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Assessing reskilling programs to manage the European green transition

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ABSTRACT

Workers' ability to navigate changing labor markets depends on their skillset, and this study examines how reskilling can [increase the job options](#) during Europe's decarbonization. We develop a data-driven simulation of reskilling journeys, comparing programs based on green, digital, and transferable skills with individually tailored reskilling. [We find that the best reskilling strategy depends on the transition direction. For workers leaving declining jobs, reskilling tailored to complement workers' existing skills opens up new job options with two-thirds fewer skills than standardized programs. For workers moving into low-carbon jobs, transferable skills work best, though these moves require learning more skills overall. Programs focused narrowly on green or digital skills perform poorly in both directions. Tailored reskilling out of declining jobs comes with a 20% income loss at first, though earnings recover with further reskilling. Across ten European countries, reskilling reduces aggregate annual income losses from around €500 to €240 million or even result in an income gain of €56 million with longer journeys. Reskilling difficulty also varies across regions and sectors, and does not correlate with the number of declining or low-carbon jobs. These findings indicate that reskilling policies for decarbonization should reflect regional labor markets and transition funding based on the number of jobs at threat alone can be misdirected.](#)

1 Introduction

The decarbonization of Europe's economy leads to structural shifts in the labor market. As firms decarbonize, the demand for workers in occupations such as diesel mechanics is projected to decrease. Meanwhile, there is a shortage of workers for the growing low-carbon economy, and demand for occupations such as wind turbine technicians is rising nearly twice as fast as the number of skilled workers available to fill them [1–3]. Historical examples show that unmanaged transitions can leave communities with long-term economic scars, underscoring the risks faced by workers and regions dependent on high-carbon industries [2–11]. Low-carbon industries, on the other hand, face productivity losses and ineffective fiscal stimulus because of skill mismatches [12, 13], and may lose out on potential job growth, which is predominantly driven by existing workers switching occupations, not by new entrants [14].

In response, policymakers across Europe allocate significant resources to reskilling programs but lack evidence on how to design these programs effectively. The European Union plans to invest €65 billion in reskilling through its "Green Deal" and "Clean Industrial Deal" [15]. Many member states have also implemented their own reskilling programs, such as "The Green Tech Skillnet" in Ireland and the "Net-Zero Industry Academy" in Finland [16]. Yet, most of the available evidence on reskilling stems from other labor market transitions, such as task automation [17–20] or from isolating causal effects of past shocks [5, 6, 8, 21–23], which are structurally different from transitions out of high-carbon and into low-carbon jobs. When available, evidence on reskilling during decarbonization focuses on specific occupations or regions [1, 2, 9] [as well as realized outcomes](#) [6, 8, 23, 24], but rarely on Europe. As a result, policymakers often rely on simplistic assumptions about reskilling. For instance, during his 2020 presidential campaign, former US president Joe Biden advised coal miners to reskill by learning computer programming [25]. Similarly, the European Clean Industrial Deal highlights digital, green, and entrepreneurial skills as particularly important for decarbonization without referencing a clear evidence base [15].

[Rather than estimating realized outcomes of previous transitions ex post](#), this study examines how different reskilling

programs can [expand the range of jobs workers can access](#) during Europe’s decarbonization to inform program design ex ante. We employ a data-driven approach to simulate a gradual process of learning new skills, called "reskilling journey," based on the administrative ESCO classification of occupations and skills, and microdata from the European Labour Force Survey (EU-LFS). In our simulations, we compare four stylized reskilling programs for two different occupational transition directions: (1) transitions out of jobs at risk of decline during decarbonization (outward), and (2) transition into jobs expected to grow during decarbonization (inward). The programs focus on (a) transferable skills, (b) green skills, (c) digital skills, and (d) individually tailored skills, and for each, we assess how many new skills workers need to learn to access at least one new job and the associated income changes. [We find that the most effective program depends on the transition direction. Tailored reskilling works best for workers leaving at-risk jobs, whereas transferable reskilling works best for those entering low-carbon jobs. Programs focused narrowly on green or digital skills underperform in both transition directions. Reskilling outcomes also vary considerably across sectors and regions, and the regions where reskilling is hardest are not necessarily those most exposed to decarbonization. These findings suggest that reskilling policies should match programs to workers’ transitions and to regional and sectoral labor market conditions.](#)

Conceptual framework

Two decarbonization transition problems

To model relevant transition directions in Europe’s decarbonization, we first identify which workers are affected. Prior classifications distinguish “green, neutral, and brown” occupations based on emission intensity [10, 26, 27], but likely overstate risk because they ignore technological change that can decarbonize high-emission activities without eliminating the associated jobs [26, 28]. Electrification of industrial processes and the use of synthetic fuels can reduce emissions while preserving occupational structures. We therefore apply the classification of Zaussinger et al. [28], which differentiates high-carbon occupations that are *at-risk*—because they depend on the extraction, processing, or direct combustion of fossil fuels—from high-carbon occupations that are *viable to decarbonize*. Thus, coal miners, gas plant operators, and diesel engine mechanics are at-risk, whereas steelworkers are not (see SI Table S1, for employment shares). Based on this classification, we simulate two transition directions (Figure 1). First, we model reskilling journeys out of at-risk jobs, allowing switches into low-carbon, neutral, and high-carbon occupations that are viable to decarbonize. This departs from studies that restrict transitions to “green” jobs [1, 2] and reflects that neutral jobs may offer more accessible pathways, particularly since they account for about 95% of employment in Europe [28]. Second, we simulate switches into low-carbon jobs.

