wage equation using 2021 hourly wage rate data meant that the presence of missing wage data reduced our sample to 5,123 of which 31.2% were considered to be green workers. Appendix B and Table B3 provide more details on our regression sample.

Table 5: Reduced form results of green wage premium (Green job)

	Dependent Variable: ln(wage)				
	(1)	(2)	(3)	(4)	(5)
Green job	0.305***	0.222***	0.164***	0.103***	0.097***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Female			-0.227***	-0.210***	-0.208***
			(0.025)	(0.025)	(0.025)
Vocational education			-0.042	-0.040	-0.036
			(0.034)	(0.034)	(0.034)
Undergraduates			0.058**	0.031	0.032
			(0.029)	(0.029)	(0.029)
Master and above			0.223***	0.136***	0.140***
			(0.047)	(0.048)	(0.047)
Tenure			0.007***	0.007***	0.007***
			(0.001)	(0.001)	(0.001)
Qualified			0.049**	0.030	0.029
			(0.022)	(0.022)	(0.022)
Age 20-29			0.145***	0.111**	0.120**
			(0.054)	(0.053)	(0.054)
Age 30-39			0.109**	0.082*	0.103**
			(0.045)	(0.045)	(0.045)
Age 40-49			0.043	0.027	0.045
			(0.041)	(0.041)	(0.041)
Age 50-64			0.033	0.022	0.035
			(0.040)	(0.040)	(0.040)
Abstract				0.134***	0.127***
				(0.017)	(0.018)
Routine				-0.001	0.002
				(0.016)	(0.016)
Manual				-0.056***	-0.053***
				(0.012)	(0.012)
Extraversion					0.026***
					(0.010)
Agreeableness					-0.032***
					(0.010)
Conscientiousness					-0.005
					(0.011)
Neuroticism					-0.029**
					(0.011)
Openness					0.020*
					(0.011)
Prefecture FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
Observations	5,123	5,123	5,123	5,123	5,123
Adjusted R2	0.031	0.091	0.127	0.143	0.149

Note: ln(wage) stands for log of hourly wages in 2021; GreenJob is a dummy variable taking value of 1 if an individual's job involves at least one green activity; Vocational education includes technical colleges and vocational schools; High school and below is omitted as the base group. Qualified is defined as having at least one qualification in professional credentials, specialized roles, or general work-related certifications. Age group > 64 is omitted as the base group; Abstract, Routine, and Manual task measures are constructed following the methodology outlined by De La Rica et al. (2020); Extroversion, Agreeableness, Conscientiousness, Neuroticism and Openness are the Big Five personality traits. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

control variables (and additional fixed effects) reduces the magnitude of the coefficients associated with the green job dummy. Column 3 is standard wage specification that includes the a set of controls such as gender, educational attainment, tenure, qualification and age plus prefecture, industry, and occupation fixed effects.[19] The result suggests that individuals with a green job have an approximately 16.4% higher hourly wage than those without, on average, assuming all other factors remain the same.

The existing literature has shown that green jobs tend to involve more abstract and analytical skills (Consoli et al. 2016), which may explain the observed wage premium. Therefore, we control for abstract, routine, and manual task measures in column 4. We replicate the task measures outlined by De La Rica et al. (2020), utilizing the same questionnaire items from the Program for the International Assessment of Adult Competencies (PIAAC). Incorporating these task measures allows us to account for wage differentials driven by task content, thereby disentangling the wage premium specifically associated with green jobs from that stemming from task composition. This enables a more precise estimation of the wage premium attributable to green jobs, independent of the nature of the tasks performed. The results show that the inclusion of task measures reduces the estimated wage premium for green jobs from 16.4% to 10.3%. This significant drop suggests that a substantial portion of the initial wage premium is explained by the nature of activities associated with green jobs, particularly abstract tasks, which command higher wages as shown in column 4.

We further incorporate Big Five personality traits variables, Extroversion, Agreeableness, Conscientiousness, Neuroticism and Openness, into the wage equation in column 5. These five traits are derived from the Five-Factor Model (FFM), which is widely used to study the relationship between individual personality traits and labor market outcomes (Alderotti et al. 2023). The inclusion of the FFM is motivated by existing literature that highlights the significant role of personality traits in shaping labor market outcomes, beyond cognitive skills (Bowles et al. 2001*a*,*b*, Rice & Robone 2022). Existing research shows that personality traits significantly impact wages, with earnings positively linked to Extroversion, Conscientiousness and Openness, and negatively associated with Agreeableness and Neuroticism (Alderotti et al. 2023). By including these personality variables in the wage equation, we aim to control for the impact of non-cognitive skills on wages, allowing for a more accurate assessment of the wage premium associated with green jobs and disentangling the portion driven by personality traits from that attributable to the green job characteristics themselves. The results indicate that the inclusion of the Big Five personality traits further reduces the estimated wage premium for green jobs from 10.3% to 9.7%. This slight drop suggests that while personality traits do have some explanatory power over wage differentials, they account for only a small portion of the wage premium associated with green jobs.

Our preferred specification is in column 5, showing a 9.7% green wage premium. Given an average hourly wage rate of our regression sample is approximately 3,899 JYP ($27.3), means an increase of approximately 378 JPY per hour, which is equivalent to 2.6 US dollars per hour (assuming an exchange rate of 1 JPY = 0.007 USD).[20]

[19] We added prefecture, industry, and occupation fixed effects one by one. The effect on the coefficients of green job dummy is marginal. Results are available upon request.

[20] Note that our sample was drawn using a stratified sampling technique, so when presenting the

In terms of the standard control variables included in Columns 5, the results are similar to standard wage equation estimates (e.g., Belzil 2007, Magnac & Roux 2021). Focusing on column 5, results show a significant wage gap between males and females with female workers earning, on average, 20.8% less than their male counterparts. Although large, this is not unusual for Japan (Hara 2018, Greaney & Tanaka 2021). In further results, we also find a positive association between wages and higher education levels (master and above), job tenure, and professional and general work-related specific qualifications in line with standard wage equation results. Moreover, younger workers in the age groups 20-29 and 30-39 are consistently shown to earn higher wages than those in the age group over 64.

Table 6 presents the estimation results examining the relationship between the KEOO index and the logarithm of hourly wages for green job only. The results suggest that a worker's KEOO index is positively correlated with the log of hourly wages for green workers. Column 5, our preferred specification, includes the full set of controls plus prefecture, industry, and occupation fixed effects. The results suggest that a 0.1 unit increase in a workers's KEOO index is associated with a 3.47% increase in the average hourly wage. An average hourly wage rate of approximately 4,798 JYP ($34) in our green job regression sample is equal to an increase of approximately 166 JPY ($1.2) per hour. The mean KEOO index for the green job sample is 0.24. Hence, increasing the average KEOO index by 10% would result in an incremental increase of 0.024, which is equivalent to an approximate 0.8% increase in hourly wages, which translates to 38 JYP ($ 0.3).

