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Authors: Martino Kuntze, Irene Brunetti, Federico Fabio Frattini, Andrea Ricci, Francesco Vona

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Skills and occupational mobility in the green transition: Evidence from Italian Administrative data*

Martino Kuntze[†] Irene Brunetti[‡] Federico Fabio Frattini[§]
Andrea Ricci[¶] Francesco Vona^{||}

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Abstract

What governs occupational mobility in the green transition? We address this question using administrative records on 13 million job-to-job moves in Italy (2012–2023), matched to the task content of each occupation. Estimating a gravity model of flows between occupations, we document that skill distance is a first-order friction: a one-standard-deviation increase cuts flows by 60 percent. The friction is selective. Mildly green occupations accept workers who lack green skills but not workers distant in general capabilities, and the most intensely green occupations do the reverse. This matters for how the transition proceeds: green occupations draw workers because they are easy to enter, not because they are more rewarding, and brown occupations shrink because few workers move in. The costs fall unevenly. Women are 13 percentage points less likely to enter a green occupation, and brown leavers are 0.7 percentage points more likely to be out of work afterwards, against a mean of 31 percent. The results are consistent with a transition governed by the cost of entering occupations rather than by workers being locked into declining ones.

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[†]Sapienza University of Rome. martino.kuntze@uniroma1.it

[‡]INAPP i.brunetti@inapp.gov.it

[§]FEEM; federico.frattini@feem.it

[¶]INAPP an.ricci@inapp.gov.it

^{||}University of Milan and FEEM. francesco.vona@unimi.it

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1 Introduction

Technological transitions typically create winners and losers in the labour market. New technologies raise the demand for some task bundles and eliminate it for others, and the adjustment falls unevenly across occupations (Autor, 2013; Goos et al., 2014; Acemoglu and Restrepo, 2018). Workers absorb such shocks mainly through reallocation across sectors and, above all, across occupations, so that the aggregate response is the sum of many individual switches (Acemoglu and Autor, 2011; Cortes et al., 2020). Such reallocation is not costless: changing occupation can destroy accumulated human capital and can carry penalties in forgone earnings, in spells of non-employment, and in the quality of the destination job (Huckfeldt, 2022; Jarosch, 2023; Neffke et al., 2024). Reallocation costs also have a demand side: expanding occupations demand competences that are still being defined (Autor et al., 2024), and the skills complementary to a new technology diffuse slowly, as informal know-how is codified into training and curricula (Vona and Consoli, 2015).

We study occupational mobility in a setting where the direction of reallocation is unusually clear. In fact, the green transition is a case of directional structural change: climate policy and directed technical change expand labour demand in green occupations (Elliott and Lindley, 2017; Marin and Vona, 2019; Vona et al., 2019; Popp et al., 2021; Bachmann et al., 2026) and contract it in the pollution-intensive activities environmental regulation targets (Greenstone, 2002; Walker, 2013; Curtis, 2018; Haywood et al., 2024).¹

Knowing the direction, however, says little about whether the reallocation is executed, at what cost, and by whom. That depends on the frictions separating occupations, which a large literature establishes to be first-order: human capital is imperfectly portable, and the bilateral distance between origin and destination skill requirements shapes both the frequency of a move and its cost (Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Macaluso, 2025). We therefore study the two margins along which the transition is realised — entry into green occupations and exit from brown ones — and ask three questions. How costly is skill mismatch along each? Net of skill distance, do green and brown occupations differ in attractiveness or in access costs? And who is positioned to make these transitions, and at what cost?

To answer these questions we combine Italian administrative data tracking the near-universe of job-to-job mobility episodes with survey data on the skill content of occupations. The employment data come from Italy’s Compulsory Communications archive (*Comunicazioni Obbligatorie*, CO), which records every contract activation, modification and termination for a representative sample of workers. This yields a matched employer–

¹We define directional structural change as a setting in which the identity of expanding and contracting occupations is known ex ante, allowing the researcher to sign the expected direction of reallocation. This distinguishes it from automation or trade exposure, where the incidence of the shock must be inferred rather than assumed.

employee panel of 2.8 million workers and slightly more than 13 million job-to-job transitions over 2012–2023, coded at the 5-digit occupational level. We merge it with an Italian survey of occupation-level skill and task content (*Indagine Campionaria sulle Professioni*, ICP) — structured along the lines of the US O*NET — and follow Vona et al. (2018) in identifying green occupations through a task-based greenness index imputed to the Italian classification, and brown occupations through their employment concentration in pollution-intensive industries (Cavallotti et al., 2025).² From ICP we compute two complementary pairwise skill-distance measures: one restricted to the general skills characterising green (General Green Skills, GGS) and brown (General Brown Skills, GBS) work; the other summarising the whole skill battery through four latent factors, following the established practice of representing occupations as vectors of factor-analytic scores (e.g. Poletaev and Robinson, 2008; Guvenen et al., 2020; Lise and Postel-Vinay, 2020).

Our analysis builds on the occupational mobility model of Cortes and Gallipoli (2018).³ Their model yields a gravity-type equation in which the ratio of switchers to stayers depends on origin and destination fixed effects and bilateral skill distance, the destination effect decomposing into an attractiveness and an access-cost component. We extend it along three dimensions: interacting skill distance with indicators for a green destination or a brown origin, to test whether the distance penalty varies across segments of the occupational landscape that matter for the green transition; varying the vector characterisation over which distance is measured; and estimating the decomposition separately by occupation type. Estimation is by Poisson pseudo-maximum likelihood (PPML; Santos Silva and Tenreyro, 2006) at the 4-digit level, with origin and destination fixed effects and dummies for transitions across broad task categories (Acemoglu et al., 2025). We then take the analysis to the worker level: linear probability models on matched samples of job changers, which hold the occupational segment and the local labour market fixed, ask who enters green occupations and what happens to those who leave brown ones.

Gravity estimates show that skill distance is a first-order friction: a one-standard-deviation increase reduces occupational flows by roughly 62% under the GGS-based distance and 61% under the factor-based one. The corresponding figure on the GBS distance is 51%, but it is expressed per standard deviation of brown-skill dissimilarity and is therefore not on a common scale with the other two. These magnitudes exceed the -0.426 per standard deviation implied by Cortes and Gallipoli (2018), and part of the gap is aggregation: re-estimating on 2-digit occupations returns -0.673 , closer to their benchmark. We retain the 4-digit estimates because aggregation compresses the dispersion of

²Occupations with greenness ≥ 0.1 are “Green”, those with greenness ≥ 0.3 “green-core”; brown occupations have more than 10% of employment in NAICS 4-digit industries above the 95th percentile of pollution intensity. See Section 3.

³Workers select into occupations to maximise a payoff depending on occupation-specific returns and an idiosyncratic match-quality draw; switching from k to j entails an iceberg cost depending on their bilateral skill distance, occupation-specific entry barriers, and an idiosyncratic component.

bilateral distances and blurs the identification of green and brown occupations.

The interactions of interest trace a pattern that depends on the vector characterisation in which distance is measured. Under the GGS and GBS characterisation, green destinations attenuate the penalty clearly: flows into them fall by roughly 55% per standard deviation, against the 63% faced by non-green destinations, suggesting that occupations at the green margin tolerate more green-task mismatch than gray ones. Green-core destinations, the most intensely green occupations, do not attenuate and stay selective on green-task content. This is true also for brown origins, whose exits face the same friction in brown-specific skills as exits elsewhere. Under the factor-based characterisation the pattern reverses: green-core destinations attenuate significantly (56% rather than 61%), brown origins comparably (55%), and marginal green destinations not at all. Different skill margins therefore bind for different segments of the transition. Entry at the green margin is constrained by broad capabilities but forgiving of green-task mismatch; the opposite is true for entry into green-core occupations; exit from brown work is eased along the general-capability margin while facing the full friction in brown-specific skills.

These results survive an extensive battery of robustness checks. The baseline penalty is invariant to the treatment of zero-flow pairs, to the gradual introduction of fixed effects and task controls, to excluding the highest-flow occupations in each group, and to a negative binomial estimator; the interactions, estimated on small segments, are less precise but keep their pattern. Under a vector characterisation that retains the entire skill battery, without prior selection or dimensionality reduction, every interaction vanishes: the differential sensitivity of green and brown transitions is not a generic feature of occupational dissimilarity, but emerges only along margins relevant to the transition or capturing the latent capability structure of occupations.

We then turn from bilateral frictions to occupation-specific ones. Decomposing the destination fixed effects, we find that reallocation across the green–brown spectrum is governed by access rather than returns. Green and green-core occupations attract disproportionately high inflows, and the gap is accounted for almost entirely by below-average entry barriers; attractiveness differentials are at most secondary, in line with the small green wage premia documented in the literature (e.g. Vona et al., 2019; Godøy and Isaksen, 2025; Kuai et al., 2025; Saussay et al., 2026; Cass et al., 2026). A plausible reading is that the skill requirements of expanding occupations remain imperfectly codified, so employers cannot yet select on them (Vona and Consoli, 2015). For brown occupations, below-average inflows reflect significantly high access costs, while their attractiveness is indistinguishable from the rest of the labour market. The premia documented for carbon-intensive work are measured at establishment, firm or sector level (Barreto et al., 2023; Haywood et al., 2024; Rud et al., 2024; Garnache et al., 2025), and need not imply an occupation-level premium of the kind our attractiveness component would register. Combined with the absence of any additional distance penalty on brown exits, this implies

that the brown segment loses ground through choked inflows rather than accelerated outflows — the pattern by which contracting segments have been shown to shrink in routine manual jobs (Cortes et al., 2020; Curtis, 2018) — just as the green segment expands through open doors rather than superior rewards.

The individual-level analysis takes these occupation-level frictions to the worker margin and asks who crosses them. Comparing job changers with their counterparts in the same occupational segment and local labour market, and measuring, following Macaluso (2025), how far a worker’s previous occupation sits from the skill profile of local green jobs, we find that skill distance is a first-order predictor of green entry: a 10 percentage point increase in distance from the local green profile lowers the probability of moving into a green occupation by 7.4 points. Occupational history matters asymmetrically. Prior green experience predicts green entry, while a brown origin lowers the probability of entering a green occupation by 4.9 points but raises that of entering a green-core one by 2.0, a reversal consistent with the overlap between brown and green skills. Access is stratified: women are 13 percentage points less likely to enter a green occupation conditional on observables, echoing the gender gaps documented elsewhere in green employment (Alexander et al., 2024; Bachmann et al., 2026), while a tertiary degree raises the probability of a green-core transition by 10 points, and green entry is disproportionately an upward move on the occupational ladder. Workers leaving brown occupations, finally, bear a modest but significant transitional cost on three margins, a higher risk of non-employment, a lower probability of an open-ended contract and a substantially wider occupational displacement, the margins along which the displacement literature locates the persistent costs of job loss (Huckfeldt, 2022; Jarosch, 2023); these costs fall hardest on women and on the less educated, whose better-educated counterparts escape them through active reallocation across sectors and occupations.

Contributions. Our paper contributes to three literatures. The first is the literature on occupational mobility and skill mismatch. The task-based framework initiated by Autor et al. (2003) established that mobility costs depend on the multidimensional distance between origin and destination task bundles, and a large body of work has since shown that human capital is imperfectly transferable and that the choice of vector characterisation determines which transitions look costly (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Sullivan, 2010; Yamaguchi, 2012; Robinson, 2018; Guvenen et al., 2020; Neffke et al., 2024; Macaluso, 2025). Cortes and Gallipoli (2018) formalised this in a gravity model separating distance frictions from occupation-specific access costs, identifying both from observed flows rather than wage regressions — the logic by which mobility costs have been recovered under trade shocks (Artuç et al., 2010; Dix-Carneiro, 2014). The closest paper to ours is Dupuy et al. (2024), who estimate a gravity model in which the

changes in skill distance brought about by digitalisation drive mobility. We contribute to this strand of literature by relaxing the assumption that the distance penalty is uniform across the occupational space: it varies systematically with the green or brown character of the pair, and the binding dimension is not the same across segments of the transition.

The second is the literature on green jobs, green skills and workforce reallocation. A first strand established that green work can be identified from occupational task content, that it differs systematically in its skill and human-capital requirements, and that climate policy shifts labour demand towards those skills (Vona et al., 2018; Consoli et al., 2016; Marin and Vona, 2019; Vona et al., 2019; Vona, 2021). On the transitions side, Saussay et al. (2026) showed that low-carbon jobs demand more, and more diverse, skills than comparable jobs in the same occupation and firm; Curtis et al. (2024) and Bluedorn et al. (2023) documented that workers rarely move from carbon-intensive to green employment, in US career histories and across 31 countries respectively; and Bachmann et al. (2026) decomposed the greening of German employment over 2012–2022 into within- and between-occupation margins of roughly equal size, showing that worker flows — and flows to and from non-employment in particular — drive the second. A parallel strand quantified the cost of leaving carbon-intensive work (Walker, 2013; Barreto et al., 2023; Haywood et al., 2024; Rud et al., 2024). Our contribution is to move from counting transitions to modelling the frictions that govern them — which dimension of skill constrains entry into green work and exit from brown, whether expanding occupations are genuinely accessible or merely growing, and whether those losing ground hold workers in — and then to show, at the individual level and within matched occupational segments and local labour markets, who makes these transitions and at what cost. We also extend the Vona et al. (2018) methodology to identify general brown skills, a set no previous study had recovered, and document their substantial overlap with green ones.

Third, we speak to the policy debate on the “just transition”, which asks how the distributional burden of decarbonisation falls across workers, communities and regions (Bowen et al., 2018; Pollin and Callaci, 2019; Carley and Konisky, 2020; Rausch et al., 2011). A large policy-facing literature has translated that concern into a skills agenda, asking whether workers displaced from brown occupations can be retrained for green ones and which competences the retraining should target (Strietska-Ilina et al., 2012; Cedefop, 2019; Czako, 2022; Granata and Posadas, 2024). The contrasting interaction profiles of our two distance measures give a direct answer: the relevant skill gap depends on the destination, so a single retraining template applied across the green spectrum would miss on one margin or the other — echoing the occupation-specific reskilling needs found in vacancy data (Saussay et al., 2026; Kershenbaum et al., 2026). Further, the decomposition adds that green occupations are already comparatively accessible, locating the binding constraint on the supply side rather than in demand-side barriers to entry.

The remainder of the paper is organised as follows. Section 2 presents the conceptual

framework and its empirical application. Section 3 describes the data sources, the measures and a set of descriptive facts. Section 4 presents the gravity-model results and the fixed effects decomposition, while Section 5 shows the individual level estimates. Lastly, Section 6 concludes.

2 A gravity approach to occupational mobility

Occupations can be represented as vectors of tasks and of the skills required to perform them (Autor et al., 2003; Acemoglu and Autor, 2011), which makes it possible to measure the skill distance between an origin and a destination occupation; a large literature shows that human capital is imperfectly transferable across occupations, and that moves spanning a larger distance are both costlier and less frequent (Gathmann and Schönberg, 2010; Guvenen et al., 2020; Macaluso, 2025). Skill distance does not exhaust the sources of mobility frictions, however. Occupations may also impose entry barriers that restrict access regardless of how close an origin job is in skill space,⁴ and growing or new occupations, such as green ones, may impose de facto lower barriers.⁵ Disentangling bilateral skill distance from occupation-specific barriers requires a framework that accommodates both.

2.1 A model of occupational choice

We build on the occupational mobility model of Cortes and Gallipoli (2018), which delivers a gravity equation linking worker flows to occupation characteristics and to the cost of switching.⁶ We summarise here only the elements needed to read our estimates.

There is a continuum of workers indexed by i and a finite set of occupations $j \in \{1, \dots, N\}$. A worker's initial occupation, k , is predetermined. Selecting into occupation j delivers the payoff

$$\varphi_j(i | k) = p_j f[X(i)] \frac{z_j(i)}{d_{j,k}}, \quad (1)$$

where p_j is the general attractiveness of occupation j common to all workers. $f[X(i)]$ is the return to the worker's own general human capital. $z_j(i)$ is an idiosyncratic match-quality draw, taken independently across workers and occupations from a Fréchet distribution of the form $z_j \sim F_j(z) = e^{-T_j z^{-\theta}}$, with T_j measuring the average quality of the draws, and θ measuring their dispersion.⁷ $d_{j,k} \geq 1$ is an iceberg transition cost (with

⁴Credential requirements, licensing, or specific training not measurable in terms of skill scores.

⁵On the one hand, the skill-set of workers in new occupations is ill-defined and still tacit, thus existing skills are less valuable performing these tasks. On the other hand, employers may be willing to accept less suitable candidates when creation of new jobs is highly rewarding or often subsidized.

⁶The model is a variant of Eaton and Kortum (2002), adapted to flows of workers across occupations; we refer the reader to their Section 2 for the derivations.

⁷Individuals can be thought of as receiving offers from a large number of potential employers within

$d_{k,k} = 1$ for stayers), which captures efficiency losses from learning a new set of skills and, more generally, from entering and adapting to a new occupation.

Since workers select the occupation offering the highest payoff and match qualities are Fréchet, the probability that a worker who starts in k selects j has the closed form

$$\pi_{j,k} \equiv \Pr\left[\varphi_j(i|k) \geq \max_s \{\varphi_s(i|k)\}\right] = \frac{T_j p_j^\theta d_{j,k}^{-\theta}}{\sum_s T_s p_s^\theta d_{s,k}^{-\theta}}. \quad (2)$$

The numerator measures how appealing j is, discounted by the cost of reaching it from k ; the denominator is that same quantity summed over every destination available to a worker in k , including k itself. The term $f[X(i)]$ enters the numerator and every element of the denominator alike, and therefore cancels out: the probability of moving from k to j does not depend on the general human capital of i , and is the same for every worker who begins the period in k . Further, because the draws are independent across the many workers who start in k , the fraction of them observed moving to j is equal to $\pi_{j,k}$. Writing $sw_{j,k}$ for the number of workers moving from k to j , $sw_{k,k}$ for the number who remain in k , and N_k for the number employed in k at the start of the period, $\pi_{j,k} = sw_{j,k}/N_k$: an individual choice probability and an aggregate flow share are the same object, so individual choices aggregate exactly into occupation-pair flows.⁸

The remaining unobservables are removed by comparing, within the same origin, destination j against k itself.⁹ Hence, $\frac{sw_{j,k}}{sw_{k,k}} = \frac{\pi_{j,k}}{\pi_{k,k}} = \frac{T_j p_j^\theta}{T_k p_k^\theta} d_{j,k}^{-\theta}$. The left-hand side is built entirely from observed counts. The right-hand side is not observable, but it contains only origin- and destination-specific terms, which occupation dummies absorb, and the bilateral cost $d_{j,k}$, which is the object of interest. Taking logarithms,

$$\ln\left(\frac{sw_{j,k}}{sw_{k,k}}\right) = \ln T_j + \theta \ln p_j - \ln T_k - \theta \ln p_k - \theta \ln d_{j,k} \quad (3)$$

one can define $\ln d_{j,k} = \beta_1 \text{dist}_{j,k} + \sum_{m=1}^4 \gamma_m \lambda_{j,k}^m + m_j + \epsilon_{j,k}$, where $\text{dist}_{j,k}$ is a bilateral, symmetric skill distance; $\lambda_{j,k}^m$ is a set of task-group switching indicators; m_j is an occupation-specific access cost; $\epsilon_{j,k}$ collects any remaining pair-specific determinant of the cost. Substituting the newly defined $\ln d_{j,k}$ into (3) yields the following gravity-type

each occupation and retaining only the best of them; the distribution of such maxima converges to an extreme-value distribution, of which the Fréchet is one case.

⁸Origin-level heterogeneity is innocuous: a shifter of the match-quality distribution specific to the worker's initial occupation scales all destinations proportionally and cancels in the ratio. Heterogeneity across destinations would not: if the returns to individual characteristics differed by destination $f[X(i)]$ would not cancel, and the aggregate coefficients would be composition-weighted averages of heterogeneous individual responses. This motivates the individual-level analysis in Section 5.

⁹Staying is costless, $d_{k,k} = 1$, so at $j = k$ leaves $\pi_{k,k} = T_k p_k^\theta / \sum_s T_s p_s^\theta d_{s,k}^{-\theta}$. The denominator is common to every destination reachable from k and cancels in the ratio; so does N_k , which scales the two flow counts alike.

equation:

$$\ln \left(\frac{sw_{j,k}}{sw_{k,k}} \right) = D_j - S_k - \theta \beta_1 \text{dist}_{j,k} - \theta \sum_{m=1}^4 \gamma_m \lambda_{j,k}^m - \theta \epsilon_{j,k}, \quad (4)$$

where $S_k \equiv \ln T_k + \theta \ln p_k$ summarises the payoff that occupation k offers its incumbents, combining the average quality of the match draws available in it (T_k) with its general attractiveness (p_k), so that occupations with a high S_k display low outflows. Meanwhile, D_j allows the following decomposition

$$D_j \equiv S_j - \theta m_j, \quad (5)$$

where S_j proxies the intrinsic attractiveness of occupation j and θm_j its occupation-specific access cost, so that occupations with high D_j display many inflows. Both S_k and D_j are identified by origin and destination fixed effects.¹⁰

The coefficients in (4) are not cost parameters but cost parameters scaled by θ , the elasticity of relative flows with respect to the transition cost: differentiating (3) gives $\partial \ln(sw_{j,k}/sw_{k,k})/\partial \ln d_{j,k} = -\theta$. The elasticity inherits this role from the dispersion of match quality: the more concentrated the draws, the less a lucky match can offset a costly move, and the more sharply flows respond to costs. Flow data therefore deliver $\theta \beta_1$, $\theta \gamma_m$ and θm_j , never the pieces separately: the coefficients of (4) are semi-elasticities of relative flows, not effects on the transition cost $d_{j,k}$. Because the same factor scales every coefficient, ratios among them identify relative magnitudes whatever the value of θ ; converting any of them to the cost scale requires a value of θ from outside the gravity equation, which the extreme-value assumption supplies.¹¹ The decomposition (5) likewise recovers θm_j rather than m_j , so that access costs are comparable across occupations under a common θ but convertible into a payoff loss only by taking a stand on its value.

2.2 An application to the green transition

We adapt this framework to the green transition, which constitutes a case of directional structural change: labour demand shifts towards green occupations and away from brown ones. In our data this appears as green occupations expanding faster than the economy and brown ones more slowly (Section 3.3); what the framework requires is the direction of reallocation, not a fall in brown employment. The question we ask is whether the

¹⁰Attractiveness is read off the origin side — workers leaving occupation j forgo S_j — and the access cost is the gap between attractiveness and the destination fixed effect. Intuitively, an occupation that many workers leave and many workers also enter must be relatively easy to access, whereas one that few leave and few enter must be attractive but hard to get into. The decomposition therefore allows evaluating whether occupations attract inflows because they are desirable or because they are relatively easier to access.

¹¹The standard deviation of ex-post log payoffs within an origin occupation equals $\pi/(\theta\sqrt{6})$. Cortes and Gallipoli (2018) back θ out from wage dispersion by initial occupation and adopt $\theta \simeq 3.23$; Appendix D.1 carries out the conversion for our estimates.

friction imposed by skill distance operates with the same intensity when the destination is green, or the origin brown, as it does elsewhere in the occupational space, and whether the occupations at either end of the transition differ in what draws workers to them.

Within the model, a directional shift in labour demand can alter observed mobility through three components. The first is attractiveness: expanding green occupations should offer improving demand conditions and possibly higher returns, hence a higher S_j ; occupations from which demand is receding the reverse. The second is the access cost m_j . Occupations at the margin of the transition, where green tasks are a small part of the job, may impose few occupation-specific requirements and display a low m_j , whereas those at its core may require specialised technical or regulatory competences that act as binding entry barriers despite strong demand; brown occupations may retain high access costs if firms that have stopped expanding have also stopped hiring. The third is the sensitivity of mobility to skill distance itself. In the baseline the penalty $\theta\beta_1$ is uniform across pairs, but employers in expanding occupations may accept larger skill gaps, and workers leaving occupations in decline may accept more distant moves, so that the same distance deters less; where the relevant skills are highly specific, it may deter more. The first two channels are read off the decomposition of the destination fixed effect; the third is what the interaction terms test.

We therefore augment (4) with an interaction term,

$$\ln \left(\frac{sw_{j,k}}{sw_{k,k}} \right) = D_j - S_k - \theta\beta_1 dist_{j,k} - \theta\beta_2 dist_{j,k} \times Green_j - \theta \sum_{m=1}^4 \gamma_m \lambda_{j,k}^m - \theta\epsilon_{j,k}. \quad (6)$$

where $Green_j$ is an indicator equal to one if the destination occupation j is green. A level term in $Green_j$ would be indistinguishable from the occupation-specific access cost m_j and is absorbed into D_j ; the coefficient of interest is $-\theta\beta_2$. A positive estimate says that the penalty attached to skill distance is smaller when the destination is green: green occupations tolerate more skill mismatch than the average destination, conditional on the fixed effects and the other controls.¹² Symmetrically, we replace $Green_j$ with $Brown_k$, an indicator for the origin occupation being brown, which the origin fixed effect S_k absorbs in levels; the interaction then measures whether exits from brown occupations face a smaller or larger distance penalty than exits from other occupations.

Cortes and Gallipoli (2018) estimate their specification by ordinary least squares; we employ a Poisson pseudo-maximum likelihood (PPML) estimator instead. The model's prediction is multiplicative: exponentiating (6) and moving the stayer count to the right-

¹²A weaker distance penalty is consistent with two readings: that distance raises the cost of entering those occupations by less, or that match quality is more dispersed there, so that the same cost deters less. Under a common θ the two scale the same object and we do not separate them; the interaction captures any mechanism through which the penalty differs.

hand side gives a conditional mean for the flow itself,

$$E[sw_{j,k}] = \exp(\tilde{\beta}_1 \text{dist}_{j,k} + \tilde{\beta}_2 \text{dist}_{j,k} \times \text{Green}_j + D_j - S_k + \sum_{m=1}^4 \tilde{\gamma}_m \lambda_{j,k}^m) \times sw_{k,k}, \quad (7)$$

with $\tilde{\beta}_1 = -\theta\beta_1$, $\tilde{\beta}_2 = -\theta\beta_2$ and $\tilde{\gamma}_m = -\theta\gamma_m$, so that the coefficients are the same objects as in (6) and, since S_k and D_j enter the exponential index, the fixed effects retain the structural content of (5). Two considerations favour the multiplicative form. Under heteroskedasticity, OLS on the log ratio is inconsistent, because the expectation of a logarithm is not the logarithm of an expectation (Santos Silva and Tenreyro, 2006), whereas PPML requires only that the multiplicative error be mean-independent, which is the assumption the model delivers. And at the 4-digit level many occupation pairs record no transition, for which the log ratio is undefined; replacing zeros with an arbitrary constant makes the estimates depend on the units of the outcome (Chen and Roth, 2024), whereas PPML operates on the level of the flow (Santos Silva and Tenreyro, 2006; Anderson, 2011; Head and Mayer, 2014). Our preferred specification excludes pairs with no flow in either direction (Head and Mayer, 2014). The stayer count $sw_{k,k}$ enters as an offset, a regressor whose coefficient is restricted to unity, reproducing the normalisation of the log-ratio dependent variable. Because $\ln(sw_{k,k})$ varies only across origins it is collinear with the origin fixed effects, so the slope coefficients are unaffected by its inclusion; what the offset delivers is the level of the origin effect, which then identifies $-S_k$ rather than $-S_k + \ln(sw_{k,k})$, as the decomposition (5) requires.¹³

Finally, we apply the decomposition (5) within the green transition. Because the fixed effects are estimated conditional on bilateral skill distance and on transitions across broad task groups, S_j and θm_j capture the residual pull or repulsion of an occupation once skill-related frictions have been netted out. This allows us to ask whether green occupations draw workers (a high D_j) because they are desirable (a high S_j) or because they are relatively easy to enter (a low θm_j), and symmetrically whether brown occupations lose ground because they have become less attractive or harder to enter.