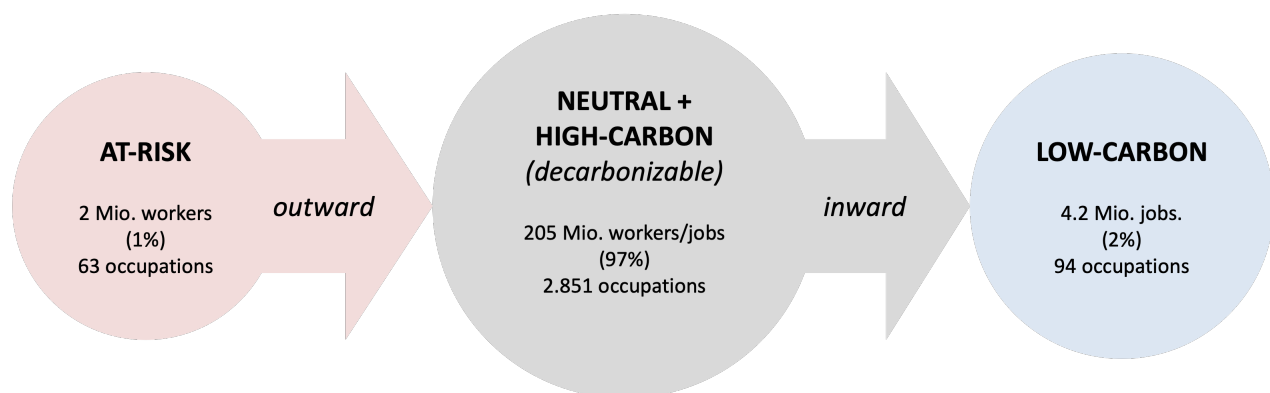


Figure 1. Transition directions in Europe’s decarbonization. Workers move outward from at-risk occupations and inward into low-carbon occupations, through the neutral and decarbonizable workforce in between. Data are from [28]; worker counts are based on EU-LFS data and occupation counts refer to the ESCO classification at the ISCO-4-digit level (SI Table S1).

49 Skill-based feasibility of job options

50 To assess whether a worker's skill profile is close enough to access another occupation from their current one, we require
51 a measure of feasibility. Building on the skill-related literature rooted in economic complexity, we adopt a network-based
52 approach that measures occupational similarity based on their skill requirements [17, 18, 20, 29]. This yields a similarity matrix
53 in which each cell reflects the degree of skill overlap between two occupations. In our simulation, higher similarity implies
54 greater feasibility of a job option. Our measure, therefore, captures whether a worker's skillset brings a target occupation
55 within a feasible range, rather than realized hiring, which additionally depends on labor demand, employer behavior, and search
56 frictions [24]. Beyond evaluating the feasibility of job options, the network-based approach allows us to assess the contribution
57 of individual skills by recalculating similarity scores after reskilling. This mechanism forms the core of our simulation: different
58 programs add different skills, thereby unlocking different job options. Consistent with the automation-related skill literature,
59 we use the network-based approach to compute skill centrality as a proxy for skill transferability, as this captures how skills are
60 empirically reused across occupations rather than relying on top-down classifications [17, 20, 30].

61 Stylized reskilling programs

62 The labor market literature generally emphasizes the importance of transferable skills, such as communication, teamwork,
63 and management, for facilitating job mobility, as these skills are embedded across many occupations [5, 19, 31, 32]. While
64 transferable reskilling can ease transitions, some studies find that it may come at the expense of income, as higher-paying jobs
65 often require more specialized skills [33, 34] and domain-specific knowledge ([35]). To assess whether reskilling programs
66 focused on a fixed set of skills (e.g., transferable skills) or programs tailored to individual skillsets are more effective in the
67 context of decarbonization, we simulate and compare four stylized reskilling programs described in Table 1. The transferable,
68 green, and digital programs are standardized, presenting the same skill sequence to every worker. The tailored program instead
69 individualizes the sequence, offering to each worker the skills that best complement their current skillset.

Table 1. Stylized reskilling programs in our model.

