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Anna Godøy and Elisabeth Isaksen

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A green wage premium?*

Anna Godøy† Elisabeth Isaksen†‡

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Abstract

Many governments have set ambitious climate goals that require a shift away from fossil fuel-intensive industries toward climate-neutral jobs. We use rich administrative register data to estimate green wage premiums in the presence of non-random sorting of workers across firms. On average, green firms pay statistically significant and economically meaningful wage premiums, consistent with a pattern of rent-sharing in high-revenue, highly innovative green firms. The premium is larger for non-college workers and those in low-skilled occupations. However, the average estimated wage premium for high-carbon firms is roughly twice as large as the green wage premium. This finding suggests that while the expansion of high-wage green firms may help mitigate the earnings losses associated with decarbonization, it is unlikely to fully offset them.

Keywords: green jobs, wage premium, polluting jobs, employment, technology

JEL codes: J31, J21, Q52, Q55

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†Ragnar Frisch Centre for Economic Research, Oslo, Norway.

‡Grantham Research Institute on Climate Change and the Environment, London School of Economics, United Kingdom (Visiting Associate).

1 Introduction

As countries attempt to tackle climate change, many governments have set ambitious climate goals that require a drastic reduction in emissions over the coming decades. EU countries have committed to cutting emissions by 55% by 2030, with a goal of reaching net-zero emissions by 2055 (Council of European Union, 2021). However, concerns have been raised that meeting these strict emissions targets could have negative consequences for workers and labor markets, as employment shifts away from high-emissions industries that typically offer higher wages (Jacobsen, 2019; Bartik et al., 2019; Hanson, 2023). The emergence of new jobs in the green economy, such as those in renewable energy and related industries, could potentially help dampen these adverse consequences for workers. This mechanism crucially depends on the relative wages offered by green jobs – that is, the sign and magnitude of the green wage premium.

Answering this seemingly simple question has proven challenging for two key reasons. First, there is no consensus on the definition of green jobs. Instead, the literature tends to use various empirical definitions, making it difficult to compare results across studies (see, e.g. Vona et al., 2019; Saussay et al., 2022; Bluedorn et al., 2023; Curtis and Marinescu, 2023). Second, identifying wage premiums is complicated by the non-random sorting of workers into firms (Eeckhout, 2018). That is, even if we observe that green jobs offer higher wages than non-green jobs, this correlation may reflect differences in worker productivity rather than a true wage premium.

In this paper, we overcome both these challenges in the context of the Norwegian labor market by leveraging two key strengths of the Norwegian setting. First, we use linked administrative data covering the universe of firms and include detailed information on activities related to the green transition. Specifically, we classify firms as green if they operate in renewable industries or related services, export a large share of environmental goods, or engage in substantial green innovation, measured through patents and R&D activity. This approach enables us to identify green jobs beyond the energy sector, based on observed firm-level activities. Conversely, firms involved in fossil fuel extraction and related activities, industries covered by the EU Emissions Trading System (EU ETS), and firms with high reported CO_2 emissions, are classified as brown. Under these definitions, most firms in the economy are classified as neither green nor brown. In our analysis, these "generic" jobs serve as the comparison group in our wage regressions; that is, we estimate green and brown wage premiums relative to wage levels in generic jobs.

Second, we take advantage of linked employer-employee data covering the entire population of workers and firms to implement a "ground-up" approach to estimating the green wage premium. We begin by applying the well-established model of Abowd et al. (1999) to estimate firm wage premiums. This model addresses non-random sorting of workers across firms by exploiting worker mobility to separately identify worker and firm fixed effects. This approach allows us to isolate firm-specific wage components from unobserved differences in worker skills and abilities. We then define the green wage premium as the difference between the employment-weighted average wage premium across green firms and the employment-weighted average wage premium in non-green, non-brown comparison firms (Abowd et al., 1999; Card et al., 2023).

The theoretical predictions regarding both the sign and magnitude of the green wage premium are a priori ambiguous. First, cross-sectional wage gaps may reflect both observed and unobserved worker skills. For example, green jobs may require skills that are highly valued in the labor market (Consoli et al., 2016). Second, wage differences between green and non-green firms could be driven by variations in firm and job characteristics. For instance, green firms may be systematically larger or more innovative than non-green firms; from the literature, these characteristics are associated with higher wages (Oi and Idson, 1999; Mueller et al., 2017; Kline et al., 2019). More broadly, in imperfectly competitive labor markets, rent-sharing models suggest that productivity differences across firms influence wages (Alan, 2011; Card et al., 2018). If green firms are more profitable than non-green firms, perhaps due to lower capital costs, these advantages could translate into higher wages, leading to a positive green wage premium. Similarly, wage gaps could reflect compensating wage differentials; if green jobs are systematically more arduous than non-green jobs, or if green firms have higher rates of layoffs, higher wages may compensate for these added risks and challenges. Third, the perception of a job as "green" could itself have a causal effect on wages, e.g. due to worker preferences. Prospective employees may prefer working for firms they view as green and may be willing to accept lower wages in exchange for the non-monetary benefits associated with such employment. If this is the case, the green wage gap could be negative (Krueger et al., 2023).

Our preferred estimates of the green wage premium fully account for both observed and unobserved components of worker skills, provided these skills remain constant over time. However, this approach does not allow us to isolate the direct wage impact of "green" from the effects of other firm and job characteristics. While a direct estimation of the causal impact of green is challenging, we conduct a simple decomposition exercise to gauge how much of the estimated wage premium can be explained by observable firm characteristics.

We have three main results. First, we find a positive and statistically significant green wage premium of approximately 6.6%. This premium remains positive across various definitions of green jobs, with estimates ranging from 5% to nearly 13%. At the same time, the estimated brown wage premiums are consistently larger; our broadest definition of brown jobs indicates a wage premium of 14%. Our baseline estimate of the green wage premium is significantly lower than the raw wage gap of 13.8%, suggesting that high-wage workers are more likely to sort into green jobs.

Second, there is significant heterogeneity in estimated green wage premiums across worker characteristics. Specifically, the green wage premium is twice as large for workers without a college degree compared to college-educated workers – a difference that is statistically significant at conventional levels. Consistent with this finding, we observe larger green wage premiums for occupations with lower educational requirements (e.g., craft and trade, elementary occupations) than for occupations that typically require a tertiary degree (e.g., professionals, technicians, and clerical workers).

Third, observable firm characteristics account for a substantial portion of the green wage premium. When we control for a sparse set of firm-level covariates, the estimated green wage premium declines by over 80%, and is no longer statistically significantly different from zero. A similar pattern emerges for the estimated brown wage premium – the residual brown wage premium drops by nearly 80% and is no longer statistically significantly different from the estimated green wage premium. This pattern is consistent with a pattern of rent-sharing where high-revenue, highly innovative green and brown firms pay higher wages.

Taken together, our results have important implications for the ongoing policy debate regarding the distributional consequences of the green transition. Our findings indicate that although green jobs do not command wages as high as brown jobs, they still offer a wage premium relative to baseline jobs in the economy. This pattern implies that the growth in high-wage green firms could help mitigate the earnings losses associated with decarbonization. This is particularly true for non-college workers, who have high estimated green wage premiums both relative to generic jobs and relative to brown jobs.[1]

Our paper contributes to the emerging literature on the labor market and distributional consequences of the green transition. One strand of this literature examines the green wage premium, with mixed findings (Vona et al., 2019; Curtis and Marinescu, 2023; Saussay et al., 2022; Colmer et al., 2023; Bluedorn et al., 2023; Krueger et al., 2023; Curtis et al., 2024). A key shortcoming of nearly all existing studies is their inability to account for worker sorting, raising the risk of conflating wage premiums with, for example, the positive selection of workers into green jobs. Relatedly, most studies do not measure actual wages at the job level but instead rely on stated wages in job advertisements or occupational averages. To our knowledge, this is the first study to estimate green wage premiums while explicitly accounting for worker sorting using a bottom-up approach. The richness of our data also allows us to examine heterogeneous wage premiums across gender and skill groups and to decompose the underlying sources of the premium.

[1] We use the term *generic* to denote jobs that are neither green nor brown.

Second, our paper contributes to a small but growing literature on the classification and characterization of green jobs. Existing studies have primarily relied on three alternative approaches: focusing on a narrow set of industries, such as the energy sector (Colmer et al., 2023; Curtis and Marinescu, 2023); using information on the share of green skills or tasks within occupations (Bowen et al., 2018; Vona et al., 2018, 2019; Bluedorn et al., 2023); or identifying green jobs based on keywords in job advertisements (Saussay et al., 2022; Curtis and Marinescu, 2023; Curtis et al., 2024). We take a different approach by using exceptionally detailed firm-level data to classify firms as green, brown, or generic. This allows us to link greenness directly to firms rather than occupations and to examine effects beyond narrow definitions based solely on energy production. Moreover, by relying on actual firm behavior instead of statements in job advertisements, we avoid potential biases arising from strategic messaging in job postings.

Lastly, our paper contributes to a broader literature on wage premiums (Krueger and Summers, 1988; Neal, 1995; Abowd et al., 1999; Card et al., 2016; Gathmann and Schönberg, 2010; Card et al., 2023). Previous studies have examined wage differentials across dimensions such as industry, gender, education, and local labor markets. The central aim of this literature is to disentangle the relative contribution of (often unobserved) worker and firm characteristics to pay premiums. We build on recent methodological advances in this literature – in particular Card et al. (2023) – to examine wage differentials between green and non-green jobs.

2 Estimating green wage premiums

In this section, we describe in detail the methodology we use to estimate the green wage premium. We first review the basic AKM wage model used to estimate the firm fixed effects that constitute the building blocks of our preferred ground-up approach. We then review a set of alternative empirical models.

2.1 Basic AKM model

Let y_{it} denote the natural logarithm of monthly earnings. Following Abowd et al. (1999) and Card et al. (2023), we estimate the following regression model:

$$y_{it} = a_i + \theta_{f(i,t)} + X_{it}\beta^x + \varepsilon_{it}, \tag{1}$$

where a_i is a worker effect capturing abilities and skills that are equally valued across jobs, θ_f is a firm effect capturing the wage premium paid by firm f. X_{it} is a vector of controls for age and calendar time. Because the model includes worker fixed effects, we cannot include both unrestricted age and calendar time effect, as age and calendar time are perfectly collinear within individuals. We follow Card et al. (2018) and include a cubic polynomial in age - 40, omitting the linear term. The residual ε_{it} is a composite error term capturing idiosyncratic match effects between workers and firms, as well as transitory shocks to workers and firms.

We follow the approach of Bonhomme et al. (2023) and estimate the model in two steps. First, we estimate a simple wage regression with calendar time dummies and a cubic polynomial in age. Second, we use the residualized log wages from this regression as the dependent variables in the two-way fixed effects model. The firm effects θ_f represent a key parameter of interest, as they serve as the building blocks for estimating the green wage premiums. For Equation (1) to yield unbiased estimates of these firm effects, several assumptions must be satisfied.

First, the model imposes a log-additive structure of wages, effectively ruling out interactions between worker and firm fixed effects (Bonhomme et al., 2023). Second, firm-to-firm mobility must be conditionally exogenous. Under this assumption, workers are allowed to move between jobs based on time-invariant unobservable characteristics; however, such mobility should be uncorrelated with the unobserved determinants of earnings. This assumption could be violated if mobility is driven by shocks to firms (i.e. workers leaving or joining firms in response to negative or positive firm-level shocks), transitory shocks to the worker (i.e. workers moving from high- to low-paying jobs in response to negative worker-level shocks), or idiosyncratic match effects (as assumed in many search and matching models of the labor market).

To evaluate the plausibility of these assumptions in our setting, we estimate a set of descriptive event-study specifications following Card et al. (2013). These models assess the validity of the additive separability and exogenous mobility assumptions by examining wage dynamics over time for a sample of job-to-job transitions between higher- and lower-paying firms. Overall, the observed patterns are consistent with the key assumptions of the model; see Section 3.4 for details.

The estimated firm effects from Equation (1) form the basis of our estimates of the green wage premiums. Within this framework, a natural definition for the green wage premium is the employment-weighted average of the normalized firm effects. Specifically, we define the wage premium for type $j = \{green, brown\}$ as the employment-weighted average firm effect among type j firms relative to the non-green, non-brown comparison group. We then estimate the green and brown wage premiums by regressing the estimated firm effects on an indicator variable for wether a job is classified as green or brown:

$$\theta_{f(i,t)} = a + \phi_{j(f)}\beta^j + \varepsilon_{it}. \tag{2}$$

A key question we want to answer is whether the green wage premium varies with worker characteristics. Specifically, we will estimate separate wage premium by gender and education. To this end, we first estimate Equation (1) separately by gender and by education (college/non-college). Each model yields a set of gender and education specific estimated firm effects. In a second step, we use these estimated firm effects as the dependent variable in Equation (2), again estimating the models separately by gender and by education. With this approach, our results will capture heterogeneity in the green wage premium arising from two distinct sources: (1) differential bargaining power within firms – that is, whether a given firm pays a larger wage premium to different worker types – and (2) differences in worker sorting across firms, specifically the extent to which workers of different genders or educational attainment are employed at high- or low-premium firms (Card et al., 2016).

2.2 Alternative models: cross-sectional wage regressions and industry mover models

We compare the results from our preferred, bottom-up AKM approach with results from two alternative models, as well as with the raw wage gap. First, we estimate the following cross-sectional wage regression, which controls for worker differences in gender, age, educational attainment, and field of study:

$$y_{it} = \theta_{j(i,t)} + X_{it}\beta^x + \varepsilon_{it}. \tag{3}$$

The model in Equation (3) accounts for selection on observables. However, the model may yield biased estimates if workers systematically sort into green or brown jobs based on unobservable characteristics.

Second, we estimate an industry mover model, in which the green wage premium is estimated based on the following equation for $j = \{green, brown\}$:

$$y_{it} = a_i + \theta_{j(i,t)} + X_{it}\beta^x + \varepsilon_{it}, \tag{4}$$

where a_i is a worker effect, X_{it} is a vector of time-varying covariates for age and calendar time, and θ_j is an indicator variable equal to 1 if the worker is employed in a $j = \{green, brown\}$-type firm. In this model, the green (brown) wage premium is identified from workers who switch between green (brown) and generic firms. The specification in Equation (4) is robust to selection on time-invariant unobservable characteristics. However, it may still yield biased estimates due to unobserved within-sector heterogeneity in firm wage premiums - for example, if workers moving between green and generic sectors systematically move between firms that differ from to the average firm in each sector. We return to the discussion of this form of attenuation bias, known as the hierarchy effect (Card et al., 2023), in Section 4.1.

3 Data and Descriptives

In this paper, we aim to expand and refine the definition of green jobs by exploiting rich administrative data. Specifically, we draw on four key sources to classify firms and their workers as green: detailed industry code, patent applications, R&D expenditures, and firm-product level export data. We rely on three key data sources at the firm-level to define brown jobs: industry code, participation in the EU ETS, and annual CO_2 emissions.

In this section, we first describe the data sources and the criteria used to define green and brown jobs. We then present a set of descriptive statistics for these job categories, followed by an analysis of job-to-job mobility to motivate our use of the two-way fixed effects model of wages from Abowd et al. (1999).

3.1 Data sources and the definition of green and brown jobs

We use registry data on emissions, innovation, and industry affiliation to define a set of criteria for green and brown jobs. These criteria are summarized in Table 1, with additional details provided in Appendix A. Our broadest definition classifies a job as green or brown if it meets at least one of these criteria. Below, we describe the data sources and empirical definitions in more detail.