3 Data, measures and descriptives

We employ a unique dataset that combines administrative job flow data with data from a survey on job characteristics.

¹³The same argument covers the difference between our stayer count and that of Cortes and Gallipoli (2018), who count all workers still employed in the origin occupation one period later: the two differ by an origin-specific rate of new match formation, which the origin fixed effects absorb.

3.1 Data sources

Administrative data on job-to-job transitions. Our primary source is the Compulsory Communications archive (*Sistema delle Comunicazioni Obbligatorie*, CO), maintained by the Italian Ministry of Labour and Social Policies, which since 2009 has recorded every activation, modification and termination of an employment relationship in Italy. For each contract we observe the worker’s age, sex and educational attainment, the contract’s duration and type (full- or part-time, fixed-term or open-ended), the province of work, and the occupation at the 5-digit level of the Italian classification of occupations (CP2011). From this archive we draw a representative sample of individuals born on four dates per month, 48 birth dates per year, and follow their employment events over time. Because the CO is an administrative census rather than a survey, and because activations and terminations are recorded by employers as they occur, the sample is free of the attrition and recall problems that affect survey-based mobility measures (e.g. Ardito et al., 2022). Two limitations matter for what follows. The archive carries no information on earnings. Further, it records flows rather than stocks: a worker counts as remaining in her occupation only when she forms a new employment relationship within it, so that our estimates describe where movers go conditional on a move taking place, rather than whether a move occurs at all. Appendix A.1 describes the archive and these features in more detail.

We restrict the sample to employees aged 15 to 64, excluding the armed forces, and drop terminations due to death or retirement together with contracts shorter than 180 days, which filters out seasonal and occasional work. We further exclude contracts initiated before 2009, when CO coverage was still incomplete, and all observations preceding 2012, so that the whole analysis period uses the CP2011 occupational classification and reclassification artefacts are not mistaken for genuine occupational mobility. Because the CO records employment events rather than employment stocks, we then construct a balanced individual-year panel by retaining, for each worker and year, a single most relevant contract, selected through an ordered set of tie-breaking rules set out in Appendix A.1. The resulting panel covers 2,793,904 workers and slightly more than 13 million job-to-job transitions over 2012–2023. For the gravity estimates we cumulate these flows over the whole period and treat the resulting matrix as a single cross-section of occupation pairs.¹⁴

Skill data. Occupational skill and task content comes from the *Indagine Campionaria sulle Professioni* (ICP), a survey of roughly 16,000 workers carried out twice, in 2007 and 2013, by INAPP (*Istituto Nazionale per l’Analisi delle Politiche Pubbliche*), which documents the skill and knowledge requirements of Italian occupations. The ICP mirrors the structure of the U.S. Occupational Information Network (O*NET) closely enough

¹⁴We also use the Italian Labour Force Survey, mainly for weighting purposes; see Appendix A.2.

for us to transpose the methodology of Vona et al. (2018) to the Italian context. Its questionnaire records 255 items, grouped in sections covering general knowledge, general skills, abilities, work values, soft skills, work activities and working conditions, and reports for each item how relevant it is to the occupation. We set aside work values and working conditions, neither of which describes transferable human capital, and soft skills, which we screen by the same procedure as the other sections but which yield no retained skill. The 109 items covering general knowledge, general skills and work activities are those we screen for green and brown intensity in Section 3.2; adding the 52 items on abilities, which workers cannot easily acquire but which shape the cost of moving between occupations, gives the 161 dimensions from which we compute our broad measure of skill distance. Appendix A.3 sets out the sections and this split in detail. We merge the ICP with the CO data using the 5-digit occupation codes.

Definition of green and brown jobs. To identify green jobs, we follow Vona et al. (2018), who construct a continuous occupation-level greenness index using a task-based approach applied to O*NET data. Greenness is defined as the share of green tasks relative to the total number of tasks assigned to an occupation, yielding a measure ranging from zero (no green tasks) to one (all tasks are green). This metric is constructed at the granular six-digit Standard Occupational Classification (SOC) level, utilizing the task classifications established as part of the O*NET Green Task Development Project (Dierdorff et al., 2009).

Because green task measures are not available in ICP, we follow a common practice in the literature (Goos et al., 2014) and impute the US O*NET greenness to Italian occupations (Elliott et al., 2024; Vona, 2021).¹⁵ Concretely, we map SOC occupations to the CP2011 classification, using the International Standard Classification of Occupations (ISCO) as a bridge. Because SOC, ISCO, and CP2011 differ in their level of aggregation, this procedure entails many-to-many mappings that may introduce measurement error. To mitigate this issue, we manually harmonise CP2011 (5-digit) and ISCO (4-digit) occupations, using the official three-digit ISCO crosswalk only as a consistency check, and perform targeted corrections to address clear misclassification. This yields a SOC(6d)–ISCO(4d)–CP2011(5d) mapping that preserves as much task-level information as possible.

The gravity specification interacts skill distance with an indicator for the destination occupation, so we discretise the greenness score. Occupations with a greenness of at least 0.1 are classified as *Green*, following Vona et al. (2018); the subset with a greenness of at

¹⁵Vona (2021) argues that this cross-walk provides an acceptable greenness measure when occupation-level data are granular enough. Further, Dicarolo et al. (2016) show that imputing O*NET tasks to other countries provides a good approximation of the task content for developed countries, but not for developing ones. This is consistent with the fact that technologies and thus tasks are more similar for countries at the same stage of development.

least 0.3 as *Green Core*. A binary green margin also keeps the destination side symmetric with the brown origin side, which is binary by construction.

Unlike the classification of green jobs, which relies on task content, no standardized taxonomy of ‘brown’ tasks exists. We therefore again follow Vona et al. (2018) and define brown occupations based on their concentration in pollution-intensive industries. We define brown occupations as those with more than 10% of employment in highly polluting industries — those above the 95th percentile of pollution intensity for multiple regulated pollutants at the NAICS 4-digit level (Cavallotti et al., 2025). To identify brown occupations in the Italian labour market, we then map this classification to the CP2011 system using the same SOC(6d)–ISCO(4d)–CP2011(5d) crosswalk procedure described above. Appendix A.4 provides the full list of green and brown occupations used in this work.

3.2 Skill measures

General Green and Brown Skills. Our goal is to identify the skills that are most relevant for green and brown occupations. This allows us to construct skill distance metrics limited to the subset of skills relevant for the green transition, thus minimising the noise that the inclusion of other, less relevant, skills would entail. In doing so, we adapt and extend the framework of Vona et al. (2018) to the Italian context.

The framework uses a simple regression model to reveal the general skills that are used intensively in green (Green General Skills, GGS) or brown jobs (Brown General Skills, GBS). More specifically, we regress the relevance score of each general skill ℓ in occupation k on the greenness indicator (or a brown job dummy) plus a set of two-digit occupational dummies:

$$Skill_k^\ell = \beta^\ell \times Greenness_k + \phi^{CP_{2D}} + \epsilon_k \quad (8)$$

We include occupational dummies ($\phi^{CP_{2D}}$) to enhance the comparability of skill profiles of occupations with similar core characteristics. We use only two-digit occupational macro-groups containing at least one green occupation, or, for the GBS regressions, at least one brown one, which eliminates broad groups with no bearing on the transition, such as “unskilled professions in domestic, recreational and cultural activities” (CP2011 82), and leaves 543 and 364 five-digit occupations respectively. Thus, we identify GGS by comparing green and non-green occupations that are relatively similar in overall task content and skill profiles. A positive (negative) and significant β^ℓ denotes that general skill ℓ is used more (less) intensively in greener occupations. All regressions are weighted using LFS employment shares at the 3-digit level. We avoid discretion in functional form choices and mitigate measurement error by running five different variations of specification 8. A general skill ℓ is classified as green when: i) β^ℓ is positive and statistically

significant at the 5% level; ii) β^ℓ is not significantly negative (at the 5% significance level) in any of the considered specifications; iii) β^ℓ is positive and statistically significant in the majority of the specifications.

We then adapt this procedure to symmetrically extract GBS. The only difference consists in changing the main explanatory variable in the regressions, replacing the greenness measure with a binary indicator for brown occupations. Further, more technical, details on the selection of GGS and GBS skills are provided in Appendix B.1.

Our procedure gathers a set of 28 General Green Skills, reported in Table B4. The overlap with Vona et al. (2018) is substantial: 11 of the 14 GGS they identify appear in our list. This overlap concentrates in engineering, technical and systems-analytic skills, and confirms that what distinguishes green jobs from comparable non-green ones is applied technical and analytical competence rather than scientific knowledge as such.

Lastly, our procedure identifies a list of 18 General Brown Skills, as reported in Table B7. The GBS are overwhelmingly technical in nature, spanning engineering and physical-science knowledge, production and process control, and technical problem-solving. Notably, 13 of the 18 GBS are also included in the list of 28 GGS.¹⁶ The overlap between general green and brown skills indicates that green and brown occupations are quite similar, consistently with findings of previous work (Vona et al., 2018). This overlap suggests scope to facilitate transitions from brown to green jobs by building on existing skill endowments, thereby limiting transitional costs and unintended distributional effects.

Skill distance metrics. We measure how dissimilar the skill requirements of two occupations are, and use that dissimilarity as a proxy for the adjustment cost a worker bears in moving between them. Following the literature on human capital specificity and occupational mobility (Gathmann and Schönberg, 2010; Ingram and Neumann, 2006; Macaluso, 2025), we characterise each occupation as a vector of skill scores and compute a pairwise distance between these vectors. We work at the 4-digit occupational level, since finer granularity leaves too few flows between specific occupation pairs (Cortes and Gallipoli, 2018). Appendix B.2 sets out the alternatives and their implications.

We construct two complementary measures that differ in how occupations are characterised as skill vectors. The first uses raw relevance scores restricted to the skills most pertinent to the transitions we study: GGS (Table B4) when we examine transitions into green occupations, and GBS (Table B7) when we examine transitions out of brown occupations. Restricting attention to the relevant subset prevents the metric from being diluted by irrelevant skills. The second measure takes a broader perspective. Following a common practice in the literature (Ingram and Neumann, 2006; Poletaev and Robin-

¹⁶The five brown skills that do not overlap reflect the production- and supervision-oriented content distinctive to polluting occupations, such as Operating Machines and Processes and Managing Material Resources.

son, 2008; Guvenen et al., 2020), we summarise the 161 items of ICP sections B, C, D and G through a factor analysis, and represent each occupation by its scores on four latent factors, which capture the overarching functional dimensions of an occupation’s skill profile.

For both vector characterisations we measure the distance between two occupations with the Manhattan (ℓ_1) norm, which is sensitive to the *level* of skill requirements and not only to their composition. Angular separation, the common alternative, registers no distance when all requirements rise proportionally, whereas occupational transitions typically involve adjustments in skill intensity. We compute unweighted distances, for transparency.

Concretely, for each occupation we collect the relevant skill scores into a vector, and rescale each component to the unit interval so that all skill dimensions are placed on a comparable scale.¹⁷ The skill distance between occupations j and k is then the average absolute difference between their rescaled vectors:

$$dist_{j,k} = \frac{1}{M} \sum_{m=1}^M \left| \tilde{R}_m^j - \tilde{R}_m^k \right|, \quad (9)$$

where, for the raw-score measure, $M = 28$ over the GGS (for transitions into green occupations) and $M = 18$ over the GBS (for transitions out of brown occupations), while $M = F = 4$ for the factor-based measure. The resulting measure is symmetric and bounded between 0 and 1, where 0 denotes identical skill profiles and higher values indicate greater skill dissimilarity. These pairwise distances form the empirical basis of our analysis of job-to-job transitions and occupational mobility.

3.3 Descriptive evidence

We document a set of stylised facts on job-to-job mobility that motivate the gravity analysis of Section 2 and characterise the scale and direction of occupational reallocation over our sample period.

Raw occupational mobility. Table 1 reports the volume of job-to-job transitions across classified 4-digit occupations. Over the sample period we observe roughly 1.5 million moves between occupations, 1.07 million once weighted by full-time equivalence.¹⁸ These account for about 12% of all job-to-job transitions in the data, the remaining 88% being moves that stay within the same 4-digit occupation. The occupation-changing moves are the object of this study.

¹⁷Formally, letting R_m^{max} and R_m^{min} denote the maximum and minimum score of component m across occupations, each score R_m^j is rescaled as $\tilde{R}_m^j = (R_m^j - R_m^{min}) / (R_m^{max} - R_m^{min})$.

¹⁸Full-time-weighted flows between classified 4-digit CP2011 occupations with a defined origin and destination, 2012–2023; this is the sample used for the gravity analysis.

Within the sample of transitions with an occupation change, 9.1% are towards a green destination and 3.3% towards a green-core one, while 2.7% are exits from a brown occupation. Our green threshold admits many occupations that are only marginally green, so the 9.1% share exceeds vacancy-based measures of green employment; the green-core share of 3.3% is close to the 2.6–3.6% reported for Europe by Cass et al. (2026) and to other estimates for Europe and the United States (Vona et al., 2019; Bluedorn et al., 2023). The direct brown-to-green channel is no larger than the average. On full-time-weighted flows, brown leavers move into green occupations at 9.4%, against a 9.1% green share of all transitions, and into green-core occupations at 3.6% against 3.3%; in levels this is 2,682 and 1,020 moves, or 0.25% and 0.10% of all transitions. The same thinness of the direct channel is found for the United States by Curtis et al. (2024) and for Germany by Bachmann et al. (2026).

Table 1: Job-to-job transitions, by destination and origin type

	Transitions (full-time weighted)	% of all transitions
<i>Panel A. By destination / origin type</i>		
All transitions	1,067,756	100.0
of which to green ($g_j \geq 0.1$)	97,627	9.1
of which to green-core ($g_j \geq 0.3$)	35,476	3.3
of which from brown	28,486	2.7
of which from brown to green	2,682	0.25
of which from brown to green-core	1,020	0.10
<i>Panel B. Occupational reach of the move</i>		
Crosses a different 3-digit occupation	951,968	89.2
Crosses a different 2-digit occupation	839,764	78.6
Crosses a different 1-digit macro-group	686,717	64.3

Notes: Full-time-weighted job-to-job transitions, 2012–2023, COB administrative data, between classified 4-digit CP2011 occupations with a defined origin and destination (armed forces and undefined-origin flows excluded). All transitions change the 4-digit occupation by construction; Panel B reports the share that additionally crosses a coarser occupational boundary (shares are monotone, since a change of 1-digit group implies a change of 2- and 3-digit code). Subsets in Panel A are nested (“of which”). Percentages are shares of all transitions.

Panel B of Table 1 characterises how far these moves travel across the occupational hierarchy. Every transition changes the 4-digit occupation by construction; beyond that, 89.2% cross a 3-digit boundary, 78.6% a 2-digit boundary and 64.3% a 1-digit macro-group. Figures C1 and C2 show the same concentration directly, for all transitions and for green, green-core and brown ones separately.

Green and brown flows across macro occupational groups. Table C1 in Appendix C aggregates these flows to 1-digit macro-groups and benchmarks each group’s

share against its share of all transitions. Two patterns matter for what follows. Green hires are drawn disproportionately from craft and elementary occupations, which supply 62% of them against 36% of all transitions, whereas professionals, clerical and service workers are under-represented by half or more; professionals nonetheless gain share between origin and destination, so that entry into green work entails some occupational upgrading. Brown leavers, more than half of whom are plant and machine operators, disperse across operator, craft, elementary and technical destinations, with a pull towards operator jobs at twice their overall weight. The first pattern anticipates the skill-selectivity of green entry, the second the portability of brown skills; the gravity estimates below quantify both.

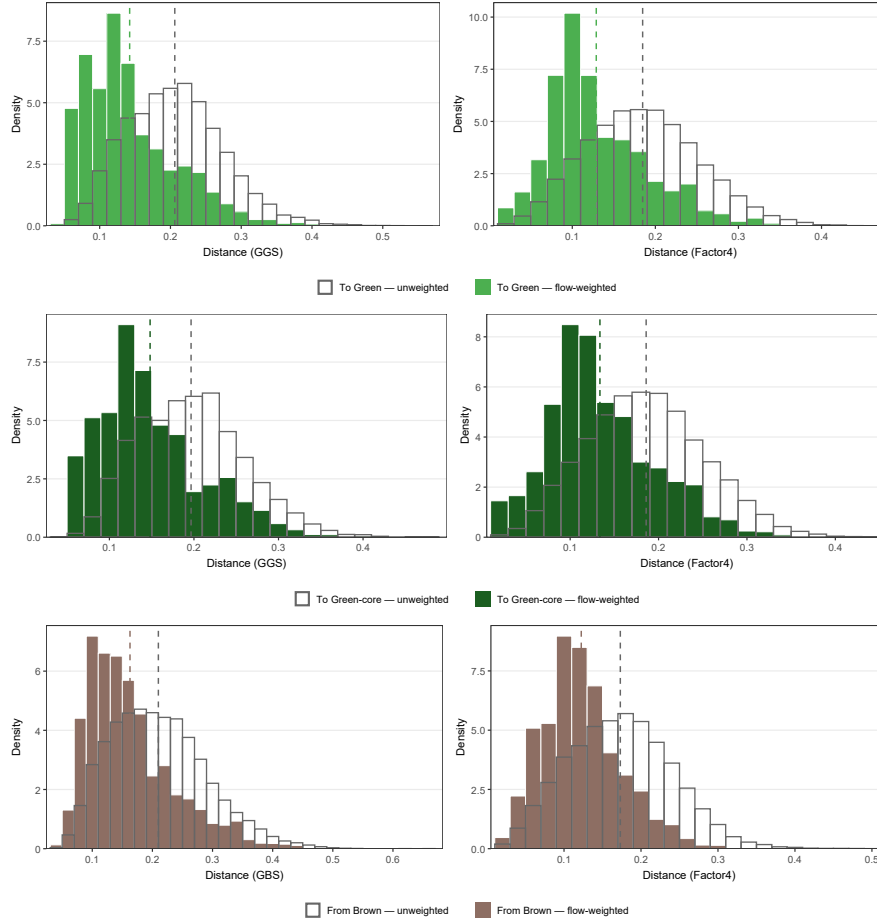
At the 4-digit level, Table C2 lists the ten largest origin–destination pairs for each direction; the largest single pair accounts for only 4% of green flows, so realised mobility is dispersed across many pairs. Flows into green destinations are dominated by short-distance moves within construction trades and within agriculture. Restricting to green-core destinations sharpens the picture into recognisable green-intensive substitutions, such as power-line fitters into civil-construction electricians, heavy-goods drivers into bus and tram drivers, and freight handlers into waste and recycling workers. Brown exits are instead lateral moves within occupations prominent in energy-intensive industries, such as foundry workers into unskilled industrial workers. The few direct brown-to-green moves (Tables C3 and C4) follow two routes: a construction-trades route, from earth-moving operators, blacksmiths and industrial painters into unskilled construction, window-and-door installation and insulation work; and a chemistry-and-environmental route, from chemical technicians and continuous-process operators into environmental-remediation, waste-recycling and water-treatment work.

The skill-distance distribution of flows. We compare, within each transition type, the distribution of skill distances across all feasible origin–destination pairs with the distribution across the pairs that workers actually traverse. Figure 1 plots, for moves into green and green-core destinations and out of brown origins, the unweighted density of pairwise distances (hollow outline) against the flow-weighted density (filled histogram). Distances are measured over the GGS for green destinations and over the GBS for brown origins, so that each direction is gauged along its own skill margin; the second column repeats the exercise with the four-factor distance.

In every panel the flow-weighted distribution is markedly shifted to the left of the unweighted one, and its right tail is nearly empty: many distant pairs exist, but few workers move between them. The flow-weighted mean sits 25–31% below the unweighted mean for green and green-core moves under the GGS metric ($0.206 \rightarrow 0.142$ and $0.197 \rightarrow 0.148$), 22% below for brown exits under the GBS metric ($0.210 \rightarrow 0.163$), and around 30% below under the factor-based metric throughout. Over all transitions (Figure C3)

the shift is slightly larger, at 32–34% whichever metric is used ($0.185 \rightarrow 0.125$ over the GGS, $0.196 \rightarrow 0.134$ over the GBS, $0.184 \rightarrow 0.122$ over the four factors). This left shift is the distance penalty of the gravity model in descriptive terms: skill distance depresses realised mobility before any occupation fixed effect is netted out, and it does so under every vector characterisation. Whether the somewhat smaller shift for green and brown transitions reflects a weaker distance penalty or a different set of feasible pairs is precisely what the gravity model separates.

Figure 1: Skill distance of realised flows vs. all occupation pairs, by transition type

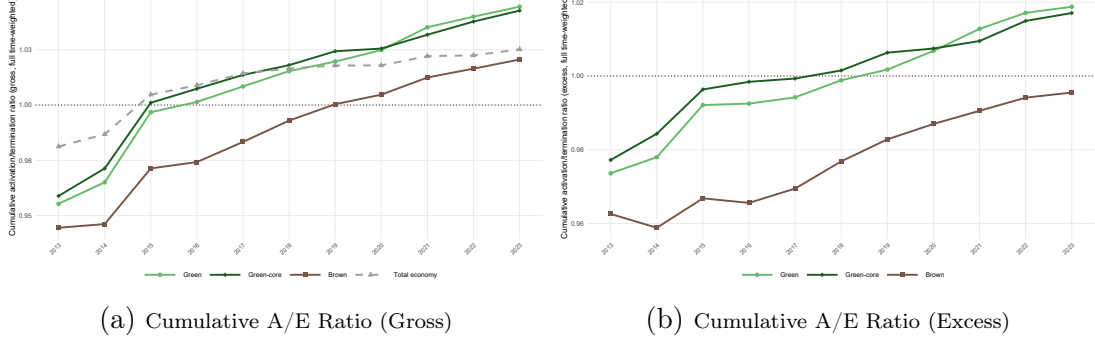


Notes: Density of pairwise skill distance for transitions into green ($g_j \geq 0.1$, top row), into green-core ($g_j \geq 0.3$, middle row) and out of brown occupations (bottom row). In each panel the hollow grey outline is the unweighted distribution over all occupation pairs in the group; the filled bars weight each pair by its full-time-weighted flow. The left column measures distance over the group-relevant raw-skill vector (General Green Skills for green rows, General Brown Skills for the brown row); the right column uses the four-factor distance. Dashed lines mark the unweighted (grey) and flow-weighted (coloured) group means. Bin width 0.02; distances standardised.

Job creation and destruction. Because the CO records flows rather than stocks, we track the trajectory of green and brown occupations through contract activations and terminations rather than employment levels. For each occupation group i (green, green-

core, brown, and the economy as a whole) we compute the activation-to-termination ratio $g_{it} = a_{it}/e_{it}$, where a_{it} and e_{it} are full-time-weighted activations and terminations in year t ,¹⁹ and its cumulative version $G_{it} = \sum_{s \leq t} a_{is} / \sum_{s \leq t} e_{is}$, which smooths year-to-year volatility. To net out aggregate labour market conditions we then take the ratio of each group’s cumulative index to the economy-wide one, $G_{it}^{excess} = G_{it}/G_t$.

Figure 2: Job creation and destruction patterns in job mobility



Notes. Sub-figure (a) plots the cumulative activation-to-termination ratio for each occupation group (green, green-core, brown) and for the total economy. A value above (below) one indicates net cumulative growth (decline) in the number of contracts since 2012. Sub-figure (b) reports the excess cumulative ratio, defined as each group’s cumulative index divided by the economy-wide cumulative index. A value above (below) one indicates that the group is expanding faster (slower) than the overall economy. Source: COB, 2013–2023.

Figure 2 plots both indices over 2013–2023. Sub-figure (a) shows that green and green-core occupations grow faster than the economy in cumulative full-time-weighted contracts, ending the period with a gross ratio of about 1.05 against 1.03 for the economy, while brown occupations lag behind throughout and end at about 1.02. In sub-figure (b), green and green-core occupations start below the economy-wide baseline, cross it in 2017–2018 and end about 2% above it; brown occupations remain below the baseline across the entire sample, recovering only towards parity by 2023.²⁰ Green occupations thus expand faster than the economy and brown occupations more slowly: this is the directional structural change that forms the backdrop against which the frictions to occupational mobility operate.

4 Results

This section reports the gravity estimates, subjects them to robustness checks, and then decomposes the destination fixed effects into attractiveness and access costs, as set out in Section 2.

¹⁹By construction, $g_{it} = 1$ indicates a stable occupation group, $g_{it} > 1$ a growing one and $g_{it} < 1$ a shrinking one.

²⁰Figure C4 shows that these conclusions are robust to measuring dynamics through cumulative net activations rather than activation-to-termination ratios.

4.1 Gravity estimates

Table 2 reports PPML estimates of (7) across 4-digit occupations, with distance measured over the GGS in columns (1)–(3) and over the GBS in column (4).²¹

Table 2: Skill distance and job to job transitions. GGS distance for green destinations; GBS distance for brown origins.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-0.9754*** (0.0438)	-1.0036*** (0.0480)	-0.9808*** (0.0456)	-0.7064*** (0.0351)
$dist_{j,k} \times Green_j$		0.2053** (0.0936)		
$dist_{j,k} \times Green\ Core_j$			0.1114 (0.0880)	
$dist_{j,k} \times Brown_k$				0.0535 (0.0617)
Num.Obs.	79848	79848	79848	79848
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance in the Green and Green-Core columns and to the GBS (brown-skill) distance in the Brown column, and to the GGS distance in the baseline column (1). $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Across all specifications the skill-distance coefficient is negative and significant, between -0.975 and -1.004 on the GGS distance. Column (1), which omits the interactions, places the average friction at -0.975 : a one-standard-deviation increase in distance reduces expected flows by 62%.²² To give a sense of what one standard deviation means, take a green-core destination such as bus and tram drivers (CP2011 7422): its closest origin in GGS space is taxi and van drivers (7421), and starting instead from construction labourers (8421), a green occupation, adds about 1.25 standard deviations of distance.²³

²¹Column (1) uses the GGS so that it nests columns (2) and (3); the GBS enters only in column (4), where brown-skill space is the relevant metric for exits from brown occupations. The two distances are standardised separately and are not on a common scale: the same baseline on the GBS gives -0.706 against -0.975 on the GGS.

²² $1 - \exp(-0.975) = 0.623$. The same conversion, $1 - \exp(\hat{\beta})$, applies to every coefficient reported below; since $dist_{j,k}$ is standardised, each is a semi-elasticity per standard deviation of distance.

²³Likewise, for renewable-energy and energy-saving technicians (3136), a green-core occupation, the

The friction is larger than in Cortes and Gallipoli (2018), whose estimates imply -0.426 per standard deviation.²⁴ Part of the gap is aggregation: on 2-digit occupations our baseline falls to -0.673 (Table D1, column (1)). We retain the 4-digit estimates as our preferred specification because aggregation averages skill profiles across occupations that are heterogeneous in task content, compressing the dispersion of bilateral distances and attenuating the friction, and because it is the level at which green, green-core and brown occupations can be identified without diluting them into broader groups.

