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in the greening economy:  
Structural drivers and the  
role of policies

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**ECONOMICS DEPARTMENT**

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By Orsetta Causa, Emilia Soldani, Maxime Nguyen, Tomomi Tanaka

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**ABSTRACT/RÉSUMÉ**

Climate change mitigation policies affect the allocation of workers on the labor market: jobs in high-polluting industries will contract, while jobs in the “green” sector will grow. A just transition in the labour market requires policies to improve the allocation of workers and their deployability, for instance towards performing green tasks; as well as to manage and minimise scarring effects associated with job losses in polluting industries. Using an econometric analysis, this paper investigates the role of structural and policy factors in shaping a number of relevant labour market transitions, uncovering heterogeneity across different groups of workers. Education is the most important individual-level driver of transitions from non-employment to green jobs, with a particularly strong effect from graduating in scientific fields for young people entering the labour market. Women are significantly less likely than men to move into green jobs out of non-employment. Workers employed in high-polluting occupations face higher displacement risks than other workers, but this does not translate into higher long-term unemployment risks. In terms of policies, the paper finds that the labour market implications of the greening economy can be addressed by general structural policies favouring labour market efficiency in terms of workers’ reallocation, labour market inclusiveness in terms of promoting equality of opportunities and minimising long-term scars. Results also suggest that place-based policies are needed to mitigate scarring effects for displaced workers.

JEL: J08, J21, Q52, Q48

Keywords: green transition, labour markets, policy analysis.

**\* \*\* \* \*\* \* \*\* \* \*\* \* \*\* \***

Les politiques d'atténuation du changement climatique affectent la répartition des travailleurs sur le marché du travail : les emplois dans les industries très polluantes sont amenés à se contracter, et les emplois dans le secteur "vert" se développer. Une transition juste sur le marché du travail nécessite des politiques visant à améliorer la répartition des travailleurs et leur redéploiement, par exemple vers des emplois verts, ainsi qu'à gérer et à minimiser les stigmates associés aux pertes d'emplois dans les industries polluantes. À l'aide d'une analyse économétrique, ce papier étudie le rôle des facteurs structurels et des politiques publiques sur un certain nombre de transitions sur le marché du travail, en mettant en évidence l'hétérogénéité entre les différents groupes de travailleurs. Le niveau d'éducation est le principal facteur individuel de transition entre le non-emploi et un emploi vert, l'obtention d'un diplôme dans un domaine scientifique ayant un effet particulièrement important sur les jeunes entrant sur le marché du travail. Toutes choses égales par ailleurs, les femmes sont nettement moins susceptibles que les hommes de passer d'une situation de non-emploi à un emploi vert. Les travailleurs employés dans des industries polluantes sont confrontés à des risques de chômage plus importants que les autres travailleurs, mais cela ne se traduit pas par des risques de chômage à long terme plus élevés. En termes de politiques, le papier constate que les implications de la transition verte sur le marché du travail peuvent être traitées par les mêmes politiques structurelles générales favorisant l'efficacité du marché du travail en termes de réaffectation des travailleurs, l'inclusivité du marché du travail en termes de promotion de l'égalité des chances et minimisant les cicatrices à long terme. Les résultats soulignent également le rôle de politiques locales afin de réduire les effets néfastes sur les individus du chômage.

JEL: J08, J21, Q52, Q48

Mots clés: Transition écologique, marché du travail, analyse des politiques.

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# Labour markets transitions in the greening economy: structural drivers and the role of policies

Orsetta Causa, Emilia Soldani, Maxime Nguyen and Tomomi Tanaka<sup>1</sup>

## Introduction and motivation

This paper considers the likely effects of public policies on workers in the transition to net zero. While aggregate employment effects could be relatively small, the combination of policies and technological change that bring about decarbonization will require considerable reallocation of production factors; hence distributional effects, with number of scholars having pointed to the possibility of rising inequalities (Pisani-Ferry, 2021<sup>[1]</sup>; Känzig, 2023<sup>[2]</sup>; Vandyck et al., 2021<sup>[3]</sup>; Demetriades, Cabrita and Fóti, 2021<sup>[4]</sup>). The green transition should provide opportunities for good jobs, especially for workers with the appropriate skills, and for investment in renewables and more climate-friendly technologies. But many of the workers whose jobs are currently linked to the production and use of fossil fuels and the communities in which they live may not be able to take advantage of these opportunities. They can be disadvantaged by their location, financial resources, levels of education and skills. Policymakers have acknowledged the need to accompany actions to decarbonize their economies with policies that achieve a “just transition” and “leave no one behind”. To support the transition and limit potential labour shortages policies are needed to help workers access green jobs and meet the related skills requirements; but also, to support workers at higher risk of a job loss, by facilitating their redeployment into new jobs and by the same token by avoiding displacement-related long-term scars.<sup>2</sup>

Against this background, this paper explores key policy issues likely to shape the viability of greening the economy from the labour market perspective, going granular on distributional aspects. The focus is on the role of structural and policy factors in shaping a selection of relevant labour market transitions, uncovering heterogeneity across different groups of workers, by e.g., skills, age, gender, area of residence. The

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<sup>2</sup> This issue is being studied not only at the international level but also at the national level. Examples of national studies include the recent report by the *Conseil d'Analyse Economique* in the case of France (Fontaine et al., 2023<sup>[79]</sup>); and regular work by the UK Office of National Statistics in the case of the United Kingdom (see [here](#) and specific references later in this paper).

analysis covers a large sample of European countries featuring relevant and harmonized data. The paper addresses the following policy questions:<sup>3</sup>

- What are the most significant baseline drivers of individuals' transitions from non-employment – including unemployment and inactivity due to study – to “green” jobs? Do workers employed in “high-polluting” jobs face higher risks of displacement? And, when displaced, do these workers exhibit higher scarring risks, for instance of long-term unemployment?
- How do structural policies - e.g., policy support for jobseekers, labour market regulations, adult training - shape such transitions? And how do their effects vary across socioeconomic group?
- Is there evidence that the stringency of environmental policies, such as carbon pricing and regulations, affects labour market transitions?
- What policy implications can be drawn to facilitate a fair green transition in the labour market, minimising the risk to leave vulnerable groups behind?

The rest of this paper is organised as follows. Section 1 lays-out the framework for the empirical analysis, building on papers about the measurement of “green” and “high-polluting jobs” (Causa, Soldani and Nguyen, 2024<sup>[5]</sup>; Causa, Nguyen and Soldani, 2024<sup>[6]</sup>). Section 2 presents baseline results on the individual and cyclical drivers of workers' transitions into green jobs and out of high-polluting jobs, including in terms of possible scars associated with displacement from high-polluting jobs. Section 3 delivers structural policies results in shaping workers' transitions in the greening economy, covering relevant policy areas such as labour market institutions, social protection, education, skills and training, product market regulations and housing. The policy analysis uncovers distributional aspects by exploring differentiated effects across socioeconomic groups defined by e.g., gender and education. Section 4 concludes with policy implications from this quantitative cross-country work and provides qualitative complementary materials from country-specific experiences.

## Framework of empirical analysis

### *The measurement approach for analyzing “green” and “high-polluting” jobs*

While the net-zero transition is expected to have modest aggregate net effects on labour markets it will likely induce a contraction of jobs in high-polluting activities and an expansion of jobs instrumental to achieving greener production processes: in the literature, the former category of occupations are referred to as “high-polluting” or “brown”, and the latter as “green”, “green-driven” or “green intensive”.<sup>4</sup> To simplify the exposition, the term green jobs is used here to identify the occupations that, irrespective of their actual impact on the environment, involve green tasks and are hence expected to face increased demand as a result of the green transition. Similarly, high-polluting jobs indicate the occupations that are over-represented in economic sectors producing large shares of air polluting emissions.

The lack of a universal, clear and operational definition of green and high-polluting jobs is a major obstacle to rigorous research on the labour market effects of environmental policies and the green transition. It is therefore the subject of significant ongoing work in both academia and national economic and statistical

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<sup>3</sup> Throughout this paper, the terms “green” and “high-polluting” jobs are used for simplicity, without prejudice to the status of any worker or job. These terms refer to a very specific definition and classification of jobs, following a careful measurement approach that puts emphasis on the intensity of green tasks by occupation and the intensity of polluting emissions by industry, as detailed in Causa et al. (2024<sup>[5]</sup>; 2024<sup>[49]</sup>). As a result, the terms green and high-polluting jobs should be interpreted only under the specific boundaries of these definitions. Also, the term green (high-polluting) job is used interchangeably with green (high-polluting) employment.

<sup>4</sup> The aggregate effects depend crucially on the speed of the transition and the use of carbon revenues.; see Chateau et al. (2018<sup>[92]</sup>), and Borroni et al. (2023<sup>[91]</sup>) for a discussion.



bodies, resulting in an array of different approaches, inevitably yielding different estimates of the shares of each category of jobs.

For green jobs, the current project adopts the definition developed by O\*NET (Dierdorff et al., 2009<sup>[7]</sup>) and Vona et al. (2018<sup>[8]</sup>) for the United States and extends it to EU economies through a complex mapping procedure detailed in Causa et al. (2024<sup>[5]</sup>). In short:

- The task-based definition of green jobs focuses on the content of occupations and on their scope, not on the environmental impact of underlying production processes and final products. Examples of green tasks under the O\*NET classification are “review and evaluate environmental impact reports pertaining to private or public planning projects or programs” and “test workplaces for environmental hazards, such as exposure to radiation, chemical or biological hazards”.
- An occupation is classified as green if at least 10% of associated tasks are considered to be green tasks (i.e., tasks that support environmental objectives).<sup>5</sup> Examples of green occupations under Vona et al. (2018<sup>[8]</sup>) approach are Environmental Engineers and Solar Photovoltaic Installers.
- The underlying idea is that the green transition entails changes in existing tasks and the emergence of new tasks, for instance complementary and instrumental to newly-developed green technologies, driving-up labour demand for workers able to perform these tasks.<sup>6</sup>
- The definition of high-polluting or high-polluting occupations complements that of green jobs by explicitly considering the air polluting emissions intensity of different economic activities:<sup>7</sup> High-polluting occupations are defined as those that are over-represented in high-polluting industrial sectors (i.e., in industrial sectors above the 85th percentile in emissions per worker for at least three of seven relevant polluting substances). Causa et al. (2024<sup>[5]</sup>; 2024<sup>[6]</sup>) provide a detailed overview of this newly-developed approach and its various operational steps. While the list of high-polluting occupations differ across countries, *Mining and mineral processing plant operators* and *Manufacturing, mining, construction, and distribution managers* are high-polluting occupations in most countries.
- The approach used in this paper defines green and high-polluting jobs as distinct binary concepts, but not exclusive. The same occupation can be both high-polluting and green: high-polluting, because it is overrepresented in high-polluting industries, green, because it entails significant green tasks. A small share of occupations are both green and high-polluting (for example, an environmental engineer working in extraction industry): the presence in highly polluting industries of workers possessing green skills should not be taken as a paradox. Rather, their presence could potentially lead to the greening of the industry. Finally, irrespective of the measurement approach, it remains the case that the vast majority of jobs are neither green nor high-polluting: typically jobs in services, which represent a notable proportion of employment across countries.
- This analytical framework and taxonomy do not imply any hierarchy in terms of desirability, quality, or value of green vis-à-vis high-polluting and other jobs; the idea is to identify which jobs are likely to face increased or decreased demand as a result of the green transition.

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<sup>5</sup> The task approach to green jobs is inspired by and largely mimics the one developed by Autor for the identification of digital jobs in Autor et al. (2003<sup>[88]</sup>) and Autor (2013<sup>[89]</sup>).

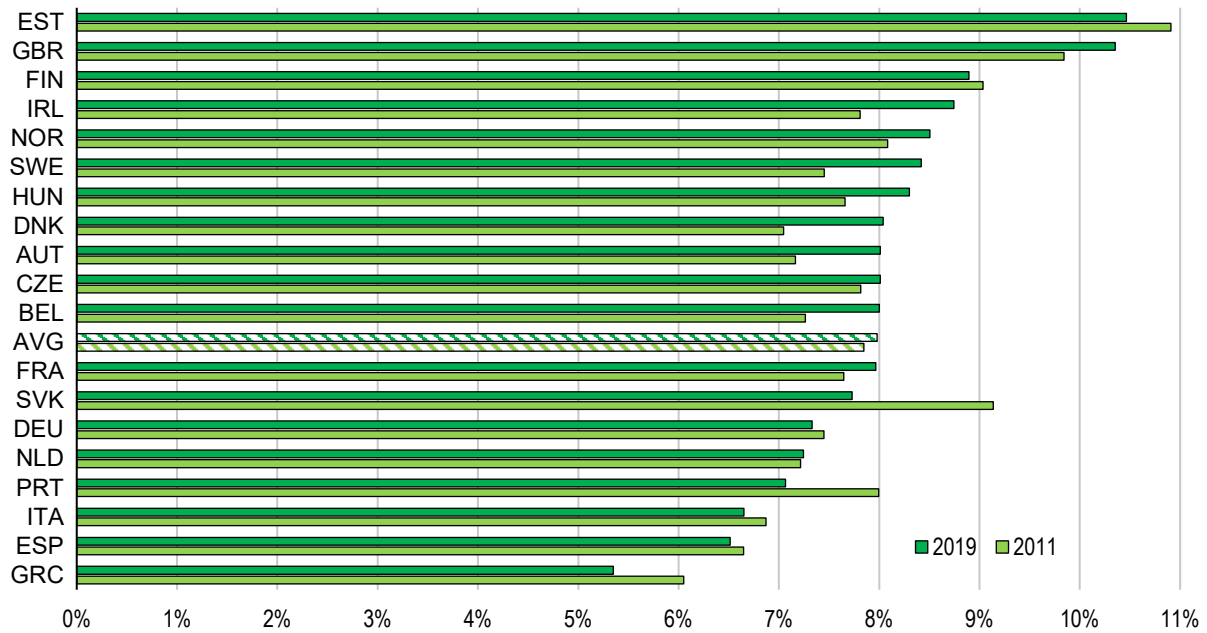
<sup>6</sup> In this context, the distinction between tasks and skills requires a clarification: tasks are meant to identify what workers are expected to do at the workplace, while skills correspond to the abilities and competences that workers should possess to perform said tasks (JRC, 2021<sup>[61]</sup>). An example of a new green task is the maintenance or installation of wind turbines, and the corresponding skills might involve climbing the wind tower and repairing the turbines.

<sup>7</sup> An alternative approach is to classify as green all the industries with greenhouse gas emission intensity below a given threshold: all workers working in said industries are then classified as having green jobs (Kapetanios C, 2020<sup>[84]</sup>).

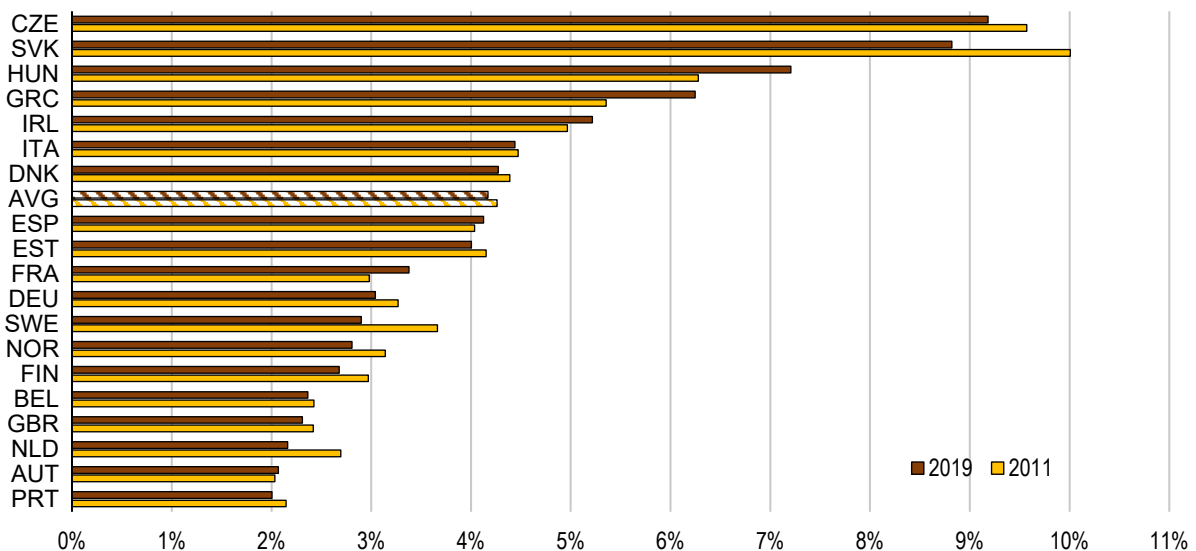
Based on this measurement approach, the data suggest that European labour markets have not become greener over the recent past, with little change in the share of green and high-polluting jobs on average, yet in a context of wide heterogeneities in the incidence of green and high-polluting jobs across countries (Figure 1).

**Figure 1. Green and high-polluting jobs: the big picture, 2011-2019**

Panel A. Share of green jobs over total employment



Panel B. Share of high-polluting jobs over total employment

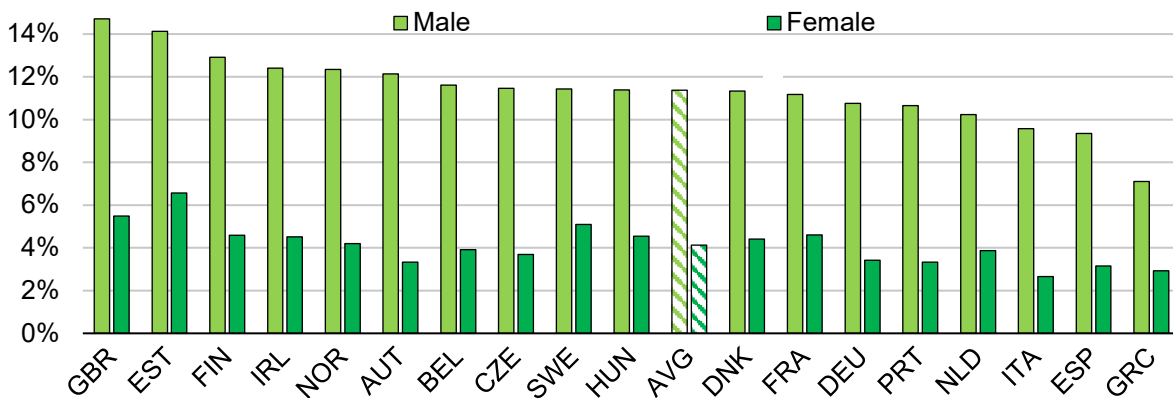


Note: How to read: The estimated employment share of green jobs in Belgium is 7.3% in 2011 and rises to 8% in 2019; while that of high-polluting jobs is stable at 2.4%. See text for definitions of green and high-polluting jobs.  
 Source: EU-LFS and OECD calculations

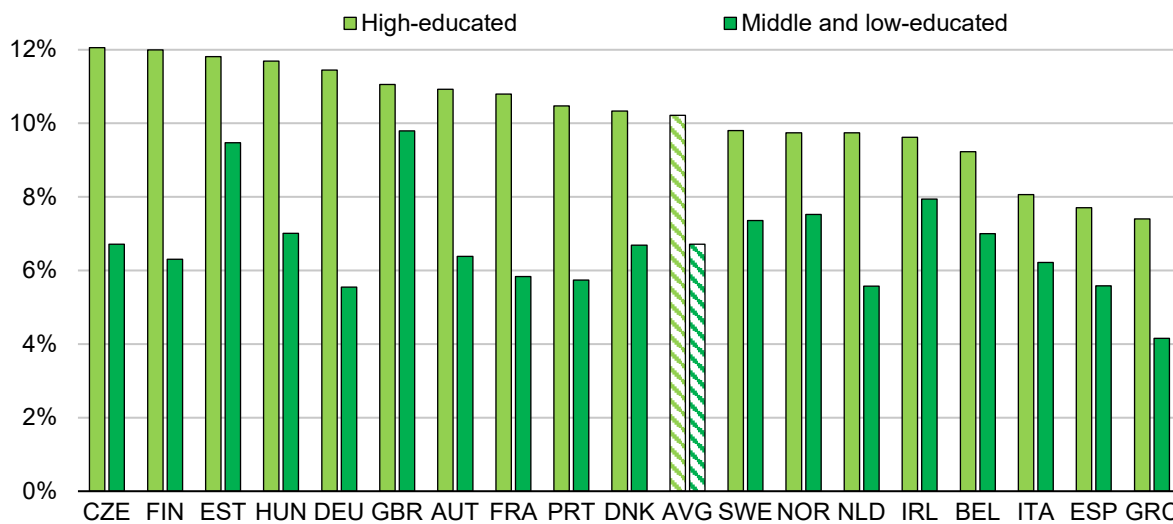
Moving beyond the aggregate picture, the evidence is that green and high-polluting jobs are systematically unequally distributed within countries. In particular: i) men are much more likely than women to hold green jobs (Figure 2A),<sup>8</sup> and ii) high-educated individuals are more likely to hold green jobs than medium and low-educated individuals. These findings are broadly in line with previous literature.<sup>9</sup> For example, in the case of the US, Consoli et al. (2016<sup>[9]</sup>) show that green occupations exhibit a stronger intensity of high-level cognitive skills. Causa et al. (2024<sup>[5]</sup>) provide a wide range of further stylised facts about the distribution of green and high-polluting jobs across socioeconomic groups.

Figure 2. Green jobs: selected distributional patterns, 2019

Panel A. Share of green jobs by gender



Panel B. Share of green jobs by educational attainment



Note: How to read: in Germany, 11.5% of high-educated individuals hold a green occupation, by contrast with 5.6% of middle and low-educated workers.

Source: EU-LFS and OECD calculations.

<sup>8</sup> Men are also much more likely to hold high-polluting jobs (Causa, Soldani and Nguyen, 2024<sup>[5]</sup>), in line with previous findings for both the EU (Vandeplas et al., 2022<sup>[65]</sup>) and the US (Christie-Miller and Luke, 2021<sup>[86]</sup>).

<sup>9</sup> Recent papers include Tyros, Andrews and de Serres (2023<sup>[81]</sup>), OECD (2023<sup>[18]</sup>) and Vona et al. (2018<sup>[50]</sup>).

While the estimated shares of green and high-polluting jobs depend on the definition and methodology, the patterns documented in this paper based on Causa et al. (2024<sup>[5]</sup>) and Causa et al. (2024<sup>[6]</sup>) are in line with previous findings in the literature, including country-specific studies.<sup>10</sup>

### *The econometric approach for analyzing workers' transitions and the role of policies in the greening economy*

The analysis is based on microdata from the EU-Labour Force Survey (EU-LFS), designed to be representative of the labour force, for 21 European countries over the period 2011-2019. Relying on individual data makes it possible to control for relevant sociodemographic characteristics and to shed light on heterogeneous effects across different categories of workers, defined by e.g., gender, age and education, ultimately allowing to uncover distributional aspects. The countries covered are Austria, Belgium, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, the Slovak Republic, Slovenia, and Sweden. The main sample includes over 21 million individuals, distributed across countries and years. The annex reports detailed information on country-specific estimation samples. The focus of the empirical exercise is on transitions from unemployment and, for individuals in the age group 20-29, from study-related inactivity into green employment, and on the incidence of long-term unemployment.

The main focus is on transitions in and out of jobs rather than job-to-job transitions between e.g., high-polluting to green, reflecting two major constraints in the EU-LFS: 1) only industry information, not occupation, is available for individuals that remain in employment from one period to the other and change job; 2) this information is of little relevance for statistical inference due to the too aggregated nature of the industry classification. For evidence on job-to-job transitions and the role of policies, see e.g., Curtis et al. (2023<sup>[10]</sup>) and Causa et al. (2022<sup>[11]</sup>).

There is no unambiguous ranking in terms of job quality between general, green, and high-polluting employment: hence, this paper does not take a normative approach about the desirability of green jobs vis-à-vis high-polluting and other jobs (Causa, Soldani and Nguyen, 2024<sup>[5]</sup>). Going further, the environmental transition requires an expansion of jobs characterized by green tasks, not a transformation of all (or even the majority of) jobs into green ones. Given the purpose of this paper, the focus is on green jobs for the non-employment-to-employment transitions and on high-polluting jobs for employment-to-unemployment transitions, because the push to a more sustainable economy is expected to induce a contraction of high-polluting jobs and an increase in the demand for green ones. Transitions out of green jobs and into high-polluting ones, although relevant, are beyond the scope of the current analysis.

#### **Box 1 Measuring labour market transitions with European Labour Force Survey data**

Labour market transitions refer to workers' flows into (hirings) and out (separations) of jobs over a specified period of time, which in the context of this study is one calendar year. These transitions are defined based on individual information about worker's labour market status at the time of the interview relative to the previous period, following literature in this area such as (Davis, Faberman and Haltiwanger, 2012<sup>[12]</sup>; Haltiwanger et al., 2018<sup>[13]</sup>; Bassanini and Garnerò, 2013<sup>[14]</sup>; Causa, Luu and Abendschein, 2021<sup>[15]</sup>). In EU-LFS data, this is based on individual retrospective information referring to the previous year, covering activity status (employed, unemployed, inactive because of study, of retirement, etc) and industry of employment.

<sup>10</sup> The lack of any significant expansion in the shares of green employment and the presence of important regional heterogeneities are in line with recent OECD evidence (OECD, 2023<sup>[18]</sup>). The finding that green jobs are more common among highly educated workers is in line with evidence from the UK (Valero et al., 2021<sup>[75]</sup>), the US (Consoli et al., 2016<sup>[85]</sup>; Bowen, Kuralbayeva and Tipoe, 2018<sup>[73]</sup>; Vona, Marin and Consoli, 2018<sup>[8]</sup>), the EU (Vandeplas et al., 2022<sup>[65]</sup>) and most OECD countries (OECD, 2024<sup>[19]</sup>).

Information on prior occupation is only available for unemployed workers who declare past work experience. Key transitions considered in this paper are:

- **Transitions from unemployment to employment:** hirings from unemployment refer to individuals who were employed in the current year and unemployed in the previous year
- **Transition from inactivity due to study to employment:** individuals who are employed in the year of the survey (same definition as above) and were inactive because of study/training in the previous year
- **Transitions from employment to unemployment:** individuals who are unemployed in the year of the survey and were employed in the previous year

See Annex for further elaborations and details on this approach.

The empirical strategy is based on reduced-form modelling, in line with the literature on labour market transitions and the role of policies (Causa et al., 2022<sup>[11]</sup>; Escudero, 2018<sup>[16]</sup>; Bassanini and Garnero, 2013<sup>[14]</sup>; Bluedorn et al., 2023<sup>[17]</sup>).

For transitions from joblessness (i.e., unemployment and, for younger individuals, study-related inactivity), to green jobs, a two-steps procedure is adopted. The first step estimates a worker's probability of moving from status  $S_{it-1}$  to employment in a given year. The second step estimates the probability that such employment is in a green occupation, conditional on the worker having indeed moved to employment.

In the first step, the probability of moving from joblessness to employment is modelled as a logit function:<sup>11</sup>

$$\text{logit} (Employed_{it}|S_{it-1}, X_{it}) = \log \left( \frac{P(Employed_{it}|S_{it-1}, X_{it})}{1 - P(Employed_{it}|S_{it-1}, X_{it})} \right) = X_{it}\beta + Z_{c,t}^1\gamma_1 + Z_{r,t}^2\gamma_2 + FE \quad (1)$$

where  $i$  denotes the individual,  $c$  the country,  $r$  the region, and  $t$  the year. Right-hand variables include individual's socio-economic and demographic characteristics ( $X_{it}$ ), macro-level cyclical controls ( $Z_{c,t}^1$ ), regional labour market conditions ( $Z_{r,t}^2$ ), and fixed effects ( $FE$ ).