Focusing on column 5, the results suggest that gender disparities also exists within the green jobs sample but it is smaller compared to the whole sample. Specifically, female green workers earn, on average, 15.2% less than their male counterparts. In addition, the results suggest that within the green job sample, individuals with higher educational attainment (master's degree and above) tend to earn higher wages. However, once task measures (abstract, routine, manual) are included into the model, the return to education becomes insignificant. More specifically, abstract tasks are associated with higher wages, while manual tasks are linked to lower wages. This indicates that the skills and abilities required to perform specific tasks in green jobs have a more substantial impact on wage determination, with the effect of education largely mediated through these task requirements. In addition, those with professional credentials, specialized roles, or work-related certifications earn significantly higher wages than those without such qualifications. Job tenure also positively affects wage outcomes. Notably, only younger workers aged 20-29 earn more than those aged over 64 within the green job sample. Finally, the Big Five personality traits exhibit signs that are generally consistent with the whole sample.

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stylized facts we maintain the original sample size. However, when estimating the wage equation using the 2021 hourly wage rate, missing wage data reduced our sample. Consequently, the average wage in this analysis cannot be considered representative of the national average wage level in Japan. Instead, it should be interpreted as representative only of our subsample. An histogram illustrating the distribution of our hourly wage variable can be found in Figure B1 of Appendix B.

Table 6: Reduced form results of green wage premium (KEOO index)

	Dependent Variable: ln(wage)				
	(1)	(2)	(3)	(4)	(5)
KEOO index	0.594***	0.612***	0.483***	0.353***	0.347***
	(0.097)	(0.100)	(0.102)	(0.102)	(0.102)
Female			-0.177***	-0.149***	-0.152***
			(0.042)	(0.042)	(0.042)
Vocational education			-0.096	-0.094	-0.090
			(0.061)	(0.060)	(0.060)
Undergraduates			-0.032	-0.055	-0.049
			(0.046)	(0.045)	(0.045)
Master and above			0.139**	0.055	0.053
			(0.065)	(0.065)	(0.065)
Tenure			0.007***	0.006***	0.006***
			(0.002)	(0.002)	(0.002)
Qualified			0.172***	0.141***	0.135***
			(0.035)	(0.035)	(0.035)
Age 20-29			0.305***	0.249***	0.253***
			(0.080)	(0.079)	(0.080)
Age 30-39			0.135**	0.082	0.093
			(0.068)	(0.067)	(0.068)
Age 40-49			0.035	0.003	0.016
			(0.060)	(0.060)	(0.061)
Age 50-64			-0.017	-0.033	-0.020
			(0.057)	(0.056)	(0.057)
Abstract				0.152***	0.148***
				(0.025)	(0.025)
Routine				0.009	0.015
				(0.024)	(0.024)
Manual				-0.050**	-0.048**
				(0.020)	(0.020)
Extraversion					0.030*
					(0.016)
Agreeableness					-0.029*
					(0.016)
Conscientiousness					-0.013
					(0.018)
Neuroticism					-0.028
					(0.018)
Openness					0.020
					(0.018)
Prefecture FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
Observations	2,058	2,058	2,058	2,058	2,058
Adjusted R2	0.021	0.093	0.131	0.157	0.160

Note: ln(wage) stands for log of hourly wages in 2021; KEOO index stands for the percentage of time spent on green activities per day; Vocational education includes technical colleges and vocational schools; High school and below is omitted as the base group. Qualified is defined as having at least one qualification in professional credentials, specialized roles, or general work-related certifications. Age group $>$ 64 is omitted as the base group; Abstract, Routine, and Manual task measures are constructed following the methodology outlined by De La Rica et al. (2020); Extroversion, Agreeableness, Conscientiousness, Neuroticism and Openness are the Big Five personality traits. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Structural model results

The reduced-form results show that workers in green jobs command higher wages than those in non-green jobs, and that the wage premium increases with the degree of green intensity (KEOO index). However, if job choice is endogenous and workers self-select into a green job because of higher wages and more favorable labor market conditions the results may be biased. Hence, we apply the Endogenous Treatment Effect (ETM) model.

We first estimate the ETM using control function approach, which estimates the correlation between the unobservables of the treatment assignment and potential outcome models. If there is no correlation between the unobservables, then there is no endogeneity. We test for the correlation, and thus for endogeneity. The endogeneity test (Durbin-Wu-Hausman test), however, indicates that we cannot reject null hypothesis that the treatment and outcome unobservables are uncorrelated ($\chi^2 = 1.02, P$ value $= 0.600$), suggesting that unobservable factors influencing the treatment (having a green job) and the outcome (hourly wage) are uncorrelated.[21] Hence, we estimate the Rubin Causal Model, also known as the potential outcomes model.[22]

An important assumption required for valid causal inference is the overlap assumption, which ensures that each individual could receive any treatment level. The overlap assumption is satisfied when there is a chance of observing individuals in both the control and treatment groups for each combination of covariate values. We checked whether the overlap assumption is violated after estimation. More specifically, we plot the estimated densities of the probability of receiving each treatment level after estimation (see Figure C1 of the Appendix C.). We do not find evidence that the overlap assumption is violated.

When the overlap assumption holds, the Augmented Inverse Probability Weighting (AIPW) and Inverse Probability Weighted Regression Adjustment (IPWRA) estimators have the double-robust property for some functional form combinations.[23] The IPWRA method first applies an inverse probability weighting and then uses regression adjustment on the weighted sample. In contrast, the AIPW method integrates outcome modeling directly into the weighting process, providing a more seamless combination of the two approaches. In terms of efficiency, AIPW generally provides more efficient estimates than IPWRA. Therefore, in our main results, we use the AIPW methods.[24]

[21]The moral test score from the father's birthplace and the green intensity of both parents' occupations, successfully passed the weak IV test, i.e., the excluded restrictions are sufficiently strong. However, when we test for endogeneity, the results indicate no significant endogeneity in the model. Table C1 of Appendix C shows the Durbin-Wu-Hausman Endogeneity Test results.

[22]The Rubin Causal Model is particularly adept at discerning the causal effects from observational data, making it more suitable for this analysis where the treatment is not randomly assigned unlike an OLS regression, which can produce biased estimates in the presence of omitted variable bias or when variables are improperly controlled. The Rubin Causal Model allows for a more structured approach to estimating causal effects by focusing on the comparison of potential outcomes. This approach ensures that the causal estimates are as close to what would be observed in a randomized experiment.

