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Transitioning to a Greener Labor Market: Cross-Country Evidence from Microdata

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ABSTRACT:
This paper builds a new set of harmonized indicators of the environmental properties of jobs using micro-level labor force survey data from 34 economies between 2005 and 2019 and analyzes the labor market implications of the green economic transition and environmental policies. Based on the new set of indicators, the paper's main findings are that greener and more polluting jobs are concentrated among smaller subsets of workers, individual workers rarely move from more pollution-intensive to greener jobs, and workers in green-intensive jobs earn on average 7 percent more than workers in pollution-intensive jobs.

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WORKING PAPERS

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Introduction

Mitigating global warming will require substantial reductions in greenhouse gas (GHG) emissions. The objective of limiting the average global temperature increase to well below 2°C and preferably no more than 1.5°C above pre-industrial levels, was endorsed by policymakers around the world in the 2015 Paris Agreement. For this goal to be met, net emissions (the difference between GHG emissions produced and GHG removed from the atmosphere) must decline to zero by 2050. The green transformation of production structures needed to achieve net zero emissions—with large changes anticipated in capital infrastructure for greener energy and products—will also entail a transformation of the labor market, changing the allocation of workers across occupations and sectors.

Aiming to better understand the potential employment shifts that the transition to a greener economy could imply for the labor market and how readily workers could move in response to it, this paper investigates and documents the environmental properties of jobs, how easily workers are able to move into greener—that is, more-sustainable, less-polluting, and emissions-lowering—employment, and how policies can help green of the labor market. To do this, we create a new cross-country, harmonized set of indicators of the environmental properties of jobs, building in part on earlier single-country studies. Data constraints mean that the analysis uses a limited sample of 34 countries (mainly the United States and advanced economies in Europe), covering 2005–19.

We examine the environmental properties of jobs through two lenses—what workers do (their occupations) and where they work (the sectors where they are employed). We take the perspective that the environmental properties of jobs are multidimensional, involving the extent to which workers undertake tasks that improve environmental sustainability (green intensity) and the degree to which their work involves activities exacerbating pollution (pollution intensity), as well as the level of emissions generated per worker (emissions intensity). Among the many occupations classified, an example of a more green-intensive occupation is a electrotechnology engineer, while a more pollution-intensive occupation is a paper mill machine operator. An example of a typically more emissions-intensive sector is utilities, including electricity and gas.

In this paper, we consider the following three sets of questions:

- *How green is the labor market?* What are the environmental properties of jobs and how do they vary across economies and sectors? How are they associated with demographic characteristics (such as educational attainment and urbanicity) and earnings?
- *How easily do workers transition into greener jobs?* What are the characteristics of workers (including their employment history and education or skills) who more readily move into these jobs?
- *How are environmental policies related to the reallocation of workers into greener jobs?* How are these relationships affected by an economy's labor market policies and structural features?

Our main findings are as follows. First, More green- and pollution-intensive jobs appear concentrated among a subset of the workforce, leading to low average green and pollution intensities of jobs. Green and pollution intensities quantify the share of activities in a given occupation that improve or degrade environmental sustainability, respectively. The lion's share of jobs are neutral, with zero green and pollution intensity scores. There is a wide dispersion of environmental properties of jobs across and within sectors, suggesting that scope exists for reallocation both across- and within-sectors to help green the labor market. Higher-skilled and urban workers tend to have more green-intensive occupations than lower-skilled and rural workers. Moreover, even controlling for skills and other individual-level characteristics, green-intensive occupations exhibit an average earnings premium of almost 7 percent compared with pollution-intensive occupations.

Second, environmental properties of jobs tend to be sticky in transitions, pointing to difficulties for workers in more pollution-intensive or neutral jobs in moving up the green ladder. The probability that a worker will transition into greener work from pollution-intensive work when changing jobs is comparatively low, though not significantly different than making that transition from a neutral job, which reflects how tough it is to change occupations. Higher skills make it easier to transition into more green-intensive work, suggesting that further human capital accumulation could help boost workers' prospects for greener employment.

Third, environmental policies tend to be more effective when labor market policies and structural features do not inhibit incentives for reallocation. More stringent environmental policies are associated with employment that is more green- and less pollution-intensive, making for a greener labor market. Labor market policies and structural features may need realignment to avoid hindering the impetus for labor reallocation from greener policies. In particular, with a strong recovery from the COVID-19 pandemic recession underway, it will be important to reduce job retention support measures to help incentivize reallocation (in line with country-specific circumstances).

This paper contributes to an emerging literature that studies the environmental properties of jobs. Our paper is closely related to Vona and others (2018), from which we draw two critical definitions: the green and pollution intensity. Our analysis expands their work in three critical dimensions: (i) we consider a large set of countries while Vona and others (2018) focus on the US[1], and (ii) we add a new sectoral dimension (pollution intensity) absent from their work, and (iii) we study the transition of workers across jobs with different environmental properties.

Our paper also contributes to a literature that studies workers' mobility across occupations (for example, Bachmann, Bechara, and Vonnahme 2020, and Carrillo-Tudela and others 2016). Our main contribution to this literature is to look at the environmental properties of occupation, its implications for job transitions, and how environmental policies impact workers' reallocation across occupations.Some important caveats to these analyses need stating. First, data limitations mean that the green and pollution intensities assigned to occupations in the empirical analysis are invariant over time. However, employment could become greener without reallocation across occupations if technological changes increased green intensities and decreased pollution intensities by occupation. Second, as noted, the results are derived using a sample composed largely of advanced economies, which makes them less applicable to the typical emerging market or developing economy, in particular those with large shares of informal employment. Third, even when the analysis of the effects of policies takes place at the individual level, omitted variables may still be a concern, which suggests that the empirical policy-related results should be interpreted as associational rather than causal. More generally, the empirical analysis relies upon historical patterns in the data to assess policy effects, which may not be representative of the size and mix of policy changes needed to achieve net zero emissions.

[1] See also Bergant and others (2022) who use a similar methodology as ours to look at the US labor market specifically, focusing on the geographical variation of green and pollution-intensive jobs.

The paper begins by defining the environmental properties of jobs and documenting their incidence and distribution. It also explores how they vary with worker characteristics. It then turns to individual-level job transitions and how they change with the environmental properties of jobs (source or destination). In the penultimate section, this paper analyzes how environmental policies can help green the employment landscape and how policy effectiveness may vary with labor market policies and structural features. The last section concludes.

Defining Environmental Properties of Employment

This paper takes the perspective that the environmental properties of jobs are multidimensional, examines three environmental properties of jobs: green-, pollution- and emissions-intensity of the job. The first two properties are based on workers' occupations (what workers do), and the third property is based on the sector in which they are employed (where they work).

An occupation can be viewed as a bundle of tasks (or work activities) that a given job requires a worker be able to execute; see Acemoglu and Autor (2011). Dierdorff and others (2009) and O*NET Center (2021) construct a taxonomy of green occupations for the United States (based on the US SOC2010 occupational classification), categorizing each occupation's underlying bundle of tasks into green or non-green tasks. Green tasks are those tasks identified as directly related to improving environmental sustainability and reducing greenhouse gas emissions. For example, the occupation "roofer" involves a task summarized as "install vapor barriers or layers of insulation on the roof decks of flat roofs and seal the seams" which is considered green as it aims to improve energy efficiency. See O*NET Center (2010) for further details on the identification of green tasks by occupation. For each occupation, a green task intensity measure can then be computed as the ratio of green tasks to total tasks. For occupations involving no green tasks, their green task intensity will be is set to zero. This 8-digit encoding is aggregated to the 6-digit level (for which employment is available) by simple averaging following the approach in Vona and others (2018).

A binary identification of polluting occupations—jobs more heavily predominant in highly polluting or environmentally-damaging sectors—is constructed by Vona and others (2018) for the United States. Polluting occupations are a subset of those occupations identified as having zero green task intensity in the US occupational classification system. Labeled “brown” by Vona and others (2018), they are identified in two steps. In a first step, polluting sub-sectors are identified as those where emissions per worker of at least three polluting substances (including CO, VOC, NOx, SO2, PM10, PM2.5, lead, and CO2) are in the top 5 percent. In a second step, polluting occupations are identified as occupations where the share of employees in these polluting sub-sectors is at least 7 times larger than the share of employees in polluting sub-sectors across all occupations.

