CHAPTER 3

A GREENER LABOR MARKET: EMPLOYMENT, POLICIES AND ECONOMIC TRANSFORMATION

Online Annex

Annex 3.1 Data Sources, Sample Coverage, Variable Definitions and Chapter Figure Notes

The chapter draws on a variety of macroeconomic and microeconomic, individual worker-level datasets. Key data sources are listed in Annex Table 3.1.1. For the European Union (EU) members, individual workers' labor market statuses, occupational and sectoral details on employment, job characteristics, and demographic characteristics are obtained from the EU Labor Force Survey (EU-LFS; 1983–2019) and the EU Statistics on Income and Living Conditions (EU-SILC; 2003–18).[1] The responsibility for all conclusions drawn from the data lies entirely with the authors. Individual-level data for the United States (US) is obtained from IPUMS Current Population Survey (CPS), covering 1976–2021 (Flood and others 2021). For Mexico and South Africa, the individual-level data comes from Mexico's National Survey of Occupation and Employment (2006–19) and Statistics South Africa's Quarterly Labour Force Survey (2008–19), respectively. All data is processed at the annual frequency, and the exact sample (country and year) varies with the analyses and exercises based on data coverage (Table 3.1.2).

Employment by sector data for most EU countries is compiled from the OECD Structural Analysis Database, OECD Annual National Accounts Database and the OECD Annual Labor

Annex Table 3.1.1 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.

[1] An overview of sectors and their abbreviations is presented in Annex Table 3.1.4.

Force Survey. The US sectoral employment data comes from the Bureau of Economic Analysis. For Bulgaria, Malta, Mexico, Portugal, Romani and South Africa, national labor force surveys were used. The EU KLEMS and ILOSTAT databases were used as complementary sectoral data sources for some countries in the sample.

To gauge the effect of environmental policies, the chapter uses the Environmental Policy Stringency Index (EPSI) of the OECD, which is available annually from 1990, ending in 2012 or 2015 depending on the country under study.[2] The index is an encompassing measure of a country's environmental policy stance, combining information on carbon pricing, research and development (R&D) spending on green technologies, and the stringency of environmental regulation, ranging from 0 (not stringent) to 6 (most stringent). See Botta and Kozluk (2014) for further details on the index and its construction.

To control for labor market policies and structural features that could affect the impact of environmental policies, the chapter examined the following three sets of variables: i) active labor market policies (job retention and worker reallocation support measures); ii) labor market structural features (the stringency of employment protection legislation, the average gross replacement rate for unemployment insurance, and the extent of coordinated and collective bargaining); and iii) product market structural features. For job retention and reallocation policies, the chapter 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.

For the labor market structural features, the index of employment protection legislation is based on Allard (2005) extended with the latest OECD indicators (Ahn and others 2019). The index ranges from 0 to 6, with higher values representing stronger employment protection.[3] The gross unemployment replacement rate is calculated as the gross unemployment benefit level as a percentage of previous gross earnings from the OECD Tax and Benefits System.[4] The data source for the coverage of collective bargaining arrangements is the Institutional Characteristics of Trade Unions, Wage setting, State Intervention and Social Pacts (ICTWSS). Collective bargaining is the share (as percent) of all wage and salary earners in employment, that are covered by coordinated, collective (wage) bargaining agreements, adjusted for the possibility that some sectors or occupations are excluded from the right to bargain. For the product market, the economy-wide product market regulation indicator from the OECD is used. The indicator covers regulation of state control of business enterprises; legal and administrative barriers to entrepreneurship; barriers to international trade and investment. The index goes from 0 to 6, where higher values indicate more stringent regulation.

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[2] The index value is extrapolated until 2018 for all countries in the sample by carrying the last available observation by country forward.

[3] The data has been spliced until 2018 using the indicators of employment protection legislation in the OECD Employment Database.

[4] The data covers two earnings levels (67% and 100%), three family situations (single, one-earner married couple, and two-earner married couple) and three durations of unemployment (60 months). For further details, see OECD (1994) and Martin (1996).

Annex Table 3.1.2. Sample of Economies included in Analytical Exercises

Exercises	Economies
Evolution of Average Carbon Emissions Intensity (Figure 3.1) Cross-Country Distribution and Evolution of Green- and Pollution-Intensive Occupations and Carbon Emissions per Worker (Figure 3.2, panel 5)	Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Cross-Country Distribution and Evolution of Green- and Pollution-Intensive Occupations and Carbon Emissions per Worker (Figure 3.2, panels 1, 2, 3 & 4) Sectoral Differences in the Distribution of Green, Pollution, and Emissions Intensities of Employment (Figure 3.3, panels 1 & 2) Distribution of General Green Skills across Countries and Sectors (Annex Figure 3.2.4) Environmental Properties of New Jobs in Transitions (Annex Figure 3.4.1)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary*, Ireland, Iceland, Italy, Latvia, Lithuania, Luxembourg, Malta, Mexico*, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia, South Africa*, Spain, Sweden, Switzerland, United Kingdom, United States
Cross-Country Distribution and Evolution of Green- and Pollution-Intensive Occupations and Carbon Emissions per Worker (Figure 3.2, panel 6) Sectoral Differences in the Distribution of Green, Pollution, and Emissions Intensities of Employment (Figure 3.3, panel 3)	Austria, Belgium, Bulgaria*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Mexico*, Portugal, Romania*, Slovak Republic, Slovenia, South Africa*, Spain, Sweden, Switzerland, United Kingdom, United States
Environmental Properties of Jobs by Worker Characteristics (Figure 3.4) Relationship between the Environmental Properties of Jobs (Annex Figure 3.1.1) Environmental Properties of Jobs by Job and Worker Characteristics (Annex Figure 3.2.2, panels 3, 4, 5 & 6) Environmental Properties of Jobs by Routinizability (Annex Figure 3.2.3)	Austria, Belgium, Bulgaria*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Mexico*, Netherlands, Portugal, Romania*, Slovak Republic, Slovenia, South Africa*, Spain, Sweden, Switzerland, United Kingdom, United States
Earnings and the Environmental Properties of Jobs (Figure 3.5)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary*, Ireland, Iceland, Italy, Latvia, Lithuania, Luxembourg, Malta, Norway, Poland*, Portugal, Romania*, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom, United States
Job Transition Rates and the Environmental Properties of Past Jobs (Figure 3.6)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary*, Ireland, Iceland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Probability of Transitioning into a Green-Intensive or Neutral Job among Job Switchers (Figure 3.7)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary*, Ireland, Iceland, Italy, Latvia, Lithuania, Luxembourg, Malta, Mexico*, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Estimated Effects of Environmental Policy Stringency (Figure 3.8) Estimated Effects of Environmental Policy Stringency Conditional on Labor Market Features (Figure 3.9)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary*, Ireland, Iceland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Cross-Country Distribution and Evolution of Employment in the Industrial Sector (Annex Figure 3.2.1)	Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Spain, United Kingdom, United States
Environmental Properties of Jobs by Job and Worker Characteristics (Annex Figure 3.2.2, panel 1)	Austria, Belgium, Bulgaria*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom
Environmental Properties of Jobs by Job and Worker Characteristics (Annex Figure 3.2.2, panel 2)	Austria, Belgium, Bulgaria*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States