The individual characteristics vector  $X_j$  includes age group, education, gender, migration status, marital status (except for study-to-work transitions, given the focus on the age group 20-29), and the degree of urbanisation of the area of residence. Educational attainment is particularly important for the purpose of this work and is a proxy for workers' skills. For the general population, this is captured on a three-levels scale: lower secondary (ISCED 1 and 2), medium (ISCED 3 and 4) or higher (ISCED 5 and higher). The data include granular information on the field of education for young individuals having finished their studies. This information is exploited in baseline models of study-to-work transitions, allowing to single out STEM fields orientation (i.e., in Science, Technology, Engineering and Mathematics) within the categories of medium and higher education.<sup>12</sup>

- The macroeconomic control vector  $Z_{c,t}^1$  includes lagged growth in GDP per capita. The regional-level labour market conditions vector  $Z_{r,t}^2$  includes lagged regional unemployment; youth unemployment for study-to-work transitions.<sup>13</sup>

<sup>11</sup> An alternative modelling option based on the use of nested logit, while theoretically appealing, involves significantly higher computational burden which makes it impossible to implement in the context of the current large scale cross-country econometric exercise. Yet explorative robustness tests conducted on baseline regressions suggest that nested logit estimations yield qualitatively similar results to the two-steps logit estimations used in the analysis.

<sup>12</sup> For policy-augmented modelling, educational attainment is measured on the 3-level scale in order to improve consistency across transitions. However, robustness analysis conducted using the 6-level scale qualitatively confirms the policy effects estimates for transitions from study to employment.

<sup>13</sup> Alternative choices are reported in the Annex under robustness checks.

- The vector FE covers country, region and year fixed effects.<sup>14</sup>

In the second step, the probability that the worker's new job is in a green occupation is estimated through the logistic regression

$$\text{logit}(\text{Job is green} | S_{it-1}, \text{Employed}_{ijt}, X_{it}) = X_{it}\tilde{\beta} + Z_{c,t}^1\tilde{\gamma}_1 + Z_{r,t}^2\tilde{\gamma}_2 + FE \quad (2)$$

- Right-hand variables are defined as above and again include individual's socio-economic and demographic characteristics ( $X_{it}$ ), macro-level cyclical controls ( $Z_{c,t}^1$ ), regional labour market conditions ( $Z_{r,t}^2$ ), and fixed effects ( $FE$ ). In addition to country, region and year fixed effects, this regression also includes industry fixed effects.
- The variable *Job is green* takes the value 1 if the occupation is green and the value 0 if the occupation has a null green score.

For transitions from employment-to-unemployment and for long-term unemployment the focus is on whether workers whose latest employment spell was in a high-polluting occupation face differential risks. This is assessed by estimating the following logistic models:

The probability to transition from employment to unemployment over a one-year-period is estimated through the logistic regression:

$$\text{logit}(\text{Unemployed}_{it} | \text{Employed}_{ijt-1}, X_{it}) = X_{it}\tilde{\beta} + Z_{c,t}^1\tilde{\gamma}_1 + Z_{r,t}^2\tilde{\gamma}_2 + \text{Brown}_{ijt-1}\tilde{\delta} + FE, \quad (3)$$

- The index  $j$  indicates the industry of employment in the previous year ( $t-1$ ). The fixed effects cover country, region, year and industry of latest employment.
- The coefficient  $\tilde{\delta}$  allows to test whether, ceteris paribus (i.e., holding fixed all other observed characteristics in  $X_{it}$ ,  $Z_{c,t}^1$  and  $Z_{r,t}^2$ ), working in a high-polluting occupation in a given year ( $t-1$ ) is associated with a higher probability of moving to unemployment in the following year.

The analysis focuses on long-term unemployment because the duration of unemployment is crucial in determining economic and human capital losses associated with job displacement.<sup>15</sup> Limiting the incidence of long-term unemployment is thus a widely-shared policy objective. The risk of long-term unemployment (defined as unemployment spell of more than one year) is estimated through:

$$\text{logit}(\text{LTUnemployed}_{it} | \text{Unemployed}_{it}, X_{it}) = X_{it}\tilde{\beta} + Z_{c,t}^1\tilde{\gamma}_1 + Z_{r,t}^2\tilde{\gamma}_2 + \text{Brown}_{ijt-1}\tilde{\delta} + FE \quad (4)$$

- The dummy variable *High-polluting* equals 1 if the worker's last job was high-polluting. This does not necessarily refer to year  $t-1$ : unemployed workers, especially long-term ones, are likely to have experienced their last employment spell more than one year before the interview. To avoid recall issues (i.e. the risk that respondents may have biases when reporting about past activities) and measurement noise surrounding the characterising of the previous job (with repercussions on whether this can be classified as high-polluting for the purpose of the current work), this information is not collected in EU-LFS for anyone whose latest job experience goes back more than seven years ago. Fixed effects cover country, region, year and industry (that is, industry of employment in the latest job).

<sup>14</sup> Baseline variants are reported in the Annex. Robustness variants include region\*year interactions instead of regional labour market controls, to absorb any region-time-specific factors. This is not possible in policy estimations because region\*year interactions are informationally equivalent to country\*year interactions, thus precluding the identification of policy effects. These variants are relevant to check the robustness of individual-level effects, e.g., education, gender, etc.

<sup>15</sup> See e.g. Burdett et al. (2020<sup>[93]</sup>), OECD country reviews on job displacement (<https://www.oecd.org/employment/displaced-workers.htm>) and the forthcoming OECD Employment Outlook on displacement out of polluting activities (OECD, 2024<sup>[19]</sup>).

The choice of logistic regression approach (also referred to as logit model) ensures that the estimated probability of a worker experiencing the relevant transition is bounded between zero and one. This probability is not linear in the estimated parameters, which are obtained by maximum likelihood estimation (MLE). Unless otherwise stated, the results are presented as odds ratios, to help the interpretation.<sup>16</sup> The term odds ratio (OR) indicates the ratio between the odds of a certain event with associated probability  $p$ :

$$OR = \frac{p}{1-p}$$

In the context of logistic regression, the coefficients  $(\beta, \gamma_1, \gamma_2)$  are to be interpreted as semi-elasticities: a slope parameter  $\beta_j$  indicates that a unitary increase in the corresponding regressor will increase the odds ratio by a multiple  $\beta_j$  (a numeric example is given below).

### *Policy-augmented modelling*

The baseline models described in the previous section are augmented to assess the effects on transitions into green jobs and out of high-polluting ones of the following structural policies, selected based on the literature on labour market transitions and data availability:<sup>17</sup>

- **Education, skills and training.** This includes various measures of education, skills and workers' access to training,<sup>18</sup> including to courses provided by firms, as well as public spending on education.
- **Policy support for jobseekers.** This includes various categories of spending on active labour market policies, such as job-search support through public employment services (PES) and through training programs, employment incentives and hiring subsidies, as well as cash support in form of unemployment benefits and social assistance for the unemployed.
- **Job protection legislation.** This includes OECD indicators measuring the strictness of regulation on dismissals.<sup>19</sup>
- **Labour taxation and wage bargaining settings.** This includes labour market institutions associated with labour taxation and wage bargaining.
- **Policy barriers to business entry and dynamism.** This includes regulatory barriers to firm entry and competition, measured by OECD indicators on product market regulations.<sup>20</sup>

<sup>16</sup> The odds ratios are obtained by taking the exponential of the estimated coefficients. In the context of this work, the ease of computation is one of the main advantages of logistic regression in comparison to probit. Cameron and Trivedi (2005<sub>[77]</sub>) note that the differences between the probabilities predicted by logit and probit models are often negligible.

<sup>17</sup> Amongst others, see Causa et al. (2022<sub>[11]</sub>), Escudero (2018<sub>[16]</sub>), IMF (2021<sub>[56]</sub>), and Bassanini and Garnero (2013<sub>[14]</sub>). Structural policy variables are introduced one at a time, as standard in the literature in the light of collinearity issues.

<sup>18</sup> Training variables in this policy area refer to actual participation to training among workers or to the share of enterprises providing training; the training indicator under active labour market policies refer to public spending on training programs aimed at helping unemployed finding jobs matching their competencies.

<sup>19</sup> See [OECD Indicators of Employment Protection](#). Employment protection refers to only one dimension of the complex set of factors that influence worker security and firm adaptability. For information on other labour market policies and institutions, see the database.

<sup>20</sup> [Indicators of Product Market Regulation - OECD](#).

- **Housing and mobility.** This includes housing policy indicators from the OECD housing portal<sup>21</sup> and metrics of internal mobility.

The analysis is extended to explore the possible effects of environmental policies on labour market transitions in the greening economy. This is based on the OECD **Environmental Policy Stringency** (EPS) index. Stringency is defined as the degree to which pollution or environmentally harmful behaviour are (implicitly or explicitly) priced. The index is based on the degree of stringency of different environmental policy instruments, primarily related to climate and air pollution; market-based policies such as CO<sub>2</sub> trading schemes and taxes; non-market-based policies such as emission limit values associated with air pollutants such as Nitrogen Oxides (NO<sub>x</sub>) and Sulphur Oxides (SO<sub>x</sub>) and technology support.<sup>22</sup>

The policy identification strategy exploits cross-country time-series variation, to the extent possible given data availability (as explained in the text and annex). The empirical analysis goes beyond average effects to investigate heterogeneous effects across socio-economic groups, proceeding as follows:

- For unemployment and study-related inactivity to employment transitions, heterogeneous effects are estimated by interacting policy variables with categorical variables corresponding to relevant socio-economic groups.
- For unemployment-related regressions, policy effects are allowed to vary depending on whether the latest employment was or not in a high-polluting occupation: this is achieved by interacting each policy variable with the indicator variable  $Brown_{ijt-1}$ , introduced in Equations (3) and (4). To avoid introducing hard-to-interpret triple interactions in the estimations, heterogeneous effects by socio-economic group are then obtained by performing groups-specific estimations.

For time-invariant policies, for instance in the area of adults' competencies and product market regulations, estimations mostly rely on illustrative regressions without country and region fixed effects. Again, to the extent possible, policy estimations are designed to shed light on distributional effects by analysing heterogeneous effects across socioeconomic groups. The Annex includes additional data-related and technical information and materials, as well as a battery of robustness tests to support the empirical analysis.

## Baseline results

Baseline results are presented by means of illustrative charts reporting key estimates. The Annex provides full regression tables and first-step estimates when relevant (e.g., transitions from unemployment to employment). The first block of results is about transitions from non-employment (that is, unemployment and study-related inactivity) to employment in green jobs, conditional on having moved from non-employment to employment. The second block is about transitions from employment to unemployment and the incidence of long-term unemployment, exploring the possible impact of displacement from high-polluting jobs.

The models are estimated using logistic regression techniques and the reported coefficients are odds ratios. The odds ratio associated with a particular socioeconomic characteristic represents the odds of e.g., moving from employment to unemployment over the odds of moving from employment to unemployment for those in the reference group. As an example, an odds ratio of 0.7 for high level education would indicate that the odds of moving from employment to unemployment are 30% lower among high education individuals than among low education individuals (the reference group).

<sup>21</sup> See <https://www.oecd.org/housing/data/> for data and analysis on housing.

<sup>22</sup> See <https://stats.oecd.org/Index.aspx?DataSetCode=EPS> to access the data and background papers.



### *Transitions from non-employment to green employment*

This section presents baseline estimates for transitions from non-employment (unemployment, study-related inactivity to green job) to green employment, conditional on moving from non-employment to employment. The presentation is based on illustrative charts quantifying the effects of relevant individual characteristics. This proceeds as follows: the unemployment to green job chart reports estimates as odds ratios associated with e.g., gender, education, area of residence for the (conditional) probability to move from unemployment to green job. The study-related inactivity to green job chart follows the same approach.

The main insights are (Figure 3):

- Education is the most important individual-level driver of transitions from non-employment to green jobs, all the more so for education in science technology engineering and mathematics (STEM) when young people are moving from study to the labour market.
  - The odds to get a green job are twice as high for workers with high levels of education relative to workers with low levels of education (Panel A).
  - The odds to transition to a green occupation are twice as high for young individuals with medium education in STEM relative to those with low education, but also relative to those with non-STEM medium education. High education students with a STEM degree in engineering are most likely to transition to green jobs, with six times higher odds than the low education reference group (Panel B).
- Irrespective of their educational attainment and field of study, women are significantly less likely than men to move into green jobs out of non-employment. Their odds of transitioning from unemployment (resp. inactivity to study) to green jobs is 60% (resp. one third) relative to men.
- Age is not the starkest determinant of transitions into green jobs, but nonetheless a significant predictor: youth have lower odds to move from unemployment to green jobs than prime-aged workers (the reference), by 10% for individuals aged 25-34 and by 20% for the youngest working-age group.
- Whether an individual lives in a rural relative to an urban area is associated with a small statistically significant effect, of equal magnitude but opposite sign for transitions from unemployment and from study to green jobs: 10% higher (lower) odds of moving from unemployment (study) to green jobs.
- This empirical evidence brings relatively clear policy implications: on the need to foster access to quality education, training and skills, in particular to remove barriers to STEM fields of study for target groups such as young women; and, related, on the need to address gender divides in the transition to greener economic activities. This requires policy actions to combat stereotypes and encourage women engaging in scientific curricula, in line with previous findings for other labour market dislocations.<sup>23</sup>

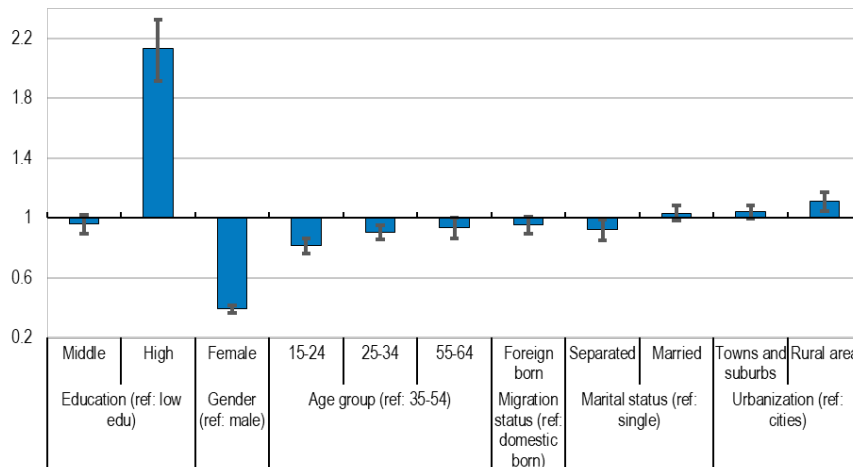
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<sup>23</sup>See <https://oecdstatistics.blog/2023/03/08/why-dont-more-women-code>, [OECD Going Digital Toolkit](#), and (OECD, 2023<sup>[94]</sup>).

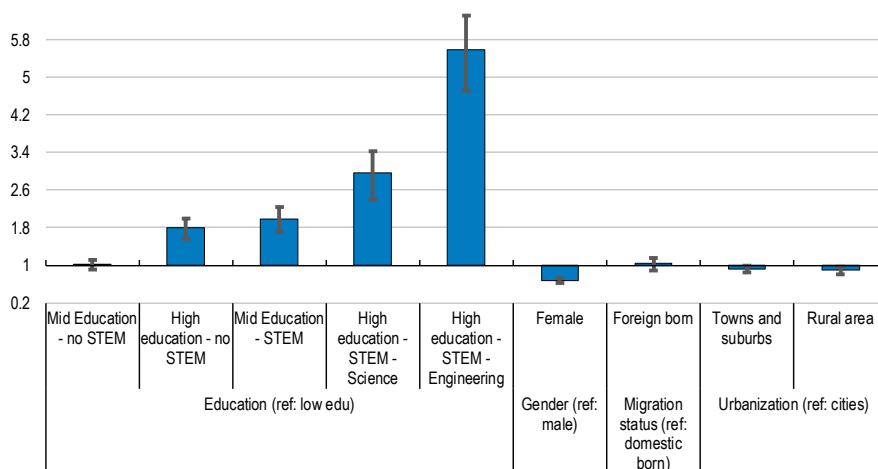
**Figure 3. Transitions from non-employment to green employment: key results**

Estimated odds ratios & confidence intervals from logistic regressions

**Panel A Transitions from unemployment to green employment**



**Panel B Transitions from study-related inactivity to green employment**



Note: Baseline results report odds ratios and confidence intervals associated with individual characteristics based on estimated transitions models from non-employment to employment. This is obtained from logistic regressions run on a panel of European OECD countries over the period 2011-2019. The sample includes working age individuals (Panel A) and individuals aged 20-29 (Panel B), conditional on those individuals having moved from unemployment (Panel A) and inactivity due to study (Panel B) on green employment. The dependent variable takes the value 1 if the individual has taken a job with a positive green score, and 0 if the individual has taken a job with a green score of 0. The high education category of STEM-Science covers natural sciences, mathematics, statistics, and information and communicating technologies. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Odds ratios greater than 1 indicate that the variable is associated with greater odds of the transition happening; odds ratios of 1 reflect similar odds of the transition materializing; odds ratios below 1 suggest that the variable is associated with lower odds of the transition happening. The Annex report complete regression tables and first-step regression tables (that is, from unemployment/ inactivity due to study to job).

How to read: Conditional on having transitioned from unemployment to employment, the odds of workers with higher levels of education to transition to a green occupation are 2.1 relative to the odds of workers with lower levels of education.

Source: OECD estimations and calculations based on EU-LFS data.

*Transitions from employment to unemployment & displacement effects from high-polluting jobs*

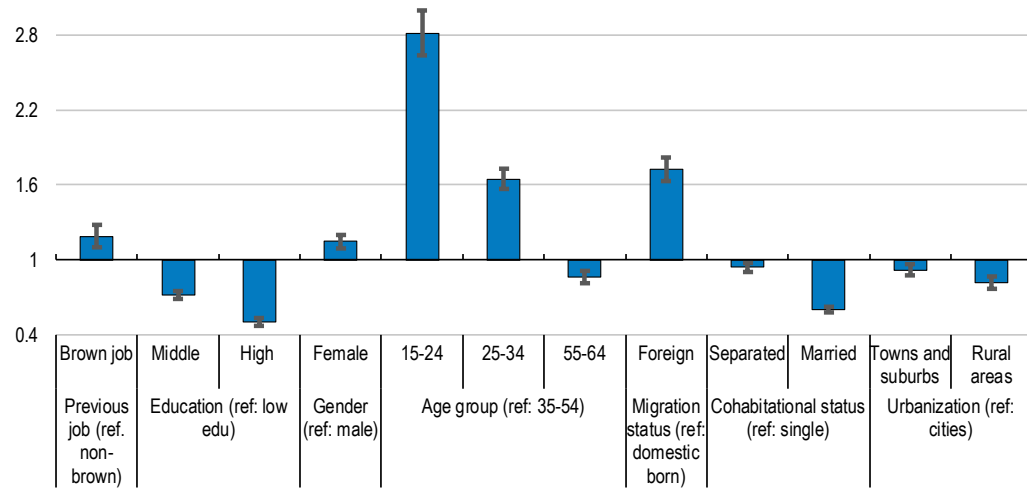
This section analyses transitions from employment to unemployment, one key question being whether the likelihood of dismissal and the incidence of long-term unemployment depend on whether a worker latest occupation was high-polluting or not. As above, baseline estimates are presented with illustrative charts quantifying the effects of relevant individual characteristics while the Annex reports comprehensive results.

Main insights on transitions from employment to unemployment are (Figure 4A):

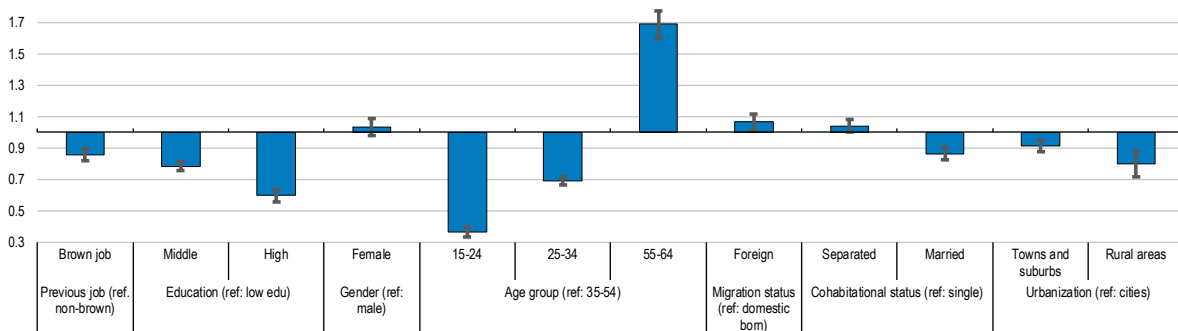
- Workers employed in high-polluting occupations face higher displacement risks than workers in non-high-polluting occupations, with 20% higher odds of unemployment. This result is unchanged by adding a dummy variable for workers employed in green occupations, with the latter displaying a small weakly significant lower displacement risk relative to their non-green and non-high-polluting counterparts (see Annex).
- Young workers are particularly exposed to unemployment: for those aged 15-24 and 25-34, the odds are respectively 2.8 and 1.6 times greater than prime-aged workers.
- Migrant workers face higher displacement risks, with odds around 70% higher than their native counterparts.
- The higher the educational attainment, the lower the odds of a layoff: by around 50% for high-educated workers and 30% for middle-educated workers, relative to low-educated ones.
- Women are more at risk of losing their job than men, with 15% lower odds.
- Workers living in non-urban areas are less likely to lose their job relative to their metropolitan counterparts, with around 20% lower odds among those living in rural areas.

**Figure 4. Transitions from employment to unemployment & displacement effects from high-polluting jobs**

**Panel A. Transitions from employment to unemployment**



**Panel B. Long-term unemployment**



Note: Baseline results report odds ratios and confidence intervals associated with individual characteristics based on estimated transitions models from employment to unemployment (Panel A) and long-term unemployment risks among unemployed individuals with past work experience (Panel B). This is obtained from logistic regressions run on a panel of European OECD countries over the period 2011-2019. The sample includes working age individuals. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Odds ratios greater than 1 indicate that the variable is associated with greater odds of the transition happening; odds ratios of 1 reflect similar odds of the transition materializing; odds ratios below 1 suggest that the variable is associated with lower odds of the transition happening. The Annex report complete regression tables.

How to read: The odds of unemployed individuals whose previous job was high-polluting to become long-term unemployed are 0.86 relative to those of unemployed individuals whose previous job was non-high-polluting, or 14% lower.

Source: OECD estimations and calculations based on EU-LFS data.

Long-term unemployed are defined as individuals that have been unemployed for more than one year, excluding those without declared past work experience.<sup>24</sup>

<sup>24</sup> See Annex for details on sample selection criteria.

Main insights on long-term unemployment are (Figure 4B):

- Unemployed individuals with previous work experience in high-polluting occupations face lower odds of long-term unemployment than those with previous work experience in non-high-polluting occupations, with 14% lower odds.<sup>25</sup>
- Older unemployed individuals display higher odds of long-term unemployment: for the age group 55-64, for example, the odds are 70% higher than prime-aged workers.
- Migrant workers face slightly higher odds of becoming long-term unemployed, around 7% higher than their native counterparts.
- The higher the education level, the lower the chances of remaining unemployed for more than one year: the odds are around 40% lower for high-educated workers and 21% for middle-educated workers, relative to low-educated ones.
- The odds of long-term unemployment are lower for individuals living in non-urban areas, by around 20% for those living in rural areas relative to those living in cities.

This empirical evidence does not allow one to draw firm conclusions about scarring effects associated with displacement from high-polluting jobs, on average across the sample of European countries over the period under consideration. On the one hand, being employed in a high-polluting job tends to (slightly) increase the risk of dismissal over a one-year-period; on the other, having been dismissed from a high-polluting job tends to (slightly) reduce the risk of remaining in unemployment for more than one year. The negative coefficient on high-polluting jobs does not seem to reflect heterogeneities and compositional effects: for instance, estimating education and period-specific coefficients does not alter the sign and significance of this coefficient. Trying to go beyond long-term unemployment, the analysis of labour market scars is extended to uncover discouragement effects, that is, a situation where jobless individuals abandon job search even though they would like to work. Box 2 provides an empirical analysis of the individual characteristics and cyclical factors which drive the discouragement effects, including a dummy variable for individuals whose last work experience was in a high-polluting occupation. The effect of this variable is not statistically significant. In other words, whether an individual lost a high-polluting as opposed to a non-high-polluting job is not a significant predictor of this individual abandoning job search by discouragement. Sociodemographic characteristics, such as education, gender and age are highly significant predictors, with higher education mitigating discouragement risks.

### Box 2. Discouragement effects: are workers displaced from high-polluting jobs different?

Discouraged workers are identified as those individuals who are not seeking employment because they believe that there is no work available, but who nevertheless would like to work. Labour force survey data and statistics have been increasingly tracking discouragement effects as relevant indicators of the labour market situation, complementing standard indicators such as (un)employment and inactivity.<sup>26</sup> The current analysis relies on EU-LFS data to identify discouraged workers and distinguish those with previous work experience in high-polluting occupations.

Main insights on discouragement effects are (Table 1):

- Individuals with previous work experience in high-polluting occupations do not feature statistically different discouragement odds than those with previous work experience in non-high-polluting occupations.

<sup>25</sup> As for transitions from employment to unemployment, this result is unchanged by adding a dummy variable for individuals previously employed in green occupations.

<sup>26</sup> See [https://www.oecd.org/els/emp/LFSNOTES\\_SOURCES.pdf](https://www.oecd.org/els/emp/LFSNOTES_SOURCES.pdf) for an overview.

- Prime-aged workers are significantly more likely to experience labour market discouragement than their younger counterparts.
- Women have significantly lower odds than men, by around 40%, to give-up job search because they are discouraged to find one.
- The higher the education level, the lower the odds of discouragement: by around 50% for high-educated workers and 30% for middle-educated workers, relative to low-educated ones.
- Migrant workers experience higher discouragement effects than natives, with around 14% higher odds.
- Discouragement effects are more likely during adverse cyclical conditions, that is, lower aggregate economic growth and higher unemployment at the local level.

**Table 1. Individual and cyclical drivers of discouragement effects**

Regressor	OR
Previous job was brown	0.981 (-0.36)
Middle education	0.698*** (-12.79)
High education	0.460*** (-11.49)
Female	0.642*** (-13.75)
Age 15-24	0.215*** (-13.42)
Age 25-34	0.474*** (-11.03)
Age 55-64	0.994 (-0.11)
Foreign born	1.139*** -3.63
Separated	0.962 (-0.89)
Married	0.774*** (-7.17)
Towns and suburbs	1.001 -0.03
Rural areas	1.091 -1.43
GDP per capita annual growth in % lagged	0.959*** (-3.91)
Regional unemployment rate lagged	1.051*** -6.94
Constant	0.054*** (-16.70)
FE	Yes
Observations	359944

Note: Baseline results report odds ratios and confidence intervals associated with the estimation of individual and cyclical drivers of labour market discouragement. This is obtained from logistic regressions run on a panel of European OECD countries over the period 2011-2019. The variable discouraged is a dummy indicator taking the value 1 if the individual is inactive, no longer in employment due to dismissal or the end of a temporary contract, believes no job is available but would nonetheless like to work. The variable takes the value 0 if the individual is inactive and no longer in employment due to dismissal or the end of a temporary contract. The sample includes working age individuals. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Odds ratios greater than 1 indicate that the variable is associated with greater odds of the transition happening and odds ratios lower than 1 suggest that the variable is associated with lower odds of the transition happening.