Column (2) interacts distance with the green-destination indicator. The interaction is positive and significant. Once it is included, the distance coefficient identifies the slope for non-green destinations, -1.00 , a 63% reduction in flows per standard deviation, while the implied slope for green destinations is -0.80 ($-1.00 + 0.21$), a 55% reduction. Distance still depresses mobility into green occupations, but less than elsewhere: marginal green destinations tolerate more green-skill mismatch.

Columns (3) and (4) find no such attenuation for green-core destinations on the GGS distance or for brown origins on the GBS distance: both interactions are positive and insignificant. The most intensely green occupations remain as selective on green-specific content as the average destination, and exits from brown occupations are neither more nor less sensitive to brown-skill mismatch than exits from other occupations.

Table 3 re-estimates the same specifications with distance measured over the four latent factors, which, as detailed in Appendix B.2, capture broad dimensions of occupational skill structure, namely analytical ability, physical dexterity, supervisory tasks and managerial competences, rather than green- or brown-specific skills.

The distance coefficient is again negative and significant in every column, between -0.93 and -0.94 . The baseline of column (1) implies a 61% reduction in flows per standard deviation, in line with the GGS estimate: mismatch in broad transferable skills is as important a friction as mismatch in green-specific ones.²⁵ Column (2) shows no attenuation for green destinations: the interaction is insignificant, so the tolerance found in Table 2 is specific to green-skill content rather than to general skills.

Column (3) reverses the earlier pattern for green-core destinations. The interaction is positive and significant, and the implied slope of -0.82 ($-0.94 + 0.11$) corresponds to a 56% reduction in flows per standard deviation, against 61% for other destinations. Read alongside the GGS result, this is a two-margin pattern: green-core occupations stay selective on the green-specific content that defines them while relaxing the requirement of proximity in general skills, as expanding occupations compromising on the margin they

closest origin is mechanical engineers (2211), also green-core; starting from production-management technicians (3315) adds roughly 1.55 standard deviations.

²⁴They report this as a 43% fall in the switcher-to-stayer ratio, reading the coefficient directly as a percentage; on our convention, $1 - \exp(\hat{\beta})$, it corresponds to about 35%. Comparisons across the two papers are therefore made on the coefficients.

²⁵On 2-digit occupations the factor-based baseline is -0.706 (Table D1, column (3)); both of our 2-digit estimates remain above the -0.426 of Cortes and Gallipoli (2018).

Table 3: Skill distance and job to job transitions. Factor analysis (4) in vector characterization.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-0.9307*** (0.0330)	-0.9276*** (0.0346)	-0.9352*** (0.0338)	-0.9341*** (0.0336)
$dist_{j,k} \times Green_j$		-0.0308 (0.0821)		
$dist_{j,k} \times Green\ Core_j$			0.1128* (0.0665)	
$dist_{j,k} \times Brown_k$				0.1317** (0.0575)
Num.Obs.	79848	79848	79848	79848
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance, standardized on the full estimation sample. $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

can afford to would (the second channel of Section 2.2). Column (4) finds the same for brown origins: the interaction is positive and significant, and the implied slope of -0.80 ($-0.93+0.13$) corresponds to a 55% reduction against 61%. Along broad skill dimensions, exits from brown occupations are less constrained by distance than other exits, which suggests that workers in brown occupations hold transferable general capabilities.

Taken together, the two tables show that different segments of the green transition tolerate different kinds of skill mismatch. Measured over green-skill content, marginal green destinations accommodate workers who lack it while the most intensely green ones remain selective; measured over general skills, the pattern reverts, with green-core destinations and brown origins tolerating larger gaps and marginal green destinations none. The two margins read consistently once one asks what each destination actually requires. In a marginally green occupation green tasks are a small part of the job, so a gap in green-specific skills is a gap in something the job needs little of: the friction relaxes because that skill is peripheral to the work, and it binds in green-core occupations because there the green content is the work. Brown exits face the full friction on brown-specific skills, which are what a leaver must leave behind, but a reduced one on general capabilities, which are what carries a leaver across; Section 3.2 showed those brown skills to

be overwhelmingly technical and largely shared with green occupations, in line with the finding of Vona et al. (2018) that brown jobs use green general skills more intensively than other non-green jobs. Which dimension of skill binds therefore depends on the occupation, as the literature on multidimensional mismatch would lead one to expect (Güvenen et al., 2020; Lise and Postel-Vinay, 2020). All magnitudes above are on the scale of flows. Expressing them as effects on the transition cost $d_{j,k}$, the scale on which Cortes and Gallipoli (2018) report their estimates, requires a value of the dispersion parameter θ , which flow data alone cannot identify; Appendix D.1 carries out that conversion and reports its sensitivity to θ . The ordering of the distance penalties across occupation types is invariant to θ , since ratios of coefficients are free of it, while their level is not.

4.2 Additional results and robustness checks

To test whether our results depend on the choice of vector characterisation, we recompute skill distance over the full set of 161 ICP dimensions, without prior selection or dimensionality reduction (Table D2). The coefficient on $dist_{j,k}$ remains negative, significant and larger in absolute value, reflecting the greater distances implied by a wider skill space, but all interaction terms become insignificant. Measuring distance over all 161 dimensions captures overall occupational dissimilarity without isolating the skills valued in the green transition, and forgoes the latent general skill structure that makes the factor-based measure informative. Our preferred vector characterisations therefore remain those of the main results: the GGS and GBS distances, which isolate the skills directly implicated in the transition, and the factor-based distance, which summarises the general skill structure of occupations.

Retaining all origin–destination pairs, including those with no observed transition (Tables D3 and D4), leaves the distance coefficients and the GGS-based interactions unchanged. The factor-based interactions for green-core destinations and brown origins keep their sign but lose significance, falling from 0.113 to 0.078 and from 0.132 to 0.047. These are the two smallest groups, and the 170,653 pairs added to the sample are structurally zero flows that carry no variation for identifying an interaction.²⁶ Our main specification, conditioning on pairs with observed flows in at least one direction, retains a more informative sample for the infrequent occupation types affected by the green transition and is therefore preferred.

Adding the fixed effects and the task-difference dummies gradually (Tables D5 and D6) leaves the distance coefficient essentially unchanged.²⁷ The interactions are more sensi-

²⁶Gross flows relative to gray occupations are 8.52% for green, 1.67% for green-core and 1.37% for brown occupations.

²⁷The task-difference dummies follow the taxonomy of Acemoglu and Autor (2011) and capture costs of switching between task groups that the distance measure does not (Cortes and Gallipoli, 2018); a distance effect that survives their inclusion reflects skill distance over and above the task-transition margin.

tive. Under the GGS–GBS characterisation the task dummies turn the green-core interaction (0.172 to 0.111) and the brown-origin interaction (0.148 to 0.054) insignificant, as task-content differences absorb variation otherwise loaded onto distance, and the green interaction is interpretable as a difference in the slope on distance only once the 4-digit fixed effects absorb occupation size and attractiveness. The factor-based interactions are stable throughout.

To check whether single occupations drive the interactions, we exclude the five largest occupations of each group, by inflow for green and green-core destinations and by outflow for brown origins, one at a time and then jointly, from both sides of the flow matrix (Tables D7, D8 and D9; the excluded occupations are listed in the table notes).²⁸ The brown-origin interaction on the factor-based distance is unaffected. The green-core interaction on the factor-based distance loses significance when motor-vehicle mechanics or waste and recycling workers are excluded singly, but survives the joint exclusion of all five. The green interaction on the GGS distance is positive and significant at the five percent level or better in every single exclusion but one, and remains so, at 0.148 and the ten percent level, when all five occupations are excluded jointly; the exception is unskilled construction workers, whose exclusion alone reduces it to 0.011 and removes its significance. The tolerance of green-skill mismatch in marginally green destinations is therefore not an artefact of the largest green destinations as a group, though it leans on one of them, a large occupation with modest GGS requirements.

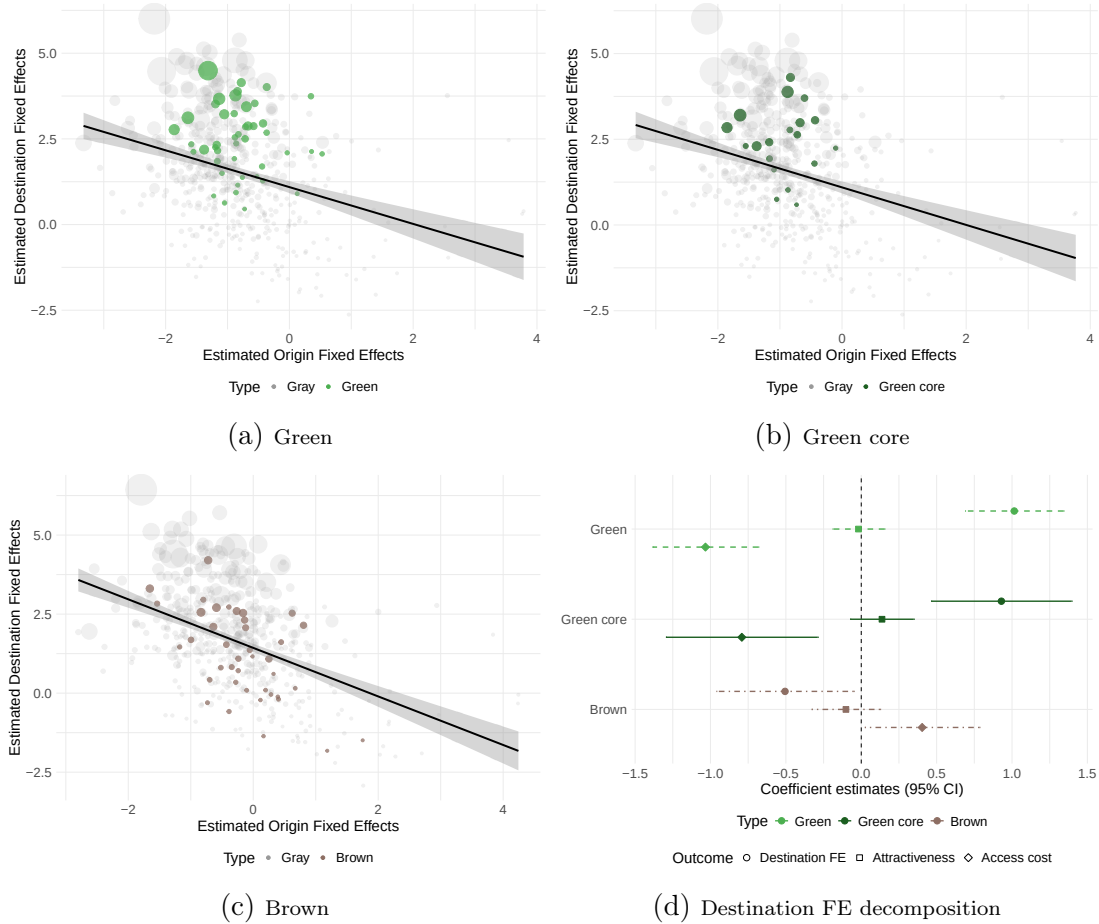
Lastly, re-estimating by negative binomial, which allows for overdispersion (Tables D13 and D14), leaves the distance coefficient negative and strongly significant, at -0.85 on the GGS and -0.83 on the factor-based distance; the marginal-green interaction keeps its sign and significance, the green-core interaction turns significant, and the factor-based brown-origin interaction loses precision. We nonetheless prefer PPML, for two reasons. It is consistent whenever the conditional mean is correctly specified, whatever the distribution of the outcome (Gourieroux et al., 1984; Santos Silva and Tenreiro, 2006), so that the severe overdispersion in our data, a Pearson statistic of 43.5 against unity under equidispersion, bears on efficiency, which clustered standard errors address, and not on consistency. And its estimates are invariant to the units of the dependent variable, whereas those of the negative binomial are not (Head and Mayer, 2014; Bosquet and Boulhol, 2014): multiplying all flows by ten leaves the PPML coefficient unchanged and moves the negative binomial one from -0.855 to -0.818 , a sensitivity that matters when the outcome is a twelve-year sum of employment-weighted flows.

²⁸Tables D10, D11 and D12 repeat the exercise for the remaining combinations of characterisation and group.

4.3 Fixed effects decomposition

Having characterised the role of skill distance within the green transition, we now decompose the destination fixed effects into their attractiveness and access-cost components, asking whether inflows into green occupations are driven by intrinsic attractiveness (S_j), by low access costs (θm_j), or by both, and, symmetrically, whether flows away from brown occupations reflect low desirability or high barriers to entry. Figure 3 reports the joint distribution of origin and destination fixed effects across occupations (sub-figures a–c) and the decomposition of D_j into its two components (sub-figure d).

Figure 3: Origin and destination fixed effects by occupation type — GGS-GBS-based distance



Notes. Sub-figures (a)–(c) plot the estimated origin fixed effect ($-\hat{S}_j$, x-axis) against the estimated destination fixed effect ($\hat{D}_j$, y-axis) for each occupation, with bubble size proportional to employment share; each occupation appears as both an origin and a destination. Green, green-core, and brown occupations are highlighted; gray occupations are shown for reference. The solid line is a linear fit across the full sample. Sub-figure (d) reports OLS estimates of the mean difference in destination FE ($\hat{D}_j$), attractiveness ($\hat{S}_j$), and implied access costs ($\hat{\theta m}_j$) between each occupation type and gray occupations, with 95% confidence intervals. Access costs are plotted in levels, so that a *positive* value denotes a *higher* cost of entry, and the three series satisfy $\hat{D}_j = \hat{S}_j - \hat{\theta m}_j$. Skill distance is measured using GGS ($G = 28$) in the green and green-core panels and GBS ($B = 18$) in the brown panel. Sample: occupation pairs with positive flows.

Sub-figures (a) and (b) show that green and green-core occupations sit predominantly above the fitted line: their destination FEs are high relative to what their position on the

origin axis would predict. Green and green-core occupations thus attract disproportionately high inflows given their origin-side behaviour.²⁹ Sub-figure (c) shows a less visually striking pattern for brown occupations, which scatter around the regression line with a modest downward displacement.³⁰

Sub-figure (d) decomposes the point estimates of the destination fixed effect (circles) into attractiveness (squares) and access costs (diamonds). For green occupations, the destination FE is positive and statistically significant. Interestingly, while the attractiveness premium is close to zero, the gap is accounted for entirely by low access costs. Workers flow into green occupations not because they are intrinsically more desirable, but because occupation-specific entry barriers are low. This is consistent with the expansion of green labour demand documented in Section 3.3: occupations with growing hiring needs post abundant vacancies, lowering the effective cost of entry.³¹ The same holds for green-core occupations: their attractiveness differential is positive but imprecisely estimated, so that low access costs remain the only statistically detectable driver of their elevated inflows. For brown occupations, the pattern reverts. The destination fixed effect is negative and statistically significant, and the decomposition attributes it to high access costs, while the attractiveness premium is indistinguishable from zero. This null does not contradict the wage premia documented for carbon-intensive work, which are measured at establishment, firm or sector level (Barreto et al., 2023; Haywood et al., 2024; Rud et al., 2024; Garnache et al., 2025) and need not translate into an occupation-level premium of the kind S_j registers; what the decomposition says is that brown occupations are costly to enter. Barriers on the entry side imply that brown employment loses ground through reduced inflows rather than through accelerated exits, the pattern by which Cortes et al. (2020) account for the decline of routine employment in the United States and by which regulated energy-intensive industries have been shown to shed workers, through decreased hiring rather than increased separations (Curtis, 2018).

Two caveats attach to this reading. First, the framework identifies an occupation-specific transition cost, and the same difference $S_j - D_j$ would be delivered by a model in which occupations are costly to leave rather than to enter.³² Because both mechanisms imply low churn, worker flows alone cannot distinguish them. The stakes are highest for

²⁹Origin and destination fixed effects are identified only up to a common normalisation, here relative to a reference occupation, so the position of an individual occupation on either axis is informative only in comparison with other occupations, and not relative to zero. All the statements below are accordingly differences with respect to gray occupations.

³⁰As noted in Section 2.2, $\hat{D}_j$ is recovered from a regression that already conditions on bilateral skill distance and on task-group switches, so both components capture the residual pull or repulsion of an occupation once skill-related frictions have been netted out.

³¹Access costs here are reduced-form barriers that co-move with demand. Within the model, the transition cost can equivalently be read as restricting the flow of offers from a destination rather than as a loss of payoff (Cortes and Gallipoli, 2018), so that expanding green demand lowers effective entry costs just as the scarce vacancies of a segment losing ground plausibly raise them.

³²See Cortes and Gallipoli (2018, Appendix B).

brown occupations: under the access-cost reading they lose ground because few workers enter, while incumbents remain free to leave; under the exit-cost reading incumbents would instead be locked into a declining segment. We follow Cortes and Gallipoli (2018) in adopting the access-cost interpretation, both because they find access costs to dominate empirically when the two are jointly modelled, and because the estimated barriers correlate with entry-side institutions such as licensing, training requirements and unionisation. Second, and consistently with this choice, exits from brown occupations show no additional distance penalty under the GBS measure (Table 2) and a significantly smaller one under the factor-based measure (Table 3), whereas a strong lock-in mechanism would predict the opposite.

Figure E1 replicates the decomposition of Figure 3 using the factor-based distance. The ranking of destination FEs is preserved, but the split between components changes. For green and green-core occupations both channels now operate: the attractiveness differential turns positive and significant, in line with the small green wage premia documented in the literature (Vona et al., 2019; Bluedorn et al., 2023; Kuai et al., 2025; Godøy and Isaksen, 2025; Saussay et al., 2026; Cass et al., 2026), alongside the still larger access-cost advantage. The brown result is unchanged: null attractiveness and significantly high access costs, confirming the GBS-based finding across characterisations. The shift on the green side follows from the fact that the destination FEs are conditional on the bilateral distance included in the gravity model. Under the GGS measure, proximity in green-skill content is absorbed by the distance term; under the factor-based measure it is not, and the residual green-specific pull surfaces in the fixed effects, part of it as attractiveness. Low access costs nonetheless remain the dominant channel, and the only one robust across both characterisations.

Taken together, the decomposition locates the occupation-specific friction on the entry side. Of the three channels set out in Section 2.2, it is access costs that separate green and brown occupations from the rest: green and green-core occupations draw inflows through low entry barriers, brown occupations lose ground through high ones, and attractiveness differentials are at most secondary, modest, positive only for green occupations and detectable under a single vector characterisation. Reallocation across the green–brown spectrum thus operates on the entry margin rather than by pushing incumbents out, as it has been shown to do for routine occupations (Cortes and Gallipoli, 2018; Cortes et al., 2020) and for regulated polluting industries (Curtis, 2018). The brown result confirms the prediction of above-average entry barriers in occupations from which demand is shifting away.

5 Individual-level analysis

The gravity model characterises mobility at the occupation-pair level and is silent on which workers make the transitions it describes. We complement it with individual-level evidence from the same archive, asking two descriptive questions through linear probability models (LPMs) estimated on matched samples: among workers who change jobs, which characteristics predict entry into green or green-core occupations, and what post-separation outcomes await workers leaving brown occupations. The analysis is descriptive rather than causal, and its purpose is to establish who is being integrated into green work and who bears the cost of leaving brown work.

5.1 Sample selection and measures

The unit of observation is the individual job-to-job transition, retrieved from the CO panel of Section 3 by retaining contract changes, including moves through short non-employment spells and first observed jobs.³³ The two analyses call for different restrictions. For transitions into green occupations the question is which job changers end up in a green destination, so we retain only moves that change the 5-digit occupation, since job switches within the same occupation are uninformative for that purpose. For exits from brown occupations the question is what happens after separation, and conditioning on an occupational change would select on the outcome; we therefore retain all contract changes originating from a brown occupation.

A raw comparison of individual transitions would confound worker characteristics with the structure of the occupational segments and local labour markets in which they occur. We therefore construct matched comparison samples: each transition into a green (or green-core) occupation is compared with transitions into grey occupations in the same destination 2-digit occupation $\times$ region cell, and each separation from a brown occupation with separations from grey occupations in the same origin 2-digit occupation $\times$ region cell.³⁴ The matching is deliberately coarse: it removes the most obvious confounders while preserving the variation in individual characteristics that is the object of the analysis. The procedure yields three samples, to-green, to-green-core and from-brown, each with its grey comparison pool.

A key regressor throughout is the local skill remoteness of a worker’s previous occupation — a (weighted) average skill distance from that occupation to all relevant destination

³³For workers transiting through non-employment, the previous occupation and skill profile are imputed from the job held before the spell, and such transitions are restricted to spells of at most one year; see Appendix F.

³⁴The matching operates at the cell level rather than one-to-one, and the analysis is restricted to cells in which the target transitions reach at least 1% of the total; Appendix F, which illustrates the sample construction process in more detail, discusses both choices, and Section 5.3 reports robustness to a 3% threshold.

occupations in the worker’s province, following Macaluso (2025). For transitions into green occupations, the relevant destination set is restricted to green occupations only, and $dist_i^{gs}$ measures how far the worker’s previous occupation sits (in terms of general green skills) from the requirements of green jobs that are locally available. For exits from brown occupations, the destination set comprises all occupations in the province, and $dist_i^{local}$ measures how far the worker’s previous occupation sits from the overall prevailing local skill demand. Appendix F provides all the details about their construction and underlying rationale.

5.2 Descriptive evidence on individual transitions

Tables F1 and F2 in Appendix F compare the target groups with their matched comparison pools at the time of the transition. Four patterns stand out for entry into green work. First, a pronounced gender gap: only 6.6% of workers entering green occupations are women, against 28.5% in the grey pool, and the gap is as wide for green-core entrants (7.9% against 28.7%), in line with Alexander et al. (2024). Education depends on the definition: green entrants are slightly less likely to hold a tertiary degree than their grey counterparts (9.3% against 11.1%), green-core entrants more likely (14.6% against 9.2%). Second, green entrants are more likely to come from full-time jobs (85.8% against 71.2%), while experience, first-job status and the incidence of prior unemployment spells are comparable across groups. Third, occupational history matters: 20.0% of green and 20.9% of green-core entrants were already in a green occupation the year before, about twice the share in the grey pools, and brown-origin workers, rare among green entrants, are over-represented among green-core entrants (2.9% against 1.9%). Fourth, green and green-core transitions are disproportionately upward moves, towards a destination in a higher broad skill group than the origin.³⁵ This is consistent with the low access costs of green occupations found in Section 4, which may allow workers to reach roles above their origin on the skill ladder.

Brown leavers differ from their matched grey counterparts only modestly in socio-demographics, with a lower female share,³⁶ but more markedly in what follows the transition: they are less likely to remain in the same 2-digit or 1-digit occupation and in the same macro-sector, a first indication that leaving a brown job entails a deeper reallocation than leaving a comparable grey one.

³⁵Skill groups are the first digit of the CP2011 code: high (1–2), medium-high (3), medium (4–5), medium-low (6) and low (7–9). Since matching conditions on the destination 2-digit occupation, the differences arise from the origin side.

³⁶Conditioning on the origin 2-digit occupation $\times$ region confines the grey comparison to the same industrial and manual segments, whose composition is male-skewed; relative to the economy as a whole both groups under-represent women.

5.3 Regression analysis of individual transitions

The regression framework, estimated on the same matched samples, isolates the association of each characteristic with the outcome conditional on the others, absorbs regional and time heterogeneity through fixed effects, and brings in the local skill distances. For transitions into green occupations we estimate

$$Y_{i,t} = \delta_1 \text{Brown}_{i,t-1} + \delta_2 \text{Green}_{i,t-1} + \delta_3 \text{dist}_i^{\text{green}} + \gamma \mathbf{Z}'_{i,t-1} + \phi_r + \mu_t + \varepsilon_{i,t} \quad (10)$$

where $Y_{i,t}$ equals one if the destination occupation of worker i at time t is green (or green-core). The variables of interest are whether the previous occupation was brown ($\text{Brown}_{i,t-1}$) or green ($\text{Green}_{i,t-1}$), and the green-specific local skill remoteness of the worker's previous occupation ($\text{dist}_i^{\text{green}}$); conditional on local skill remoteness, the two indicators capture whether access to green roles is easier or harder for workers on either side of the transition. $\mathbf{Z}'_{i,t-1}$ includes age and its square, gender, education, tenure, the type of the previous contract (full-time, open-ended), a dummy for involuntary termination and an indicator for a prior unemployment spell of at most one year; ϕ_r and μ_t are region and year fixed effects. Standard errors are clustered at the province level.³⁷ For exits from brown occupations we estimate

$$Y_{i,t} = \delta_1 \text{Brown}_{i,t-1} + \delta_2 \text{dist}_i^{\text{local}} + \gamma \mathbf{Z}'_{i,t-1} + \phi_r + \mu_t + \varepsilon_{i,t}, \quad (11)$$

where $Y_{i,t}$ is one of five post-separation outcomes: non-employment, an open-ended contract, a full-time open-ended contract, a change of 1-digit sector, and a change of 2-digit occupation.³⁸ The coefficient of interest is δ_1 , which measures whether brown leavers face systematically different outcomes from their grey counterparts; $\text{dist}_i^{\text{local}}$ replaces the green distance, and controls and fixed effects are as above. We estimate both equations as linear probability models, which remain tractable with fixed effects at our sample sizes and deliver coefficients that read directly as probability changes; probit estimates, reported in Appendix F, yield similar results.

Predictors of green and green-core transitions. Table 4 reports the main coefficients for transitions into green (columns 1–3) and green-core (columns 4–6) occupations, for any destination contract and for open-ended and full-time contracts separately.

Consistent with the gravity model, skill distance from local green requirements is a first-order predictor of green entry: one standard-deviation increase in $\text{dist}^{\text{green}}$ is associated with a 3.3 percentage point lower probability of moving to a green occupation. The

³⁷The distance regressor varies at the previous occupation $\times$ province level; clustering at the province allows arbitrary error correlation within local labour markets and is the more conservative choice.

³⁸Non-employment is defined residually, as exit from the archive's coverage, and therefore includes unemployment and inactivity alongside unobserved moves into self-employment or the public sector.

coefficient remains negative and significant for green-core destinations but is smaller in magnitude — possibly reflecting the fact that having constructed the skill distance against general green skill requirements makes the indicator less directly relevant to green-core transitions.

Occupational history matters, and asymmetrically. Coming from a green occupation raises the probability of entering another green occupation by 7.4 percentage points and a green-core one by 5.1. A previous brown job lowers the probability of entering a green occupation by 4.1 points, across contract types,³⁹ but raises the probability of entering a green-core one by 2.0 points (column 4), with positive and significant coefficients across contract types. This sign reversal, which echoes the over-representation of brown-origin workers among green-core entrants, is the most substantive difference between the two panels: a brown background is a hurdle for green occupations broadly and a relative advantage for the most intensely green roles.