Jobs and workers: Our key data source is the Norwegian State Register of Employers and Employees, which covers the universe of workers and firms. Our sample spans the period 2010–2023. The dataset contains job spell-specific information on earnings, occupation, contracted weekly hours, start date, and end date. We construct the monthly average wage as our main outcome of interest.[2] We link the job-spell data to a range of individual and firm characteristics via unique identifiers. All nominal values are deflated to 2023 NOK using the consumer price index.

For workers, we include information on age, gender, educational attainment, and field of study (two-digit classification). For firms, we include information on the five-digit industry code (SN2007). Using this variable, we classify firms as green if they operate in one of the 18 industries listed in Appendix Table A.2. These industries - part of electricity, gas and steam (35), sewage (37), waste collection and material recovery (38), or civil engineering (42) - largely correspond to the narrow definition of the green economy commonly used in the literature. We also define a set of brown industries linked to fossil fuel extraction and related services, together with petroleum-oriented industries as defined by Statistics Norway.

Exports: We identify green exports by combining firm-product level export data from

[2]Monthly wage is winsorized at the 99th percentile.

administrative registers with a list of approximately 220 products (six-digit HS code) classified as environmental goods by the International Monetary Fund (IMF, 2021). Environmental goods are defined as products that either contribute to environmental protection or have been adapted to be more environmentally friendly or "cleaner" (IMF, 2021). In our baseline model, firms are defined as green if environmental goods account for at least 50% of their total exports.[3]

Innovation: To measure green R&D, we use firm-level data from Statistics Norway's R&D survey, which covers a stratified sample of firms in the business enterprise sector. Since 2008, the survey has collected data on intramural R&D expenditures by thematic area, several of which related to climate mitigation, climate adaptation, and environmental protection. Appendix Table A.5 lists the thematic areas that we classify as green. In our baseline definition, firms are classified as green if at least 50% of their intramural R&D expenditures are allocated to green thematic areas.

We also include data on patents. The European Patent Office (EPO) uses the Y02 tag to classify technologies that "control, reduce or prevent anthropogenic emissions of greenhouse gases, in the framework of the Kyoto Protocol and the Paris Agreement", as well as technologies that "allow adapting to the adverse effects of climate change" (European Patent Office, 2024). We combine firm-level data on all patent applications submitted to the Norwegian Patent Office between 2010 and 2023 with information on the Y02 classification of each patent. In our baseline definition, firms are classified as green if 50% or more of their patent applications were classified as Y02 patents.

Emissions: The Norwegian Environment Agency collects data on emissions from most stationary sources in Norway that are deemed to cause significant harm.[4] These data allow us to observe CO_2 emissions at the plant level for high-emission facilities. We classify firms as brown if they operate at least one plant that reports positive CO_2 emissions in any year during the sample period.

We also use data on firm-level participation in the EU Emissions Trading System (EU ETS), which primarily covers large, emission-intensive establishments in manufacturing, power generation, and natural resource extraction. We use these data to identify five-digit industries with likely high emission intensity and classify firms as brown if they belong to an industry in which at least one firm participates in the EU ETS during the sample period.

The green and brown definitions above are not mutually exclusive. As a result, a

[3]In sensitivity analyses, we show that our main results are robust to alternative thresholds for green exports and innovation, ranging from just above 0% to 80%; see Figure 6.

[4]Under Norway's Pollution Control Act, any activity that may cause pollution requires a permit unless specifically exempted. Exemptions apply to pollution from activities such as agriculture, forestry, buildings, and temporary construction work, as well as to emissions deemed unlikely to cause significant harm or nuisance.

small share of jobs (around 2.4%) are classified as both green and brown according to the criteria above; see Appendix A.3. We exclude these ”mixed” jobs from both the green and brown categories. In our analysis, we compare green and brown jobs to the set of jobs that are neither green nor brown. We refer to these jobs as *generic jobs*.

Table 1: Definitions of green and brown jobs

Green jobs	**Brown jobs**
(i) Green industries: Firms operating in one of 18 "green" industries in electricity, gas and steam (35); sewage (37); waste collection and material recovery (38), or civil engineering (42).[1]	*(i) Brown industries:* Firms in fossil fuel extraction and related services, as well as petroleum-oriented manufacturing industries.[2]
(ii) Environmental goods: Firms with an average export share of environmental goods $\geq$ 50%.[3]	*(ii) EU ETS participation:* Five-digit industries in which at least one firm participated in the EU ETS.
(iii) Green patent applications: Firms with $\geq$ 50% of patent applications classified as Y02 patents.	*(iii) CO_2 emissions:* Firms reporting positive CO_2 emissions to the Environment Agency in any year of the sample period.
(iv) Green R&D expenditures: Firms with $\geq$ 50% of intramural R&D expenditures devoted to green thematic areas.	

In our baseline specification, firms are classified as green or brown if they meet one or more criteria listed above. Firms that are simultaneously classified as both green and brown ("mixed jobs") are excluded from the sample. Firms that are neither green nor brown - referred to as generic jobs - form the comparison group in our wage regressions. Further details on the green and brown definitions, along with employment shares, are provided in Appendix A.

[1] See Appendix Table A.2 for a full list of included five-digit industry codes.

[2] Petroleum-oriented industries (as defined by Statistics Norway) supply goods and services primarily targeted at the extraction of petroleum products and are therefore likely to be affected by the energy transition. See Appendix Table A.9 for details.

[3] Sensitivity analyses show that results are robust to alternative thresholds ranging from just above 0% to 80%; see Figure 6.

3.2 Estimation sample

The starting point of our estimation sample is all wage and salaried employees aged 20 to 61. Following the literature, we restrict our attention to full-time employees (working 35 hours per week or more) in private-sector firms. In the two-way fixed effects model of log wages (Equation 1), firm and worker fixed effects are separately identified through worker mobility as workers move between firms. In this framework, the firm effects are identified only within each connected sets of firms, i.e. firms that are connected through at least one worker. A well-known problem in this literature is that the variance of the estimated firm effects will be biased upward when few movers connect firms (Andrews et al., 2008; Bonhomme et al., 2023). While this issue is a known problem for variance decompositions, it is less relevant for our purpose, as we focus on mean differences in firm effects across groups of firms and workers.

To address limited mobility bias in the variance decomposition, we implement the heteroskedasticity-robust leave-one-out bias correction proposed by Kline et al. (2020). In this approach, the model is fitted on the leave-one-out connected set, defined as the largest connected set that remains after any single worker is removed from the sample (Kline et al., 2020). Observations with missing wage information or missing data on education are also excluded from the sample.

The final estimation sample consists of 13,455,307 person-year observations and 71,403 unique firms. This corresponds to 95% of the person-year observations and 44% of firms in the full sample.

3.3 Descriptives of green and brown jobs

Table 2 presents summary statistics for firms and workers by the type of job, i.e., green, brown, or generic. Columns (1)-(4) are based on the full sample, while columns (5)-(8) are based on our baseline estimation sample, i.e. the leave-one-out connected set.

Employment shares: Using our broadest definition of green jobs (i.e., based on all four criteria described in Section 3.1), the green employment share is approximately 8.3% of total private-sector employment in our estimation sample (column (6)). Employment in green R&D firms account for 2.2%, the share of employment in green industries is around 2.3%, employment in green exporting firms is 4.5%, and firms with green patents represent just 0.5% of total private-sector employment (see Appendix Table A.13). By comparison, the employment share in brown jobs is 11.5% (column 7), with extraction and petroleum industries constituting the single largest category (7.7%) (see Appendix Table A.13).

Figure 1 shows the development of total green and brown employment over time. While the share of brown jobs declines significantly after 2014, the share of green employment remains relatively stable throughout the sample period. The decline in brown employment after 2014 must be understood in the context of the sharp and unexpected fall in oil prices in the summer of 2014, which triggered a substantial contraction in petroleum-related employment (Garnache et al., 2025).

	Full sample				Connected set			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Green	Brown	Generic	All	Green	Brown	Generic
Panel A: Firm characteristics								
Firm size	590.4	309.0	2001.8	415.7	621.6	312.7	2018.7	442.8
	(1627.3)	(490.1)	(3430.8)	(1153.1)	(1664.1)	(491.9)	(3440.3)	(1185.3)
Total hires	409.3	282.7	1058.7	323.9	430.9	286.1	1067.6	345.1
	(915.5)	(410.0)	(1663.5)	(752.5)	(934.4)	(411.3)	(1667.7)	(772.0)
Log of revenues	12.32	12.76	14.66	11.86	12.54	12.80	14.71	12.12
	(2.605)	(1.980)	(2.645)	(2.454)	(2.466)	(1.937)	(2.586)	(2.305)
Patents (yes = 1)	0.0815	0.135	0.388	0.0202	0.0857	0.136	0.391	0.0214
	(0.274)	(0.341)	(0.487)	(0.141)	(0.280)	(0.343)	(0.488)	(0.145)
R&D (yes = 1)	0.325	0.497	0.752	0.232	0.342	0.503	0.758	0.247
	(0.469)	(0.500)	(0.432)	(0.422)	(0.475)	(0.500)	(0.428)	(0.431)
Exports (yes = 1)	0.691	0.939	0.955	0.620	0.719	0.941	0.961	0.651
	(0.462)	(0.240)	(0.206)	(0.485)	(0.449)	(0.236)	(0.194)	(0.477)
Panel B: Worker characteristics								
Age	40.76	41.31	42.64	40.40	40.58	41.25	42.61	40.15
	(11.14)	(11.17)	(10.93)	(11.13)	(11.14)	(11.17)	(10.93)	(11.12)
Female	0.292	0.232	0.220	0.312	0.290	0.232	0.221	0.310
	(0.455)	(0.422)	(0.414)	(0.463)	(0.454)	(0.422)	(0.415)	(0.463)
Non-college	0.646	0.649	0.627	0.649	0.645	0.649	0.625	0.648
	(0.478)	(0.477)	(0.484)	(0.477)	(0.478)	(0.477)	(0.484)	(0.477)
College	0.354	0.351	0.373	0.351	0.355	0.351	0.375	0.352
	(0.478)	(0.477)	(0.484)	(0.477)	(0.478)	(0.477)	(0.484)	(0.477)
Monthly wage	60781.2	64519.3	74205.1	58251.6	61290.0	64590.6	74374.2	58729.2
	(37279.1)	(35208.4)	(42774.2)	(36190.6)	(37351.2)	(35168.4)	(42780.0)	(36255.5)
Unemployed next year	0.0802	0.0588	0.0679	0.0842	0.0780	0.0582	0.0675	0.0817
	(0.272)	(0.235)	(0.252)	(0.278)	(0.268)	(0.234)	(0.251)	(0.274)
N worker-year	14,167,704	1,127,853	1,567,342	11,139,211	13,455,307	1,114,274	1,554,229	10,454,290
N workers	2,074,806	248,506	281,286	1,820,454	1,979,852	245,170	278,351	1,721,880
N firms	238,026	6,989	6,355	225,498	105,403	4,949	4,015	97,129
Emp. share	1	.0796	.111	.786	1	.0828	.116	.777
Sample	Full	Full	Full	Full	Connected	Connected	Connected	Connected

Table 2: Summary statistics

Note: This table shows summary statistics from the full sample (columns 1-4) and the estimation sample (columns 5-8). The full sample consists of full-time private sector employees aged 20–61. The estimation sample is further restricted to the leave-one-out connected sets of firms, as well as workers with nonmissing data on wages, educational attainment, and field of study (see Section 3.2). The firm characteristics in panel A are weighted by firm-level employment. The variables *Patents*, *R&D* and *Exports* are time-invariant firm characteristics and are equal to 1 in the case of positive values in 2010–2018. The employment shares of green, brown, and generic workers do not sum up to 1 as mixed workers are excluded from the table.

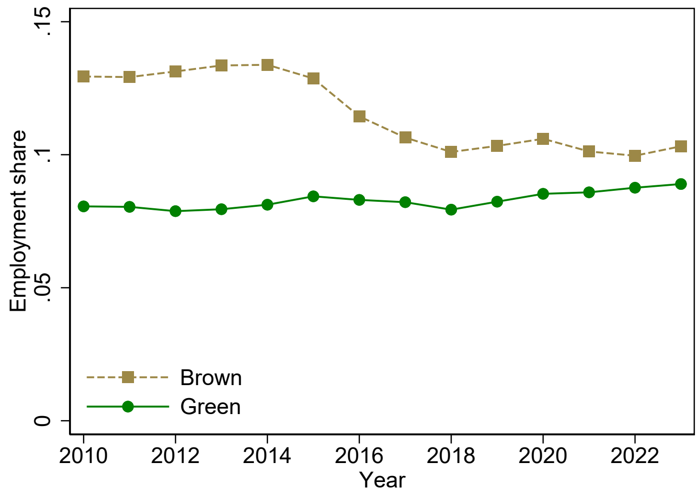


Figure 1: Green and brown employment shares 2010-2023

Note: The figure plots employment in green and brown jobs as a share of all private-sector full-time employees aged 20-61. The population is restricted to our estimation sample.

Table 3 lists the four-digit industries with the highest number of workers in green and brown jobs. The three largest green industries are *71.12 Engineering activities and related technical consultancy*, *35.13 Distribution of electricity*, and *35.11 Production of electricity*. The top ten green industries account for around 43% of total green employment in our estimation sample. The largest share of brown workers are employed in petroleum-oriented industries, such as *09.10 Support activities for petroleum and natural gas extraction*, *06.10 Extraction of crude petroleum*, and *Building of ships and floating constructions*. The top ten brown industries account for nearly 60% of total brown employment.

Firm characteristics: Green firms have a smaller number of employees and new hires compared to the average generic private-sector firm. The (employment-weighted) firm characteristics also show that green firms have slightly higher revenues and are much more likely to export (0.94 vs. 0.65), patent (0.14 vs. 0.02), and have intramural R&D expenditures (0.50 vs. 0.25). Brown firms are much larger than the average generic private-sector firm, and are also more likely to export (0.96), patent (0.40), and do R&D (0.76).

Worker characteristics: Compared to the average generic private-sector worker, employees in green and brown firms are more likely to be male. While the share of employees with a college degree is similar for green and generic firms (0.35), employees in brown firms are more likely to have a college degree (0.38). The latter implies that employees in brown firms appear to be positively selected relative to generic private-sector firms. Lastly, workers employed in green firms are less likely to receive unemployment benefits in the following year compared to those in generic firms (5.8% vs.