Source: IMF staff compilation.

[1]Asterisk(*) denotes emerging market and developing economies as classified by the October 2021, World Economic Outlook.

Environmental Properties of Jobs: Definition and Construction

The chapter examines three environmental properties of employment: green-, pollution- and emissions-intensity of the job. The first two properties are based on workers' occupations, and the third property is based on the sector in which they are employed. 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, expressed as a percent (ranging from 0 to 100). For occupations involving no green tasks, their green task intensity 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).[5]

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- and pollution-intensive job classifications are crosswalked 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 in the range

Annex Table 3.1.3. Example Occupations by Environmental Property

	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 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.

[5] O*NET also identifies a set of occupations that may see increased demand.

from 0 to 100 for each occupation. For each worker, green and pollution intensity scores are assigned based on the worker's occupation. Green intensity is then the average, employment-weighted share of green tasks out of 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, green and pollution intensities under ISCO-08 may both be positive for some occupations. See Table 3.1.3 for example occupations by green and pollution intensities.

For the sectors in which workers are employed, emissions intensity of employment is measured by carbon emissions (in CO_2 tons) per worker. For a given sector, the chapter 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 CO_2 emissions. Sectoral employment is obtained from the sources

Annex Table 3.1.4 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.

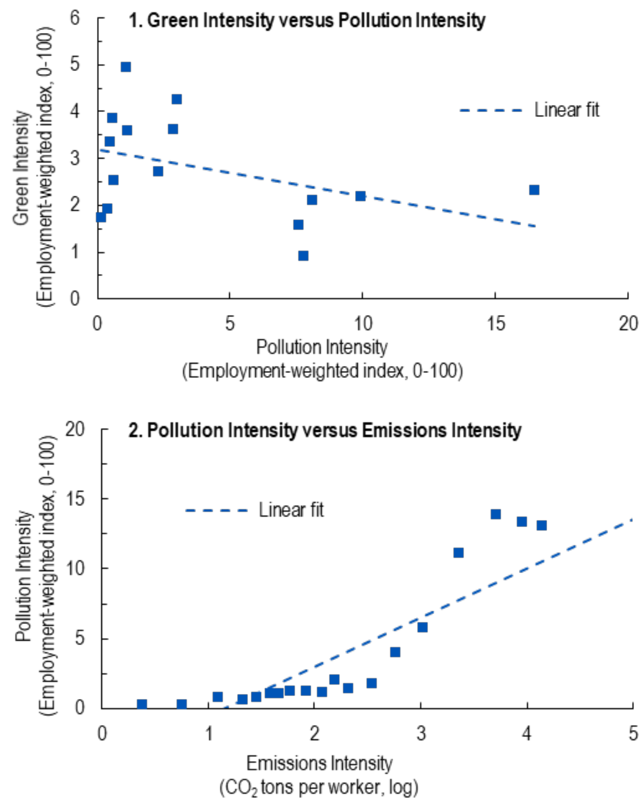
Source: IMF staff compilation.

listed in Annex Table 3.1.1 for the ISIC revision 4 top-level sectors listed in Annex Table 3.1.4. 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.

Annex Figure 3.1.1 exhibits how these environmental properties of jobs are related to each other within the sample of individual-level data, based on their links to workers' occupations and sectors of employment. As mentioned in the main text, 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. More pollution-intensive jobs are positively related to more emissions-intensive jobs.

Annex Figure 3.1.1. Relationships between the Environmental Properties of Jobs

Green intensive jobs are generally less polluting, with pollution and emissions intensities showing a strong positive correlation.



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); and IMF staff calculations.
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.

Contributions to Changes in Emissions Intensity

Figure 3.1 uses a shift-share analysis to decompose the evolution of changes in the average carbon emissions intensity over time. Define emissions intensity per worker (Y_t) for the whole economy in year *t* as:

$$Y_t = \frac{E_t}{L_t} = \sum_{s=1}^{N} \left(\frac{L_{s,t}}{L_t}\right)\left(\frac{E_{s,t}}{L_{s,t}}\right)$$

where E_t and L_t denote total emissions and number of workers, respectively, and $E_{s,t}$ and $L_{s,t}$ are the respective sector-level quantities. Emissions per worker (E_t/L_t) can be written as the employment-weighted average of emissions per worker across all sectors in the economy indexed by *s* (with a total number of sectors *N*). The change in emissions intensity from time *t-k* to *t* can then be decomposed as follows:

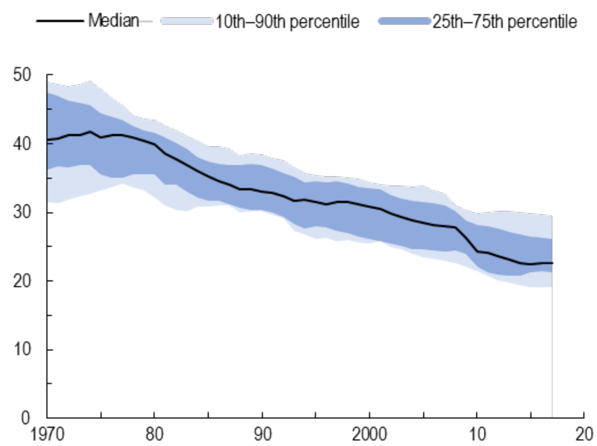
$$\Delta_k Y_t = \frac{E_t}{L_t} - \frac{E_{t-k}}{L_{t-k}} = \sum_{s=1}^{N} \left(\frac{L_{s,t}}{L_t}\right)\left(\frac{E_{s,t}}{L_{s,t}}\right) - \sum_{s=1}^{N} \left(\frac{L_{s,t-k}}{L_{t-k}}\right)\left(\frac{E_{s,t-k}}{L_{s,t-k}}\right)$$

$$= \underbrace{\sum_{s=1}^{N} \left(\Delta_k \left(\frac{L_{s,t}}{L_t} \right) \right) \left(\frac{E_{s,t}}{L_{s,t}} \right)}_{Labor\ reallocation} + \underbrace{\sum_{s=1}^{N} \left(\Delta_k \left(\frac{E_{s,t}}{L_{s,t}} \right) \right) \left(\frac{L_{s,t-k}}{L_{t-k}} \right)}_{Sectoral\ efficiency}$$

The final expression shows that it may be decomposed into a component reflecting the contribution of labor reallocation across sectors, and a component capturing sectoral emissions intensity changes holding constant the initial distribution of employment across sectors. The second component reflects sectoral efficiency changes in emissions intensity over time. Figure 3.1 takes the year 2005 as the initial year, and then shows the total cumulative change in emissions intensity (as a percent of 2005 emissions intensity) with its two components.

Annex Figure 3.2.1. Cross-Country Distribution and Evolution of Employment in the Industrial Sector
(Percent of employment)

Employment in the industrial sector witnessed a steady decline since the mid-1970s reaching 22.7 percent in 2017.



Sources: EU Labor Force Survey; ILOSTAT database; US Current Population Survey; and IMF Staff Calculations.
Note: The chart is constructed using a restricted sample of 12 countries with comprehensive employment-by-sector data over the entire sample period. The industrial sector includes sectors B (Mining and quarrying), C (Manufacturing), D & E (Utilities), F (Construction) and H (Transportation).

The kernel density estimates in Figure 3.2 represent the average of kernel density estimates for employment by green, pollution, and emissions intensities across countries in the sample. Given the skewed and long-tailed shape of the distributions, the chapter 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.

Annex 3.2. Additional Findings

Secular Trend in Industrial Sector Employment Share

The gradual decline in the emissions intensity of employment, as shown in Figure 3.2 (panel 5), partly reflects the movement of workers away from high pollution-intensive occupations and high emissions-intensive sectors over time. Annex Figure 3.2.1 illustrates this long-term trend by showing the decline in the share of employment in sectors typically characterized by high emissions intensity (mining, manufacturing, utilities, construction, and transportation) since 1970. In addition to the gradual decline in the median share of employment in these sectors, the dispersion of the cross-country distribution (measured by the 25th-75th percentile range) has also shrunk to its lowest level in 2017 signaling convergence among the countries in the sample.[6]

[6] As a robustness check, the cross-country average share of the industrial sector in total employment was estimated using a larger sample of countries with varying time coverage. To account for the uneven entry/exit of countries in the sample in different years, the Karabarbounis and Neiman (2014) algorithm was used. The algorithm regresses the variable-of-interest on country and time fixed effects, with the initial time period excluded from the time fixed effects. The simple cross-country average in the initial time period is used as initial value for the average share estimate. The time fixed effects for the subsequent periods are then added to the initial value to recover an estimate of the entire time series. This method delivers a declining trend between 1970 and 2017, similar to what is shown in the figure.

Job Characteristics and Environmental Properties

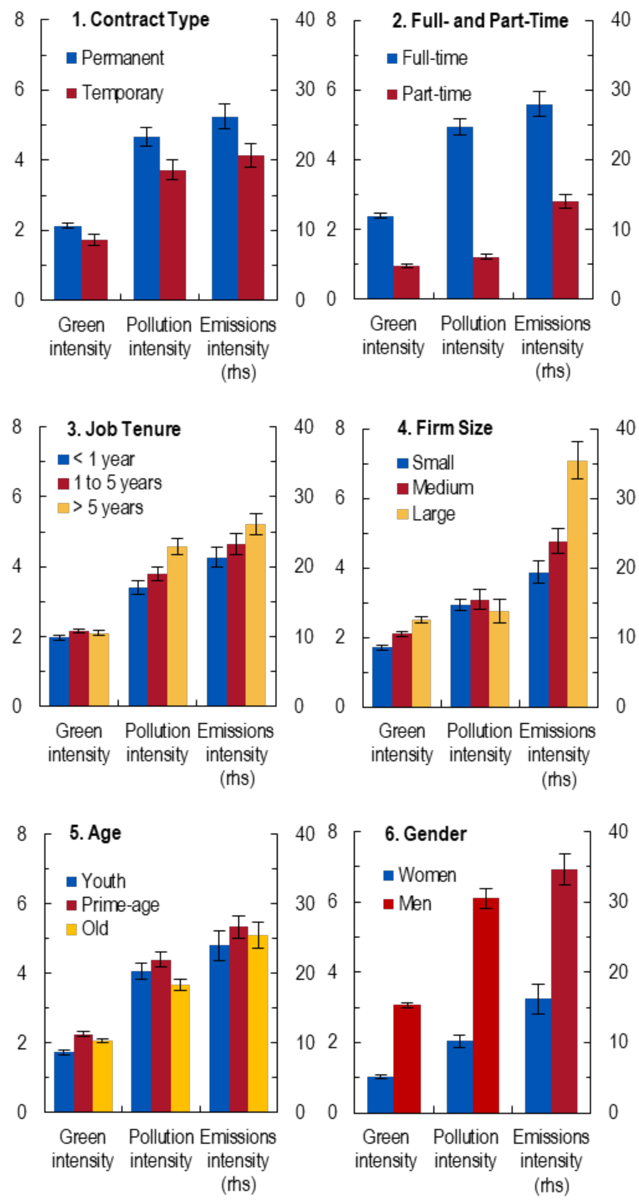
Annex Figure 3.2.2 presents additional stylized facts on the environmental properties of employment among the following dimensions: the nature of employment (permanent vs. temporary and full vs. part-time), job tenure and firm size. The individual-level data shows that green, pollution and emissions intensities are higher among permanent, full-time workers. While green intensity does not seem to change with the number of years a worker spends in the job, both pollution and emissions intensities increase with job tenure. With respect to firm size, larger firms have occupations with higher green intensity on average, with no discernible difference in pollution intensity across firms of different size. However, the emissions intensity of employment is distinctly higher in larger firms. Age and gender show common patterns across the environmental properties of employment: prime-age and older workers have higher green and lower pollution intensities than younger workers on average (Annex Figure 3.2.2, panel 5), and employed men have simultaneously higher green, pollution, and emissions intensities than employed women (Figure 3.2.2, panel 6).