Table 4: Factors Linked to Transitioning to Green and Green-Core Jobs

	Transition to Green			Transition to Green-Core		
	Any (1)	OE (2)	FT (3)	Any (4)	OE (5)	FT (6)
<i>Green Occupation (t-1)</i>	0.074*** (0.008)	0.049*** (0.005)	0.065*** (0.008)	0.051*** (0.003)	0.028*** (0.002)	0.046*** (0.002)
<i>Brown Occupation (t-1)</i>	-0.041*** (0.008)	-0.012*** (0.005)	-0.037*** (0.008)	0.020*** (0.006)	0.013*** (0.004)	0.022*** (0.006)
<i>Green Local Distance</i>	-0.033*** (0.002)	-0.013*** (0.001)	-0.031*** (0.002)	-0.009*** (0.001)	-0.004*** (0.001)	-0.008*** (0.001)
Observations	643,094	643,035	643,094	420,074	420,015	420,074
Mean dep. var	0.178	0.099	0.158	0.077	0.042	0.063

Notes. Each column reports LPM estimates from our preferred specification (equation 10), including the full set of sociodemographic controls, labor market history, and year and region fixed effects. Column headers indicate the dependent variable in each specification. Columns (1)–(3) report transitions to Green jobs; Columns (4)–(6) report transitions to Green-Core jobs. Abbreviated column headers denote: *Any* (any job transition within the target category), *OE* (transition specifically into an open-ended green or green-core contract), and *FT* (transition specifically into a full-time green or green-core contract). The sample is restricted to (region $\times$ 2-digit occupation) cells with a share of target-category workers $\geq 1\%$. Standard errors are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The full set of coefficients (Table F3) confirms the descriptive picture. Women are 13 percentage points less likely to move into a green occupation and 6 points less likely to move into a green-core one, conditional on all other characteristics.⁴⁰ A tertiary degree raises the probability of a green transition by 5 points and of a green-core transition by 10.

³⁹Table F4, which compares increasingly richer specifications, highlights an interesting result: the brown coefficient is insignificant until distance from local green skill requirements is controlled for. This suggests that two offsetting forces may be at work: brown workers' skills sit somewhat closer to green requirements than grey workers', consistent with the overlap between GGS and GBS documented in Section 3.2, but they face a penalty unrelated to skill alignment, which emerges once that advantage is controlled for.

⁴⁰The conditional gap is smaller than the raw one, so part of the gender sorting operates through the occupational selection absorbed by the cell matching and the controls.

Post-separation outcomes from brown occupations. Table 5 reports the outcomes of workers leaving brown occupations relative to their matched grey counterparts.

Table 5: Effect of Transitioning from Brown Jobs Across Outcomes

	Not Employed	Open-Ended	FT + OE	Sector Change	Occupation Change
	(1)	(2)	(3)	(4)	(5)
<i>Brown Occupation ($t - 1$)</i>	0.007** (0.004)	-0.032*** (0.004)	-0.012*** (0.004)	0.006 (0.007)	0.113*** (0.005)
<i>Local Skill Distance</i>	0.031*** (0.004)	-0.026*** (0.004)	-0.008*** (0.003)	0.033*** (0.004)	0.062*** (0.006)
Observations	524,544	524,538	524,538	396,534	396,534
Mean dep. var	0.313	0.458	0.376	0.444	0.576

Notes. Each column reports results from our preferred specification, including sociodemographic and labor-market controls, as well as year and region fixed effects. Main regressors: previous brown job indicator and local skills distance. The analysis is restricted to (region $\times$ 2-digit occupation) cells with a percentage of previously brown workers $\geq 1\%$. All specifications cluster standard errors at the province level (in $t - 1$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Even after controlling for local skill distance, brown leavers are 0.7 percentage points more likely to be non-employed after separation (column 1), against a mean of 31.3%; they are also less likely to hold an open-ended contract (column 2), as well as a full-time open-ended contract (column 3). Moreover, brown leavers who regain employment do not differ from the grey matched pool in their probability of sector change (Column 4), whereas their probability of changing 2-digit occupations is 11.3 percentage points higher (Column 5).⁴¹ Leaving a brown occupation thus carries a transitional cost on three margins: a higher risk of non-employment, a lower probability of permanent employment, and an increased rate of occupational reallocation — all consistent with reallocation from occupations in decline.

In line with the results of Macaluso (2025), higher distance from local skill profiles is systematically associated with worse post-transition outcomes, both across contract stability and mobility margins. A one standard deviation increase in local skill distance is associated with a higher likelihood of non-employment (+3.1 percentage points), and with lower probabilities of holding an open-ended, or full-time open ended contract (-2.6 and -0.8 percentage points, respectively). Concurrently, greater skill distance predicts a higher likelihood of sectoral movement and occupational reallocation.

The full set of coefficients (Table F7) shows that these costs fall unevenly. Women leaving brown occupations are 8.2 points more likely to be non-employed and 11.8 points less likely to secure a full-time open-ended contract, a compounded disadvantage at the intersection of brown exit and gender. Education reveals a more nuanced picture. Tertiary-educated leavers face lower non-employment risk and obtain better contracts, but are also more likely to change sector and occupation. This pattern is consistent with differences in reallocation capacity: higher-educated workers seem better equipped to navigate transitions through active reallocation into different labour market segments.

⁴¹All outcomes are conditional on a contract change, given the construction of the sample.

Both sets of results are robust to raising the cell-selection threshold to 3% (Tables F5 and F8) and to probit estimation (Tables F6 and F9), which leave signs and significance essentially unchanged.

Shifting from aggregate flows to individual transitions thus uncovers patterns the gravity model cannot: skill distance again shapes outcomes, but prior green or brown experience, gender and education matter independently. Read with the gravity results, and mindful that the analysis is not causal, the picture is one of green restructuring with uneven distributional consequences. Alongside opportunities, such as the pathway from brown to green-core roles, lie frictions and compounded disadvantages for specific groups of workers, and both bear on the design of labour market policies for a less disruptive transition.

6 Conclusion

This paper has examined occupational mobility during the green transition, a case of directional structural change in which labour demand shifts towards green occupations and away from brown ones, along the two margins through which the transition is realised: entry into green occupations and exit from brown ones. Combining the near-universe of Italian job-to-job transitions with occupation-level skill content, we estimated a gravity model following Cortes and Gallipoli (2018) in which bilateral skill distance is interacted with the green and brown character of occupations, decomposed the destination fixed effects into attractiveness and access costs, and added individual-level evidence on who moves. Measuring distance along the brown margin required extending the Vona et al. (2018) procedure to general brown skills, which no previous study had identified and which overlap substantially with their green counterparts.

Skill distance is a first-order friction. A one-standard-deviation increase reduces occupational flows by roughly 60%, and this magnitude is stable across skill measures and specification checks. The friction is not uniform, however. When distance is measured over green- and brown-specific content, only marginal green destinations attenuate it; when it is measured over broad capabilities, only green-core destinations and brown origins do. Which skill dimension constrains a transition therefore depends on the destination: broad capabilities for occupations at the green margin, green-task content for the most intensely green ones, and brown-specific content for exits from brown work. These interactions are less precisely estimated: the attenuation for marginal green destinations survives every specification and sample, though it rests in part on one large occupation, while the factor-based results for green-core destinations and brown origins keep their sign but lose significance once structurally zero pairs are added. The pattern is nonetheless specific to the relevant skill dimensions: every interaction vanishes under a vector characterisation that retains the entire skill battery.

The decomposition of the destination fixed effects shows that reallocation across the green–brown spectrum is governed by access costs rather than by attractiveness. The disproportionate inflows into green and green-core occupations are accounted for almost entirely by below-average entry barriers, with an attractiveness differential that is modest and detectable only when distance is measured over general capabilities. For brown occupations the pattern reverts: their below-average inflows reflect significantly high access costs, whereas their attractiveness is indistinguishable from that of gray occupations. Combined with the absence of an additional distance penalty on brown exits, this implies that the brown segment loses ground on the entry margin rather than through accelerated separations, and that green occupations expand because they are easy to enter more than because they are rewarding.

The individual-level estimates show that these margins are traversed unevenly. Distance from the local green skill profile is a first-order predictor of green entry. Occupational history matters asymmetrically: prior green experience predicts entry into green occupations, whereas a previous brown job lowers the probability of entering green occupations broadly but raises it for green-core roles, a reversal consistent with, though not shown to be caused by, the overlap between general green and brown skills. Access is also stratified by gender, with women 13 percentage points less likely to enter a green occupation, and 6 points less likely to enter a green-core one, conditional on observables. Workers leaving brown occupations face a modest but statistically significant transitional cost, being more likely to be non-employed, less likely to obtain an open-ended contract and considerably more likely to change occupation, and these costs fall disproportionately on women and on the less educated.

Three limitations bound these conclusions. Our greenness and skill measures are fixed over the sample period, while a substantial share of labour-market greening occurs within occupations rather than between them, so that we recover the between-occupation margin only. The decomposition identifies an occupation-specific transition cost that a model of costly exit would reproduce as readily as one of costly entry; we follow Cortes and Gallipoli (2018) in adopting the access-cost reading, but worker flows alone cannot settle the question. And because the archive records employment events rather than stocks, our estimates describe where movers go conditional on a move taking place, not whether a move occurs. Throughout, the analysis is descriptive and structural rather than causal.

The results carry implications for policy, although the limitations just noted counsel caution in drawing them. First, a negative finding: exits from brown occupations carry no additional skill-distance penalty, facing the ordinary friction on brown-specific skills and a somewhat smaller one on general capabilities. We find no evidence of the skill lock-in that accounts of workers stranded in contracting sectors often presume, and the brown segment appears to lose ground mainly on the entry margin. This should not be

over-read: it concerns the mobility margin alone, the individual-level estimates show that leaving does carry a cost in job security, and the archive is silent on wages. Second, because the binding skill dimension differs across destinations, retraining designed around green skills in general may miss the margin that binds for one group or the other; and since green occupations already display below-average entry barriers, what limits reallocation appears to lie in the supply of skills rather than in access to these jobs. Third, the costs and opportunities we document are unevenly distributed across gender, education, occupations and places, and this unevenness is likely to matter for the political sustainability of climate policy (Vona, 2019; Cavallotti et al., 2025).

References

- Acemoglu, Daron and David Autor (2011). “Skills, tasks and technologies: Implications for employment and earnings”. In: *Handbook of Labor Economics*. Vol. 4. Elsevier, pp. 1043–1171.
- Acemoglu, Daron, Fredric Kong, and Pascual Restrepo (2025). “Tasks at work: Comparative advantage, technology and labor demand”. In: *Handbook of Labor Economics*. Vol. 6. Elsevier, pp. 1–114.
- Acemoglu, Daron and Pascual Restrepo (2018). “The race between man and machine: Implications of technology for growth, factor shares, and employment”. In: *American Economic Review* 108.6, pp. 1488–1542.
- Alexander, Naomi-Rose, Mauro Cazzaniga, Stefania Fabrizio, Florence Jaumotte, Longji Li, Jorge Mondragon, Sahar Priano, and Marina Mendes Tavares (2024). *Green jobs and the future of work for women and men*. Washington, DC: International Monetary Fund.
- Anderson, James E. (2011). “The gravity model”. In: *Annual Review of Economics* 3.1, pp. 133–160.
- Ardito, Chiara, Fabio Berton, Lia Pacelli, and Filippo Passerini (2022). “Employment protection, workforce mix and firm performance”. In: *The B.E. Journal of Economic Analysis & Policy* 22.3, pp. 611–621.
- Artuç, Erhan, Shubham Chaudhuri, and John McLaren (2010). “Trade shocks and labor adjustment: A structural empirical approach”. In: *American Economic Review* 100.3, pp. 1008–1045.
- Autor, David (2013). “The task approach to labor markets: An overview”. In: *Journal of Labor Market Research* 46.3, pp. 185–199.
- Autor, David, Caroline Chin, Anna Salomons, and Bryan Seegmiller (2024). “New frontiers: The origins and content of new work, 1940–2018”. In: *The Quarterly Journal of Economics* 139.3, pp. 1399–1465.

- Autor, David, Frank Levy, and Richard J. Murnane (2003). “The skill content of recent technological change: An empirical exploration”. In: *The Quarterly Journal of Economics* 118.4, pp. 1279–1333.
- Bachmann, Ronald, Markus Janser, Florian Lehmer, and Christina Vonnahme (2026). “Disentangling the greening of the labor market: The role of changing occupations and worker flows”. In: *Journal of Environmental Economics and Management*, p. 103329.
- Barreto, Cesar, Robert Grundke, and Zeev Krill (2023). *The cost of job loss in carbon-intensive sectors: Evidence from Germany*. OECD Economics Department Working Paper 1774. Paris: OECD Economics Department.
- Bluedorn, John, Niels-Jakob Hansen, Diaa Noureldin, Ippei Shibata, and Marina M. Tavares (2023). “Transitioning to a greener labor market: Cross-country evidence from microdata”. In: *Energy Economics* 126, p. 106836.
- Bosquet, Clément and Hervé Boulhol (2014). “Applying the GLM variance assumption to overcome the scale-dependence of the negative binomial QGPML estimator”. In: *Econometric Reviews* 33.7, pp. 772–784.
- Bowen, Alex, Karlygash Kuralbayeva, and Eileen L. Tipoe (2018). “Characterising green employment: The impacts of ‘greening’ on workforce composition”. In: *Energy Economics* 72, pp. 263–275.
- Carley, Sanya and David M. Konisky (2020). “The justice and equity implications of the clean energy transition”. In: *Nature Energy* 5.8, pp. 569–577.
- Cass, Leanne, Federico Fabio Frattini, Aurélien Saussay, Misato Sato, and Francesco Vona (2026). *Returns to green tasks in Europe: Evidence from online job vacancies*. Working Paper 449. London: Grantham Research Institute on Climate Change, the Environment, London School of Economics, and Political Science.
- Cavallotti, Enrico, Italo Colantone, Piero Stanig, and Francesco Vona (2025). *Green col-lars at the voting booth: Material interest and environmental voting*. Nota di Lavoro 09.2025. Milan: Fondazione Eni Enrico Mattei.
- Cedefop (2019). *Skills for a greener future*. Reference Series. Luxembourg: European Centre for the Development of Vocational Training (Cedefop). URL: <https://www.cedefop.europa.eu/en/publications/9139>.
- Chen, Jiafeng and Jonathan Roth (2024). “Logs with zeros? Some problems and solutions”. In: *The Quarterly Journal of Economics* 139.2, pp. 891–936.
- Consoli, Davide, Giovanni Marin, Francesco Vona, and Thomas Zwick (2016). “Do green jobs differ from non-green jobs in terms of skills and human capital?” In: *Research Policy* 45.5, pp. 1046–1060.
- Cortes, Guido Matias and Giovanni Gallipoli (2018). “The costs of occupational mobility: An aggregate analysis”. In: *Journal of the European Economic Association* 16.2, pp. 275–315.

- Cortes, Guido Matias, Nir Jaimovich, Christopher J. Nekarda, and Henry E. Siu (2020). “The dynamics of disappearing routine jobs: A flows approach”. In: *Labour Economics* 65, p. 101823.
- Curtis, E. Mark (2018). “Who loses under cap-and-trade programs? The labor market effects of the NOx budget trading program”. In: *The Review of Economics and Statistics* 100.1, pp. 151–166.
- Curtis, E. Mark, Layla O’Kane, and R. Jisung Park (2024). “Workers and the green-energy transition: Evidence from 300 million job transitions”. In: *Environmental and Energy Policy and the Economy* 5.1, pp. 127–161.
- Czako, Veronika (2022). *Skills for the clean energy transition*. JRC Technical Report. Luxembourg: European Commission, Joint Research Centre.
- Dicarlo, Emanuele, Salvatore Lo Bello, Sebastian Monroy-Taborda, Ana Maria Oviedo, Maria Laura Sanchez Puerta, and Indhira Santos (2016). *The skill content of occupations across low and middle income countries: Evidence from harmonized data*. IZA Discussion Paper. Bonn: IZA Institute of Labor Economics.
- Dierdorff, Erich C., Jennifer J. Norton, Donald W. Drewes, Christina M. Kroustalis, David Rivkin, and Phil Lewis (2009). *Greening of the world of work: Implications for O*NET-SOC and new and emerging occupations*. Report. Raleigh, NC: National Center for O*NET Development.
- Dix-Carneiro, Rafael (2014). “Trade liberalization and labor market dynamics”. In: *Econometrica* 82.3, pp. 825–885.
- Dupuy, Arnaud, Morgan Raux, and Sara Signorelli (2024). *Digitalization, change in skill distance between occupations and worker mobility: A gravity model approach*. IZA Discussion Paper 17535. Bonn: IZA Institute of Labor Economics.
- Eaton, Jonathan and Samuel Kortum (2002). “Technology, geography, and trade”. In: *Econometrica* 70.5, pp. 1741–1779.
- Elliott, Robert J. R., Wenjing Kuai, David Maddison, and Ceren Ozgen (2024). “Eco-innovation and (green) employment: A task-based approach to measuring the composition of work in firms”. In: *Journal of Environmental Economics and Management* 127, p. 103015.
- Elliott, Robert J. R. and Joanne K. Lindley (2017). “Environmental jobs and growth in the United States”. In: *Ecological Economics* 132, pp. 232–244.
- Fedorets, Alexandra (2019). “Changes in occupational tasks and their association with individual wages and occupational mobility”. In: *German Economic Review* 20.4, e295–e328.
- Fredriksson, Peter, Lena Hensvik, and Oskar Nordström Skans (2018). “Mismatch of talent: Evidence on match quality, entry wages, and job mobility”. In: *American Economic Review* 108.11, pp. 3303–3338.

- García Vaquero, Martín, Antonio Sánchez-Bayón, and José Lominchar (2021). “European Green Deal and recovery plan: Green jobs, skills and wellbeing economics in Spain”. In: *Energies* 14.14, p. 4145.
- Garnache, Cloé, Elisabeth T. Isaksen, and Maria Nareklishvili (2025). *Labor market impacts of the green transition: Evidence from a contraction in the oil industry*. CESifo Working Paper 12057. Munich: CESifo.
- Gathmann, Christina and Uta Schönberg (2010). “How general is human capital? A task-based approach”. In: *Journal of Labor Economics* 28.1, pp. 1–50.
- Godøy, Anna and Elisabeth Isaksen (2025). *A green wage premium?* Working Paper 432. London: Grantham Research Institute on Climate Change, the Environment, London School of Economics, and Political Science.
- Goos, Maarten, Alan Manning, and Anna Salomons (2014). “Explaining job polarization: Routine-biased technological change and offshoring”. In: *American Economic Review* 104.8, pp. 2509–2526.
- Gourieroux, Christian, Alain Monfort, and Alain Trognon (1984). “Pseudo maximum likelihood methods: Applications to Poisson models”. In: *Econometrica* 52.3, pp. 701–720.
- Granata, Julia and Josefina Posadas (2024). *Why look at tasks when designing skills policy for the green transition*. Policy Research Working Paper 10753. Washington, DC: World Bank.
- Greenstone, Michael (2002). “The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures”. In: *Journal of Political Economy* 110.6, pp. 1175–1219.
- Güvenen, Fatih, Burhanettin Kuruscu, Satoshi Tanaka, and David Wiczer (2020). “Multidimensional skill mismatch”. In: *American Economic Journal: Macroeconomics* 12.1, pp. 210–244.
- Haywood, Luke, Markus Janser, and Nicolas Koch (2024). “The welfare costs of job loss and decarbonization: Evidence from Germany’s coal phaseout”. In: *Journal of the Association of Environmental and Resource Economists* 11.3, pp. 577–611.
- Head, Keith and Thierry Mayer (2014). “Gravity equations: Workhorse, toolkit, and cookbook”. In: *Handbook of International Economics*. Vol. 4. Elsevier, pp. 131–195.
- Huckfeldt, Christopher (2022). “Understanding the scarring effect of recessions”. In: *American Economic Review* 112.4, pp. 1273–1310.
- Ingram, Beth F. and George R. Neumann (2006). “The returns to skill”. In: *Labour Economics* 13.1, pp. 35–59.
- Jarosch, Gregor (2023). “Searching for job security and the consequences of job loss”. In: *Econometrica* 91.3, pp. 903–942.
- Kambourov, Gueorgui and Iouri Manovskii (2009). “Occupational specificity of human capital”. In: *International Economic Review* 50.1, pp. 63–115.

- Kershenbaum, Jonathan, Misato Sato, Aurélien Saussay, and Leanne Cass (2026). *Reskilling-burden and outside options for workers in the green transition*. Working Paper. Version of 24 August 2026. London: London School of Economics and Political Science.
- Kuai, Wenjing, Robert J. R. Elliott, Toshihiro Okubo, and Ceren Ozgen (2025). *Estimating the green wage premium*. IZA Discussion Paper. Bonn: IZA Institute of Labor Economics.
- Lise, Jeremy and Fabien Postel-Vinay (2020). “Multidimensional skills, sorting, and human capital accumulation”. In: *American Economic Review* 110.8, pp. 2328–2376.
- Macaluso, Claudia (2025). “Skill remoteness and post-layoff labor market outcomes”. In: *American Economic Journal: Macroeconomics* 17.2, pp. 134–176.
- Marin, Giovanni and Francesco Vona (2019). “Climate policies and skill-biased employment dynamics: Evidence from EU countries”. In: *Journal of Environmental Economics and Management* 98, p. 102253.
- Neffke, Frank, Ljubica Nedelkoska, and Simon Wiederhold (2024). “Skill mismatch and the costs of job displacement”. In: *Research Policy* 53.2, p. 104933.
- Poletaev, Maxim and Chris Robinson (2008). “Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000”. In: *Journal of Labor Economics* 26.3, pp. 387–420.
- Pollin, Robert and Brian Callaci (2019). “The economics of just transition: A framework for supporting fossil fuel-dependent workers and communities in the United States”. In: *Labor Studies Journal* 44.2, pp. 93–138.
- Popp, David, Francesco Vona, Giovanni Marin, and Ziqiao Chen (2021). “The employment impact of a green fiscal push: Evidence from the American Recovery and Reinvestment Act”. In: *Brookings Papers on Economic Activity*.
- Rausch, Sebastian, Gilbert E. Metcalf, and John M. Reilly (2011). “Distributional implications of alternative U.S. greenhouse gas control measures”. In: *The B.E. Journal of Economic Analysis & Policy* 11.1, pp. 1–47.
- Robinson, Chris (2018). “Occupational mobility, occupation distance, and specific human capital”. In: *Journal of Human Resources* 53.2, pp. 513–551.
- Rud, Juan-Pablo, Michael Simmons, Gerhard Toews, and Fernando Aragón (2024). “Job displacement costs of phasing out coal”. In: *Journal of Public Economics* 236, p. 105167.
- Santos Silva, J. M. C. and Silvana Tenreyro (2006). “The log of gravity”. In: *The Review of Economics and Statistics*, pp. 641–658.
- Saussay, Aurélien, Misato Sato, and Francesco Vona (2026). “Emerging skills and wage gaps in the low-carbon transition: Evidence from online job vacancy data”. In: *Journal of the Association of Environmental and Resource Economists*. Forthcoming.
- Strietska-Ilina, Olga, Christine Hofmann, Mercedes Durán Haro, and Shinyoung Jeon (2012). *Skills for green jobs: A global view*. Geneva: International Labour Organization.

- Sullivan, Paul (2010). “Empirical evidence on occupation and industry specific human capital”. In: *Labour Economics* 17.3, pp. 567–580.
- Vona, Francesco (2019). “Job losses and political acceptability of climate policies: Why the ‘job-killing’ argument is so persistent and how to overturn it”. In: *Climate Policy* 19.4, pp. 524–532.
- (2021). *Labour markets and the green transition: A practitioner’s guide to the task-based approach*. JRC Technical Report. Luxembourg: European Commission, Joint Research Centre.
- Vona, Francesco and Davide Consoli (2015). “Innovation and skill dynamics: A life-cycle approach”. In: *Industrial and Corporate Change* 24.6, pp. 1393–1415.
- Vona, Francesco, Giovanni Marin, and Davide Consoli (2019). “Measures, drivers and effects of green employment: Evidence from US local labor markets, 2006–2014”. In: *Journal of Economic Geography* 19.5, pp. 1021–1048.
- Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp (2018). “Environmental regulation and green skills: An empirical exploration”. In: *Journal of the Association of Environmental and Resource Economists* 5.4, pp. 713–753.
- Walker, W. Reed (2013). “The transitional costs of sectoral reallocation: Evidence from the Clean Air Act and the workforce”. In: *The Quarterly Journal of Economics* 128.4, pp. 1787–1835.
- Yamaguchi, Shintaro (2012). “Tasks and heterogeneous human capital”. In: *Journal of Labor Economics* 30.1, pp. 1–53.

Appendix

A Additional details on the data

A.1 Compulsory Communications archive data

The Compulsory Communications archive collects the notifications that Italian employers are legally required to file whenever an employment relationship begins, changes or ends. Coverage is universal from 2009 onwards, and the recorded events include hirings, dismissals, resignations, retirements, expirations of fixed-term contracts, and conversions from temporary to permanent employment. Beyond the variables used in the analysis, each communication reports the sector of activity of the employing firm, classified according to the Italian ATECO system.⁴² We do not exploit the sector dimension in what follows, since our unit of analysis is the occupation.

The sample is drawn by selecting individuals born on four dates per month, for a total of 48 birth dates per year, and retrieving every employment event associated with them. Because selection operates on the date of birth alone, the resulting sample is random with respect to labour market outcomes.

Three features make the archive well suited to the study of job-to-job mobility. First, it is an administrative census of employment relationships rather than a survey, so the sample we draw from it is not subject to the self-selection or attrition problems that typically affect panel surveys. Second, because each communication links a worker to a firm, the CO effectively constitutes a matched employer–employee panel, allowing individual career trajectories to be reconstructed with precision. Third, activation and termination dates are recorded contemporaneously by employers rather than reported retrospectively by workers, which avoids the recall bias common to survey-based mobility measures. These features have made CO data a standard source in the recent Italian labour literature on worker flows and mobility (e.g. Ardito et al., 2022).

Two limitations follow from the design of the archive. The CO carries no information on earnings, which is why the paper is silent on the wage consequences of the transitions it studies. And because it records flows, such as new hires, rather than stocks, such as employment levels, it over-represents workers who change jobs more frequently, typically younger individuals. A related consequence is that a worker counts as remaining in her occupation only when she forms a new employment relationship within that occupation, and not whenever she continues to be employed there.

This last point is the one respect in which our stayer count departs from Cortes and Gallipoli (2018). In the monthly CPS data they use, the diagonal cell counts all workers

⁴²The ATECO classification corresponds to the European NACE Rev. 2, while CP2011 is embedded in ISCO.

still employed in the same occupation one period later; in the CO it counts those who form a new employment relationship within it. The distinction leaves the switcher-to-stayer ratio of Section 2 intact. Writing observed flows as $sw_{j,k} = \lambda_k N_k \pi_{j,k}$, with λ_k the origin-specific rate at which workers form a new match, the factor $\lambda_k N_k$ is common to all destinations, the diagonal included, and cancels exactly as N_k does, provided that rate is independent of the destination a worker would draw. The same conclusion follows directly in the PPML specification: $\ln(\lambda_k N_k)$ varies only across origin occupations and is therefore absorbed by the origin fixed effects, leaving the distance coefficients unaffected.

Where a worker is observed under more than one contract in a given year, we retain a single, most relevant contract for that person-year. The following criteria are applied in fixed order, each used only to break ties left unresolved by the preceding one: (1) the longest contract within the year; (2) full-time over part-time contracts; (3) permanent over fixed-term contracts; (4) the longest contract over the whole sample period; (5) for the negligible number of cases still exhibiting overlaps, one contract is selected at random. This final tie-breaking step affects only 0.36% of observations.

A.2 Labour Force Survey

We use the Italian Labour Force Survey (LFS), a quarterly nationally representative survey, to compute occupation-level employment shares. These shares mainly serve as weights in the analysis on general green and brown skills, and are employed in some robustness checks. To maintain temporal consistency with the ICP—which is centered on 2013—we rely on LFS waves spanning the 2011–2014 period. We exclude individuals in the armed forces and restrict the sample to working-age individuals (20–64). Employment shares are computed by averaging occupation-level at 3-digit employment across years, a procedure intended to mitigate sensitivity to year-specific labour market fluctuations and sampling noise.

