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Skills and occupational mobility in the green transition: evidence from italian administrative data

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ABSTRACT

Skills and occupational mobility in the green transition: evidence from italian administrative data

We study how differences in skill requirements between occupations shape worker mobility during the green transition. Using about 13 million job-to-job transitions from a representative sample of Italian administrative data (2012-2023), combined with survey information on occupational skills, we estimate a gravity model of flows between 4-digit occupations. A one-standard-deviation increase in skill distance reduces worker flows by roughly 60%. Which skills matter differs across occupations: marginally green occupations tolerate gaps in green-specific skills but not in general capabilities, whereas green-core occupations appear less forgiving of skill mismatch, especially in terms of green skills. Exits from brown occupations, in turn, are eased along the general-skills margin. The analysis of gravity-model fixed effects suggests that green occupations attract workers mainly because they are easy to enter, not because they are more rewarding. At the individual level, the likelihood of green entry declines with skill distance and varies with prior occupation and gender. Workers leaving brown occupations face higher non-employment and are more likely to change 2-digit occupation.

PAROLE CHIAVE: competenze green, transizione ecologica, mobilità occupazionale, dati amministrativi

JEL CODES: J24, J6, F64

Questo lavoro analizza in che misura la distanza tra le competenze richieste dalle diverse occupazioni ostacoli o favorisca la mobilità dei lavoratori nel contesto della transizione verde. Unendo i dati relativi a circa 13 milioni di transizioni lavorative osservate nei dati amministrativi italiani (2012-2023) con informazioni sulle competenze professionali, stimiamo un modello gravitazionale dei flussi occupazionali. I risultati mostrano che la distanza tra i profili di competenza rappresenta un ostacolo significativo alla mobilità: un aumento di una deviazione standard riduce i flussi di lavoratori di circa il 60%. L'importanza delle diverse competenze varia, tuttavia, tra occupazioni verdi e brown. I risultati mostrano che l'importanza delle diverse competenze varia in base alla tipologia di occupazione: le professioni marginalmente verdi risultano relativamente accessibili anche a lavoratori che non possiedono le competenze specificamente legate alla sostenibilità ambientale, mentre le professioni green-core, direttamente connesse alle attività della transizione ecologica, richiedono una corrispondenza più elevata tra competenze possedute e competenze richieste. Per i lavoratori impiegati nelle professioni brown, il passaggio verso altre occupazioni è favorito soprattutto dalla trasferibilità delle competenze generali. L'analisi suggerisce inoltre che le occupazioni verdi attraggono lavoratori principalmente perché presentano minori barriere di accesso, più che per la presenza di migliori prospettive occupazionali. A livello individuale, la probabilità di accedere a un'occupazione verde diminuisce all'aumentare della distanza tra le competenze richieste dalla nuova occupazione e quelle possedute dal lavoratore; tale probabilità varia, inoltre, in funzione dell'occupazione di provenienza e del genere. Infine, i lavoratori che lasciano professioni brown presentano un rischio più elevato di attraversare periodi di non occupazione e una maggiore probabilità di dover cambiare ambito professionale.

KEYWORDS: *green skills, green transition, occupational mobility, administrative data*

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1. Introduction

Technological transitions typically create winners and losers in the labour market, and adjustment costs fall unevenly across occupations (Autor 2013; Goos *et al.* 2014; Acemoglu and Restrepo 2018). Workers respond to these labour market changes 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 have also 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). As a result, in most technological transitions it is unclear which occupations workers should move out of and which they should move into, and this makes the costs of reallocation hard to identify.

We contribute to this literature by studying 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]. However, knowing the direction 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 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–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 delle Professioni*, ICP), structured

[1] We 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.

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 (Brunetti *et al.* 2025)[2].