Applying the same definitions for green and pollution intensity to other economies, the underlying green-intensive and polluting job classifications are cross-walked to the international standard ISCO-08 occupational classification scheme using occupational employment weights from the US within code where there are nonunique matches. This results in indices which are scaled to range from 0 to 100 for each occupation. For each worker, a green- and pollution-intensity score is assigned based on the worker’s occupation. Green intensity is the average, employment-weighted share of green tasks in total tasks involved in an international standard occupation, expressed as a percent. Pollution intensity is interpreted as the average, employment-weighted share of polluting activities in an international standard occupation, expressed as a percent. As a result of the crosswalk with employment weights, pollution intensity and green intensity under ISCO-08 may both be positive in some cases. See Table 1 for example occupations by green and pollution intensities.[2]

Table 1. Examples of Occupations by their Environmental Properties

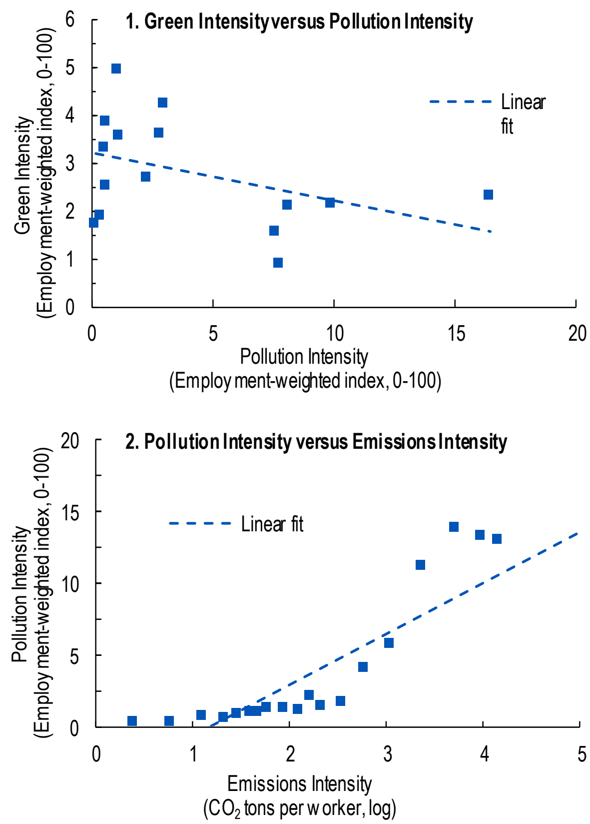
	Zero green intensity	Positive green intensity
Zero pollution intensity	Legislators and senior officials Medical doctors Waiters and bartenders	Electrotechnology engineers Refuse workers
Positive pollution intensity	Garment and related trades workers Rubber, plastic and paper products machine operators	Manufacturing labourers Life science professionals

Sources: Dierdorff and others (2009); Occupational Information Network (O*NET) Resource Center (2021); Vona and others (2018); and IMF staff compilation.

[2] Annex Table I.1 provides a full list of occupations by their pollution and greenness intensity, respectively.

For the sectors in which workers are employed, emissions intensity of employment is measured by carbon emissions (in CO2 tons) per worker. For a given sector, this paper uses total carbon emissions, which cover both the sector's direct emissions and indirect emissions based on the sector's derived demand from other sectors in the economy. The latter is calculated using the input-output sectoral linkages in the economy. The data source for this measure is the IMF Climate Change Indicators Dashboard (December 2021 vintage), available for the years 2005–15, and is based on gross CO2 emissions. Sectoral employment is obtained from the sources listed in Annex Table I.2 for the ISIC revision 4 top-level sectors listed in Annex Table I.3. Emissions intensity varies by sector, year, and country. An individual worker's employment can be characterized as more or less emissions-intensive, matched to emissions intensity by worker's sector of employment, country, and year.

Figure 1. Relationships between the Environmental Properties of Jobs



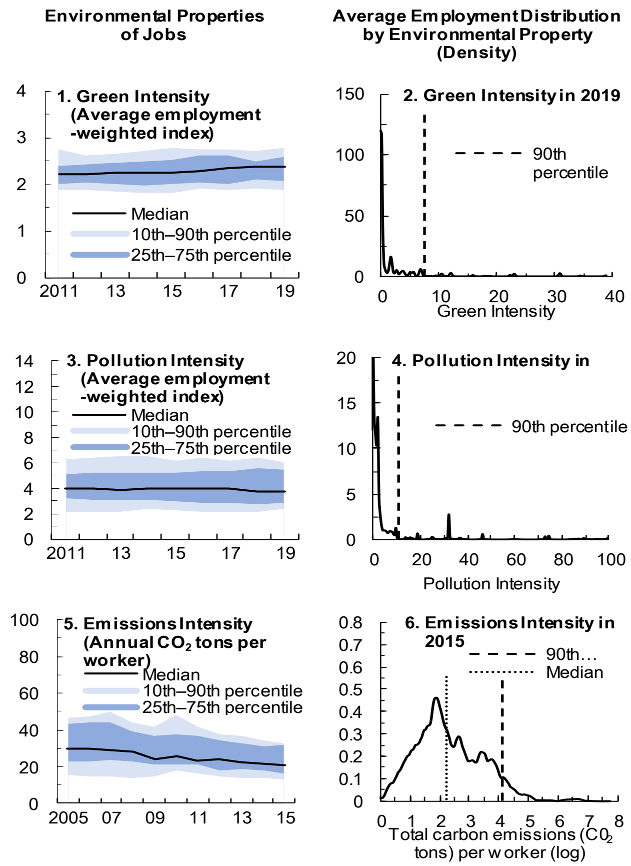
Sources: EU Labor Force Survey; ILOSTAT database; IMF Climate Change Indicators Dashboard; Mexico National Survey of Occupation and Employment; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: The panels show binned scatterplots (Chetty, Friedman, and Rockoff 2014) based on individual-level observations, with the sample constrained to be identical across charts to ensure comparability (covering 2008-15 due to data availability). Total carbon emissions (CO_2) per worker are presented on a log scale.

A natural question is how these environmental properties of jobs relate to each other, as they each capture a different environmental dimension of a given job. The green and pollution intensities of employment show a negative relationship to each other within the sample of employed workers, reflecting a general property that more green-intensive occupations tend to be less polluting (Figure 1). More pollution-intensive jobs are positively related to jobs in more emissions-intensive sectors. Taken together, these findings provide reassurance that the three environmental properties of jobs are sensibly associated with each other.

Evolution and Prevalence of Employment across Environmental Properties

The average employment-weighted green intensity of occupations ranges from around 2 to 3 percent for most economies in the sample, while the average employment-weighted pollution intensity of occupations goes from about 2 to 6 percent (Figure 2, panels 1 and 3). In fact, most occupations have very low green and/or pollution intensities, with the bulk of jobs being neutral. The average distribution of green and pollution intensity is shown in the densities in Figure 2 (panels 2 and 4).[3] The bulk of the distribution is centered around zero, perhaps unsurprising since the pollutive jobs are concentrated in a small subset of occupation. By the same token, those tasks that contribute positively towards environmental conservation also represent a small share of employment. Also, the rise in average

Figure 2. Cross-Country Distribution and Evolution of Green- and Pollution-Intensive Occupations and Carbon Emissions per Worker



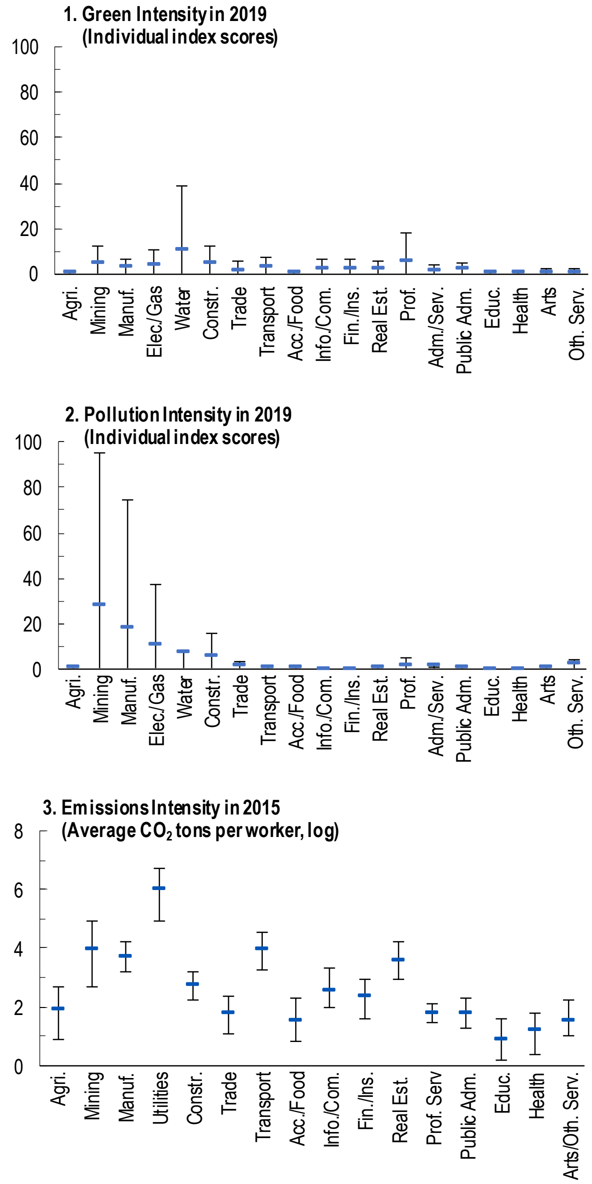
Sources: EU Labor Force Survey; ILOSTAT database; IMF Climate Change Indicators Dashboard; Mexico National Survey of Occupations and Employment; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Panels 1 and 3 are computed by the share of occupational tasks in the total economy that are green-intensive and the share of occupations that are pollution-intensive, respectively, weighted by employment for each country. Panel 5 exhibits carbon emissions intensity for the average worker in each country. Data are shown over the time periods for which they are available. Panels 2, 4, and 6 shows the average kernel density for employment (see Silverman 1986).