Source: OECD estimations and calculations based on EU-LFS data.

One cautious implication from this analysis is that, at least across European countries over the 2011-2019 period under consideration, there is no evidence that workers displaced from high-polluting jobs faced higher labour market scars in terms of long-term unemployment and discouragement effects than otherwise comparable workers. The lack of significant aggregate effects does not rule out the possibility of significant effects at the local level, given the spatial concentration of industries and sectors and therefore of high-polluting jobs (OECD, 2023<sub>[18]</sub>). Cross-country data such as the EU-LFS used in this paper have

the advantage of comparability and harmonization but at the cost of granularity. Country-level data from administrative sources can provide complementary insights on displacement effects from high-polluting activities: this approach, based on linked employer-employee data, is being used in the 2024 edition of the OECD Employment Outlook (OECD, 2024<sup>[19]</sup>) to document displacement effects from high-polluting sectors.

## Policy results

This section presents new empirical evidence on the link between structural policies and labour market transitions in the greening economy, based on the econometric set-up presented in the framework section. As indicated above, the analysis focuses on the areas of education, skills and training, publicly provided support to jobseekers and labour market institutions associated with job protection and wage settings, housing and policies affecting geographical mobility, and business regulations.

Although this is the first paper to empirically investigate the impact of structural policies on labour market transitions in the greening economy, existing literature on policies and labour market transitions provides a relevant analytical basis for assessing underlying economic mechanisms. For example:

- Formal education, actual adults' competencies and access to training programs should facilitate labour market transitions in the greening economy. The baseline results in this paper suggest that, consistently with previous studies (Consoli et al., 2016<sup>[9]</sup>; OECD, 2023<sup>[18]</sup>), green jobs are indeed associated with higher skills and education, in a context where a vast literature has shown that job-finding rates increase with education levels (OECD, 2023<sup>[20]</sup>; Causa, Luu and Abendschein, 2021<sup>[15]</sup>).<sup>27</sup>
- Well-designed active labour market policies can help workers cope with cyclical and structural changes (Boeri and Burda, 1996<sup>[21]</sup>; Card, Kluge and Weber, 2015<sup>[22]</sup>; Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>).<sup>28</sup> These policies should therefore play an important role in supporting labour market adjustments associated with the green transition. Active labour market programs should be complemented with balanced and adequate income support to help unemployed individuals finding jobs that match their qualifications and preferences.<sup>29</sup>
- Stringent job protection on regular jobs can contribute to labour market segmentation, misallocation and mismatches (Adalet McGowan and Andrews, 2017<sup>[24]</sup>; Hijzen, Mondauto and Scarpetta, 2017<sup>[25]</sup>), including by reducing incentives for job mobility (Bassanini and Garnerò, 2013<sup>[14]</sup>; Causa and Pichelmann, 2020<sup>[26]</sup>; Causa et al., 2022<sup>[11]</sup>), and labour market responsiveness to changes in economic conditions (Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>). This could create obstacles to labour market reallocations associated with the green transition, especially for new entrants.
- Overly strict regulations creating barriers to entry in business and occupations have been found to depress workers' mobility and job ladders (Boal and Ransom, 1997<sup>[27]</sup>; Lopez-Garcia, 2009<sup>[28]</sup>; Adalet McGowan and Andrews, 2017<sup>[24]</sup>), with significant detrimental effects for young people entering the labour market (Causa et al., 2022<sup>[11]</sup>; Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>). Associated policy settings also tend to slow innovation and technology diffusion (Andrews and

<sup>27</sup> This argument is supported by country-specific studies, for example in the case of Germany and France (OECD, 2023<sup>[104]</sup>; OECD, 2021<sup>[105]</sup>).

<sup>28</sup> This argument is also supported by country-specific studies, for example in the case of Canada (OECD, 2018<sup>[106]</sup>) and South Korea (Jones and Urasawa, 2013<sup>[107]</sup>).

<sup>29</sup> See [OECD portal on active labour market policies](#) for comprehensive materials.

Criscuolo, 2013<sup>[29]</sup>; Calvino, Criscuolo and Verhac, 2020<sup>[30]</sup>; Aghion, Bergeaud and Van Reenen, 2021<sup>[31]</sup>), and may therefore discourage green innovation and jobs creation.

- The literature suggests that housing-related factors and policies have a strong influence on labour market transitions and dynamism, by affecting individuals' decisions and possibilities to move, in particular insofar as housing costs prevent people to move towards areas characterised by better jobs opportunities (Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>; Causa and Pichelmann, 2020<sup>[26]</sup>; Andrews, Caldera Sánchez and Johansson, 2011<sup>[32]</sup>).

In what follows, policy results are presented by means of stylized tables reporting the sign and statistical significance of estimated effects, for each dependent variable and explanatory policy variable. The Annex delivers comprehensive regression tables and a variety of robustness tests e.g., using alternative cyclical controls and performing multivariate policy analysis. Policy estimations focus on a selection of clearly identified policy objectives and targets: i) supporting transitions from unemployment and study to jobs, and to green jobs; and ii) reducing the risk of long-term unemployment following dismissal from any job and from high-polluting jobs. Employment to unemployment transitions are therefore covered in the baseline analysis to identify individual and cyclical drivers of workers' dismissals, but not in the subsequent policy analysis which focuses on the objective of reducing the risk of long-term unemployment following displacement. Estimations systematically explore distributional aspects by zooming on different socioeconomic groups, based on interaction terms (in transitions from non-employment to green employment), or group-specific regressions (in long-term unemployment) -- as detailed in the framework section.

### *Transitions from non-employment to green employment*

This section delivers policy results for transitions from non-employment (unemployment, study-related inactivity) to green employment, conditional on moving from non-employment to employment, for the whole (working age) sample and for a variety of socioeconomic groups (Tables 2-5). The presentation and discussion systematically cover first-stage estimates, that is, policy effects on transitions from non-employment to employment.

Policies conducive to increasing skills and equality of opportunities in the area of education, training and requalification are key to achieve a green transition that is efficient and fair. This has been widely recognised by policy analysis and strongly suggested by the effects of individual education in the baseline estimates of this paper.<sup>30</sup> However, delivering quantitative cross-country empirical evidence in this area is hampered by the lack of harmonised indicators on the design and functioning of skill and training policies. In this context, the current approach is to deliver a cautious regression analysis based on the data that is currently available. Relevant indicators for the purpose of the current work, for example in the area of adults' training, are time-invariant; this implies that associated estimates cannot include country fixed effects and therefore should not be interpreted causally. Having set the background and its caveats, main insights on skills, training and education are (Tables 2A and 2B):

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<sup>30</sup> References in the area of skills and the green transition are numerous, including efforts by international organisations and by countries' statistical offices, e.g. (OECD, 2023<sup>[46]</sup>; European Commission, 2022<sup>[63]</sup>; CEPS, 2023<sup>[54]</sup>; ONS, 2023<sup>[69]</sup>; Consoli et al., 2016<sup>[85]</sup>). The empirical findings presented in this paper offer additional support to the view, expressed in this literature, that education and training are crucial for an effective and just transition. For relevant material in the area of apprenticeships for the green transition, see recent work by CEDEFOP and the OECD (CEDEFOP and OECD, 2022<sup>[47]</sup>). This topic will be covered in the 2024 edition of the OECD Employment Outlook.



**Table 2. Transitions from non-employment to green employment: main results on education, skills and training policies**

Panel A Non employment to green employment

Unemployment to green employment											Study-related inactivity to green employment											
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)
<b>Education, skills and training</b>																						
PIAAC - Percentage of adults scoring high in numeracy (i)	1.009*	<b>1.001</b>	1.023**	<b>1.009*</b>	=	=	0.975***	<b>0.990</b>	1.018*	1.039***	<b>1.017***</b>	0.988***	=	1.011*	<b>1.014*</b>	=	<b>0.998</b>	=	=	<b>1.005</b>	1.017*	=
PIAAC - Percentage of adults scoring low in numeracy (i)	0.990***	<b>0.996</b>	0.983***	<b>0.990***</b>	=	=	1.017***	<b>0.998</b>	=	0.982**	<b>0.986***</b>	1.008*	=	0.990*	<b>0.988**</b>	=	<b>1.001</b>	=	0.982*	<b>0.995</b>	0.988*	=
PIAAC - Mean numeracy score (i)	1.005***	<b>1.002</b>	1.009***	<b>1.005**</b>	=	=	0.991***	<b>0.999</b>	=	1.012**	<b>1.007***</b>	0.996**	=	1.005*	<b>1.007**</b>	=	<b>1.000</b>	=	1.009*	<b>1.003</b>	1.007*	=
PIAAC - Percentage of adults scoring high in literacy (i)	1.009*	<b>1.001</b>	1.023**	<b>1.013**</b>	=	=	0.974**	<b>0.978***</b>	1.035***	1.050***	<b>1.018***</b>	0.985***	0.982**	1.000	<b>1.003</b>	=	<b>0.993</b>	=	=	<b>0.997</b>	=	=
PIAAC - Percentage of adults scoring low in literacy (i)	0.987***	<b>0.994</b>	0.981***	<b>0.987***</b>	=	=	1.022***	<b>1.004</b>	0.982***	0.972***	<b>0.983***</b>	1.008**	=	0.992	<b>0.988*</b>	=	<b>1.000</b>	=	=	<b>0.995</b>	=	=
PIAAC - Mean literacy score (i)	1.006**	<b>1.002</b>	1.010***	<b>1.006**</b>	=	=	0.988***	<b>0.995</b>	1.012***	1.018***	<b>1.008***</b>	0.995**	=	1.003	<b>1.005</b>	=	<b>0.999</b>	=	=	<b>1.001</b>	=	=
Share of population with tertiary education	1.029	<b>1.025</b>	1.010***	<b>1.034*</b>	0.993*	0.992**	=	<b>1.020</b>	1.011**	1.011*	<b>1.029</b>	=	=	1.013	<b>1.013</b>	=	<b>1.019</b>	=	=	<b>1.015</b>	=	=
Adults' participation in training - Formal (i)	1.015***	<b>1.006</b>	1.026***	<b>1.026***</b>	=	0.977***	=	<b>1.013</b>	=	=	<b>1.016**</b>	=	=	0.995	<b>0.991</b>	=	<b>0.984</b>	=	=	<b>0.996</b>	=	=
Adults' participation in training - Formal and non-formal (i)	1.002	<b>0.998</b>	1.011**	<b>1.002</b>	=	=	0.984***	<b>0.989*</b>	1.012**	1.023***	<b>1.005</b>	=	=	1.005	<b>1.004</b>	=	<b>1.002</b>	=	=	<b>1.003</b>	=	=
Adults' participation in training - Job-related non-formal (i)	1.006*	<b>1.002</b>	1.011*	<b>1.005</b>	=	=	0.979***	<b>0.988**</b>	1.019***	1.030***	<b>1.010**</b>	0.993*	0.990*	1.008*	<b>1.009</b>	=	<b>0.998</b>	=	=	<b>1.005</b>	=	=
Adults' participation in training - Non-job-related non-formal (i)	0.992	<b>0.994</b>	=	<b>0.989*</b>	=	1.010*	=	<b>0.987</b>	=	=	<b>0.990</b>	=	=	1.002	<b>1.003</b>	=	<b>1.033**</b>	0.975*	0.966*	<b>1.012</b>	0.981*	0.976*
Adults' participation in training - Job-related non-formal, sponsored by the employer (i)	1.007***	<b>1.005</b>	1.008*	<b>1.007**</b>	=	=	0.982***	<b>0.993</b>	1.015***	1.021***	<b>1.011***</b>	0.995*	0.992*	1.006	<b>1.007</b>	=	<b>0.994</b>	=	=	<b>1.005</b>	=	=
Share of enterprises providing courses and other forms of training (i)	1.001	<b>1.000</b>	=	<b>1.004*</b>	0.995**	0.997*	0.995*	<b>0.997</b>	1.007***	1.007**	<b>1.002</b>	=	=	1.001	<b>1.001</b>	=	<b>0.993</b>	1.011*	=	<b>1.002</b>	=	=
Educational spending - T total expenditure on tertiary education per student relative to GDP per capit	1.001	<b>0.998</b>	1.008**	<b>1.004</b>	=	=	0.988**	<b>0.994</b>	1.009***	1.009*	<b>1.002</b>	=	=	1.002	<b>1.002</b>	=	<b>1.006</b>	=	=	<b>1.003</b>	=	=
Educational spending - T total public expenditure on primary-tertiary education as % of total gov. exp	0.984	<b>0.966</b>	1.050***	<b>1.000</b>	=	=	0.927***	<b>0.930*</b>	1.076***	1.091***	<b>1.001</b>	0.977*	0.964*	1.091	<b>1.095</b>	=	<b>1.062</b>	=	=	<b>1.094</b>	=	=
Educational spending - T total public expenditure on tertiary education as % of total gov. expenditure	1.059	<b>1.000</b>	1.160***	<b>1.096</b>	=	=	0.858***	<b>0.896</b>	1.205***	1.277***	<b>1.108</b>	0.926	0.909**	1.056	<b>1.067</b>	=	<b>0.986</b>	=	=	<b>1.042</b>	=	=

Panel B Non employment to employment (“first-stage”)

Unemployment to employment											Study-related inactivity to employment													
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)		
<b>Education, skills and training</b>																								
PIAAC - Percentage of adults scoring high in numeracy (i)	1.015	<b>1.001</b>	1.032***	<b>1.012</b>	1.026***	=	0.987*	<b>0.991</b>	1.036***	1.036***	<b>1.013</b>	=	=	1.028**	<b>1.022*</b>	1.012***	<b>1.013</b>	1.027**	=	<b>1.026*</b>	=	=	=	
PIAAC - Percentage of adults scoring low in numeracy (i)	0.994	<b>1.002</b>	0.982***	<b>0.997</b>	0.982***	=	1.010*	<b>1.009</b>	0.978***	0.978***	<b>0.995</b>	=	=	1.010	<b>1.013</b>	0.995*	<b>1.020*</b>	0.983**	=	<b>1.012</b>	=	=	=	
PIAAC - Mean numeracy score (i)	1.002	<b>0.998</b>	1.011***	<b>1.001</b>	1.010***	=	=	<b>0.993*</b>	1.014***	1.013***	<b>1.002</b>	=	=	0.998	<b>0.996</b>	1.003***	<b>0.993</b>	1.010**	=	<b>0.997</b>	=	=	=	
PIAAC - Percentage of adults scoring high in literacy (i)	1.034**	<b>1.019</b>	1.033***	<b>1.028**</b>	1.027***	=	0.984*	<b>1.016</b>	1.022***	1.030**	<b>1.041**</b>	=	=	1.077***	<b>1.070***</b>	1.013**	<b>1.044***</b>	1.039***	1.027**	<b>1.074***</b>	=	=	=	
PIAAC - Percentage of adults scoring low in literacy (i)	0.979**	<b>0.989</b>	0.977***	<b>0.984*</b>	0.976***	=	=	<b>0.999</b>	0.971***	0.968***	<b>0.975**</b>	=	=	0.985	<b>0.988</b>	0.994*	<b>1.006</b>	0.972***	=	<b>0.985</b>	=	=	=	
PIAAC - Mean literacy score (i)	1.012**	<b>1.006</b>	1.014***	<b>1.010*</b>	1.013***	=	=	<b>1.002</b>	1.015***	1.017***	<b>1.015**</b>	=	=	1.020***	<b>1.018***</b>	1.004**	<b>1.008</b>	1.017***	=	<b>1.021**</b>	=	=	=	
Share of population with tertiary education	1.047***	<b>1.041**</b>	1.011***	<b>1.047***</b>	=	=	0.992*	<b>1.045***</b>	1.004*	=	<b>1.046***</b>	=	=	1.136***	<b>1.131***</b>	1.008***	<b>1.146***</b>	=	=	<b>1.133***</b>	1.011**	=	=	
Adults' participation in training - Formal (i)	1.069***	<b>1.065***</b>	=	<b>1.080***</b>	0.989*	=	=	<b>1.080***</b>	0.987*	0.979*	<b>1.067***</b>	=	=	1.081***	<b>1.073***</b>	1.015**	<b>1.061***</b>	1.026*	=	<b>1.071***</b>	1.035***	=	=	
Adults' participation in training - Formal and non-formal (i)	1.021***	<b>1.014***</b>	1.014***	<b>1.014***</b>	=	=	0.993***	<b>1.014***</b>	1.008***	1.011**	<b>1.017***</b>	=	1.008**	1.027***	<b>1.021***</b>	1.010***	<b>1.040***</b>	0.988*	0.984**	<b>1.028***</b>	=	0.993*	=	
Adults' participation in training - Job-related non-formal (i)	1.026***	<b>1.017***</b>	1.018***	<b>1.013***</b>	=	=	0.993***	<b>1.013***</b>	1.015***	1.017***	<b>1.022***</b>	=	=	1.029***	<b>1.023***</b>	1.011***	<b>1.046***</b>	0.987*	0.979***	<b>1.032***</b>	=	0.990*	=	
Adults' participation in training - Non-job-related non-formal (i)	1.022***	<b>1.016***</b>	1.012***	<b>1.011</b>	0.989**	0.995*	0.990***	<b>1.011</b>	1.016***	=	<b>1.008</b>	1.013**	1.029***	1.009	<b>1.005</b>	1.007*	<b>1.041***</b>	0.968***	0.969**	<b>1.004</b>	=	1.017*	=	
Adults' participation in training - Job-related non-formal, sponsored by the employer (i)	1.023***	<b>1.017***</b>	1.014***	<b>1.014***</b>	=	=	0.996*	<b>1.014***</b>	1.011***	1.013***	<b>1.021***</b>	=	=	1.025***	<b>1.020***</b>	1.009***	<b>1.043***</b>	0.984**	0.978***	<b>1.028***</b>	=	0.990*	=	
Share of enterprises providing courses and other forms of training (i)	1.016***	<b>1.013***</b>	1.005***	<b>1.016***</b>	=	=	0.994***	<b>1.016***</b>	=	=	<b>1.016***</b>	=	=	1.018***	<b>1.015***</b>	1.005***	<b>1.029***</b>	0.990***	0.988***	<b>1.020***</b>	=	0.992***	=	
Educational spending - T total expenditure on tertiary education per student relative to GDP per capita	1.008**	<b>1.000</b>	1.016***	<b>1.008**</b>	=	=	=	<b>1.002</b>	1.007***	1.011***	<b>1.006*</b>	=	1.004*	1.012*	<b>1.008</b>	1.007***	<b>1.011</b>	=	=	<b>1.009</b>	1.007**	=	=	
Educational spending - T total public expenditure on primary-tertiary education as % of total gov. expenditure	1.066**	<b>1.027</b>	1.089***	<b>1.060*</b>	=	=	=	<b>1.023</b>	1.055***	1.085***	<b>1.075***</b>	=	=	1.158**	<b>1.142**</b>	1.028*	<b>1.110</b>	1.072**	=	<b>1.131**</b>	1.055**	1.042*	=	
Educational spending - T total public expenditure on tertiary education as % of total gov. expenditure	1.025	<b>0.939</b>	1.225***	<b>1.023</b>	=	=	=	<b>0.925*</b>	1.137***	1.201***	<b>1.040</b>	=	=	1.193**	<b>1.142*</b>	1.086***	<b>1.099</b>	1.167***	=	<b>1.161*</b>	=	=	=	

Note: The baseline specifications presented in Figures 3A and 3B are augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable, covering both conditional transitions to green employment and transitions from non-employment to employment (“first-stage”). The interpretation of the odds ratios of the interacted socioeconomic groups is relative to the odds ratios of the reference group. For the reference group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening. For each interacted group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening relative to the group of reference. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and (except in first-stage ones) industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.

- Transitions from jobless to green jobs are more likely in countries where adults' proficiency in numeracy and literacy is high, and where the incidence of underperforming adults is low, as measured by PIAAC indicators. The association between adults' competency scores and the first-stage probability to move from joblessness to a job are consistently positive and highly statistically significant. Corroborating these findings on skills, transitions to jobs and to green jobs are more likely in countries featuring higher shares of population with tertiary education attainment.
- The estimates suggest that well-developed systems of adults' learning through training and job-related education can help workers seize new opportunities provided by green jobs, yet particularly high and middle-educated workers rather than the low-educated ones. At the same time, looking at first-stage estimates, the data indicate highly significant positive associations between various metrics of adult's training and hirings from unemployment, and consistently so across various socioeconomic groups. Countries where adults participate more in formal and non-formal education and where employers and firms provide training activities enjoy higher transition chances from unemployment and from study to employment, especially among the low-educated.
- Higher shares of government spending allocated to education, not least tertiary education, are associated with higher chances of jobless to green jobs transitions among women. The positive effect of public spending on education is particularly strong and significant for the first-stage probability to move from jobless to employment.

Main results in the area of labour market policies and institutions are (Tables 3A, 3B):

- The association between active labour market policies (ALMP) and transitions from non-employment to green jobs is weakly significant overall, being heterogenous across socioeconomic groups and spending categories.<sup>31</sup> The results suggest that spending on training, public employment services (PES) and employment incentives can be effective at supporting transitions from jobless to green jobs, especially among high-educated workers. Importantly from a policy perspective, ALMP are found to significantly increase the (first-stage) probability to move from jobless to a job, in line with previous literature (Boeri and Burda, 1996<sup>[21]</sup>; Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>).

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<sup>31</sup> The measures refer to spending in total and per category/programme relative to GDP per unemployed, as standard in the literature. Results are robust to omitting the normalisation by the number of unemployed. Results on active labour market policies and unemployment benefits are broadly stable when entered jointly in the regressions.

Table 3. Transitions from non-employment to green employment: main results on labour market policies &amp; institutions

Panel A Non employment to green employment

Unemployment to green employment										Study-related inactivity to green employment												
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)
<b>Policy support for job seekers</b>																						
ALMP spending per GDP per unemployed - PES and administration	1.056	1.005	=	1.051	=	=	=	0.875	1.157*	1.393***	1.125*	0.902**	0.863***	1.023	1.140	0.902	0.964	=	1.322***	1.131	=	0.889*
ALMP spending per GDP per unemployed - Training	0.930	0.931	=	0.921	=	1.067*	=	0.794***	1.177***	1.350***	0.984	0.938*	0.888***	1.008	1.160	0.922	1.072	=	1.190***	1.167*	=	0.910*
ALMP spending per GDP per unemployed - Employment incentives	0.906	0.871	=	0.884	=	=	=	0.797*	=	1.359**	1.016	0.878*	0.803***	1.048	1.126	=	0.946	=	1.357***	1.156	=	0.862*
Unemployment benefits 67% AW; 2m unemployment	0.983	0.986	0.992*	0.981	=	=	=	0.989	0.989**	=	0.983	=	=	0.983	0.989	=	0.971	=	1.030*	0.988	=	=
Unemployment benefits 67% AW; 1y unemployment	0.999	0.999	=	0.999	0.995***	=	0.996*	0.994***	1.006***	1.012***	1.000	=	0.996**	0.995*	0.995*	=	0.989*	=	=	0.994*	=	=
Unemployment benefits 67% AW; 5y unemployment	0.986**	0.984**	1.008***	0.987*	0.996*	=	0.991***	0.979***	1.009***	1.015***	0.987*	=	=	non applicable								
<b>Job protection</b>																						
Employment protection legislation on regular workers	0.892	0.965	0.782***	0.811*	=	1.234**	=	0.879	=	=	0.905	=	=	0.809	0.834	=	0.778	=	=	0.787	=	=
Employment protection legislation on regular workers -- Collective dismissal	0.917	0.944	0.915*	0.878*	=	1.087*	=	0.970	0.912*	=	0.922	=	=	0.822	0.820	=	0.854	=	=	0.792	=	=
Employment protection legislation on regular workers -- Individual dismissal	0.930	0.991	0.827***	0.870	=	1.171**	=	0.893	=	=	0.940	=	=	0.906	0.943	=	0.842	=	=	0.902	=	=
<b>Labour taxation and wage bargaining settings</b>																						
Average tax wedge (67% of AW)	1.014	1.017	=	1.007	=	1.016**	=	1.016	=	=	1.016	=	=	1.014	1.010	=	1.012	=	=	1.014	=	=
Min wage relative to median wages	1.011	1.013*	=	1.007	=	1.012***	1.012***	1.000	1.013***	1.021***	1.012	=	=	0.998	1.003	=	1.004	=	=	0.878***	1.006***	1.008***
Union/ bargaining coverage (i)	0.998***	1.000	0.994***	0.997***	=	1.002***	1.005***	0.997*	=	=	0.998*	=	=	1.001	1.002**	=	0.997	=	=	1.002	=	=
Centralization of wage bargaining (i)	1.121**	1.043	1.224**	1.176**	=	0.863*	=	1.225*	=	0.778*	1.011	1.167**	1.262**	0.963	0.904	=	1.371	=	=	0.946	=	=

Unclassified

Panel B Non employment to employment ("first-stage")

Unemployment to employment										Study-related inactivity to employment												
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)
<b>Policy support for job seekers</b>																						
ALMP spending per GDP per unemployed - PES and administration	1.273***	1.159*	1.203***	1.303***	=	=	=	1.080	1.246***	1.221***	1.239***	=	=	1.013	1.023	=	0.980	=	=	0.890	1.241**	1.287***
ALMP spending per GDP per unemployed - Training	1.359***	1.278**	1.135***	1.392***	=	=	=	1.288**	1.086***	1.066**	1.313***	1.054*	1.056*	1.236	1.145	=	1.094	=	=	1.045	1.168***	1.181***
ALMP spending per GDP per unemployed - Employment incentives	1.467***	1.405***	1.093*	1.514***	0.858**	=	=	1.271**	1.230***	1.238***	1.466***	=	=	1.289*	1.383**	0.917***	1.205	1.227**	=	1.112	1.366***	1.409***
Unemployment benefits 67% AW; 2m unemployment	0.989	0.995	0.988***	0.991	=	=	0.989**	0.996	0.994*	0.986***	0.986*	=	1.006*	0.972**	0.979	0.994*	0.981	=	=	0.980	0.990*	=
Unemployment benefits 67% AW; 1y unemployment	1.002**	1.001	1.004***	1.002*	1.004***	=	0.993***	1.001	1.002*	=	1.002	=	=	1.005***	1.003*	=	1.008**	=	0.994*	1.006**	=	=
Unemployment benefits 67% AW; 5y unemployment	1.010**	1.005	1.011***	1.009**	1.004**	=	0.993**	1.004	1.008***	1.010***	1.009***	=	=	non applicable								
<b>Job protection</b>																						
Employment protection legislation on regular workers	0.756**	0.800***	0.882*	0.769***	=	=	0.826**	0.761***	=	=	0.735***	=	=	0.554***	0.581**	0.915*	0.637*	=	=	0.629**	0.767***	=
Employment protection legislation on regular workers – Collective dismissal	0.907**	0.937	0.929*	0.936	=	=	=	0.938	0.945*	=	0.892**	=	=	0.668***	0.672**	=	0.689**	=	=	0.725**	0.856***	0.878**
Employment protection legislation on regular workers – Individual dismissal	0.735**	0.763***	=	0.734***	=	=	0.876**	0.728***	=	=	0.723***	=	=	0.646***	0.680**	0.910**	0.743	0.854*	=	0.703**	0.823***	=
<b>Labour taxation and wage bargaining settings</b>																						
Average tax wedge (67% of AW)	1.009	1.009	=	1.009	=	0.994**	0.984***	1.009	=	=	1.012	=	1.014***	0.928***	0.929***	=	0.937**	=	=	0.934***	0.983***	=
Min wage relative to median wages	1.011*	1.007	1.009***	1.011*	=	=	=	1.007	1.005*	1.009**	1.007	=	1.005*	1.006	1.008	0.997*	1.018*	=	0.986*	1.004	=	1.009**
Union/ bargaining coverage (i)	0.995	0.996	=	0.997	0.993***	=	=	0.996	=	=	0.985***	1.012***	1.022***	0.996**	0.996**	=	1.003	0.994***	0.991***	0.995**	=	1.004**
Centralization of wage bargaining (i)	0.994	0.989	=	0.839	1.938***	=	1.290*	0.854	=	=	2.527**	3.392**	0.182***	0.904	0.938	=	0.601**	=	1.937***	0.913	=	=

Note: The baseline specifications presented in Figures 3A and 3B are augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable, covering both conditional transitions to green employment and transitions from non-employment to employment ("first-stage"). The interpretation of the odds ratios of the interacted socioeconomic groups is relative to the odds ratios of the reference group. For the reference category, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening. For each interacted group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening relative to the group of reference. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Source: OECD estimations and calculations based on EU-LFS data.