Our analysis builds on the occupational mobility model of Cortes and Gallipoli (2018)[3] extending their framework along three dimensions. First, by 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; second, by exploring the sensitivity of our estimates to alternative definitions of skill distance. Third, we expand their fixed effects decomposition to systematically examine the specific attributes of green and brown jobs. We then take the analysis to the worker level: linear probability models on matched samples of job changers, to shed light on those who enter green occupations, and what happens to those who leave brown ones. Gravity estimates confirm that skill distance is a first-order friction which shapes occupational mobility. Moreover, the interactions of interest trace a pattern that depends on the approach used to measure skill distances. When looking at skill distances in terms of general green and general brown skills, green destinations attenuate the penalty clearly. For green-core destinations, the most intensely green occupations, and for brown origins the evidence is weaker: neither interaction is statistically significant, which is consistent with, but does not firmly establish, green-core occupations remaining selective on green-task content and brown exits facing the same friction in brown-specific skills as exits elsewhere. When measuring skill distances in terms of latent factors, the pattern changes. Different skill margins therefore bind for different segments of the transition. Entry at the green margin is constrained by broad capabilities but tolerates mismatch in green-skills, whereas green-core occupations appear less forgiving of such mismatch; exit from brown work is eased along the general-capability margin while facing the full friction in brown-specific skills. Only the attenuation for marginally green destinations holds firmly across our robustness checks; the other differences are estimated with less precision and shift with the estimation sample. When computing skill distances on the entire skill battery, without prior selection or dimensionality reduction, interaction terms instead become insignificant: 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.

Then, we 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

[2] Occupations 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.

[3] Workers 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.

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. Earnings premia for carbon-intensive work have been estimated for establishments, firms or sectors (Barreto *et al.* 2023; Haywood *et al.* 2024; Rud *et al.* 2024; Garnache *et al.* 2025) rather than for occupations, and are therefore not at odds with this result. 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 (Curtis 2018; Cortes *et al.* 2020), 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. Measuring, following Macaluso (2025), how far a worker's previous occupation sits from the skill profile of local green jobs, we find that distance from local skill requirements is a first-order predictor of green entry: a one-standard-deviation increase in distance from local requirements is associated with a 3.3 percentage point lower probability of moving into a green occupation. Occupational history matters asymmetrically. Prior green experience predicts green entry, while a brown origin lowers the probability of entering a green occupation by 4.1 points but raises that of entering a green-core one by 2.0, a result that holds in our baseline sample but disappears when the cell-selection threshold is raised from 1% to 3%. 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. Workers leaving brown occupations 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); after separation, women and the less educated fare worse than other job leavers, a gap that concerns brown and grey leavers alike rather than those exiting brown work in particular, while better-educated workers do better through active reallocation across sectors and occupations.

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 (Consoli *et al.* 2016; Vona *et al.* 2018; 2019; Marin and Vona 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, who makes these transitions and at what cost.
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 (Rausch *et al.* 2010; Bowen *et al.* 2018; Pollin and Callaci 2019; Carley and Konisky 2020). 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.* 2011; 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 appear comparatively accessible, suggesting that the binding constraint lies on the supply side rather than in barriers to entry.

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,

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

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

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

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 $d_{k,k} = 1$ 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

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

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 a given state k, the fraction of them observed moving to another state 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, $\pi_{j,k} =$

[5] On 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 subsidised.

[6] The 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.

[7] Individuals can be thought of as receiving offers from many potential employers within 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.

$sw_{j,k}/N_k$: 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,

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

one can define $\ln d_{j,k} = \beta_1\, dist_{j,k} + \sum_{m=1}^{4} \gamma_m\, \lambda_{j,k}^{m} + m_j + \epsilon_{j,k}$, where $dist_{j,k}$ 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 equation:

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

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

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

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

[8] Origin-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.

[9] Staying 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.

[10] Attractiveness 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.

$\partial \ln(sw_{j,k}/sw_{k,k})/\partial \ln d_{j,k} = -\theta$. 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 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,

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

[11] The 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 C.1 carries out the conversion for our estimates.