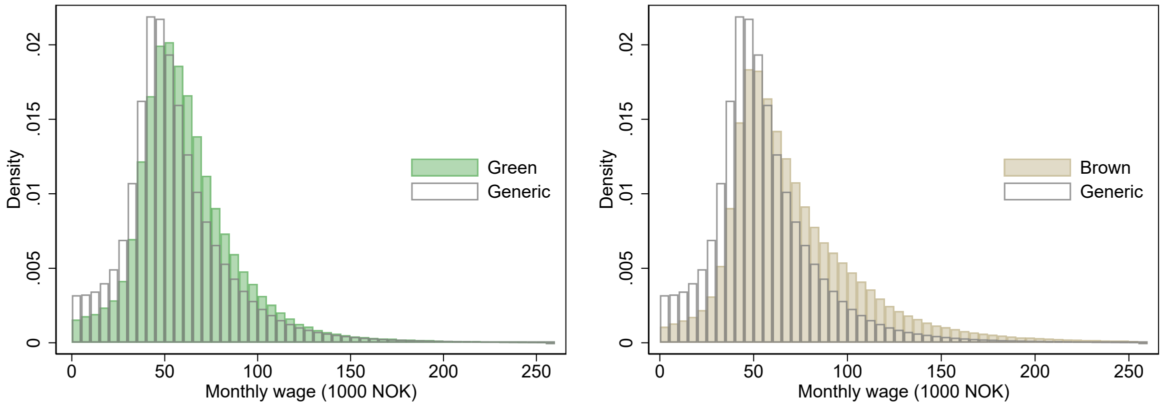
Industry	Workers	Share
Panel A: Green workers (N= 81,358)		
71.12: Engineer. act./rel. tech. consult	6,658	0.24
35.13: Distrib. of electricity	4,870	1.00
35.11: Prod of electricity	4,867	0.99
50.20: Sea/coast. freight water transp.	3,801	0.37
38.11: Coll. of non-hazardous waste	2,833	1.00
42.22: Constr. utility proj. el./telecomm.	2,640	1.00
46.69: W.sale other mach. and equip.	2,368	0.22
43.22: Plumbing etc.	2,328	0.15
43.21: Electrical installation	2,236	0.09
45.11: Sale of cars/light mot veh.	2,168	0.21
Panel A: Brown workers (N= 111,080)		
09.10: Supp. for petro/natural gas extrac	15,198	0.88
06.10: Extraction of crude petroleum	13,765	0.99
30.11: Build. ships/floating struct.	10,990	0.79
33.12: Rep. of machinery	5,074	0.85
10.51: Oper. of dairies /cheese making	4,095	0.99
28.92: Manuf. mach. mining/quarry./constr.	3,493	0.98
10.11: Processing and preserving of meat	3,386	0.84
25.62: Machining	3,307	0.88
25.11: Manuf. of metal structures, parts	3,221	0.84
10.20: Process. and preserv. of fish etc.	3,195	0.48

Table 3: Top 10 green and brown industries

Note: The table lists the four-digit industries with the largest number of green (Panel A) and brown (Panel B) workers. Column (1) shows the average number of green (brown) workers per year over 2010-2023. Column (2) shows the share of green (brown) employment within each respective four-digit industry. See Table 1 for definitions of green and brown. Industry codes follow the Sn2007 classification. The average number of green (brown) workers per year over 2010-2023 is 81,577 (110,657). See Appendix A for more detailed lists of green and brown employment shares.

8.2%), while workers in brown firms fall in between (6.8%). These figures indicate that green jobs may be less risky than generic jobs in terms of job stability, although the difference may also reflect sorting.

Wage gaps: Before turning to our estimates of the green wage premium, we first present descriptive evidence of raw wage differences across sectors. The average monthly salary in green jobs is nearly 57,000 NOK,which is 8.3% higher than the average in generic jobs. In contrast, brown jobs pay an average monthly wage of almost 65,000 NOK, corresponding to an unadjusted wage gap of 24% compared to generic jobs. These earnings differences persist across the entire wage distribution. Figure 2 shows the distribution of wages in green and brown jobs. Consistent with the summary statistics reported in Table 2, the earnings distribution for green jobs is shifted to the right relative to that for generic jobs, and the gap is even larger for brown jobs. Appendix Figure B.1 shows that this pattern holds for both college- and non-college-educated workers, as well as for both men and women.



(a) Green jobs

(b) Brown jobs

Figure 2: Monthly wages in green and brown jobs

Note: Figure plots the distribution of monthly earnings for workers in green jobs (panel a) and brown jobs (panel b), relative to a comparison group of workers in generic jobs.

3.4 Analysis of job mobility

The AKM modeling framework relies on a number of assumptions about wage formation, most notably additive separability and conditionally exogenous job mobility. To assess the plausibility of these assumptions in our setting, we estimate a series of event-study specifications following Card et al. (2013).

First, we assign each person-year observation in the sample to quartiles based on the mean wage of co-workers.[5] We then focus on the subsample of job-to-job transitions in which workers have at least two consecutive years of work experience at both the origin and destination firms. For this subsample, observations are assigned to one of sixteen cells using the quartile of co-worker wages in the origin and destination firms. We then calculate average wages within a four-year window around the job transition for each of these sixteen cells.

Figure 3 presents the estimated wage trajectories for job movers originating in the first and fourth quartiles. Overall, the patterns are consistent with the main assumptions of the model and closely resemble findings from other contexts (e.g., Card et al., 2013, 2016). Moves from low- to high-paying firms (e.g., Q1 to Q4) are associated with substantial wage gains, whereas moves from high- to low-paying firms (Q4 to Q1) are, on average, associated with sizable wage losses. Within each quartile of origin jobs, workers who transition to higher-paying firms tend to have higher wages in both their origin and destination jobs. Moreover, the groups tend to follow parallel pre-move

[5] Constructed as the leave-out mean log wage for all other workers in the firm-year, including both movers and stayers.

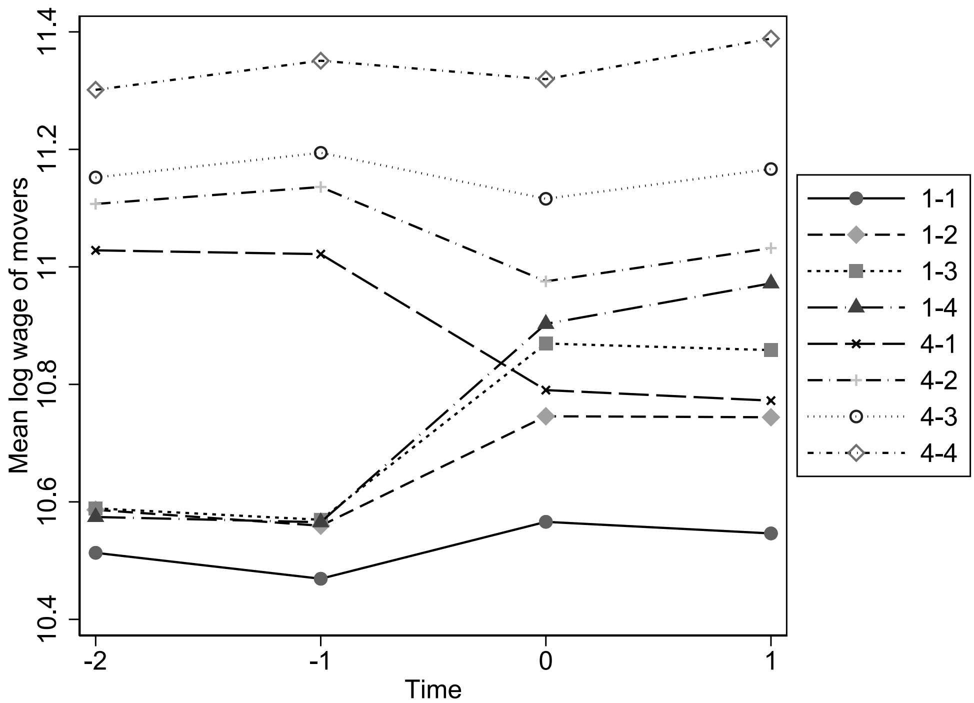


Figure 3: Wage profiles of job movers, classified by quartile of co-worker wages at origin and destination

Note: The figure shows mean log wages of workers who changed jobs and held their previous job for at least two years and their new job for at least two years. Jobs are classified into quartiles based on the mean log wage of co-workers (Card et al., 2013).

wage trends, meaning that pre-transition wage growth does not systematically differ by the direction or magnitude of the move. This pattern suggests that mobility is correlated with the worker fixed effect a_i, however, it does not indicate a violation of the conditional exogeneity assumption related to job mobility (Card et al., 2013).

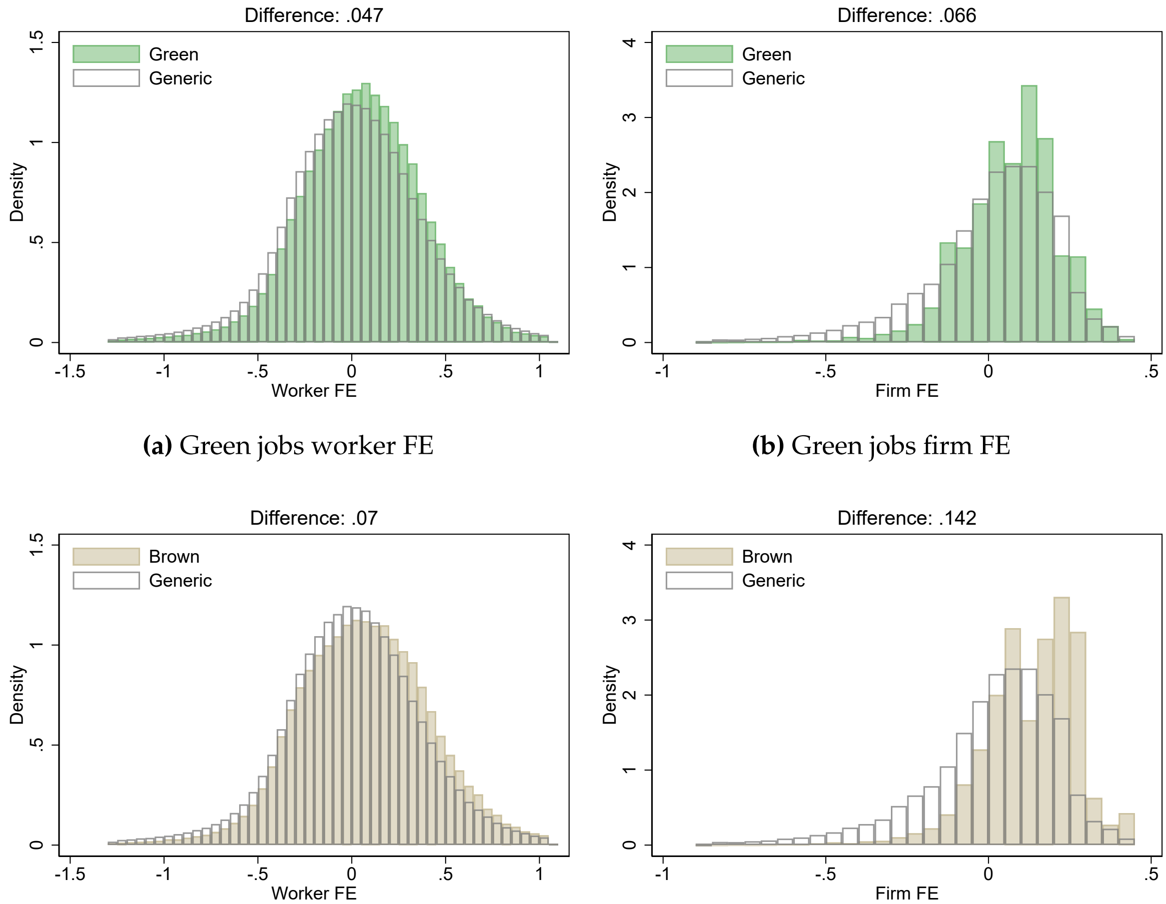
We estimate the AKM model for the pooled sample as well as separately by gender and by education (undergraduate degree or higher vs. high school or less).[6]

Appendix Table B.1 presents a variance decomposition of wages based on the estimated AKM models. In the pooled sample, firm effects account for 15% of the total estimated wage variance, while 4% can be attributed to sorting. Overall, the estimated variance shares attributable to firms are similar across genders and educational attainment. The role of sorting is somewhat smaller for non-college workers (2%) than for college-educated workers (6%).

[6]Estimation and bias-corrected variance decomposition are implemented in Python using the `pytwoway` package of Bonhomme et al. (2023).

4 Results

In this section, we present our main findings on the green wage premium. First, we show that estimated firm-level wage premiums are higher for green firms relative to generic firms. Second, the average green wage premium is positive and statistically significant. Third, the estimated wage premium for high-emission brown jobs is approximately twice the size of the green wage premium. We then present a series of robustness checks examining how the results vary with alternative definitions of green jobs, showing that our main findings are qualitatively unchanged. Finally, we present analyses of heterogeneity across workers by gender, education, and occupation.



(a) Green jobs worker FE

(b) Green jobs firm FE

(c) Brown jobs worker FE

(d) Brown jobs firm FE

Figure 4: Estimated firm and worker fixed effects in green and brown jobs

Note: The figure plots the distribution of estimated worker and firm effects for workers in green jobs (panels a - b) and brown jobs (panels c - d), relative to a comparison group of workers in generic jobs. "Difference" refers to the gap in log earnings between green (brown) and generic jobs.

4.1 Green and brown wage premiums

We start by presenting the distribution of the estimated firm and worker fixed effects in green and brown jobs, relative to the comparison group of generic jobs (Figure 4). The distribution of estimated worker fixed effects in green firms lies to the right of the distribution of workers in generic firms, showing that workers in green firms tend to be positively selected (panel a). On average, this difference corresponds to a 0.047 log points gap in earnings. A key advantage of the AKM ground-up approach is that it allows us to account for such non-random sorting of workers to firms when estimating firm wage premiums. The estimated distribution of firm fixed effects for green jobs lies to the right of the distribution for generic jobs, indicating that green firms tend to have systematically higher wages - controlling for worker sorting. A qualitatively similar pattern is found for brown jobs, with more pronounced gaps. On average, workers in brown firms have 0.07 log points higher estimated person fixed effects relative to generic firms.

Table 4 presents our baseline estimates of the green wage premium using the broadest definition of green jobs. The unadjusted green wage gap is 0.13.8 (column (1)), meaning that, on average, green jobs pay nearly 14% more than generic jobs. Adjusting for observable worker characteristics (column (2)), the estimated gap decreases to 7.6%. Thus, roughly half of the raw wage gap differential can be explained by differences in observable worker characteristics.

Table 4: Green and brown wage premiums

	(1) Raw gap	(2) Covariates	(3) Movers	(4) AKM
Panel A: Green jobs				
Green	0.138***	0.076***	0.048***	0.066***
	(0.019)	(0.012)	(0.005)	(0.009)
N	11,568,564	11,568,564	11,568,564	11,568,564
Panel B: Brown jobs				
Brown	0.267***	0.153***	0.082***	0.142***
	(0.050)	(0.026)	(0.005)	(0.017)
N	12,008,519	12,008,519	12,008,519	12,008,519

Note: Table shows estimated wage premiums in green and brown firms relative to generic jobs. Column (1) shows the raw wage gap, column (2) shows estimate from a cross-sectional wage regression (Equation (3)), column (3) shows the estimate from the industry mover model (Equation (4)), column (4) shows estimates from the AKM-based approach (Equations (1) and (2)). Standard errors clustered at the firm level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (3) presents results for the movers model in Equation (4), where the green wage premium is estimated directly based on indicators for job type (green or generic) rather than employment-weighed firm fixed effects. Using this specification, the estimated wage premium drops further to 4.8%. In our preferred specification (column (4)), the average green wage premium is estimated at 6.6%. This indicates that even after accounting for unobserved worker heterogeneity, the green wage premium remains positive and statistically significantly different from zero. Under the assumptions of our model, this point estimate implies that a worker who is exogenously shifted from a typical generic firm to a typical green firm can expect a wage gain of 6.6%.

The estimated effect from our preferred AKM-based specification is remarkably similar to the estimate from the cross-sectional wage regression reported in column (2). This similarity suggests that, in our context, controlling for a rich set of observable worker characteristics goes a long way toward accounting for the non-random sorting of workers across firms. In contrast, the estimate from the movers model of Equation (4), reported in column (3), is substantially smaller. One explanation for this difference is the so-called hierarchy effect (Card et al., 2023). In a standard job search model in which workers accept or reject job offers based on wages, workers moving from a high-paying sector to a lower-paying sector tend to originate from firms that pay relatively low wages within the high-paying sector and transition to firms that pay relatively high wages within the low-paying sector. In our setting, this mechanism would imply that workers moving from green firms to generic firms are disproportionately moving from below-average paying green firms to above-average paying generic firms, leading to an attenuated estimate of the green wage premium.