[23]The double-robust property means that the estimator remains consistent if either the model for the treatment assignment or the model for the outcome is correctly specified, but not necessarily both. This property provides additional protection against model misspecification compared to estimators that rely on only one of these models being correctly specified (see (Wooldridge 2010).

[24]The results using IPWRA are almost identical and the results are available upon request.

The structural model estimation results by AIPW are reported in Table 7. There is a robust significant positive average treatment effect (ATE) across all the columns and the magnitude of the green wage premium decreases while adding more controls. The top row of column 4 reports an ATE of 0.073, suggesting that on average, having a green job leads to a 7.3% increase in hourly wages compared to not having a green job, which is slightly smaller than reduced form estimates of a 9.7% wage premium. This suggest that the reduced form model using OLS mightbe upwardly biased due to selection bias. With an average hourly wage of around 3,899 JPY ($27.3) in our regression sample, this translates to an increase of roughly 285 JYP ($2).[25]

Table 7: Structure model results of green job wage premium (Green job)

	Dependent Variable: ln(wage)			
	(1)	(2)	(3)	(4)
Green vs Non-green				
Average Treatment Effect	0.078***	0.072***	0.071**	0.073***
	(0.028)	(0.028)	(0.028)	(0.028)
Treatment assignment equation				
Father's Moral Score	0.468*			0.477*
	(0.248)			(0.247)
Parent's KEOO index		0.911**		
		(0.362)		
Father's KEOO index			0.609	0.612
			(0.620)	(0.620)
Mother's KEOO index			1.124**	1.137**
			(0.508)	(0.508)
Personal controls	Yes	Yes	Yes	Yes
Task intensity	Yes	Yes	Yes	Yes
Big Five	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Observations	5,123	5,123	5,123	5,123

Note: ln(wage) stands for log of hourly wages in 2021; ATE stands for average treatment effect between green jobs and non-green jobs; Robust standard errors in parentheses; The outcome variable in treatment assignment equation is Y = $GreenJob$, which is a dummy variable indicating worker is in a green job. The ancient moral test score for father's birthplace is used as excluded variables in the treatment assignment equations in Column 1. In column 2, the average of both parents' indices (Parent's KEEO index) is used. Column 3 incorporates both parents' occupational KEEO indices, while Column 4 builds on column 3 by additionally including the father's birthplace moral test score. Personal controls, task variables, and Big Five personality traits, prefecture, industry, and occupation fixed effects are included in both regimes and treatment assignment equation. Robust standard errors in parentheses. Constants are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The treatment assignment equations include several excluded variables to identify the allocation of green jobs. These excluded variables include the moral test score for father's birthplace, the average of both parents' occupational KEOO indices, and the individual KEOO indices of both parents. Specifically, the moral test score of the father's birthplace

[25]Table 7 with full controls is available upon request.

is used to proxy for regional level cultural and ethical norms associated with environmental preferences. The coefficient is positive and marginally significant, suggesting that workers with father from regions with higher moral scores are more likely to participate in green jobs. In addition, the KEOO indices of both parents' occupations reflect the intergenerational transmission of occupational characteristics, with a particular focus on the green intensity of parental occupations. The result indicates a strong positive association, meaning that individuals with parents working in more green intensive occupations are more likely to work in green jobs. This positive effect is mainly driven by mother's influence.

4.3 Heterogeneity analysis

Panel A of Table 8 presents the results from the structural model of the green wage premium by comparing green jobs and non-green jobs for a range of different worker characteristics, while Panel B of Table 8 reports the reduced form results of the green wage premium as a function of KEOO index, showing how increases in the green intensity index affect hourly wage outcomes for workers within the green jobs sample.

Columns 1 and 2 of Panel A and Panel B compare the green wage premium between workers with a university degree (high skill) and those without a university degree (low skill). The ATE between green and non-green jobs indicates that switching to a green job leads to an increase in the log of hourly wages by approximately 5.7% for high-skilled workers and no significant effect for low-skilled workers. This suggests that only high-skilled workers benefit from higher wages when engaged in a green job.

When focusing solely on the green job sample (columns 1 and 2 of Panel B), the regression of the log of hourly wages on the green intensity index shows a distinct impact. For every 0.1 unit increase in the KEOO index, hourly wages increase by approximately 2.16% for high-skilled workers and 5.6% for low-skilled workers, highlighting that the wage response to green intensity is notably stronger for the low-skilled group. This is in line with other studies which suggest a larger green wage premium for low-skilled workers (e.g., Muro et al. 2019, Vona et al. 2019, Curtis & Marinescu 2023) and also with the specific labor market conditions in Japan such that there is a pressing need for technicians and support professionals. Hence, we find support for a green wage premium for both high-skilled and low-skilled workers, and this premium increases with the green intensity of the job for both worker types.

Columns 3 and 4 of Panel A and Panel B show a precisely estimated green wage premium (8.4%) for male workers. The coefficient for females are similar but less precise. When we examine only those employed in green jobs (columns 3 and 4 of Panel B) the picture becomes clearer. For each 0.1 unit increase in the KEOO index, the log of hourly wages for male workers increases by 2.32% and for females 5.02%. Females who are currently employed in a green job benefit more from an increase in the green intensity of their jobs. A larger wage premium for females in green jobs may therefore play a role in helping to reduce the gender pay gap.

Finally, columns 5 and 6 of Panel A and Panel B present a comparison of the green wage premium by age group. Results suggest that younger workers benefit more from transitioning to a green jobs in terms of wage premium and older workers seeing no significant premium. Focusing on the green job sample (Columns 5 and 6 of Panel B), there is again a green wage premium for younger workers as the green intensity of green job increases. More specifically, for each 0.1 unit increase in the KEOO index, the log of hourly wages for younger workers increases by 4.89%. This result is in line with our expectation, since 53% of the very dark green job workers are in 20-40 years old, while 65% the very light green job workers are 50+ years old; meaning highest green-intensity jobs are held by very young workers in Japan.