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-hand side gives a conditional mean for the flow itself,

$$E[sw_{j,k}] = \exp\left(\tilde{\beta}_1\, dist_{j,k} + \tilde{\beta}_2\, dist_{j,k} \times Green_j + D_j - S_k + \sum_{m=1}^{4} \tilde{\gamma}_m\, \lambda_{j,k}^{m}\right) \times sw_{k,k}, \qquad (7)$$

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. 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.

[12] A 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 readings scale the same object and we do not separate them; the interaction captures any mechanism through which the penalty differs.

3. Data, measures and descriptives

3.1 Data sources

Administrative data on job-to-job transitions

Our primary source is a sample[13] of 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). Two limitations matter for what follows. Firstly, the archive carries no information on earnings. Secondly, because it records data only upon contractual events (e.g., hirings, terminations, or contract changes), workers who remain continuously in the same job throughout the sample period may be unobserved. Measures of worker flows are therefore captured reliably, whereas stocks less so. 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, as well as 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. 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 gravity estimates we cumulate these flows over the whole period and treat the resulting matrix as a single cross-section of occupation pairs.

Skill data

Occupational skill and task content comes from the *Indagine Campionaria delle 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. These data, which merge with the CO archive at the 5-digit level, serve as the basis for the general green and brown skill indicators and pairwise skill distance measures developed in Brunetti *et al.* (2025). We utilise these established metrics directly, deferring to the same Brunetti *et al.* (2025) for full methodological details.

Definition of green and brown jobs

To identify green and brown jobs in the Italian context, we adopt the occupational classification proposed by Brunetti *et al.* (2025). Following Vona *et al.* (2018), greenness is defined as the share of

[13] Specifically, from this archive, we observe a representative sample of individuals born on four dates per month and follow their employment events over time.

green tasks relative to total occupational tasks, based on the O*NET Green Task Development Project (Dierdorff *et al.* 2009). Since the ICP lacks green task measures, greenness scores of Italian occupations are imputed from US O*NET scores, following a common practice in the literature (Goos *et al.* 2014; Vona 2021; Elliott *et al.* 2024)[14]. Concretely, this is done by mapping SOC occupations to the CP2011 classification, using the International Standard Classification of Occupations (ISCO) as a bridge. A comprehensive discussion of this methodology and its associated limitations is available in Brunetti *et al.* (2025). Since the gravity-model specification interacts skill distance with an indicator for the destination occupation, we then discretise the greenness score. Following Vona *et al.* (2018), occupations with a greenness of at least 0.1 are classified as *Green*, the subset with a greenness of at least 0.3 as *Green Core*. A binary green margin also keeps the destination side symmetric with the brown origin side, which – in the classification proposed by Brunetti et al. (2025) – is binary by construction. Since no standardised taxonomy of 'brown' tasks exists, brown occupations are defined based on their concentration in pollution-intensive industries. Full methodological details are available in Brunetti *et al.* (2025), while Appendix A.3 provides the complete list of green and brown occupations analysed in this paper.

3.2 Skill measures

General Green and Brown Skills

For our analysis, we utilise the lists of General Green Skills (GGS) and General Brown Skills (GBS) derived specifically for the Italian context in our previous work (Brunetti *et al.* 2025), to which we refer the reader for full methodological details. In short, these lists are obtained by adapting to the Italian context the approach of Vona *et al.* (2018): the main idea is to identify, within the overall skill battery, the items that are used with systematically greater intensity in green or brown occupations relative to comparable non-green, non-brown ones. Concretely, the relevance scores of each general skill ℓ in occupation k are regressed on the greenness indicator (or a brown job dummy) plus a set of two-digit occupational dummies:

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

A positive (negative) and significant β^{ℓ} denotes that general skill ℓ is used more (less) intensively in greener occupations. The exact same regression, substituting $Brown_k$ instead of $Greenness_k$, is then used to identify General Brown Skills. As documented in Brunetti *et al.* (2025), Italian-specific GGS align closely with the list derived by Vona *et al.* (2018) for the US labour market. Furthermore, a pronounced convergence exists between green and brown skill sets within the Italian context: notably, 13 of the 18 GBS are encompassed within the broader list of 28 GGS[15]. The overlap between general green and brown

[14] Vona (2021) argues that this crosswalk provides an acceptable greenness measure when occupation-level data are granular enough. Further, Dicarlo *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.
[15] The 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.