- The effects of unemployment benefits on the conditional probability to transition from non-employment to green jobs are weakly statistically significant and positive. Similar to findings on active support for jobseekers, cash support is generally associated with a higher (first-stage) probability to transition from unemployment to employment, particularly for individuals experiencing relatively long episodes of unemployment. This in line with literature showing that adequate levels of benefits can enhance the quality of job search and lift job finding rates.<sup>32</sup>
- Job protection on regular contracts does not overall significantly affect the chances of getting green jobs out of jobless, with some exceptions, notably negative effects on women. Results in this area are stronger for first-stage jobless to-job estimates, whereby strong protection on regular contracts is associated to less frequent hirings, especially from study-related inactivity among young people, and from unemployment, especially among vulnerable groups such as lower-educated individuals.<sup>33</sup>
- The association between labour tax wedges and transitions into green jobs out of unemployment and study-related inactivity is generally not statistically significant. First-stage results feature significant estimates, that is, higher labour tax wedges in the lower part of the wage distribution are associated with lower chances of moving from study to job among young individuals. Minimum (relative to median) wages floors carry positive effects on transitions into jobs and green jobs among some socioeconomic groups, for example low-educated and rural youth entering the labour market. The estimates for union coverage are mixed and heterogenous across socioeconomic groups, being slightly negative for women's and slightly positive for seniors' workers transitions to green jobs. The results suggest that centralised wage bargaining can support transitions to green jobs for women, low-educated and rural individuals moving out of unemployment.

The analysis of product market regulations (PMR) delivers the following insights (Tables 4A,4B):

- Transitions from unemployment to green jobs are less likely in countries featuring more restrictive product market and occupational entry regulations.
- The link between the stringency of products market regulations and labour market hirings from jobless is more pronounced in first-stage transitions from unemployment and study-related inactivity to employment (regardless of this employment being green), in line with previous literature on the link between business and labour market dynamism.<sup>34</sup> The results suggest that the negative effect of high restrictive product market regulations on hirings is particularly strong for youth moving from study to work. Corroborating these findings, transitions from jobless to work are more likely in countries featuring lower occupational entry regulations, especially for unemployed with lower levels of education.

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<sup>32</sup> Empirical evidence on the employment effects of unemployment benefits is relatively mixed: some studies fail to detect any significant effect (Le Barbanchon, 2016<sub>[108]</sub>; Rothstein, 2011<sub>[114]</sub>), a number of recent studies suggest that adequate benefits can support workers' transitions into jobs (Causa et al., 2022<sub>[111]</sub>) and into better jobs (Kugler, Muratori and Farooq, 2022<sub>[111]</sub>; Nekoei and Weber, 2017<sub>[112]</sub>); some earlier studies found that higher benefits can have a detrimental impact on job-finding rates, essentially by reducing incentives for job-search (Lalive, Van Ours and Zweimüller, 2006<sub>[109]</sub>; Card, Chetty and Weber, 2007<sub>[110]</sub>; Schmieder, von Wachter and Bender, 2012<sub>[113]</sub>).

<sup>33</sup> This finding is in line with evidence in the literature pointing to reduced labour market dynamism in countries characterized by excessive protection on regular contracts and labour market segmentation (Bassanini and Garnero, 2013<sub>[14]</sub>; Causa et al., 2022<sub>[111]</sub>).

<sup>34</sup> This is largely in line with the literature (Bartelsman, Haltiwanger and Scarpetta, 2013<sub>[116]</sub>; Criscuolo et al., 2021<sub>[117]</sub>; Engbom, 2022<sub>[118]</sub>; Causa et al., 2022<sub>[111]</sub>).

Results on housing patterns and countries' internal mobility deliver the following insights (Tables 5A and 5B), consistent with previous evidence summarized above:

- Hirings from non-employment, both from unemployment or from study among young people, are more likely in countries where geographical mobility is higher; this result does not carry over the propensity to getting a green job, meaning that it is essentially driven by a positive link between internal mobility and labour market dynamism. A similar finding applies to real house price dynamics, with house prices possibly hampering hirings of jobless individuals by creating barriers to mobility.
- Social rental housing and the provision of housing allowances (i.e., housing-related monetary benefits) are both associated with better chances to move from jobless to job. But the benefits of housing allowances are more widespread than those of social housing: probably because the design of eligibility criteria for social housing, or simply the insufficient supply of social housing relative to the demand for it, may unintentionally preclude access for some socioeconomic groups in need, typically young people living outside their family. In the case of both social housing and housing allowances, the significantly positive correlations materialise at the first stage of transitions to any job, being generally positive but non-significant on the chance to get a green job conditional on getting any job. Finally, the results on housing policies also suggest that too strict rent control could create barriers to mobility from jobless to job (also, conditional on any job, to green job transitions).

**Table 4. Transitions from non-employment to green employment: main results on policy barriers to business entry and competition, occupational entry regulations**

Panel A Non employment to green employment

Unemployment to green employment										Study-related inactivity to green employment														
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)		
<b>Policy barriers to business entry and competition, occupational entry regulations (PMR, OER)</b>																								
PMR: Network Sectors	1.023	1.077	=	0.971	=	=	1.281*	0.955	=	=	0.988	=	=	1.018	1.101	=	0.917	=	=	1.113	0.818*	=	=	
Overall PMR (i)	0.683***	0.757*	=	0.661*	=	=	2.484***	0.997	0.643*	0.584*	0.615***	=	1.439*	1.208	1.315	=	0.872	=	=	1.315	=	=	=	
OER: personal and professional services (i)	0.864***	0.951	0.758***	0.768***	=	1.325***	=	0.851*	=	=	0.876*	=	=	1.056	1.123	=	1.152	=	=	1.047	=	=	=	

Panel B Non employment to employment ("first-stage")

Unemployment to employment										Study-related inactivity to employment														
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)		
<b>Policy barriers to business entry and competition, occupational entry regulations (PMR, OER)</b>																								
PMR: Network Sectors	0.810*	0.843	=	0.786*	1.172***	1.066*	0.725***	0.807*	=	=	0.797*	=	=	0.489**	0.529*	0.860***	0.553*	=	=	0.480**	=	=	=	
Overall PMR (i)	0.400***	0.517***	0.560***	0.372***	=	1.191**	=	0.649*	0.572***	0.451***	0.431***	=	=	0.255***	0.333***	0.602***	0.209***	=	=	0.230***	=	1.722**	=	
OER: personal and professional services (i)	0.571***	0.567***	=	0.590***	=	0.909*	=	0.479***	1.300***	1.328**	0.530***	=	1.296**	0.413***	0.420***	=	0.516***	0.789*	0.794*	0.444***	0.730**	=	=	

Note: The baseline specifications presented in Figures 3A and 3B are augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable, covering both conditional transitions to green employment and transitions from non-employment to employment ("first-stage"). The interpretation of the odds ratios of the interacted socioeconomic groups is relative to the odds ratios of the reference group. For the reference group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening. For each interacted group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening relative to the group of reference. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and (except in first-stage ones) industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.



**Table 5. Transitions from non-employment to green employment: main results on housing & geographical mobility**

Panel A Non employment to green employment

Unemployment to green employment										Study-related inactivity to green employment												
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)
<b>Housing &amp; geographical mobility</b>																						
Inter-regional migration	1.334	<b>1.225</b>	1.195***	<b>1.369</b>	=	=	0.835**	<b>1.165</b>	=	1.273**	<b>1.377</b>	=	0.912*	0.958	<b>0.960</b>	=	<b>1.091</b>	=	=	<b>0.965</b>	=	=
Real house price index	1.002	<b>1.002</b>	=	<b>1.001</b>	=	=	=	<b>1.004</b>	=	=	<b>1.001</b>	=	=	1.002	<b>1.003</b>	=	<b>0.999</b>	=	=	<b>1.004</b>	=	=
Public spending on housing allowances (i)	0.929	<b>0.887*</b>	=	<b>0.957</b>	=	=	0.803*	<b>0.857</b>	=	=	<b>0.960</b>	=	=	0.878	<b>0.825**</b>	=	<b>1.285</b>	=	=	<b>0.888</b>	=	=
Social rental housing stock (i)	0.996	<b>0.999</b>	=	<b>0.997</b>	=	=	=	<b>0.983**</b>	1.019**	1.018*	<b>0.999</b>	=	0.986**	0.993*	<b>0.994</b>	=	<b>1.001</b>	=	=	<b>0.999</b>	0.986*	0.983*
Rent control	0.562*	<b>0.469**</b>	1.614*	<b>0.669</b>	0.529**	=	0.634*	<b>0.411**</b>	=	2.561**	<b>0.652</b>	=	=	1.027	<b>0.908</b>	=	<b>0.887</b>	=	=	<b>0.956</b>	=	=

Panel B Non employment to employment ("first-stage")

Unemployment to employment										Study-related inactivity to employment												
	Working-age pop	Men (ref)	Women (interaction)	Age 35-54 (ref)	Age 15-24 (interaction)	Age 25-34 (interaction)	Age 55-64 (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)	Age 20-29	Men (ref)	Women (interaction)	Low-edu (ref)	Middle-edu (interaction)	High-edu (interaction)	Cities (ref)	Towns and suburbs (interaction)	Rural areas (interaction)
<b>Housing &amp; geographical mobility</b>																						
Inter-regional migration	1.412**	<b>1.254*</b>	1.270***	<b>1.452***</b>	0.917**	0.939**	=	<b>1.326*</b>	1.087**	1.112*	<b>1.362**</b>	=	1.155***	2.443**	<b>2.285**</b>	1.137***	<b>2.528**</b>	=	=	<b>2.376**</b>	1.090*	=
Real house price index	0.998	<b>1.000</b>	0.996***	<b>0.998</b>	=	=	0.995**	<b>0.999</b>	=	0.996**	<b>0.998</b>	=	=	0.985***	<b>0.987***</b>	0.996***	<b>0.997</b>	0.985***	0.992**	<b>0.982***</b>	1.006*	1.009**
Public spending on housing allowances (i)	1.495***	<b>1.310***</b>	1.361***	<b>1.571***</b>	0.861**	0.929*	=	<b>1.235*</b>	1.265**	1.436***	<b>1.394***</b>	=	1.293**	2.440***	<b>2.155***</b>	1.271***	<b>2.416***</b>	=	=	<b>2.351***</b>	1.166*	=
Social rental housing stock (i)	1.019***	<b>1.018**</b>	=	<b>1.021***</b>	0.989**	=	=	<b>1.020**</b>	=	=	<b>1.023**</b>	=	=	1.022*	<b>1.021*</b>	=	<b>1.015*</b>	=	=	<b>1.015</b>	1.018*	=
Rent control	0.491***	<b>0.420***</b>	1.384*	<b>0.493***</b>	=	=	=	<b>0.504***</b>	=	=	<b>0.501***</b>	=	=	0.242***	<b>0.244***</b>	=	<b>0.157***</b>	1.957***	=	<b>0.264***</b>	=	=

Note: The baseline specifications in Figures 3A and 3B are augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable, covering both conditional transitions to green employment and transitions from non-employment to employment (first stage). For the reference group, odds ratios greater than 1 indicate that an increase in the policy variable is associated with greater odds of the transition happening. The odds ratios of the interaction between policies and socioeconomic groups are interpreted relative to those of the reference group: if greater than 1 they indicate that the policy affects the corresponding group more (or less negatively) than the reference group. An equal sign indicates that the null hypothesis of homogenous effects cannot be rejected. The regressions include cyclical controls at the country and region level, as well as country, year, region and (except in the first-stage) industry fixed effects. (i): the policy is time-invariant, and therefore country and region fixed effects are not included. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.

One key policy implication from this new empirical evidence is that supporting workers' transitions from non-employment to employment is a policy priority, not only in its own right, but also to encourage transitions towards those green jobs that are needed to reach environmental objectives. This requires well-functioning and well-targeted labour market policies in the area of training, job-search and profiling services, articulated with adequate income support for the unemployed. Such policies have generally been found to be effective in the wider labour market literature on workers' transitions (Causa et al., 2022<sup>[11]</sup>; Bassanini and Garnero, 2013<sup>[14]</sup>). Priority should also go to working on and anticipating the skills needed for the transition, for young people entering the labour market, but also more widely for workers' mobility and requalification. While the current analysis cannot identify the effect of specific policies in this area due to the lack of quantitative indicators, the significant results on the importance of STEM fields of study for young people, especially young women, and on the importance of adults' training, provide a strong basis to expand and fine-tune public interventions in the area of skills, fostering collaboration with schools, employers and public employment services at the local level.<sup>35</sup>

### *Long-term unemployment risks and displacement from high-polluting jobs*

This section presents policy results for long-term unemployment. Minimising the risk of long-term unemployment and, more generally, scarring and labour market detachment, is particularly important in the context of the green transition, which may entail significant job dismissals out of polluting activities. As already mentioned, the identification of policy effects is based on cross-country repeated cross-sectional data; this is not ideal to uncover displacement effects as it does not allow displaced individuals to be followed over time, hence to analyse the duration of job search and the quality of jobs, e.g. in terms of pay, for individuals moving from unemployment to employment.<sup>36</sup> These caveats notwithstanding, the empirical analysis investigates the impact of policy settings and institutions on long-term unemployment risks, following displacement from high-polluting/non-high-polluting jobs. This is complemented by a focus on socioeconomic groups that are more vulnerable to long-term unemployment, that is, low-educated and senior workers. The results are summarized in Tables 6-9.<sup>37</sup>

The analysis of skills and training delivers the following insights (Table 6):

- The incidence of long-term unemployment is lower in countries featuring high performance in adults' skills, both in numeracy and literacy, but also less unequally distributed performance (as measured by the share of low and high-performing adults). Based on estimated interaction effects, the impact of skills and training variables is generally not statistically significant among former high-polluting jobs workers, given offsetting odds ratios relative to the reference group.
- Long-term unemployment risks are lower where the share of population with tertiary education is higher and where adults' participation in training is more widespread. These effects are significant and of similar magnitude among unemployed individuals displaced from high-polluting/non-high-polluting jobs.

<sup>35</sup> See recent complementary OECD work in this area: (OECD, 2023<sup>[46]</sup>) and (CEDEFOP and OECD, 2022<sup>[47]</sup>).

<sup>36</sup> Forthcoming 2024 edition of the OECD Employment Outlook, will shed some light on this question for a selection of OECD countries, thanks to the use of linked employer-employee data.

<sup>37</sup> The regression analysis in this section systematically includes interaction terms between policy variables and high-polluting jobs dummy variables. This makes it difficult to add interaction terms between policy variables and individual socioeconomic variables as the previous section does because it would result in hard-to-identify and interpret triple interaction terms. To shed light on distributional aspects beyond the high-polluting nature of the latest job, the analysis in this section is thus extended by running regressions on key socioeconomic groups that are particularly vulnerable to unemployment and scars, hence target groups for policy actions such as e.g., the low-educated.

**Table 6. Long-term unemployment following high-polluting/non-high-polluting displacement: main results on education, skills and training policies**

	Working-age pop		Age 55-64		Low-edu	
	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)
<b>Education, skills and training</b>						
PIAAC - Percentage of adults scoring high in numeracy (i)	0.975**	1.030***	0.979*	1.022**	0.974**	1.022**
PIAAC - Percentage of adults scoring low in numeracy (i)	1.012*	0.981***	1.011	0.985**	1.014**	0.985**
PIAAC - Mean numeracy score (i)	0.994	1.012***	0.994	1.009**	0.993*	1.009**
PIAAC - Percentage of adults scoring high in literacy (i)	0.949***	1.026***	0.962***	=	0.953***	1.022*
PIAAC - Percentage of adults scoring low in literacy (i)	1.025***	0.974***	1.027***	0.982*	1.025**	0.980**
PIAAC - Mean literacy score (i)	0.983***	1.014***	0.985***	1.009*	0.984***	1.011**
Share of population with tertiary education	0.943***	=	0.937***	=	0.944*	=
Adults' participation in training - Formal (i)	0.929***	=	0.937***	=	0.938***	=
Share of enterprises providing courses and other forms of training (i)	0.985***	=	0.988***	=	0.989***	=

Note: The baseline specification on long-term unemployment presented in Figure 4B is augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable. Each regression is run separately on the working age population, on senior workers and on low-educated workers. The interpretation of the odds ratios for the interacted group of previously high-polluting workers is relative to the odds ratios of the reference group. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.

Relevant results in the area of labour market policies and institutions are (Table 7):

- Cross-country regressions suggest that spending on ALMP does not systematically mitigate long-term unemployment risks, with lower than one but statistically insignificant estimated odds ratios for the whole sample, combined with offsetting interactions for former high-polluting jobs workers. These results should be taken with care because inference based on aggregate spending metrics may well mask the possible effects of granular interventions, for instance active labour market programs targeted to the long-term unemployed – which cannot be analysed in a cross-county empirical setting. Moving from active to passive support for jobseekers, estimated effects of unemployment benefits are weakly significant, precluding drawing robust policy conclusions.
- Strong job protection on regular contracts is associated with increased long-term unemployment risks, with no statistical difference between workers displaced from high-polluting jobs and others. Zooming on those socioeconomic groups most exposed to long-term unemployment, the results indicate that low-educated workers are particularly affected by job protection, especially by too rigid regulations regarding collective dismissal.
- Higher levels of labour taxation in the lower part of the wage distribution are associated with higher long-term unemployment risks; while the opposite effect holds for minimum relative to median wages.

- Turning to the role of unionization, the estimates suggest that wider union coverage and less centralized bargaining are associated with lower odds of long-term unemployment among workers dismissed from high-polluting jobs.

**Table 7. Long-term unemployment following high-polluting/non-high-polluting displacement: main results on labour market policies & institutions**

	Working-age pop		Age 55-64		Low-edu	
	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)
<b>Policy support for job seekers</b>						
ALMP spending per GDP per unemployed - PES and administration	0.910	1.231**	0.777	=	0.975	1.183*
ALMP spending per GDP per unemployed - Training	0.929	1.138***	1.071	=	1.115	1.114**
ALMP spending per GDP per unemployed - Employment incentives	0.906	1.201**	1.065	=	1.212	1.182*
Unemployment benefits 67% AW; 2m unemployment	0.993	0.997*	1.028*	=	1.021*	0.987*
Unemployment benefits 67% AW; 1y unemployment	0.997*	=	0.999	=	0.999	=
Unemployment benefits 67% AW; 5y unemployment	1.003	1.005*	1.018*	=	1.011	=
<b>Job protection</b>						
Employment protection legislation on regular workers	1.259**	=	1.037	=	1.148	=
Employment protection legislation on regular workers – Collective dismissal	1.300***	=	1.059	=	1.227**	=
Employment protection legislation on regular workers – Individual dismissal	1.087	=	1.009	=	1.018	=
<b>Labour taxation and wage bargaining settings</b>						
Average tax wedge (67% of AW)	1.027**	=	1.012	=	1.024*	=
Min wage relative to median wages	0.978*	=	0.967**	=	0.993	=
Union/ bargaining coverage (i)	1.001	0.998*	1.004*	0.997*	1.003	0.996**
Centralization of wage bargaining (i)	1.049	1.228*	0.854	1.289*	0.951	1.402***

Note: The baseline specification on long-term unemployment presented in Figure 4B is augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable. Each regression is run separately on the working age population, on senior workers and on low-educated workers. The interpretation of the odds ratios for the interacted group of previously high-polluting workers is relative to the odds ratios of the reference group. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.

The results on regulatory settings suggest that risks of long-term unemployment are significantly higher in countries featuring more restrictive product market regulations, and more restrictive occupational entry rules, with senior workers being particularly affected. The effects of product market regulations are milder for workers displaced from high-polluting jobs (Table 8).

**Table 8. Long-term unemployment following high-polluting/non-high-polluting displacement: main results on policy barriers to business entry and competition, occupational entry regulations**

	Working-age pop	Age 55-64	Low-edu
	All individuals Former brown workers (interaction)	All individuals Former brown workers (interaction)	All individuals Former brown workers (interaction)
<b>Policy barriers to business entry and competition, occupational entry regulations (PMR, OER)</b>			
PMR: Network Sectors	0.800* =	1.018 =	0.719* =
Overall PMR (i)	3.490***0.567**	5.449***	2.558*** =
OER: personal and professional services (i)	1.826*** =	1.777*** =	1.687*** =

Note: The baseline specification on long-term unemployment presented in Figure 4B is augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable. Each regression is run separately on the working age population, on senior workers and on low-educated workers. The interpretation of the odds ratios for the interacted group of previously high-polluting workers is relative to the odds ratios of the reference group. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Source: OECD estimations and calculations based on EU-LFS data.

Housing policies and geographical mobility are found to significantly impact long-term unemployment risks, with no differential effect for workers displaced from high-polluting jobs (Table 9):

- Long-term unemployment is less likely in countries where geographical mobility is more frequent.
- Housing support, both cash benefits under housing allowances and in-kind benefits under social housing, is associated with significantly lower risks of long-term unemployment, especially for low-educated workers, irrespective of whether the latest job was in a high-polluting occupation or not.

**Table 9. Long-term unemployment following high-polluting/non-high-polluting displacement: main results on housing and geographical mobility**

	Working-age pop		Age 55-64		Low-edu	
	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)
<b>Housing &amp; geographical mobility</b>						
Inter-regional migration	0.678	=	0.557**	=	0.619*	=
Real house price index	1.002	=	0.996	=	1.003	=
Public spending on housing allowances (i)	0.737***	=	0.717**	=	0.737***	=
Social rental housing stock (i)	0.975***	=	0.973***	=	0.978***	=
Rent control	1.058	=	1.086	=	0.940	=

Note: The baseline specification on long-term unemployment presented in Figure 4B is augmented with policy indicators, entered one at a time. This table summarises the policy results by reporting odds ratios associated with a one-unit increase in the policy variable. Each regression is run separately on the working age population, on senior workers and on low-educated workers. The interpretation of the odds ratios for the interacted group of previously high-polluting workers is relative to the odds ratios of the reference group. An equal sign indicates that the difference of the effect between the reference group and the interacted group is not statistically significant. As explained in the text, the regressions include cyclical controls at the country and region level, as well as country, year, region and industry fixed effects. Policies featuring an (i) are time-invariant: for these, the regressions do not include country or region fixed effects. Standard errors are clustered at the region-level; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Source: OECD estimations and calculations based on EU-LFS data.

This new empirical evidence suggests that risks of long-term unemployment are not that different for workers displaced from high-polluting jobs relative to other displaced workers, at least on the basis of the cross-country data analysed in this paper. This may in part reflect the fact that the period under consideration (2011-2019) was not characterized by major and generalized dismissal events out of polluting activities, on average across the countries covered by the analysis; yet these events may become more frequent in the future as a result of climate mitigation policies. One implication is that structural policies and institutional settings facilitating workers' redeployment by minimising long-term unemployment and scarring risks can help coping with displacement effects from high-polluting jobs. Policies in the area of e.g. labour market regulations, training, taxation and housing, which the literature found to be generally effective in supporting re-employment (OECD, 2018<sup>[33]</sup>; Kluve, 2010<sup>[34]</sup>; Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>), will probably need to be complemented with local interventions, for instance place-based policies at the level of communities affected by plant's closures and layoffs.<sup>38</sup> Yet the evidence in this paper is that the targeting of interventions in this area, whether local or national, should systematically consider those socioeconomic groups that are more vulnerable to long-term unemployment and therefore scarring risks, e.g. lower-educated and senior workers.

<sup>38</sup> Forthcoming 2024 edition of the OECD Employment Outlook will deliver country-specific evidence about individuals labour market trajectories following mass dismissals out of polluting jobs (OECD, 2024<sup>[19]</sup>).

### Environmental policy and labour market transitions

A comprehensive exploratory empirical analysis on the association between recently developed OECD indicators of environmental policy stringency (EPS, including the various components measuring market and non-market based instruments) and the labour market transitions covered in this paper did not deliver significant and meaningful results.<sup>39</sup> This is in line with recent findings in this area, in particular Frohm et al. (2023<sub>[35]</sub>), as well as with earlier evidence in OECD (2021<sub>[36]</sub>) and probably reflects the fact that policy action in this area has so far been relatively limited (especially in the early years of the sample period 2011-2019) and would take some time to significantly impact labour market transitions. Available evidence on the impact of EPS on economic outcomes is still limited and tends to focus on firms' investment. Recent research suggests that more stringent environmental regulations can support productivity growth by spurring energy efficiency investment, for instance in cases of energy price shocks (Demmou et al., 2023<sub>[37]</sub>); and green investment, for instance by complementing green management practices (Unsal et al., 2023 forthcoming<sub>[38]</sub>). Future work in this area, relying on forthcoming vintages of labour market data, may shed light on the possible effects of EPS on workers' outcomes and transitions.

### Wrap-up and illustrative simulations

To wrap-up the policy results, Table 10 delivers a snapshot overview of relevant policy findings based on the significance and sign of estimated coefficients, zooming on selected socioeconomic groups to shed some light on distributional aspects.

**Table 10. Wrapping-up key results on policies and labour market transitions in the greening economy: a snapshot overview**

Policy areas and variables	Transitions from unemployment to green job		Transitions from study-related inactivity to green job		Long-term unemployment risk following dismissal from brown jobs		
	Working-age pop		Young individuals		Working-age pop	Seniors	Low-edu
	1st-stage	2nd-stage	1st-stage	2nd-stage			
<b>Education, skills and training</b>							
Mean Literacy score	+	+	+	n.s	n.s*	n.s*	n.s*
Mean Numeracy score	n.s	+	n.s	+	n.s*	n.s*	n.s*
Adults' participation in formal training	+	+	+	n.s	-	-	-
Share of population with tertiary education	+	n.s	+	n.s	-	-	-
<b>Labour market policies and institutions</b>							
ALMP, Spending on Public Employment Services	+	n.s	n.s	n.s	n.s*	n.s	n.s*
Unemployment benefits 67% AW; 1y unemployment	+	n.s	+	-	-	n.s	n.s
Employment protection legislation on regular workers	-	n.s	-	n.s	+	n.s	n.s
Average tax wedge (67% of average wage)	n.s	n.s	-	n.s	+	n.s	+
<b>Policy barriers to business entry and competition</b>							
Product Market Regulation, overall index	-	-	-	n.s	+	+	+
Occupational Entry Regulations	-	-	-	n.s	+	+	+
<b>Housing and geographical mobility</b>							
Inter-regional migration	+	n.s	+	n.s	n.s	-	-
Public spending on housing allowances	+	n.s	+	n.s	-	-	-

Note: This table provides a summary overview of selected policy results based on the estimations presented in the paper (Tables 2-9). The symbol "+" indicates a statistically significant (at the 10% level) positive estimated coefficient, "-" indicates a statistically significant and negative coefficient, and "n.s." indicates a not statistically significant estimate. For the analysis of long-term unemployment, this table presents total effects on workers previously employed in high-polluting occupations, while Tables 6-9 separately report the estimated effect on general workers and the differential effect on those previously working in high-polluting occupations (estimated through an interaction term, as detailed above). In this table, the symbol "n.s.\*" indicates that the effects of the policy on workers previously employed in high-polluting occupations and on general workers (both of which are reported in Tables 6 to 9) are statistically different and opposite in sign, resulting in an overall not statistically significant effect on workers previously employed in high-polluting occupations.