[3] The kernel density plots show the average of kernel density estimates for employment by green, pollution and emissions intensity across countries in the sample. Given the skewed and long-tailed shape of the distributions, this paper uses a country-specific optimal bandwidth for the kernel given by $\hat{h} = 1.06An^{-1/5}$, where $A = min(\hat{\sigma}, IQR/1.349)$, n is the sample size, $\hat{\sigma}$ is the sample standard deviation and IQR is the interquartile range; see Silverman (1986) for details.

green intensity and fall in average pollution intensity over the last decade have been only very incremental.

From the sectoral perspective, the emissions intensity of employment has fallen noticeably over the same period for the economies in the sample (Figure 2, panel 5). This partly reflects labor reallocation away from higher- to lower-emissions-intensive sectors induced by the underlying secular trend of expansion in the services sector in many advanced and emerging economies. In fact, the average share of employment in the higher-emissions-intensive sectors of mining, manufacturing, and utilities went from around 18 percent in 2005 to 15 percent in 2015. While the median individual-level emissions intensity for the average country within the sample stood at about 8 CO2 tons per worker in 2015, there is a substantial right skew in the average employment distribution, indicating that there is only a small share of workers involved in activities generating high carbon emissions (Figure 2, panel 6). This is consistent with the distribution of the pollution intensity measure in Figure 2 (panel 4) .

Figure 3. Sectoral Differences in the Distribution of Green, Pollution, and Emissions Intensities of Employment



Sources: EU Labor Force Survey; ILOSTAT database; IMF Climate Change Indicators Dashboard; Mexico National Survey of Occupation and Employment; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Heavy bars represent the mean for the sector across individuals in the sample, while whiskers represent the 10th–90th percentile range. Sectors are classified according to ISIC Revision 4.

The average green, pollution and emissions intensities mask a large degree of within- and across-sector heterogeneity, particularly for pollution and emissions intensities. At the occupational level, mining, manufacturing, and utilities tend to have occupations with substantially higher pollution intensity scores, followed by the construction sector (Figure 3, panels 1 and 2). A few examples can help shed light on the large within-sector heterogeneity, especially in mining and manufacturing. For instance, a *mining plant operator* has a pollution intensity score equal to 1 as opposed to an *accountant* in the same sector whose job is neutral (neither pollutive nor green) with a pollution intensity score of zero. Similarly in the manufacturing sector, a *steel factory worker* would have a high pollution intensity score while an *aerospace firm engineer* would have a lower score. With regards to green intensity, and considering the water supply sector, a *water resource specialist* would have a high green intensity, while a *motor vehicle driver* in the same sector would have a low green intensity, since the latter occupation does not involve green tasks.

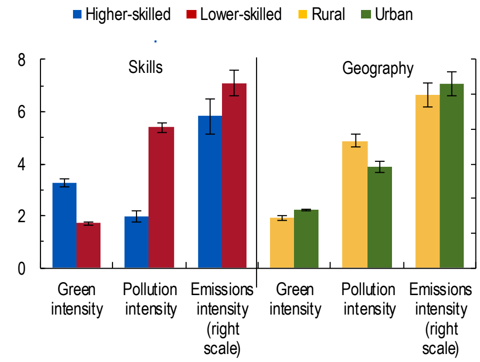
The previous examples also highlight while the sector-based environmental measure (i.e. emissions intensity) provides a complementary perspective as it would treat all workers and clerical staff, say in a mining firm, as having an equal emissions intensity score based on their sectoral affiliation. This sector-level measure also has significant within- and across-sector heterogeneity (Figure 3, panel 3) noting the logarithmic scale in the chart. Here we also see mining, manufacturing and utilities as the highest sectors in terms of emissions intensity, followed by transportation, construction and real estate. Since all workers in a particular sector-country have equal emissions intensity scores, the whiskers here reflect differences in emissions intensity across countries for a given sector. Such heterogeneity encapsulates cross-country variation in the levels of efficiency in energy use, partly determined by the overall country energy mix, as well as differences in production technologies.

The large within-sector variation in the three environmental properties of employment suggests substantial room for further greening within each sector. This will be one margin for adjustment during the green transition. Along with labor reallocation across sectors, both margins will likely be at work to achieve NZE by 2050. To better understand the scope for workers to switch occupations withing the same sector or change their sector of employment, we turn next to the nexus between different worker/job characteristics and the environmental properties of employment.

The environmental properties of jobs also differ with the workers' skill level, measured by their educational attainment, and their geographic location (Figure 4). Higher-skilled workers tend to be in occupations with higher green and lower pollution and emissions intensities relative to lower-skilled workers. Urban workers tend to have higher green and lower pollution intensities than rural workers. At the same time, urban workers' average emissions intensity is higher. This seeming discrepancy reflects the greater need for more green-intensive occupations in sectors with higher emissions intensities, which are more urban.

Figure 4. Environmental Properties of Jobs by Worker Characteristics

(Average individual index; CO_2 tons per worker for emissions



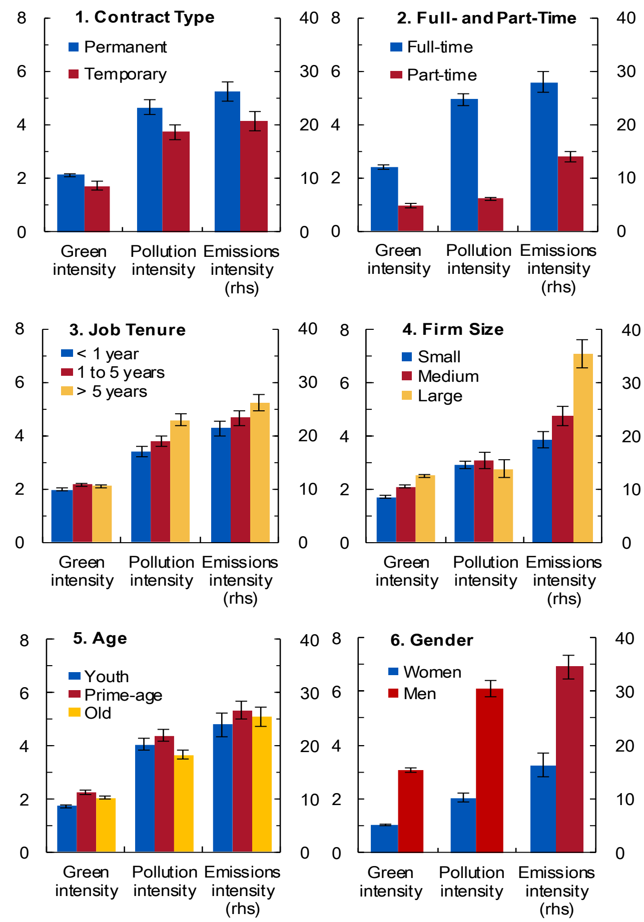
Sources: EU Labor Force Survey; IMF Climate Change Indicators Dashboard; Mexico National Survey of Occupation and Employment; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Bars show the averages for the property over the employment-weighted sample of individuals with the characteristic indicated. Lower-skilled workers have at most secondary and nontertiary education or below, while higher-skilled workers have post secondary or tertiary education. Whiskers depict the 90 percent confidence band around the estimate.