A.3 Skill data

The ICP questionnaire consists of 255 items, divided into thematic sections as follows: section B refers to general knowledge; section C to general skills; section D to abilities, defined as individual attributes that tend to remain relatively stable over time and are not easily altered; section E to the values required by the occupation; section F to soft skills; section G to generalised work activities; and section H to working conditions. Sections B, C, D and G share a consistent structure: for each item both a relevance score and a level score are reported, indicating respectively how important the item is in performing the occupation and the level at which the corresponding skill or task is required. The two are highly correlated, with a Pearson coefficient of 0.833 computed across all occupations, so

we work with relevance scores throughout. To improve the interpretability of the results, all scores from the sections we use are rescaled to the unit interval.

We set aside section E, on work values, and section H, on working conditions, neither of which speaks to transferable human capital. The four sections we retain contain 33 items in B, 35 in C, 52 in D and 41 in G, together with the 16 items of section F, which we screen separately.

In line with Vona et al. (2018), the identification of the skills critical to the green transition rests on sections B, C and G, those most directly related to the notion of a skill, and therefore on 109 items in total. Section D is excluded at this stage precisely because it records individual characteristics that are, by definition, “relatively stable over time and hard to modify”. Such attributes are of limited relevance to the retraining and skill adjustment with which the identification of green and brown skills is concerned. For the same reason, however, they are retained when we measure distances between occupations: characteristics that workers cannot readily acquire are exactly those that shape the cost of reallocating across occupations. Sections B, C, D and G together span 161 dimensions of skill heterogeneity, and it is on these that we perform the factor analysis described in Appendix B.2 and compute the all-skills distance used as a robustness check in the main text.

Section F is the one section we screen but do not retain. Its 16 items describe personal characteristics that may affect job performance rather than skills or tasks as such, and they are put through the same procedure as the other sections; as reported in Appendix B.1, no soft skill satisfies the classification criteria applied to general green skills, so none enters our final lists. Consistent with this, neither the 28 general green skills nor the 18 general brown skills identified below contains an item from section D or section F.

A.4 Green, green-core and brown occupations

Table A1: Green Occupations (5-digit CP2011)

CP (5D)	Occupation
12230	General managers of construction firms
12261	General managers of transport and warehousing firms
12350	Procurement and distribution department managers
13130	Entrepreneurs and managers of small construction firms
13161	Entrepreneurs and managers of small transport and warehousing firms
21161	Geologists
21163	Geophysicists
21164 [†]	Meteorologists
22111	Mechanical engineers
22112	Naval engineers

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Table A1 – continued from previous page

CP (5D)	Occupation
22114 [†]	Energy and nuclear engineers
22130	Electrical and industrial-automation engineers
22141	Electronic engineers
22152 [†]	Materials engineers
22161 [†]	Civil and environmental engineers
22162 [†]	Hydraulic engineers
22180	Biomedical engineers and bioengineers
22211	Architects
22212	Planners, landscape architects and land-conservation specialists
23117 [†]	Ecologists
23130	Agronomists and foresters
25143	Financial specialists
25160	Public relations and communications specialists
31360 [†]	Energy-saving and renewable-energy technicians
31414	Water-treatment plant operation and control technicians
31421	Thermal and electrical energy production technicians
31422	Water and fluid network operation technicians
31423	Electricity-distribution network operation technicians
31520	Construction-site management technicians
31831 [†]	Environmental control technicians
31832 [†]	Waste-treatment and environmental-remediation technicians
32151	Environmental and workplace prevention technicians
32212 [†]	Forestry technicians
32220 [†]	Animal-husbandry technicians
32231 [†]	Biochemical laboratory technicians
61310 [†]	Roofers and roof waterproofers
61340	Installers of insulation and soundproofing systems
61361	Plumbers in civil construction
61370 [†]	Electricians and installers of electrical systems in buildings
61380	Installers of doors, windows and fixtures
62313 [†]	Bicycle and similar-vehicle mechanics
62331	Repairers and maintainers of industrial machinery and plant
62411	Installers and repairers of industrial electrical systems
62413	Electromechanics
62414 [†]	Installers and repairers of electricity generation and storage equipment
62420	Maintainers and repairers of industrial electronic equipment
62450	Installers and maintainers of electrical lines and cabling
64131 [†]	Skilled gardeners and nursery workers (flowers, ornamental plants)
64132	Skilled workers in greenhouse and protected horticulture
64140	Skilled workers in mixed-crop farming
64411 [†]	Tree fellers and reforestation workers
71621	Waste recovery and recycling plant operators
71622	Water purification, treatment and distribution plant operators
73110	Operators of fixed installations in agriculture and livestock

continued on next page

Table A1 – continued from previous page

CP (5D)	Occupation
74110 [†]	Railway train drivers
74120 [†]	Train inspection, movement and marshalling operators
74220 [†]	Bus, tram and trolleybus drivers
74310	Agricultural tractor drivers
74321	Operators of harvesting, chopping and baling machines
74322	Combine-harvester operators
74323	Operators of crop-harvesting machines (beet, potato, fruit, grape, vegetables)
74330	Forestry machine operators
81450 [†]	Refuse collectors and waste sorters
83120 [†]	Unskilled green-space maintenance workers
83210 [†]	Unskilled forestry workers
84210	Labourers and unskilled workers in civil construction

Note: This table lists the five-digit CP2011 occupations classified as green, i.e. with a greenness score above 0.1. [†] denotes the green occupations, with a greenness score equal or above 0.3.

Table A2: Brown Occupations (5-digit CP2011)

CP (5D)	Occupation
21121	Chemists and related professions
21161	Geologists
21163	Geophysicists
22121	Metallurgical engineers
22122	Mining engineers
22151	Chemical and petroleum engineers
31120	Chemical technicians
31322	Mining technicians
31323	Metallurgical technicians
31411	Metal-production plant operation and control technicians
31412	Chemical-plant operation and control technicians
31421	Thermal and electrical energy production technicians
31423	Electricity-distribution network operation technicians
31510	Mining and quarrying production technicians
52312	Travel and cruise attendants
61110	Blasters and shot-firers in mines and quarries
62211	Blacksmiths
62212	Forgers
62370	Craft and industrial painters
63221	Glass blowers and shapers
63222	Glass cutters, grinders and polishers
63230	Glass engravers and etchers
65150	Skilled artisanal dairy workers
65160	Skilled tobacco-leaf preparation and processing workers
71110	Machine operators in mines and quarries
71120	Operators of plants for the primary treatment of minerals and stone
71131	Well drillers
71132	Operators of prospecting drills and boring rigs
71211	Blast-furnace operators
71212	Casting operators
71221	Second-melting furnace operators
71222	Rolling-mill operators
71230	Metal heat-treatment plant operators
71241	Metal wire-drawing machine operators
71242	Metal extrusion and profiling machine operators
71251	Thermal-plant operators for non-ferrous metal production
71252	Electrochemical-plant operators for non-ferrous metal production
71310	Operators of dosing/mixing plants for glass, ceramics and brick production
71321	Glass-production furnace operators
71322	Glass-processing plant operators
71341	Brick-forming plant operators
71342	Brick-production kiln operators
71511	Gas and petroleum refining plant operators
71512	Petroleum-product gauging plant operators
71520	Operators of base- and fine-chemicals plants
71531	Pharmaceutical-production machine operators
71532	Operators of machines producing chemical derivatives (excl. pharmaceuticals)
71820	Operators of kilns for mineral heat treatment
72120	Operators of machines producing cement and similar products
72210	Metal finishers and operators of coating and plating plants
72310	Tyre-making and vulcanising machine operators
72320	Operators of machines making other rubber articles
73130	Milk refrigeration, hygienic treatment and primary-processing workers
73220	Operators of industrial dairy-processing equipment
73270	Tobacco-product processing machine operators
74410	Earth-moving machine operators
84110	Labourers and unskilled workers in mines and quarries

B Additional details on the measures employed

B.1 GGS and GBS

Our analysis leverages the ICP and the relevance each 5-digit occupation possesses in terms of tasks and skills. In the ICP, each 5-digit occupation is defined by two vectors of scores across tasks and skills: a *relevance* score and a *level* score. Given the high correlation between the two—the Pearson correlation coefficient computed across all occupations equals 0.833—we restrict our analysis to relevance scores. We estimate (12) on sections B (general knowledge), C (general skills), D (abilities), F (soft skills) and G (work activities) of the ICP, excluding section E on work values and section H on work context and conditions. Green and brown skills are then retained from sections B, C and G alone: section D records attributes that are, by definition, stable over time and hard to modify, and section F is examined separately below. This choice aligns with Vona et al. (2018) and related work, the only novelty being the screening of section F, which we exploit below to examine the role of soft skills.

To identify GGS we regress the relevance score of each general task (or skill) ℓ in occupation k on the Greenness indicator plus a set of two-digit occupational dummies:

$$Skill_k^\ell = \beta^\ell \times Greenness_k + \phi^{CP_{2D}} + \epsilon_k. \quad (12)$$

The occupational dummies $\phi^{CP_{2D}}$ enhance the comparability of skill profiles across occupations with similar core characteristics, so that GGS are identified by comparing green and non-green occupations that are relatively similar in overall task content.⁴³ We retain only two-digit occupational macro-groups containing at least one job with positive greenness, thereby eliminating broad categories that bear no relevance to green jobs, such as “unskilled professions in domestic, recreational and cultural activities” (CP2011 82). Tables B1 and B2 list the two-digit groups excluded on this basis for the green and brown regressions, respectively; the restriction retains 543 five-digit occupations for the GGS regressions and 364 for the GBS regressions. A positive (negative) and statistically significant β^ℓ denotes that skill ℓ is used more (less) intensively in greener occupations. All regressions are weighted using LFS employment shares at the 3-digit level.

We depart from Vona et al. (2018) in adopting a 5% rather than a 1% significance threshold.⁴⁴

⁴³Including two-digit dummies differs slightly from Vona et al. (2018), who use three-digit dummies. This adjustment reflects the less granular occupational coding in the Italian context, which uses 5-digit codes rather than 6-digit codes.

⁴⁴This adjustment addresses concerns about the imperfect crosswalk from SOC to CP2011, which yields a less precise measurement of occupational greenness and may introduce a stronger attenuation bias in our regressions.

Table B1: Occupational Groups Without Green Occupations

CP (2D)	Occupation
11	Members of legislative and government bodies
24	Health specialists
26	Education and research specialists
41	Clerks and office machine operators
42	Money-handling and customer service clerks
44	Documentation collection, control, preservation, and delivery clerks
51	Skilled occupations in commercial activities
52	Skilled occupations in hospitality and food services
53	Skilled occupations in healthcare and social services
54	Skilled occupations in cultural services
63	Craftsmen and specialized workers in precision mechanics and artistic craftsmanship
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities

Note: This table lists 2-digit occupational groups that do not include any occupations with a greenness score greater than zero. These groups are hence excluded from the main regression specification on general *green* skills, which employs 2-digit occupational dummies.

Table B2: Occupational Groups Without Brown Occupations

CP (2D)	Occupation
11	Members of legislative and government bodies
12	Entrepreneurs, managers, and directors of large companies
13	Entrepreneurs and managers of small businesses
23	Specialists in life sciences
24	Health specialists
25	Specialists in humanities, social sciences, arts, and management
26	Education and research specialists
32	Technical professions in health and life sciences
33	Technical professions in organization, administration and commercial activities
34	Technical professions in public services and personal services
41	Clerks and office machine operators
42	Money-handling and customer service clerks
43	Administrative, accounting, and financial management clerks
44	Documentation collection, control, preservation, and delivery clerks
51	Skilled occupations in commercial activities
53	Skilled occupations in healthcare and social services
54	Skilled occupations in cultural services
64	Skilled agricultural workers, forest workers and livestock farmers
81	Unskilled occupations in commerce and services
82	Unskilled occupations in domestic, recreational, and cultural activities
83	Unskilled occupations in agriculture, landscaping, farming, forestry, and fishing

Note: This table lists 2-digit occupational groups that do not include any occupations with a positive brownness. These groups are hence excluded from the main regression specification on general *brown* skills, which employs 2-digit occupational dummies.

The empirical approach involves conducting $\ell = 177$ distinct regressions. This raises concerns about the validity of hypothesis testing and highlights the potential need for multiple-testing corrections to mitigate the risk of identifying false-positive green skills. At the same time, the imperfect measurement of greenness—our primary regressor of

interest—likely introduces attenuation bias, which operates in the opposite direction and increases the risk of false-negatives. Because accurately quantifying the extent of these biases is challenging, we instead estimate a battery of alternative specifications to strengthen the robustness of the classification. In addition to the baseline in Equation 12, we consider four alternatives: (i) no occupational dummy; (ii) as in (i), but restricting the sample to occupations belonging to a two-digit macro-group in which at least one occupation has positive greenness; (iii) one-digit occupational dummies ($\phi^{CP_{1D}}$); and (iv) three-digit occupational dummies ($\phi^{CP_{3D}}$).

From the resulting pool of potentially relevant green skills (Table B3), we extract the final list of GGS by imposing three restrictions: β^ℓ must be positive and statistically significant at the 5% level; β^ℓ must not be significantly negative (at the 5% level) in any specification; and β^ℓ must be positive and statistically significant in the majority (3 out of 5) of the specifications. This procedure yields the 28 GGS reported in Table B4. Figure B1 plots the point estimates and statistical significance of the β parameters under the baseline specification.

Table B3: List of Potential General Green Skills

Code	Skill Name
B02	Clerical
B10	Engineering and Technology
B11	Design
B12	Building and Construction
B13	Mechanical
B14	Mathematics
B15	Physics
B16	Chemistry
B17	Biology
B20	Geography
B29	Public Safety and Security
B30	Law and Government
B33	Transportation
C01	Written Comprehension
C03	Writing
C05	Mathematics
C06	Science
C17	Complex Problem Solving
C18	Operations Analysis
C19	Technology Design
C20	Equipment Selection
C21	Installation
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C28	Repairing
C29	Systems Analysis
C30	Systems Evaluation
C31	Judgment and Decision Making
G01	Getting Information
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G07	Evaluating Information to Determine Compliance with Standards
G08	Processing Information
G09	Analyzing Data or Information
G10	Making Decisions and Solving Problems
G12	Updating and Using Relevant Knowledge
G19	Working with Computers
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G23	Repairing and Maintaining Electronic Equipment
G24	Documenting/Recording Information
G31	Resolving Conflicts and Negotiating with Others

Note: This table reports all skills *potentially* identified as general green skills, meaning those associated with a significantly positive β parameter for "greenness" in at least one of the five considered specifications.

Table B4: List of General Green Skills

Code	Skill Name
B10	Engineering and Technology
B11	Design
B13	Mechanical
B15	Physics
B16	Chemistry
B17	Biology
B20	Geography
B29	Public Safety and Security
B33	Transportation
C01	Written Comprehension
C03	Writing
C19	Technology Design
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C29	Systems Analysis
C30	Systems Evaluation
G01	Getting Information
G02	Identifying Objects, Actions and Events
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G07	Evaluating Information to Determine Compliance with Standards
G12	Updating and Using Relevant Knowledge
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G31	Resolving Conflicts and Negotiating with Others

Note: This table presents the list of skills identified as "General Green Skills".

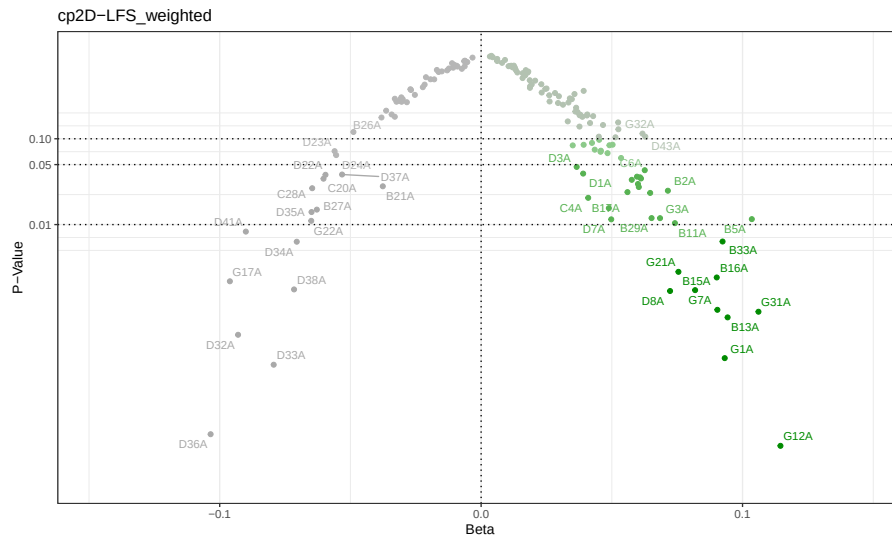
Our results on general green skills display substantial similarity with those of Vona et al. (2018). As noted in the main text, 11 of the 14 GGS they identify are included in our list of 28 GGS (Table B4).⁴⁵ This close alignment between the U.S. and Italian labour markets points to a degree of universality in the demand for green skills across countries at a similar stage of economic development, while lending external validity both to our data-driven identification strategy and to the crosswalk through which we obtain the greenness and brownness indicators.

We also attempted to extend the framework to soft skills, motivated by the growing suggestion that non-cognitive traits may matter for the green transition.⁴⁶ The attempt

⁴⁵These are: Engineering and Technology, Design, Mechanical, Drafting, Estimating the Quantifiable Characteristics of Products, Systems Analysis, Systems Evaluation, Updating and Using Relevant Knowledge, Evaluating Information to Determine Compliance with Standards, Physics, and Biology. The three that do not map are Building and Construction, Provide Consultation and Advice to Others, and Law and Government.

⁴⁶This suggestion is gaining traction in surveys of industry stakeholders (Czako, 2022) and in forward-

Figure B1: Point-estimate and statistical significance of β parameters



Note: This figure presents the point estimates of the β parameters (x-axis) and their corresponding p-values (y-axis) for the main specification. Skills associated with higher intensity of use in greener occupations (i.e., $\beta > 0$) are highlighted in green, with increasingly darker shades representing higher levels of statistical significance.

ultimately did not pay out. We identify soft skills with section F of the ICP, which focuses on personal characteristics (16 in total) that can affect job performance, rather than on specific skills or tasks.⁴⁷ Applying the same methodology as for GGS, we isolate a set of 8 candidate soft skills—those associated with a statistically significant positive β in at least one specification (Table B5). None, however, satisfies the classification criteria used for GGS, as none is significant across the majority of specifications, so we retain no soft skill in our final set. This null result may indicate that hard skills play a more central role in the green transition, though it could also reflect limitations in how soft skills are defined and measured. In either case, it points to the need for further work to better assess the role of soft skills and to refine their measurement.

looking analyses of current European environmental policies (García Vaquero et al., 2021).

⁴⁷ Examples include attitudes towards leadership, cooperation, and social orientation.

Table B5: List of Potential Soft Green Skills

Code	Skill Name
F01	Achievement/Effort
F03	Initiative
F04	Leadership
F12	Attention to Detail
F13	Integrity
F14	Independence
F15	Innovation
F16	Analytical Thinking

Note: This table reports all *soft* skills identified as *potentially* relevant for the green transition. However, none of these skills meets the main criteria to ultimately be classified as a general green skill.

We then adapt this methodology to symmetrically extract GBS. To the best of our knowledge, this represents a novel empirical contribution. The only difference relative to the green case consists in replacing the greenness measure with an indicator of brownness of occupations as the main explanatory variable:

$$Task\ Rel_k^\ell = \gamma^\ell \times Brownness_k + \phi^{CP_{2D}} + \epsilon_k. \quad (13)$$

The same battery of five specifications and the same classification rule are applied. The procedure yields the 18 GBS reported in Table B7, extracted from the pool of potential brown skills in Table B6.

Table B6: List of Potential General Brown SKills

Code	Skill Name
B06	Personnel and Human Resources
B07	Production and Processing
B10	Engineering and Technology
B11	Design
B12	Building and Construction
B13	Mechanical
B15	Physics
B16	Chemistry
C06	Science
C10	Monitoring
C18	Operations Analysis
C19	Technology Design
C20	Equipment Selection
C21	Installation
C23	Quality Control Analysis
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C28	Repairing
C29	Systems Analysis
C30	Systems Evaluation
C34	Management of Material Resources
C35	Management of Personnel Resources
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G18	Controlling Machines and Processes
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G36	Guiding, Directing, and Motivating Subordinates

Note: This table reports all skills *potentially* identified as general browns skills, meaning those associated with a significantly positive β parameter for "brownness" in at least one of the five considered specifications.

Table B7: List of General Brown Skills

Code	Skill Name
B07	Production and Processing
B10	Engineering and Technology
B13	Mechanical
B15	Physics
B16	Chemistry
C19	Technology Design
C23	Quality Control Analysis
C24	Operations Monitoring
C25	Operation and Control
C27	Troubleshooting
C29	Systems Analysis
C30	Systems Evaluation
C34	Management of Material Resources
C35	Management of Personnel Resources
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G18	Controlling Machines and Processes

Note: This table presents the list of skills identified as "General Brown Skills".

B.2 Skill distance metrics

The main text outlines our preferred skill distance measures; here we detail the choices they rest on, review the main alternatives, and present supporting evidence. As Robinson (2018) notes, all approaches share two steps: characterizing occupations as vectors of skills, and choosing a metric to compare them.

On the first step, two approaches prevail. The first employs raw scores to represent occupational characteristics (Cortes and Gallipoli, 2018; Gathmann and Schönberg, 2010); the second applies transformations such as principal component or factor analysis (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Guvenen et al., 2020; Lise and Postel-Vinay, 2020). Raw scores preserve the original information, whereas transformations ease computation and improve interpretability by condensing a complex dataset. We exploit both. Our raw-score measure is restricted to the skills most pertinent to the margin under study—the GGS for transitions into green occupations and the GBS for transitions out of brown ones; our factor-based measure applies factor analysis to the 161 items of ICP sections B, C, D and G, held fixed across both directions, and is constructed below.

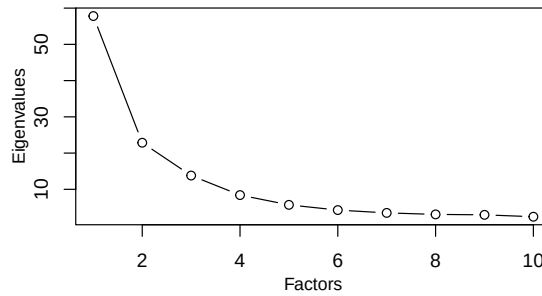
On the second step, two families recur. The first relies on angular separation (cosine similarity), common in the trade and innovation literature (Gathmann and Schönberg, 2010; Cortes and Gallipoli, 2018); the second on an ℓ_p -norm, usually the Manhattan (ℓ_1 , e.g., Fredriksson et al., 2018; Guvenen et al., 2020; Macaluso, 2025) or Euclidean (ℓ_2 , e.g., Fedorets, 2019; Robinson, 2018) distance. Angular separation captures differences in relative skill composition but ignores their intensity, assigning zero distance to pro-

portional increases in requirements. Since transitions typically involve level adjustments, absolute-difference measures are more appropriate. Absent a strong argument for disproportionately penalizing larger deviations, as the Euclidean distance does, we adopt the Manhattan distance.

A further choice is whether to weight individual skills. The literature considers unweighted measures and weighted alternatives, based on factor loadings, destination-occupation relevance, or acquisition-cost proxies. We adopt an unweighted approach, for transparency; below we show that loading-weighting the factor-based measure barely changes the distances.

For the factor-based measure we start from the raw relevance scores of all items in ICP sections B, C, D and G. Section D—stable, hard-to-modify individual characteristics—is excluded from identifying green and brown skills, being less relevant to retraining, but retained here precisely because such traits shape adjustment costs and can bar transitions. Section G, though it refers to tasks rather than skills, is included following Yamaguchi (2012), for whom “observed tasks can be interpreted as a noisy signal of unobserved skills.” These sections span 161 dimensions. As Ingram and Neumann (2006) note, few correspond to distinct traits, so we reduce dimensionality by factor analysis, choosing the number of factors ex post. The Kaiser criterion (eigenvalues > 1) would retain 17 factors, and a stricter threshold ($\lambda > 2$) still 12—too many minor, uninterpretable factors. We therefore rely on the scree plot (Figure B2): it shows no clear “elbow” but two inflection points, at $F = 2$ and, more subtly, $F = 4$. As two factors would discard relevant information, we adopt $F = 4$.

Figure B2: Scree Plot



Note: The Scree plot displays the eigenvalues of the factors, ordered from largest to smallest.

Table B8 reports the highest-loading skills for each factor; the labels are assigned manually. The first loads on inductive and deductive reasoning, critical thinking and active learning (*analytical intelligence*); the second on gross-body coordination, equilibrium and flexibility (*dexterity*); the third on troubleshooting, operation and control, and quality-control analysis (*supervision* of technical processes); the fourth on administration, financial-resource management and staffing (*managerial* content). Figure B3 plots occupations over the first two factors within each one-digit macro-group, sized by em-

ployment share, with green and brown occupations highlighted. It recovers the expected gradient—professionals and managers high on analytical intelligence, craft, plant-operator and elementary occupations high on dexterity—and shows green and brown occupations dispersed across macro-groups rather than confined to one region of the skill space.

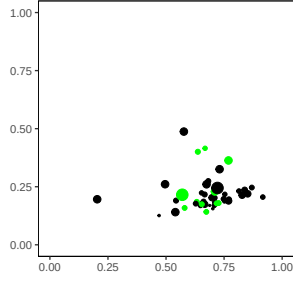
Table B8: Factor Analysis - Skills with Highest Loadings

F1 - Analytical Intelligence		F2 - Dexterity	
D9A	Inductive Reasoning	D39A	Gross Body Coordination
C7A	Critical Thinking	D40A	Gross Body Equilibrium
D8A	Deductive Reasoning	D38A	Dynamic Flexibility
C8A	Active Learning	D37A	Extent Flexibility
G1A	Getting Information	D26A	Multilimb Coordination
F3 - Supervisioning		F4 - Managing	
C27A	Troubleshooting	G41A	Monitoring and Controlling Resources
C25A	Operation and Control	B1A	Administration and Management
C23A	Quality Control Analysis	C33A	Management of Financial Resources
C19A	Technology Design	G40A	Staffing Organizational Units
C29A	Systems Analysis	B6A	Personnel and Human Resources

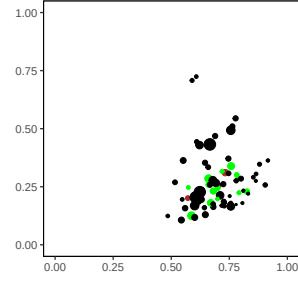
Note: This table reports, for each of the first four factors extracted through factor analysis, the skills with the highest loadings. Factor names are manually assigned, reflecting a subjective interpretation of the common features shared by the skills with the highest loadings.