Program	Hypothesis	Model implementation	Real-world examples
(1) Transferable (standardized)	Transferable skills bridge unrelated occupations [17, 36, 37], but higher-paying roles require specialized skills, so mobility may come at lower income [33–35].	Workers learn skills in descending order of centrality in the overall ESCO skill network; the most central are management and communication skills.	(i) Singapore’s SkillsFuture gives citizens aged 25+ a topped-up training credit spendable on any approved course, from languages to project management [38]. (ii) France’s CPF offers annual funding per worker to take certified transferable courses [39].
(2) Green (standardized)	Decarbonization policy increasingly emphasizes green skills as specialized reskilling [26, 34, 40]; these may open well-paid green roles but fewer job options overall.	Workers learn skills in descending order of centrality from the ESCO green-skills list (e.g. pollution prevention, heat-pump installation).	(i) EU RES-SKILL reskills coal-plant workers as wind and solar installers through 1–4 month practical courses [41]. (ii) Spain’s Just Transition Institute conditions renewable-project grid access on reskilling displaced coal workers in the same region [42].
(3) Digital (standardized)	Decarbonization and automation policy likewise emphasize digital skills [26, 40], which can be both specialized and transferable, with unclear job prospects.	Workers learn skills in descending order of centrality from the ESCO/DigComp list [43] (e.g. digital communication through to programming).	(i) UK Skills Bootcamps deliver 12–16 week courses in cloud, data and cybersecurity, with a job interview guaranteed on completion [44]. (ii) EU coding bootcamps offer intensive 3–6 month programming courses, often co-financed for eligible participants [45].
(4) Tailored (individualized)	Skill complementarity may matter beyond transferability or specialization [18, 46]; not all workers benefit equally from learning the same skill [47].	Workers learn individualized skills that complement their current skills, raising overlap with the occupations it already resembles.	(i) Germany’s education vouchers fund reskilling with a caseworker, matched to target occupations [48]. (ii) France’s CPF de transition funds occupational change, with courses chosen around individual career plans [49].

Measures of successful reskilling

Even when reskilling enables job mobility, workers may not always be willing to actually switch. To assess the relative effectiveness of reskilling programs in Europe’s decarbonization, we evaluate outcomes along reskilling intensity and potential income change. First, reskilling intensity is defined as the number of new skills a worker must learn to unlock additional job options. Because workers and firms face time and resource constraints, we treat programs requiring fewer new skills as more effective, consistent with evidence that shorter and less time-intensive training attracts higher participation [50, 51]. Second, high-carbon jobs and especially those in extractive industries, frequently pay wage premiums relative to comparable manufacturing jobs [7, 52, 53]. Workers may thus reject local alternatives offering lower pay. We therefore assume the most relevant job option is the one offering the highest potential income. Additionally, we also acknowledge that at-risk workers are often geographically concentrated and typically prefer to remain in place due to housing, family, and identity-related factors [54–56]. For instance, Romania’s RenewAcad project, which aimed to retrain coal workers for wind and solar installation, experienced limited uptake due to the requirement for relocation [57]. We therefore restrict feasible job options to occupations present within the worker’s region of employment and draw feasible job options in proportion to the regional employment share.

Results

We structure the results along the five key findings of our simulation. First, our simulation shows that the effectiveness of reskilling programs depends on the transition direction, i.e., whether the policy challenge is moving workers out of at-risk jobs or into growing low-carbon jobs. To move out of at-risk jobs, tailored reskilling is most effective and workers unlock a first new job option after acquiring around four tailored skills (Figure 2, SI Figures S1-2). Transferable reskilling requires

more intensive reskilling, with workers learning around thirteen skills to unlock a first option. Reskilling into low-carbon jobs follows a different pattern: Transferable reskilling unlocks a first low-carbon job option after workers learn around seventeen skills, fewer than the twenty-six required under tailored reskilling (see Figure 2b). This is consistent with evidence from the United States and the United Kingdom, where low-carbon jobs require more, and more diverse and complex, skills [34, 58, 59]. Because tailored skills broaden the skill overlap with similar occupations, they are less effective when the target is a narrow, specialized set of jobs, whereas transferable skills are closer to what low-carbon occupations require.