Figure 5 documents further variation in the environmental properties of jobs along additional job and worker charactersitics. Here, some common, but perhaps unsurprising, patterns emerge. Workers with permanent contracts and those in full-time employment tend to have higher green, pollution and emissions intensities (Figure 5, panels 1 and 2). With respect to job tenure, green intensity does not seem to change with the number of years a worker spends in the job, however, both pollution and emissions intensities increase with job tenure. Also, larger firms have occupations with higher green intensity on average, with no discernible difference in pollution intensity across firms of different size, but the emissions intensity of employment is distinctly higher in larger firms (Figure 5, panels 3 and 4).

The green, pollution and emissions intensity also change with the workers' demographic profile (Figure 5, panels 5 and 6). Young workers have higher green intensities than both prime-age and older workers. They also tend to exhibit lower emissions intensity which is a sector-level dimension of the environmental properties. From the occupational perspective, however, they show higher pollution intensities. This is potentially driven by their above-average representation in highly-polluting occupations in the coal mining and petroleum sectors for example. On the other hand, Female workers have lower green intensities coupled with distinctly lower pollution and emissions intensities. This could be reflecting their lower share of employment in the highly polluting sectors such as mining, manufacturing and utilities.

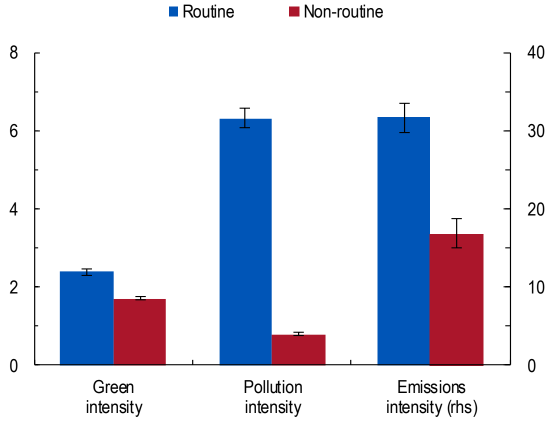
A job's vulnerability to automation—its routinizability—also shows a relationship to its environmental properties. Jobs that are more vulnerable to automation or routine have systematically higher green, pollution, and emissions intensities on average (Figure 6). This may reflect the greater incidence of routine jobs in industrial sectors. Interestingly however, the size of the gap between routine and non-routine jobs varies dramatically by environmental property. For instance, the relative gap for pollution intensity is about 6 times the size of that for green intensity (the gap is defined as the intensity for routine occupations divided by that for non-routine). Emissions intensity shows a similar pattern although with a smaller gap. This indicates that jobs that are more vulnerable to automation are more likely to have higher pollution and emissions intensity.

Figure 5. Environmental Properties of Jobs by Job and Worker Characteristics
(Average employment-weighted index; CO_2 tons per worker for emissions intensity)



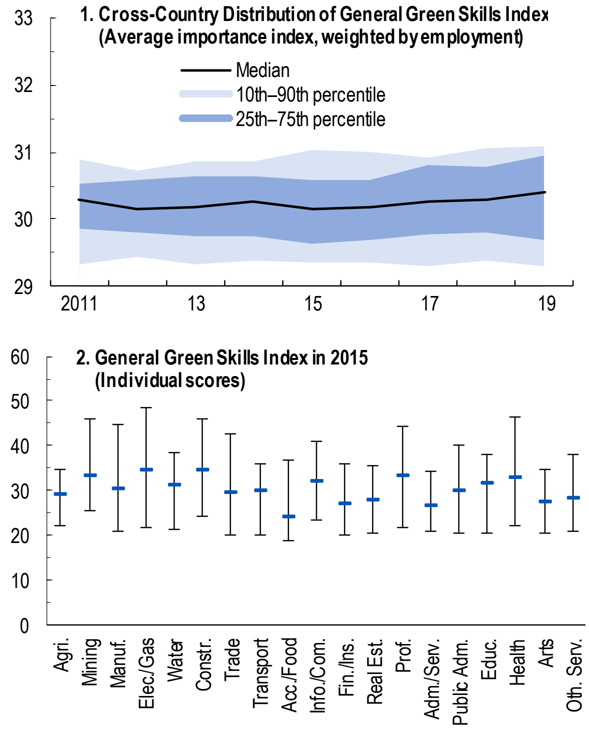
Sources: EU Labor Force Survey; Mexico National Survey of Occupation and Employment; IMF Climate Change Indicators Dashboard; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Each bar is the estimated coefficient from a regression of the environmental property of jobs of interest on the job characteristic indicated. Youth are 15–29 years-old, prime-age is 30–54 years-old, and old are 55–64 years-old, spanning the working-age population. The whiskers depict the 90 percent confidence interval around the estimated coefficient.

Figure 6. Environmental Properties of Jobs by Routinizability
(Average employment-weighted index; CO_2 tons per worker for



Sources: EU Labor Force Survey; IMF Climate Change Indicators Dashboard; Occupational Information Network; Mexico National Survey of Occupation and Employment; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Each bar is the estimated coefficient from a regression of the environmental property of jobs of interest on the job characteristic indicated. The whiskers depict the 90 percent confidence interval around the estimated coefficient.

Figure 7. Distribution of General Green Skills across Countries and Sectors



Sources: EU Labor Force Survey; Mexico National Survey of Occupations and Employment; Occupational Information Network; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018).
Note: Panel 1 shows the distribution of country average scores. Panel 2 shows the mean level of general green skills for individuals in the relevant sectors. Whiskers indicate the 10th–90th percentile range.

As appears from these stylized facts, the skill dimension seems crucial as it also co-varies with the workers' demographic profile and the some of job characteristics. In Figure 7, we show the temporal evolution and the sectoral variation in "general green skills" as in Vona and others (2018). The skills are identified as those with the highest association with more green-intensive employment, and they are strongly related to the broad areas of engineering and technical skills, operations management, monitoring/surveillance, and science; see O*NET (2010) for further details. Such skills are relatively evenly distributed across the sectors in the economy and their importance have been rising marginally since 2015 (Figure 7, panels 1 and 2). The wide dispersion within sectors and the similar levels across the sectors suggests that there is potential for further greening of the economy going forward. Moreover, the general skills useful in more green-intensive occupations are prevalent among workers, further suggesting that appropriate (re)training could help workers repurpose and reorient their skills toward greener job opportunities.

Earnings Premium of Green Intensive Jobs vis-à-vis Pollution Intensive Jobs

This section studies the earnings premium for the average green-intensive jobs vis-à-vis the average pollution intensive job. We estimate the following regression:

$$Y_{i,s,c,t} = \alpha + \alpha_{ct} + \beta GreenInt_{i,s,c,t} + \gamma PolInt_{i,s,c,t} + \theta' X_{i,s,c,t} + \varepsilon_{i,s,c,t}$$

where the outcome of interest (Y) is log earnings (real in US 2015 dollars) or related measure of individual labor income (conditional on being employed in the current year t).[4] Individuals are indexed by i, occupation/sector of employment by s, country where employed by c, and time (year) by t. This is a Mincer-type regression. The green- and pollution-intensity variables (*GreenInt* and *PolInt*) are the respective green and pollution intensity scores by occupation. X is a column vector of individual-level characteristics including indicator variables for age (youth, prime, old), educational attainment (low/high), gender (female/male), and location (urban/rural). The baseline group is young, female, low educational attainment, rural, and employed in a neutral job.

The difference in earnings premium between green- and pollution-intensive jobs, relative to a neutral job, is given by $(\beta - \gamma)$, after controlling for these individual-level characteristics. Hence, it represents the earnings premium over and above that commanded by higher-skilled, more experience, or urban workers.

To account for level differences across countries and sectors, and potential confounding common trend effects, country-year fixed effects are included in the regression. Standard errors are clustered at the level of the country-year. The coefficients on the earnings premia are scaled appropriately to the range of the underlying green and pollution intensities in the sample. In particular, the estimated average difference between the earnings for green- versus pollution-intensive jobs (average earnings premium) is:

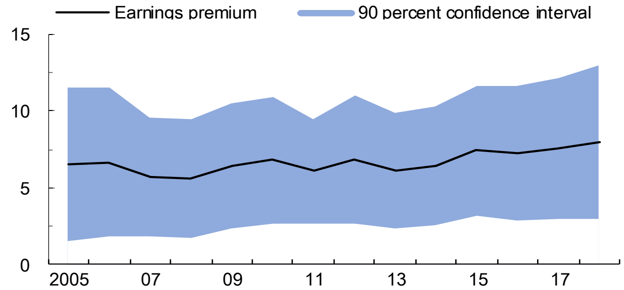
$$\hat{\beta}\text{Mean}\left(GreenInt_{i,s,c,t}\right) - \hat{\gamma}\text{Mean}\left(PolInt_{i,s,c,t}\right)$$

where the hat indicates the estimated value, and the mean is taken over the estimation sample using the sample weights.