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

To proxy the skill adjustment costs workers face when transitioning between jobs, we measure the dissimilarity in occupational requirements using the skill distance metrics developed by Brunetti *et al.* (2025). Grounded in the literature on human capital specificity (Ingram and Neumann 2006; Gathmann and Schönberg 2010; Macaluso 2025), these measures are constructed by first characterising occupations as vectors of skill scores to then compute pairwise distances between such vectors[16].

Specifically, we adopt 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 when examining transitions into green occupations, and GBS skills for out-of-brown transitions. Restricting attention to the relevant subset prevents the metric from being diluted by irrelevant skills. The second measure, following a common practice in the literature (Ingram and Neumann 2006; Poletaev and Robinson 2008; Guvenen *et al.* 2020), summarises instead all relevant skill items 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, distance between two occupations is measured with the Manhattan (ℓ_1) norm, which is sensitive to the *level* of skill requirements and not only to their composition. Concretely, the relevant skill scores for each occupation are collected into a vector and rescaled 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 given by the average absolute difference between their rescaled vectors:

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

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. We refer the reader to Brunetti *et al.* (2025) for a much more detailed discussion of their underlying framework.

[16] We work at the 4-digit occupational level, since finer granularity leaves too few flows between specific occupation pairs (Cortes and Gallipoli 2018).

[17] Formally, 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 $\tilde{R}_m^j = (R_m^j - R_m^{min})/(R_m^{max} - R_m^{min})$.

3.3 Descriptive evidence

We document a set of stylised facts on job-to-job mobility that motivate the analysis of Section 4 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]. This accounts 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.

Within the transitions sample 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). 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.

Green and brown flows across macro-occupational groups

Table B1 in Appendix B 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 (Table B1, panel C). The first pattern anticipates the skill-selectivity of green entry, the second the portability of brown skills; the gravity estimates below quantify both.

[18] Full-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.

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

	Transitions (full-time weighted)	% of all transitions
Panel A. By destination / origin type		
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
Panel B. Occupational reach of the move		
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, CO 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.
Source: Authors' elaborations on CO data 2012-2023

The skill-distance distribution of flows

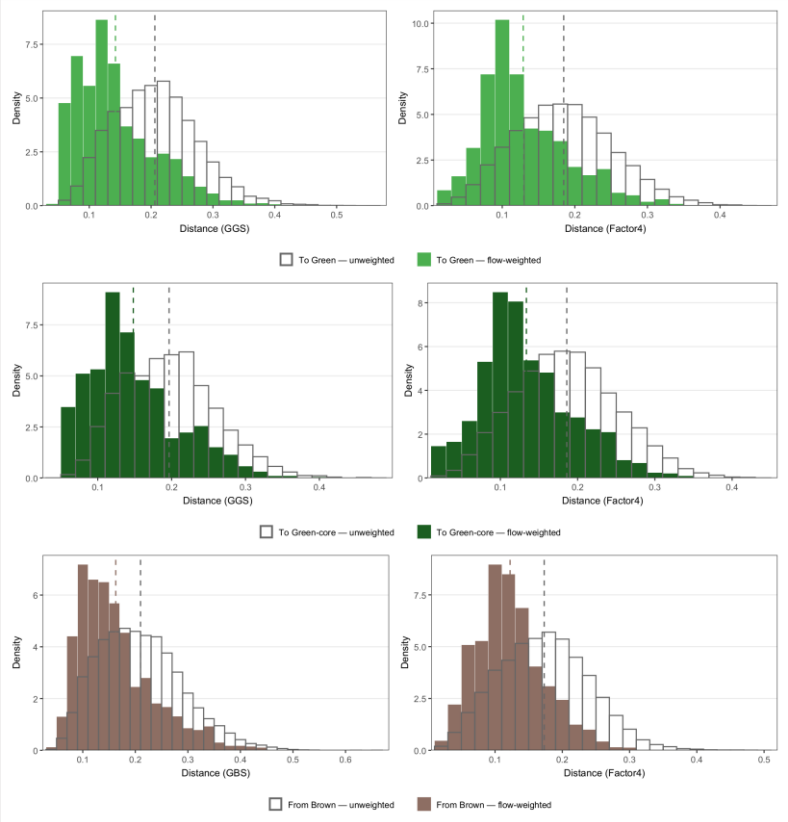
We compare, within each transition type, the distribution of skill distances across all feasible origin–destination pairs with the distribution across the pairs that workers actually traverse. Figure 1 plots, for moves into green and green-core destinations and out of brown origins, the unweighted density 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 B1) 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.