Table 8: Green wage premium: Heterogeneity tests

Panel A: Structural model results of green wage premium						
	(1)	(2)	(3)	(4)	(5)	(6)
	High skill	Low skill	Male	Female	Young	Old
Green vs Non-green						
Average Treatment Effect	0.068**	0.070	0.084***	0.065	0.146***	0.011
	(0.030)	(0.044)	(0.027)	(0.052)	(0.045)	(0.036)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes
Task intensity	Yes	Yes	Yes	Yes	Yes	Yes
Big Five	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,781	2,342	2,978	2,145	2,095	3,028
Panel B: Reduced form results of green wage premium						
	(1)	(2)	(3)	(4)	(5)	(6)
	High skill	Low skill	Male	Female	Young	Old
KEOO index	0.216*	0.560***	0.232**	0.502**	0.489***	0.197
	(0.124)	(0.192)	(0.112)	(0.240)	(0.145)	(0.151)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes
Task intensity	Yes	Yes	Yes	Yes	Yes	Yes
Big Five	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,287	771	1,448	610	855	1,203

Note: Dependent variable is log of hourly wages in 2021; The structural model's excluded variables incorporate both parents' occupational KEOO indices and the father's birthplace moral test score. High skill refers to those who have a university degree or above, while low skill refers to those without a university degree; Younger workers are defined as individuals below the age of 45, and older workers are those who are over 45 years old; Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Robustness checks

In a study of Japan one might be concerned that the results are driven by the agricultural sector. Hence, we exclude the agriculture sectors and associated occupations from our sample. The rationale is as follows. First, the agriculture sector in Japan is predominantly characterized by small, family-run farms so individuals born into farming families are likely to inherit their jobs, and associated farms and lands, from their parents. The agriculture sector is also heavily protected through various measures including tariffs and subsidies, making it particularly challenging for new entrants. Hence, families engaged in agriculture tend to enjoy a stable and potentially higher incomes.

The combination of government protection, barriers to entry, and the tradition of job inheritance means the choice of employment in agriculture is not independent, raising endogeneity concerns. Excluding the agriculture sector means we avoid these complexities and potential biases. Table 9 presents the structural results excluding agriculture sectors and occupations. The results are similar to our previous findings.[26]

Table 9: Structural model results of green job premium: Excluding agriculture

	Dependent Variable: ln(wage)			
	(1)	(2)	(3)	(4)
Green vs Non-green				
Average Treatment Effect	0.082***	0.076***	0.075***	0.077***
	(0.028)	(0.028)	(0.028)	(0.028)
Treatment assignment equation				
Father's Moral Score	0.457*			0.467*
	(0.248)			(0.248)
Parent's KEOO index		0.861**		
		(0.366)		
Father's KEOO index			0.541	0.545
			(0.624)	(0.624)
Mother's KEOO index			1.088**	1.103**
			(0.511)	(0.511)
Personal controls	Yes	Yes	Yes	Yes
Task intensity	Yes	Yes	Yes	Yes
Big Five	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Observations	5,088	5,088	5,088	5,088

Note: ln(wage) stands for log of hourly wages in 2021; ATE stands for average treatment effect between green jobs and non-green jobs; Robust standard errors in parentheses. The outcome variable in treatment assignment equation is Y = $GreenJob$, which is a dummy variable indicating worker is in a green job. The moral test score for father's birthplace is used as excluded variables in the treatment assignment equations in column 1. In column 2, the average of both parents' indices (Parent's KEEO index) is used. Column 3 incorporates both parents' occupational KEEO indices, while column 4 builds on column 3 by additionally including the father's birthplace moral test score. Personal controls, task variables, and Big Five personality traits, prefecture, industry, and occupation fixed effects are included in both regimes and treatment assignment equation. Robust standard errors in parentheses. Constants are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[26] The results remain consistent when applying a reduced form estimation and for comparable heterogeneity analysis. Results are available upon request.

4.5 Decomposition analysis

To provide an insight into the factors that may be driving the green wage premium, we first apply a DiNardo-Fortin-Lemieux (DFL) reweighting method which constructs a semi-parametric estimation of the wage distribution, enabling us to analyze the entirety of wage distributions.[27] Specifically, they suggest that a counterfactual distribution is constructed using a reweighting method that adjusts the weights of individuals in the sample to reflect the distribution of characteristics in the other group. This involves the calculation of a counterfactual density function that represents the distribution of wages in one group under the hypothetical scenario where that group had the same characteristics distribution as the other group (DiNardo et al. 1996). Hence, the adjusted wage distribution for non-green workers represents what non-green worker's wages would look like if non-green workers had the same distribution of characteristics (education, tenure, etc.) as green workers, but still faced the same wage structure (i.e., returns to these characteristics) that non-green workers actually face.[28] The density and the counterfactual density are estimated using a kernel density method.[29]

Figure 2 reports the actual wage distribution of non-green jobs, green jobs and adjusted non-green jobs. The counterfactual wage distribution assumes that non-green jobs have the same distribution of characteristics as green jobs. A comparison of kernel density distributions of actual wage distribution of green jobs and non-green job reveals that the wage distribution among green workers is more compressed, with the peak of the distribution for green workers skewed towards higher income levels. This suggests that green workers tend to have wages that cluster more tightly around higher wage levels, indicating less variability in wages within this group. Adjusting non-green jobs to match green job wage attributes leads to an increase in non-green job wages, which is observed by the rightward shift of the adjusted non-green job wage distribution. Observe that the adjusted non-green job distribution and actual green job distribution almost overlap after adjustment, indicating that the wage difference between green jobs and non-green jobs is mainly due to difference in endowments and that after adjustments, the unexplained green wage premium is predominantly found at the higher end of the income distribution.

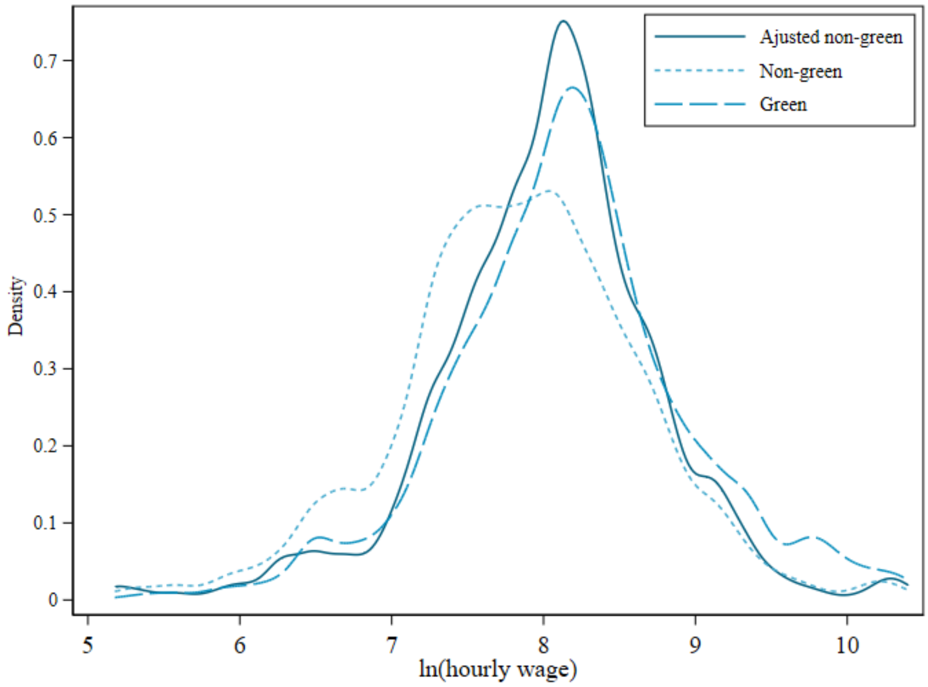
To provide an insight into the factors that contribute to the green wage premium, we apply the FFL decomposition method introduced by Firpo et al. (2007) who propose a two-stage procedure to decompose changes or differences in the distribution of wages (or of other variables). Based on the DFL reweighting method, the first stage divides the distributional changes or differences into a wage structure effect and a composition effect by constructing counterfactual wage distributions. The second stage further decomposes the two parts into the contribution of each explanatory variable using recentered influence function (RIF) regressions. The FFL decomposition method generalizes the Oaxaca-Blinder decomposition method by extending the decomposition to any distribu-