[4] The earnings in our study is defined as gross cash near-cash employee income, which includes monetary component of employees' compensations and does not include other non-monetary income components.

Table 2 shows the underlying regression results and the implied earnings premium of average green-intensive job vis-à-vis average pollution intensive job of 6.7 log points.[5] Furthermore, Figure 8 plots the trend of earnings premium over the year where the regressions are run for each year with country fixed effects included between 2005 and 2018.

Figure 8. Evolution of Earnings Premium
(Percent)



Sources: EU Labor Force Survey; Occupational Information Network; Organisation for Economic Co-operation and Development; US Current Population Survey; Vona and others (2018).

Transition across environmental properties of jobs

This section studies how green and pollution-intensity of jobs affect three basic labor market transitions: (i) job-to-job transition (ii) out-of-work job transition, and (iii) job separation likelihoods, and how green and pollution-intensities of jobs affect these transitions.

Specifically, we run the following regressions.

$$Z_{i,s,c,t} = \alpha + \alpha_c + \alpha_t + \theta' X_{i,s,c,t} + \gamma' Y_{i,s,c,t-k} + \varepsilon_{i,s,c,t}$$

where Z is one of three dummy variables: i) job-to-job transition—a dummy equal to one if individual i, employed in occupation/sector s, and country c has been employed for two consecutive years, denoted as "*EE*" and changed job between *t* and *t-1*, and zero if individual *i* has been employed for two consecutive years but did not change job; ii) out-of-work job transition—a dummy equal to one if individual *i* has been employed in *t-2*, not employed in *t-1* and found a job in *t* (denoted as "ENE"), and zero if individual *i*¸has been employed in *t-2*, not employed in *t-1* and *t*; iii) job-separation transition—a dummy equal to one if individual *i* was employed in *t-1* but separated into non-employed in *t* (denoted "EN"). α_c and α_t are country and year fixed effects. X is a column vector of individual-level characteristics including indicator

[5] To give a sense of the size of the earnings premium of green-intensive jobs vis-à-vis pollution-intensive jobs, college earnings premium in our sample is estimated to be around 40 percent, which is broadly in line with the literature of 30 percent college wage premium estimated for 22 OECD countries by van der Velden and Bijlsma (2016). In the EU-SILC, occupational encoding is only available at the 1-digit level and sector of employment is not available. Conceptually, the above specification remains correct, but the level of variation across individuals is reduced with the coarser occupational encoding. For the US CPS, the estimation can be done with green- and pollution-intensity encoded at the 3-digit ISCO-08 level, in common with the other exercises

Table 2. Earnings Premium

	(1)
	Log real earnings
Green-intensity	4.625***
	(0.397)
Pollution-intensity	0.335***
	(0.0218)
Prime Age (30-54 yrs old) Dummy	0.434***
	(0.0104)
Elderly (55-64 yrs old) Dummy	0.462***
	(0.0145)
Male Dummy	0.310***
	(0.00581)
High-Skill Dummy	0.410***
	(0.00729)
Urban Dummy	0.111***
	(0.00497)
Constant	8.178***
	(0.00921)
Country FE	No
Year FE	No
Country x Year FE	Yes
Indiv. Char	Yes
Observations	2,243,990
R-squared	0.858
Adjusted R-squared	0.858
Implied Earnings Premium*	0.067197***
	(0.006776)

Standard errors are clustered at country x year cells and in parentheses. *, **, ***, denotes p<0.10, p<0.05, and p<0.01, respectively. Implied Earnings Premium is calculated for the average green-intensive job vis-à-vis the average pollution-intensive job.
Countries in the sample are AUT, BEL, BGR, CHE, CYP, CZE, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ISL, ITA, LTU, LUX, LVA, MLT, NOR, POL, PRT, ROU, SVK, SWE, and USA.

variables for age (youth, prime, old), educational attainment (low/high), gender (female/male), and location (urban/rural). The baseline group (here and throughout) are young, female workers with low educational attainment and living in a rural area. The lagged column vector of variables Y contains either occupation-based or sector-based environmental job properties. When considering the green- and pollution-intensity of jobs, then $Y = (GreenInt, PolInt)'$. When considering the emissions intensity of jobs, then $Y = EmisInt$. The environmental property of jobs Y are defined by the job in the past period, *k=1*—that is environmental job property from *t-*

1 (a year ago) when looking at i) job-to-job transition and iii) job-separation transition and *k=2* when looking at ii) out-of-work job transition. Note that the sector detail is not available when using EU-SILC in the estimation sample.

Table 3. Basic Job Transition Rates

	(1) EEcj Job-switch	(2) EN Job separation	(3) ENE Job finding
Constant	0.0765***	0.0604***	0.517***
	(0.00219)	(0.00146)	(0.0151)
Country FE	No	No	No
Year FE	No	No	No
Country x Year FE	No	No	No
Indiv. Char	No	No	No
Observations	1,393,240	1,690,588	19,829
R-squared	0.0765	0.0604	0.517
Adjusted R-squared	0.0765	0.0604	0.517

Regression results concerning emissions intensities were estimated using the EU-LFS while those concerning green and pollution -intensities were estimated using the EU-SILC. As a first step, the estimation is conducted by regressing $Z_{i,s,c,t}$ on a constant without any controls or fixed effects, which recovers the average job-to-job transition rate in the sample (via the estimated α) with standard errors clustered at country-year level (Table 3). This provides the benchmark transition likelihood estimates for (i) job-to-job transition (ii) job separation, and (iii) out-of-work job transition, respectively. In the sample, job-to-job transition rates are around 8 percent, 6 percent, and 52 percent, respectively (Table 3 Column (1)-(3)).[6]

As a second step, the regression is run including fixed effects and individual-level characteristics. This shows how one of the three transition likelihoods of the dependent variable varies with the environmental property of the past job (*t-1* for job-to-job transition and job separation, and *t-2* for out-of-work job transition) after controlling for demographic characteristics. The estimated coefficient γ shown in Table 4 is then rescaled by the mean of the environmental property and divided by the respective baseline labor market transition rates shown in Table 3. The rescaled coefficients are thus expressed as percent change of the average

[6] These rates are similar to those found in the literature. See Elsby, Hobijn and Şahin (2013) and Hobijn and Şahin (2009), among others.

Table 4. Transition Rates x Past Environmental Properties (Raw Coefficients)

	(1) EEcj	(2) EN	(3) ENE
Past Green Intensity	-0.128***	-0.145***	0.496
	(0.0283)	(0.0228)	(0.412)
Past Pollution Intensity	-0.0142*	-0.0352***	0.123
	(0.00723)	(0.00672)	(0.0778)
Prime Age (30-54 yrs old) Dummy	-0.0803***	-0.0631***	-0.0276*
	(0.00247)	(0.00253)	(0.0148)
Elderly (55-64 yrs old) Dummy	-0.115***	-0.0236***	-0.293***
	(0.00341)	(0.00339)	(0.0186)
Male Dummy	0.00506***	-0.0166***	0.0302***
	(0.00101)	(0.00109)	(0.0108)
High-Skill Dummy	0.00224*	-0.0295***	0.0360***
	(0.00130)	(0.00122)	(0.0120)
Urban Dummy	0.00557***	-0.000612	-0.000392
	(0.00120)	(0.000985)	(0.0110)
Constant	0.148***	0.133***	0.564***
	(0.00294)	(0.00297)	(0.0166)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country x Year FE	No	No	No
Indiv. Char	Yes	Yes	Yes
Observations	1,319,907	1,527,289	18,785
R-squared	0.0323	0.0260	0.246
Adjusted R-squared	0.0323	0.0260	0.245

baseline transition rates and are shown in Table 5 for green-intensity and pollution-intensity relative to those who previously held neutral jobs, respectively. We find that those who previously held green-intensive jobs and pollution-intensive jobs are less likely to experience on-the-job job switch and job separation than those who previously held neutral jobs. Those who previously held green-intensive jobs (pollution-intensive jobs) are 2.9 (0.75) percent less likely to experience on-the-job switch than those who previously held neutral jobs. They were not statistically significantly different in terms of job finding rates.