Job creation and destruction

Because the CO records flow 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 $G_{it} = \sum_{s \le t} a_{is} \,/\, \sum_{s \le t} e_{is}$, 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 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 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.

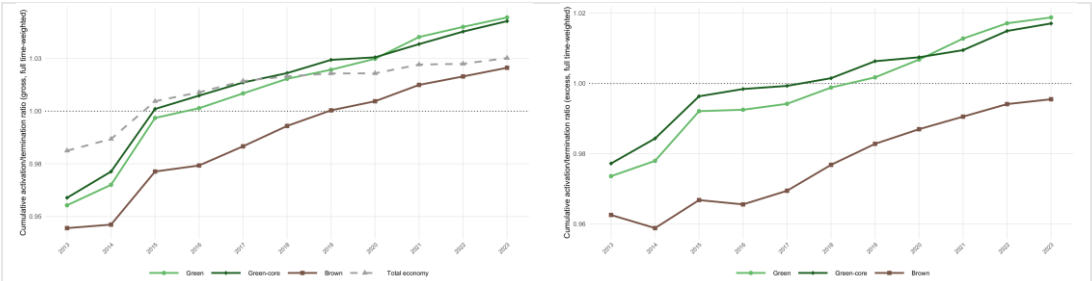
Figure 1 Skill distance of realised flows vs. all occupation pairs, by transition type



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.
Source: Authors' elaborations on CO-ICP data 2012-2023

[19] By construction, $g_{it} = 1$ indicates a stable occupation group, $g_{it} > 1$ a growing one and $g_{it} < 1$ a shrinking one.
[20] Figure B2 shows that these conclusions are robust to measuring dynamics through cumulative net activations rather than activation-to-termination ratios.

Figure 2 Job creation and destruction patterns in job mobility



(a) Cumulative A/E Ratio (Gross) (b) Cumulative A/E Ratio (Excess)

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: Authors' elaborations on CO data 2012-2023

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.

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] . 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]. 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

[21] Column (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.
[23] Likewise, for renewable-energy and energy-saving technicians (3136), a green-core occupation, the closest origin is mechanical engineers (2211), also green-core; starting from production-management technicians (3315) adds roughly 1.55 standard deviations.
[24] They 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.

occupations our baseline falls to -0.673 (Table C1, 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 $(-1.004 + 0.205)$, 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.

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***	−1.0036***	−0.9808***	−0.7064***
	(0.0438)	(0.0480)	(0.0456)	(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. $dist_{j,k}$ 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: NCj,k if k and j are in two different task groups and j is non-routine cognitive; RCj,k if j is routine cognitive; RMj,k if j is routine manual; NRMj,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). * = 0.1, ** = 0.05, *** = 0.01
Source: Authors' elaborations on CO-ICP data 2012-2023

Table 3 re-estimates the same specifications with distance measured over the four latent factors, which 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. In Table 3, column (3) finds a positive interaction for green-core destinations, significant at the 10% level: the implied slope of -0.82 $(-0.935 + 0.113)$ corresponds to a 56% reduction in flows per standard deviation, against 61% for other destinations. The same interaction estimated with the GGS distance (Table 2, column 3) is virtually identical in size, but not statistically significant.