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 (Annex Figure 3.2.3). 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.

Annex Figure 3.2.2. Environmental Properties of Jobs by Job and Worker Characteristics

(Average employment-weighted index; CO_2 tons per worker for emissions intensity)

Green, pollution and emissions intensities are higher among permanent, full-time workers. Pollution and emissions intensity increases with job tenure, and larger firms have higher green and emissions intensity.

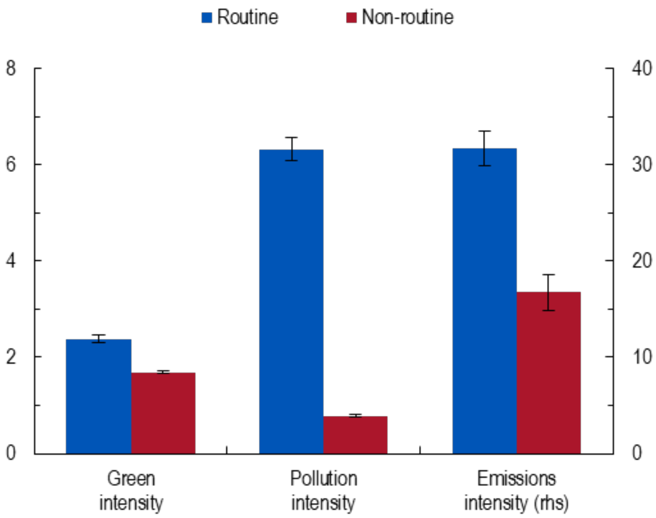


Sources: EU Labor Force Survey; Mexico National Survey of Occupation and Employment; IMF Climate Change Indicators Dashboard; Occupational Information Network; Organisation for Economic Co-operation and Development; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; Vona and others (2018); and IMF staff calculations.
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.

Annex Figure 3.2.3. Environmental Properties of Jobs by Routinizability

(Average employment-weighted index; CO_2 tons per worker for emissions intensity)

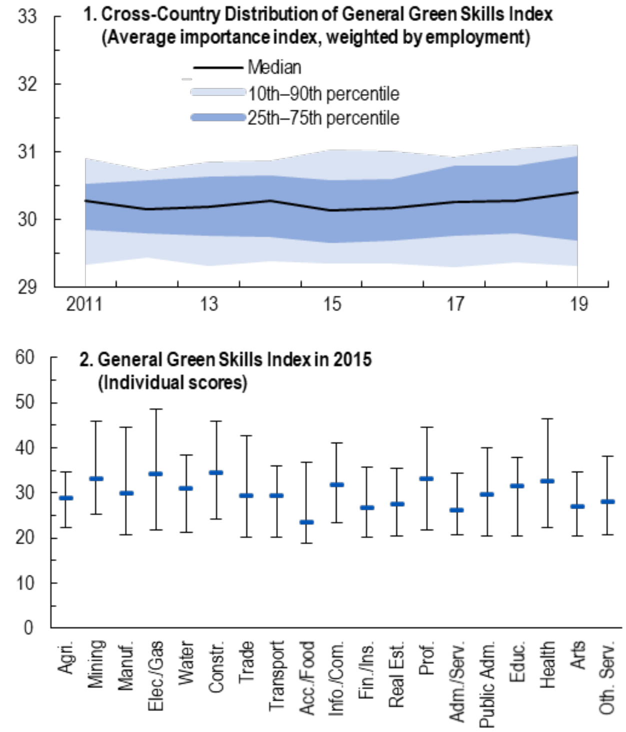
Routinizable jobs have systematically higher green, pollution and emissions intensities on average.



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); and IMF staff calculations.
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.

Annex Figure 3.2.4. Distribution of General Green Skills across Countries and Sectors

General green skills, associated with conducting green tasks, are common across the economy, with broad dispersion across 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); and IMF staff calculations.
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.

General Green Skills Distribution and Trends

General green skills are identified as those with the highest association with more green-intensive employment (Vona and others 2018). They mostly relate to the broad areas of engineering and technical skills, operations management, monitoring/surveillance, and science, as designated by O*NET. Such skills are relatively evenly distributed across the sectors in the economy and their importance have been rising marginally since 2015 (Annex Figure 3.2.4, 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.

Annex 3.3. Earnings Premium

The earnings premium for the average green-intensive job versus the average pollution-intensive job (Figure 3.5) is estimated from the following regression specification:

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

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).[7] 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 $PollInt$) are the respective green and pollution intensity scores by occupation (based on the common ISCO-08 encoding). 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 (for example).

To account for level differences across countries and sectors, and potential confounding common trend effects, country and year fixed effects are included in the regression. Standard errors are clustered at the level of the country-year. For Figure 3.5, the regressions are run for each year with country fixed effects included between 2005 and 2018.