[27]The DFL adjustment is a method introduced by DiNardo, Fortin, and Lemieux in 1996 that focuses on the distributional aspects of wage differences, rather than just differences in mean wages which is what would be obtained from a more traditional Oaxaca-Blinder decomposition.

[28]We include all personal controls, task variables, Bige Five personality traits and fixed effects

[29]A Kernel Density Plot, also known as a Kernel Density Estimate (KDE), is a way to estimate the probability density function of a continuous random variable non parametrically. In simple terms, it provides a smoothed version of a histogram and can be used to visualize the underlying probability distribution of a set of continuous or interval data.

Figure 2: DFL decomposition of log of hourly wage



Note: The adjusted wage distribution for non-green workers represents what non-green worker's wages would look like if non-green workers had the same distribution of characteristics (education, tenure, etc.) as green workers, but still faced the same wage structure (i.e., returns to these characteristics) that non-green workers actually face. The density and the counterfactual density are estimated using a kernel density method.

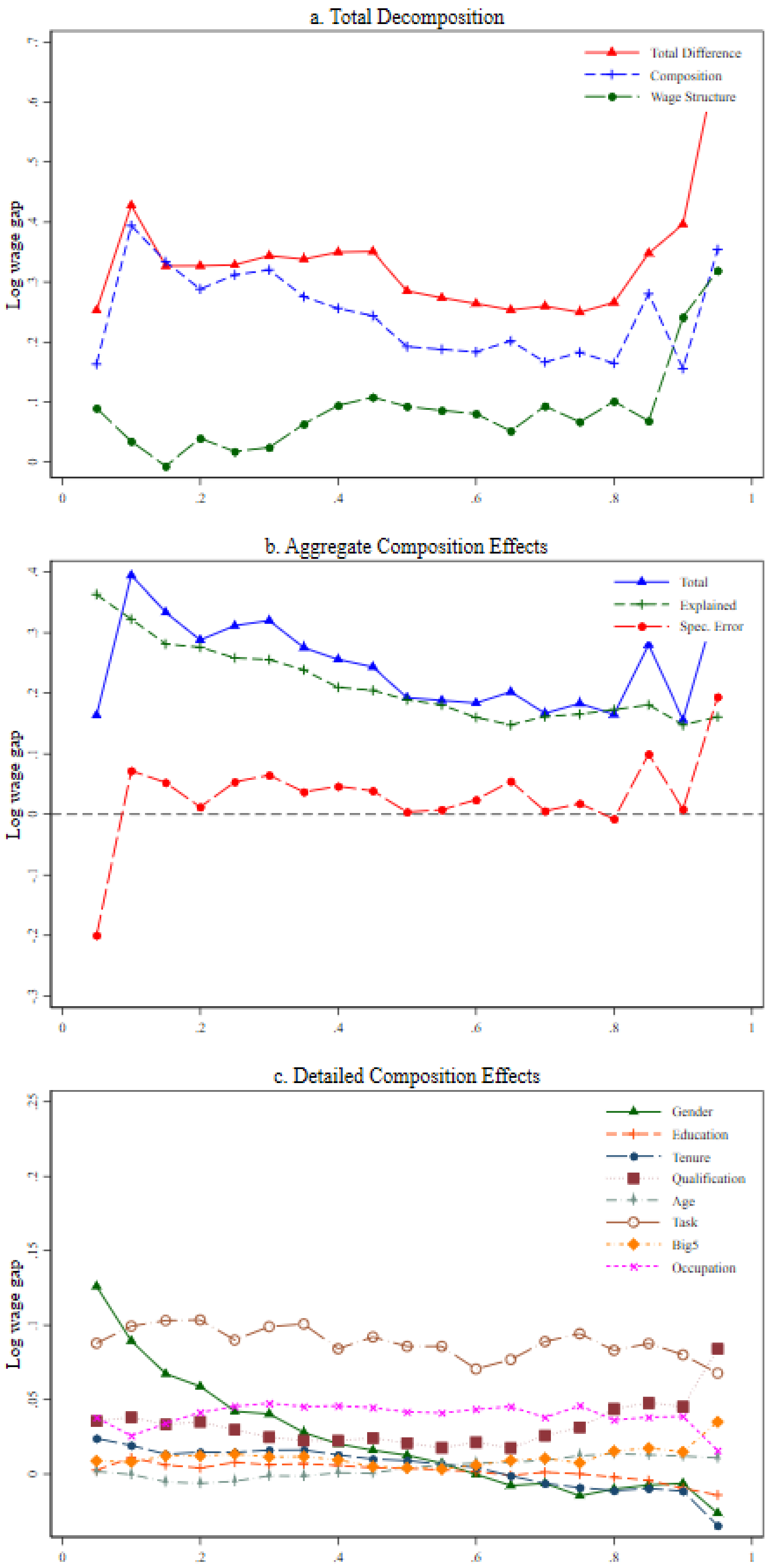
tional measure (besides the mean) and by allowing for a much more flexible wage setting model (Firpo et al. 2007).

Figure 3 shows the wage gap based on the difference in log wages between green and non-green jobs across quantiles. Figure 3a presents the total log wage gap at each percentile and decomposed into a composition and wage structure effect. The composition effect in the FFL decomposition examines how much of the wage differential is due to differences in observable characteristics between the two groups, across the entire wage distribution, while the wage structure effect looks at how much of the wage differential is due to differences in the returns to these observable characteristics across the entire wage distribution (Firpo et al. 2007).