Persistence of Environmental Properties of Jobs and Its Impact on Transitions

Two key policy relevant questions are (i) is transitioning from pollution-intensive job to green-intensive job easy and (ii) how are the green, pollution, or emissions intensity of the previous job (origin) are associated with the current job (destination) environmental property? To answer these questions, we study i) how persistent the environmental properties of jobs (i.e.,

Table 5. Transition Rates x Past Environmental Properties (Rescaled Coefficients)

	(1) EEcj	(2) EN	(3) ENE
Past Green Intensity	-.0291***	-.0417***	.01469
	(.00642)	(.00656)	(.0122)
Past Pollution Intensity	-.00755*	-.0234***	.00888
	(.00384)	(.00447)	(.0056)
Prime Age (30-54 yrs old) Dummy	-0.0803***	-0.0631***	-0.0276*
	(0.00247)	(0.00253)	(0.0148)
Elderly (55-64 yrs old) Dummy	-0.115***	-0.0236***	-0.293***
	(0.00341)	(0.00339)	(0.0186)
Male Dummy	0.00506***	-0.0166***	0.0302***
	(0.00101)	(0.00109)	(0.0108)
High-Skill Dummy	0.00224*	-0.0295***	0.0360***
	(0.00130)	(0.00122)	(0.0120)
Urban Dummy	0.00557***	-0.000612	-0.000392
	(0.00120)	(0.000985)	(0.0110)
Constant	0.148***	0.133***	0.564***
	(0.00294)	(0.00297)	(0.0166)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country x Year FE	No	No	No
Indiv. Char	Yes	Yes	Yes
Observations	1,319,907	1,527,289	18,785
R-squared	0.0323	0.0260	0.246
Adjusted R-squared	0.0323	0.0260	0.245

Standard errors in parentheses

green, pollution, and emission intensities) are and ii) how easily workers can transition from say pollution-intensive jobs into green-intensive jobs. To this end, the previous regression is adjusted in two dimensions: i) the dependent variable is now the environmental property of the current job and ii) the sample is restricted to the ones who have actually experienced a transition. This entails restricting the sample to individuals with $Z = 1$ at time *t*. For on-the-job transitions, the sample is restricted to those who were continuously employed EE *and* changed jobs. For out-of-work-job transitions, the sample is restricted to those who were employed *t-2* (two years ago), not employed in *t-1*, and employed again in *t*. Job-separation transitions cannot be estimated in this setting as individual's new job is not observed. To be more precise, the regression specifications are as follows:

$$V_{i,s,c,t} = \alpha + \alpha_c + \alpha_t + \theta' X_{i,s,c,t} + \gamma' Y_{i,s,c,t-1} + \varepsilon_{i,s,c,t}$$

where $V \in \{GreenInt, PolInt, EmisInt\}$ is one of the environmental properties of a job. The lagged environmental properties, Y, is included to assess the persistence of environmental properties of jobs in job-to-job transitions (green, pollution, and emissions intensity). When the dependent variable is either green- or pollution-intensity, Y includes the lagged environmental properties of both green- and pollution intensities. When the dependent variable is emission intensity, then Y only includes emission intensity. When the dependent variable and the lagged environmental property differ (for example, green versus lagged pollution intensities), the estimated effects γ indicate how past job properties impact current job properties along a different dimension. This is particularly important for the pollution-intensive job-to-green job transition to assess whether a past pollution-intensive job helps or hurts the probability of finding a greener job relative to the neutral job. Note that, out-of-work transitions which require individuals to be tracked over three years can only be estimated using the EU-SILC sample and thus it is not estimated for emissions intensity due to data unavailability.

Among both on the-job job switchers and those who found jobs via out-of-job, green-intensities of the destination job were positively associated with high-skilled, prime-age or older, men relative to the base group. The association of living in urban areas was positively associated at a 10 percent significance level only for the on-the-job switchers and was not statistically significantly associated with green-intensity of the destination job for those who found a job via out-of-job.

Policies and the Green Transition

How are environmental policies associated with environmental properties of employment? While we will not be able to provide the causal inferences due to potential endogeneity and reverse causality, we will explore the potential links using individual level environmental properties with differences in environmental policies across different countries.

Table 6. Transition: Persistency of Environmental Properties

	EEcj		ENE	
	(1) Green-intensity	(2) Pollution-intensity	(3) Green-intensity	(4) Pollution-intensity
Past Green Intensity	0.477***	0.0374**	0.516***	0.152***
	(0.00894)	(0.0171)	(0.0183)	(0.0512)
Past Pollution Intensity	0.00210	0.480***	-0.00217	0.468***
	(0.00128)	(0.0107)	(0.00285)	(0.0197)
Prime Age (30-54 yrs old) Dummy	0.00113***	0.000565	0.00102***	-0.00121
	(0.000154)	(0.000616)	(0.000391)	(0.00177)
Elderly (55-64 yrs old) Dummy	0.000710***	-0.000324	0.00119**	-0.00334
	(0.000236)	(0.000906)	(0.000536)	(0.00235)
Male Dummy	0.00278***	0.0153***	0.00272***	0.0178***
	(0.000167)	(0.000663)	(0.000354)	(0.00138)
High-Skill Dummy	0.00379***	-0.0112***	0.00256***	-0.00555***
	(0.000187)	(0.000582)	(0.000396)	(0.00152)
Urban Dummy	0.000244*	-0.00122**	0.000406	-0.00133
	(0.000144)	(0.000613)	(0.000336)	(0.00154)
Constant	0.00518***	0.0175***	0.00417***	0.0127***
	(0.000229)	(0.000826)	(0.000428)	(0.00188)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country x Year FE	No	No	No	No
Indiv. Char	Yes	Yes	Yes	Yes
Observations	101988	101988	8807	8807
R-squared	0.302	0.311	0.343	0.317
Adjusted R-squared	0.302	0.310	0.340	0.313

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

To be specific, the following regression was run to gauge how environmental policies are associated with employment in green- and pollution-intensive occupations and the level of emissions per worker among the employed:

$$V_{i,s,c,t} = \alpha_c + \alpha_t + \beta' X_{i,s,c,t} + \theta' W_{c,t} + \delta P_{c,t} + \mu' W_{c,t} \cdot P_{c,t} + \varepsilon_{i,s,c,t}$$

where i, s, c, t denotes individual, occupation/sector, country and time, respectively. The sample consists of those individuals who are employed. $V_{i,s,c,t}$ is green, pollution, or emissions intensity of employment for an individual worker. α_c and α_t are country and time fixed effects. $X_{i,s,c,t}$ represents the column vector of individual-specific characteristics as in the previous section. $P_{c,t}$

is a country-specific environmental policy indicator, which is the overall environmental policy stringency measured by the OECD environmental policy stringency index (EPSI).
$W_{c,t}$ is a column vector of country-specific characteristics or structural features and other controls that do not vary across individuals within a country. Given the interest in understanding how particular features may influence the effects of environmental policies, these variables and their interactions with the EPSI are estimated in the second stage.

The core variables of interest in $\mathrm{W}_{\mathrm{c,t}}$ include the following three sets of variables: i) labor market policies (job retention policies and reallocation policies); ii) labor market structural features (environmental protection legislation, replacement rate, and collective bargaining); and iii) product market structural features.[7] To keep things manageable, each group of variables are considered separately, one group at a time. The interaction between W and P allows for the levels of W to influence the marginal effect of P. Coefficient δ captures the level impact of the EPSI. To express the coefficients as a percent change in environmental properties, we rescale it by multiplying the estimated coefficient by the difference between 25th and 75th percentile of EPSI, and dividing it by the mean of environmental property of jobs. Note that regression results concerning emissions intensities were estimated using the EU-LFS while those concerning green and pollution intensities were estimated using the EU-SILC.

Table 7 shows the estimated associations of policies with environmental properties of jobs among the employed. When expressed as a percent change in environmental properties, we find that when a change in environmental policy stringency index (EPSI) from the 25th and 75th percentile (.9083 in the unit of the Index) is associated with a 1.83 percent (raw coefficient of .000349) higher green intensity (Column 1) and a 4.22 lower pollution-intensity (Column 2) among the employed. In other words, green intensity (pollution) intensity among employed is higher (lower) in countries with more stringent environmental policies. For emissions intensity (Column 3), an increase in the EPSI from the 25th and 75th percentile is associated with a 5.76 percent reduction in emissions intensity (raw coefficient of .0635 noting that emisions intensity is measured in logarithm).

[7] Beyond those economic characteristics directly related to labor market and structural features, there are studies that suggest that the effectiveness of environmental policies may also be related to institutional quality (Aldieri and others 2021).