Figure B3: Distribution of Factor Scores across Occupational Groups

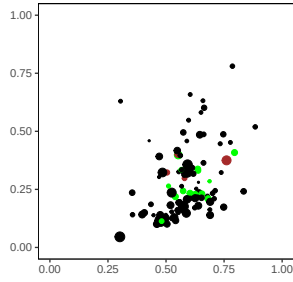
(a) Legislators, Entrepreneurs and Managers



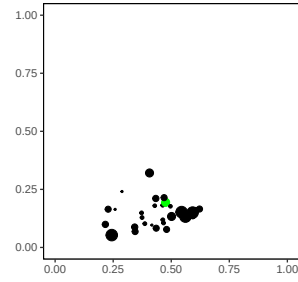
(b) Professionals



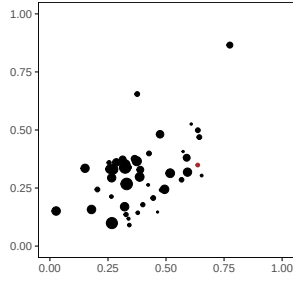
(c) Technical and Associate Professionals



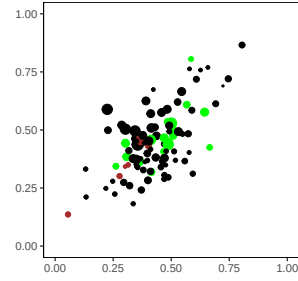
(d) Clerical Support Workers



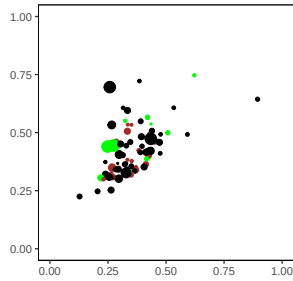
(e) Service and Sales Workers



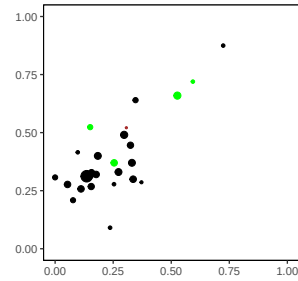
(f) Craftsmen and Skilled Workers



(g) Plant Operators and Vehicle Drivers



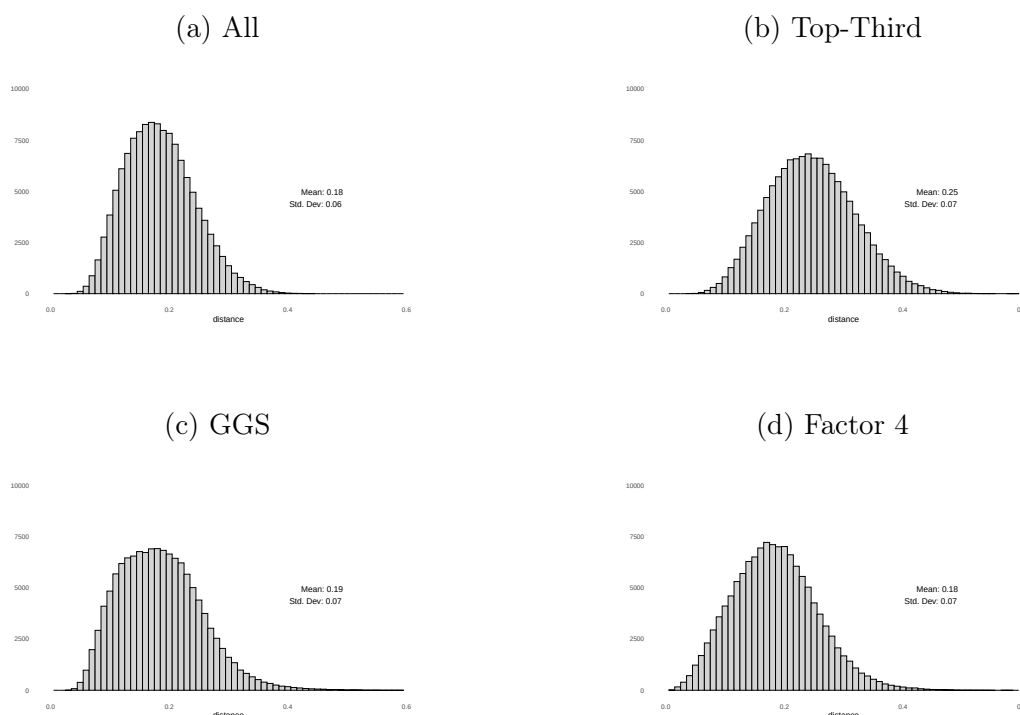
(h) Elementary Occupations



Note: This figure displays the distribution of scores for the first two principal factors: Factor 1 (related to analytical intelligence, shown on the x-axis) and Factor 2 (associated with dexterity and physical skills, shown on the y-axis) across the 8 broad 1-digit occupational macrogroups. Each dot represents an occupation, with dot sizes proportional to the relative share of the occupation within its respective macrogroup. Occupations classified as green 8 (i.e. greenness > 0) or brown are highlighted using their respective colors.

Figure B4 reports the empirical distributions of the pairwise distances under four characterizations—all skills, the top tertile, the GGS subset, and the four factors. Table B9 shows how closely they agree: the factor-based distances correlate strongly with the all-skills measure (0.85 for four factors) and with one another, whereas the GGS-based distance is the most distinct (0.76 with all-skills, 0.66 with four factors). This is by design—restricting to green skills isolates variation the broader measures average out—and confirms that our two main measures capture complementary margins. The same holds for the two raw-score measures. Although 13 of the 18 GBS also appear among the 28 GGS, the two distances they generate are far from interchangeable: they correlate at 0.87 across all 4-digit occupation pairs and at 0.85 over the pairs with a brown origin, which are the ones for which the GBS distance is used. Their mean absolute difference is 0.034, against a mean GGS distance of 0.185, so tailoring the raw-score measure to the direction of the transition under study materially changes the distance we assign to a given pair. Table B10 varies the number of factors and the use of loading weights: distances are very stable across four to six factors (0.85–0.92) and across weighting schemes (0.90 between weighted and unweighted four-factor distances; weighted variants near-collinear at 0.98–0.99), supporting our parsimonious choice of four unweighted factors.

Figure B4: Empirical Distributions of Skill Distances



Note: This figure presents the histograms referring to the empirical distribution of skill distance measures under the four main alternative specifications we examine to test the robustness of our preferred metric.

Table B9: Correlation between Skill Distance Measures

	all	top33	GGS	F4	F5	F6
all	1	0.89	0.76	0.85	0.82	0.78
top33	0.89	1	0.63	0.77	0.75	0.72
GGS	0.76	0.63	1	0.66	0.61	0.57
F4	0.85	0.77	0.66	1	0.92	0.86
F5	0.82	0.75	0.61	0.92	1	0.93
F6	0.78	0.72	0.57	0.86	0.93	1

Note: This table reports the Pearson correlation coefficient between pairwise skill distance measures (for 4-digit occupations), computed using different approaches for vector characterization. The "all," "top33," and "ggs" criteria use raw scores: "all" considers all skill dimensions, "top33" dynamically select - for each pair of occupations - only skills that are most relevant (i.e. in the top tertile of the distribution), and "GGS" restricts the analysis to the list of "general green skills." The remaining columns rely on factor analysis, with the only difference being the number of factors used: F4, F5, and F6 represent specifications with 4, 5, and 6 factors, respectively.

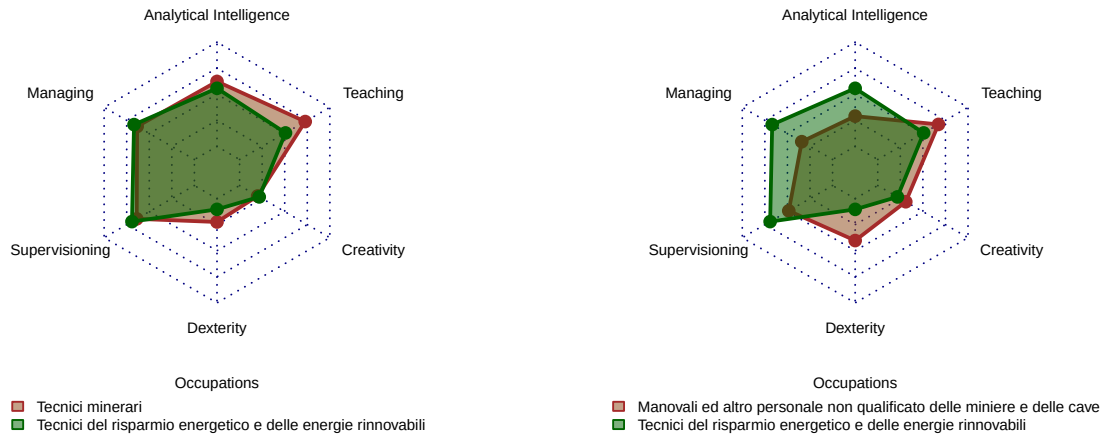
Table B10: Correlation between Skill Distances based on Factor Analysis

	4F	5F	6F	4F-W	5F-W	6F-W
4F	1	0.92	0.85	0.90	0.88	0.89
5F	0.92	1	0.93	0.84	0.86	0.87
6F	0.85	0.93	1	0.77	0.79	0.83
4F-W	0.90	0.84	0.77	1	0.99	0.98
5F-W	0.88	0.86	0.79	0.99	1	0.98
6F-W	0.89	0.87	0.83	0.98	0.98	1

Note: This table reports the Pearson correlation coefficient between pairwise skill distance measures computed using slightly different approaches for factor analysis. Specifically, the columns represent distance measures obtained with varying numbers of factors (4, 5, or 6) and whether factor loadings are used as weights to compute the Manhattan distance (with columns labeled "W" indicating weighted distance measures).

Two exhibits confirm the metric behaves sensibly. Figure B5 compares a green occupation—an energy-saving and renewable-energy technician—to two brown ones: its profile lies close to a mining technician's and far from that of unskilled mine and quarry personnel. The distance thus tracks skill similarity, not sectoral labels, so a green and a brown occupation can be near-neighbours. Tables B11 and B12 list the ten closest and ten most distant pairs: the closest are near-synonyms (systems designers and software analysts; reinforced-concrete and stone-and-brick masons), the most distant match highly cognitive with elementary manual occupations (animal-drawn-vehicle operators versus engineering professors). Both accord with intuition and lend the measure face validity.

Figure B5: Example of Radar Charts for Skill Profiles Comparison



Note: These two radar charts serve as a graphical tool to visualize the differences and similarities in skill profiles. The figure on the left compares the skill profile of a green occupation (Energy-saving and Renewable-Energy Technician) to a brown occupation (Mining Technician), which appears relatively similar in terms of skills. The figure on the right, in contrast, compares the same green occupation to another brown occupation (Unqualified Personnel in Mines and Quarries), highlighting the key dimensions where their skill requirements differ.

Table B11: Most Similar Occupation Pairs

Occupation 1	Occupation 2
Systems Designers and Administrators	Software Analysts and Designers
Researchers and Graduates in Engineering Sciences	University Professors in Engineering Sciences
Furriers and Fur Modelers	Tailors, Modelers, and Milliners
Reinforced Concrete Bricklayers	Stone and Brick Masons
General Managers in Trade Companies	Managers of Large Companies in Logistics
Executives in Central Administrations	General and Departmental Directors
Travel Agency Clerks	Travel Agents
University Professors in Law and Social Sciences	University Professors in History & Philosophy
Managers of Small Companies in Social Assistance	Managers of Large Companies in Social Assistance
Managers of Large Companies in Logistics	Managers of Large Trade Companies

Note: This table reports the 10 most similar 4-digit occupation pairs in ascending distance order (i.e., starting with the lowest distance) based on our distance metric.

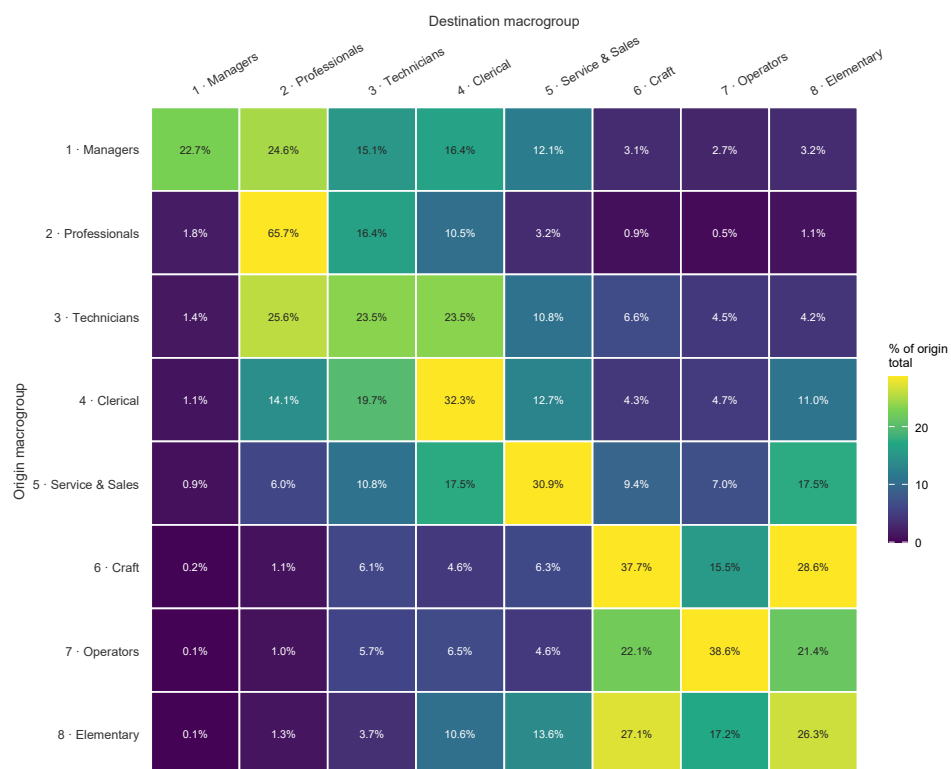
Table B12: Most Different Occupation Pairs

Occupation 1	Occupation 2
Animal-drawn Vehicle Operators	University Professors in Engineering Sciences
Boiler and Nautical Equipment Operators	Ambassadors, Ministers, and Senior Diplomats
Steam Boiler and Thermal Engine Operators	Retail Sales Clerks
Street Vendors	Steam Boiler and Thermal Engine Operators
Dairy Product Preparation Workers	Divers and Underwater Workers
Unskilled Fishing and Aquaculture Workers	Protocol and Document Sorting Clerks
Retail Sales Clerks	Aircraft Commanders and Pilots
Stage Machinists and Technicians	Dairy Product Preparation Workers
Switchboard Operators	University Professors in Life and Earth Sciences
Electronic Device Maintenance Workers	Athletes

Note: This table reports the 10 most different 4-digit occupation pairs in descending distance order (i.e., starting with the highest distance) based on our distance metric.

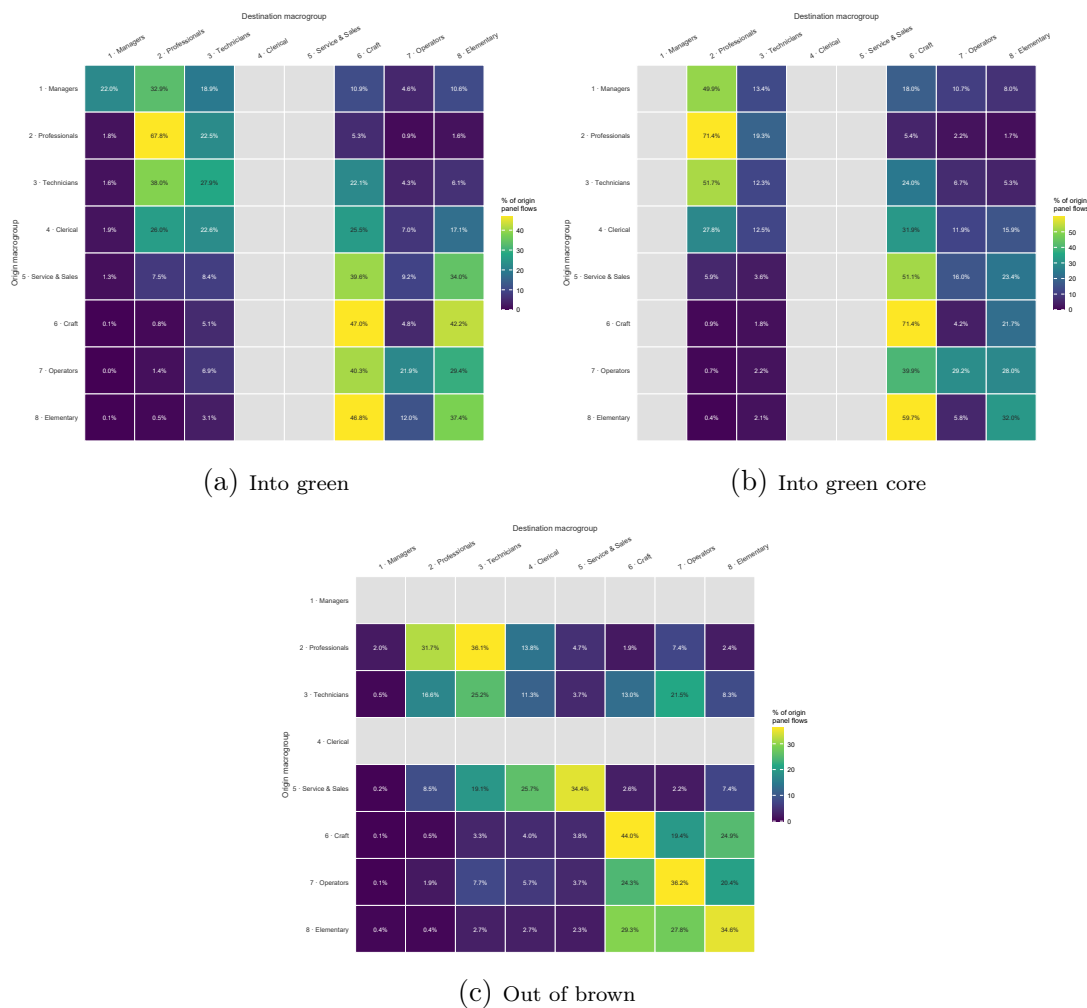
C Additional descriptives

Figure C1: Row-normalised job-to-job flows across 1-digit macro-groups



Notes: Each cell is the full-time-weighted flow from the row (origin) to the column (destination) macro-group, as a percentage of all flows originating in that row; rows sum to 100%. Diagonal cells are within-macro-group switches (different 4-digit occupation). The colour scale is capped at the largest off-diagonal share so that inter-group cells remain distinguishable; the high-retention diagonal cells saturate at the top colour. Armed forces (code 9) excluded.

Figure C2: Row-normalised job-to-job flows across 1-digit macro-groups, by transition type



Notes: Each panel restricts the matrix of Figure C1 to one transition type and re-normalises within it: each cell is the full-time-weighted flow from the row (origin) to the column (destination) macro-group, as a percentage of the row's flows of that type; rows sum to 100% within each panel. Panels (a) and (b) restrict destinations to green and green-core 4-digit occupations; panel (c) restricts origins to brown 4-digit occupations, leaving destinations unrestricted. Rows and columns are 1-digit macro-groups with at least one occupation in the respective group. Grey cells are combinations with no relevant occupation. Diagonal cells are within-macro-group switches. The colour scale is capped per panel. Panel totals: 97,627 transitions into green (9.1% of all flows), 35,476 into green-core (3.3%), 28,486 out of brown (2.7%), of 1,067,756 overall. Armed forces (code 9) excluded.

Table C1: Origin and destination macrogroup shares of green and brown transitions

Code	Macrogroup	% of origin flows		% of destination flows	
		panel	all	panel	all
<i>Panel A. Into green destinations ($g_j \geq 0.1$) — 97,627 transitions</i>					
1	Managers	0.42	0.72	0.62	0.95
2	Professionals	5.37	13.46	9.99	15.26
3	Technicians	9.36	11.00	9.13	11.56
4	Clerical	5.96	13.70	—	14.84
5	Service & Sales	7.41	16.38	—	12.68
6	Craft	33.02	15.13	39.76	16.29
7	Operators	9.65	9.12	8.70	11.76
8	Elementary	28.81	20.50	31.79	16.67
<i>Panel B. Into green-core destinations ($g_j \geq 0.3$) — 35,476 transitions</i>					
1	Managers	0.32	0.72	—	0.95
2	Professionals	5.07	13.46	11.77	15.26
3	Technicians	9.87	11.00	4.80	11.56
4	Clerical	6.95	13.70	—	14.84
5	Service & Sales	8.41	16.38	—	12.68
6	Craft	27.61	15.13	51.32	16.29
7	Operators	12.90	9.12	9.59	11.76
8	Elementary	28.87	20.50	22.52	16.67
<i>Panel C. Out of brown origins — 28,486 transitions</i>					
1	Managers	—	0.72	0.29	0.95
2	Professionals	7.27	13.46	6.49	15.26
3	Technicians	15.11	11.00	12.40	11.56
4	Clerical	—	13.70	8.17	14.84
5	Service & Sales	6.66	16.38	5.81	12.68
6	Craft	16.80	15.13	22.86	16.29
7	Operators	53.24	9.12	26.69	11.76
8	Elementary	0.92	20.50	17.29	16.67

Notes: Share of full-time-weighted flow (2012–2023, COB data) attributable to each 1-digit CP2011 macrogroup, on the origin side and destination side separately. Each panel restricts the sample to one transition type, and its *panel total* — 97,627 transitions into green, 35,476 into green-core and 28,486 out of brown, against 1,067,756 job-to-job transitions overall — is the denominator of the *panel* columns, so each sums to 100% within its panel. The *all* columns report each macrogroup’s share of the origins and destinations of all 1,067,756 transitions, so that the ratio of adjacent columns is a location quotient. Destination shares in Panels A and B, and origin shares in Panel C, largely reflect the composition of the green and brown occupation sets; the opposite side of each panel is the one informative about mobility. An em-dash marks a macrogroup that contains no qualifying occupation on that side (no green destinations in macrogroups 4 and 5, no green-core destinations in 1, 4 and 5, no brown origins in 1 and 4); these are structural absences rather than small shares, and the remaining cells still sum to 100%. Armed forces (code 9) excluded throughout. This table reports marginal shares only, not the full origin×destination flow matrix (see the heatmap exhibit for the latter).

Table C2: Ten most frequent 4-digit transitions, by direction

Rank	Origin → destination	Codes	% of panel
<i>Panel A. Into green destinations ($g_j \geq 0.1$) — 97,627 transitions</i>			
1	Stone & brick masons → Construction labourers	6121 → 8421	4.1
2	Farm day labourers → Mixed-crop farmers	8311 → 6414	3.7
3	Farm day labourers → Construction labourers	8311 → 8421	2.0
4	Construction electricians → Power-line fitters	6137 → 6245	1.7
5	Farm day labourers → Tractor operators	8311 → 7431	1.5
6	Power-line fitters → Construction electricians	6245 → 6137	1.5
7	Construction carpenters → Construction labourers	6123 → 8421	1.4
8	Freight handlers → Construction labourers	8131 → 8421	1.2
9	Industrial labourers → Construction labourers	8431 → 8421	1.0
10	Domestic workers → Construction labourers	8221 → 8421	1.0
<i>Panel B. Into green-core destinations ($g_j \geq 0.3$) — 35,476 transitions</i>			
1	Power-line fitters → Construction electricians	6245 → 6137	4.1
2	Farm day labourers → Specialised gardeners	8311 → 6413	2.6
3	Farm day labourers → Grounds maintenance	8311 → 8312	2.0
4	Taxi & van drivers → Bus & tram drivers	7421 → 7422	1.8
5	Industrial draughtspeople → Mechanical engineers	3137 → 2211	1.4
6	Industrial labourers → Construction electricians	8431 → 6137	1.4
7	Heavy-goods drivers → Bus & tram drivers	7423 → 7422	1.3
8	Industrial labourers → Motor-vehicle mechanics	8431 → 6231	1.2
9	Farm day labourers → Unskilled farm workers	8311 → 8321	1.2
10	Specialised gardeners → Grounds maintenance	6413 → 8312	1.2
<i>Panel C. Out of brown origins — 28,486 transitions</i>			
1	Foundry workers → Industrial labourers	7121 → 8431	2.3
2	Earth-moving operators → Heavy-goods drivers	7441 → 7423	2.1
3	Earth-moving operators → Other plant operators	7441 → 7443	1.3
4	Production machine operators → Other machinery operators	7232 → 7233	1.0
5	Blacksmiths → Metal-parts assemblers	6221 → 6214	0.9
6	Industrial painters → Vehicle panel beaters	6237 → 6218	0.8
7	Blacksmiths → Industrial labourers	6221 → 8431	0.8
8	Chemical technicians → Data-entry clerks	3112 → 4112	0.8
9	Chemists → Chemical technicians	2112 → 3112	0.7
10	Industrial painters → Industrial labourers	6237 → 8431	0.7

Notes: Ten largest 4-digit origin→destination occupation pairs by full-time-weighted flow (2012–2023, COB data). Each panel restricts the sample to one transition type, and its panel total — 97,627 transitions into green, 35,476 into green-core and 28,486 out of brown, against 1,067,756 job-to-job transitions overall — is the denominator of the last column. Occupation names in the table are shortened for legibility; codes are 4-digit CP2011, and the full English names are: 2112 Chemists & related scientists; 2211 Mechanical & energy engineers; 3112 Chemical technicians; 3137 Industrial draughtspeople; 4112 Keyboard & data-entry clerks; 6121 Stone & brick masons; 6123 Construction carpenters & joiners; 6137 Civil-construction electricians; 6214 Metal-parts assemblers; 6218 Vehicle bodywork & panel beaters; 6221 Blacksmiths, press & forge operators; 6231 Motor-vehicle mechanics & repairers; 6237 Industrial & craft painters; 6245 Power-line fitters & cable layers; 6413 Specialised gardeners & nursery workers; 6414 Mixed-crop specialised farmers; 7121 Foundry & blast-furnace workers; 7232 Production machinery operators; 7233 Other machinery operators; 7421 Taxi & car/van drivers; 7422 Bus, tram & trolleybus drivers; 7423 Heavy-goods vehicle drivers; 7431 Agricultural tractor operators; 7441 Earth-moving machinery operators; 7443 Other plant & machinery operators; 8131 Freight handlers & porters; 8221 Domestic workers; 8311 Agricultural day labourers; 8312 Grounds-maintenance workers; 8321 Unskilled agricultural workers; 8421 Unskilled construction workers; 8431 Unskilled industrial workers. Stayers and armed forces excluded.