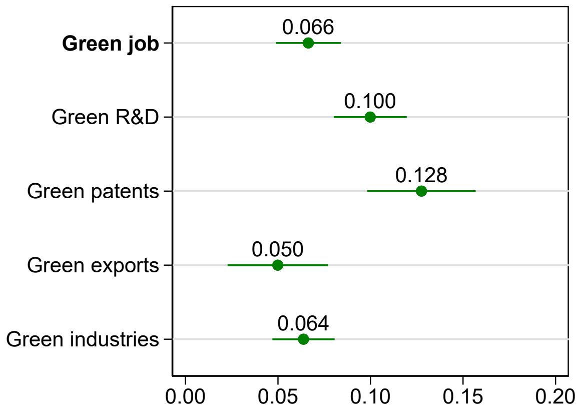
We next assess how the estimated green wage premium compares with the wage premium in brown jobs. Panel (B) of Table 4 presents our estimates of the brown wage premium across the four estimators. As with the green wage premium, we find that the raw wage gap substantially overstates the brown wage premium. For brown jobs (column (1)) the unadjusted wage gap is 0.267, meaning that, on average, brown jobs pay 26.7% more than generic jobs. Adjusting for observable worker characteristics reduces the estimated gap to 15.3% (column (2)), while using the industry mover model further reduces the estimated premium to 8.2% (column (3)). Our preferred specification (column (4)) indicates a brown wage premium of 14.2%. Our results thus suggest that brown jobs are systematically better paid than both green and generic jobs.

4.2 Green and brown wage premiums across definitions

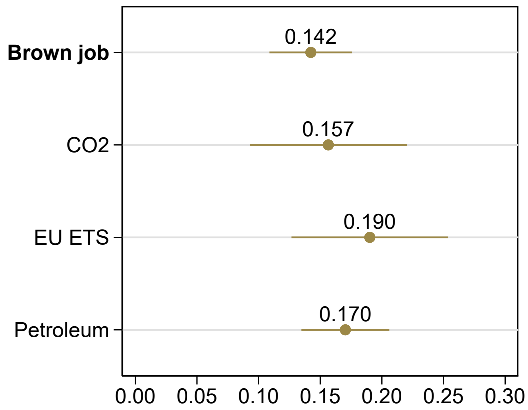
The green wage premium reported in Table 4 corresponds to our broad definition of green jobs, where a firm is classified as green if it meets at least one of four criteria: (1) a high share of green R&D, (2) a high share of green patents, (3) a high share of green exports, or (4) the firm belongs to a pre-defined set of green industries. To consider how the estimated wage premiums vary across definitions of green jobs, we re-estimate Equation (2) on separate samples consisting of green jobs in each category and the set of generic firms. Results from this exercise are presented in panel (a) of Figure 5, while raw wage gaps and corresponding estimates from models (3) and (4) are reported in Appendix Table C.1.

Qualitatively, the finding that the green wage premium is positive and statistically significantly different from zero is robust across all alternative definitions of green. Quantitatively, we find the largest estimated wage premiums among firms with a high share of green patents. Using the AKM approach, we estimate a wage premium of 0.128 for this category. These firms constitute a relatively small share of the overall economy. For firms with high green R&D investments, the estimated wage premium is 0.10 in our preferred specification. The lowest green wage premiums are found for definitions based on a high share of green exports (0.050) and for those based on industry classification alone (0.064).

We also examine how the estimated brown wage premium depends on the definition of brown firms by estimating Equation (2) separately for each of the three definitions of brown. Results from this exercise are presented in panel (b) of Figure 5. Overall, the estimated brown wage premium is not very sensitive to the definition of brown jobs: although the point estimates vary somewhat (ranging from 14.2% to 19%), the corresponding confidence intervals all overlap.



(a) Green



(b) Brown

Figure 5: Green and brown wage premiums across definitions.

Note: The figure shows estimated wage premiums in green jobs relative to generic jobs from our preferred AKM-based approach (Equations (1) and (2)). "Green job" is our baseline definition of green jobs, "Green R&D" is ≥50% green R&D, "Green patents" is ≥50% green patents, "Green exports" is ≥50% green exports, and "Green industries" is a list of green industries based on 5-digit NACE codes. "Brown job" is our baseline definition of brown jobs, "CO2" is positive emissions in at least one of the years 2010–2023, EU-ETS is participation in the EU-ETS scheme (at the five-digit industries level), "Petroleum" is fossil fuels, closely related services, and petroleum-oriented manufacturing. Whiskers indicate 95% confidence intervals; standard errors clustered at the firm level.

Of the four criteria used to identify green firms, three are binary transformations of underlying continuous measures: the firm's share of green R&D, green patents, and green exports. In our baseline definition, firms are classified as green if any of these shares exceed 50% - an admittedly arbitrary threshold. To assess the robustness of our results to this choice, we re-estimate Equation (2) for a set of alternative thresholds ranging from 0 to 80%.

Results from this exercise, presented in Figure 6, show that our finding of a positive and statistically significant green wage premium is qualitatively robust to the choice of threshold. Quantitatively, the estimated premium declines monotonically with the cut-off used to define a firm as green. At the lowest possible threshold – any positive share of green exports, patenting, or R&D activity (>0) – we estimate a green wage premium of nearly 14% - more than twice the baseline estimate of 6.6%. Using stricter thresholds (above 50%) slightly lowers the estimated premium. As the threshold approaches 100%, the sample of firms shrinks, and the estimate converge toward the green wage premium for green industries, which are always included by in the sample.[7]

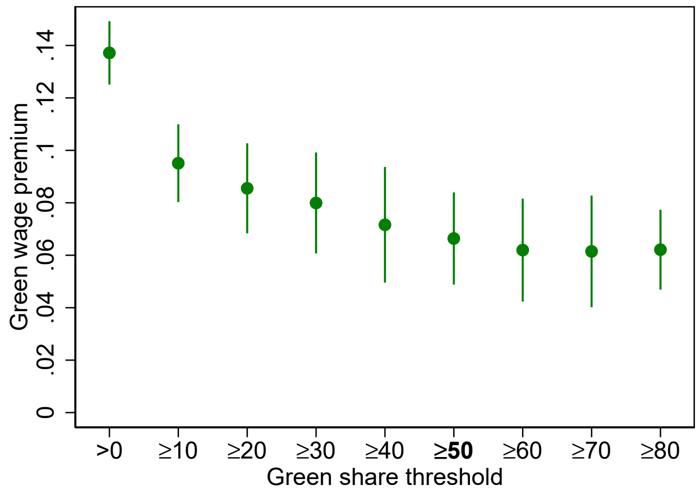


Figure 6: Green wage premium by different thresholds of green

Note: The figure shows how the estimated wage premiums from Equation (5) vary with different cutoffs used to define a firm as green. The coefficient plotted at ≥50 corresponds to our main point estimate reported in Table 4, column (4). Whiskers denote 95% confidence intervals; standard errors are clustered at the firm level. Note that one of the categories – green industry codes – does not rely on a threshold and is always included.

4.3 Heterogeneity in the green wage premium

A key question for assessing the distributional consequences of the green transition is how the green wage premium varies across groups of workers. To address this, we

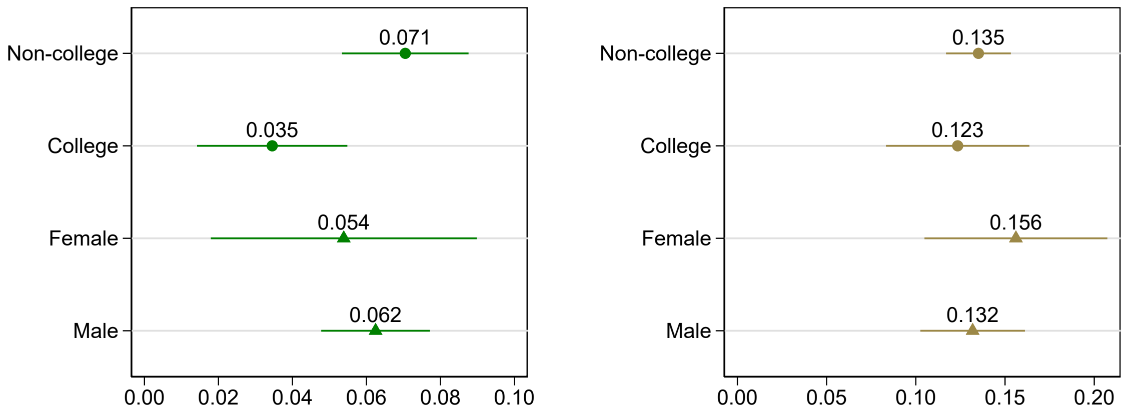
[7]Firms with a green share below the threshold are classified as non-green and are therefore included in the comparison group of generic firms.

estimate green wage premiums separately by gender and by educational attainment.

In the first step, we estimate the AKM model in Equation (1) separately for men and women, and for college-educated and non-college workers, thereby allowing firms to have distinct wage premia by gender and education. In the second step, we estimate Equation (2) to obtain the average green wage premium for each group of workers. Results from this analysis are presented in Figure 7.

We find substantial variation in the estimated green wage premium by educational attainment. For non-college workers, the average green wage premium is 0.071, whereas for college-educated workers the green wage premium is 0.035. This difference is statistically significant at conventional levels. By contrast, when estimating the models separately by gender, the differences are much less pronounced: men have slightly higher green wage premiums on average relative to women (0.062 vs 0.054), but the difference is not statistically significant.

As an additional point of comparison, we also estimate heterogeneous wage premiums for brown jobs. Results from this exercise are presented in panel (b) of Figure 7. Workers without a college degree have slightly higher estimated brown wage premiums than college educated workers, but the difference is not statistically significant. Similarly, we find no statistically significant differences in the brown wage premium by gender.



(a) Green

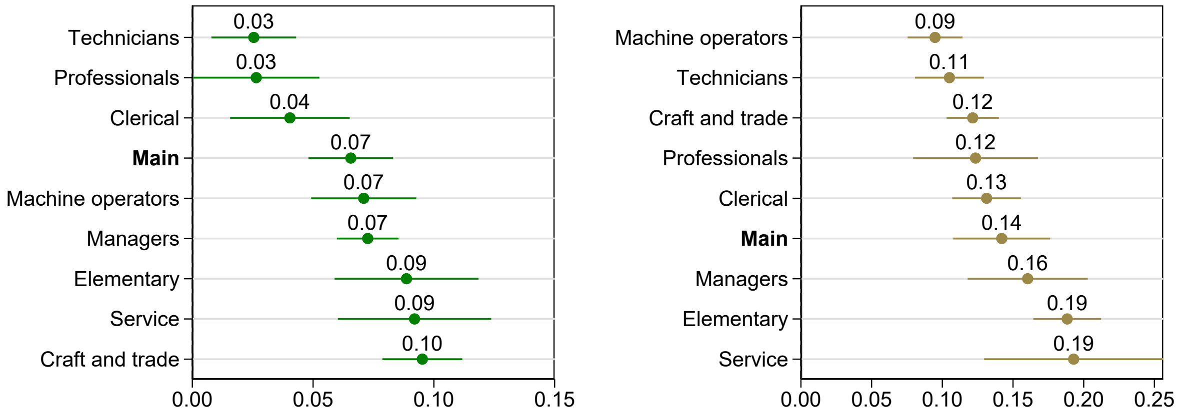
(b) Brown

Figure 7: Green and brown wage premiums by worker type

Note: The figure shows estimated wage premiums in green firms relative to generic jobs, based on our preferred AKM specification (Equations (1) and (2)), estimated separately by gender and education (non-college vs. some college or more). Whiskers denote 95% confidence intervals; standard errors are clustered at the firm level.

In our previous analyses in Section 4.2, we found that the estimated green wage premium varies across definitions of green jobs. A natural question is whether these patterns reflect differential sorting of workers across the various types of green jobs. To assess this possibility, we estimate the average green wage premium by worker type for each definition of green. Across all definitions, non-college workers consistently exhibit higher estimated green wage premiums than college-educated workers (see Appendix Table C.3).

Our finding that the green wage premium is larger for less-educated workers is consistent with a number of previous studies estimating green wage differentials by occupation (Vona et al., 2019). To relate our findings more directly to this literature, we estimate green wage premiums by occupational category. These estimates are based on firm fixed effects obtained from estimating Equation (1) on the pooled sample, meaning that our model does not allow firms to pay different wage premiums by occupation. Instead, the estimates capture differential sorting of workers across firms by occupation. Results from this analysis, presented in Figure 8, indicate that the green wage premium is larger for low-skilled occupations (*Craft and trade*, *Service*, and *Elementary*) compared to high-skilled occupations (*Professionals* and *Technicians*).



(a) Green

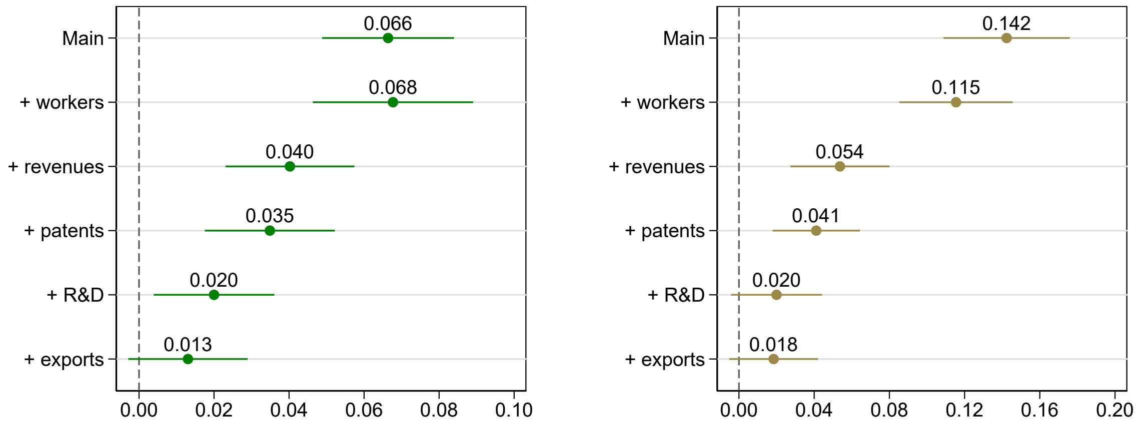
(b) Brown

Figure 8: Green and brown wage premiums within occupations

Note: The figure shows estimated wage premiums by occupation for green (panel a) and brown jobs (panel b). Occupations are classified according to STYRK-08, which is based on ISCO-08. Agriculture occupations are excluded due to a limited number of observations. Whiskers denote 95% confidence intervals; standard errors are clustered at the firm level.

5 Sources of the green and brown wage premium

In this section, we turn to the question of how the green wage premium relates to firm characteristics. Our preferred specification yields an average estimated green wage premium of 6.6%. Although the AKM approach fully accounts for time-invariant worker characteristics, this estimate should not be interpreted as the causal effect of job "greenness" per se. Rather, it may capture a combination of the causal green premium and systematic differences in observed or unobserved firm and job characteristics.



(a) Green

(b) Brown

Figure 9: Wage premiums accounting for firm characteristics

Note: Figure shows how the estimated wage premiums from Equation (5) evolve as more covariates are added to the regression specification. The leftmost point in each panel shows the baseline estimate from equation (2) without firm level covariates of β^j with 95% confidence intervals. The remaining points in the figure corresponds to a point estimate of β^j from Equation (5) with 95% confidence intervals when more covariates are added to the specification.