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. Data from the US CPS and EU-SILC sources are used in the estimation, with the country sample as detailed in Table 3.1.2. The earnings premium is estimated to be around 6.7 percent for the full sample.[8] Year-by-year estimates are provided in Figure 3.5.

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.

Annex 3.4. Labor Market Transitions

Impacts of past environmental properties of jobs on transitions

The following regression specification for the calculation of (i) job-to-job transition (ii) out-of-work job transition, and (iii) job separation likelihoods in the chapter is estimated:

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

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

[8] 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).

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 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. Throughout Annex 3.4, 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). Standard errors are clustered at country-year level, allowing for confidence bands to be constructed around the estimate. This provides the benchmark transition likelihood estimate shown in Figure 3.6 (panel 1) for (i) job-to-job transition (ii) out-of-work job transition, and (iii) job separation, respectively.

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 is then rescaled by the mean of the environmental property and divided by the respective baseline labor market transition rates from step 1. The rescaled coefficients are thus expressed as percent change of the average baseline transition rates and are shown in Figure 3.6, panel 2 for green-intensity and panel 3 for pollution-intensity relative to those who previously held neutral jobs, respectively. The estimates inform, for instance, whether workers who previously held average green-intensive job are more/less likely to experience job-to-job/out-of-work job finding/job separation.

Persistence of environmental properties of jobs and its impact on transitions

As a third step, the chapter studies how the green, pollution, or emissions intensity of the previous job (origin) are associated with the current job (destination) environmental property. In other words, the chapter investigates i) how persistent the environmental properties of jobs (i.e., 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:

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

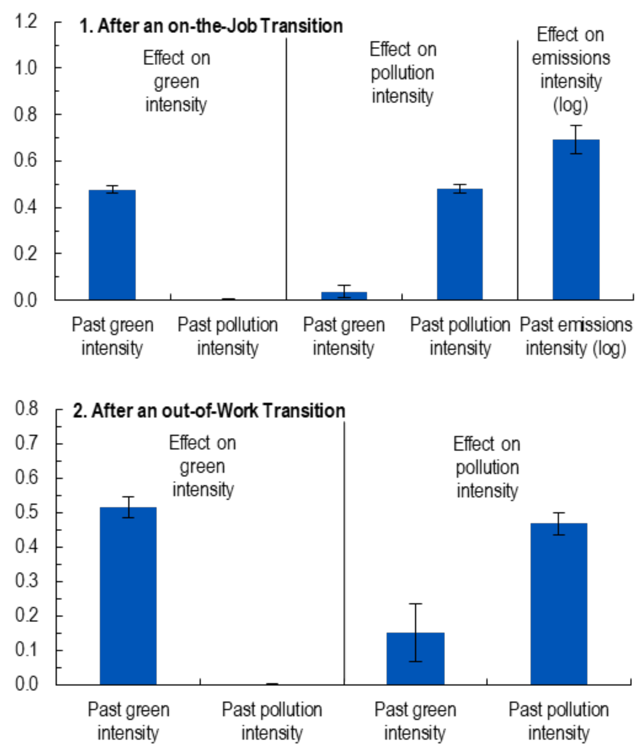
where $V \in \{GreenInt, PolInt, EmisInt\}$ is one of the environmental properties of a job. The lagged environmental properties, Y, is included to assess the persistence of environmental properties of jobs in job-to-job transitions (green, pollution, and emissions intensity). When the dependent variable 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. The estimated coefficients (not rescaled) are plotted in Annex Figure 3.4.1, panel 1 for on-the-job transitions and panel 2 for out-of-work transition. 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 are 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.

Annex Figure 3.4.1. Environmental Properties of New Jobs in Transitions

(Coefficient)

Holding a pollution-intensive job bears no higher cost in transitioning into a greener job relative to a neutral job.



Sources: EU Labor Force Survey; EU Statistics on Income and Living Conditions, Mexico National Survey of Occupation and Employment; Statistics South Africa Quarterly Labour Force Survey; US Current Population Survey; and IMF staff calculations.

Note: The charts show the coefficient on the indicated lagged dependent variable in the regression specification. If it equals 1 then, workers tend to find jobs with identical environmental properties to their previous jobs (that is, environmental properties of jobs are permanent for a worker). For emissions intensity (log), it has the interpretation of an elasticity. See Online Annex 3.1 for details on the country sample for the charts.

Discretized transition probabilities based on environmental properties of past jobs and its impact on transitions

While the coefficients from the regressions reflect the continuous nature of the environmental properties of employment, the chapter also demonstrates more intuitively how easily workers transition into greener jobs by showing discretized transition into green-intensive or neutral jobs from previous green-intensive, pollution-intensive, and neutral jobs in Figure 3.7. In this figure, green-intensive jobs are defined as the ones with strictly positive green intensity *and* zero pollution intensity (and vice versa for pollution-intensive jobs), while neutral jobs are defined as those with zero green intensity *and* zero pollution intensity. The transition probabilities and corresponding standard errors (clustered at the country-year level) are estimated by regressing on a constant a dummy equal to one if individual *i* held a pollution-intensive job (as defined in this subsection) in *t-1* *and* transitioned into green-intensive job in *t*, and zero if individual *i* held a pollution-intensive job in *t-1* but did not transition into a green-intensive job in *t*. Figure 3.7 shows the estimated coefficients with the sample restricted to those who experienced job-to-job and out-of-work transitions, respectively.

Annex 3.5. Empirical Policy Analysis

Association between environmental policies and environmental properties of employment

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 Annex 3.4. $P_{c,t}$ 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 $W_{c,t}$ 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.[9] To keep things manageable, each group of variables are estimated separately, one group at a time. The interaction between $W_{c,t}$ and $P_{c,t}$ allows for the levels of $W_{c,t}$ to influence the marginal effect of $P_{c,t}$. Figure 3.8 (panel 1) shows the estimates δ, which captures the level impact of the EPSI rescaled by multiplying the estimated coefficient by the difference between

[9] 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).

25th and 75th percentile of EPSI, and dividing it by the mean of environmental property of jobs to be expressed as a percent change in environmental properties. Note that throughout Annex 3.5, regression results concerning emissions intensities were estimated using the EU-LFS while those concerning green and pollution intensities were estimated using the EU-SILC.