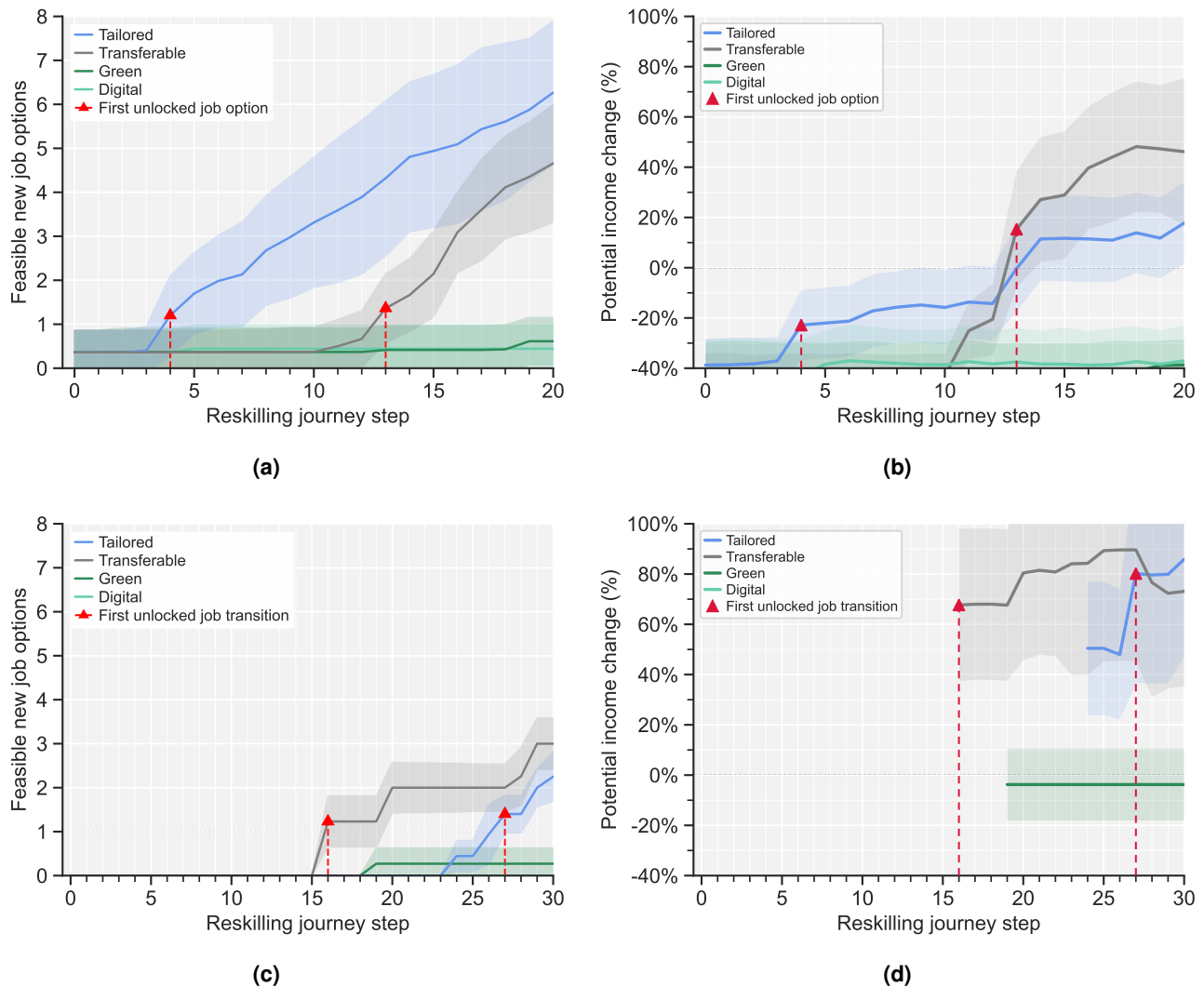


Figure 2. Reskilling journeys across transition directions. (a) Number of unlocked job options at each reskilling step for workers leaving at-risk jobs. (b) Potential annual income change for switching workers leaving at-risk jobs. (c) Number of unlocked job options at each reskilling step for workers entering low-carbon jobs. (d) Potential annual income change for switching workers entering low-carbon jobs. Lines show the median across workers; shaded areas show ± 1 standard deviation.

Second, green and digital reskilling alone, although often referenced in policy discussions, are largely ineffective in both transition directions. The median worker unlocks no new job option in either program within the simulated range (Figure 2), and green reskilling helps only a narrow set of origin occupations, mainly engineering, machinery maintenance, and supervisory roles in manufacturing and construction (SI Table S2). The reason appears to lie in the skill requirements of occupations where green skills are essential in many occupations, but account for only around 9% of what a low-carbon job requires (SI Table S3). The remaining requirements are general skills used throughout the economy, which is why transferable reskilling reaches

low-carbon jobs sooner than a green program does. Digital skills unlock even fewer transitions, as they are optional for most occupations in our data. Notably, the occupations that benefit from green reskilling are not those with the highest green-skill share, which suggests that (additional) green skills are not what enable these job options (SI Table S2). Studies that identify green skills empirically from occupational task content reach a similar conclusion, finding that green work draws heavily on high-level general and technical competencies rather than on a distinct and separable set of green skills [26, 60].

Third, we find that faster transitions can lead to higher income losses. For at-risk workers, tailored reskilling is most effective, but comes with an average potential income loss of 20% (Figure 2b; SI Table S4). Losses then narrow as reskilling continues, and average annual income returns to workers' prior level at around thirteen skills. Transferable reskilling reaches workers' previous income level after the same number of skills, which suggests that the advantage of the shorter reskilling journey under tailored reskilling mainly lies in the speed and ease of unlocking a first new job option. With further skills, transferable reskilling unlocks even better-paid job options than tailored reskilling, reaching potential gains of around 50% at twenty skills, against 20% under tailored reskilling. For workers moving into low-carbon jobs, transferable reskilling also unlocks the highest-paid options, and does so well before tailored reskilling unlocks any (Figure 2d). Both programs are associated with large potential gains, though these are positive by construction, as workers in our model only switch to a low-carbon job if it raises their earnings (see Methods).