Against the background of these findings and in order to provide tentative quantitative insights about the policy effects, the estimations are used to run illustrative policy simulations. The results of this exercise are

<sup>39</sup> A wide range of EPS-related estimates (including performing diff-in diff techniques based on industries' exposure to regulations) is available upon request.

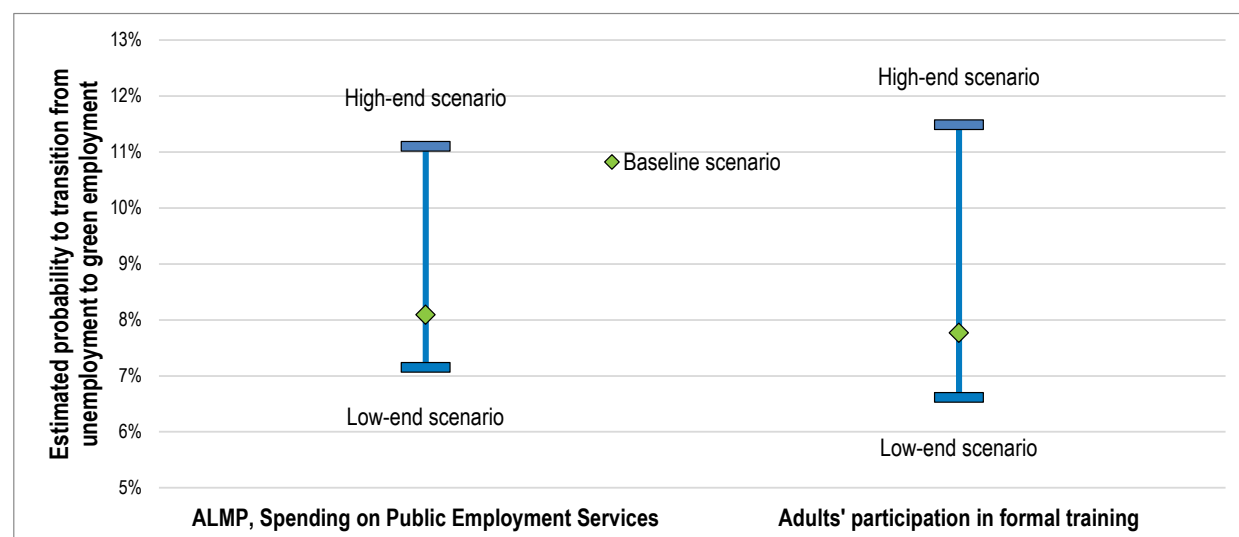
reported in figures, showing how different policies influence the probabilities considered in the analysis: i) chances of moving from unemployment to green jobs, ii) chances of moving from study-related inactivity to green jobs, and iii) risks of long-term unemployment following displacement from high-polluting jobs. The baseline scenario is the estimated probability evaluated at the median of the cross-country policy distribution, all other variables being left unchanged. The distance between the low/high-end scenario and the baseline is the change in probability associated with a policy change from median to bottom/ top decile of the policy distribution.

The first block of simulations focuses on transitions from non-employment to green jobs, taking into account first-stage estimates on transitions from non-employment to any job, and, conditional on that, to green jobs. As emphasized before, the empirical results in this paper imply that policy effectiveness to support transitions from non-employment to green jobs is largely driven by transitions from non-employment to jobs more generally. Making progress in this area, through policies focused not only on quantity but also on job quality, is crucial to channel individuals and their skills towards those jobs that are likely to be increasingly demanded in the greening economy.

Policy simulations on transitions from unemployment to green jobs show that stepping-up ALMP on job-search counselling can help individuals exiting unemployment and support hirings into green jobs. According to the estimates, increasing spending on public employment services from the median to the top decile of the policy distribution would move the probability to transition to green jobs out of unemployment from around 8% to around 11%. A consistent and quantitatively slightly stronger result applies to policies aimed at boosting adults' participation in training (Figure 5).

### Figure 5. Transitions from unemployment to green employment: illustrative policy simulations

AMPL, spending on PES; adults' participation in training



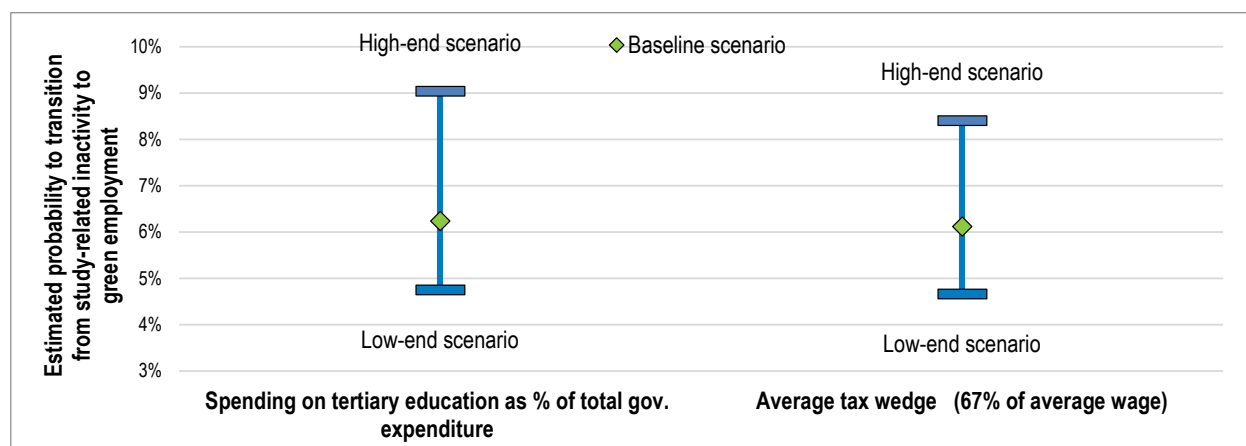
Note: OECD calculations based on estimates from Tables 2-5. The exercise combines the effects of a policy change on the probability to move from unemployment to job, and conditional on that, on the probability to move to a green job, in line with the framework of analysis. The dot is the estimated probability to move from unemployment to green employment at the policy median. The distance between the d1/d9 and the median is the change in the estimated probability associated with a policy change. How to read: Stepping up ALMP spending on public employment services from the median (baseline scenario) to the top decile (high-end scenario) of the policy distribution is estimated to trigger a rise in the probability to move from unemployment to green job: from 8.1% in the baseline scenario to 11.1% in the high-end scenario. Conversely, going from the median to bottom decile reduces the probability of moving from unemployment to green employment from 8.1% to 7.1%. The policy indicators used refer to the latest available year in the estimation sample (around 2019).



Policy simulations on transitions from study-related inactivity to green jobs demonstrate that helping young people transitioning from study to job and to green jobs requires devoting adequate public resources to education: illustrative simulations show that increasing the share of government expenditure devoted to tertiary education from the bottom to the top decile of the policy distribution would move the probability to transition to green jobs out of study-related inactivity from around 5% to around 9%. The quantification exercise also suggests that high labour costs for new entrants in the labour market (proxied by labour tax wedges at two thirds of the average wage) can create obstacles to the recruitment of young inexperienced individuals looking for a job after completing their training.

**Figure 6. Transitions from study-related inactivity to green employment: illustrative policy simulations**

Spending on tertiary education; labour tax wedges in the lower-part of the earnings distribution



Note: OECD calculations based on estimates from Tables 2-5. The exercise combines the effects of a policy change on the probability to move from study-related inactivity to job, and conditional on that, on the probability to move to a green job, in line with the framework of analysis. The dot is the estimated probability to move from study-related inactivity to green employment at the policy median. The distance between the d1/d9 and the median is the change in the estimated probability associated with a policy change. How to read: increasing the share of government expenditure devoted to tertiary education from the bottom to the top decile of the policy distribution would move the probability to transition to green jobs out of study-related inactivity from 4.8 % to 9%. The policy indicators used refer to the latest available year in the estimation sample (around 2019).

The second block of simulations focuses on long-term unemployment risks and therefore possible scars from job displacement in the greening economy. The above-discussed results from the empirical analysis suggest that the effectiveness of policies to minimise long-term unemployment risks is not different for workers losing their job in high-polluting activity than for workers losing any job, controlling for key individual, structural and cyclical factors. So as for jobless to green job findings, policy actions to reduce the risk of long-term unemployment, especially among exposed groups like the low-educated and seniors, would go a long way towards reducing the risk of long unemployment workers for displaced from high-polluting jobs in the greening economy.

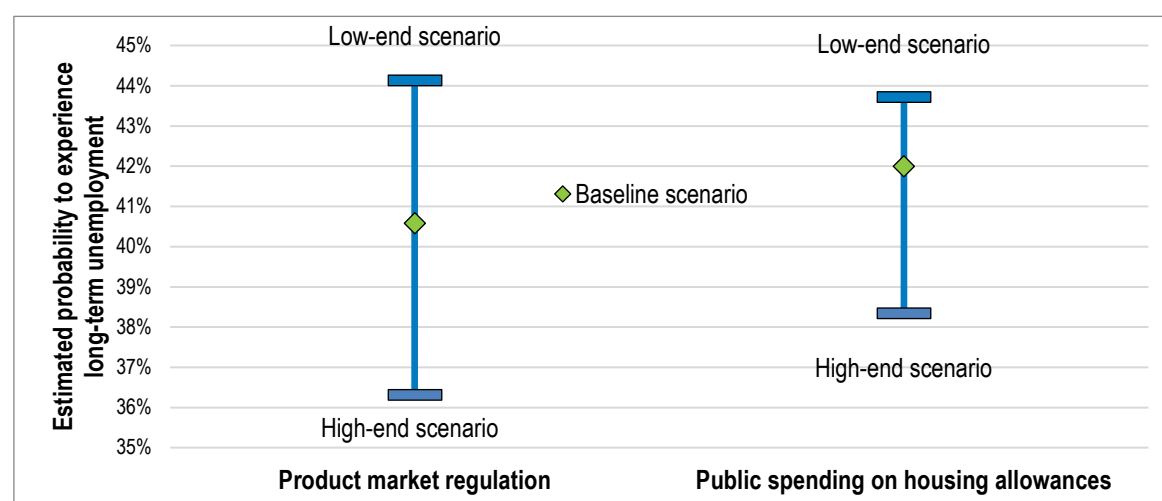
Illustrative policy simulations suggest that easing overly restrictive product market regulations can help mitigating long-term unemployment risks for displaced workers, possibly because enhanced business dynamism can support labour market dynamism and reduce the duration of job search (Figure 7).

Moving to housing, the results of this paper echo the argument that housing conditions and policies have a strong influence on the functioning of labour markets, in particular by affecting workers' mobility (OECD, 2021<sup>[39]</sup>). According to the estimates, moving from the bottom decile to the median of public spending on housing allowances distribution would reduce the probability of long-term unemployment from around 44% to around 42% (Figure 7). Overall, this suggests that adequate and portable housing allowances can

reduce unemployment duration. Against this background, such policies may help damp labour market disruptions and facilitation reallocations associated with the greening economy by reducing jobseekers' barriers to geographical mobility (Causa, Abendschein and Cavalleri, 2021<sup>[23]</sup>).

**Figure 7. Long-term unemployment risks following displacement from high-polluting jobs: illustrative policy simulations**

Product market regulations; housing allowances



Note: OECD calculations based on estimates from Tables 8 and 9. The dot is the estimated probability of long-term unemployment at the policy median. The distance between the d1/d9 and the median is the change in the estimated probability associated with a policy change. The distance between the d1/d9 and the median is the change in the estimated probability associated with a policy change. How to read: reducing the stringency of product market regulations from the top decile to the median of the policy distribution would reduce the probability of long-term unemployment from 44% % to 41%. The policy indicators used refer to the latest available year in the estimation sample (around 2019).

## Policy implications for supporting workers' just transition in the greening economy

This paper provides new evidence on the labour market implications of the green transition and the role of policies, taking into account distributional aspects by considering heterogeneities across various socioeconomic groups such as workers with different education levels. The analysis is based on an empirical framework that defines and quantifies “green” and “high-polluting” jobs, and therefore to use individual data to study the structural, cyclical and policy drivers of labour market transitions in the greening economy. Based on a large sample of European countries over the period 2011-2019, the cross-country econometric analysis delivers a number of relevant insights, in particular on the importance of skills and education, notably in STEM fields for workers' transitions to green jobs, in particular young people finishing their studies; and on the significant socioeconomic divides in the distribution of green jobs, notably gender gaps, to a large extent reflecting the under-representation of females in scientific fields of study.

Policy regression results suggest that structural policies and framework conditions can support efficient and inclusive labour markets in the greening economy, in particular for vulnerable workers and those facing displacement and scarring risks associated with the downsizing of polluting activities. These policies include: i) effective support for jobseekers, articulating adequate income transfers with targeted active labour market policies such as job-search counselling services and requalification programs, ii) investment in youth' education and in adult lifelong learning, iii) well-designed, e.g. progressive and mobility-friendly

housing-related policies and support, and iv) balanced product and labour market regulations to support business and labour market dynamism.

While the evidence in this paper is based on regression analysis performed on a sample of European countries, some key policy implications are very likely applicable to a larger set of countries, including emerging economies. This includes in particular the importance of access to quality education and training as well as the need to foster inclusive and efficient labour markets by supporting workers' transitions into jobs that offer adequate pay, working conditions and social protection.

The empirical findings of this paper suggest that the labour market implications of the greening economy can be addressed by general structural policies favouring labour market efficiency in terms of workers' reallocation, and labour market inclusiveness in terms of promoting equality of opportunities and minimising long-term scars. This should not lead to the conclusion that specific and targeted interventions to promote green jobs and to reduce displacement costs from high-polluting jobs are not needed. Rather, general policies and place or group-specific policies are likely needed in combination with each other. In this context, this final section provides illustrative insights on two areas of interventions that cannot be formally analysed in a cross-country regression analysis but that are likely to be complementary to structural interventions: place-based policies and skill anticipation exercises.

This paper shows that the impact of the transition to a greener economy and climate mitigation policies is uneven across people (e.g. socioeconomic groups characterised by different educational and skill background), but also importantly is uneven across places (e.g. territories and regions characterised by different industrial specialization structures). This calls for place-based policy interventions to accompany the transition process at the community level (OECD, 2023<sup>[18]</sup>). Successful policy experiences in the past can help national and sub-national governments building tailored approaches to support an efficient and fair labour market transition process (Box 3).

### **Box 3. Place-based policies to support workers and communities affected by the downsizing of high-polluting activities: lessons from countries' experiences**

The greening of the labour market will likely have complex effects on people, places, and firms. At the labour market level, for example, new types of jobs will emerge, creating opportunities in occupations that may not yet exist, yet the transition will likely also result in the loss of some existing jobs, especially in highly polluting activities such as coal and gas extraction. Because the geography of these transitions will differ, a place-based strategy will be vital, with local economic development and business support programs complementing national green transition policies. A "just" green transition requires targeted policy action.

This box provides a short overview of place-based policies that can help preparing communities, workers, and firms for the labour market changes driven by the green transition, building on past successful country-specific strategies to accompany and support the phasing-out of fossil fuels activities, for instance in the coal sector. These interventions encompass short-term measures supporting wage losses and medium-long term measures to accompany workers in new occupations and encouraging local economic development.

#### ***Place-based policies to alleviate the impact of the coal transition for affected workers***

##### **Canada**

Canada's federal government has been pursuing the objective of exiting coal power production, implying significant job losses concentrated in the province of Alberta. To mitigate transition costs and accompany affected workers, the government has been providing financial assistance up to 75% of previous wages for individuals losing their job, with longer assistance for older workers close to retirement. To support geographical mobility in the transition, displaced workers who find employment elsewhere received a relocation assistance. On top of reducing the risk of economic and social hardships for displaced workers and their families, structural policy measures such as the financing of training or tuition, as well as onsite targeted career counselling, have been designed to mitigate longer-term risks of labour detachment and scarring (OECD, 2023<sup>[40]</sup>; Alberta.com, n.d.<sup>[41]</sup>).

##### **Germany**

The German progressive exit of coal has been a major labour market disruption for highly-specialized regions: for instance, the number of coal workers in the Ruhr went down from 180 to 4 thousands between 1969 and 2018. The authorities addressed the transition by relying on effective social dialogue between firms, unions and social partners, resulting in large plans to support affected workers. This included government-funded retraining, redundancy payments and early retirement schemes. These measures helped avoiding a sharp rise in unemployment in affected regions while supporting displaced workers' reallocation towards expanding industries (OECD, 2023<sup>[40]</sup>) (European Commission, 2020<sup>[42]</sup>).

#### ***Place-based policies to accompany displaced workers in finding their way back to employment***

##### **Scotland**

Scotland faced the closure of no longer profitable oil and gas facilities in 2014, triggering thousands of lay-offs. The authorities created the Oil and Gas Transition Training Fund to support workers in the transition. This £12M financing scheme offered two retraining paths for laid-off workers, which could choose between either (i) following an individual training path with guidance on the possible employment prospects or (ii) following an already established skills training path, designed to match emerging job opportunities and shortages of skilled workers (e.g. in railway engineering, wind turbine engineering or in welding). The Fund financed the retraining of 4 thousand workers, around 90% of which transitioned into a new job.

##### **Australia**

In the context of a major powerplant shutdown in the Australian state of Victoria (the Hazelwood Power Plant) in 2016, the local authorities reacted to protect displaced workers in the short-term while paving the ground for medium and long-term regional economic rebound. To support individuals losing their job, the authorities invested AUD 20m in retraining. To support local economic development, the authorities provided subsidies and tax rebates to businesses setting up in the newly created "Economic Growth Zone", including tax exemptions on land purchase and hiring subsidies for displaced workers. These measures helped mitigating economic and social damages associated with the transition out of polluting

activities, by supporting both income adequacy new employment opportunities for displaced workers (European Commission, 2021<sup>[43]</sup>; Burke, Best and Jotzo, 2019<sup>[44]</sup>).

These examples show that well-designed policy packages can support a transition out of polluting activities that puts people and places at the core of policy actions. Lessons drawn from past experiences can help countries currently embarking in large-scale transitions towards more climate-friendly growth models. Such is the case of Estonia: the government committed to put an end to oil shale production by 2040. This is challenging because the industry generates two-thirds of total primary energy supply and is currently a major source of revenue and jobs in the eastern region of Ida-Viru. Announced measures are targeted to places and individuals at risk of economic and social hardship. This includes local strategies to attract businesses and investment in environment-friendly activities, government-sponsored job-to-job incentives schemes, and increased support for helping at-risk and displaced workers find new opportunities (e.g. higher unemployment benefits and additional counselling and reskilling services). See (OECD, 2022<sup>[45]</sup>).

Policy packages are likely to be more effective by articulating lessons learnt from past policy experiences with forward-looking policy approaches anticipating and facilitating the shift towards a more sustainable economy. This requires better information on the types of skills crucial for the green transition, and the occupations and sectors where these skills are needed. To shed light on this issue, recent OECD work (OECD, 2023<sup>[46]</sup>) seeks to identify effective strategies for turning qualitative and quantitative information on skill needs emerging from the transition to a green economy into relevant policy action. Based on a comparative assessment of the practices in selected OECD countries, this work explores methodological and governance innovations in carrying out skills assessment and anticipation (SAA) exercises for the green (Box 4). Progress in this area will require a strong partnership between education providers, companies, sectoral and regional players to teach green skills through apprenticeships, as discussed in CEDEFOP and OECD (2022<sup>[47]</sup>).

#### **Box 4. Skills-assessment and anticipation exercises to help matching supply and demand for green skills: insights from recent OECD work**

The green transition in labour markets is likely to bring considerable changes in skills requirements, for instance due to the emergence of new occupations and associated task-content, as well as to changes in tasks, skills, and knowledge for existing occupations. This process may induce skill mismatch and labour shortages, slowing down the green transition and possibly inducing labour market disruptions and scars for individuals and communities. To mitigate transition costs and enable workers to smoothly adapt to the new labour market environment, governments need to plan ahead and implement public policies enhancing skills and employment.

Skills assessment and anticipation (SAA) exercises are tools to inform policy makers about current and future skills needs of the labour market and therefore often conducted prior to policy implementation. Results of SAA exercises feed into various policies and actions including adult learning (e.g., updating the content of training courses for adults), formal education (e.g., developing apprenticeship programmes), career guidance (e.g., providing labour market information to individuals), employment policies (e.g., updating occupational standards), industrial policies (e.g., identifying areas that require intensive R&D investment), and migration policies (e.g., determining the entry requirements for migrant workers).

Recent OECD work delivers a comprehensive overview of SAA exercises experimented by OECD countries so far (OECD, 2023<sup>[46]</sup>). This is a new area of policy design and action, and the report provides structured guidelines and highlights key issues in the design and implementation of SAA exercises in the context of the green transition. This box showcases some of the key defining factors, approaches and challenges associated with SAA, as discussed in the OECD report.

**Units of analysis.** SAA exercises focus on either sector (industry), occupation (jobs), or skills (tasks). In many cases, studies first define a corresponding “green” unit with various methods and approaches and then produce unit-level outcomes. Each approach carries its advantages and drawbacks. For instance, methodological and practical barriers are lowest in the sector-based approach, while the skill-based exercise provides more granular information to develop targeted policies. While being relatively infrequent so far, some green SAA exercises carry out skill-based analyses. Examples include the Jobs and Skills Australia (using a country-specific taxonomy of green skills: “Australian Skills Classification”), Deloitte Access Economics in Australia (using O\*NET green categories of skills), and the National Observatory for Jobs and Occupations in the Green Economy in France (in which green skills are identified and defined through the “*Répertoire Opérationnel des Métiers et des Emplois*”).

**Quantitative and qualitative methodologies.** Methods and data used in SAA exercises can be classified into quantitative and qualitative ones. Quantitative SAA exercises exploit statistical and econometric techniques relying on data regularly collected by national statistics offices. In principle, this ensures good data coverage and replicability, but in practice this method still faces obstacles associated with data granularity and the matching with workers’ and employers’ information gathered at the local labour market level. Qualitative SAA exercises include written or oral input from experts collected through interviews, surveys, desk research or workshops, aiming at uncovering new emerging skill needs and jobs that cannot be easily captured with quantitative methods. One disadvantage is that qualitative approaches are partial in nature insofar as they generally apply to one specific sector or group of occupations, hence overlooking broader effects on labour market dynamics. The report argues that a best practice should probably combine quantitative and qualitative approaches, being complementary to each other. Indeed, some existing green SAA exercises employ mixed methods. Examples are the program run by the Department of Employment and Workplace Relations in Australia (combining quantitative employment forecasts with surveys and focus groups with key stakeholders), the Just Transition Action Plan in Austria (combining desk research with input-output analysis), and the Norwegian Committee on Skill Needs (combining quantitative forecasts with qualitative interview results).

**Big data and machine learning techniques.** Big data, coupled with machine learning techniques, are increasingly being used in quantitative SAA exercises. Such is typically the case of big data coming from online job vacancies, for instance through Lightcast and LinkedIn Economic Graph. This enables labour market research and analysis to map out skill requirements by occupation and identify green jobs/skills. Two main advantages of big data analysis are high frequency and granularity, allowing for timely and accurate SAA exercises. However, one disadvantage is that these data are not necessarily representative of all occupations, essentially covering those occupations whose recruitment takes place online; this is likely to miss or underrepresent occupations in construction, fishing, or agriculture sectors as well as jobs in small enterprises. Despite this limitation, big data and machine learning techniques have been used in a number of green SAA exercises by both public and private institutions, namely the Jobs and Skills Australia (assessing in-demand skills), the European Classification of Occupations, Skills and Competences (defining green skills), the Federal Ministry for the Environment in Germany (forecasting jobs for the green transition), Yonsei University in Korea (measuring mismatch for green jobs), the LinkedIn Economic Graph (assessing green skills), O\*NET (identifying the links between green jobs and training), and the Department of Business, Energy and Industrial Strategy in the United Kingdom (identifying clean growth jobs).

**Challenges of using SAA exercises for green policy making.** Reviewing research on skills and SAA exercises for the green transition, the OECD report presents and discusses key challenges that governments face in producing and translating reliable evidence on skills into policy action. One of them is the lack of common definitions regarding what “green” sectors, jobs and skills are, which hampers interoperability among different skills assessments and forecasting. Going further, green SAA exercises have not yet been systematically overviewed and studied at the country-level with the aim of actually shaping the policymaking process and its effectiveness in supporting an effective and inclusive green transition in labour markets. Finally, one important challenge weighting on the deployment of consistent green SAA-based policy strategies relates to policy coordination among various stakeholders and government levels, for instance between central government and local authorities within countries.

**Key elements for effectively translating skills analysis into policies.** To conclude with some specific policy recommendations based on the evidence accumulated to date, the report calls for: i) active involvement of multiple stakeholders (including regional, sub-regional, and non-state actors, such as the private sector and social partners), ii) increased reliance on skill-based SAA exercises and, iii) combined use of mixing quantitative and qualitative methods.

This paper focuses on the labour market implications of the green transition: policies to support environmental goals require significant shifts in economic activities and therefore workers’ opportunities



and risks associated with the reallocation towards cleaner production processes. The evidence suggests that the distributional impact of greening labour markets will not be neutral: transition's costs could weight disproportionately on vulnerable works such as the low-educated, and on rural territories where polluting activities tend to be concentrated. This could aggravate inequalities across individuals and places, in a context where rising energy prices to reduce fossil-fuel consumption would also affect low-income and rural households the most.<sup>40</sup> Disequalising effects are not unavoidable: as shown in this paper, policies can make a difference to support a just transition, in various domains such as education and skills, as well as labour market institutions to support mobility and job quality. Achieving progress in this area ideally requires complementing evidence-based economic analysis with evidence-based political economy analysis, looking into people's perceptions and concerns in this area. This has become possible in practice, thanks to the availability of large-scale micro-based evidence on individual attitudes towards climate change and climate change policies (Dechezlepretre et al., 2022<sup>[48]</sup>). Overall, in spite of remaining data-related limitations and challenges, policy action can rely on a solid amount of accumulated analysis to guide and shape countries' approaches to address the labour market implications of the green transition.

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<sup>40</sup> See e.g. (Causa et al., 2022<sup>[82]</sup>).

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## Annex

The Annex covers: i) further details on the interpretation of odds ratios in a logistic regression ii) detailed information on data sources, definitions and technical adjustments to ensure accuracy and consistency in the regression analysis iii) complete regression tables underlying the results presented in the paper, and iv) a battery of robustness tests to support the econometric analysis presented in the paper

### The interpretation of odds ratios in logistic regression models

As indicated in the text, a slope parameter  $\beta_j$  in the context of logistic regression is to be interpreted as semi-elasticity: a unitary increase in the corresponding regressor will increase the odds ratio by a multiple  $\beta_j$ . To see this, note that Equation (1) above implies that:

$$\frac{P(S_{ijt}|S_{ijt-1}, X_{it})}{1 - Pr(S_{ijt}|S_{ijt-1}, X_{it})} = \exp(X_{it}\beta + Z_{c,t}^1\gamma_1 + Z_{c,t}^2\gamma_2 + FE)$$

$$Pr(S_{ijt}|S_{ijt-1}, X_{it}) = \frac{\exp(X_{it}\beta + Z_{c,t}^1\gamma_1 + Z_{c,t}^2\gamma_2 + FE)}{1 + \exp(X_{it}\beta + Z_{c,t}^1\gamma_1 + Z_{c,t}^2\gamma_2 + FE)}$$

### Data sources, definitions and technical adjustments

1. The empirical framework builds on and assembles multiple datasets in order to: (i) account for individual characteristics of workers and their labour market status in the reference period and, retrospectively, one year before; (ii) define and measure green and high-polluting occupations/ jobs; and (iii) provide an econometric investigation on the impact of structural policies on labour market transitions in the greening economy.