The composition effect almost overlaps with the total difference at the higher end of the wage distribution, while the wage structure effect shows an increasing trend. This indicates that, among higher paid jobs, the differences in the returns to observable characteristics become increasingly significant in contributing to the wage gap between green and non-green jobs, indicating that in positions at the upper end of the wage distribution, green workers may receive better wages for the same qualifications and abilities than their non-green counterparts. This finding is consistent with the conclusions drawn from our DFL decomposition analysis.

The advantage of using FFL decomposition is that we can further decompose the composition effect into the contribution of the explanatory variables using Recentered

Figure 3: FFL decomposition of log wage gap



Influence Function (RIF) regressions. Figure 3b and 3c present the results of aggregate decomposition effect and a detailed decomposition effect. Figure 3b first compares the overall composition effect and the composition effect explained by the RIF regression, where the difference between the two curves is the specification error. The error term is relatively small fluctuating around zero and does not exhibit a systematic pattern. This means that the RIF-regression model does relatively well at tracking down the composition effect estimated consistently using the reweighting procedure.

Figure 3c then divides the composition effect (explained by the RIF-regressions) into the contribution of the main sets of factors.[30] The detailed composition effects reveal that the task-related differences between green and non-green jobs play the most significant role in explaining the wage gap across the wage distribution. Tasks account for a consistent portion of the wage disparity, hovering around 0.1 to 0.15 log points across the distribution. This suggests that the nature of the work involved in green jobs is a primary driver of wage differentials. In addition, occupation type plays a substantial role, particularly in the middle wage percentiles, further emphasizing the structural differences between green and non-green jobs as a key determinant of wage outcomes.

Gender differences also contribute significantly to the wage gap, particularly in the lower wage percentiles, where they account for a larger share of the disparity. However, this effect diminishes at higher wage levels, indicating that gender is a more critical factor in lower-paid roles. Education maintains a consistent, moderate impact across the wage distribution, contributing around 0.05 log points. This steady effect underscores that while education matters in determining wages, the wage differences are more associated with the nature of the work and job classification, rather than individual educational attainment. In contrast, factors such as tenure, age, and qualification contribute minimally to the wage gap, with their effects remaining close to zero throughout the distribution. Similarly, Big 5 personality traits play an insignificant role in explaining wage differences. These findings suggest that individual attributes such as experience, age, and personality have limited influence on the wage disparity between green and non-green jobs, with structural job characteristics being the predominant drivers of the observed wage gap.

5 Conclusions

Using a unique, representative survey of workers in Japan that includes questions on the activities that are undertaken as part of a job and can be considered green, we document that green jobs are systematically different from non-green jobs in terms of certain human capital and demographic characteristics. Our results reveal that green jobs tend to be concentrated among the older and younger works and to be male dominated. Workers in green jobs are more likely to have a university degree and work-related qualifications and are more likely to be found in high-skilled occupations such as Managers and Professions and Technicians. Green workers are more likely to be found in high-polluting industries such as Elasticity, Gas and Water Supply and Mining and Construction sectors

[30]We included all variables in the wage equation, including gender, education, tenure, qualification, age, task intensities, big5 personality traits, occupation, industry, and prefecture. However, for presentation purposes, we only display those variables that have a significant impact. The complete set of graphical representations can be found in Figure C2 the Appendix C.

which have more reason to hire workers who can implement green technologies and green management practices in response to stricter regulations and pressure from stakeholders.

A second contribution is to explore whether there is a green wage premium, and if there is, how this premium changes with the degree of greenness of a job. We show that workers in green jobs earn a 7.3% wage premium compared to those in non-green jobs, and this premium grows as the green intensity of the job increases. Our binary results are consistent with other studies such as Muro et al. (2019), Vona et al. (2018), Curtis & Marinescu (2022), Sato et al. (2023), who also found the existence of a green wage premium. Moreover, we extend this type of analysis and focus on how wages are impacted by the 'greenness' of a job. More specifically, our estimation results suggest that on average, a 10% increase in the level of a workers KEOO index is associated with an approximate 0.8% increase in the average hourly wage. Finally, we explore the green wage premium by demographic groups, finding that the green wage premium is almost ubiquitous and holds for both high skill and low skill workers, males and females, for the young workers. The fact that we find a similar green wage premium across groups leaves little doubt that this premium is widespread and cannot be easily attributed to one social phenomenon.

Finally, we examine the individual contribution of each potential factor to the green wage premium. The degree of the wage premium in green jobs could be influenced by various factors. However, the existing literature does not explain what determines the wage premium although this information is arguably important for policy makers and workers trying to navigate and adapt to the changing labor market triggered by the green transition. Our FFL decomposition results suggest that the wage structure effect is particularly strong at the upper end of the wage distribution which suggests that for higher income groups, the labor market assigns greater value to identical worker attributes in green jobs compared to non-green jobs. This could be because green skills are in high demand and as a result, individuals with these green skills, particularly those in high-income groups, receive higher rewards. This leads to a wage premium that cannot be fully explained by other factors, such as education or experience, compared to individuals in the same income group who do not possess these green skills. When examining the composition effect, we show that the wage gap is primarily influenced by job task difference and occupational difference, while at the lower end of the wage distribution, gender difference also contribute significantly to the wage gap.

The observed disparities in gender in participation in green jobs suggests that while the transition towards a green economy is crucial for sustainability, it might inadvertently exacerbate existing inequalities. Such disparities are primarily due to the fact that green jobs are concentrated in male-dominated occupations and industries but it could also stem from a variety of factors, including existing biases, unequal access to training and education in green skills, or structural barriers in employment practices. Existing study has found gender disparities were expanded in labor markets, particularly in times of structural change such as those caused by COVID-19 (Hu et al. 2024).

A more recent study of Maczulskij (2024) shows that the shift toward green jobs, and the reduction in brown jobs, is predominantly driven by occupational changes among individual workers; However, it also highlights that younger generations and previously unemployed individuals are less likely to transition into green jobs. This highlights the importance of ensuring that the shift towards a green economy is accompanied by policies and practices that actively promote inclusivity and equity and emphasizes the need for a just transition that not only focuses on environmental outcomes but also on social equity.

Though a disparity in gender participation have been detected in green jobs, the green wage premium, which is found across various demographic groups, reflects the increasing importance of environmental sustainability in business and industry, and the recognition that workers who contribute to these efforts may be more valuable and in-demand than those in traditional or less sustainable jobs. Given the fact that workers often base their decisions on anticipated earnings when making career choices (Arcidiacono et al. 2020), the existence of such a green wage premium could magnify the attractiveness of green jobs, thereby speeding up the transition towards a more sustainable economy as the workforce becomes increasingly endowed with the skills needed for a green transition.