Table 7: Associations of Environmental Policy with Environmental Properties among Employed

	(1) Green-int.	(2) Pollution-int.	(3) Emissions-int.	(4) Green-int.	(5) Pollution-int.
EPSI	0.000349**	-0.00170***	-0.0635***	0.000729***	-0.00468***
	(0.000169)	(0.000602)	(0.0202)	(0.000202)	(0.00102)
Retention				0.000830***	
				(0.000239)	
Retention x EPSI				-0.000370***	
				(0.0000799)	
Reallocation				0.000472**	
				(0.000224)	
Reallocation x EPSI				-0.0000141	
				(0.0000591)	
ColBar					0.00000239
					(0.000135)
EPR					0.00111
					(0.00262)
RepRate					-0.000563***
					(0.000161)
ColBarxEPSI					-0.0000606*
					(0.0000360)
EPRxEPSI					0.000247
					(0.000884)
RepRatexEPSI					0.000271***
					(0.0000450)
Constant	0.00692***	0.0371***	2.402***	0.00503***	0.0482***
	(0.000519)	(0.00183)	(0.0624)	(0.000633)	(0.00600)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country x Year FE	No	No	No	No	No
Indiv. Char	Yes	Yes	Yes	Yes	Yes
Observations	1,754,565	1,754,565	7,312,510	1,754,565	1,754,565
R-squared	0.0662	0.0757	0.242	0.0666	0.0762
Adjusted R-squared	0.0662	0.0756	0.242	0.0666	0.0762

Moreover, when interacted with labor market policies--specifically job retention policies and worker reallocation policies, we see that the *total* impact of EPSI for a country with average retention policy is associated with a -1.66 percent lower green intensity among the employed

Table 8: Association of Environmental Properties among On-the-job Switchers

	(1) Green Int.	(2) Emission Int.
EPSI	-0.000247	0.0338
	(0.000443)	(0.0356)
Past Green Int.	0.337***	
	(0.0552)	
Past Pollution Int.	0.0311***	
	(0.00888)	
Past Emissions Int.		0.706***
		(0.0492)
Past Green Int. x EPSI	0.0570***	
	(0.0188)	
Past Pollution Int. x EPSI	-0.00744**	
	(0.00293)	
Past Emissions Int. x EPSI		-0.0224
		(0.0155)
Constant	0.00476***	0.708***
	(0.00131)	(0.116)
Country FE	Yes	Yes
Year FE	Yes	Yes
Country x Year FE	No	No
Indiv. Char	Yes	Yes
Observations	65,417	454,351
R-squared	0.313	0.540
Adjusted R-squared	0.312	0.540

(Column 4).[8] In other words, for a country with average level of retention policy spending, environmental policy may not be as effective.

When interacted with labor market institutions—measured by replacement rate for the unemployed insurance, we find that pollution intensities among employed workers are 22.6 percent lower for a country with the average level of collective bargaining index and 9.2 percent higher for a country with the average level of unemployment insurance spending between countries of 25th and 75th percentile of the environmental policy stringency index (Column 5).

[8] For job retention and reallocation policies, this paper uses expenditures on specific policy programs from the OECD Labor Market Programmes Database. Job retention support includes expenditure on the following policy programs: benefits administration; training; workplace training; special support for apprenticeships; employment maintenance incentives; partial unemployment benefits; and part-time unemployment benefits. Job reallocation support comprises spending on institutional and integrated training, both expressed in percent of GDP per capita, per unemployed.

This in part reflects the impact of policies on job transitions. To investigate the impact of policies on job transitions, similar regressions are run for on-the-job switchers (shown in Table 8). When environmental policies are more stringent, the average green intensity of new-found jobs of workers who switch while employed tends to be higher, and the average emissions intensity of these jobs tends to be lower. For a country shifting from the 25th to the 75th percentile of environmental policy stringency, destination jobs for on-the-job job switchers have about 4 percent higher average green intensity, while their average emissions intensity is about 2 percent lower.

The above findings on the labor market greening effects of environmental policies point to their role in helping further the green transition. However, these average effects may mask the impacts of differences in countries' labor market policies and structural features on the effectiveness of environmental policies. This sub-section attempts to unpack these effects, by considering how they may be mediated by such country-specific characteristics. This is accomplished by expanding upon the earlier linear regression analysis of the effects of environmental policy stringency through the inclusion of interactions with selected labor market policy and structural feature indicators.

The results suggest that labor market policies and features associated with reduced incentives for worker reallocation in the economy tend to dampen the effectiveness of environmental policies in greening the labor market. In particular, higher spending on job retention support and greater generosity of unemployment insurance are associated with declining effectiveness of environmental policies in spurring increases in the green intensity and decreases in the pollution intensity of employment, respectively. Worker reallocation support (including spending on training programs) was not found to significantly alter the effectiveness of environmental policies (showed no statistically significant relationship), suggesting that it has historically not been designed to support labor market greening. By contrast, there is evidence that environmental policies are more effective in reducing the pollution intensity of employment in countries with a greater prevalence of more coordinated labor market and collective bargaining arrangements. Why might this be the case? Such arrangements could help social partners—businesses, workers, and the government—coordinate on shared actions to support a green transformation as a common objective and ease any associated labor market adjustment.

In summary, the empirical analysis suggests that more stringent environmental policies help promote a greener labor market. However, endogeneity, the lack of granularity on alternative policy instruments, and the unprecedented nature of the climate change mitigation challenge argue for caution in extrapolating too widely from these empirical findings.

Conclusion

Reducing the profound downside risks from climate change calls for a green transformation of the economy: production structures must change to lower global GHG emissions. In this paper, we investigated the labor market implications of such a green economic transformation, using a mix of empirical and model-based analyses.

The paper began by quantifying the environmental properties of individual workers' jobs through three different metrics, reflecting how green, polluting, and carbon-emitting each job is. More green- and pollution-intensive jobs both appear to be concentrated among subsets of workers: economy-wide average green and pollution intensities are relatively low. Still, there is a wide dispersion of these environmental properties across and within sectors, suggesting the capacity exists for labor reallocation along both dimensions. In particular, industrial sectors tend to be simultaneously more green-, pollution-, and emissions-intensive, than services.

Second, the paper looked at the relationship between workers' demographic characteristics and the environmental properties of their jobs. It found that more green-intensive occupations tend to have higher-skilled and more urban workers, while the reverse is true for more pollution-intensive jobs. Importantly, even after controlling for skills, green-intensive jobs exhibit an earnings premium—almost 7 percent—compared with pollution-intensive jobs on average.

Third, reallocation could be challenging for individual workers. The paper found that a worker with a history of more pollution-intensive or neutral work is less likely to move into a more green-intensive job. Higher skills do make for an easier match to a more green-intensive job, pointing to the importance of a worker's human capital in easing transitions. Targeted and effective training programs to boost the human capital of lower-skilled workers in pollution-intensive or neutral occupations could help, by improving their ability to move into more green-intensive occupations.

Fourth, environmental policies are effective in shifting employment towards greener jobs, but they work best in economies where incentives for reallocation are not inhibited. This points to the importance of moving from job retention to measures that support worker reallocation as COVID-19 shifts from pandemic to endemic. Recent labor market dynamics indicate that greener employment was relatively more resilient during the COVID-19 recession.

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Annex I. Additional Tables

Annex Table I.1. Greenness and Pollution intensity by Occupations, ISCO 08, 3 digits

Code	Title	Greenness intensity	Pollution intensity
111	Legislators and Senior Officials	0.0	0.0
112	Managing Directors and Chief Executives	15.8	0.0
121	Business Services and Administration Managers	0.0	0.0
122	Sales, Marketing and Development Managers	22.2	0.0
131	Production Managers in Agriculture, Forestry and Fisheries	1.8	0.0
132	Manufacturing, Mining, Construction and Distribution Managers	22.9	0.0
133	Information and Communications Technology Services Managers	0.0	0.0
134	Professional Services Managers	0.0	0.0
141	Hotel and Restaurant Managers	0.0	0.0
142	Retail and Wholesale Trade Managers	0.0	0.0
143	Other Services Managers	0.0	0.0
211	Physical and Earth Science Professionals	11.2	46.9
212	Mathematicians, Actuaries and Statisticians	0.0	0.0
213	Life Science Professionals	34.3	2.3
214	Engineering Professionals (excluding Electrotechnology)	30.8	5.0
215	Electrotechnology Engineers	9.4	0.0
216	Architects, Planners, Surveyors and Designers	11.9	0.0
221	Medical Doctors	0.0	0.0
222	Nursing and Midwifery Professionals	0.0	0.0
223	Traditional and Complementary Medicine Professionals	0.0	0.0
224	Paramedical Practitioners	0.0	0.0
225	Veterinarians	0.0	0.0
226	Other Health Professionals	0.0	0.0
231	University and Higher Education Teachers	0.0	0.0
232	Vocational Education Teachers	0.0	0.0
233	Secondary Education Teachers	0.0	0.0
234	Primary School and Early Childhood Teachers	0.0	0.0
235	Other Teaching Professionals	0.0	0.0
241	Finance Professionals	5.1	0.0
242	Administration Professionals	1.4	0.0
243	Sales, Marketing and Public Relations Professionals	3.9	0.0
251	Software and Applications Developers and Analysts	0.2	0.0
252	Database and Network Professionals	0.0	0.0