Fourth, when shifting the focus from the worker to economic sectors, we find substantial variation. We focus on the transition out of at-risk jobs because that is where sectoral variation matters most for policymaking and we show results for tailored reskilling, which enables the fastest transition (see above). Workers in construction, electricity and manufacturing unlock a first option after around three tailored skills, whereas workers in transport and agriculture require up to seven (see Figure 3a). The gap widens with further reskilling, as construction and electricity workers continue to unlock options roughly twice as fast as those in transport (see SI Figure S3 for the transition into low-carbon jobs where sectoral differences expectedly matter less). As shown in Figure 3b, income outcomes also differ across sectors. Leaving at-risk jobs, workers in mining and electricity incur the largest income losses (€17,000-25,000), and recover only after extended reskilling, while workers in wholesale, construction, and manufacturing find job options that reach their previous income levels soonest.

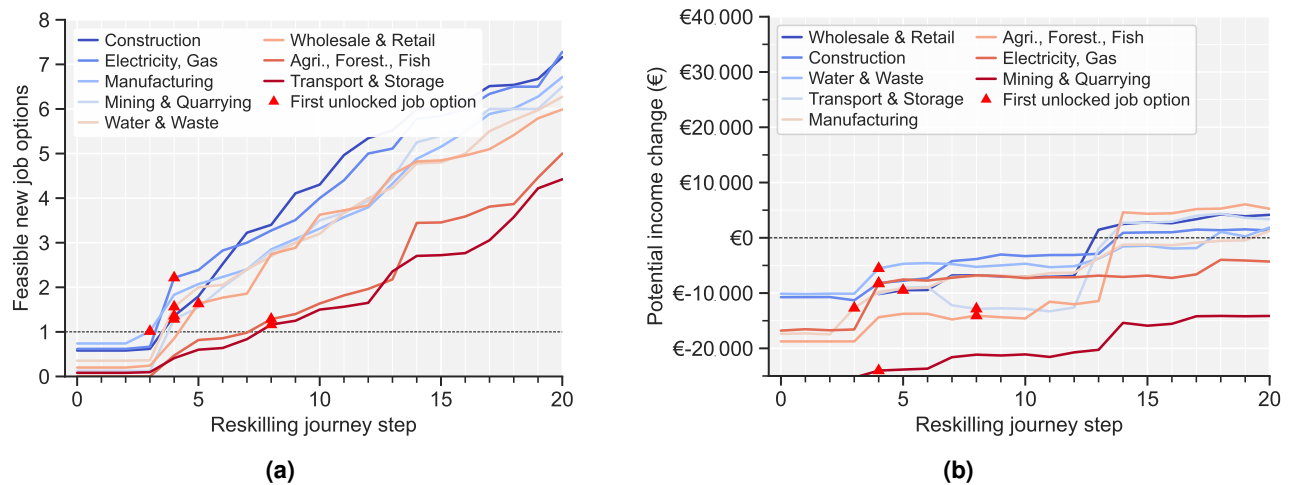


Figure 3. Tailored reskilling journeys out of at-risk jobs, by sector. (a) Number of job options unlocked at each reskilling step. **(b)** Potential annual income change (€) for switching workers. Sectors are colour-coded from best-performing (blue) to worst-performing (red).

Finally, we also identify substantial regional variation in the reskilling difficulty, which does not correlate with the prevalence of at-risk or low-carbon jobs. Figure 4 maps each region's employment exposure to the reskilling difficulty (left panel for at-risk, right panel for low-carbon). Regions of greatest policy concern to move workers out of at-risk jobs are shown in

purple and appear in northern France, central Germany, northern Scandinavia and western Ireland (Figure 4a). Rather than forming a cluster, these regions are scattered across Europe. Regions colored in light blue combine a high share of at-risk employment with comparatively easy reskilling, therefore showing great potential to manage the transition with adequate policy support. These regions are located in Finland, southern Germany and the coal belt spanning Poland, the Czech Republic, Slovakia, Hungary and Romania. Finally, regions colored in red, much of Spain and Greece, face difficulties in reskilling its comparatively small at-risk workforce. For transitions into low-carbon jobs, reskilling is more challenging (Figure 4b). Here, the critical regions are those where low-carbon jobs are relatively abundant, but workers cannot reach them, pointing to a potential labor market bottleneck. These regions (shown in purple) concentrate in France, northern Italy, southern Scandinavia and Greece, while Finland, southern Romania and northern Germany show high shares of low-carbon jobs with relatively easy reskilling.