Association between environmental policies and job transitions

To shed light on how the green intensity among the employed is impacted by the environmental policies, the chapter also looks at green intensity among those who experience different labor market transitions. While both (i) job-to-job (on-the-job) and (ii) out-of-work job transitions were investigated, only job-to-job transitions showed statistically significant results. The coefficients are estimated using a similar regression as above but with restricting the sample to those who experienced on-the-job switch.

$$V_{i,s,c,t} = \alpha_c + \alpha_t + \beta' X_{i,s,c,t} + \theta' Y_{i,s,c,t-1} + \delta P_{c,t} + \mu' Y_{i,s,c,t-1_{c,t}} \cdot P_{c,t} + \varepsilon_{i,s,c,t}$$

where variables are defined as before. The marginal effects of a change in EPSI from the 25th to the 75th percentile on the environmental property of job (green-, pollution-, or emission-intensity) is evaluated at the mean of the environmental properties of jobs and is expressed as percent change in the environmental property (Figure 3.8, panel 2).

Interaction effects of environmental policies with structural features

The estimated coefficient μ in the regression above captures how the impact of environmental policies on the environmental properties of jobs are affected by structural features. Figure 3.9 plots the coefficient μ rescaled as percent of the mean environmental property (green- and pollution intensity) in response to a change in the EPSI from the 25th to the 75th percentile under zero structural policies and for the mean value of structural policies. Figure 3.9 (panel 1) plots the estimated effect when retention policy is set to zero ("Zero retention support") and set to the mean value ("Mean retention support"), respectively. Figure 3.9 (panel 2) plots the rescaled coefficients when labor market arrangements are set to zero ("No labor market arrangements") and collective bargaining index was set to mean value ("Mean coverage of coordinated labor market arrangements.") and lastly the replacement rate was evaluated at its mean value ("Mean generosity of unemployment insurance").

Annex 3.6 Task-Based Model of the Labor Market

To quantify the impact of environmental policies on labor reallocation and workers' welfare, a new task-based modeling framework is developed founded on Acemoglu and Restrepo (2021) and Drozd, Taschereau-Dumouchel, and Tavares (forthcoming). In this framework, goods are produced using a fixed set of tasks that can be performed using labor (higher-skilled or lower-skilled) or capital. The task framework is augmented to consider two different types of goods that differ in their emission intensity, capital intensity, and lower-skilled and higher-skilled labor intensity, informed by empirical estimates. Households maximize future discounted utility over consumption goods and leisure. The endogenous labor supply decision allows the simulation of the impact of policies on total hours worked. The model is calibrated to a representative advanced economy and an emerging market economy, respectively. The main difference between these two economies is the higher-emissions-intensive sector's importance in total output and the difference in the labor intensity across sectors (see the calibration section below). Overall emissions of the economy are a function of the mix of higher-emissions-intensive output and lower-emissions-intensive output.

Plants

In this framework, goods are produced using a fixed set of tasks. Production requires completing a random subset of tasks varying in complexity on the real line, which is determined once and for all upon the inception of a plant—the basic unit of production in the model. Tasks differ in capital productivity depending on complexity, which determines the use of capital versus high or low skilled labor. Complexity corresponds to the measure of tasks that must be completed to produce a piece of capital specific to a particular task (complexity). Specifically, each plant faces a cost minimizing problem choosing how much skilled labor (L^s), lower-skilled labor (L^u), and capital (K) to employ.

$$\min_{\{q^*,q^{**}\}} c(w,r) = rK + w^s L^s + w^u L^u$$

Such that

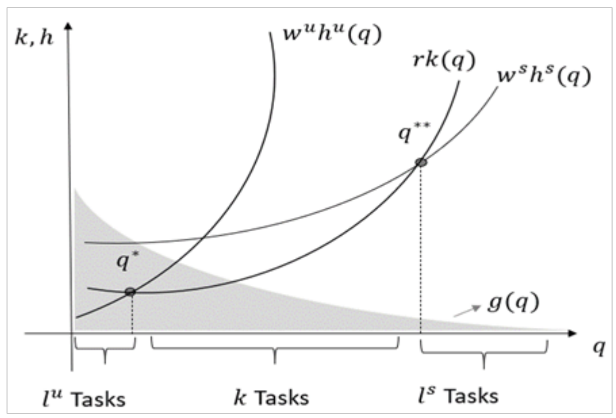
$$L^u = Y\int_{\bar{q}}^{q^*} h^u(q)d\mu$$

$$K = Y\int_{q^*}^{q^{**}} k\,(q)d\mu$$

$$L^s = Y\int_{q^{**}}^{\infty} h^s(q)d\mu$$

Solving this cost minimization problem results in a cutoff complexity below which all tasks are completed using lower-skilled labor (q^*), an intermediary cut-off complexity where tasks are completed using capital (q^{**}). Above this intermediary cut-off all tasks are completed using higher-skilled labor (Annex Figure 3.6.1).

Annex Figure 3.6.1. Plant Cut-Off Solutions



Note: In the figure q denotes the complexity level of a given plant. $w^u h^u(q)$, $rk(q)$, and $w^s h^s(q)$ is the cost (under cost-minimization) for unskilled labor, skilled labor, and capital for production of a unit of output. For $q<q^*$ all tasks are completed using lower skilled labor, for $q^*<q<q^{**}$ all tasks are completed using capital and for $q>q^{**}$ all tasks are completed using higher-skilled labor.

Households

Households in the model maximize future discounted utility over higher- and lower emissions-intensive goods consumption and leisure. There are two representative households in the model: lower-skilled and higher-skilled households. Both are assumed to have perfect foresight.