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 reverses, with green-core destinations and brown origins tolerating larger gaps and marginal green destinations none. The two margins appear consistent once one asks what each destination actually requires. In marginally green occupations, green tasks represent a small share of the job. As a result, deficiencies in green-specific skills concern capabilities that are only peripheral to the work, so the matching friction is relatively weak. In green-core occupations, by contrast, green skills are fundamental for performing that job, making any skill gap more consequential and binding. 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 (Guvenen *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 C.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.

[25] On 2-digit occupations the factor-based baseline is -0.706 (Table C1, 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 characterisation

	(1)	(2)	(3)	(4)
$dist_{j,k}$	−0.9307***	−0.9276***	−0.9352***	−0.9341***
	(0.0330)	(0.0346)	(0.0338)	(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, standardised 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: NCj,k if k and j are in two different task groups and j is non-routine cognitive; RCj,k if j is routine cognitive; RMj,k if j is routine manual; NRMj,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).
Source: Authors' elaborations on CO-ICP data 2012-2023

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 C2). 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 C3 and C4), 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,

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

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 C5 and C6) leaves the distance coefficient essentially unchanged[27]. The interactions are more sensitive. 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.

Lastly, re-estimating by negative binomial, which allows for overdispersion (Tables C7 and C8), 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 GGS-based green-core interaction turns significant at the 10% level, 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 Tenreyro 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.

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).

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[28]. Sub-figure (c) shows a less visually striking pattern for brown occupations, which scatter

[27] The 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.

[28] Origin 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 grey occupations.

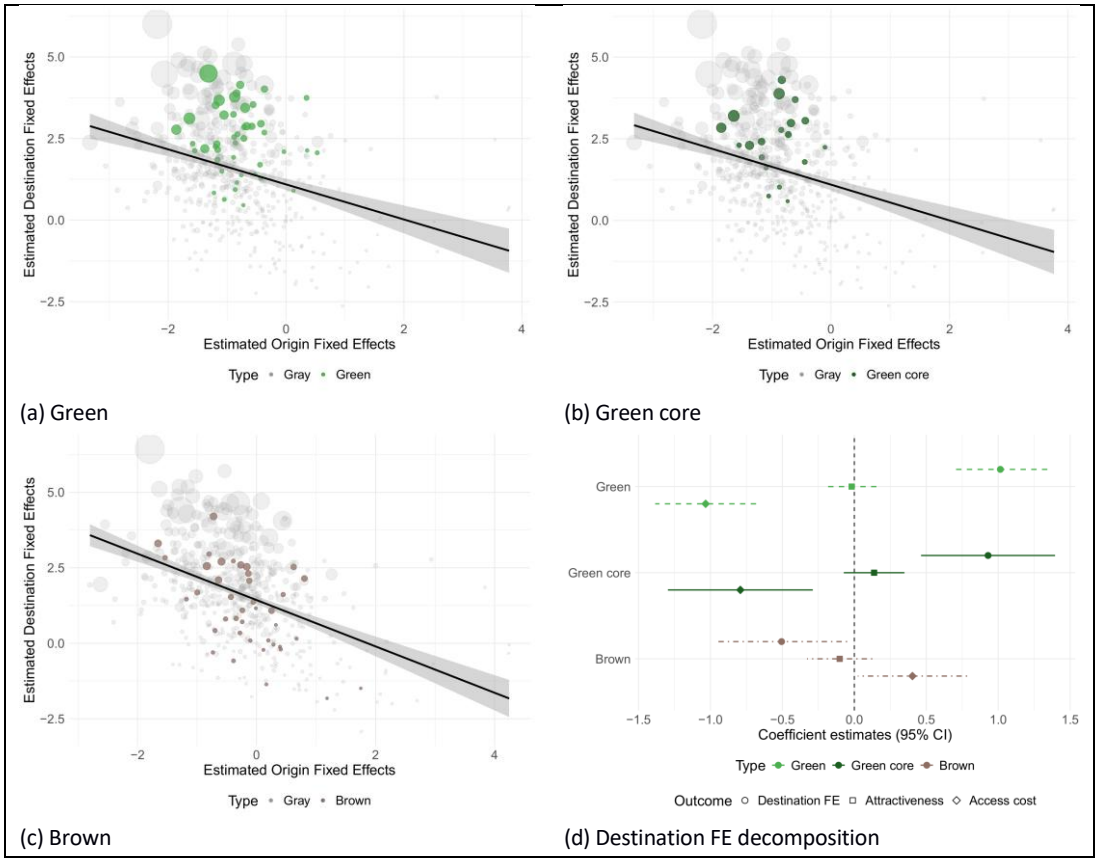
around the regression line with a modest downward displacement[29]. Sub-figure (d) decomposes the point estimates of the destination fixed effect (circles) into attractiveness (squares) and access costs (diamonds).