Table C3: Origin and destination macrogroup shares of direct brown-to-green transitions

Code	Macrogroup	% of origin flows	% of destination flows
<i>Panel A. Brown → green — 2,682 transitions</i>			
1	Managers	—	0.11
2	Professionals	9.06	12.59
3	Technicians	20.24	16.78
4	Clerical	—	—
5	Service & Sales	1.34	—
6	Craft	18.46	37.08
7	Operators	48.88	9.12
8	Elementary	2.02	24.32
<i>Panel B. Brown → green-core — 1,020 transitions</i>			
1	Managers	—	—
2	Professionals	10.29	13.13
3	Technicians	17.44	12.15
4	Clerical	—	—
5	Service & Sales	1.57	—
6	Craft	24.26	52.30
7	Operators	44.66	7.21
8	Elementary	1.78	15.21

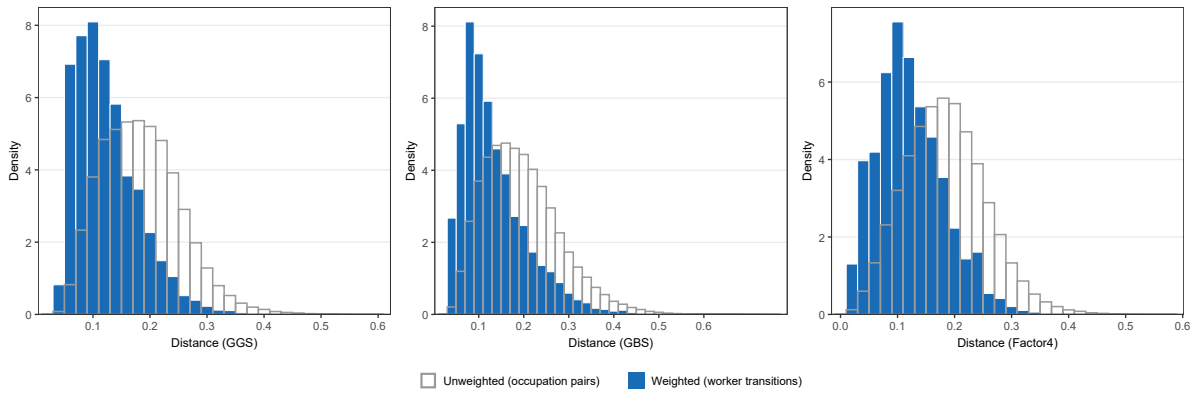
Notes: Share of full-time-weighted flow (2012–2023, COB data) attributable to each 1-digit CP2011 macrogroup, on the origin side and destination side separately. Each panel restricts the sample to one transition type, and its *panel total* — 2,682 brown-to-green transitions and 1,020 brown-to-green-core transitions, against 1,067,756 job-to-job transitions overall — is the denominator of both percentage columns, so each column sums to 100% within its panel. An em-dash marks a macrogroup that contributes no flow on that side; these are structural absences rather than small shares, and the remaining cells still sum to 100%. Armed forces (code 9) excluded throughout. This table reports marginal shares only, not the full origin×destination flow matrix.

Table C4: Most frequent 4-digit brown-to-green transitions

Rank	Origin → destination	Codes	% of panel
<i>Panel A. Brown → green — 2,682 transitions</i>			
1	Earth-moving operators → Construction labourers	7441 → 8421	4.3
2	Chemical technicians → Biochemical technicians	3112 → 3223	3.9
3	Blacksmiths → Construction labourers	6221 → 8421	2.9
4	Blacksmiths → Window & door installers	6221 → 6138	2.6
5	Concrete machine operators → Construction labourers	7212 → 8421	1.7
6	Process plant technicians → Waste-recycling operators	3141 → 7162	1.5
7	Industrial painters → Construction labourers	6237 → 8421	1.4
8	Industrial painters → Insulation installers	6237 → 6134	1.3
9	Chemists → Biochemical technicians	2112 → 3223	1.3
10	Chemical technicians → Biologists	3112 → 2311	1.2
<i>Panel B. Brown → green-core — 1,020 transitions</i>			
1	Blacksmiths → Window & door installers	6221 → 6138	7.0
2	Industrial painters → Insulation installers	6237 → 6134	3.4
3	Chemical engineers → Mechanical engineers	2215 → 2211	2.9
4	Industrial painters → Motor-vehicle mechanics	6237 → 6231	2.7
5	Chemical technicians → Environmental technicians	3112 → 3183	2.2
6	Earth-moving operators → Waste collectors	7441 → 8145	1.9
7	Foundry workers → Construction electricians	7121 → 6137	1.8
8	Blacksmiths → Motor-vehicle mechanics	6221 → 6231	1.8
9	Geologists → Environmental technicians	2116 → 3183	1.7
10	Blacksmiths → Construction electricians	6221 → 6137	1.7

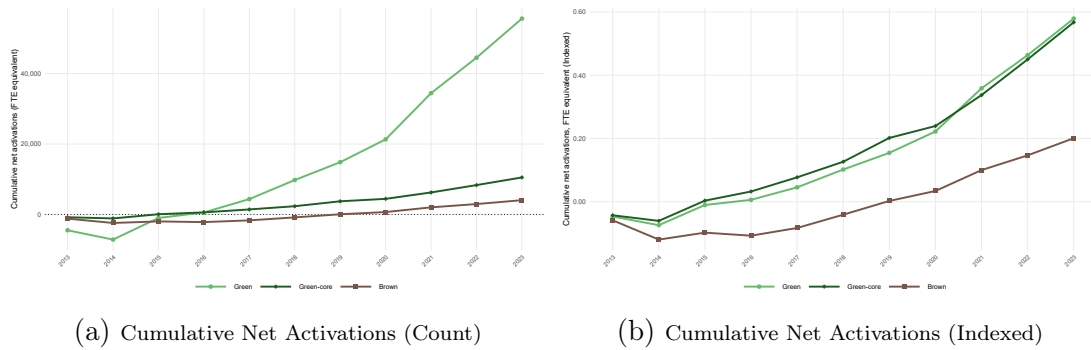
Notes: Ten largest 4-digit origin→destination occupation pairs among brown-origin transitions into green (Panel A) and green-core (Panel B) destinations, by full-time-weighted flow (2012–2023, COB data). Each panel’s total — 2,682 brown-to-green transitions and 1,020 brown-to-green-core transitions, against 1,067,756 job-to-job transitions overall — is the denominator of the last column. Occupation names in the table are shortened for legibility; codes are 4-digit CP2011, and the full English names are: 2112 Chemists & related scientists; 2116 Geologists, meteorologists & geophysicists; 2211 Mechanical & energy engineers; 2215 Chemical, petroleum & materials engineers; 2311 Biologists, botanists & zoologists; 3112 Chemical technicians; 3141 Continuous-process plant technicians; 3183 Environmental control & remediation technicians; 3223 Biochemical technicians; 6134 Insulation & soundproofing installers; 6137 Civil-construction electricians; 6138 Window & door installers; 6221 Blacksmiths, press & forge operators; 6231 Motor-vehicle mechanics & repairers; 6237 Industrial & craft painters; 7121 Foundry & blast-furnace workers; 7162 Waste-recycling & water-treatment operators; 7212 Concrete-product machine operators; 7441 Earth-moving machinery operators; 8145 Waste collectors & recycling sorters; 8421 Unskilled construction workers. Stayers and armed forces excluded.

Figure C3: Skill distance of realised flows vs. all occupation pairs, by distance metric



Notes: Density of pairwise skill distance over all switcher occupation pairs. In each panel the hollow grey outline is the unweighted distribution and the filled blue bars weight each pair by its full-time-weighted flow. Panels differ in the distance metric: General Green Skills (left), General Brown Skills (centre), and the four-factor distance (right). Bin width 0.02.

Figure C4: Cumulative Net Activations in Green, Greencore and Brown Occupations



Notes. The figure plots cumulative net activations (activations minus terminations) for each occupation group (green, green-core, brown), weighted by full-time equivalence (full-time = 1, part-time = 0.6). A positive (negative) value indicates that cumulative activations have exceeded (fallen short of) cumulative terminations over the sample period. Sub-figure (a) reports the count of cumulative net activations, while Sub-figure (b) normalises each series by the group's gross activations in 2013. Source: COB, 2013–2023.

D Additional gravity estimates

Table D1: Skill distance and job to job transitions. Aggregation to 2-digit occupations.

	GGs	GBs	FACTOR4
$dist_{j,k}$	-0.6734*** (0.0464)	-0.4442*** (0.0429)	-0.7057*** (0.0504)
Num.Obs.	1112	1112	1112
Skill vector	GGs	GBs	Factor4
Orig. occ. FE	✓	✓	✓
Dest. occ. FE	✓	✓	✓
Task diff. dummies	✓	✓	✓

Notes. Origin by destination occupations clustered SE, at the 2-digit level. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill), GBS (brown-skill), or Factor4 distance, standardized on the full estimation sample at this aggregation level. The PPML model offsets on the number of stayers in occupation k , and also includes origin and destination occupation fixed effects at the 2-digit level, plus task-content dummies. No group interaction terms are included: this exhibit compares the baseline (average) skill-distance friction across distance measures at this aggregation level to Cortes and Gallipoli (2018). Base sample; excludes origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Table D2: Skill distance and job to job transitions. All skills (161 dimensions) in vector characterization.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-1.3391*** (0.0416)	-1.3435*** (0.0426)	-1.3416*** (0.0424)	-1.3386*** (0.0420)
$dist_{j,k} \times Green_j$		0.0437 (0.1078)		
$dist_{j,k} \times Green\ Core_j$			0.0752 (0.0868)	
$dist_{j,k} \times Brown_k$				-0.0220 (0.0718)
Num.Obs.	79848	79848	79848	79848
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Manhattan distance computed over the full (161-dimension) skill vector, standardized on the full estimation sample. $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Table D3: Skill distance and job to job transitions. GGS distance for green destinations; GBS distance for brown origins. All transitions, no zero-flow restriction.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-1.0291*** (0.0434)	-1.0544*** (0.0474)	-1.0327*** (0.0452)	-0.7426*** (0.0355)
$dist_{j,k} \times Green_j$		0.1864** (0.0933)		
$dist_{j,k} \times Green\ Core_j$			0.0728 (0.0856)	
$dist_{j,k} \times Brown_k$				0.0009 (0.0622)
Num.Obs.	250501	250501	250501	250501
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance in the Green and Green-Core columns and to the GBS (brown-skill) distance in the Brown column, and to the GGS distance in the baseline column (1). $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; contains all origin-destination pairs of occupation, including those with zero flow in either direction.

Table D4: Skill distance and job to job transitions. Factor analysis (4) in vector characterization. All transitions, no zero-flow restriction.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-0.9701*** (0.0325)	-0.9647*** (0.0341)	-0.9732*** (0.0334)	-0.9714*** (0.0332)
$dist_{j,k} \times Green_j$		-0.0532 (0.0823)		
$dist_{j,k} \times Green\ Core_j$			0.0781 (0.0658)	
$dist_{j,k} \times Brown_k$				0.0473 (0.0551)
Num.Obs.	250501	250501	250501	250501
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance, standardized on the full estimation sample. $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; contains all origin-destination pairs of occupation, including those with zero flow in either direction.

Table D5: Skill distance and job to job transitions. Gradual inclusion of fixed effects and controls. GGS distance for green destinations; GBS distance for brown origins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$dist_{j,k}$	-0.9322*** (0.0434)	-1.1661*** (0.0414)	-0.9754*** (0.0438)	-0.9327*** (0.0478)	-1.1975*** (0.0447)	-1.0036*** (0.0480)	-0.9340*** (0.0449)	-1.1734*** (0.0428)	-0.9808*** (0.0456)	-0.7285*** (0.0438)	-0.8910*** (0.0455)	-0.7064*** (0.0351)
$dist_{j,k} \times Green_j$				-0.1794* (0.1080)	0.2580*** (0.0947)	0.2053** (0.0936)						
$dist_{j,k} \times Green Core_j$							0.0156 (0.1001)	0.1719** (0.0873)	0.1114 (0.0880)			
$dist_{j,k} \times Brown_k$										0.3327*** (0.0737)	0.1482** (0.0752)	0.0535 (0.0617)
Num.Obs.	79858	79848	79848	79858	79848	79848	79858	79848	79848	79858	79848	79848
N. at origin	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE		✓	✓		✓	✓		✓	✓		✓	✓
4D-orig. occ. FE		✓	✓		✓	✓		✓	✓		✓	✓
Task diff. dummies			✓			✓			✓			✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance in columns (1)-(9) and to the GBS (brown-skill) distance in columns (10)-(12). $Green_j$, $Green Core_j$ and $Brown_k$ are as defined in Table 2. The PPML model offsets on the number of stayers in occupation k . Columns (1)/(4)/(7)/(10) include no fixed effects; columns (2)/(5)/(8)/(11) add 4-digit origin and destination occupation fixed effects; columns (3)/(6)/(9)/(12) further add task-content dummies ($NC_{j,k}$, $RC_{j,k}$, $RM_{j,k}$, $NRM_{j,k}$), matching the preferred specification of Table 2. Columns (1)-(3) report the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Table D6: Skill distance and job to job transitions. Gradual inclusion of fixed effects and controls. Factor analysis (4) in vector characterization.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$dist_{j,k}$	-0.9049*** (0.0421)	-1.0851*** (0.0288)	-0.9307*** (0.0330)	-0.9044*** (0.0461)	-1.0847*** (0.0302)	-0.9276*** (0.0346)	-0.9070*** (0.0437)	-1.0900*** (0.0296)	-0.9352*** (0.0338)	-0.9122*** (0.0433)	-1.0890*** (0.0294)	-0.9341*** (0.0336)
$dist_{j,k} \times Green_j$				-0.0101 (0.0867)	-0.0041 (0.0818)	-0.0308 (0.0821)						
$dist_{j,k} \times Green\ Core_j$							0.0842 (0.0795)	0.1346** (0.0653)	0.1128* (0.0665)			
$dist_{j,k} \times Brown_k$										0.3687*** (0.0681)	0.1547*** (0.0576)	0.1317** (0.0575)
Num.Obs.	79858	79848	79848	79858	79848	79848	79858	79848	79848	79858	79848	79848
N. at origin	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE		✓	✓		✓	✓		✓	✓		✓	✓
4D-orig. occ. FE		✓	✓		✓	✓		✓	✓		✓	✓
Task diff. dummies			✓			✓			✓			✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance, standardized on the full estimation sample. $Green_j$, $Green\ Core_j$ and $Brown_k$ are as defined in Table 2. The PPML model offsets on the number of stayers in occupation k . Columns (1)/(4)/(7)/(10) include no fixed effects; columns (2)/(5)/(8)/(11) add 4-digit origin and destination occupation fixed effects; columns (3)/(6)/(9)/(12) further add task-content dummies ($NC_{j,k}$, $RC_{j,k}$, $RM_{j,k}$, $NRM_{j,k}$), matching the preferred specification of Table 2. Columns (1)-(3) report the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Table D7: Skill distance and job to job transitions. Green destinations, GGS distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-1.0036*** (0.0480)	-1.0208*** (0.0487)	-1.0049*** (0.0482)	-1.0084*** (0.0484)	-0.9977*** (0.0478)	-1.0041*** (0.0482)	-1.0214*** (0.0494)
$dist_{j,k} \times Green_j$	0.2053** (0.0936)	0.0113 (0.1026)	0.2215** (0.0972)	0.2283** (0.0972)	0.2728*** (0.0759)	0.2080** (0.0969)	0.1480* (0.0767)
Num.Obs.	79848	79158	79184	79220	79312	79232	76734
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 8421 (Unskilled construction workers); (3) = 6245 (Power-line fitters & cable layers); (4) = 6137 (Civil-construction electricians); (5) = 6414 (Mixed-crop specialised farmers); (6) = 6231 (Motor-vehicle mechanics & repairers). $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D8: Skill distance and job to job transitions. Green-core destinations, Factor4 distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-0.9352*** (0.0338)	-0.9353*** (0.0340)	-0.9386*** (0.0339)	-0.9352*** (0.0338)	-0.9371*** (0.0339)	-0.9353*** (0.0339)	-0.9409*** (0.0344)
$dist_{j,k} \times Green\ Core_j$	0.1128* (0.0665)	0.1330** (0.0619)	0.0589 (0.0715)	0.1123 (0.0691)	0.1178* (0.0695)	0.1559** (0.0718)	0.1614** (0.0818)
Num.Obs.	79848	79220	79232	79288	79314	79406	77084
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 6137 (Civil-construction electricians); (3) = 6231 (Motor-vehicle mechanics & repairers); (4) = 8145 (Waste collectors & recycling sorters); (5) = 8312 (Grounds-maintenance workers); (6) = 2211 (Mechanical & energy engineers). $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D9: Skill distance and job to job transitions. Brown origins, Factor4 distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-0.9341*** (0.0336)	-0.9342*** (0.0336)	-0.9339*** (0.0336)	-0.9361*** (0.0337)	-0.9341*** (0.0336)	-0.9352*** (0.0336)	-0.9371*** (0.0339)
$dist_{j,k} \times Brown_k$	0.1317** (0.0575)	0.1796*** (0.0568)	0.1558*** (0.0552)	0.1213** (0.0594)	0.1499** (0.0594)	0.1214** (0.0605)	0.2456*** (0.0556)
Num.Obs.	79848	79332	79414	79360	79310	79326	77368
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 7121 (Foundry & blast-furnace workers); (3) = 7441 (Earth-moving machinery operators); (4) = 6237 (Industrial & craft painters); (5) = 3112 (Chemical technicians); (6) = 7232 (Production machinery operators). $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D10: Skill distance and job to job transitions. Green-core destinations, GGS distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-0.9808*** (0.0456)	-0.9840*** (0.0461)	-0.9812*** (0.0459)	-0.9797*** (0.0459)	-0.9851*** (0.0458)	-0.9850*** (0.0459)	-0.9919*** (0.0471)
$dist_{j,k} \times Green\ Core_j$	0.1114 (0.0880)	0.1160 (0.0861)	0.1059 (0.0943)	0.1054 (0.0922)	0.1419 (0.0878)	0.0978 (0.0999)	0.1454 (0.1219)
Num.Obs.	79848	79220	79232	79288	79314	79406	77084
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 6137 (Civil-construction electricians); (3) = 6231 (Motor-vehicle mechanics & repairers); (4) = 8145 (Waste collectors & recycling sorters); (5) = 8312 (Grounds-maintenance workers); (6) = 2211 (Mechanical & energy engineers). $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D11: Skill distance and job to job transitions. Brown origins, GBS distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-0.7064*** (0.0351)	-0.7065*** (0.0352)	-0.7059*** (0.0352)	-0.7066*** (0.0352)	-0.7062*** (0.0352)	-0.7065*** (0.0352)	-0.7058*** (0.0355)
$dist_{j,k} \times Brown_k$	0.0535 (0.0617)	0.0780 (0.0637)	0.0865 (0.0585)	0.0579 (0.0619)	0.0435 (0.0631)	0.0720 (0.0620)	0.1616*** (0.0574)
Num.Obs.	79848	79332	79414	79360	79310	79326	77368
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GBS (brown-skill) distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 7121 (Foundry & blast-furnace workers); (3) = 7441 (Earth-moving machinery operators); (4) = 6237 (Industrial & craft painters); (5) = 3112 (Chemical technicians); (6) = 7232 (Production machinery operators). $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D12: Skill distance and job to job transitions. Green destinations, Factor4 distance. Top-5 occupations excluded.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dist_{j,k}$	-0.9276*** (0.0346)	-0.9268*** (0.0339)	-0.9280*** (0.0347)	-0.9296*** (0.0347)	-0.9243*** (0.0347)	-0.9308*** (0.0347)	-0.9276*** (0.0344)
$dist_{j,k} \times Green_j$	-0.0308 (0.0821)	-0.0858 (0.0699)	-0.0161 (0.0863)	-0.0137 (0.0860)	0.0003 (0.0789)	-0.0594 (0.0868)	-0.0496 (0.0637)
Num.Obs.	79848	79158	79184	79220	79312	79232	76734
N. at origin	✓	✓	✓	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance. Column (1) includes all occupations; columns (2)-(6) each exclude one of the top-5 occupations of the relevant group by total flow, removed as both origin and destination; column (7) excludes all five together. Excluded occupations: (2) = 8421 (Unskilled construction workers); (3) = 6245 (Power-line fitters & cable layers); (4) = 6137 (Civil-construction electricians); (5) = 6414 (Mixed-crop specialised farmers); (6) = 6231 (Motor-vehicle mechanics & repairers). $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. The PPML model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows), applied after each exclusion.

Table D13: Skill distance and job to job transitions. Negative binomial. GGS distance for green destinations; GBS distance for brown origins.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-0.8548*** (0.0100)	-0.8664*** (0.0106)	-0.8583*** (0.0102)	-0.6597*** (0.0095)
$dist_{j,k} \times Green_j$		0.0843*** (0.0255)		
$dist_{j,k} \times Green\ Core_j$			0.0685* (0.0392)	
$dist_{j,k} \times Brown_k$				-0.0206 (0.0279)
Num.Obs.	79848	79848	79848	79848
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the GGS (green-skill) distance in the Green and Green-Core columns and to the GBS (brown-skill) distance in the Brown column, and to the GGS distance in the baseline column (1). $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The negative binomial model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

Table D14: Skill distance and job to job transitions. Negative binomial. Factor analysis (4) in vector characterization.

	(1)	(2)	(3)	(4)
$dist_{j,k}$	-0.8309*** (0.0104)	-0.8330*** (0.0109)	-0.8344*** (0.0106)	-0.8323*** (0.0107)
$dist_{j,k} \times Green_j$		0.0173 (0.0256)		
$dist_{j,k} \times Green\ Core_j$			0.0668* (0.0380)	
$dist_{j,k} \times Brown_k$				0.0286 (0.0297)
Num.Obs.	79848	79848	79848	79848
N. at origin	✓	✓	✓	✓
4D-dest. occ. FE	✓	✓	✓	✓
4D-orig. occ. FE	✓	✓	✓	✓
Task diff. dummies	✓	✓	✓	✓

Notes. 4-digit origin by 4-digit destination occupations clustered SE. * = 0.1, ** = 0.05, *** = 0.01. $dist_{j,k}$ refers to the Factor4 distance, standardized on the full estimation sample. $Green_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.1. $Green\ Core_j$ is a dummy variable that identifies 4-digit destination occupations with greenness higher or equal than 0.3. $Brown_k$ is a dummy variable that identifies 4-digit origin brown occupations. The negative binomial model offsets on the number of stayers in occupation k , and also includes 4-digit origin and destination occupation fixed effects. It also includes a set of dummies aimed at capturing broad differences in tasks content not captured by the set of fixed effects. These are: $NC_{j,k}$ if k and j are in two different task groups and j is non-routine cognitive; $RC_{j,k}$ if j is routine cognitive; $RM_{j,k}$ if j is routine manual; $NRM_{j,k}$ and j is non-routine manual. Column (1) reports the baseline specification, without any group dummy or interaction term: the coefficient is the average skill-distance friction across all transitions. Base sample; excludes 4-digit origin-destination pairs of occupation that don't show any transitions both ways (noflows).

D.1 From flow elasticities to transition costs

The gravity coefficients reported in Section 4 are semi-elasticities of relative flows, not of transition costs. As set out in Section 2.1, each combines a cost parameter with the dispersion parameter θ , so that what (4) delivers is $\theta\beta_1$, $\theta\gamma_m$ and θm_j rather than the underlying cost parameters. Converting to the scale on which Cortes and Gallipoli (2018) report their own magnitudes requires a value of θ from outside the gravity equation. This appendix carries out that conversion for the baseline frictions and for the three interactions that are statistically significant in the main tables, and documents how much it depends on the value assumed.

Two routes to θ are available. The first is to adopt the benchmark of Cortes and Gallipoli (2018), $\theta \simeq 3.23$, recovered from the dispersion of wages by initial occupation among young workers: the extreme-value assumption implies that the standard deviation of ex-post log payoffs within an origin occupation equals $\pi/(\theta\sqrt{6})$. We cannot replicate this directly, since the CO archive records no earnings. The second uses the gravity estimates alone. Imposing the normalisation $m_{ref} = 1$ alongside $S_{ref} = 0$ makes the estimated constant equal to $-\theta$, so that the implied value of θ is the estimated access cost of whichever occupation is taken as reference (Cortes and Gallipoli, 2018, Appendix D). Applied to our estimates this yields $[3.71, 9.88]$ across possible reference occupations at the 2-digit level and $[3.27, 12.57]$ at 4 digits, against the $[3.63, 8.87]$ that Cortes and Gallipoli (2018) obtain in the same way. That our data reproduce their range closely at their own level of aggregation is reassuring for adopting their benchmark.

This second exercise is not, however, an independent estimate of θ . What it recovers is θm_{ref} , so the implied value depends on the occupation chosen as reference and, tellingly, on the level of aggregation, with the median rising from 5.94 at 2 digits to 9.00 at 4, which a structural dispersion parameter cannot do. Nor does the Cortes and Gallipoli (2018) anchor transport: they normalise on executives and managers, a large high-churn category that happens to deliver their lowest value, whereas the corresponding Italian codes do not deliver the lowest value in ours. We therefore treat it as a plausibility check on the benchmark rather than as a competing estimate, and report magnitudes at three values of θ : the Cortes and Gallipoli (2018) benchmark of 3.23, and the medians of 5.94 and 9.00 implied by our own estimates at the 2- and 4-digit level.

Three points follow. First, on the level: at the Cortes and Gallipoli (2018) benchmark a one-standard-deviation increase in skill distance raises the transition cost by about 35% in our baseline, against the roughly 14% they report. This is not an independent finding but the same difference already visible on the flow scale, since both figures are divided by the same θ ; and it narrows substantially at their level of aggregation, where our 2-digit coefficient of -0.673 implies $+23.2\%$. The residual gap is consistent with the aggregation bias documented in Section 4.

Table D15: Skill distance: flow scale and implied transition-cost scale

	Coefficient	Flows	Implied effect on $d_{j,k}$		
			$\theta = 3.23$	$\theta = 5.94$	$\theta = 9.00$
<i>Panel A. Green-skill distance (GGS)</i>					
All transitions (col. 1)	−0.975	−62.3%	+35.3%	+17.8%	+11.4%
Non-green destinations (col. 2)	−1.004	−63.3%	+36.4%	+18.4%	+11.8%
Green destinations	−0.798	−55.0%	+28.0%	+14.4%	+9.3%
<i>Panel B. Factor-based distance</i>					
All transitions (col. 1)	−0.931	−60.6%	+33.4%	+17.0%	+10.9%
Non-green-core destinations (col. 3)	−0.935	−60.7%	+33.6%	+17.1%	+11.0%
Green-core destinations	−0.822	−56.1%	+29.0%	+14.8%	+9.6%
Non-brown origins (col. 4)	−0.934	−60.7%	+33.5%	+17.0%	+10.9%
Brown origins	−0.802	−55.2%	+28.2%	+14.5%	+9.3%

Notes: Coefficients are taken from Table 2 (Panel A) and Table 3 (Panel B); indented rows sum the baseline and interaction terms of the column indicated. Only the three interactions that are statistically significant in those tables are reported here, green destinations under the GGS measure, and green-core destinations and brown origins under the factor-based measure; the remaining interactions are not statistically distinguishable from zero and are not converted. The effect on flows is $1 - \exp(\hat{\beta})$ per standard deviation of distance. The implied effect on the transition cost is $\exp(|\hat{\beta}|/\theta) - 1$. $\theta = 3.23$ is the benchmark of Cortes and Gallipoli (2018); $\theta = 5.94$ and $\theta = 9.00$ are the medians implied by their Appendix D normalisation applied to our own estimates at the 2- and 4-digit level.