To explore this issue, we begin with a simple exercise examining the role of selected firm characteristics. Specifically, we augment the regression model in Equation (2) by including a vector of firm-level covariates X_f. Prior research has shown that these firm characteristics tend to be systematically correlated with wages – for instance, there is a well-established positive wage-firm size gradient (Oi and Idson, 1999). More broadly, the rent-sharing literature suggests that in frictional labor markets, patents and other productivity shocks to firms can spill over to wages (Card et al., 2018; Kline et al., 2019). In our full specification, X_f includes controls for firm size, log revenue, patenting volume, and an indicator for intramural R&D activity.

$$\theta_{f(i,t)} = a + \phi_{j(f)}\beta^j + X_{f(i,t)}\beta^f + \varepsilon_{it} \tag{5}$$

Results from this exercise are presented in Figure 9. Panel (a) shows how the estimated green wage premium changes as firm-level covariates are sequentially added to the regression. The top point in the figure corresponds to our baseline estimate of 6.6%. Adding a control for firm size (number of employees) has little effect on this estimate. However, once we include log revenues, the estimated green wage premium declines by roughly 40%. In the most saturated specification – adding controls for patenting volume, intramural R&D activity, and export status – the green wage premium falls to 1.3% and is no longer statistically distinguishable from zero.

Next, we examine the role of firm characteristics in explaining the brown wage premium. Results from this analysis are shown in panel (b) of Figure 9. While the estimated wage premiums are larger in magnitude, the qualitative pattern mirrors that observed for green jobs. In particular, controlling for log revenues substantially reduces the brown wage premium, consistent with the interpretation that resource rents are a key main driver of high wages in brown firms. In the most saturated specification – adding controls for patenting volume, intramural R&D activity and export status – the residual brown wage premium is 1.8%, and is not statistically distinguishable from zero.

Finally, we estimate a set of models of green and brown wage premiums within exporting and innovative firms (see Appendix C.2). Overall, these results indicate that accounting for firms' export and innovation status substantially reduces both the magnitude and statistical significance of the estimated green and brown wage premiums.

6 Comparing findings to the existing literature

Overall, our results show that workers in green firms earn a positive wage premium relative to workers in generic firms. However, this premium becomes considerably smaller – and eventually disappears – once we control for firm characteristics such as revenues, innovation activity, and export status. In this section, we compare our findings with results from the existing literature.

Figure 10 summarizes estimated green wage premiums across existing studies; see also Appendix Table D.1 for details on each study. When comparing our findings with those in the existing literature, it is important to recognize that estimated wage premiums can differ for serval reasons. As discussed above, the type of premium being estimated – wether conditional or unconditional on other firm and job characteristics – plays an important role. In addition, studies differ in their data sources, definitions of green jobs, comparison groups, and country and time coverage. For all these reasons, the estimates are not necessarily directly comparable. Nonetheless, by situating our findings within the broader literature, we can identify potential similarities and patterns across estimates of the green wage premium.

Magnitude: Overall, most studies report positive green wage premiums, although the magnitudes differ substantially. Curtis and Marinescu (2023) report the largest premium, finding an occupational wage premium of 20–23% for wind and solar jobs in the United States. Renewable jobs are identified based on keywords in online job advertisements, and the estimates compare median occupational wages in solar and wind jobs to other, non-fossil jobs in the U.S. economy, controlling for average educational requirements. When comparing the premium within two-digit occupations, the estimated premium declines substantially – to 15% for solar jobs and to 5.5% (and statistically indistinguishable from zero) for wind jobs. Colmer et al. (2023) also focus on the

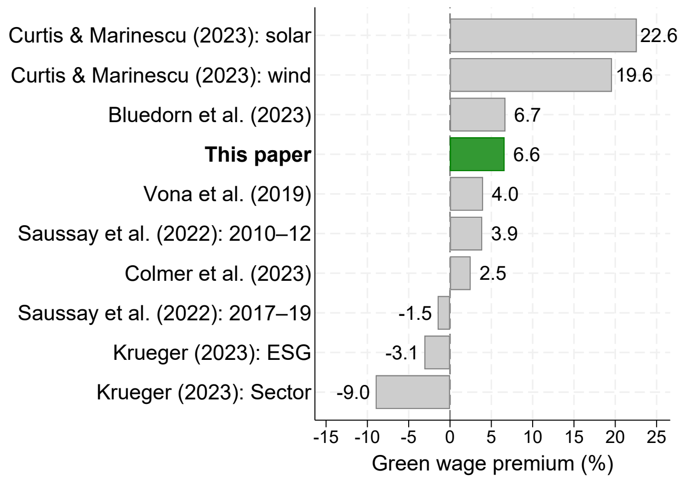


Figure 10: Green wage premiums across studies
Note: The figure shows estimated green wage premiums across studies. Further details on each study are provided in Appendix Table D.1.

U.S. energy sector but define green (or "clean") energy jobs based on industry codes and company. While the estimated wage premium is substantially lower (2.5%), this figure reflects the wage gap between clean and legacy ("brown") energy jobs. When comparing green jobs to jobs outside the energy sector, the estimated premium rises to roughly 33.5% – the highest among the studies reviewed.

Saussay et al. (2022) use a broader definition of green jobs in the U.S. by combining online job advertisement data with low-carbon keywords. They estimate the green wage premium separately for eight major occupational groups, using stated wages in ads and controlling for factors such as two-digit industry, six-digit occupation codes, commuting zones, and broad educational requirements. For the period 2010–2012, all occupational green wage premiums are positive except one, yielding an unweighted average premium across occupations of 3.9%. When focusing on 2017–2022, however, the average premium turns negative (–1.5%). Vona et al. (2019) also use a broad definition of green jobs, based on task requirements in U.S. occupations, and find a positive wage premium of roughly 4% relative to comparable non-green occupations. The broader definitions beyond the energy sector, combined with comparisons within narrowly defined occupations, may help explain some of the discrepancy in magnitudes between these two studies and those of Curtis and Marinescu (2023) and Colmer et al. (2023).

A few studies also examine green jobs outside the United States. Bluedorn et al. (2023) use data from labor force surveys covering 31 countries in Europe and the United States. Controlling for individual characteristics, country-year fixed effects, and the pollution intensity of jobs, they find that green-intensive jobs (measured in a manner similar to Vona et al. (2018)) pay, on average, a 6.7% premium relative to pollution-intensive jobs, and a 9–14% premium relative to neutral jobs.[8] Lastly, Krueger et al. (2023) combine matched employer-employee data from Sweden with firm-level ESG-scores and a sector-level sustainability measure. Their main specification, which includes individual characteristics and occupational-year fixed effects, shows a negative green wage premium of -9% for the sector-measure and around -3% for the ESG score. Using an industry-mover model with worker fixed effects reduces the former gap to -5.5%.

By worker type: Our finding that the green wage premium is higher for non-college workers appears to be consistent with the existing literature. Vona et al. (2019) find that green wage premiums are larger in low-skill manual occupations than in high-skill occupations (8% vs. 2%). Similarly, Curtis and Marinescu (2023) find that green energy wage premiums are higher for jobs that do not require a college degree (15-30%) relative to jobs that require a bachelor's degree (5-10%). Krueger et al. (2023) also finds that the negative sustainability gap is larger for high-skilled workers. Moreover, they report no significant gender differences, consistent with our results.

By occupation: We find that the green wage premium is lowest for high-skilled occupations (e.g., Professionals, Technicians) and highest for low-skilled occupations (e.g., Craft and trade, Elementary, Service). Saussay et al. (2022) present a more mixed picture, with no clear overall pattern. The most persistent and statistically significant positive green wage gaps are found for "Engineering and Technicians" and "Installation, Maintenance, and Repair."

7 Conclusion

Reducing carbon emissions requires a structural shift away from fossil fuel-intensive industries. As jobs in these industries have traditionally offered relatively high wages, there is concern that this transition may entail income losses for affected workers. The magnitude and sign of the green wage premium are therefore central for assessing whether the emergence of new green employment opportunities can help mitigate these losses.

In this paper, we estimate an average wage premiums in green jobs of 6.6%, while the average premium in brown jobs is just over 14%. These premiums remain positive across alternative definitions of green and brown firms, as well as across educational attainment, gender, and occupational groups. We find significantly higher green wage premiums for non-college workers, but do not detect a similar difference for the brown wage premium, or across gender. To examine the source of the wage premiums, we

[8] The latter interval is calculated using the stated average green intensity, which ranges between 2 and 3%.

control for a set of firm characteristics (size, revenues, patenting and R&D activity, and export status). After accounting for these factors, the residual wage premiums for both green and brown jobs are close to zero and not statistically significant. This result is consistent with a pattern of rent-sharing, where high-revenue, highly innovative brown and green firms pay higher wages to otherwise similar workers.

Taken together, our results have important implications for the expected labor market impacts of the green transition. The large estimated wage premiums in brown jobs suggests that a contraction in fossil fuel-intensive employment is likely to lead to earnings losses for displaced workers. At the same time, the positive green wage premium indicates that the creation of new green jobs may help offset some of these losses. Moreover, the larger estimated green wage premiums for non-college workers – both relative to generic jobs and to brown jobs – suggests that the expansion of high-paying green jobs could improve the distributional consequences of the green transition.

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Online supporting material

A green wage premium?

Authors: Anna Godøy and Elisabeth T. Isaksen

Contents

Appendix A Green and brown definitions

A.1 Green jobs

Industry	Green workers N	Share	Emp. shares by definition Export	Patent	R&D	Sn2007
71.12: Engineer. act./rel. tech. consult	6,658	0.24	0.11	0.02	0.13	0.00
35.13: Distrib. of electricity	4,870	1.00	0.10	0.04	0.05	1.00
35.11: Prod of electricity	4,867	0.99	0.19	0.00	0.59	0.98
50.20: Sea/coast. freight water transp.	3,801	0.37	0.34	0.01	0.04	0.00
38.11: Coll. of non-hazardous waste	2,833	1.00	0.28	0.00	0.33	1.00
42.22: Constr. utility proj. el./telecomm.	2,640	1.00	0.07	0.00	0.00	1.00
46.69: W.sale other mach. and equip.	2,368	0.22	0.18	0.02	0.04	0.00
43.22: Plumbing etc.	2,328	0.15	0.15	0.00	0.01	0.00
43.21: Electrical installation	2,236	0.09	0.07	0.00	0.02	0.00
45.11: Sale of cars/light mot veh.	2,168	0.21	0.21	0.00	0.00	0.00
38.32: Recov. of sorted materials	1,839	0.90	0.28	0.00	0.50	0.90
81.21: General cleaning of buildings	1,825	0.29	0.29	0.00	0.00	0.00
72.19: Other R&D on natural sciences etc.	1,806	0.29	0.17	0.12	0.04	0.00
43.22: Plumbing, heat and air-conditioning installation	1,751	0.12	0.11	0.00	0.01	0.00
35.14: Trade of electricity	1,584	1.00	0.04	0.00	0.27	1.00
45.20: Maint./repair of motor vehicles	1,497	0.09	0.09	0.00	0.00	0.00
69.20: Account./bookkeep./tax consult.	1,397	0.09	0.09	0.00	0.00	0.00
46.74: W.sale hardware, plumb, heat equip.	1,268	0.21	0.06	0.00	0.16	0.00
03.21: Marine aquaculture	1,239	0.25	0.04	0.20	0.01	0.00
42.21: Construc. utility proj. for fluids	1,144	1.00	0.12	0.00	0.06	1.00
41.20: Construction of buildings	1,136	0.03	0.01	0.00	0.01	0.00
35.12: Transmission of electricity	1,087	1.00	0.00	0.00	0.00	1.00
50.10: Sea/coast. passenger water transp.	1,015	0.16	0.03	0.12	0.01	0.00
75.00: Veterinary activities	858	0.75	0.75	0.00	0.00	0.00
43.99: Other spec. construc. act. n.e.c.	807	0.08	0.05	0.00	0.03	0.00
46.63: W.sale mining., construc mach. etc.	774	0.17	0.15	0.00	0.02	0.00
52.29: Other transp. supply serv.	731	0.10	0.05	0.00	0.05	0.00
23.61: Concrete prod. for construc. purposes	715	0.28	0.04	0.00	0.24	0.00
71.20: Technical testing and analysis	684	0.14	0.11	0.00	0.03	0.00
56.29: Other food services	682	0.23	0.22	0.00	0.00	0.00
37.00: Sewerage	674	1.00	0.10	0.00	0.10	1.00
42.11: Construc. of roads and motorways	641	0.11	0.01	0.00	0.10	0.00
52.22: Serv. act. to water transp.	602	0.22	0.14	0.04	0.08	0.00
43.12: Site preparation	592	0.04	0.02	0.00	0.02	0.00
52.23: Serv. act. to air transp.	585	0.13	0.13	0.00	0.00	0.00
46.46: W.sale pharmaceut. goods	520	0.10	0.09	0.00	0.01	0.00
10.20: Process. and preserv. of fish etc.	502	0.07	0.01	0.02	0.04	0.00
62.02: Computer consultancy act.	488	0.03	0.02	0.00	0.01	0.00
71.11: Architectural act.	475	0.11	0.01	0.00	0.10	0.00
46.73: W.sale wood, construc. mach. etc.	475	0.06	0.05	0.01	0.02	0.00
55.10: Hotels and sim. accomm.	463	0.05	0.05	0.00	0.00	0.00
49.41: Freight transp. by road	459	0.03	0.02	0.00	0.01	0.00
62.01: Computer programming act.	452	0.04	0.03	0.00	0.01	0.00
81.29: Other cleaning act.	452	0.47	0.47	0.00	0.00	0.00
16.10: Sawing and planing of wood	446	0.19	0.00	0.00	0.19	0.00
64.19: Other monetary intermed.	370	0.02	0.02	0.00	0.00	0.00
10.71: Manuf. of bread/ fresh cakes etc.	361	0.10	0.10	0.00	0.00	0.00
08.12: Operation of gravel and sand pits	360	0.25	0.07	0.00	0.18	0.00
38.21: Treat./disp. of non-hazard. waste	339	0.81	0.17	0.02	0.45	0.81
47.76: Ret. sale flowers, plants etc.	326	0.20	0.20	0.00	0.00	0.00

Table A.1: Top 50 green industries

Note: This table lists the 4 digit industries with the highest number of green workers. A firm is defined as green if the average patent, export, or R&D share in 2010-2023 exceeds 50%, or if the firm operates in a 5 digit industry classified as green. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

Green based on industry code

Code	Title
35.111	Production of electricity through water power
35.112	Production of electricity through wind power
35.113	Production of electricity through biofuel
35.120	Transmission of electricity
35.130	Distribution of electricity
35.140	Trade of electricity
35.300	Steam and air conditioning supply
36.000	Water collection, treatment and supply
37.000	Sewerage
38.110	Collection of non-hazardous waste
38.120	Collection of hazardous waste
38.210	Treatment and disposal of non-hazardous waste
38.220	Treatment and disposal of hazardous waste
38.310	Dismantling of wrecks
38.320	Recovering of sorted materials
39.000	Remediation activities and other waste management services
42.210	Construction of utility projects for fluids
42.220	Construction of utility projects for electricity and telecommunications

Table A.2: Green industries based on industry code

Note: This table lists the 5 digit industries defined as green. The industry codes correspond to the Sn2007 classification.