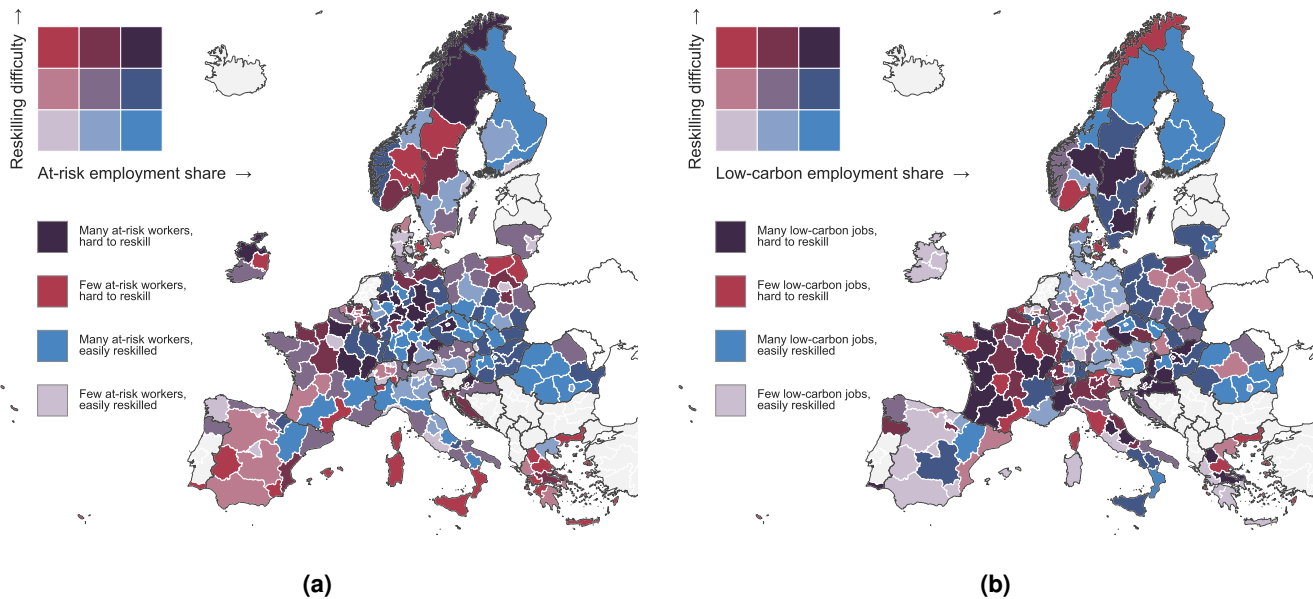


Figure 4. Regional distribution of reskilling difficulty and employment exposure. (a) Transitions out of at-risk jobs, under tailored reskilling. (b) Transitions into low-carbon jobs, under transferable reskilling. Maps show regional employment share and reskilling difficulty for NUTS-2 regions, for the most effective program in each direction (Figure 2), at the step where the median worker unlocks a first job option (4 skills outward, 16 inward). Along each axis, regions are grouped into tertiles; darker shades denote higher reskilling difficulty and higher employment share.

Discussion

This study makes three contributions to research and policy debates on skills and decarbonization. We first develop a generalizable approach to analyzing reskilling journeys, second apply it to Europe's decarbonization context, and third compare four stylized reskilling programs. Our results show that the regions where reskilling is most difficult are not necessarily those with the highest shares of at-risk or low-carbon employment. Therefore, support allocated on the basis of employment exposure alone, as much transition funding currently is, may miss the regions where reskilling is hardest [11]. Reskilling difficulty also differs markedly across sectors, and these differences persist across program designs. Policies should therefore retain flexibility to reflect local occupational structures and sectoral composition rather than employment exposure alone. Moreover, we find that at-risk workers likely experience initial income losses during their reskilling journey, but that these aggregated losses at least halve once reskilling unlocks a first job option (see SI Table S5). Table 2 shows that, across the ten countries with earnings data, income losses without reskilling aggregate to almost €500 million per year. Tailored reskilling can halve

these losses to €240 million (-€8,300 per worker) and transferable reskilling even results in annual income gains of €56 million (+€2,000 per worker). This creates a dilemma for policymakers. Transferable reskilling is the most effective route overall, but it requires longer journeys (see Table 2), during which workers forgo income. Tailored reskilling shortens these journeys for at-risk workers and may be more feasible, since workers learn skills that complement those they already have, but it is likely more costly to deliver (see SI Table S6). Either route may need to be paired with income support [61], which is reinforced by evidence from past energy transitions: following coal's decline, cross-industry and geographic mobility did little to offset earnings losses [8], and local training investment did not rise automatically in affected regions [62]. Future work should therefore compare the effectiveness of income subsidies with that of longer reskilling pathways. Transitions into low-carbon jobs, where they occur, are associated with substantial potential income gains of 68 - 82% annually per worker, and €800 million - €1,1 billion aggregated (Table 2), but they remain attainable for only a minority of workers, which points to the challenge of addressing labor shortages.

Table 2. Annual income impact of reskilling for countries where earnings data are available (Denmark, Finland, France, Greece, Ireland, Norway, Portugal, Slovakia, Sweden, Switzerland)

Direction	Program	New skills needed	Potential income Δ, per-worker (€, %)	Aggregated across countries (€ million)	
				No reskilling	With reskilling
Outward	Tailored	4	-8,300 (-22%)	-494	-240
	Transferable	13	+2,000 (+16%)		+56
Inward	Tailored	27	+18,500 (+82%)	0	+1,140
	Transferable	16	+16,700 (+68%)		+797

For program design, our results caution against a generic emphasis on specific skill types such as green or digital skills, as the European "Clean Industrial Deal" currently proposes [15]. We find that at-risk workers reskill fastest when the program complements their existing skills, whereas workers entering low-carbon jobs are best served by transferable reskilling, since these jobs draw heavily on widely shared skills. Programs built narrowly around green or digital skills underperform in both and they are not cheaper either (see SI Table S6). Transferable reskilling programs tend to be cheapest in both directions, while tailored reskilling enables faster job transitions, but its individualized assessment and counseling raise delivery costs.