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Appendix

A Survey

The survey was conducted on a website constructed by Nikkei Research Co, which is the largest research company in Japan. The survey takes a stratified random sampling strategy. Japan is stratified into five regions by regional classification and six age groups for each gender (12 age groups per region). The number of samples for 60 region–age groups was determined by labor force ratio. The Labor Force Survey (Ministry of Internal Affairs and Telecommunication) was employed as the sampling unit. The survey is constructed as a panel with the intention of keeping the same respondents over waves as much as possible. Some respondents repeatedly joined the survey and others did not. Thus, new respondents were added to ensure the allocated number of responses was reached in each unit. See Okubo (2022) for more details and see also the NIRA website on the survey (https://nira.or.jp/paper/data/2022/26.html).

We are aware that the issue of self-report bias is a common challenge in survey-based research. Unfortunately, there is no perfect solution. Although this limitation is inherent to the nature of survey methodologies, we have implemented several strategies to mitigate the limitations associated with using self-reported survey data, from the initial design through to the conduct of the survey. A list of actions we have taken to reduce self-report bias is listed below:

1. We contracted the largest research company (Nikkei Research, Co.) in Japan to conduct a detailed and extensive internet survey.
2. This research project is funded by a combination of Japanese government grants (KAKENHI, Grants-in-aid for Scientific Research, 19H01487 and 23H00821), Asahi Glass Research Foundation, and Research Project for Next Generation (Keio University) and NIRA.
3. To ensure that survey questions are as clear and specific as possible to minimize interpretative ambiguity, together with Okubo, NIRA, and Nikkei Research, we engaged in multiple discussions and review sessions. For example, we provided precise definitions and examples of 'green job activities' to help respondents understand and answer accurately. This collaborative effort was essential in refining the survey content and enhancing the overall reliability of the data collected. The questionnaires were reviewed by the research ethics committee in NIRA.
4. At the beginning of the survey, we include a brief instruction encouraging respondents to answer honestly, emphasizing the importance and practical applications of the survey results.
5. While Nikkei Research manages the sample and is aware of respondent details such as names and addresses, this information is concealed from us. Participants were assured that, although their responses are linked to their identities, all data will be treated with the utmost confidentiality. Participants are clearly informed how their data will be used, who will have access to it, and the measures taken to protect their confidentiality.

B Sample details

Our annual income data (in JPY) was reported by respondents in 2021. Missing information means our sample is reduced to 7,987. To mitigate the impact of outliers the wage data has undergone two-sided winsorization which removes extreme values from both the upper and lower ends of the distribution. Note that the missing information on Big Five personality variables, parental occupation further reduced our sample to 5,123.

We have three working hour variables in the datasets: average hours worked per day at the usual workplace during the first week of September 2021, the Olympic period (July 23 - August 8, 2021), and early July 2021, for both regular and teleworking days. To obtain the average hours worked per day while preserving as much information as possible, we first calculate the average of hours reported for regular commuting and teleworking days. If an individual only commutes, the average hours worked per day will be based solely on the reported commuting hours. Similarly, if an individual only teleworks, the average hours worked per day will be based solely on the reported teleworking hours.

Then we use the value from early July 2021 as a starting point, fill in any missing values with data from the first week of September 2021 (filling 89 missing values), and then fill any remaining missing with data from the Olympic period (no additional values filled). To handle outliers, we exclude data below the 1st and above the 99th percentile of working hours. Finally, our working hour variable has a mean of approximately 7 hours, with a minimum of 1 hour and a maximum of 13 hours. See Table B3 for details.

Considering Japan has 16 public national holidays, an average of 10 vacation days, and 104 weekend days (52 weeks), resulting in 235 working days per year, we can calculate the hourly wage rate by dividing the annual income by the product of total working days and the average working hours per day. By including the working hours for both regular and teleworking days and accounting for various periods within the year, we can ensure that the calculated hourly wage rate accurately reflects the diverse working conditions and schedules of all respondents, providing a precise measurement for both regular and non-regular workers.

Table B1: Employment Status of Sample Respondents

Employment status	**Frequency**	**Percentage**
Regular worker	5,673	54.8
Non-Regular worker	3,311	32
CEO	265	2.6
Self-employed (with employees)	244	2.4
Self-employed (without employees)	729	7
Assisting with family business, home-based work	126	1.2
Total	**10,348**	**100**

Note: The table shows the distribution of employment status among the sample of 10,348 respondents. Non-regular worker includes three types: (1) part-time or temporary non-regular workers, (2) contracted non-regular workers.

Table B2: Summary Statistics of the Whole Sample

	N	Mean	SD	Min	Max
KEOO index	10,348	0.077	0.162	0	1
Green jobs	10,348	0.308	0.462	0	1
Very dark green jobs	10,348	0.071	0.256	0	1
Dark green jobs	10,348	0.039	0.193	0	1
Light green jobs	10,348	0.052	0.223	0	1
Very light green jobs	10,348	0.146	0.353	0	1
Non-green jobs	10,348	0.692	0.462	0	1
Female	10,348	0.444	0.497	0	1
Age group	10,348	3.065	1.266	1	5
University Graduates	10,348	0.507	0.500	0	1
Tenure	10,348	11.690	11.156	0	60
Qualified	10,348	0.511	0.500	0	1

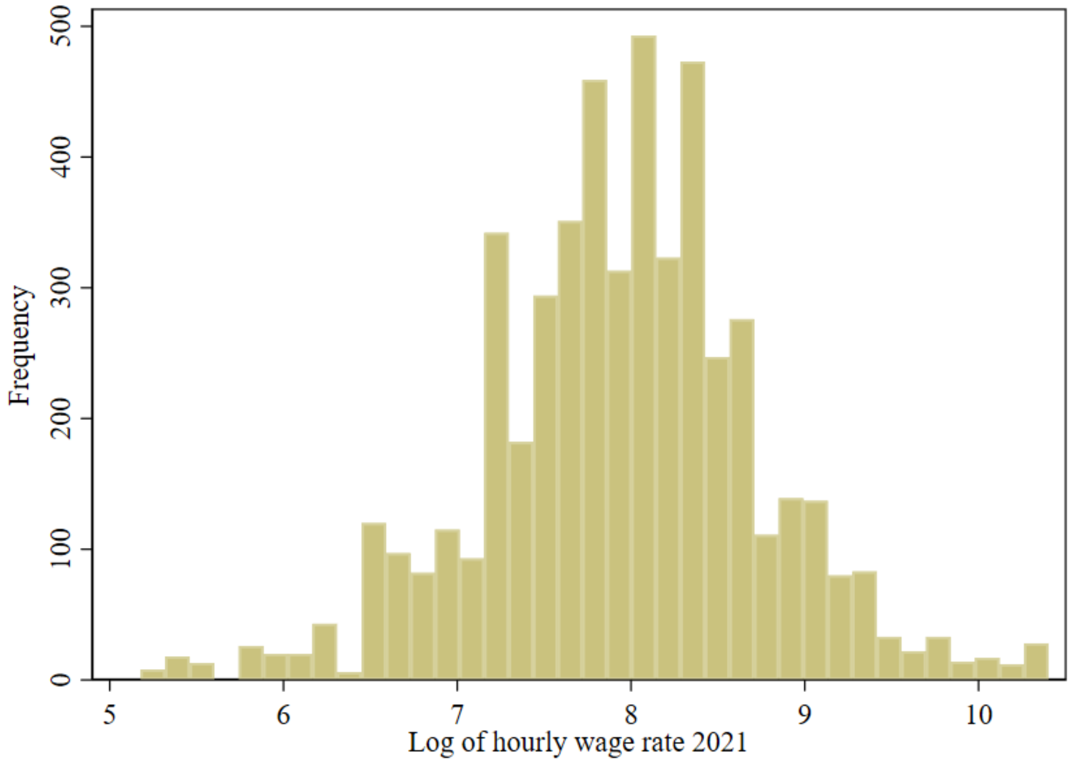
Note: Data source from Okubo-NIRA Telework Survey.