The lower-skilled household chooses how much to consume of each good, and how much labor to supply subject to a budget constraint. That is, this lower-skilled household solves the following constrained maximization problem

$$\max_{\{c_t^{g,u},c_t^{b,u},l_t^u\}} \sum\nolimits_t u\left(c_t^{g,u}, c_t^{b,u}, l_t^u\right)$$

$$(1+\tau_t^b)\,c_t^{b,u} + (1-\tau_t^g)p_t^g c_t^{g,u} = (1-\tau_t^u)w_t^u l_t^u + T_t^u$$

where $c_t^{g,u}$ and $c_t^{b,u}$ is the consumption of lower- and higher-emissions-intensive goods, respectively, while l_t^u is the supply of labor. τ_t^b is a tax on higher-emissions-intensive consumption, while τ_t^g is a subsidy on lower-emissions-intensive consumption. τ_t^u is a wage subsidy to lower-skilled workers, and T_t^u is a lump-sum transfer to lower-skilled workers.

The higher-skilled household owns the capital stock of the economy. In addition to their consumption and leisure decisions, the higher-skilled household also chooses how much to invest in each sector of the economy. The two sectors' capital stock follows a law of motion of capital and is subject to capital adjustment costs. The capital stock in each sector is not allowed to move freely across sectors. This means that the higher-skilled household solves the following problem:

$$\max_{\{c_t^{g,s}, c_t^{b,s}, l_t^s, x_t^b, x_t^g\}} \sum\nolimits_t u\left(c_t^{g,s}, c_t^{b,s}, l_t^s\right)$$

$$(1+\tau_t^b)(c_t^{b,s} + x_t^b) + \left(1-\tau_t^g\right)(x_t^g + p_t^g c_t^{g,s}) = (1-\tau_t^s) w_t^s l_t^s + r_t^b k_t^b + r_t^g k_t^g + T_t^s$$

$$x_t^b = k_{t+1}^b - (1-\delta^b) k_t^b + \gamma^b \frac{\left(k_{t+1}^b - k_t^b\right)^2}{2}$$

$$x_t^g = k_{t+1}^g - (1-\delta^g) k_t^g + \gamma^g \frac{\left(k_{t+1}^g - k_t^g\right)^2}{2}$$

The notation is similar to that for the lower-skilled household, although the superscript *s* denotes that the household is higher-skilled. As the higher-skilled household hold all the capital x_t^b and x_t^g denotes the holdings in higher- and lower-emissions-intensive capital, respectively. r_t^b and r_t^g are the associated returns to higher- and lower-emissions-intensive capital.

Government

The government in the model collects a carbon tax (modelled via τ_t^b) and progressive labor income tax and spends the revenue on government transfers, earned income tax credit, investment in infrastructure, training, and research and development. It is assumed that the government intertemporal budget constraints hold in equilibrium.

Equilibrium

A competitive equilibrium in this framework is a set of allocations to each household, a set of allocations for each plant, prices, and government policies such that: 1) the household maximization problem is solved, 2) the plant maximization problem is solved 3) capital, labor, and goods markets clear, and 4) the government's intertemporal budget constraint holds.

Functional Forms

To solve the model a set of functional forms is chosen. Household's utility is assumed to be logarithmic and separable in the consumption of each good:

$$u\left(c_t^c, c_t^b, l_t\right) = \log c_t^b + \kappa \log c_t^c - \psi \frac{l^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} .$$

The complexity distribution is assumed to be a Pareto distribution and specific to each good:

$$G^j(q) = 1 - \left(\frac{q_0}{q}\right)^{\zeta^j}.$$

The capital requirement distribution is assumed to be increasing in complexity $\boldsymbol{q}$ and decrease in good-specific productivity $\boldsymbol{Z^{j,t}}$, that captures possible increases in productivity over time t:

$$k^j(q) = \frac{\theta^j - \zeta^j}{\zeta^j \, Z^{j,t}} \, q^{\theta^j} + \frac{\bar{q}}{Z^{j,t}}.$$

The low-skilled worker human capital requirement is also assumed to be increasing in complexity:

$$h^{u,j}(q) = \frac{\theta^j - \zeta^j}{\zeta^j} q^{\theta^j}.$$

Last, the high-skilled worker human capital requirement is normalized equal to 1. After assuming these functional forms, it is possible to solve for the cut-offs analytically and solve for the production function implicitly.

Calibration

The model is calibrated to representative (typical) advanced and emerging market economies (Annex Table 3.6.1). These two economies share many parameters that are obtained from the literature, including the Frisch elasticity of labor supply (set at 3.5, within the range of the literature), capital depreciation rates, and adjustment costs parameters. To explore the implications for a specific country, the calibration would need to be further adjusted (for example, some emerging market economies have much lower dependence on higher-emissions-intensive output).

Annex Table 3.6.1 Key Model Moments

	Advanced Economy	Emerging Market Economy
Demographics		
Initial share of employment in lower-emissions-intensity sector	0.71	0.29
Initial share of employment in higher-emissions-intensity sector	0.50	0.50
Production		
Higher-skilled labor intensity in lower-emissions-intensive sector	0.33	0.22
Lower-skilled labor intensity in lower-emissions-intensive sector	0.17	0.29
Higher-skilled labor intensity in higher-emissions-intensive sector	0.23	0.18
Lower-skilled labor intensity in higher-emissions-intensive sector	0.19	0.25
Capital intensity in lower-emissions-intensive sector	3.70	5.00
Capital intensity in higher-emissions-intensive sector	5.16	6.50
Preferences		
Discount factor	0.96	0.90
Consumption share of lower-emissions-intensive good	0.71	0.53
Consumption share of higher-emissions-intensive good	0.29	0.47

Source: IMF staff calculations.
Note: The table shows key model moment for the representative advanced and emerging market economy, respectively. Consumption share is consumption expenditures spent on the indicated good as a share of total consumption expenditures. A factor intensity is the average indicated input used per unit output in the sector.