Two main limitations of our study relate to data and the absence of information on reskilling costs and duration. The EU-LFS provides cross-sectional data at a coarser occupational level than the ESCO-based classification (see Methods), meaning skillsets reflect only current occupations and transitions occur between broader groups. Moreover, although feasibility is modeled via skill overlap, we cannot distinguish skills that require greater training investment. We therefore avoid imposing normative cost weights on skills, as there is no data on cost or learning time to acquire each ESCO skill. Instead, we opt for comparing costs at the level of programs (see SI Table S6). Future research could extend the reskilling approach proposed here to other transitions and refine it with more granular data, including forthcoming EU-LFS panel releases and national microdata. Linking the simulation to job vacancy data, such as the online job advertisements collected in Eurostat's Web Intelligence Hub or Cedefop's Skills-OVATE, would enable aligning reskilling supply with labor demand and help identify bottlenecks in emerging low-carbon labor markets, which remains a crucial policy question [34, 58].

The results of our simulation provide a regionally disaggregated perspective on the effectiveness of different reskilling programs regarding the number of required skills to transition to a new job and the associated potential income changes and point to implications for policymakers at the European, national, and regional levels. However, to facilitate optimal job switches during the green transition at the regional level, further research is needed to pair reskilling with regional labor demand (forecasts) and detailed information on reskilling program cost and time requirements. This line of work will be critical to inform policy design (e.g., the Clean Industrial Deal) and to ensure that the green transition is not jeopardized by political backlash due to labor market frictions.

Methods

Data

We link administrative data on occupations and skills to micro-level data on employed individuals in Europe. **ESCO** is a standardized European Commission taxonomy containing 3,039 occupations and 13,939 skills, mapped to ISCO-08 and classified as “essential” or “optional”; we use version v1.1.0. The **EU-LFS** provides representative labor market microdata on employment, occupation, industry, workplace, income, education, and demographics; we use the 2023 wave. Regions are observed at the NUTS-2 level. We retain respondents who are economically active ($WKSTAT \in \{1, 2\}$; $ILOSTAT \in \{1, 2\}$), aged 15–77, living in private households, and employed in their country of residence. Cross-border commuters are excluded because workplace regions are missing; although they account for only 0.84% of the sample overall, they are concentrated in some countries (e.g., Luxembourg 10.3%). Country coverage varies by analysis due to data availability (SI Table S7). From all EU-LFS countries in 2023, including Norway, Switzerland, and Iceland, we exclude Bulgaria, Malta, and Slovenia owing to missing ISCO 3-digit occupational data ($N = 27$). For regional analysis, we additionally drop the Netherlands, Iceland, Cyprus, Luxembourg, Latvia, and Estonia because NUTS-2 workplace identifiers are unavailable ($N = 21$). For income-based comparisons, we exclude Italy, the Netherlands, Germany, Hungary, Austria, Romania, Poland, Estonia, Lithuania, Cyprus, Belgium, the Czech Republic, Croatia, Iceland, and Latvia, where fewer than 20% of respondents report income data ($N = 10$).

Occupational similarity and skill centrality

To quantify similarity between occupations, we follow the literature [17, 28] and construct an occupational similarity matrix $M_{os} \in \mathbb{R}^{m \times n}$, where $m = 3,039$ occupations and $n = 13,939$ skills. Essential skills are weighted as 1.0 and optional skills as 0.5 for our main results. We test the sensitivity of this choice by excluding optional skills entirely ($w=0$), see SI Table S8. Based on this, we first derive a skill co-occurrence matrix:

$$M_{ss} = M_{os}^T M_{os}$$

where each entry $M_{ss}(i, j)$ reflects how frequently skill s_i co-occurs with skill s_j across all occupations. This forms a weighted, undirected skill network where nodes are skills and edges represent shared usage. To rank the transferability of skills in terms of their network centrality, we compute a coreness score k_i for each skill s_i using a composite centrality metric:

$$k_i = 0.5 \left(\frac{b_i}{\max(b)} + \frac{e_i}{\max(e)} \right) \cdot (1 - c_i)$$

where: - b_i is betweenness centrality (how often a skill connects other skills), - e_i is eigenvector centrality (importance within the network), - c_i is the local clustering coefficient (connectivity of neighboring nodes). This metric favors transferable skills that are well-connected to others, but whose neighbors are not strongly interconnected. Zaussinger et al. (2025) [28] validate this measure by comparing coreness scores across ESCO’s reuse label categories and find that cross-sector skills have the highest average scores. We then construct a pairwise skill-overlap, i.e., occupational similarity matrix $M_{oo} \in \mathbb{R}^{m \times m}$ by comparing skill vectors for each occupation pair. Each entry represents the weighted count of overlapping skills. Self-transitions are excluded, yielding $N = 9,048,064$ pairwise comparisons. For assessing the feasibility of occupational transitions, we define the necessary threshold of skill overlap as 3.7 skills, derived as the across-group mean minus one standard deviation of within-ISCO-08-4-digit-group skill overlap, following Kandera et al. [17].