	Green workers	
Industry	N	Share
35.13: Distrib. of electricity	4,870	1.00
35.11: Prod of electricity	4,805	0.98
38.11: Coll. of non-hazardous waste	2,833	1.00
42.22: Constr. utility proj. el./telecomm.	2,640	1.00
38.32: Recov. of sorted materials	1,839	0.90
35.14: Trade of electricity	1,584	1.00
42.21: Construc. utility proj. for fluids	1,144	1.00
35.12: Transmission of electricity	1,087	1.00
37.00: Sewerage	674	1.00
38.21: Treat./disp. of non-hazard. waste	339	0.81
38.12: Coll. of hazardous waste	267	0.91
38.22: Treat./disp. of hazardous waste	153	0.78
35.30: Steam and air conditioning supply	125	0.31
36.00: Water supply	49	1.00
39.00: Remediation, other waste managem.	47	1.00
38.31: Dismantling of wrecks	16	0.91

Table A.3: Top green industries based on industry code

Note: This table lists the 4 digit industries with the highest number of green workers. A firm is defined as green if operates in a 5 digit industry classified as green. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2018 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

Green based on patent data

Industry	Green workers N	Share
03.21: Marine aquaculture	1,020	0.20
50.10: Sea/coast. passenger water transp.	776	0.12
72.19: Other R&D on natural sciences etc.	729	0.12
71.12: Engineer. act./rel. tech. consult	502	0.02
13.94: Manuf. of cordage, rope etc.	244	0.43
46.69: W.sale other mach. and equip.	242	0.02
35.13: Distrib. of electricity	211	0.04
20.59: Manuf. of other chemical prod. n.e.c.	154	0.23
10.20: Process. and preserv. of fish etc.	149	0.02
50.20: Sea/coast. freight water transp.	119	0.01
03.22: Freshwater aquaculture	110	0.13
52.22: Serv. act. to water transp.	108	0.04
28.93: Manuf. mach. food/beverages/tobacco	80	0.12
46.73: W.sale wood, construc. mach. etc.	49	0.01
22.29: Manuf. of other plastic products	44	0.06
13.95: Manuf. of non-wovens and -articles	37	0.99
74.90: Prof. scient/tech. act. n.e.c.	34	0.02
22.23: Manuf. of builders' ware of plastic	33	0.05
72.11: R&D on biotechnology	32	0.07
22.21: Manuf. of plastic plates, sheets etc.	28	0.03
29.31: Electric/electron. equip. motor veh.	28	0.11
74.10: Specialised design act.	20	0.01
62.01: Computer programming act.	19	0.00
26.11: Manuf. of electronic components	17	0.03
46.76: W.sale other intermediate prod.	12	0.01
33.11: Rep. of fabricated metal prod.	12	0.02
23.61: Concrete prod. for construc. purposes	12	0.00
27.40: Manuf. of electric lighting equip.	12	0.03
43.22: Plumbing etc.	11	0.00
70.22: Business/oth. manage. consult act.	10	0.00
52.29: Other transp. supply serv.	10	0.00

Table A.4: Top 30 green patenting industries

Note: This table lists the 4 digit industries with the highest number of green patenting workers. A firm is defined as green if the average green patenting share exceeds 50%. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries. Industries with less than 10 green workers are excluded from the table.

Green based on R&D data

Thematic area	Broad area
Environmental technology	Environment
Onshore environment and society	Environment
Other environmental research	Environment
Climate technology and other emission reductions	Climate
Climate and climate change adaption	Climate
Carbon capture and storage (CCS)	Climate
Renewable energy	Energy

Table A.5: Thematic areas in the R&D survey labeled as green

	Green workers	
Industry	N	Share
71.12: Engineer. act./rel. tech. consult	3,623	0.13
35.11: Prod of electricity	2,896	0.59
38.32: Recov. of sorted materials	1,055	0.50
46.74: W.sale hardware, plumb, heat equip.	952	0.16
38.11: Coll. of non-hazardous waste	939	0.33
41.20: Construction of buildings	614	0.01
23.61: Concrete prod. for construc. purposes	607	0.24
42.11: Construc. of roads and motorways	603	0.10
43.21: Electrical installation	505	0.02
16.10: Sawing and planing of wood	445	0.19
71.11: Architectural act.	434	0.10
46.69: W.sale other mach. and equip.	431	0.04
35.14: Trade of electricity	423	0.27
52.29: Other transp. supply serv.	377	0.05
50.20: Sea/coast. freight water transp.	364	0.04
43.99: Other spec. construc. act. n.e.c.	331	0.03
43.12: Site preparation	321	0.02
10.20: Process. and preserv. of fish etc.	301	0.04
35.13: Distrib. of electricity	264	0.05
08.12: Operation of gravel and sand pits	254	0.18
72.19: Other R&D on natural sciences etc.	233	0.04
16.23: Manuf. builders' carp./joinery etc.	226	0.04
43.11: Demolition	209	0.29
43.22: Plumbing etc.	207	0.01
52.22: Serv. act. to water transp.	205	0.08
49.31: Urb./suburb. passenger land trans.	201	0.03
62.02: Computer consultancy act.	189	0.01
49.41: Freight transp. by road	187	0.01
38.21: Treat./disp. of non-hazard. waste	186	0.45
49.39: Other pass. land transp. n.e.c.	184	0.05

Table A.6: Top 30 green R&D industries

Note: This table lists the 4 digit industries with the highest number of green R&D workers. A firm is defined as green if the average green R&D share exceeds 50%. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

Green based on exporting data

Industry	Green workers N	Share
50.20: Sea/coast. freight water transp.	3,544	0.34
71.12: Engineer. act./rel. tech. consult	2,992	0.11
43.22: Plumbing etc.	2,214	0.15
45.11: Sale of cars/light mot veh.	2,168	0.21
46.69: W.sale other mach. and equip.	1,912	0.18
81.21: General cleaning of buildings	1,825	0.29
43.21: Electrical installation	1,767	0.07
43.22: Plumbing, heat and air-conditioning installation	1,645	0.11
45.20: Maint./repair of motor vehicles	1,497	0.09
69.20: Account./bookkeep./tax consult.	1,397	0.09
72.19: Other R&D on natural sciences etc.	1,074	0.17
35.11: Prod of electricity	934	0.19
75.00: Veterinary activities	858	0.75
38.11: Coll. of non-hazardous waste	796	0.28
46.63: W.sale mining., construc mach. etc.	685	0.15
56.29: Other food services	676	0.22
52.23: Serv. act. to air transp.	585	0.13
38.32: Recov. of sorted materials	578	0.28
71.20: Technical testing and analysis	546	0.11
41.20: Construction of buildings	522	0.01
43.99: Other spec. construc. act. n.e.c.	499	0.05
35.13: Distrib. of electricity	497	0.10
46.46: W.sale pharmaceut. goods	484	0.09
55.10: Hotels and sim. accomm.	463	0.05
81.29: Other cleaning act.	450	0.47
52.22: Serv. act. to water transp.	386	0.14
64.19: Other monetary intermed.	370	0.02
62.01: Computer programming act.	357	0.03
10.71: Manuf. of bread/ fresh cakes etc.	353	0.10
46.73: W.sale wood, construc. mach. etc.	345	0.05

Table A.7: Top 30 green exporting industries

Note: This table lists the 4 digit industries with the highest number of green exporting workers. A firm is defined as green if the average green export share exceeds 50%. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

A.2 Brown jobs

Industry	Workers	Share	Emp. shares by definition CO2	EU ETS	Petroleum
09.10: Supp. for petro/natural gas extrac	15,198	0.88	0.11	0.00	0.88
06.10: Extraction of crude petroleum	13,765	0.99	0.87	0.99	0.99
30.11: Build. ships/floating struct.	10,990	0.79	0.23	0.00	0.79
33.12: Rep. of machinery	5,074	0.85	0.09	0.00	0.85
10.51: Oper. of dairies /cheese making	4,095	0.99	0.96	0.99	0.00
28.92: Manuf. mach. mining/quarry./constr.	3,493	0.98	0.00	0.00	0.98
10.11: Processing and preserving of meat	3,386	0.84	0.84	0.00	0.00
25.62: Machining	3,307	0.88	0.00	0.00	0.88
25.11: Manuf. of metal structures, parts	3,221	0.84	0.06	0.00	0.84
10.20: Process. and preserv. of fish etc.	3,195	0.48	0.08	0.42	0.00
24.42: Aluminium production	3,170	0.98	0.87	0.98	0.00
28.22: Manuf. lifting/handling equip.	2,509	0.91	0.23	0.00	0.91
33.15: Rep./maint. of ships and boats	2,071	0.78	0.00	0.00	0.78
52.23: Serv. act. to air transp.	1,840	0.40	0.40	0.00	0.00
33.20: Install. of ind. mach. and equip.	1,732	0.90	0.00	0.00	0.90
25.99: Manuf. of other fabr. metal products	1,670	0.74	0.14	0.00	0.74
10.91: Manuf. of prep. feeds for farm anim.	1,663	0.97	0.59	0.97	0.00
10.13: Prod. of meat/poultry meat prod.	1,323	0.46	0.46	0.00	0.00
27.12: Elec. distrib. and control apparatus	1,319	0.67	0.01	0.00	0.67
06.20: Extraction of natural gas	1,280	1.00	0.95	1.00	1.00
26.51: Measuring, testing, navig. instrum.	1,121	0.28	0.00	0.00	0.28
25.12: Manuf. of doors/windows of metal	1,078	0.96	0.00	0.00	0.96
28.13: Manuf. of other pumps, compressors	1,031	0.49	0.25	0.00	0.49
20.13: Manuf. of other inorg. basic chem.	969	0.75	0.75	0.75	0.00
10.89: Manuf. of other products n.e.c.	921	0.99	0.67	0.99	0.00
25.61: Treatment and coating of metals	872	0.74	0.01	0.00	0.74
72.19: Other R&D on natural sciences etc.	827	0.13	0.13	0.00	0.00
24.10: Manuf. basic iron and steel etc.	796	0.83	0.77	0.83	0.00
46.21: W.sale grain, unmanuf. tobacco etc.	769	0.78	0.78	0.00	0.00
20.14: Manuf. of other organic basic chem.	769	0.98	0.86	0.98	0.00
21.20: Manuf. of pharm. preparations	755	0.45	0.45	0.00	0.00
20.30: Manuf. of paints,varnishes,coatings	716	0.79	0.79	0.00	0.00
16.21: Veneer sheets, wood-based materials	702	0.94	0.49	0.94	0.00
17.12: Manuf. of paper and paperboard	687	0.91	0.78	0.91	0.00
23.99: Manuf. of other non-met. min. prod.	676	0.41	0.04	0.41	0.00
19.20: Manuf. of refined petroleum prod.	625	0.99	0.98	0.99	0.00
28.29: Other gen-purp. machinery n.e.c.	614	0.61	0.00	0.00	0.61
27.90: Manuf. of other electrical equip.	591	0.74	0.19	0.00	0.74
27.11: Electric motors, generators etc.	553	0.85	0.01	0.00	0.85
28.12: Manuf. of fluid power equip.	451	0.56	0.07	0.00	0.56
17.21: Manuf. of corrugat. paper and -board	450	0.75	0.48	0.75	0.00
20.15: Fertilisers and nitrogen compounds	432	0.59	0.00	0.59	0.00
24.45: Other non-ferrous metal production	430	1.00	1.00	0.00	0.00
28.99: Manuf. other spec. purp. mach.	419	0.44	0.00	0.00	0.44
10.52: Manufacture of ice cream	405	0.57	0.57	0.00	0.00
28.25: Non-domestic. cool./ventil. equip.	396	0.48	0.00	0.00	0.48
10.82: Manuf. of cocoa, chocolate etc.	341	0.52	0.52	0.00	0.00
25.93: Manuf. wire prod., chain and springs	332	0.83	0.00	0.00	0.83
21.10: Manuf. of basic pharm. products	331	1.00	0.90	1.00	0.00
10.41: Manufacture of oils and fats	327	0.86	0.44	0.69	0.00

Table A.8: Top 50 brown industries

Note: This table lists the 4 digit industries with the highest number of brown workers. A firm is defined as brown if the the firm operates in a 5 digit industry classified as a extraction or petroleum oriented manufacturing, has positive CO2 emissions, or is part of the EU ETS. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the brown employment share within the respective 4 digit industries.

Brown based on petroleum-related industry

Industry	Brown workers N	Share
09.10: Supp. for petro/natural gas extrac	15,198	0.88
06.10: Extraction of crude petroleum	13,765	0.99
30.11: Build. ships/floating struct.	10,990	0.79
33.12: Rep. of machinery	5,074	0.85
28.92: Manuf. mach. mining/quarry./constr.	3,493	0.98
25.62: Machining	3,307	0.88
25.11: Manuf. of metal structures, parts	3,221	0.84
28.22: Manuf. lifting/handling equip.	2,509	0.91
33.15: Rep./maint. of ships and boats	2,071	0.78
33.20: Install. of ind. mach. and equip.	1,732	0.90
25.99: Manuf. of other fabr. metal products	1,670	0.74
27.12: Elec. distrib. and control apparatus	1,319	0.67
06.20: Extraction of natural gas	1,280	1.00
26.51: Measuring, testing, navig. instrum.	1,121	0.28
25.12: Manuf. of doors/windows of metal	1,078	0.96
28.13: Manuf. of other pumps, compressors	1,031	0.49
25.61: Treatment and coating of metals	872	0.74
28.29: Other gen-purp. machinery n.e.c.	614	0.61
27.90: Manuf. of other electrical equip.	591	0.74
27.11: Electric motors, generators etc.	553	0.85
28.12: Manuf. of fluid power equip.	451	0.56
28.99: Manuf. other spec. purp. mach.	419	0.44
28.25: Non-domestic. cool./ventil. equip.	396	0.48
25.93: Manuf. wire prod., chain and springs	332	0.83
33.14: Rep. of electrical equip.	200	0.52
28.11: Manuf. of engines and turbines	179	0.15
25.29: Other metal tanks, reservoirs etc.	163	0.70
28.14: Manuf. of taps and valves	160	0.45
49.50: Transport via pipeline	94	1.00
28.91: Manuf. mach. for metallurgy	48	1.00

Table A.9: Top 30 brown petroleum-related industries

Note: This table lists the 4 digit industries with the highest number of green exporting workers. A firm is defined as green if the average green export share exceeds 50%. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

Brown based on EU ETS

Industry	Brown workers N	Share
06.10: Extraction of crude petroleum	13,765	0.99
10.51: Oper. of dairies /cheese making	4,095	0.99
24.42: Aluminium production	3,170	0.98
10.20: Process. and preserv. of fish etc.	2,821	0.42
10.91: Manuf. of prep. feeds for farm anim.	1,663	0.97
06.20: Extraction of natural gas	1,280	1.00
20.13: Manuf. of other inorg. basic chem.	969	0.75
10.89: Manuf. of other products n.e.c.	921	0.99
24.10: Manuf. basic iron and steel etc.	796	0.83
20.14: Manuf. of other organic basic chem.	769	0.98
16.21: Veneer sheets, wood-based materials	702	0.94
17.12: Manuf. of paper and paperboard	687	0.91
23.99: Manuf. of other non-met. min. prod.	676	0.41
19.20: Manuf. of refined petroleum prod.	625	0.99
17.21: Manuf. of corrugat. paper and -board	450	0.75
20.15: Fertilisers and nitrogen compounds	432	0.59
21.10: Manuf. of basic pharm. products	331	1.00
20.16: Manuf. of plastics in primary forms	284	0.74
10.41: Manufacture of oils and fats	262	0.69
24.43: Lead, zink and tin production	210	1.00
17.11: Manufacture of pulp	148	0.82
17.29: Manuf. of other art. of paper/-board	141	0.96
23.62: Plaster prod. for construc. purposes	132	1.00
20.12: Manuf. of dyes and pigments	130	1.00
17.22: Manuf. of household and sanitary goods	61	1.00
08.99: Other mining and quarrying n.e.c.	33	0.45
23.14: Manuf. of glass fibres	25	0.07
23.32: Construction prod. in baked clay	11	1.00
35.22: Distrib. gaseous fuels through mains	10	0.25
35.11: Prod of electricity	10	0.00

Table A.10: Top 30 brown EU ETS industries

Note: This table lists the 4 digit industries with the highest number of EU ETS workers. The industry codes correspond to the Sn2007 classification. A 5-digit industry is defined as brown if the industry has at least one firm part of the EU ETS. The following industries are excluded from the brown definition despite reporting activity: 70.220 (Business and other management), 52.230 (Service activities incidental to air transportation), 46.710 (Wholesale of solid, liquid, and gaseous fuels), 41.109 (Other development and sale of real estate), 38.210 (Treatment and disposal of non-hazardous waste), 35.300 (Steam and air conditioning supply), 35.111 (Production of electricity through water power), and 35.120 (Transmission of electricity). Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. *Share* refers to the brown employment share within the respective 4 digit industries.