#### Measuring labour market transitions with EULFS Data

2. The analysis relies on the EU-Labour Force Survey (EULFS) data, for 19 countries (Austria, Belgium, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Greece, Hungary, Italy, Norway, Poland, Portugal, the Slovak Republic, Slovenia, and Sweden) over the years 2011 to 2019. The EULFS is a cross-sectional longitudinal household survey that constitutes the reference for labour market statistics in the European Union.<sup>41</sup> The survey reports the labour market status of respondents in the reference period and, retrospectively, in the previous one year. The data include information on occupation and industry of employment for employed individuals, and on latest occupation and industry of employment for the non-employed. The survey covers a wide range of individual socioeconomic characteristics including age, gender, educational attainment, migration status and area of residence. Sampling weights assigned to responding individuals ensure statistical representativeness. One important data limitation for the purpose of analysing labour market transitions is the absence of

<sup>41</sup> [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU\\_labour\\_force\\_survey](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey)



information on previous occupation for individuals currently employed, precluding from studying job-to-job transitions, in particular through the greening angle.

Against this background, labour market transitions build on the following definitions and EULFS variables:

- **Unemployment to employment:** hirings from unemployment refer to individuals who were employed in the current year (variable *mainstat* takes value 1 - "Carries out a job or profession, including unpaid work for a family business or holding, including an apprenticeship or paid traineeship, etc." or, if *mainstat* is not observed for the individual, variable *ilostat* takes value 1 – "Employed") and unemployed in the previous year (variable *wstat1y* takes value 2 – "Unemployed").
- **Study-related inactivity to employment:** individuals who are employed in the year of the survey (same definition as above) and were inactive due to study in the previous year (variable *wstat1y* takes value 3 – "Pupil, student, further training, unpaid work experience").
- **Employment to unemployment:** individuals who are unemployed in the year of the survey (variable *mainstat* equals 2 – "Unemployed" or *mainstat* value unavailable and *ilostat* equals 2 – "Unemployed") and were employed in the previous year (variable *wstat1y* takes value 1 – "Carried out a job or profession, including unpaid work for a family business or holding, including an apprenticeship or paid traineeship, etc.").
- **Long-term unemployment:** individuals who are unemployed in the year of the survey and who have been so for more than a year (variable *durune* equals 3 – "Duration of unemployment 1 year or longer").

### ***Defining and measuring green and high-polluting occupations/ jobs***

3. The information on labour market transitions is complemented with information on the green, high-polluting or non-green non-high-polluting nature of the current or previous occupation of sampled individuals. Green jobs are defined based on the share of green tasks required on the job, while high-polluting jobs are the occupations that are over-represented in high-polluting industrial sectors, as defined in Causa, Soldani and Nguyen (2024<sub>[49]</sub>). For the econometric analysis, only the binary dimension is considered: all jobs with a positive green score are considered green, and all jobs with a positive high-polluting score are considered high-polluting. The same occupation could be both green and high-polluting, or also neither green nor high-polluting.

**Table A11. Data sources used for the construction of green and high-polluting jobs indicators**

<b>Data</b>	<b>Source</b>
Labour force survey data from a selected sample of EU countries. The microdata is collected at the individual level and cover the demographic and socio-economic characteristics of the respondent, including information on current or latest employment. These data provide a representative sample for each member country.	Eurostat, EULFS microdata, repeated cross-section 2011-2019
List of occupations classified as green based on the O*NET detailed taxonomy of occupations for the United States. Occupations are observed at the SOC 8-d level of aggregation.	(Vona et al., 2018 <sup>[50]</sup> )
Weighted crosswalk from SOC 6-digit to ISCO 4-digit. This is used to match each of the green occupations from Vona et al. (2018 <sup>[50]</sup> ) to the corresponding ISCO 4-digit occupations.	(Scholl, Turban and Gal, 2023 <sup>[51]</sup> )
Number of workers in each SOC 6-digit occupation. This is necessary to define employment-based weights to be used in the crosswalk, following Dingel and Neiman's (2020 <sup>[52]</sup> ) approach	US Bureau of Labour Statistics, 2016-2018
Number of workers employed in each NACE 2-digit industry, for each country and year.	Eurostat National Accounts Employment Statistics <sup>42</sup>
Pollution emitted by the production activities, across 7 pollutants, 2011-2019	Eurostat Air Emissions Accounts <sup>43</sup> , 2011-2019
Number of workers in each occupation-industry combination.	UK Office for National Statistics, 2011 Census <sup>44</sup>
Official Crosswalk from UK SOC 4-digit to ISCO 4-digit	UK Office for National Statistics <sup>45</sup>

<sup>42</sup> [Employment statistics within national accounts - Statistics Explained \(europa.eu\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Greenhouse_gas_emission_statistics_-_air_emissions_accounts&oldid=551152#Analysis_by_economic_activity/)

<sup>43</sup> [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Greenhouse\\_gas\\_emission\\_statistics\\_-\\_air\\_emissions\\_accounts&oldid=551152#Analysis\\_by\\_economic\\_activity/](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Greenhouse_gas_emission_statistics_-_air_emissions_accounts&oldid=551152#Analysis_by_economic_activity/)

<sup>44</sup> [CT0144 \(Occupation \(full\) by industry \(full\) \(national\)\) - Nomis - Official Census and Labour Market Statistics \(nomisweb.co.uk\)](https://nomisweb.co.uk/nomisweb/CT0144/Occupation%20(full)%20by%20industry%20(full)%20(national))%20-%20Nomis%20-%20Official%20Census%20and%20Labour%20Market%20Statistics)

<sup>45</sup> <https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/classifyingthestandardoccupationalclassification2020soc2020totheinternationalstandardclassificationofoccupationsisc008>

Figure A8. From US green tasks classifications to green jobs scores across European countries: a cross-walking and weighting exercise

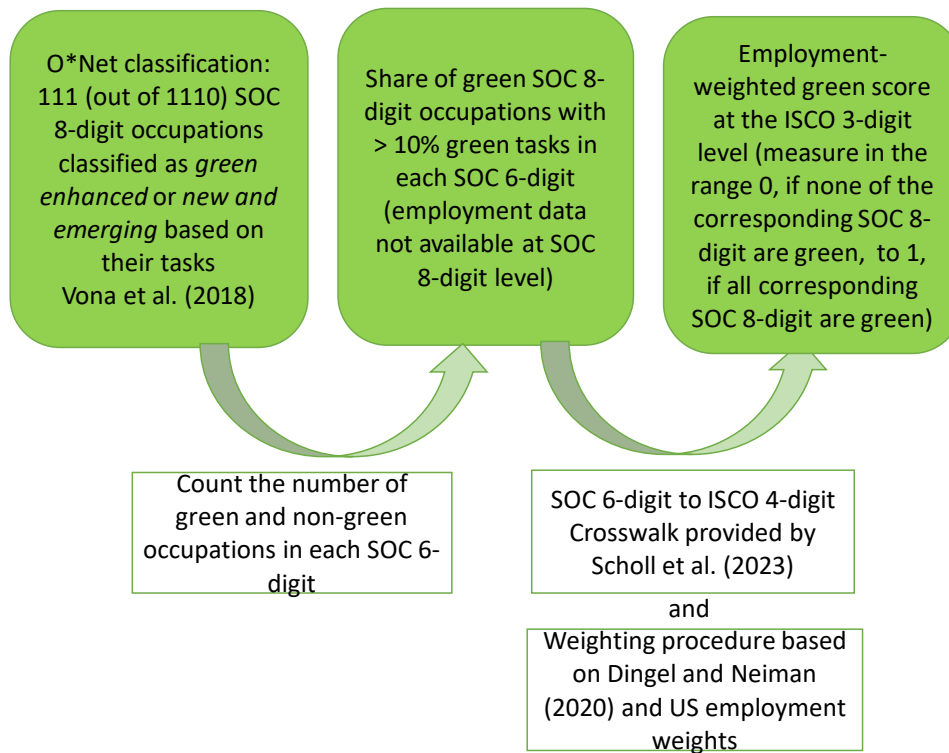
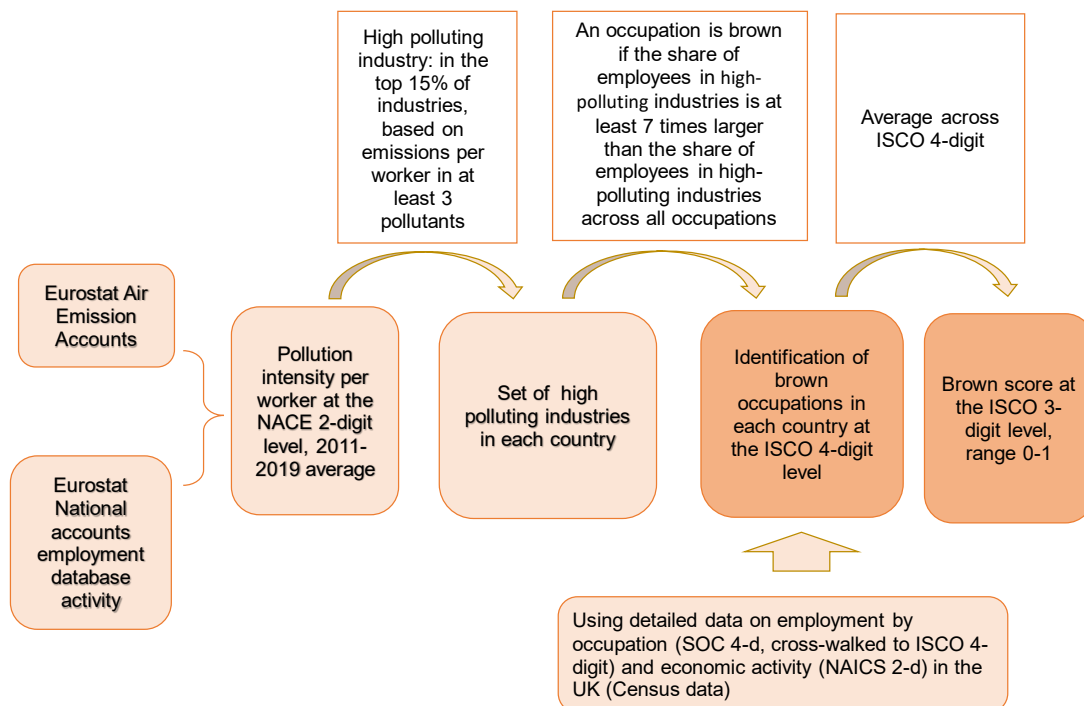


Figure A9. From Eurostat air emission accounts to high-polluting jobs scores across European countries: overview of a new approach



## Recoding and technical adjustments to EULFS data

### Regional classification

4. The EULFS data provides detailed information on the region of residence of individuals. The definition of regions follows the European NUTS classification, with the level of granularity available depending on the country. A consistent analysis across time and individuals requires some adjustments in the data to the region of an individual. The adjustments performed are twofold: (i) a recoding of regions to ensure the similarity of regions across time, despite the changes in boundaries brought by revisions to the NUTS classification; (ii) an aggregation of cities identified as regions in the EULFS data into a wider territorial unit. The recoding of regions across time is needed for a consistent estimation across the years. The recoding of city-regions into a broader geographical zone allows to avoid unbiasedness of estimates, as city-regions are colinear to the degree of urbanization. This procedure is documented in Table A2.

**Table A12. Recoding of regions**

Country	Regions recoded
Belgium	BEL10 (Arrondissement of Brussels-Capital) merges with BEL24 (Flemish Brabant)
Czechia	CZE01 (Prague) merges with CZE01 (Central Bohemian Region)
Germany	<ul style="list-style-type: none"> <li>• DEU30 (Berlin) merges with DEU40 (Brandenburg)</li> <li>• DEU50 (Bremen) merges with DEU90 (Lower Saxony)</li> <li>• DEU60 (Hamburg) merges with DEUF0 (Schleswig-Holstein)</li> </ul>
Hungary	HUN11 (Budapest) and HUN12 (Pest) merge into HUN10 (Central Hungary)
Ireland	Regions of Ireland merge into a single region due to the 2016 revisions of the NUTS boundaries
Poland	POL91 (Warszawski stoleczny) and POL92 (Mazowiecki regionalny) merge into POL12 (Mazowieckie)
Spain	ESP63 (Ceuta) and ESP64 (Melilla) merges with ESP6 (Andalusia)

### STEM field-of-study classification

5. The analysis highlights the importance of education in smoothing transitions towards employment in the context of the greening of the economy. The construction of the variable indicating whether an individual studied in a Science, Technology, Engineering, Mathematics (STEM) related field builds on the field of education variable in EULFS (variable HATFIELD). The first step consists in harmonizing the ISCED field of education classifications in the data (EULFS variable HATLEVEL), following the equivalence tables presented in the UNESCO Institute for Statistics (2014<sub>[53]</sub>). The second step identifies as STEM the following fields: 05 (Natural Sciences, mathematics and statistics), 06 (Information and Communication Technologies) and 07 (Engineering, manufacturing and construction). All other fields are classified as non-STEM. Such granular information is only available for individuals having recently finished their studies, implying that STEM curricula can only be covered in the analysis of young individuals' transitions from study-related inactivity to employment.

### Sources and definitions for policy and cyclical explanatory variables

6. Table A3 provides information on the definition, source, time and country coverage of policy and cyclical explanatory variables included in the regression analysis, their exact overview of control, and policy variables included in the regression analysis.

Table A13. Data definitions and sources for policy and cyclical explanatory variables

Variable	Description	Source	Time coverage	Countries missing
Lagged regional unemployment rate	Number of unemployed divided by the labour force in the region, lagged	Eurostat Regional Unemployment database	2011-2019	-
GDP per capital, annual growth in %, national currency, real value, base 2015, lagged	Lagged growth of GDP per capita in national currency, in real terms (base year 2015)	OECD Economic Outlook	2011-2019	-
Youth (18-24) regional unemployment rate, computed with EULFS	Number of youth (18-24) unemployed divided by the number of youth in the labour force	OECD elaborations based on the EULFS	2011-2019	-
Spending on total active labour market policies	Public spending on total active labour market policy in % of GDP over the number of unemployed.	OECD Labour Market Programmes Database	2011-2019	GBR (present up to 2011)
Spending on active labour market policies, PES and administration	Public spending on public employment services and administration in % of GDP over the number of unemployed.	OECD Labour Market Programmes Database	2011-2019	GBR, GRC,
Spending on active labour market policies, training	Public spending on training in % of GDP over the number of unemployed.	OECD Labour Market Programmes Database	2011-2019	GBR
Spending on active labour market policies, employment incentives	Public spending on employment incentives in % of GDP over the number of unemployed.	OECD Labour Market Programmes Database	2011-2019	GBR
Unemployment benefit replacement rate at 67% of average wage after 2 months /1 year /5 years/average unemployment spell	Measure of the proportion of previous in-work income that is maintained after 2 months/1 year/5 years/average spell of unemployment, formerly earning 67% of the average wage.	OECD Social Protection and Well-being Database	2011-2019	-
Employment protection legislation on regular workers	Overall indicator of employment protection legislation for regular workers, derived as a weighted sum of the legislation on individual and collective dismissals	LFS – Strictness of EPL Database		
Job protection on regular contracts, individual dismissals	The OECD indicators of employment protection legislation measure the procedures and costs involved in dismissing individuals and the procedures involved in hiring workers on fixed-term (Version 3).	LFS – Strictness of EPL Database	2011-2019	-
Job protection on regular contracts, collective dismissals	The OECD indicators of employment protection legislation measure the procedures and costs involved in dismissing groups of workers and the procedures involved in hiring workers on fixed-term contracts (Version 2).	LFS – Strictness of EPL Database	2011-2019	-
Minimum wages relative to median wages	Minimum wages divided by median wages for full time employees	OECD Employment and Labour Market Statistics database	2011-2019	DNK, FIN, ITA, NOR, SWE
Collective bargaining coverage (Latest year available)	The adjusted collective bargaining coverage rate is defined as the number of employees covered by a collective agreement in force as a proportion of the number of eligible employees equipped (i.e., the total number of employees minus the number of employees legally excluded from the right to bargain). Data reported in this Table refer to the AdjCov_hist variable of the OECD/AIAS ICTWSS database and combine estimates based either on administrative sources or labour force surveys or both.	OECD/AIAS ICTWSS database	2015-2021	

Trade union density (Latest year available)	The trade union density is defined as the number of net union members (i.e. excluding those who are not in the labour force, unemployed and self-employed) as a proportion of the number of employees. Data reported in this Table refer to the UD_hist variable of the OECD/AIAS ICTWSS database and combine estimates based either on administrative sources or labour force surveys or both.	OECD/AIAS ICTWSS database	2015-2020	
Average tax wedge, (67% of average wage)	Average tax wedge, 67%/ 100% of average wage, single person without children	OECD Going for Growth 2019	2011-2018	-
PIAAC - Percentage of adults scoring high in numeracy	Percentage of adults scoring high in numeracy (at level 4 or 5)	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
PIAAC - Percentage of adults scoring low in numeracy	Percentage of adults scoring low in numeracy (at or below level 1)	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
PIAAC - Mean numeracy score	Mean numeracy score of adults	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
PIAAC - Percentage of adults scoring high in literacy	Percentage of adults scoring high in literacy (at level 4 or 5)	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
PIAAC - Percentage of adults scoring low in literacy	Percentage of adults scoring low in literacy (at or below level 1)	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
PIAAC - Mean literacy score	Mean literacy score	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2018	PRT
Share of population with tertiary education	Share of adults aged 25-64 with tertiary education. Population with tertiary education is defined as those having completed the highest level of education. This includes both theoretical programmes leading to advanced research or high skill professions such as medicine and more vocational programmes leading to the labour market.	Education at a Glance	2011-2019	
Adults' participation in training - Formal	Percentage of adults participating in formal education and training	Adult Education Survey (AES)	2016 (DEU: 2018)	
Adults' participation in training - Formal and non-formal	Percentage of adults participating in formal and non formal education and training	Adult Education Survey (AES)	2016 (DEU: 2018)	
Adults' participation in training - Job-related non-formal	Percentage of adults participating job-related non formal education and training	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2016 (IRL: 2012)	
Adults' participation in training - Non-job-related non-formal	Percentage of adults participating in job-related and non-formal education and training	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2016 (IRL: 2012)	

Adults' participation in training - Job-related non-formal, sponsored by the employer	Percentage of employed adults participating in job-related non-formal education and training, sponsored by the employer	OECD Adult Education Survey (AES), Survey of Adult Skills (PIAAC)	2016	
Share of enterprises providing courses and other forms of training	Share of enterprises which provided either continuing vocational training (CVT) courses or other forms of CVT for their persons employed during the reference year	Continuing Vocational Training Survey (CVTS)	2015	
Educational spending - Total expenditure on tertiary education per student relative to GDP per capita	Total expenditure (public, private, international) includes expenditure on core educational goods and services such as teaching staff, school buildings, and school books and teaching materials, and peripheral educational goods and services such as research and development services (R&D), ancillary services, general administration and other activities	OECD Education database	2011-2019	2011: AUT, GBR, GRC, HUN; 2012: DNK; 2015: DNK; 2016: GRC
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. expenditure	Public expenditure on education covers expenditure on educational institutions and expenditure outside educational institutions such as support for students' living costs and other private expenditure outside institutions. Public expenditure on education includes expenditure by all public entities, including the education ministry and other ministries, local and regional governments, and other public agencies	OECD Education database	2011-2019	2011: AUT, GBR, GRC; 2015: DNK; 2016: GRC
Educational spending - Total public expenditure on tertiary education as % of total gov. expenditure	Public expenditure on education covers expenditure on educational institutions and expenditure outside educational institutions such as support for students' living costs and other private expenditure outside institutions. Public expenditure on education includes expenditure by all public entities, including the education ministry and other ministries, local and regional governments, and other public agencies	OECD Education database	2011-2019	2011: AUT, CZE, DNK, EST, GBR, GRC, IRL, ITA, NOR, PRT, SVK; 2015: DNK; 2016: GRC
Network sector Product Market Regulation	Average sector PMR over 6 sectors: electricity, natural gas, rail, air, road transport, and ecommunications.	OECD Product Market Regulation Database	2010-2018	

Product Market Regulation, overall	Average overall PMR 2008 and 2013	OECD Product Market Regulation Database	2008 and 2013 average	
Occupational entry restrictions, overall	Overall indicator of occupational entry restrictions for both personal and professional services.	Bambalaite, I., Nicoletti, G., and von Rueden, C. (2020). Occupational entry regulations and their effects on productivity in services: Firm-level evidence.	2018	CZE, DNK, EST, GRC, LTU, LUX, LVA, NLD, NOR, SVK
Rent control	Data from 2017 OECD Questionnaire on Affordable and Social Housing (QuASH) extrapolated using data from the DIW (Deutsches Institut für Wirtschaftsforschung) rental market regulation index. The indicator accounts for the number of regulations that restrict rents with respect to real rent freeze, nominal rent freeze, rent level control, intertenancy control and other specific rent controls. The values range between 0 and 1 with larger values indicating stronger rental control.	2017 OECD Questionnaire on Affordable and Social Housing (QuASH), DIW (Deutsches Institut für Wirtschaftsforschung) Rental Market Regulation Index	2011-2017	LTU, GRC, HUN, SVN
Country-level inter-regional in-migration	Sum of total number of regional in-migrants over total population in the previous year.	OECD Regional Database	2012-2019	EST, GRC, LUX, LVA, PRT
Real house price index	The index measures the evolution of residential property prices over time. It is originally computed based on nominal values and transformed to real values by means of the private consumption deflator with base year in 2010	OECD House Prices Database	2011-20219	-
Public spending on housing allowances	This indicator measures public spending on housing allowances, where housing allowances denote means- and/or income-tested income transfers to households directed at supporting households in meeting their housing costs	OECD Affordable Housing Database	2020 or latest	BEL, ESP, HUN, ITA
Social rental housing stock	Number of social rental dwellings as a share of the total number of dwellings, 2020 or latest year available	OECD Affordable Housing Database	2020 or latest	-
Environmental Policy Stringency	Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour. The index is based on the degree of stringency of 13 environmental policy instruments, primarily related to climate and air pollution. The index ranges from 0 (not stringent) to 6 (highest degree of stringency)	OECD Environment Database	2011-2019	Latvia, Lithuania



## Detailed information on estimations and regression outputs

### Estimation samples

**Table A14. Estimation samples by transition and country (number of observations)**

Country	Unemployment to employment (first-stage)	Unemployment to green employment (second-stage)	Study-related inactivity to employment (first-stage)	Study-related inactivity to green employment (second-stage)	Employment to unemployment	Long-term unemployment
AUT	39,115	14,835	34,872	5,550	529,859	30,757
BEL	27,774	6,112	28,411	4,110	232,229	17,857
CZE	8,543	3,586	11,569	1,639	125,292	7,559
DEU	89,044	22,819	105,301	29,700	1,062,099	48,731
DNK	19,563	8,438	40,887	10,611	280,826	18,688
ESP	86,343	18,797	30,813	4,186	246,775	63,265
EST	7,642	3,312	6,675	1,270	75,254	5,351
FIN	9,051	2,709	6,717	1,725	61,911	7,218
FRA	40,677	11,846	23,578	5,082	250,177	18,293
GBR	12,914	5,672	11,174	4,027	231,618	11,268
GRC	192,971	20,977	58,975	2,568	535,717	125,736
HUN	115,616	41,044	66,137	8,986	615,418	72,866
ITA	406,918	79,330	153,600	10,758	1,337,243	209,045
NOR	3,235	1,346	4,870	1,364	-	-
POL	131,894	-	84,577	-	-	-
PRT	103,144	27,138	41,916	5,369	412,359	73,872
SVK	40,713	9,793	21,821	2,992	187,405	17,740
SVN	28,530	-	23,332	-	-	-
SWE	49,860	20,438	48,156	13,547	516,828	58,039
<b>Total</b>	<b>1,413,547</b>	<b>298,192</b>	<b>803,381</b>	<b>113,484</b>	<b>6,701,010</b>	<b>786,285</b>

### Baseline regression tables and variants

- This section provides complete baseline regression along with robustness variants.