Model setup

We develop an agent-based micro-simulation, in which heterogeneous worker groups (agents) undergo sequential skill acquisitions and occupation transitions under predefined reskilling programs. We evaluate the relative effectiveness of each reskilling program by comparing the intensity of the reskilling journey, the regional presence of unlocked job options, and the income associated with the best-paying option. We report income changes in two ways: for workers who switch jobs, to describe the individual gain or loss from a transition, and averaged across all workers in a group including those who do not switch, to describe the aggregate income exposure of the affected workforce. To do so, we match ESCO occupations to actual jobs as reported in the EU-LFS and therefore aggregate them to the ISCO-08 3-digit occupational level by using average values for the skill profiles. Each occupation is encoded as a skill vector based on the ESCO occupation–skill matrix, $M_{os} \in \{0, 0.5, 1\}^{3039 \times 13939}$. Our unit of analysis is the EU-LFS data point, which groups individuals with identical characteristics and applies population weights to account for the sample’s representativeness. We then model job options as *reskilling journeys*—sequences of incremental skill acquisitions. Correspondingly, the simulation follows a five-step iterative procedure for each worker group (i.e., EU-LFS data point):

1. **Baseline assessment:** For each group of workers with their initial skillset based on their occupation $S_{w,0} \subseteq \{s_1, \dots, s_{13939}\}$, we estimate feasible job options through the occupational similarity matrix and the corresponding income changes without reskilling.
2. **Skill acquisition:** One new skill s_j is added to the worker’s skillset based on the assigned reskilling program (green, digital, transferable, or tailored).
3. **Matrix update:** The occupational similarity matrix M_{os} is updated for that specific skill with a weight of one (corresponding to an essential skill), and a new matrix $M'_{oo} = M_{os}M_{os}^\top$ is calculated.
4. **Constraint filtering:** Additional transitions enabled by reskilling are filtered according to 4 constraints in line with our conceptual framework:
 - *Skill overlap:* We allow only "feasible" target jobs whose occupational skill requirements overlap with the workers’ updated skillset $S_{w,t}$ by at least 3.7 skills;
 - *Valid target job:* From the set of feasible job options, we retain only those that are considered low-carbon, neutral, or viable to decarbonize for the outward transition direction. For the inward transition direction, we retain only low-carbon occupations as valid targets;
 - *Regional presence:* Next, we constrain workers’ search for jobs within their NUTS-2 region of employment, as reported in the EU-LFS (REGION_2DW). If the employment region is missing, we use the region of residence. Additionally, we weight feasible target occupations by their share of NUTS-2 employment, so that occupations that are more common in a region contribute more to a worker’s feasible options than rare ones.; and
 - *Potential income change:* Among the remaining options, we assume the relevant option is the one offering the highest potential income. EU-LFS provides income data in deciles; we map these to median income estimates by ISCO-08 3-digit group and NUTS-2 region using the EU-SILC and ECHP datasets (2023 release). If no target jobs remain after applying all constraints, an at-risk worker is assumed to become unemployed and incurs an income loss equivalent to one year of their previous salary. In contrast, a worker trying to move to a low-carbon job is assumed to keep her job and income in that case. This asymmetry reflects that at-risk workers face the loss of their current job, whereas workers trying to move into low-carbon jobs are not themselves at risk and therefore retain their job and income if no low-carbon option is feasible.

5. **Iteration and logging:** Unlocked job options and the skill added are stored, and the simulation proceeds to the next reskilling step. The updated occupational similarity matrix now serves as the baseline, and a second skill is added. This loop continues until 20-30 new skills have been added, depending on the transition direction.

To account for training uncertainty and ensure model stochasticity, we randomize the order of worker groups within regions for each simulation run. For the transferable, green, and digital programs, which draw on fixed skill lists, workers learn skills in descending order of centrality within the relevant list, namely all skills, the ESCO ‘green’ list, or the ‘DigComp’ list. Each standardized program therefore presents the same sequence to every worker, while only the tailored program individualizes the sequence to complement a worker’s skillset. We acknowledge that the sequence in which skills are learned can influence results, and we treat this as a necessary model simplification.

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Data access

This study builds on public data from ESCO, which can be downloaded at: <https://esco.ec.europa.eu/en/use-esco/download>. Additionally, we use microdata from the EU-LFS, which researchers need to register for at Eurostat, after which they will be able to fully replicate our study with the code and package environment available at: <https://github.com/clarakraemer/Simulating-Re-Skilling-Journeys>. We used the Python programming language (version 3.11) for data analysis.

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Author contributions

All three authors developed the research design. C.K. and F.Z. prepared the data. C.K. performed the analyses and created the results and visualizations. C.K. wrote the first draft with input from F.E., F.E. and F.Z. then edited subsequent drafts. F.E. supervised the work.

Ethics statement

The ESCO classification is public and contains no personal information. The EU-LFS is accessible through formal registration procedures. All analyses were conducted in accordance with the EU-LFS data usage agreement, and the results are reported at the group or regional level to prevent the disclosure of individual records.

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Declaration of interests

The authors declare no competing interests.

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