Brown based on CO_2-emissions

Industry	Brown workers N	Share
06.10: Extraction of crude petroleum	12,050	0.87
10.51: Oper. of dairies /cheese making	3,966	0.96
10.11: Processing and preserving of meat	3,386	0.84
30.11: Build. ships/floating struct.	3,045	0.23
24.42: Aluminium production	2,815	0.87
52.23: Serv. act. to air transp.	1,840	0.40
09.10: Supp. for petro/natural gas extrac	1,539	0.11
10.13: Prod. of meat/poultry meat prod.	1,323	0.46
06.20: Extraction of natural gas	1,216	0.95
10.91: Manuf. of prep. feeds for farm anim.	1,019	0.59
20.13: Manuf. of other inorg. basic chem.	964	0.75
72.19: Other R&D on natural sciences etc.	827	0.13
46.21: W.sale grain, unmanuf. tobacco etc.	769	0.78
21.20: Manuf. of pharm. preparations	755	0.45
24.10: Manuf. basic iron and steel etc.	735	0.77
20.30: Manuf. of paints,varnishes,coatings	716	0.79
20.14: Manuf. of other organic basic chem.	676	0.86
28.22: Manuf. lifting/handling equip.	670	0.23
10.89: Manuf. of other products n.e.c.	632	0.67
19.20: Manuf. of refined petroleum prod.	617	0.98
17.12: Manuf. of paper and paperboard	591	0.78
33.12: Rep. of machinery	562	0.09
28.13: Manuf. of other pumps, compressors	532	0.25
10.20: Process. and preserv. of fish etc.	499	0.08
24.45: Other non-ferrous metal production	430	1.00
10.52: Manufacture of ice cream	405	0.57
16.21: Veneer sheets, wood-based materials	361	0.49
10.82: Manuf. of cocoa, chocolate etc.	341	0.52
25.99: Manuf. of other fabr. metal products	316	0.14
10.85: Manuf. of prepared meat and dishes	311	0.50

Table A.11: Top 30 brown CO2 emitting industries

Note: This table lists the 4 digit industries with the highest number of workers i CO2 emitting firms. A firm is defined as brown if the firm has positive CO2 emissions. Firms that are classified as both brown and green are recoded as mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the brown employment share within the respective 4 digit industries.

A.3 Mixed jobs

When defining green and brown jobs based on industry code or firm activities, we find that a small set of firms are classified as both green and brown. Workers in these firms make up an employment share of around 2.5% (see Figure A.1).

This overlap illustrates the difficulty of defining a job as either green or brown. As an example, a firm operating in an industry defined as brown (e.g., building platforms and modules) may at the same time engage in green patenting and R&D activities. As the greenness of dirtiness of these jobs are ambiguous, we exclude them from our estimation sample. Table A.12 lists the 4 digit industries with the highest number of mixed workers.

	Mixed workers	
Industry	N	Share
30.11: Build. ships/floating struct.	2,838	0.21
26.51: Measuring, testing, navig. instrum.	2,820	0.72
09.10: Supp. for petro/natural gas extrac	2,124	0.12
28.13: Manuf. of other pumps, compressors	1,060	0.51
28.11: Manuf. of engines and turbines	947	0.85
23.99: Manuf. of other non-met. min. prod.	940	0.59
33.12: Rep. of machinery	888	0.15
27.12: Elec. distrib. and control apparatus	652	0.33
25.11: Manuf. of metal structures, parts	629	0.16
33.15: Rep./maint. of ships and boats	599	0.22
25.99: Manuf. of other fabr. metal products	561	0.26
28.99: Manuf. other spec. purp. mach.	543	0.56
10.20: Process. and preserv. of fish etc.	537	0.08
25.62: Machining	456	0.12
28.25: Non-domestic. cool./ventil. equip.	426	0.52
28.29: Other gen-purp. machinery n.e.c.	385	0.39
20.13: Manuf. of other inorg. basic chem.	350	0.25
28.12: Manuf. of fluid power equip.	345	0.44
11.05: Manufacture of beer	312	0.22
23.14: Manuf. of glass fibres	312	0.93
25.61: Treatment and coating of metals	298	0.26
28.15: Bearings, gears, gear./driv. elements	289	0.97
20.15: Fertilisers and nitrogen compounds	288	0.41
35.30: Steam and air conditioning supply	282	0.69
42.11: Construc. of roads and motorways	249	0.04
24.51: Casting of iron	236	0.58
23.51: Manuf. of cement	235	1.00
28.22: Manuf. lifting/handling equip.	215	0.09
27.90: Manuf. of other electrical equip.	212	0.26
27.52: Manuf. non-elec. domestic appliances	207	0.98

Table A.12: Top 30 mixed industries

Note: This table lists the 4 digit industries with the highest number of mixed workers. Numbers reflect the 2010-2023 average. The industry codes correspond to the Sn2007 classification. *Share* refers to the green employment share within the respective 4 digit industries.

A.4 Employment shares of green, brown, and mixed workers

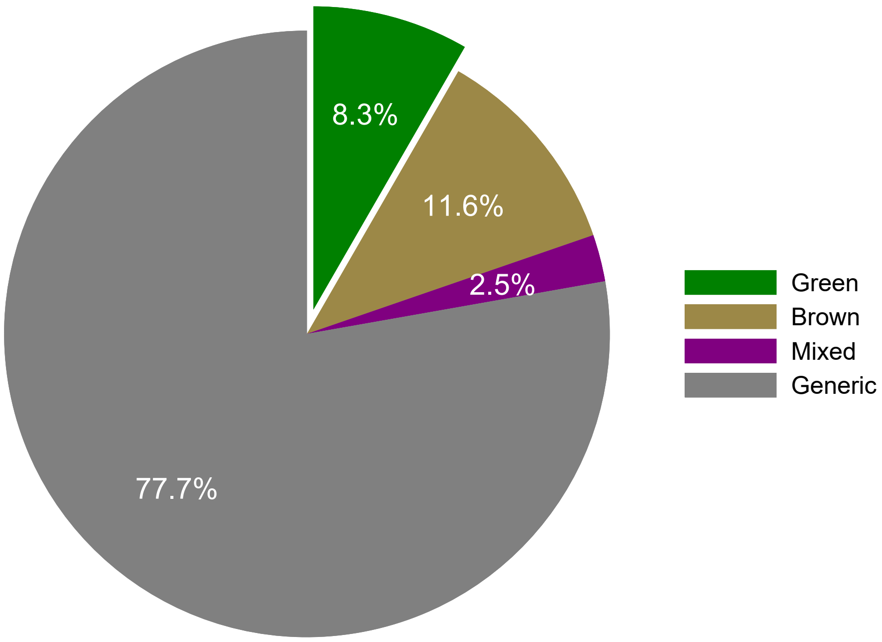


Figure A.1: Employment shares of green, brown, mixed, and generic workers.
Note: The figure shows the average employment shares of green, brown, mixed, and generic workers in 2010–2023 in our estimation sample.

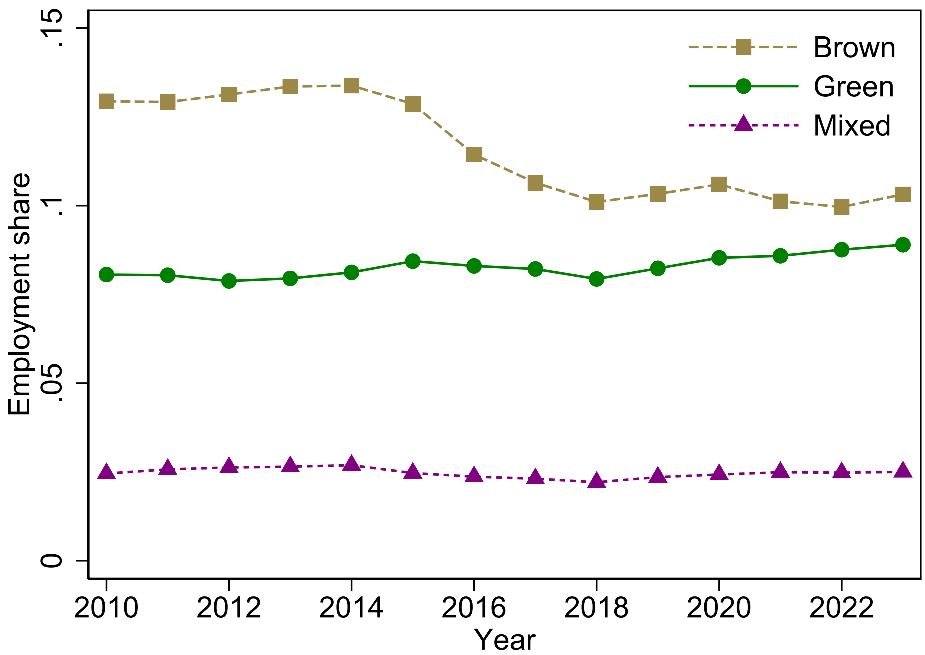


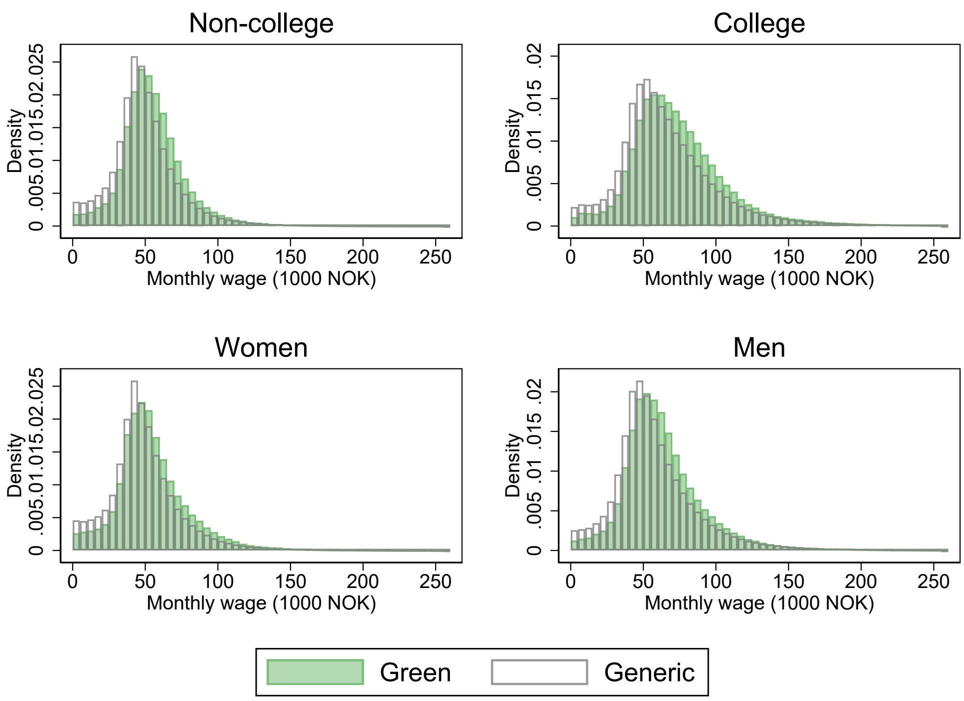
Figure A.2: Employment shares of green, brown and mixed workers. 2010-2023
Note: The figure plots employment shares in green, brown and mixed jobs as a share of all private sector full-time employees aged 20-61 in our estimation sample.

Table A.13: Employment shares by definitions

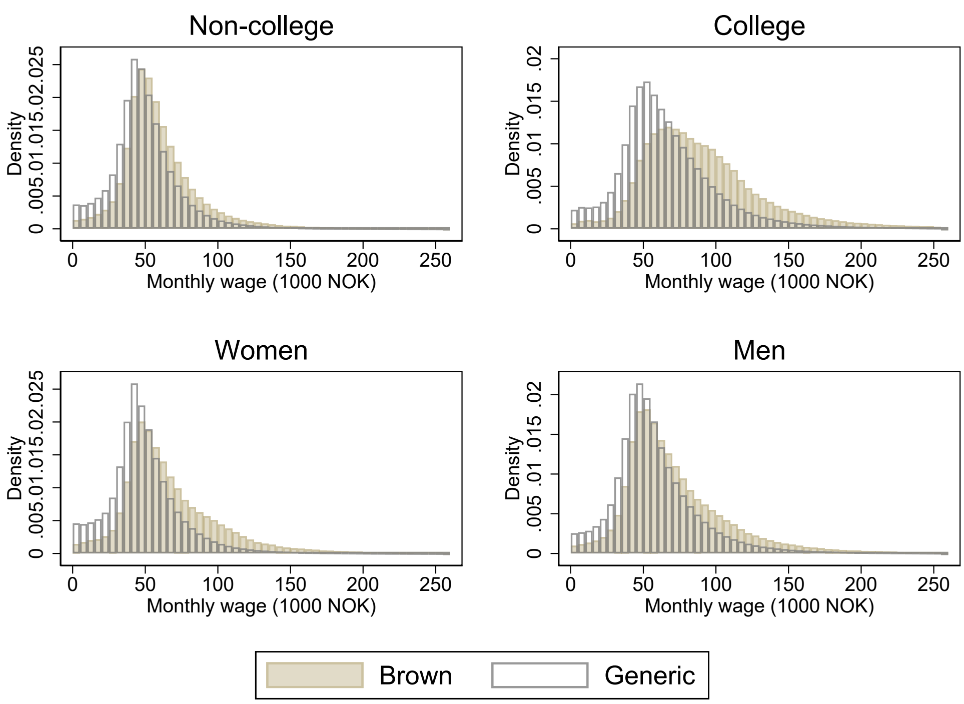
	All	Non-college	College	Women	Men
Green job	0.0828	0.0832	0.0820	0.0663	0.0896
	(0.276)	(0.276)	(0.274)	(0.249)	(0.286)
GreenR&D	0.0217	0.0196	0.0257	0.0170	0.0237
	(0.146)	(0.138)	(0.158)	(0.129)	(0.152)
Green patents	0.00517	0.00483	0.00578	0.00388	0.00569
	(0.0717)	(0.0694)	(0.0758)	(0.0622)	(0.0752)
Green exports	0.0448	0.0457	0.0430	0.0395	0.0469
	(0.207)	(0.209)	(0.203)	(0.195)	(0.211)
Green industries	0.0234	0.0246	0.0212	0.0150	0.0268
	(0.151)	(0.155)	(0.144)	(0.121)	(0.162)
Brown job	0.116	0.112	0.122	0.0878	0.127
	(0.320)	(0.315)	(0.327)	(0.283)	(0.333)
CO2	0.0533	0.0458	0.0668	0.0517	0.0539
	(0.225)	(0.209)	(0.250)	(0.221)	(0.226)
EU ETS	0.0370	0.0281	0.0532	0.0373	0.0369
	(0.189)	(0.165)	(0.224)	(0.189)	(0.188)
Petroleum	0.0770	0.0697	0.0903	0.0502	0.0880
	(0.267)	(0.255)	(0.287)	(0.218)	(0.283)
N	13,455,307	8,684,430	4,770,877	3,902,495	9,552,812
N workers	1,979,852	1,327,285	713,827	679,303	1,300,549
N firms	105,403	101,708	79,683	79,551	100,807

Note: Table shows

Appendix B Descriptives



(a) Green jobs



(b) Brown jobs

Figure B.1: Monthly wages in green and brown jobs

	(1) Baseline	(2) Female	(3) Male	(4) HS or less	(5) BA+	(6) Non-resid	(7)
Total variance	0.2862	0.2916	0.2678	0.2558	0.2539	0.3392	
Bias corrected variance decomposition (KSS)							
Firm FE-HE	0.0436	0.0509	0.0393	0.0355	0.0351	0.0780	
Cov psi, alpha HE	0.0127	0.0119	0.0126	0.0058	0.0141	0.0092	
Residual variance	0.3204	0.3498	0.2989	0.3096	0.2722	0.3927	
Firm FE variance share	15.23 %	17.46 %	14.69 %	13.89 %	13.82 %	22.98 %	
Sorting share	4.45 %	4.08 %	4.70 %	2.25 %	5.55 %	2.72 %	
Sample	All	Female	Male	HS or less	BA+	All	
Wage measure	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	
Residualized	Yes	Yes	Yes	Yes	Yes	No	

Table B.1: Variance decomposition AKM model

Note: Table shows estimated variance share from the twoway fixed effects wage regression. Estimates and associated variance decomposition following Kline et al. (2020) produced using the `pytwoway` Python package (Bonhomme et al., 2023).