**Table A15. Transition from non-employment to green employment: baseline results and robustness variants**

Panel A: Estimated odds ratios from logistic regressions, “first-stage” regression			Panel B: Estimated odds ratios from logistic regressions, “second-stage”				
Variable	Reference	Variant: Adding region*year FE	Variable	Reference	Variant: Adding region*year FE	Variant: Removing the industry FE	Variant: Adding region*year FE and Removing the industry FE
Female	0.796*** (-10.05)	0.795*** (-10.09)	Female	0.393*** (-29.78)	0.385*** (-30.16)	0.283*** (-38.61)	0.278*** (-39.15)
Foreign born	0.868*** (-4.42)	0.885*** (-3.99)	Foreign born	0.953 (-1.56)	0.957 (-1.40)	0.854*** (-3.96)	0.852*** (-4.03)
Towns and suburbs	1.094*** (5.49)	1.093*** (5.46)	Separated	0.921* (-2.14)	0.920* (-2.19)	0.910** (-3.14)	0.910** (-3.18)
Rural areas	1.157*** (8.05)	1.160*** (7.85)	Married	1.032 (1.27)	1.034 (1.30)	1.135*** (5.27)	1.137*** (5.39)
Separated	1.111*** (4.80)	1.110*** (4.75)	Middle education	0.958 (-1.26)	0.953 (-1.38)	0.918** (-2.63)	0.914** (-2.75)
Married	1.207*** (8.25)	1.212*** (8.31)	High education	2.131*** (15.40)	2.146*** (15.28)	2.204*** (17.11)	2.219*** (17.25)
Middle	1.539*** (24.31)	1.536*** (24.24)	Age 15-24	0.814*** (-6.52)	0.812*** (-6.43)	0.749*** (-9.85)	0.745*** (-9.95)
High	2.176*** (26.26)	2.183*** (26.15)	Age 25-34	0.907*** (-3.69)	0.909*** (-3.60)	0.880*** (-4.74)	0.879*** (-4.86)
Age 15-24	1.476*** (18.06)	1.486*** (17.96)	Age 55-64	0.933 (-1.81)	0.918* (-2.18)	0.932 (-1.88)	0.921* (-2.14)
Age 25-34	1.448*** (27.03)	1.455*** (27.47)	Towns and suburbs	1.042* (1.99)	1.036 (1.69)	1.051* (2.14)	1.047 (1.95)
Age 55-64	0.429*** (-36.34)	0.426*** (-36.54)	Rural areas	1.109*** (3.65)	1.108*** (3.48)	1.120*** (4.93)	1.116*** (4.71)
GDP per capita annual growth in % lagged	1.061*** (9.31)	1.073*** (31.81)	GDP per capita annual growth in %, lagged	1.006 (0.79)	0.876*** (-19.16)	1.004 (0.55)	0.839*** (-43.54)
Regional unemployment rate lagged	0.975*** (-6.27)		Regional unemployment rate lagged	1.002 (0.44)		0.999 (-0.18)	
Constant	0.354*** (-24.94)	0.364*** (-40.30)	Constant	0.049*** (-14.90)	0.057*** (-15.22)	0.648*** (-7.46)	0.886** (-2.80)
FE	Yes	Yes	IndustryFE	Yes	Yes	No	No
Observations	1413547	1413611	Observations	297430	297372	298192	298134

Source: OECD elaborations based on EULFS

Table A16. Transition from study-related inactivity to green employment: baseline results and robustness variants

Panel A. Estimated odds ratios from logistic regressions, “first-stage”, sample aged 20-29			Panel B. Estimated odds ratios from logistic regressions, “second-stage”, sample aged 20-29				Panel C. Estimated odds ratios from logistic regressions, first-stage and second-stage, variant with sample aged below 30			
Variable	Reference	Variant: Adding region*year FE	Variable	Reference	Variant: Adding region*year FE	Variant: removing industry FE	Variant: Adding region*year FE and removing industry FE	Variables	Study-related inactivity to job transition (first-stage)	Study-related inactivity to green job transition (second-stage)
Female	1.017 (0.89)	1.014 (0.72)	Female	0.676*** (-9.91)	0.664*** (-9.98)	0.574*** (-15.13)	0.568*** (-15.04)	Female	0.953* (-2.28)	0.467*** (-20.08)
Foreign born	0.681*** (-8.16)	0.752*** (-6.36)	Foreign born	1.035 (0.54)	1.032 (0.46)	0.975 (-0.36)	0.959 (-0.56)	Foreign born	0.739*** (-5.72)	0.928 (-1.17)
Towns and suburbs	1.078** (2.65)	1.079** (2.60)	M - no STEM	1.010 (0.19)	1.014 (0.26)	0.994 (-0.12)	1.009 (0.15)	Towns and suburbs	1.171*** (8.31)	1.032 (0.88)
Rural areas	1.155*** (4.16)	1.168*** (4.37)	M - STEM	1.986*** (10.27)	1.977*** (9.84)	2.705*** (16.05)	2.734*** (15.54)	Rural areas	1.268*** (11.24)	1.024 (0.54)
M - no STEM	0.963 (-0.86)	0.971 (-0.64)	H - no STEM	1.797*** (9.63)	1.835*** (10.17)	1.928*** (10.10)	1.963*** (10.10)	M - no STEM	3.151*** (15.04)	0.683*** (-9.35)
M - STEM	1.368** (3.08)	1.400** (3.26)	H - STEM - Science	2.962*** (12.41)	3.132*** (13.27)	4.289*** (17.89)	4.577*** (18.64)	M - STEM	4.640*** (14.03)	1.949*** (11.94)
H - no STEM	3.291*** (26.19)	3.440*** (25.90)	H - STEM - Engineering	5.578*** (23.62)	5.990*** (23.12)	9.198*** (28.27)	10.026*** (28.79)	H - no STEM	11.781*** (32.80)	1.516*** (8.30)
H - STEM - Science	2.547*** (16.58)	2.659*** (17.08)	Towns and suburbs	0.927* (-1.99)	0.931 (-1.74)	0.968 (-0.80)	0.968 (-0.76)	H - STEM - Science	8.488*** (23.93)	3.246*** (17.43)
H - STEM - Engineering	3.297*** (27.12)	3.482*** (26.95)	Rural areas	0.898* (-2.33)	0.906* (-2.02)	0.941 (-1.26)	0.928 (-1.42)	H - STEM - Engineering	11.294*** (29.33)	6.687*** (24.50)
GDP per capita annual growth in % lagged	1.093*** (8.20)	0.868*** (-24.24)	GDP per capita annual growth in %, lagged	1.030* (2.53)	0.821*** (-18.84)	1.027* (2.16)	0.827*** (-24.29)	GDP per capita annual growth in % lagged	1.099*** (8.65)	1.011 (1.10)
Regional youth unemployment rate lagged	0.949*** (-4.36)		Regional youth unemployment rate lagged	2.891** (2.60)		2.049 (1.77)		Regional youth unemployment rate lagged	0.955*** (-4.21)	0.998 (-0.24)
Constant	0.122*** (-20.94)	0.117*** (-43.39)	Constant	0.138*** (-8.47)	0.162*** (-8.19)	0.344*** (-9.84)	0.538*** (-10.35)	Constant	0.046*** (-23.63)	0.613*** (-5.46)
FE	Yes	Yes	IndustryFE	Yes	Yes	No	No	FE	Yes	Yes
Observations	789302	789200	Observations	111161	110689	111482	111013	Observations	2042967	167302

Source: OECD elaborations based on EULFS

Table A17. Transitions from employment to unemployment: baseline results and robustness variants

<i>Panel A. Transitions from employment to unemployment: estimated odds ratios from logistic regressions, alternative specifications</i>				<i>Panel B. Long-term unemployment: estimated odds ratios from logistic regressions with/without a dummy variable for workers previously employed in green occupations</i>					
Variables	Reference	Variant: removing industry FE	Variant: adding a previous green job dummy	Variables	Reference	Variant: Adding region*year FE	Variant: removing industry FE	Variant: Adding region*year FE and removing industry FE	Variant: adding a previous green job dummy
Latest job was brown	1.186*** (4.39)	1.133** (3.00)	1.184*** (4.33)	Latest job was brown	0.858*** (-7.23)	0.857*** (-7.41)	0.725*** (-4.00)	0.724*** (-4.03)	0.857*** (-7.19)
Female	1.147*** (5.83)	1.051** (2.63)	1.139*** (5.18)	Female	1.036 (1.36)	1.039 (1.48)	0.988 (-0.62)	0.993 (-0.40)	1.034 (1.29)
Foreign born	1.723*** (18.83)	1.915*** (22.41)	1.722*** (18.73)	Foreign born	1.066** (2.67)	1.045 (1.95)	1.018 (0.80)	0.995 (-0.22)	1.066** (2.68)
Towns and suburbs	0.921*** (-3.48)	0.945** (-3.16)	0.921*** (-3.47)	Towns and suburbs	0.915*** (-4.47)	0.915*** (-4.28)	0.900*** (-4.70)	0.899*** (-4.53)	0.915*** (-4.47)
Rural areas	0.817*** (-6.73)	0.599*** (-27.66)	0.817*** (-6.73)	Rural areas	0.802*** (-4.41)	0.797*** (-4.57)	0.769*** (-4.38)	0.763*** (-4.51)	0.802*** (-4.42)
Separated	0.941** (-3.19)	0.683*** (-17.86)	0.941** (-3.18)	Separated	1.042* (2.05)	1.037 (1.80)	1.035* (1.97)	1.031 (1.71)	1.042* (2.05)
Married	0.602*** (-28.16)	0.417*** (-30.51)	0.602*** (-28.19)	Married	0.864*** (-6.10)	0.860*** (-6.32)	0.883*** (-5.62)	0.879*** (-5.84)	0.864*** (-6.11)
Middle	0.720*** (-14.71)	3.047*** (29.84)	0.721*** (-14.58)	Middle	0.785*** (-12.48)	0.789*** (-12.46)	0.799*** (-10.36)	0.804*** (-10.30)	0.785*** (-12.55)
High	0.506*** (-22.31)	1.716*** (22.52)	0.510*** (-21.71)	High	0.610*** (-14.71)	0.609*** (-14.68)	0.616*** (-13.46)	0.615*** (-13.43)	0.611*** (-14.42)
Age 15-24	2.811*** (31.02)	0.839*** (-5.80)	2.809*** (31.14)	Age 15-24	0.366*** (-23.96)	0.362*** (-23.86)	0.358*** (-26.66)	0.355*** (-26.54)	0.365*** (-23.99)
Age 25-34	1.648*** (20.86)	0.917*** (-3.62)	1.648*** (20.90)	Age 25-34	0.691*** (-18.57)	0.688*** (-18.54)	0.691*** (-19.33)	0.687*** (-19.29)	0.691*** (-18.58)
Age 55-64	0.863*** (-4.89)	0.819*** (-6.27)	0.862*** (-4.90)	Age 55-64	1.690*** (19.79)	1.702*** (19.93)	1.690*** (19.47)	1.702*** (19.63)	1.691*** (19.71)
GDP per capita annual growth in %, lagged	0.921*** (-8.66)	0.926*** (-8.18)	0.921*** (-8.66)	GDP per capita annual growth in %, lagged	0.996 (-0.62)	1.153*** (17.61)	0.992 (-0.96)	1.153*** (18.48)	0.996 (-0.61)
Regional unemployment rate lagged	1.030*** (3.93)	1.032*** (5.01)	1.030*** (3.93)	Regional unemployment rate lagged	1.057*** (9.41)		1.055*** (10.46)		1.057*** (9.42)
Latest job was green			0.955* (-1.97)	Latest job was green					0.984 (-1.15)
Industry FE	Yes	No	Yes	Industry FE	Yes	Yes	No	No	Yes
Observations	6701010	7527618	6701010	Observations	838000	838009	913316	913325	838000

Source: OECD elaborations based on EULFS

**Policy regression tables**

8. This section provides complete policy regression results.

**Table A18. Policy regressions – full regression output**

Panel A. Unemployment to employment (“first-stage”)

Policy support for job seekers, job protection, labour taxation and wage bargaining settings													
Dependent variable: dummy variable indicating the transition from unemployment to employment													
Female	0.784***	0.778***	0.779***	0.796***	0.796***	0.796***	0.796***	0.796***	0.796***	0.796***	0.791***	1.032	0.949
Foreign born	0.838***	0.841***	0.842***	0.868***	0.869***	0.869***	0.870***	0.869***	0.869***	0.868***	0.873**	0.892	0.941
Separated	1.097***	1.100***	1.100***	1.094***	1.093***	1.094***	1.111***	1.111***	1.111***	1.111***	1.067*	0.994	1.095
Married	1.200***	1.198***	1.198***	1.157***	1.156***	1.157***	1.208***	1.207***	1.208***	1.207***	1.139***	1.104*	1.029
Middle	1.535***	1.526***	1.527***	1.111***	1.111***	1.110***	1.539***	1.539***	1.539***	1.539***	1.549***	1.239***	1.326***
High	2.142***	2.128***	2.130***	1.207***	1.207***	1.207***	2.177***	2.177***	2.176***	2.176***	2.099***	1.712***	1.693***
Age 15-24	1.473***	1.472***	1.473***	1.539***	1.539***	1.539***	1.477***	1.477***	1.477***	1.476***	1.544***	1.402***	1.247**
Age 25-34	1.444***	1.446***	1.447***	2.176***	2.177***	2.177***	1.449***	1.448***	1.448***	1.448***	1.474***	1.294***	1.181**
Age 55-64	0.418***	0.421***	0.421***	1.476***	1.476***	1.477***	0.429***	0.429***	0.429***	0.429***	0.394***	0.648***	0.843**
Towns and suburbs	1.098***	1.094***	1.094***	1.448***	1.448***	1.448***	1.094***	1.094***	1.094***	1.094***	1.084***	1.174	1.172
Rural areas	1.161***	1.153***	1.153***	0.429***	0.429***	0.429***	1.157***	1.157***	1.157***	1.157***	1.152***	0.907	0.886
GDP per capita annual growth in % lagged	1.068***	1.063***	1.062***	1.060***	1.062***	1.058***	1.055***	1.059***	1.054***	1.061***	1.042***	1.098**	1.090*
Regional unemployment rate lagged	0.979***	0.979***	0.978***	0.977***	0.971***	0.973***	0.969***	0.971***	0.970***	0.977***	0.975***	1.028	1.022
ALMP spending per GDP per unemployed - PES and administration	1.273***												
ALMP spending per GDP per unemployed - Training		1.359***											
ALMP spending per GDP per unemployed - Employment incentives			1.467***										
Unemployment benefits 67% AW; 2m unemployment				0.989									
Unemployment benefits 67% AW; 1y unemployment					1.002***								
Unemployment benefits 67% AW; 5y unemployment						1.010***							
Employment protection legislation on regular workers							0.756***						
Employment protection legislation on regular workers -- Collective dismissal								0.907**					
Employment protection legislation on regular workers -- Individual dismissal									0.735***				
Average tax wedge (67% of AW)										1.009			
Min wage relative to median wages											1.011*		
Union/ bargaining coverage (i)												0.995	
Centralization of wage bargaining (i)													0.994

Product market and occupational entry regulations (PMR, OER), housing policies and geographical mobility								
Dependent variable: dummy variable indicating the transition from unemployment to employment								
Female	0.800***	0.812***	0.817***	0.792***	0.796***	0.899***	0.905***	0.796***
Foreign born	0.862***	0.968	0.961	0.868***	0.870***	0.882***	0.843***	0.864***
Separated	1.109***	1.116***	1.101***	1.089***	1.094***	1.023	1.051	1.092***
Married	1.212***	1.178***	1.149***	1.148***	1.157***	1.106*	1.097*	1.154***
Middle	1.537***	1.475***	1.432***	1.105***	1.111***	1.123***	1.142***	1.103***
High	2.190***	2.316***	2.171***	1.204***	1.207***	1.206***	1.182***	1.224***
Age 15-24	1.470***	1.491***	1.472***	1.530***	1.538***	1.568***	1.596***	1.530***
Age 25-34	1.447***	1.405***	1.403***	2.177***	2.176***	2.450***	2.488***	2.199***
Age 55-64	0.430***	0.437***	0.426***	1.459***	1.477***	1.637***	1.653***	1.468***
Towns and suburbs	1.094***	1.034	1.053	1.434***	1.449***	1.427***	1.419***	1.451***
Rural areas	1.159***	1.141***	1.113**	0.435***	0.429***	0.419***	0.407***	0.423***
GDP per capita annual growth in % lagged	1.057***	1.098***	1.020	1.065***	1.058***	1.047***	0.992	1.047***
Regional unemployment rate lagged	0.972***	0.972**	0.961***	0.981***	0.969***	0.943***	0.947***	0.975***
PMR: Network Sectors	0.810*							
Overall PMR		0.400***						
OER: personal and professional services			0.571***					
Inter-regional migration				1.412**				
Real house price index					0.998			
Public spending on housing allowances (i)						1.495***		
Social rental housing stock (i)							1.019***	
Rent control								0.491***

### Education, skills and training

Dependent variable: dummy variable indicating the transition from unemployment to employment

Female	0.808***	0.807***	0.807***	0.811***	0.809***	0.810***
Foreign born	0.996	0.997	0.997	0.994	1.000	0.999
Separated	1.105***	1.107***	1.109***	1.099***	1.097***	1.098***
Married	1.143***	1.138***	1.139***	1.142***	1.139***	1.140***
Middle	1.419***	1.418***	1.420***	1.412***	1.409***	1.409***
High	2.264***	2.265***	2.266***	2.227***	2.249***	2.242***
Age 15-24	1.487***	1.486***	1.485***	1.473***	1.477***	1.476***
Age 25-34	1.374***	1.373***	1.373***	1.374***	1.371***	1.372***
Age 55-64	0.442***	0.444***	0.445***	0.437***	0.441***	0.439***
Towns and suburbs	1.034	1.032	1.032	1.050	1.041	1.044
Rural areas	1.090	1.086	1.089	1.101*	1.084	1.090*
GDP per capita annual growth in % lagged	1.074***	1.074***	1.077***	1.064***	1.061***	1.062***
Regional unemployment rate lagged	0.970**	0.967***	0.967***	0.972**	0.973**	0.973**
Percentage of adults scoring high in numeracy	1.015					
Percentage of adults scoring low in numeracy		0.994				
Mean numeracy score			1.002			
Percentage of adults scoring high in literacy				1.034**		
Percentage of adults scoring low in literacy					0.979**	
Mean literacy score						1.012**

## Education, skills and training (continued)

Female	0.796***	0.814***	0.809***	0.808***	0.805***	0.809***	0.806***	0.795***	0.795***	0.800***
Foreign born	0.872***	0.928*	0.947	0.954	0.971	0.951	0.898**	0.867***	0.867***	0.866***
Separated	1.111***	1.103***	1.118***	1.118***	1.131***	1.120***	1.121***	1.108***	1.110***	1.106***
Married	1.207***	1.163***	1.197***	1.190***	1.169***	1.189***	1.204***	1.203***	1.204***	1.200***
Middle	1.536***	1.467***	1.477***	1.476***	1.435***	1.486***	1.510***	1.536***	1.537***	1.538***
High	2.172***	2.158***	2.300***	2.310***	2.259***	2.320***	2.231***	2.174***	2.175***	2.177***
Age 15-24	1.477***	1.478***	1.522***	1.515***	1.505***	1.508***	1.516***	1.482***	1.483***	1.488***
Age 25-34	1.449***	1.415***	1.418***	1.413***	1.398***	1.412***	1.430***	1.450***	1.449***	1.450***
Age 55-64	0.429***	0.428***	0.430***	0.432***	0.441***	0.434***	0.425***	0.427***	0.428***	0.427***
Towns and suburbs	1.094***	1.064*	1.043	1.044	1.028	1.042	1.072**	1.093***	1.092***	1.091***
Rural areas	1.156***	1.132***	1.129**	1.129**	1.092*	1.129**	1.164***	1.157***	1.157***	1.156***
GDP per capita annual growth in % lagged	1.056***	1.060***	1.087***	1.088***	1.092***	1.085***	1.075***	1.061***	1.055***	1.061***
Regional unemployment rate lagged	0.977***	0.958***	0.975***	0.976**	0.968***	0.975**	0.965***	0.976***	0.977***	0.975***
Share of population with tertiary education	1.047***									
Participation in formal education and training		1.069***								
Participation in formal and non-formal education and training			1.021***							
Job-related non-formal education and training				1.026***						
Non-job-related non-formal education and training					1.022***					
Share of employed adults participating in job-related non-formal education and t						1.023***				
Share of enterprises providing courses and other forms of training							1.016***			
Total expenditure on tertiary education per student relative to GDP per capita								1.008**		
Total public expenditure on primary-tertiary education as % of total government									1.066**	
Total public expenditure on tertiary education as % of total government expendit										1.025



## Panel B. Unemployment to green employment (“second-stage”)

Policy support for job seekers, job protection, labour taxation and wage bargaining settings													
Dependent variable: binary indicator of the greenness of an occupation													
Female	0.380***	0.382***	0.381***	0.393***	0.393***	0.393***	0.393***	0.393***	0.393***	0.393***	0.390***	0.400***	0.391***
Foreign born	0.935*	0.937*	0.937*	0.953	0.953	0.951	0.954	0.954	0.953	0.952	0.918*	0.971	0.979
Towns and suburbs	1.043	1.045*	1.045*	1.043*	1.043*	1.042*	1.042*	1.042*	1.042*	0.921*	0.956	0.921*	0.919
Rural areas	1.115***	1.115***	1.115***	1.110***	1.110***	1.109***	1.109***	1.109***	1.109***	1.032	1.053	1.028	1.034
Separated	0.948	0.944	0.944	0.921*	0.922*	0.922*	0.921*	0.921*	0.921*	0.958	0.926	0.949	0.978
Married	1.027	1.028	1.028	1.032	1.032	1.032	1.032	1.032	1.032	2.131***	2.082***	2.060***	2.097***
Middle	0.946	0.943	0.944	0.958	0.958	0.959	0.958	0.958	0.958	0.814***	0.798***	0.817***	0.805***
High	2.144***	2.126***	2.128***	2.131***	2.131***	2.132***	2.132***	2.132***	2.132***	0.906***	0.890**	0.910***	0.914*
Age 15-24	0.804***	0.806***	0.805***	0.813***	0.814***	0.813***	0.813***	0.813***	0.814***	0.933	0.961	0.919*	0.930
Age 25-34	0.920**	0.920**	0.919**	0.906***	0.907***	0.906***	0.907***	0.906***	0.907***	1.042*	1.061	1.033	1.046
Age 55-64	0.951	0.958	0.957	0.933	0.933	0.934	0.933	0.932	0.933	1.110***	1.182***	1.108***	1.100**
GDP per capita annual growth in % -real, lagged	1.018*	1.012	1.013	1.005	1.006	1.011	1.003	1.003	1.004	1.005	1.004	1.020**	1.030***
Lagged unemployment share at regional level	1.007	1.005	1.005	1.005	1.004	1.006	1.000	0.999	1.001	1.005	1.011	1.003	1.008***
ALMP spending per GDP per unemployed - PES and administration	1.056												
ALMP spending per GDP per unemployed - Training		0.930											
ALMP spending per GDP per unemployed - Employment incentives			0.906										
Unemployment benefits 67% AW; 2m unemployment				0.983									
Unemployment benefits 67% AW; 1y unemployment					0.999								
Unemployment benefits 67% AW; 5y unemployment						0.986**							
Employment protection legislation on regular workers							0.892						
Employment protection legislation on regular workers -- Collective dismissal								0.917					
Employment protection legislation on regular workers -- Individual dismissal									0.930				
"Average tax wedge (67% of AW)"										1.014			
Min wage relative to median wages											1.011		
Union/ bargaining coverage (i)												0.998***	
Centralization of wage bargaining (i)													1.121**

Product market and occupational entry regulations (PMR, OER), housing policies and geographical mobility								
Dependent variable: binary indicator of the greenness of an occupation								
Female	0.391***	0.397***	0.387***	0.396***	0.393***	0.408***	0.412***	0.378***
Foreign born	0.962	0.969	0.967	0.963	0.951	0.932*	0.947	0.996
Towns and suburbs	0.911*	0.938	0.939	1.031	1.042*	0.993	1.010	1.033
Rural areas	1.031	1.043	1.052	1.103**	1.109***	1.025	1.092*	1.125***
Separated	0.959	0.955	0.952	0.904*	0.922*	0.919	0.948	0.900*
Married	2.107***	2.114***	2.094***	1.025	1.032	1.079	1.059	1.036
Middle	0.803***	0.823***	0.820***	0.935	0.958	1.087	1.025	0.978
High	0.908***	0.912***	0.919**	2.087***	2.132***	2.500***	2.405***	2.126***
Age 15-24	0.932	0.928	0.928	0.827***	0.813***	0.834***	0.851***	0.794***
Age 25-34	1.035	1.036	1.041	0.897***	0.906***	0.933	0.936	0.909**
Age 55-64	1.118***	1.116***	1.105**	0.912*	0.933	0.880**	0.857***	0.918*
GDP per capita annual growth in % -lagged- national currency -real value- base 2	1.009	1.031***	1.020*	1.008	1.009	1.024*	1.056***	1.002
Lagged unemployment share at regional level	1.006	1.005*	1.002	1.011	1.008	0.988**	1.000	1.008
PMR: Network Sectors	1.023							
Overall PMR		0.683***						
OER: personal and professional services			0.864***					
Inter-regional migration				1.334				
Real house price index					1.002			
Public spending on housing allowances (i)						0.929		
Social rental housing stock (i)							0.996	
Rent control								0.562*

Education, skills and training							
Dependent variable: binary indicator of the greenness of an occupation							
Female	0.399***	0.399***	0.399***	0.400***	0.399***	0.400***	0.393***
Foreign born	0.980	0.981	0.982	0.977	0.980	0.978	0.955
Towns and suburbs	0.930	0.925	0.927	0.931	0.926	0.928	0.921*
Rural areas	1.046	1.044	1.045	1.046	1.045	1.046	1.032
Separated	0.944	0.938	0.940	0.946	0.939	0.942	0.957
Married	2.084***	2.082***	2.084***	2.077***	2.073***	2.074***	2.130***
Middle	0.833***	0.834***	0.833***	0.830***	0.828***	0.829***	0.814***
High	0.910***	0.908***	0.909***	0.910***	0.908***	0.909***	0.907***
Age 15-24	0.931	0.930	0.930	0.931	0.930	0.930	0.933
Age 25-34	1.037	1.034	1.035	1.042	1.042	1.042	1.042*
Age 55-64	1.110***	1.101***	1.104***	1.119***	1.109***	1.114***	1.109***
GDP per capita annual growth in % -lagged- national currency -real value- base 2	1.031***	1.024***	1.027***	1.033***	1.025**	1.028***	1.002
Lagged unemployment share at regional level	1.005	1.006*	1.006*	1.004	1.007*	1.006	1.002
Percentage of adults scoring high in numeracy	1.009*						
Percentage of adults scoring low in numeracy		0.990***					
Mean numeracy score			1.005***				
Percentage of adults scoring high in literacy				1.009*			
Percentage of adults scoring low in literacy					0.987***		
Mean literacy score						1.006**	
Share of population with tertiary education							1.029

## Education, skills and training (continued)

Dependent variable: binary indicator of the greenness of an occupation

Female	0.393***	0.397***	0.396***	0.396***	0.396***	0.396***	0.396***	0.391***	0.389***	0.391***
Foreign born	0.955	0.959	0.970	0.970	0.974	0.968	0.967	0.953	0.954	0.948
Towns and suburbs	0.921*	0.938	0.943	0.942	0.939	0.941	0.943	0.920*	0.920*	0.912*
Rural areas	1.032	1.045	1.046	1.046	1.042	1.045	1.046	1.027	1.029	1.029
Separated	0.957	0.957	0.951	0.951	0.951	0.953	0.952	0.953	0.953	0.951
Married	2.130***	2.089***	2.108***	2.110***	2.108***	2.113***	2.102***	2.135***	2.132***	2.131***
Middle	0.814***	0.825***	0.830***	0.829***	0.829***	0.827***	0.829***	0.814***	0.813***	0.810***
High	0.907***	0.915***	0.913***	0.912***	0.911***	0.912***	0.913***	0.905***	0.905***	0.904***
Age 15-24	0.933	0.926*	0.931	0.930	0.930	0.931	0.931	0.931	0.931	0.926
Age 25-34	1.042*	1.041	1.033	1.035	1.033	1.036	1.036	1.039	1.038	1.037
Age 55-64	1.109***	1.115***	1.105***	1.105***	1.114***	1.105***	1.109***	1.110***	1.111***	1.111***
GDP per capita annual growth in % -real, lagged	1.002	1.029***	1.033***	1.030**	1.037***	1.027**	1.033***	1.007	1.006	1.007
Lagged unemployment share at regional level	1.002	1.000	1.003	1.005	1.001	1.005*	1.002	1.004	1.004	1.005
Share of population with tertiary education	1.029									
Participation in formal education and training		1.015***								
Participation in formal and non-formal education and training			1.002							
Job-related non-formal education and training				1.006*						
Non-job-related non-formal education and training					0.992					
Share of employed adults participating in job-related non-formal education and t						1.007***				
Share of enterprises providing courses and other forms of training							1.001			
Total public expenditure on primary-tertiary education as % of total government							0.984			
Total expenditure on tertiary education per student relative to GDP per capita								1.001		
Total public expenditure on tertiary education as % of total government expendit										1.059