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 almost 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[30]. 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 reverses. 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).

[29] As noted in Section 2.2, $\widehat{D}_j$ 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.

[30] Access costs here are reduced-form barriers that co-move with demand. Within the model, the transition cost can equivalently be regarded 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.

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; grey 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 ($\theta\widehat{m}_j$) between each occupation type and grey 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 $\hat{D}_j = \hat{S}_j - \theta\widehat{m}_j$. 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.
Source: Authors' elaborations on CO-ICP data 2012-2023

Three caveats attach to this interpretation. 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[31]. Because both mechanisms imply low churn, worker flows alone cannot distinguish them. The stakes are highest for 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 in 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

[31] See Cortes and Gallipoli (2018, Appendix B).

(Table 2) and a significantly smaller one under the factor-based measure (Table 3), whereas a strong lock-in mechanism would predict the opposite. Third, the estimated access costs, obtained as a residual, may partly reflect differences in occupational growth.

Figure D1 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, consistent with the modest green wage premia reported in previous studies (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. 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[32]. 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 confuse 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 × region cell, and each separation from a brown occupation with separations from grey occupations in the same origin 2-digit occupation × region cell[33]. 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, i.e. the (weighted) average skill distance from that occupation to all relevant destination 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 $dist_i^{\text{green}}$ 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 $dist_i^{\text{local}}$ measures how far the worker's previous occupation sits from the overall prevailing local skill demand. Appendix E provides all the details about their construction and underlying rationale.

5.2 Descriptive evidence on individual transitions

Table E1 in Appendix E compares 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 are 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

[32] For 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 E.
[33] The 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 E, which illustrates the sample construction process in more detail, discusses both choices, and Section 5.3 reports robustness to a 3% threshold.

higher broad skill group than the origin.[34] 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,[35] 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.

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

$$Y_{i,t} = \delta_1 \, Brown_{i,t-1} + \delta_2 \, Green_{i,t-1} + \delta_3 \, dist_i^{green} + \gamma \, \mathbf{Z}'_{i,t-1} + \phi_r + \mu_t + \varepsilon_{i,t} \qquad (10)$$

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 ($Brown_{i,t-1}$) or green ($Green_{i,t-1}$), and the green-specific local skill remoteness of the worker's previous occupation ($dist_i^{green}$); 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.36 For exits from brown occupations we estimate

$$Y_{i,t} = \delta_1 \, Brown_{i,t-1} + \delta_2 \, dist_i^{local} + \gamma \, \mathbf{Z}'_{i,t-1} + \phi_r + \mu_t + \varepsilon_{i,t}, \qquad (11)$$

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.[37] The coefficient of interest is δ_1, which measures whether brown leavers face systematically different outcomes from their grey counterparts; $dist_i^{local}$ replaces the green distance, and controls and fixed effects are as above. We estimate both equations as linear probability models, which remain tractable

[34] Skill 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.

[35] Conditioning on the origin 2-digit occupation × 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.

[36] The distance regressor varies at the previous occupation × province level; clustering at the province allows arbitrary error correlation within local labour markets and is the more conservative choice.