Appendix C Supporting results

C.1 Wage premiums by definitions and worker type

Table C.1: Green wage premiums across definitions

	(1) Green Job	(2) Green R&D	(3) Green patents	(4) Green exports	(5) Green industries
Panel A: Raw gap					
Green	0.138***	0.207***	0.223***	0.094***	0.194***
	(0.019)	(0.024)	(0.026)	(0.029)	(0.022)
N	11,568,564	10,746,861	10,523,850	11,056,521	10,768,907
Panel B: With covariates					
Green	0.076***	0.100***	0.131***	0.054***	0.105***
	(0.012)	(0.014)	(0.026)	(0.018)	(0.011)
N	11,568,564	10,746,861	10,523,850	11,056,521	10,768,907
Panel C: Movers					
Green	0.048***	0.070***	0.073***	0.038***	0.056***
	(0.005)	(0.006)	(0.012)	(0.007)	(0.008)
N	11,568,564	10,746,861	10,523,850	11,056,521	10,768,907
Panel D: AKM					
Green	0.066***	0.100***	0.128***	0.050***	0.064***
	(0.009)	(0.010)	(0.015)	(0.014)	(0.009)
N	11,568,564	10,746,861	10,523,850	11,056,521	10,768,907

Note: Table shows estimated wage premiums in green firms relative to generic jobs. Panel A shows the raw wage gaps. Panel B shows estimates from a cross-sectional wage regression (Equation (3)). Panel C shows the estimate from the industry mover model (Equation (4)). Panel D shows estimates from the AKM-based approach (Equations (1) and (2)). Column (1) is our baseline definition of green jobs, column (2) is ≥50% green R&D, column (3) is ≥50% green patents, column (4) is ≥50% green exports, and column (5) is a list of green industries based on 5-digit NACE codes. Standard errors clustered at the firm level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Brown wage premiums across definitions

	(1) Brown Job	(2) CO2	(3) EU ETS	(4) Petroleum
Panel A: Raw gap				
Brown	0.267***	0.326***	0.408***	0.339***
	(0.050)	(0.094)	(0.100)	(0.056)
N	12,008,519	11,170,823	10,952,254	11,490,549
Panel B: With covariates				
Brown	0.153***	0.178***	0.234***	0.198***
	(0.026)	(0.050)	(0.052)	(0.028)
N	12,008,519	11,170,823	10,952,254	11,490,549
Panel C: Movers				
Brown	0.082***	0.081***	0.102***	0.092***
	(0.005)	(0.009)	(0.009)	(0.005)
N	12,008,519	11,170,823	10,952,254	11,490,549
Panel D: AKM				
Brown	0.142***	0.157***	0.190***	0.170***
	(0.017)	(0.033)	(0.032)	(0.018)
N	12,008,519	11,170,823	10,952,254	11,490,549

Note: Table shows estimated wage premiums in brown firms relative to generic jobs. Panel A shows the raw wage gaps. Panel B shows estimates from a cross-sectional wage regression (Equation (3)). Panel C shows the estimate from the industry mover model (Equation (4)). Panel D shows estimates from the AKM-based approach (Equations (1) and (2)). "Brown job" is our baseline definition of brown jobs, "CO2" is positive emissions in at least one of the years 2010–2023, EU-ETS is participation in the EU-ETS scheme (at the five-digit industries level), "Petroleum" is fossil fuels, closely related services, and petroleum-oriented manufacturing. Standard errors clustered at the firm level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Heterogeneous green wage premiums across definitions

	(1) Green Job	(2) Green R&D	(3) Green patents	(4) Green exports	(5) Green industries
Panel A: Non-college					
Green	0.071***	0.099***	0.140***	0.053***	0.079***
	(0.009)	(0.011)	(0.020)	(0.013)	(0.007)
N	7,347,812	6,799,523	6,672,441	7,023,570	6,843,069
Panel B: College					
Green	0.035***	0.057***	0.065***	0.025	0.013
	(0.010)	(0.011)	(0.018)	(0.017)	(0.012)
N	3,830,389	3,571,293	3,476,694	3,647,230	3,547,977
Panel C: Women					
Green	0.054***	0.128***	0.148***	0.012	0.087***
	(0.018)	(0.016)	(0.021)	(0.026)	(0.014)
N	3,274,778	3,092,853	3,042,543	3,174,401	3,083,093
Panel D: Men					
Green	0.062***	0.082***	0.115***	0.057***	0.047***
	(0.007)	(0.010)	(0.014)	(0.012)	(0.008)
N	7,921,975	7,295,800	7,124,145	7,515,063	7,325,498
Panel D: Men					
Green	0.062***	0.082***	0.115***	0.057***	0.047***
	(0.007)	(0.010)	(0.014)	(0.012)	(0.008)
N	7,921,975	7,295,800	7,124,145	7,515,063	7,325,498

Note: Table shows estimated wage premiums in green firms relative to generic jobs from our preferred AKM-based approach (Equations (1) and (2)). Column (1) is our baseline definition of green jobs, column (2) is ≥50% green R&D, column (3) is ≥50% green patents, column (4) is ≥50% green exports, and column (5) is a list of green industries based on 5-digit NACE codes. Standard errors clustered at the firm level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Wage premiums in exporting and innovative firms

Here, we re-estimate Equation (2) on three subsets of firms: exporting firms, patenting firms, and R&D firms. These models yield estimates of the average green and brown wage premium within each category of firms.

Results from this exercise, presented in Table C.4, indicate that accounting for the export and innovation status of firms significantly reduces both the estimated green and brown wage premiums. From Panel A, we see that the green wage premiums are either small in magnitude (1.8% for exporting firms), close to zero (patenting firms), or even negative (R&D firms). These results imply that within these smaller groups of more similar firms, there is no positive wage premium for being green. The brown wage premium (Panel B) also becomes small and insignificant for the sample of R&D firms, while it remains positive and significant for exporting and patenting firms.

Table C.4: Green and brown wage premiums for exporting and innovative firms

	(1)	(2)	(3)
Sample:	Exporting firms	Patenting firms	R&D firms
Panel A: Green wage premium			
Green	0.018*	0.007	-0.019**
	(0.010)	(0.015)	(0.009)
N	7,855,291	375,032	3,144,395
Panel B: Brown wage premium			
Brown	0.098***	0.071**	0.030
	(0.018)	(0.028)	(0.021)
N	8,300,664	831,226	3,761,724

Note: The table shows the estimated green (Panel A) and brown (Panel B) wage premium estimated from the AKM-model (Equation 1). Each column shows estimated effects for different subsamples indicated by the column heading. Standard errors clustered at the firm level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

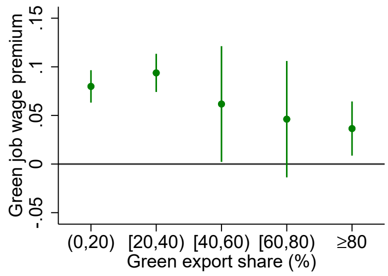
In the specifications in Table C.4, the comparison group of generic firms includes firms where the share of green exports or innovation is above zero but below 50%, potentially diluting the estimate of the green wage premium. To assess this possibility, we examine how the job wage premium vary with a binary measure of *any* green as well as the *intensity* of green within each sub-sample. Results from this exercise, presented in Table C.5, suggest that the green wage premium associated with having *any* green exports or patents is positive and statistically significant, but that the premium slightly decreases with the intensity of green for exporting and innovative firms.

This pattern is corroborated by Figure C.1. Panel (a) shows a positive green wage premium across bins of green export intensity, positive the magnitude declines as the green export share increases. For patenting, a positive premium is observed only for firms with green patent shares between 0 and below 20%. For R%D firms, the premium is close to zero for green shares below 60% and turns negative for shares above 80%.

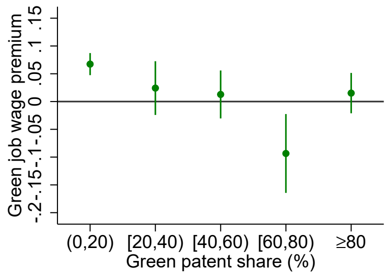
Table C.5: Wage premiums by green intensity

Sample:	Exporting firms		Patenting firms		R&D firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Green export (yes)	0.076***	0.084***				
	(0.008)	(0.009)				
Green export share		-0.044**				
		(0.020)				
Green patent (yes)			0.030**	0.058***		
			(0.014)	(0.016)		
Green patent share				-0.051**		
				(0.025)		
Green R&D (yes)					-0.006	0.004
					(0.009)	(0.010)
Green R&D share						-0.036**
						(0.014)
N (worker-year)	7,855,291	7,855,291	375,032	375,032	3,144,395	3,144,395
N (firms)	31,113	31,113	870	870	4,908	4,908
N (workers)	1,333,116	1,333,116	80,886	80,886	569,479	569,479
Any green	0.66	0.66	0.36	0.36	0.46	0.46
Green share (if green>0)	0.18	0.18	0.55	0.55	0.30	0.30

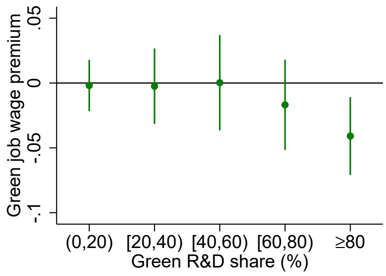
Note: Table shows wage premiums by the green intensity of exporting firms (columns 1-2), patenting firms (columns 3-4), and R&D firms (columns 5-6). Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, ***.



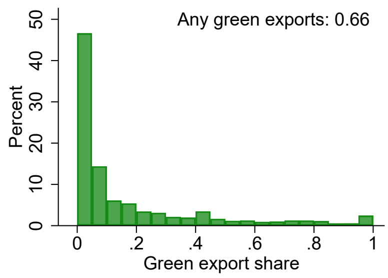
(a) Exporting firms



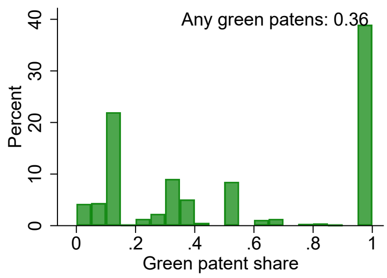
(b) Patenting firms



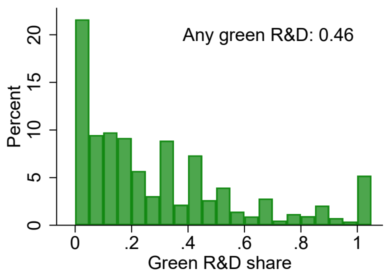
(c) R&D firms



(d) Green exporting firms



(e) Green patenting firms



(f) Green R&D firms

Figure C.1: Wage premiums by green intensity

Notes: Panels (a) - (c) show job wage premiums by the green intensity of firms. Panel (a) shows coefficients from a regression with dummy variables for different intervals of the green export share, where the sample is restricted to green and generic exporting firms. Panel (b) shows coefficients from a regression with dummy variables for different intervals of the green patent share, where the sample is restricted to green and generic patenting firms. Panel (c) shows coefficients from a regression with dummy variables for different intervals of the green R&D share, where the sample is restricted to green and generic R&D firms. Panels (d) - (f) show the distribution of worker-year observations by the green intensity of firms. Samples are restricted to firms with positive green exports (panel a), positive green patents (b), or positive green R&D (panel c). Brown jobs are excluded from all samples. *Any green exports* is the share of firms with positive green exports in a sample of green and generic exporting firms. *Any green patents* is the share of firms with positive green patents in a sample of green and generic patenting firms. *Any green R&D* is the share of firms with positive green R&D in a sample of green and generic R&D firms.

Appendix D Green wage premiums in the literature

Paper	Green premium	Green definition	Comparison group	Data & controls	Country	Period
This paper	6.6%	green NACE, patents, R&D, exports	Non-green, non-brown firms	Linked employer-employee (worker FE)	Norway	2010-2023
Vona et al. (2019)	4%	Job task requirements of occupations (O*NET)	Comparable non-green occupation	Wage estimates by occupation-area	USA	2006–2014
Curtis and Marinescu (2023)	20-23%	Wind and solar jobs (keywords in job ads)	other, non-fossil jobs	Job ads, occupational wages, educational FE	USA	2007, 2010-2019
Saussay et al. (2022)	3.9% (-24% to 16%)	low-carbon words in job ads	non-green jobs	Job ads (occupation, education requirements)	USA	2010-2012
Saussay et al. (2022)	-1.5% (-8.7% to 4.4%)	low-carbon words in job ads	non-green jobs	Job ads (occupation, education requirements)	USA	2017-2019
Bluedorn et al. (2023)	6.7%	Green tasks intensity (O*NET)	Pollution-intensive jobs.	Labor force survey data.	31 countries (Europe, North America)	2005-2019
Krueger et al. (2023)	- 3.1% to -4.3%	ESG-score	Other private-sector firms	Linked employer-employee (individual characteristics, four-digit occupation-year FE, sector)	Sweden	2000-
Krueger et al. (2023)	- 9%	Sector-wide sustainability measure	Other private-sector firms	Linked employer-employee (individual characteristics, four-digit occupation-year FE)	Sweden	2000-
Colmer et al. (2023)	2.47%	Clean energy firms	Legacy ("brown") energy firms	Linked employer-employee (industry mover model)	USA	2005–2019

Table D.1: Green wage premiums in the literature