Code	Title	Greenness intensity	Pollution intensity
261	Legal Professionals	0.0	0.0
262	Librarians, Archivists and Curators	0.0	0.0
263	Social and Religious Professionals	2.7	0.0
264	Authors, Journalists and Linguists	0.4	0.0
265	Creative and Performing Artists	0.0	0.0
311	Physical and Engineering Science Technicians	5.6	3.7
312	Mining, Manufacturing and Construction Supervisors	0.0	37.1
313	Process Control Technicians	1.3	87.2
314	Life Science Technicians and Related Associate Professionals	17.6	0.0
315	Ship and Aircraft Controllers and Technicians	0.0	0.0
321	Medical and Pharmaceutical Technicians	0.0	0.0
322	Nursing and Midwifery Associate Professionals	0.0	0.0
323	Traditional and Complementary Medicine Associate Professionals	0.0	0.0
324	Veterinary Technicians and Assistants	0.0	0.0
325	Other Health Associate Professionals	0.3	0.0
331	Financial and Mathematical Associate Professionals	0.2	0.0
332	Sales and Purchasing Agents and Brokers	6.7	0.0
333	Business Services Agents	0.6	0.0
334	Administrative and Specialized Secretaries	0.0	0.0
335	Government regulatory associate professionals	0.0	0.0
341	Legal, Social and Religious Associate Professionals	0.0	0.0
342	Sports and Fitness Workers	0.0	0.0
343	Artistic, Cultural and Culinary Associate Professionals	0.0	0.0
351	Information and Communications Technology Operations and User Support Technicians	0.0	0.0
352	Telecommunications and Broadcasting Technicians	0.0	0.0
411	General Office Clerks	0.0	0.0
412	Secretaries (general)	0.0	0.0
413	Keyboard Operators	0.0	0.0
421	Tellers, Money Collectors and Related Clerks	0.0	0.0
422	Client Information Workers	0.0	0.0
431	Numerical Clerks	0.0	0.0
432	Material recording and Transport Clerks	1.8	0.0
441	Other Clerical Support Workers	0.0	0.0
511	Travel Attendants, Conductors and Guides	0.0	0.0
512	Cooks	0.0	0.0

Code	Title	Greenness intensity	Pollution intensity
513	Waiters and Bartenders	0.0	0.0
514	Hairdressers, Beauticians and Related Workers	0.0	0.0
515	Building and Housekeeping Supervisors	0.0	0.0
516	Other Personal Services Workers	0.0	0.0
521	Street and Market Salespersons	0.0	0.0
522	Shop Salespersons	0.0	0.0
523	Cashiers and Ticket Clerks	0.0	0.0
524	Other Sales Workers	0.0	0.0
531	Child Care Workers and Teachers' Aides	0.0	0.0
532	Personal Care Workers in Health Services	0.0	0.0
541	Protective Services Workers	0.0	0.0
611	Market Gardeners and Crop Growers	0.0	0.0
612	Animal Producers	0.0	0.0
613	Mixed Crop and Animal Producers	0.0	0.0
621	Forestry and Related Workers	0.0	4.5
622	Fishery Workers, Hunters and Trappers	0.0	0.0
631	Subsistence Crop Farmers	0.0	0.0
632	Subsistence Livestock Farmers	0.0	0.0
633	Subsistence Mixed Crop and Livestock Farmers	0.0	0.0
634	Subsistence Fishers, Hunters, Trappers and Gatherers	0.0	0.0
711	Building Frame and Related Trades Workers	1.7	0.1
712	Building Finishers and Related Trades Workers	10.5	0.0
713	Painters, Building Structure Cleaners and Related Trades Workers	0.0	15.9
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers	3.6	2.9
722	Blacksmiths, Toolmakers and Related Trades Workers	1.7	25.5
723	Machinery Mechanics and Repairers	1.6	7.6
731	Handicraft Workers	0.0	6.1
732	Printing Trades Workers	0.0	0.0
741	Electrical Equipment Installers and Repairers	0.0	8.2
742	Electronics and Telecommunications Installers and Repairers	0.0	1.8
751	Food Processing and Related Trades Workers	0.0	31.7
752	Wood Treaters, Cabinet-makers and Related Trades Workers	0.0	100.0
753	Garment and Related Trades Workers	0.0	32.4
754	Other Craft and Related Workers	4.9	1.1
811	Mining and Mineral Processing Plant Operators	0.6	95.2

Code	Title	Greenness intensity	Pollution intensity
812	Metal Processing and Finishing Plant Operators	0.0	100.0
813	Chemical and Photographic Products Plant and Machine Operators	0.9	60.3
814	Rubber, Plastic and Paper Products Machine Operators	0.0	73.2
815	Textile, Fur and Leather Products Machine Operators	0.0	13.9
816	Food and Related Products Machine Operators	0.0	85.7
817	Wood Processing and Papermaking Plant Operators	0.0	100.0
818	Other Stationary Plant and Machine Operators	0.0	88.2
821	Assemblers	0.2	0.0
831	Locomotive Engine Drivers and Related Workers	0.0	1.4
832	Car, Van and Motorcycle Drivers	0.0	0.0
833	Heavy Truck and Bus Drivers	6.9	0.0
834	Mobile Plant Operators	0.0	3.2
835	Ships' Deck Crews and Related Workers	0.0	0.0
911	Domestic, Hotel and Office Cleaners and Helpers	0.0	0.0
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers	0.0	0.5
921	Agricultural, Forestry and Fishery Labourers	0.0	0.0
931	Mining and Construction Labourers	12.1	1.7
932	Manufacturing Labourers	2.7	2.3
933	Transport and Storage Labourers	1.8	0.0
941	Food Preparation Assistants	0.0	0.0
951	Street and Related Services Workers	0.0	0.0
952	Street Vendors (excluding Food)	0.0	0.0
961	Refuse Workers	38.7	0.0
962	Other Elementary Workers	3.3	0.5

Sources: Dierdorff and others (2009); Occupational Information Network (O*NET) Resource Center (2021); Vona and others (2018); and IMF staff compilation.

Annex Table I.2. Data Sources

Indicator	Sources
Individual-level labor force survey indicators	European Union Labor Force Survey; European Union Statistics on Income and Living Conditions; Mexico National Survey of Occupation and Employment; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey
Green- and pollution-intensive occupations	Occupational Information Network (O*NET); Vona and others (2018)
Sector-level emissions	IMF Climate Change Indicators Dashboard
Sector-level and total employment	EU KLEMS; European Union Labor Force Survey; International Labour Organization; Mexico National Survey of Occupation and Employment; OECD Annual Labor Force Survey; OECD Annual National Accounts database; OECD Structural Analysis database; Statistics South Africa Quarterly Labour Force Survey; US Bureau of Economic Analysis
Real output (gross) by industry and the ratio of the capital stock (net) to gross output	US Bureau of Economic Analysis; EU KLEMS; World KLEMS
Environmental Policy	OECD Environmental Policy Stringency Index database
Labor market policies (spending on job retention and reallocation policies; collective (wage) bargaining coverage rate)	Allard (2005); Database on Institutional Characteristics of Trade Unions, Wage setting, State Intervention and Social Pacts (ICTWSS); OECD Employment Database; OECD Indicators of Product Market Regulation; OECD Labor Market Programmes Database; OECD Tax and Benefits System

Source: IMF staff compilation.

Annex Table I.3. Sectoral Abbreviations, ISIC Rev. 4

Sector code	Sector description	Sector abbreviation
A	Agriculture, forestry and fishing	Agri.
B	Mining and quarrying	Mining
C	Manufacturing	Manuf.
D	Electricity, gas, steam and air conditioning supply	Elec./Gas
E	Water supply; sewerage, waste management and remediation activities	Water
F	Construction	Constr.
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Trade
H	Transportation and storage	Transport
I	Accommodation and food service activities	Acc./Food
J	Information and communication	Info./Com.
K	Financial and insurance activities	Fin./Ins.
L	Real estate activities	Real Est.
M	Professional, scientific and technical activities	Prof.
N	Administrative and support service activities	Adm./Serv.
O	Public administration and defence; compulsory social security	Public Adm.
P	Education	Educ.
Q	Human health and social work activities	Health
R	Arts, entertainment and recreation	Arts
S	Other service activities	Oth. Serv.
	* More aggregated sectors	
	D & E	Utilities
	M & N	Prof. Serv.
	R & S	Arts/Oth. Serv.

Source: IMF staff compilation.

PUBLICATIONS

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