Table B3: Summary Statistics of Regression Sample

Variable	N	Mean	S.D.	Min	Max
Ln(wage)	5,123	7.949	0.800	5.178	10.404
workhour	5,123	7.338	2.165	1	13
KEOO index	5,123	0.073	0.153	0	1
Green jobs	5,123	0.312	0.463	0	1
Female	5,123	0.419	0.493	0	1
Age group	5,123	3.221	1.167	1	5
University Graduates	5,123	0.543	0.498	0	1
Tenure	5,123	12.761	11.265	0	60
Qualified	5,123	0.521	0.500	0	1
Abstract	5,123	0.022	0.982	-0.833	4.010
Routine	5,123	-0.051	0.986	-3.065	1.072
Manual	5,123	-0.018	0.974	-0.891	2.558
Extraversion	5,123	3.733	1.167	1	7
Agreeableness	5,123	4.424	1.108	1	7
Conscientiousness	5,123	4.116	1.081	1	7
Neuroticism	5,123	3.915	1.068	1	7
Openness	5,123	3.830	1.050	1	7
Father's moral score	5,123	3.822	0.102	3.472	3.991
Mother's KEOO index	5,123	0.047	0.040	0	0.203
Father's KEOO index	5,123	0.083	0.033	0	0.203
Parent's KEOO index	5,123	0.065	0.056	0	0.203

Note: Data source from Okubo-NIRA Telework Survey. The variable Ln(wage) is defined as the hourly wage expressed in Japanese Yen (JPY) for the year 2021.

Figure B1: Histogram of log of hourly wage distribution



Note: N=5,123. Data source from Okubo-NIRA Telework Survey.

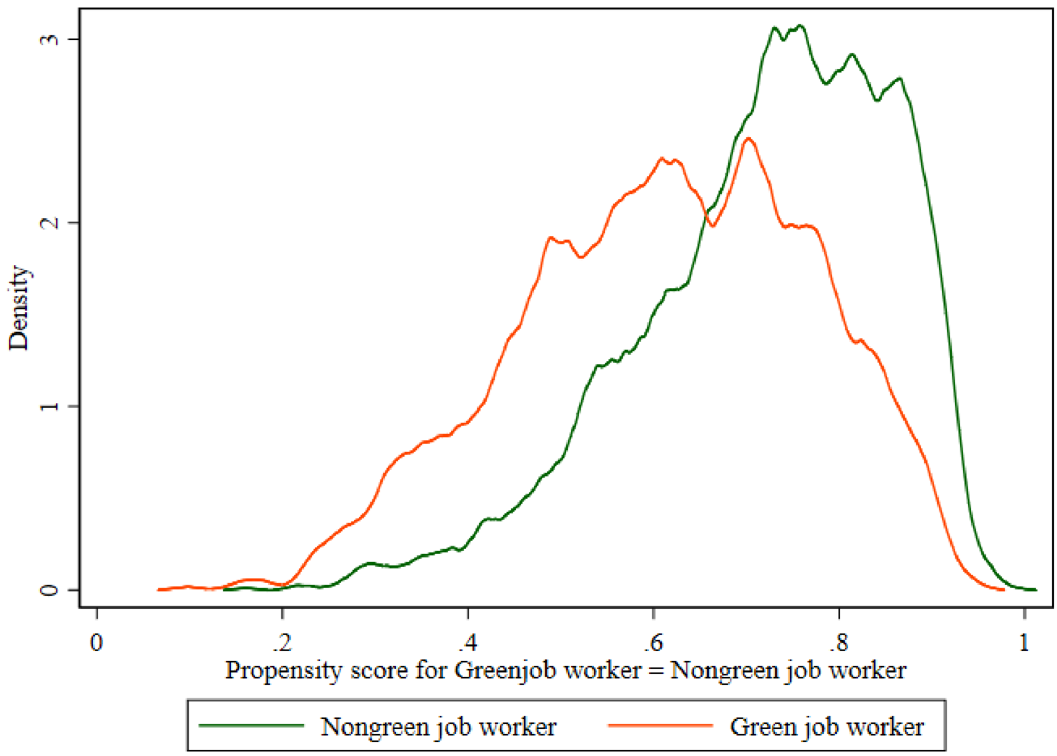
C Supplementary Tables and Figures

Table C1: Durbin-Wu-Hausman Endogeneity Test Results

	Model 1	Model 2	Model 3	Model 4
χ^2	1.85	3.09	3.51	1.02
P value	0.397	0.213	0.172	0.600
N	5,123	5,123	5,123	5,123

Note: In Model 1, the moral test score from the father's birthplace is used as the excluded variable. In Model 2, the average of both parents' indices (Parents' KEOO index) is used as excluded variable. In Model 3, both parents' KEOO indices is used as the excluded variable. In Model 4, both parents' KEOO indices and the moral test score from the father's birthplace are used as excluded variables.

Figure C1: Estimated Density of Predicted Probabilities for Overlap Assumption Testing



Note: N=5,123. Data source Okubo-NIRA Telework Survey. The figure displays the estimated density of the predicted probabilities that a green job worker is a non-green job worker and the estimated density of the predicted probabilities that a non-green job worker is a non-green job worker. Neither plot indicates excessive probability mass near 0 or 1, and the two estimated densities have most of their respective masses in regions where they overlap. There is no evidence that the overlap assumption is violated.

Figure C2: Detailed Composition Effects