## Panel C. Study-related inactivity to employment (first-stage)

Policy support for job seekers, job protection, labour taxation and wage bargaining settings												
Dependent variable: dummy variable indicating the transition from study-related inactivity to employment												
Female	0.895***	0.896***	0.896***	0.943**	0.943**	0.998	0.998	0.998	0.997	0.951*	0.989	0.986
Foreign born	0.792***	0.794***	0.794***	0.681***	0.681***	0.617***	0.617***	0.616***	0.619***	0.729***	0.732***	0.729***
Towns and suburbs	1.153***	1.154***	1.154***	1.171***	1.170***	1.091**	1.091**	1.092**	1.005	0.918	0.925	1.014
Rural areas	1.269***	1.271***	1.272***	1.262***	1.261***	1.170***	1.170***	1.170***	3.083***	2.963***	2.963***	3.108***
Middle	3.507***	3.518***	3.519***	3.330***	3.330***	1.006	1.006	1.006	1.093**	1.099***	0.940	0.895
High	11.185***	11.302***	11.289***	10.534***	10.521***	3.084***	3.087***	3.081***	1.169***	1.203***	0.904*	0.900
GDP per capita annual growth in % lagged	1.112***	1.109***	1.106***	1.086***	1.087***	1.069***	1.074***	1.073***	1.080***	1.022*	1.035	1.092***
Lagged youth unemployment rate at regional level	0.115***	0.119***	0.120***	0.117***	0.084***	0.061***	0.061***	0.067***	0.051***	0.094***	0.034***	0.022***
ALMP spending per GDP per unemployed - PES and administration	1.013											
ALMP spending per GDP per unemployed - Training		1.236										
ALMP spending per GDP per unemployed - Employment incentives			1.289*									
Unemployment benefits 67% AW; 2m unemployment				0.972**								
Unemployment benefits 67% AW; 1y unemployment					1.004**							
Employment protection legislation on regular workers						0.554***						
Employment protection legislation on regular workers -- Collective dismissal							0.668***					
Employment protection legislation on regular workers -- Individual dismissal								0.646***				
*Average tax wedge (67% of AW)*									0.928***			
Min wage relative to median wages										1.006		
Union/ bargaining coverage (i)											0.996**	
Centralization of wage bargaining (i)												0.904

### Product market and occupational entry regulations (PMR, OER), housing policies and geographical mobility

Dependent variable: dummy variable indicating the transition from study-related inactivity to employment								
Female	1.005	0.981	0.986	0.990	0.998	1.014	0.985	1.008
Foreign born	0.605***	0.675***	0.656***	0.624***	0.622***	0.557***	0.623***	0.597***
Middle	1.036	0.939	0.954	1.033	1.007	0.991	1.017	1.094
High	3.144***	2.932***	3.000***	3.179***	3.098***	2.931***	3.112***	3.280***
Towns and suburbs	1.067*	0.956	0.987	1.084**	1.093**	1.088*	1.000	1.037
Rural areas	1.153***	1.015	0.985	1.155***	1.171***	1.176***	0.992	1.122**
GDP per capita annual growth in % lagged	1.055***	1.109***	1.014	1.110***	1.057***	1.072***	1.000	1.028**
Lagged youth unemployment rate at regional level	0.097***	0.071***	0.021***	0.109***	0.022***	0.055***	0.013***	0.220***
PMR: Network Sectors	0.489**							
Overall PMR		0.255***						
OER: personal and professional services			0.413***					
Inter-regional migration				2.443**				
Real house price index					0.985***			
Public spending on housing allowances (i)						2.440***		
Social rental housing stock (i)							1.022*	
Rent control								0.242***

Education, skills and training							
Dependent variable: dummy variable indicating the transition from study-related inactivity to employment							
Female	0.997	0.972	0.972	0.972	0.974	0.971	0.972
Foreign born	0.627***	0.734***	0.745***	0.745***	0.680***	0.734***	0.713***
Middle	1.008	0.938	0.915	0.919	0.943	0.924	0.931
High	3.103***	2.994***	2.893***	2.914***	2.958***	2.921***	2.928***
Towns and suburbs	1.092**	0.936	0.946	0.942	0.972	0.941	0.949
Rural areas	1.171***	0.940	0.948	0.942	0.972	0.935	0.939
GDP per capita annual growth in % lagged	1.047***	1.052**	1.058**	1.054**	1.040*	1.044*	1.037*
Lagged youth unemployment rate at regional level	0.111***	0.066***	0.025***	0.030***	0.106***	0.050***	0.083***
Share of population with tertiary education	1.136***						
Percentage of adults scoring high in numeracy		1.028**					
Percentage of adults scoring low in numeracy			1.010				
Mean numeracy score				0.998			
Percentage of adults scoring high in literacy					1.077***		
Percentage of adults scoring low in literacy						0.985	
Mean literacy score							1.020***

### Education, skills and training (continued)

Dependent variable: dummy variable indicating the transition from study-related inactivity to employment

Female	0.980	0.978	0.976	0.970	0.976	0.978	0.996	0.996	0.997
Foreign born	0.644***	0.717***	0.719***	0.749***	0.712***	0.687***	0.619***	0.618***	0.616***
Middle	0.992	0.946	0.941	0.918	0.940	0.966	1.004	1.001	1.001
High	3.063***	2.971***	2.944***	2.897***	2.920***	2.907***	3.074***	3.064***	3.069***
Towns and suburbs	0.980	0.961	0.955	0.948	0.951	0.967	1.086**	1.085**	1.084**
Rural areas	0.993	0.990	0.976	0.951	0.971	0.984	1.166***	1.163***	1.161***
GDP per capita annual growth in % lagged	1.059***	1.103***	1.097***	1.061***	1.093***	1.102***	1.072***	1.083***	1.089***
Lagged youth unemployment rate at regional level	0.034***	0.096***	0.086***	0.035***	0.073***	0.057***	0.095***	0.081***	0.076***
Participation in formal education and training	1.081***								
Participation in formal and non-formal education and training		1.027***							
Job-related non-formal education and training			1.029***						
Non-job-related non-formal education and training				1.009					
Share of employed adults participating in job-related non-formal education or training					1.025***				
Share of enterprises providing courses and other forms of training						1.018***			
Total public expenditure on primary-tertiary education as % of total government							1.158**		
Total expenditure on tertiary education per student relative to GDP per capita								1.012*	
Total public expenditure on tertiary education as % of total government expenditure									1.193**

Panel D. Study-related inactivity to green employment ("second-stage")



Policy support for job seekers, job protection, labour taxation and wage bargaining settings													
Dependent variable: binary indicator of the greenness of an occupation													
Female	0.513***	0.513***	0.513***	0.514***	0.514***	0.514***	0.572***	0.572***	0.573***	0.573***	0.577***	0.566***	0.573***
Foreign born	1.07	1.07	1.069	1.049	1.048	1.048	1.083	1.084	1.083	1.081	1.229**	1.136*	1.094
Middle	0.918	0.918	0.918	0.929	0.929	0.929	0.924*	0.924*	0.924*	1.194***	1.172**	1.207***	1.178*
High	2.043***	2.041***	2.042***	2.009***	2.007***	2.007***	0.907*	0.908*	0.907*	2.403***	2.392***	2.417***	2.401***
Towns and suburbs	0.962	0.962	0.962	0.968	0.968	0.967	1.193***	1.193***	1.193***	0.924*	0.900*	0.922	0.961
Rural areas	0.961	0.961	0.96	0.953	0.953	0.952	2.404***	2.404***	2.403***	0.907*	0.883*	0.904	0.921
GDP per capita annual growth in % lagged	1.005	1.002	1.003	1.006	1.008	1.008	1.013	1.014	1.017	1.021	1.018	1.042***	1.045**
Lagged youth unemployment rate at regional level	2.618**	2.428**	2.550**	1.965*	2.090*	1.785	2.635*	2.608*	2.730*	2.979*	3.932**	0.767	0.989
ALMP spending per GDP per unemployed - PES and administration	1.023												
ALMP spending per GDP per unemployed - Training		1.008											
ALMP spending per GDP per unemployed - Employment incentives			1.048										
Unemployment benefits 67% AW; 2m unemployment				0.983									
Unemployment benefits 67% AW; 1y unemployment					0.995*								
Unemployment benefits 67% AW; 5y unemployment						0.993							
Employment protection legislation on regular workers							0.809						
Employment protection legislation on regular workers – Collective dismissal								0.822					
Employment protection legislation on regular workers – Individual dismissal									0.906				
"Average tax wedge (67% of AW)"										1.012			
Min wage relative to median wages											0.998		
Union/ bargaining coverage (i)												1.001	
Centralization of wage bargaining (i)													0.963

Product market and occupational entry regulations (PMR, OER), housing policies and geographical mobility								
Dependent variable: binary indicator of the greenness of an occupation								
Female	0.568***	0.575***	0.579***	0.580***	0.573***	0.572***	0.571***	0.570***
Foreign born	1.091	1.137*	1.140*	1.065	1.082	1.158*	1.149*	1.045
Middle	1.185**	1.187***	1.156**	1.120*	1.194***	1.206**	1.159*	1.178*
High	2.374***	2.403***	2.282***	2.314***	2.403***	2.464***	2.355***	2.330***
Towns and suburbs	0.900*	0.920	0.925	0.926	0.924*	0.921	0.929	0.926
Rural areas	0.907	0.903	0.902	0.910	0.907*	0.884	0.897	0.942
GDP per capita annual growth in % lagged	1.024*	1.034***	1.034**	1.020	1.023	1.027*	1.018	1.023
Lagged youth unemployment rate at regional level	2.198	0.677*	0.828	3.817**	3.372**	0.648	0.959	2.035
PMR: Network Sectors	1.018							
Overall PMR		1.208						
OER: personal and professional services			1.056					
Inter-regional migration				0.958				
Real house price index					1.002			
Public spending on housing allowances (i)						0.878		
Social rental housing stock (i)							0.993*	
Rent control								1.027

Education, skills and training							
Dependent variable: binary indicator of the greenness of an occupation							
Female	0.579***	0.578***	0.578***	0.578***	0.579***	0.579***	0.572***
Foreign born	1.125*	1.129*	1.127*	1.129*	1.119*	1.122*	1.085
Middle	1.185***	1.187***	1.186***	1.180**	1.179**	1.180**	1.192***
High	2.377***	2.387***	2.384***	2.356***	2.348***	2.352***	2.402***
Towns and suburbs	0.922	0.917	0.918	0.924	0.923	0.924	0.924*
Rural areas	0.903	0.895*	0.897	0.906	0.902	0.905	0.908*
GDP per capita annual growth in % lagged	1.031**	1.026**	1.028**	1.033**	1.030**	1.032**	1.015
Lagged youth unemployment rate at regional level	0.948	0.985	1.007	0.729	0.896	0.831	2.857*
Percentage of adults scoring high in numeracy	1.011*						
Percentage of adults scoring low in numeracy		0.990*					
Mean numeracy score			1.005*				
Percentage of adults scoring high in literacy				1.000			
Percentage of adults scoring low in literacy					0.992		
Mean literacy score						1.003	
Share of population with tertiary education							1.013

## Robustness analysis

9. This section presents robustness analysis of the policy regression results. The following tests are conducted:

1. Alternative macroeconomic controls (lagged output gap instead of lagged GDP per capita growth).
2. A reweighted regression framework to give equal weights to each country the regression, proceeding as follows: i) a “total weight” is derived by summing the individual weights for each country-year cell; ii) the regression analysis is based on adjusted weights obtained by rescaling individual weights by the “total weight”. By the definition, the adjusted individual weights sum up to one at the country-year level.
3. Policy variables entered in lagged form.
4. Policy variables included simultaneously in multivariate policy regressions.

10. Tables A9A-A9C and A10A-A10E present the results of this analysis. This shows that the majority of the policy results are qualitatively unchanged under the various robustness exercises; the following policy result is found to be less robust: the effect of job protection on long-term unemployment in a multivariate regression framework (Table A10E explicits the reference effect).

Table A19. Robustness analysis 1, 2 and 3: alternative cyclical variables, reweighting, lagged policy variables

Panel A: Transitions from non-employment to green employment

	Working age pop.				Pop. aged 20-29			
	Reference	Alternative cyclical variables	Reweighting	Lagged policies	Reference	Alternative cyclical variables	Reweighting	Lagged policies
<b>Policy support for job seekers</b>								
ALMP spending per GDP per unemployed - PES and administration	1.056	✓	✓	✓	1.023	✓	-	✓
ALMP spending per GDP per unemployed - Training	0.930	✓	✓	✓	1.008	✓	-	✓
ALMP spending per GDP per unemployed - Employment incentives	0.906	✓	✓	✓	1.048	✓	✓	✓
Unemployment benefits 67% AW; 2m unemployment	0.983	✓	✓	✓	0.983	✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	0.999	✓	✓	-	0.995*	✓	-	-
Unemployment benefits 67% AW; 5y unemployment	0.986**	-	-	✓				
<b>Job protection</b>								
Employment protection legislation on regular workers	0.892	-	✓	-	0.809	✓	✓	✓
Employment protection legislation on regular workers -- Collective dismissal	0.917	-	✓	✓	0.822	✓	✓	✓
Employment protection legislation on regular workers -- Individual dismissal	0.930	✓	✓	✓	0.906	✓	✓	✓
<b>Labour taxation and wage bargaining settings</b>								
Average tax wedge (67% of AW)	1.014	✓	✓	-	1.014	✓	✓	✓
Min wage relative to median wages	1.011	-	✓	✓	0.998	✓	✓	✓
Union/ bargaining coverage (i)	0.998***	✓	✓		1.001	✓	-	
Centralization of wage bargaining (i)	1.121**	✓	✓		0.963	✓	✓	
<b>Education, skills and training</b>								
PIAAC - Percentage of adults scoring high in numeracy (i)	1.009*	✓	-		1.011*	✓	✓	
PIAAC - Percentage of adults scoring low in numeracy (i)	0.990***	✓	✓		0.990*	✓	✓	
PIAAC - Mean numeracy score (i)	1.005***	✓	✓		1.005*	✓	✓	
PIAAC - Percentage of adults scoring high in literacy (i)	1.009*	✓	✓		1.000	✓	✓	
PIAAC - Percentage of adults scoring low in literacy (i)	0.987***	✓	✓		0.992	-	-	
PIAAC - Mean literacy score (i)	1.006**	✓	✓		1.003	✓	-	
Share of population with tertiary education	1.029	✓	-	✓	1.013	✓	✓	✓
Adults' participation in training - Formal (i)	1.015***	✓	-		0.995	✓	✓	
Adults' participation in training - Formal and non-formal (i)	1.002	-	✓		1.005	-	-	
Adults' participation in training - Job-related non-formal (i)	1.006*	✓	-		1.008*	✓	✓	
Adults' participation in training - Non-job-related non-formal (i)	0.992	✓	✓		1.002	✓	✓	
Adults' participation in training - Job-related non-formal, sponsored by the employer (i)	1.007***	✓	-		1.006	-	-	
Share of enterprises providing courses and other forms of training (i)	1.001	✓	✓		1.001	✓	-	
Educational spending - Total expenditure on tertiary education per student relative to GDP per capita	1.001	✓	✓	✓	1.002	✓	✓	✓
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. exp.	0.984	✓	✓	-	1.091	-	✓	✓
Educational spending - Total public expenditure on tertiary education as % of total gov. expenditure	1.059	✓	✓	✓	1.056	✓	✓	✓
<b>Product market and occupational entry regulations (PMR, OER)</b>								
PMR: Network Sectors	1.023	✓	✓	✓	1.018	✓	✓	✓
Overall PMR (i)	0.683***	✓	-		1.208	✓	✓	
OER: personal and professional services (i)	0.864***	✓	✓		1.056	✓	✓	
<b>Housing policies &amp; geographical mobility</b>								
Inter-regional migration	1.334	✓	✓	✓	0.958	✓	✓	✓
Real house price index	1.002	✓	-	✓	1.002	✓	✓	✓
Public spending on housing allowances (i)	0.929	-	-		0.878	✓	-	
Social rental housing stock (i)	0.996	-	✓		0.993*	-	-	
Rent control	0.562*	-	-	✓	1.027	✓	✓	✓

Panel B: Transitions from non-employment to employment (first-stage)

	Working age pop.				Pop. aged 20-29			
	Reference	Alternative cyclical variables	Reweighting	Lagged policies	Reference	Alternative cyclical variables	Reweighting	Lagged policies
<b>Policy support for job seekers</b>								
ALMP spending per GDP per unemployed - PES and administration	1.273***	✓	✓	✓	1.013	✓	-	✓
ALMP spending per GDP per unemployed - Training	1.359***	✓	✓	✓	1.236	✓	-	✓
ALMP spending per GDP per unemployed - Employment incentives	1.467***	✓	✓	✓	1.289*	✓	✓	✓
Unemployment benefits 67% AW; 2m unemployment	0.989	-	✓	✓	0.972**	✓	-	✓
Unemployment benefits 67% AW; 1y unemployment	1.002***	-	-	✓	1.005***	✓	-	✓
Unemployment benefits 67% AW; 5y unemployment	1.010***	✓	✓	✓				
<b>Job protection</b>								
Employment protection legislation on regular workers	0.756***	✓	✓	✓	0.554***	✓	✓	✓
Employment protection legislation on regular workers -- Collective dismissal	0.907**	✓	-	✓	0.668***	✓	✓	✓
Employment protection legislation on regular workers -- Individual dismissal	0.735***	✓	✓	✓	0.646***	✓	✓	✓
<b>Labour taxation and wage bargaining settings</b>								
Average tax wedge (67% of AW)	1.009	-	✓	✓	0.928***	✓	✓	✓
Min wage relative to median wages	1.011*	✓	-	✓	1.006	✓	✓	✓
Union/ bargaining coverage (i)	0.995	✓	✓		0.996**	✓	-	
Centralization of wage bargaining (i)	0.994	✓	✓		0.904	✓	✓	
<b>Education, skills and training</b>								
PIAAC - Percentage of adults scoring high in numeracy (i)	1.015	-	✓		1.028**	✓	✓	
PIAAC - Percentage of adults scoring low in numeracy (i)	0.994	-	-		1.010	✓	✓	
PIAAC - Mean numeracy score (i)	1.002	✓	-		0.998	✓	✓	
PIAAC - Percentage of adults scoring high in literacy (i)	1.034**	✓	-		1.077***	✓	✓	
PIAAC - Percentage of adults scoring low in literacy (i)	0.979**	✓	✓		0.985	✓	-	
PIAAC - Mean literacy score (i)	1.012**	✓	✓		1.020***	✓	✓	
Share of population with tertiary education	1.047***	✓	-	✓	1.136***	✓	-	✓
Adults' participation in training - Formal (i)	1.069***	✓	✓		1.081***	✓	✓	
Adults' participation in training - Formal and non-formal (i)	1.021***	✓	✓		1.027***	✓	✓	
Adults' participation in training - Job-related non-formal (i)	1.026***	✓	✓		1.029***	✓	✓	
Adults' participation in training - Non-job-related non-formal (i)	1.022***	✓	-		1.009	✓	✓	
Adults' participation in training - Job-related non-formal, sponsored by the employer (i)	1.023***	✓	✓		1.025***	✓	✓	
Share of enterprises providing courses and other forms of training (i)	1.016***	✓	✓		1.018***	✓	✓	
Educational spending - Total expenditure on tertiary education per student relative to GDP per capita	1.008**	✓	-	✓	1.012*	✓	-	✓
Educational spending - Tot public exp on primary-tertiary education as % of total gov. expenditure	1.066**	✓	✓	✓	1.158**	✓	-	✓
Educational spending - Total public expenditure on tertiary education as % of total gov. expenditure	1.025	-	✓	✓	1.193**	-	-	✓
<b>Product market and occupational entry regulations (PMR, OER)</b>								
PMR: Network Sectors	0.810*	✓	✓	✓	0.489**	✓	✓	✓
Overall PMR (i)	0.400***	✓	✓		0.255***	✓	✓	
OER: personal and professional services (i)	0.571***	✓	✓		0.413***	✓	✓	
<b>Housing policies &amp; geographical mobility</b>								
Inter-regional migration	1.412**	-	-	-	2.443**	✓	-	✓
Real house price index	0.998	-	-	-	0.985***	✓	✓	✓
Public spending on housing allowances (i)	1.495***	✓	-		2.440***	✓	✓	
Social rental housing stock (i)	1.019***	✓	-		1.022*	-	✓	
Rent control	0.491***	✓	✓	✓	0.242***	✓	✓	✓

## Panel C: Long-term unemployment

	Reference		Alternative cyclical variables		Reweighting		Lagged policies	
	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)	All individuals	Former brown workers (interaction)
<b>Policy support for job seekers</b>								
ALMP spending per GDP per unemployed - PES and administration	0.910	1.231**	✓	✓	-	-	✓	✓
ALMP spending per GDP per unemployed - Training	0.929	1.138***	✓	✓	-	-	✓	✓
ALMP spending per GDP per unemployed - Employment incentives	0.906	1.201**	✓	✓	✓	-	-	✓
Unemployment benefits 67% AW; 2m unemployment	0.993	0.997*	✓	-	✓	-	✓	-
Unemployment benefits 67% AW; 1y unemployment	0.997*	=	✓	✓	✓	-	✓	✓
Unemployment benefits 67% AW; 5y unemployment	1.003	1.005*	-	✓	✓	✓	✓	✓
<b>Job protection</b>								
Employment protection legislation on regular workers	1.259**	=	✓	✓	-	✓	-	✓
Employment protection legislation on regular workers – Collective dismissal	1.300***	=	✓	✓	✓	✓	✓	✓
Employment protection legislation on regular workers – Individual dismissal	1.087	=	✓	✓	-	-	✓	✓
<b>Labour taxation and wage bargaining settings</b>								
Average tax wedge (67% of AW)	1.027**	=	✓	✓	✓	-	✓	✓
Min wage relative to median wages	0.978*	=	✓	✓	-	-	-	✓
Union/ bargaining coverage (i)	1.001	0.998*	✓	✓	-	-	-	-
Centralization of wage bargaining (i)	1.049	1.228*	✓	✓	-	-	-	-
<b>Education, skills and training</b>								
PIAAC - Percentage of adults scoring high in numeracy (i)	0.975**	1.030***	✓	✓	-	✓	-	-
PIAAC - Percentage of adults scoring low in numeracy (i)	1.012*	0.981***	✓	✓	-	✓	-	-
PIAAC - Mean numeracy score (i)	0.994	1.012***	✓	✓	✓	✓	✓	✓
PIAAC - Percentage of adults scoring high in literacy (i)	0.949***	1.026***	✓	✓	✓	✓	✓	✓
PIAAC - Percentage of adults scoring low in literacy (i)	1.025***	0.974***	✓	✓	-	✓	-	-
PIAAC - Mean literacy score (i)	0.983***	1.014***	✓	✓	✓	✓	✓	✓
Share of population with tertiary education	0.943***	=	✓	✓	-	✓	✓	✓
Adults' participation in training - Formal (i)	0.929***	=	✓	✓	✓	✓	✓	✓
Share of enterprises providing courses and other forms of training (i)	0.985***	=	✓	✓	✓	-	-	-
<b>Product market and occupational entry regulations (PMR, OER)</b>								
PMR: Network Sectors	0.800*	=	-	✓	-	✓	✓	✓
Overall PMR (i)	3.490***	0.567**	✓	✓	✓	✓	✓	✓
OER: personal and professional services (i)	1.826***	=	✓	✓	✓	✓	✓	✓
<b>Housing policies &amp; geographical mobility</b>								
Inter-regional migration	0.678	=	✓	✓	✓	✓	✓	✓
Real house price index	1.002	=	✓	✓	✓	✓	✓	✓
Public spending on housing allowances (i)	0.737***	=	✓	✓	✓	✓	✓	✓
Social rental housing stock (i)	0.975***	=	✓	✓	✓	✓	✓	✓
Rent control	1.058	=	✓	✓	✓	✓	✓	✓

Note: This table evaluates the robustness of policy results on long-term unemployment estimates for the working-age population. The column "Reference" reports the sign and significance of the estimated coefficient, as in the paper. "✓" indicates that the sign and significance of the coefficient is robust to changing the regression specification according to the robustness tests, whereas "-" indicates that the result is not robust, i.e. either the sign changes or the coefficient is no longer (in-)significant (at least at the 10% level); an empty space indicates that the specification is not tested for the robustness (e.g. lagging the policy when the policy data does not vary over the time span covered).

Source: OECD elaborations based on EULFS

Table A20. Robustness analysis 4: multivariate policy regression framework

## Panel A. Non-employment to green employment ("second-stage")

	Reference	ALMP - PES and administration	ALMP - Training	Unemployment benefits	EPL	Average tax wedge	Educational spending
ALMP spending per GDP per unemployed - PES and administration	1.056			✓	✓	✓	✓
ALMP spending per GDP per unemployed - Training	0.930			✓	✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	0.999	✓	✓		-	✓	-
Employment protection legislation on regular workers	0.892	✓	✓	-		✓	✓
Average tax wedge (67% of AW, single without children)	1.014	-	-	✓	✓		-
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. expenditure	0.984	-	-	✓	-	✓	

## Panel B. Non-employment to employment ("first-stage")

	Reference	ALMP - PES and administration	ALMP - Training	Unemployment benefits	EPL	Average tax wedge	Educational spending
ALMP spending per GDP per unemployed - PES and administration	1.273***			✓	✓	✓	✓
ALMP spending per GDP per unemployed - Training	1.359***			✓	✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	1.002***	✓	✓		-	✓	✓
Employment protection legislation on regular workers	0.756***	✓	✓	✓		✓	✓
Average tax wedge (67% of AW, single without children)	1.009	✓	✓	✓	✓		✓
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. expenditure	1.066**	✓	✓	✓	-	✓	

## Panel C. study-related inactivity to green employment ("second-stage")

	Reference	ALMP - PES and administration	ALMP - Training	Unemployment benefits	EPL	Average tax wedge	Educational spending
ALMP spending per GDP per unemployed - PES and administration	1.093			✓	✓	✓	✓
ALMP spending per GDP per unemployed - Training	1.097			✓	✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	0.996*	-	-		✓	-	✓
Employment protection legislation on regular workers	0.793	✓	✓	-		✓	✓
Average tax wedge (67% of AW, single without children)	1.014	✓	✓	✓	✓		✓
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. expenditure	1.091	-	-	✓	✓	✓	



Panel D. study-related inactivity to employment ("first-stage")

	Reference	ALMP - PES and administration	ALMP - Training	Unemployment benefits	EPL	Average tax wedge	Educational spending
ALMP spending per GDP per unemployed - PES and administration	1.030			✓	✓	✓	✓
ALMP spending per GDP per unemployed - Training	1.250			✓	✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	0.983	-	-		✓	✓	✓
Employment protection legislation on regular workers	0.549***	✓	✓	✓		✓	✓
Average tax wedge (67% of AW, single without children)	0.928***	✓	✓	✓	✓		✓
Educational spending - Total public expenditure on primary-tertiary education as % of total gov. expenditure	1.158**	✓	✓	✓	✓	✓	

Panel E. Long-term unemployment

	Reference	ALMP - PES and administration	ALMP - Training	Unemployment benefits	EPL	Average tax wedge
ALMP spending per GDP per unemployed - PES and administration	0.910			✓	✓	-
ALMP spending per GDP per unemployed - PES and administration x wasbrown	1.231**			✓	✓	✓
ALMP spending per GDP per unemployed - Training	0.929			✓	✓	✓
ALMP spending per GDP per unemployed - Training x wasbrown	1.138***			✓	✓	✓
Unemployment benefits 67% AW; 1y unemployment	0.997*	✓	✓		-	-
Unemployment benefits 67% AW; 1y unemployment x wasbrown	=	✓	✓		✓	✓
Employment protection legislation on regular workers	1.259**	-	-	-		✓
Employment protection legislation on regular workers x wasbrown	=	✓	✓	✓		✓
Average tax wedge (67% of AW, single without children)	1.027**	✓	✓	✓	✓	
Average tax wedge (67% of AW, single without children) x wasbrown	=	✓	✓	✓	-	

Note: This table evaluates the robustness of policy results on unemployment to green job transitions regressions for the working-age population. The columns "Reference" reports the sign and significance of the estimated coefficient, as in the paper. "a" indicates that the sign and significance of the coefficient of the policy in the first column is robust to adding in the regression framework the policy associated with the column, whereas "-" indicates that the result is not robust, i.e. either the sign changes or the coefficient is no longer (in-)significant (at least at the 10% level).

Source: OECD elaborations based on EULFS