Scenarios

In the calibrated economy, a series of counterfactual exercises are performed. The baseline assumed (Business-As-Usual) is broadly similar to that in Chapter 3 of the October 2020 WEO. The policy package is calibrated to make an approximately one-third reduction in overall emissions by 2032, consistent with a path to achieve net zero emissions (NZE) by 2052. As noted, this is done by shifting the mix of higher-emissions-intensive and lower-emissions-intensive outputs. The package's mitigatory effects are assumed to generate an economy-wide 3 percent boost to total factor productivity from avoiding damages due to climate change (introduced at a rate of 0.2 percent per year from 2023 through 2042). The policy package comprises:

1) Gradually rising carbon taxes - starting with a small increase from 2023 which slowly builds, with a sharper rate of increase from 2029
2) A green investment push consisting of green infrastructure investment and a subsidy for R&D in lower-emissions-intensive production
    a. The investment push is deployed from 2023 onwards and then slowly reduced from 2029.
    b. The R&D push is assumed to boost long-term productivity in the lower-emissions-intensive sector. This boost is added slowly from 2023 at 0.4 percent per year, until it cumulates to 3 percent in the long-term.
3) A training program - starting in 2023
    a. Training boosts the productivity of lower-skilled workers in lower-emissions-intensive jobs by 5 percent.
4) Earned income tax credit program (EITC) starting in 2029
    a. In the emerging market economy case, a targeted cash-transfer program supplements.

The total impact is calculated when the combined policies are implemented, incorporating interactions in general equilibrium.

To better gauge the importance of the technological and productivity improvements introduced by the package, an alternative scenario was run where the green infrastructure push (element 2) and the training program (element 3) are removed from the package. In this alternative scenario, the carbon price is the sole lever used to get the economy onto the NZE path, with excess tax revenues returned to households via lump-sum transfers. Without the technology, efficiency gains, and productivity impacts of policies, the carbon price must rise over 10 times the level as that under the baseline to achieve the emission reductions needed for the NZE path. The emissions reduction occurs entirely through shrinking the higher-emissions-intensive sector and shifting labor from the higher- to the lower-emissions-intensive sector, leading to an overall employment drop and massive output decline. This finding highlights the crucial role of technological, efficiency gains, and productivity improvements in achieving a manageable transition, complementing the effects from the carbon price instrument (which is essential for reallocation).

Annex 3.7 Additional Details on Boxes: Data and Analytics

Box 3.1. The geography of green- and pollution-intensive jobs: Evidence from the United States

The box uses two main datasets. First, the maps use a dataset of green- and pollution-intensive employment at the county-level which itself merges three data sources: (i) definitions of green-intensive and polluting occupations; (ii) occupation-industry-state employment in 2016; and (iii) industry-county employment in 2016. Employment weighted green- and pollution intensities at the industry-state level are obtained from merging (i) and (ii), which are then merged with (iii) to obtain employment-weighted average green- and pollution-intensities at the county level. To create the two maps, counties are then ranked according to their green- and pollution-intensities and split into 20 buckets and assigned shades of green and brown, respectively. The sources for (i)-(iii) are:

i. **Definitions of green-intensive and polluting occupations** are as defined in the Online Annex 3.1 above. For this box the definitions are applied on the SOC2010 6-digit level.
ii. **Occupation-industry-state employment in 2016** is sourced from the U.S. Bureau of Labor Statistics Occupational Employment Wage Statistics. Industry-state occupations are defined at the SOC2010 6-digit level. Industries are disaggregated at varying degrees ranging from NAICS2017 4- to 6-digit levels.
iii. **County-industry employment in 2016** is sourced from Eckert and others (2021) who harmonize data and fill censored observations from the Census County Business Patterns. Industries are disaggregated at NAICS2017 6-digit level.

Second, green and pollution county-level intensities as defined above are regressed on characteristics at the county- or commuting zone-level to support the associations mentioned in the text. County-level characteristics include: rural-urban continuum code from the Center for Disease Control; median annual income; share of population with a bachelor's degree or higher; share of people above 45 years old; unemployment (all these variables are sourced from the US Department of Agriculture); and being located in a broad U.S. region, using five commonly defined regions by the National Geographic as dummies in bilateral regressions.

Finally, state-level unionization is sourced from the Union Membership and Coverage Dataset as discussed in Hirsch and Macpherson (2003) and imputed to 2010 census commuting zones using state-employment weights within each commuting zone. This measure is then regressed on employment-weighted green- and polluting job intensities at the commuting zone level. Commuting zones are widely used in the labor literature as measures of local labor markets, see for example Autor and Dorn (2013).

These findings can only hint at possible implications for the labor market caused by a much-needed climate transition. To better understand the resulting structural shifts, future research will analyze the effects of past environmental policy shocks. The hypothesis is that adhering to new regulation potentially increases input costs so that the overall demand for labor might be reduced for affected sectors, particularly polluting-intensive jobs, while it may generate new green jobs in other sectors or even some residual green jobs in affected industries.

Box 3.2. A greener post-COVID job market?

The high frequency green hiring rates shown are based on available data from professional networking website LinkedIn through the Development Data Partnership. Hiring rates are computed as the ratio of LinkedIn members who added a new employer over a given time period divided by the total number of LinkedIn members in a location (country). Green hiring rates correspond to the same ratio for LinkedIn members classified as green talent. A member is classified as a green talent if they have either added at least one green skill or if they belong to an occupation where a high share of workers employed report green skills. LinkedIn uses a proprietary definition of green skills—skills the enable environmental sustainability of economic activities—based on internationally accepted definitions from the literature. Figure 3.2.1 shows the median green hiring rate (12-month moving average) across a sample of 48 countries (31 advanced economies and 17 emerging market and developing economies), indexed by dividing by the median observed in January 2019. The shaded areas portray the 10th-90th and 25th-75th percentile ranges respectively. The black line (right axis) shows the median ratio, across countries, between the green hiring rate and the hiring rate for all members, also indexed using the value observed in January 2019.

Job postings data come from the job search platform Indeed. Figure 3.2.2 shows the worldwide average of job postings (12-month average) across 34 countries (20 advanced economies and 14 emerging and developing economies), indexed by dividing by the value observed in January 2019. Sectors available in the platform data were matched to the main chapter's average employment-weighted green task intensity by ISIC rev. 4 sector (based on the sample of economies available). Green job postings were those associated to sectors with above average green skill intensity, with the rest classified as non-green. See Online Annex 3.1 for discussion on the construction of the green intensity index.