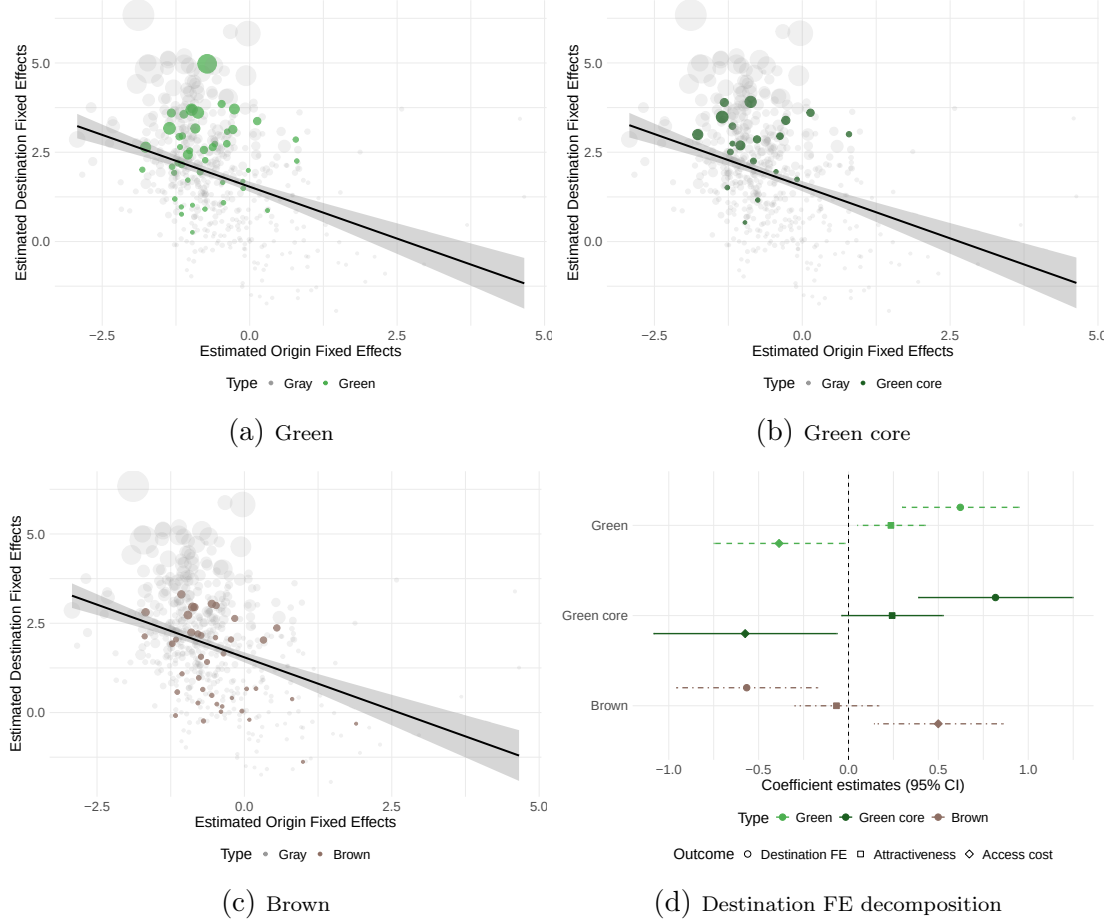
Second, on the differences across occupation types, all three attenuations compress sharply as θ rises. At $\theta = 3.23$ the distance penalty facing green destinations is 8.4 percentage points below that facing non-green ones (28.0% against 36.4%); the green-core gap is 4.6 points and the brown-origin gap 5.3 points under the factor-based measure. At $\theta = 9.00$ the same three gaps are 2.5, 1.4 and 1.6 points. Percentage-point statements of this kind are therefore only meaningful once a value of θ is fixed.

Third, and most usefully, the ordering is invariant even though the levels are not. Because the same factor scales every coefficient, ratios are free of θ altogether: the distance penalty facing green destinations is 0.80 of that facing non-green ones, that facing green-core destinations 0.88 of its comparison group, and that facing brown origins 0.86, whatever value θ takes.⁴⁸ The interaction results reported in the main text, which are ratios of this kind, therefore require no assumption about θ ; only the absolute cost magnitudes do, and, as noted in Section 2.1, the same applies to the access costs recovered by the decomposition of the destination fixed effects.

⁴⁸The invariance is exact for the ratio of the log cost effects, $\hat{\beta}_{\text{green}}/\hat{\beta}_{\text{non-green}}$, and only approximate for the ratio of the percentage effects, since $\exp(\cdot)$ is convex. This is why the percentage-point gaps in the table compress as θ rises while the underlying ratio does not.

E Additional fixed effects decomposition exhibits

Figure E1: Origin and destination fixed effects by occupation type — factor-based distance



Notes. Sub-figures (a)–(c) plot the estimated origin fixed effect ($-\hat{S}_j$, x-axis) against the estimated destination fixed effect ($\hat{D}_j$, y-axis) for each occupation, with bubble size proportional to employment share. Each occupation appears as both an origin and a destination; the x-axis plots the origin fixed effect (structural $-S_j$), while the y-axis plots the destination fixed effect (D_j). Green, green-core, and brown occupations are highlighted; gray occupations are shown for reference. The solid line is a linear fit across the full sample. Sub-figure (d) reports OLS estimates of the mean difference in destination FE ($\hat{D}_j$), attractiveness ($\hat{S}_j$), and implied access costs ($-\hat{\theta}\hat{m}_j$) between each occupation type and gray occupations, with 95% confidence intervals. Skill distance measured using factor analysis ($F=4$). Sample: occupation pairs with positive flows (noflows baseline).

F Additional details on individual analysis

F.1 Sample construction

The individual-level samples are built from the CO panel by retaining contract changes, interpreted broadly to include transitions from and to non-employment and workers entering their first observed job. For transitions through non-employment, the previous occupation and skill profile, which are central to the analysis, are imputed from the job held immediately before the spell; since the prior occupation becomes an increasingly unreliable proxy as the spell lengthens, such transitions are restricted to spells of at most one year.

Matching is at the cell level rather than one-to-one. Each transition into a green (or green-core) occupation is assigned to its destination 2-digit occupation $\times$ region cell, and each separation from a brown occupation to its origin 2-digit occupation $\times$ region cell. Once a cell qualifies, all observations in it are retained, target and comparison alike, and the grey transitions in the cell serve collectively as the comparison group rather than being paired individually to a green or brown observation. A cell qualifies when the target transitions reach at least 1% of its total. The threshold is arbitrary but conservative: it excludes cells in which the target group is negligibly small relative to its aggregate weight in the economy, which is above 1% for all three groups, and all results are replicated at a 3% threshold in Section 5.3

F.2 Local Skill Distances

This section describes the construction of two skill-distance measures used in the individual-level analysis, i.e. $dist_i^{\text{green}}$ and $dist_i^{\text{local}}$. Both follow Macaluso (2025) in capturing *local skill remoteness*: rather than measuring the distance between two specific occupations, each measure quantifies how far a worker’s previous occupation sits from the local labour market’s skill requirements, by computing a weighted average of pairwise distances to all relevant destination occupations in the province.

Following the framework of Macaluso (2025), and building upon the pairwise skill distances illustrated in section 3.2 and Appendix B.2, we construct our measures in two steps. Firstly, we compute occupation-specific labour demand shares at the province level. Secondly, we use such shares as weights to compute the local skill distance measure - i.e. a metric that measures how distant each occupation is from the local labour market’s skill requirements.

Let $d(j, k)$ denote the pairwise skill distance between occupations j and k , as computed in Section 3.2. For each province p , we construct occupation-specific weights w_{kp} using new contract activations A_{kp} , summed over the full sample period (2012–2023).

These proxy for local labour demand — reflecting the intensity with which employers recruit into each occupation in each region — in place of the employment shares used by Macaluso (2025), which cannot be computed using COB data. Specifically, the weight for occupation k in province p is defined as:

$$w_{kp} = \frac{A_{kp}}{\sum_{o \in \mathcal{D}} A_{op}} \equiv \frac{\sum_{t=2012}^{2023} A_{kpt}}{\sum_{t=2012}^{2023} \sum_{o \in \mathcal{D}} A_{opt}},$$

where $\mathcal{D}$ is the relevant set of destination occupations. The local skill remoteness of occupation j in province p is then computed as the weighted average of the relevant pairwise distance measure $d(\cdot, \cdot)$.

$$dist_{jp} = \sum_{k \in \mathcal{D}} w_{kp} \cdot d(j, k).$$

The two measures, $dist_{ip}^{\text{local}}$ and $dist_{ip}^{\text{ggs}}$, are based on this similar construction but differ along both key dimensions, i.e. in terms of the relevant set of destination occupations $\mathcal{D}$ — and hence of the resulting weights w — and of the choice of skill distance measure $d(\cdot, \cdot)$. This distinction is motivated by the conceptual difference between the two measures: while $dist^{\text{local}}$ follows Macaluso (2025) in capturing the remoteness of a worker’s previous occupation from the general skill requirements of the local labour market, $dist^{\text{ggs}}$ is more specifically designed to quantify how distant that occupation is from the green-specific local skill demands, and thus reflects the skill barrier specific to green labour market entry in each province.

For the analysis of (short-term) labour market outcomes following a job transition from a brown occupation, we use the distance measure $dist_{ip}^{\text{local}}$, for which the destination set $\mathcal{D}$ comprises all occupations in the province and $d^{F4}(\cdot, \cdot)$ is the Manhattan skill distance measured over the four latent factors, which, as detailed in Appendix B.2, capture broad dimensions of occupational skill structure. This yields a measure of how far the worker’s previous occupation is from the full local occupational structure, which mirror closely the skill-remoteness measure by Macaluso (2025):

$$dist_{jp}^{\text{local}} = \sum_k w_{kp} \cdot d^{F4}(j, k), \quad w_{kp} = \frac{A_{kp}}{A_p} \equiv \frac{A_{kp}}{\sum_o A_{op}}$$

For the analysis of job transitions towards green (and green-core) occupation, the relevant destination set $\mathcal{D} = \mathcal{G}$ is instead restricted to green occupations (greenness ≥ 0.1 , brown $\neq 1$), and weights are therefore shares of activations within green occupations only:

$$w_{ip}^G = \frac{A_{ip}}{\sum_{o \in \mathcal{G}} A_{op}}, \quad j, o \in \mathcal{G}.$$

To further focus on skill dimensions that are most relevant for green transitions, the

green-specific local skill distance $dist_{ip}^{green}$ is then computed as the weighted average of GGS-specific pairwise distances illustrated in section 3.2. Hence:

$$dist_{jp}^{green} = \sum_k w_{kp}^G \cdot d^{GGS}(j, k) \quad k \in \mathcal{G}.$$

For both measures, weights are winsorized at the 95th percentile, to prevent individual high-employment (or high-churn) occupations to dominate the weighted average of specific local markets, and then renormalized to sum to one within each province. To improve the interpretability of the estimates, and to align them to skill distance measures used in the gravity model, both local skill distance measures are then standardized to mean zero and unit variance before entering the regression specifications.

Two further clarifications are in order. First, for each occupation-province pair, both measures are time-invariant: rather than recomputing them year by year, we pool activations over the full sample period (2012–2023), so that weights reflect the average provincial profile of occupational demand across the period rather than its evolution. This abstracts from potential changes in local skill demand over time, but minimises noise from transitory fluctuations and yields a more stable characterisation of each province’s structural skill requirements. Second, we assign to each worker the skill distance corresponding to their previous occupation and province of employment, under the assumption that workers search for new jobs locally. This implicitly assumes, as a first-order approximation, that workers search for new employment in the same province, abstracting from inter-provincial mobility – a phenomenon which extends beyond the scope of our analysis.

F.3 Descriptive Tables

Table F1: To Green and Green-Core vs. Matched Grey Transitions

Variable	To Green Panel		To Green Core Panel	
	To Green	To Grey	To Green-Core	To Grey
<i>Sociodemographics</i>				
Female	6.6%	28.5%	7.9%	28.7%
Age	37.91	37.56	37.46	37.86
Education Level				
Primary / Lower Secondary	65.1%	64.7%	58.2%	65.5%
Upper Secondary	25.6%	24.2%	27.2%	25.4%
Tertiary	9.3%	11.1%	14.6%	9.2%
<i>Labour Market Characteristics</i>				
Full-Time (t-1)	85.8%	71.2%	78.4%	63.0%
Open-Ended Contract (t-1)	53.0%	47.5%	49.8%	53.5%
Experience	2.65	2.55	2.61	2.61
First Job	57.8%	59.6%	58.8%	58.7%
From Unemployment	11.3%	10.5%	10.3%	10.1%
<i>Transition Dynamics</i>				
Origin: Green Occupation ^a	20.0%	10.6%	20.9%	10.9%
Origin: Brown Occupation ^a	2.4%	2.5%	2.9%	1.9%
Same 1-Digit Occupation ^b	36.5%	31.2%	38.0%	31.7%
Same 2-Digit Occupation ^b	16.7%	18.9%	17.4%	21.0%
Same 1-Digit Sector ^b	36.5%	36.2%	31.9%	37.5%
Transition to Lower Skill ^b	28.1%	34.6%	22.4%	35.9%
Transition to Same Skill ^b	42.8%	39.1%	44.6%	38.7%
Transition to Higher Skill ^b	29.1%	26.3%	33.0%	25.4%

Notes: The full baseline sample size is $N_{\text{To Green}} = 326,101$ and $N_{\text{To Grey}} = 1,567,819$ for the Green panel; $N_{\text{To Green-Core}} = 92,518$ and $N_{\text{To Grey}} = 1,103,204$ for the Green-Core panel. The matched pool of transitions is restricted to (region $\times$ 2-digit occupation) cells where the share of to-green (or green-core) transitions is at least 1%. Comparison is then further strictly restricted to between-occupation transitions (at the 5-digit occupational level). All variables are measured at the time of the transition. Age and Experience are reported in years. Changes in skill levels (Transition to Lower/Same/Higher Skill) are defined by comparing the broad skill tiers of the origin and destination occupations based on 1-digit CP2011 code classifications. By construction, *Transition Dynamics* variables are defined only for job-to-job movers (i.e., workers with a non-missing previous employment spell). Superscripts denote variations in sample size due to missing values or sub-sample restrictions: ^a $N_{\text{Green}} = 114,470$, $N_{\text{Grey}} = 528,686$ / $N_{\text{Green-Core}} = 32,205$, $N_{\text{Grey}} = 387,908$ (job-to-job movers with non-missing previous job); ^b $N_{\text{Green}} = 100,930$, $N_{\text{Grey}} = 468,667$ / $N_{\text{Green-Core}} = 28,584$, $N_{\text{Grey}} = 343,957$ (job-to-job movers with complete occupation/sector codes).

Table F2: From Brown vs. From Matched Grey Transitions
(Including Within-Occupation Transitions)

Variable	From Brown	From Grey
<i>Sociodemographics</i>		
Female	14.8%	16.8%
Age	38.19	38.96
Education Level		
Primary / Lower Secondary	59.7%	60.8%
Upper Secondary	29.5%	30.0%
Tertiary	10.8%	9.3%
<i>Labour Market Characteristics</i>		
Full-Time (t) ^a	91.0%	82.2%
Open-Ended Contract (t) ^a	60.5%	67.1%
Experience	4.92	5.17
<i>Transition Dynamics</i>		
To Non-Employment	32.1%	31.2%
Destination: Brown Occ. ^a	27.0%	3.0%
Destination: Green-Core Occ. ^a	2.8%	2.3%
Same 1-Digit Occupation ^a	46.8%	55.2%
Same 2-Digit Occupation ^a	33.1%	47.9%
Same 1-Digit Sector ^b	44.0%	48.5%
Transition to Lower Skill ^a	15.4%	18.0%
Transition to Same Skill ^a	57.3%	61.0%
Transition to Higher Skill ^a	27.3%	21.0%

Notes: The full baseline sample size is $N_{\text{From Brown}} = 43,657$ and $N_{\text{From Grey}} = 480,915$. Comparison includes both within-occupation and between-occupation transitions for re-employed workers. Age and Experience are reported in years. Sociodemographic variables are measured at the time of transition or exit, while full-time and open-ended refers to the characteristics of the job held in t , i.e. after the transition. Skill categories are derived from the 1-digit CP2011 code classifications. Superscripts denote variations in sample size due to sub-sample restrictions or missing data: ^a $N_{\text{Brown}} = 29,661$, $N_{\text{Grey}} = 330,939$ (restricted to re-employed workers).

F.4 Regression Results & Robustness Checks

Table F3: Factors Associated with Transitioning to Green and Green-Core Jobs

	To Green			To Green-Core		
	Any (1)	OE (2)	FT (3)	Any (4)	OE (5)	FT (6)
<i>Key Regressors</i>						
Green Occupation ($t - 1$)	0.074*** (0.008)	0.049*** (0.005)	0.065*** (0.008)	0.051*** (0.003)	0.028*** (0.002)	0.046*** (0.002)
Brown Occupation ($t - 1$)	-0.041*** (0.008)	-0.012*** (0.005)	-0.037*** (0.008)	0.020*** (0.006)	0.013*** (0.004)	0.022*** (0.006)
Green Local Distance	-0.033*** (0.002)	-0.013*** (0.001)	-0.031*** (0.002)	-0.009*** (0.001)	-0.004*** (0.001)	-0.008*** (0.001)
<i>Sociodemographics</i>						
Female	-0.134*** (0.004)	-0.084*** (0.002)	-0.114*** (0.003)	-0.063*** (0.003)	-0.036*** (0.002)	-0.049*** (0.002)
Age	0.001** (0.001)	0.005*** (0.000)	0.001*** (0.001)	0.001** (0.000)	0.003*** (0.000)	0.001 (0.000)
Age ²	-0.000 (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000** (0.000)
Primary/Lower Sec. Educ.	0.008** (0.004)	0.007** (0.003)	0.002 (0.004)	0.013*** (0.003)	0.010*** (0.001)	0.008*** (0.003)
Upper Secondary Educ.	0.025*** (0.004)	0.031*** (0.004)	0.019*** (0.004)	0.025*** (0.003)	0.020*** (0.002)	0.021*** (0.003)
Tertiary Education	0.059*** (0.013)	0.065*** (0.011)	0.054*** (0.012)	0.100*** (0.005)	0.086*** (0.005)	0.096*** (0.005)
<i>Labour Market History</i>						
Tenure ($t - 1$)	0.003*** (0.001)	0.001*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Full-time ($t - 1$)	0.038*** (0.002)	0.031*** (0.001)	0.061*** (0.002)	0.006*** (0.002)	0.008*** (0.001)	0.020*** (0.001)
Open-ended ($t - 1$)	-0.015*** (0.003)	0.040*** (0.002)	-0.007*** (0.003)	-0.009*** (0.001)	0.013*** (0.001)	-0.003** (0.001)
From unemployment ($t - 1$)	0.008*** (0.002)	-0.007*** (0.001)	0.003 (0.002)	0.005*** (0.001)	-0.004*** (0.001)	-0.002 (0.001)
Involuntary termination ($t - 1$)	-0.000 (0.002)	-0.009*** (0.002)	-0.001 (0.002)	-0.009*** (0.001)	-0.011*** (0.001)	-0.009*** (0.001)
Observations	643,094	643,035	643,094	420,074	420,015	420,074
Mean dep. var	0.178	0.099	0.158	0.077	0.042	0.063

Notes. Columns (1)–(3) present results for transitions into green occupations; Columns (4)–(6) present results for transitions into green-core occupations. OE denotes open-ended contract transitions; FT denotes full-time contract transitions. All specifications estimate linear probability models with controls, year fixed effects, and region fixed effects. The sample is restricted to between-occupation transitions (5-digit code changes) in (region $\times$ 2-digit occupation) cells with a share of green (or green-core) workers $\geq 1\%$. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F4: LPM - To Green - Specifications Comparison

	<i>Transition to Green</i>		
	(1)	(2)	(3)
<i>Green Occupation (t-1)</i>	0.122*** (0.007)	0.103*** (0.008)	0.074*** (0.008)
<i>Brown Occupation (t-1)</i>	0.009 (0.008)	-0.019** (0.008)	-0.041*** (0.008)
<i>Green Local Distance</i>		-0.046*** (0.002)	-0.033*** (0.002)
Observations	643,156	643,115	643,094
Mean dep. var	0.178	0.178	0.178
Region FE	✓	✓	✓
Year FE	✓	✓	✓
Controls			✓

Notes. Each column reports Linear LPM estimates where the dependent variable is an indicator for a transition into a green occupation. Main regressors include indicators for previous green or brown occupation status ($t - 1$) and the skill distance from the green profile. Specification (1) includes baseline fixed effects. Specification (2) adds the skill distance metric alongside an indicator for temporary unemployment prior to the switch. Specification (3) incorporates full sociodemographic controls (age, age-squared, gender, education) and labor market characteristics (tenure, full-time status, open-ended contract, involuntary termination). The sample is restricted to (region $\times$ 2-digit occupation) cells with a share of target-category workers $\geq 1\%$. Standard errors are clustered at the province level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F5: Factors Associated with Transitioning to Green and Green-Core Jobs
(3% Threshold on Cell Selection)

	To Green			To Green-Core		
	Any (1)	OE (2)	FT (3)	Any (4)	OE (5)	FT (6)
Green Occupation ($t - 1$)	0.423*** (0.008)	0.269*** (0.010)	0.373*** (0.008)	0.045*** (0.004)	0.023*** (0.003)	0.041*** (0.003)
Brown Occupation ($t - 1$)	0.024*** (0.008)	0.026*** (0.005)	0.020** (0.008)	-0.009 (0.006)	-0.000 (0.005)	-0.003 (0.006)
Green Local Distance	-0.006** (0.003)	0.007*** (0.002)	-0.003 (0.003)	-0.018*** (0.002)	-0.007*** (0.002)	-0.016*** (0.002)
Controls & FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	752,404	752,394	752,404	221,928	221,920	221,928
Mean dep. var	0.208	0.121	0.185	0.121	0.065	0.101

Notes. Columns (1)–(3) report results for transitions into green occupations; Columns (4)–(6) report results for transitions into green-core occupations. OE denotes open-ended contract transitions; FT denotes full-time contract transitions. The sample includes between-occupation transitions restricted to (region $\times$ 2-digit occupation) cells with a share of green (or green-core) workers $\geq 3\%$. All specifications estimate linear probability models including the full set of sociodemographic and labor market history controls, as well as year and region fixed effects. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F6: Factors Associated with Transitioning to Green and Green-Core Jobs
Probit Coefficients

	To Green			To Green-Core		
	Any (1)	OE (2)	FT (3)	Any (4)	OE (5)	FT (6)
Green Occupation ($t - 1$)	0.246*** (0.024)	0.225*** (0.021)	0.225*** (0.025)	0.282*** (0.014)	0.246*** (0.017)	0.284*** (0.015)
Brown Occupation ($t - 1$)	-0.153*** (0.031)	-0.066** (0.026)	-0.147*** (0.032)	0.129*** (0.036)	0.129*** (0.030)	0.153*** (0.039)
Green Local Distance	-0.145*** (0.007)	-0.082*** (0.007)	-0.144*** (0.008)	-0.074*** (0.007)	-0.047*** (0.008)	-0.070*** (0.007)
Controls & FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	643,094	643,035	643,094	420,074	420,015	420,074
Mean dep. var	0.178	0.099	0.158	0.077	0.042	0.063

Notes. Columns (1)–(3) report Probit coefficients for transitions into green occupations; Columns (4)–(6) report Probit coefficients for transitions into green-core occupations. OE denotes open-ended contract transitions; FT denotes full-time contract transitions. The sample includes only between-occupation transitions (5-digit code changes), restricted to (region $\times$ 2-digit occupation) cells with a share of green (or green-core) workers $\geq 1\%$. All specifications include the full set of sociodemographic and labor market history controls, as well as year and region fixed effects. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F7: Factors Linked to Post-Brown Job Outcomes

	Not Employed (1)	Open-Ended (2)	FT + Open-Ended (3)	Sector Change (4)	Occupation Change (5)
<i>Key Regressors</i>					
<i>Brown ($t-1$)</i>	0.007** (0.004)	-0.032*** (0.004)	-0.012*** (0.004)	0.006 (0.007)	0.113*** (0.005)
<i>Local Skill Distance</i>	0.031*** (0.004)	-0.026*** (0.004)	-0.008*** (0.003)	0.033*** (0.004)	0.062*** (0.006)
<i>Sociodemographics</i>					
Female	0.082*** (0.008)	-0.075*** (0.007)	-0.118*** (0.005)	0.007 (0.007)	0.097*** (0.005)
Age	-0.026*** (0.001)	0.036*** (0.001)	0.032*** (0.001)	-0.001 (0.001)	-0.006*** (0.001)
Age ²	0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	0.000 (0.000)
Primary/Lower Secondary Educ.	0.002 (0.006)	-0.031*** (0.007)	0.035*** (0.006)	0.012 (0.007)	0.009 (0.006)
Upper Secondary Education	-0.057*** (0.007)	0.028*** (0.009)	0.096*** (0.006)	0.025*** (0.009)	0.068*** (0.005)
Tertiary Education	-0.107*** (0.012)	0.141*** (0.007)	0.229*** (0.007)	0.045*** (0.011)	0.105*** (0.012)
<i>Labour Market History</i>					
Tenure ($t-1$)	0.029*** (0.001)	-0.017*** (0.001)	-0.009*** (0.001)	0.010*** (0.001)	0.014*** (0.001)
Full-time ($t-1$)	-0.056*** (0.004)	0.040*** (0.006)	0.231*** (0.005)	-0.030*** (0.007)	-0.036*** (0.009)
Open ended ($t-1$)	-0.097*** (0.003)	0.224*** (0.005)	0.169*** (0.006)	-0.031*** (0.004)	-0.141*** (0.005)
Observations	524,544	524,538	524,538	396,534	396,534
Mean dep. var	0.313	0.458	0.376	0.444	0.576

Notes. Each column reports results from specification (3), with controls as well as year and region fixed effects. Regressors include: key regressors (previous brown job indicator and skill distance from the local profile), sociodemographics (gender, age, age-squared, education levels), and labor market history ($t - 1$ tenure, full-time status, open-ended contract status). The analysis is restricted to (region $\times$ 2-digit occupation) cells with a share of previously brown workers greater than or equal to 1%. All specifications cluster standard errors at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F8: Effect of Transitioning from Brown Jobs Across Outcomes
(3% Threshold on Cell Selection)

	Not Employed	Open-ended	FT + Open-ended	Sector Change	Occupation Change
	(1)	(2)	(3)	(4)	(5)
<i>Brown Occupation (t - 1)</i>	0.010** (0.004)	-0.036*** (0.004)	-0.020*** (0.004)	0.010 (0.007)	0.109*** (0.005)
<i>Local Skill Distance</i>	0.029*** (0.005)	-0.022*** (0.004)	-0.005 (0.003)	0.030*** (0.005)	0.052*** (0.007)
Observations	422,937	422,934	422,934	321,390	321,390
Mean dep. var	0.308	0.458	0.393	0.442	0.592

Notes. Each column reports results from our preferred specification, including sociodemographic and labor-market controls, as well as year and region fixed effects. Main regressors: previous brown job indicator and local skills distance. The analysis is restricted to (region $\times$ 2-digit occupation) cells with a percentage of previously brown workers $\geq 3\%$. All specifications cluster standard errors at the province level (in $t - 1$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F9: Factors linked to Post-Brown Job Outcomes
Probit Coefficients

	Not Employed	Open-Ended	FT + Open-Ended	Sector Change	Occupation Change
	(1)	(2)	(3)	(4)	(5)
<i>Brown Occupation (t - 1)</i>	0.034*** (0.011)	-0.091*** (0.013)	-0.040*** (0.013)	0.015 (0.019)	0.325*** (0.017)
<i>Local Skill Distance</i>	0.085*** (0.013)	-0.065*** (0.013)	-0.022** (0.009)	0.082*** (0.012)	0.167*** (0.017)
Observations	524,544	524,538	524,538	396,534	396,534
Mean dep. var	0.313	0.458	0.376	0.444	0.576

Notes. Each column reports Probit coefficients from specification (3), with demographic and labor-market controls, as well as year and region FE. Main regressors: previous brown job indicator and local skills distance. The analysis is restricted to (region $\times$ 2-digit occupation) cells with a percentage of previously brown workers greater or equal to 1%. All specifications cluster standard errors at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



Skills for labour markets in the digital and green transition

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