[37] Non-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.

with fixed effects at our sample sizes and deliver coefficients that read directly as probability changes; probit estimates, reported in Appendix E, 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: a one-standard-deviation increase in $dist^{\text{green}}$ is associated with a 3.3 percentage point lower probability of moving to a green occupation. The 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[38], 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, although, as shown below, this advantage does not survive a stricter cell selection.

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

	Transition to Green			**Transition to Green-Core**		
	Any	OE	FT	Any	OE	FT
	(1)	(2)	(3)	(4)	(5)	(6)
Green Occ. (t-1)	0.074***	0.049***	0.065***	0.051***	0.028***	0.046***
	(0.008)	(0.005)	(0.008)	(0.003)	(0.002)	(0.002)
Brown Occ. (t-1)	−0.041***	−0.012***	−0.037***	0.020***	0.013***	0.022***
	(0.008)	(0.005)	(0.008)	(0.006)	(0.004)	(0.006)
Green Local Dist.	−0.033***	−0.013***	−0.031***	−0.009***	−0.004***	−0.008***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(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, labour 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 × 2-digit occupation) cells with a share of target-category workers $\geq 1\%$. Standard errors are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

[38] Table E3, 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.

The full set of coefficients (Table E2) 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[39]. A tertiary degree raises the probability of a green transition by 5 points and of a green-core transition by 10.

Post-separation outcomes from brown occupations

Table 5 reports the outcomes of workers leaving brown occupations relative to their matched grey counterparts. 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).[40] 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 E6) shows that post-separation outcomes also differ across groups of workers. In the pooled sample of brown and grey leavers, women are 8.2 points more likely to be non-employed and 11.8 points less likely to secure a full-time open-ended contract. 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. The results are robust to probit estimation (Tables E5 and E8), which leaves signs and significance essentially unchanged. Raising the cell-selection threshold to 3% (Tables E4 and E7) confirms all results except the association between a brown origin and green-core entry, whose coefficient becomes small, negative and statistically insignificant (Table E4, columns 4–6). 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. The evidence suggests possible opportunities, such as a pathway from brown to green-core roles, although this does not survive a stricter sample selection, alongside frictions and disadvantages for women and less-educated workers, which emerge among job leavers as a whole and not only among those coming from

[39] The 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.

[40] All outcomes are conditional on a contract change, given the construction of the sample.

brown occupations; both may be relevant for the design of labour market policies aimed at a less disruptive transition.

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)
Brown Occ. $(t-1)$	0.007**	−0.032***	−0.012***	0.006	0.113***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)
Local Skill Distance	0.031***	−0.026***	−0.008***	0.033***	0.062***
	(0.004)	(0.004)	(0.003)	(0.004)	(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 labour-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 × 2-digit occupation) cells with a percentage of previously brown workers $\geq 1\%$. All specifications cluster standard errors at the province level (in $t-1$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' elaborations on CO-ICP data 2012-2023

6. Conclusion

This paper has examined occupational mobility in the green transition, a case of directional structural change in which labour demand shifts towards green occupations and away from brown ones. We focused on the two margins through which this shift is realised: entry into green occupations and exit from brown ones. Combining a large representative administrative sample of Italian job-to-job transitions with occupation-level skill content, we estimated a gravity model of occupational flows in which bilateral skill distance is interacted with the green and brown character of occupations. We then decomposed the destination fixed effects into attractiveness and access costs and complemented the analysis with individual-level evidence.

Skill distance emerges as a first-order friction: a one-standard-deviation increase reduces occupational flows by roughly 60%, a magnitude that is stable across skill measures and specifications. However, the friction is not uniform: measured over green- and brown-specific skills, it is attenuated only for marginally green destinations; measured over broad capabilities, for brown origins and, more weakly, for green-core destinations. On the green-skill margin, green-core destinations show no comparable attenuation; unlike marginally green ones, they appear to tolerate mismatch in broad capabilities more than mismatch in green-specific skills. The skill gap that matters therefore varies across occupations: broad capabilities for marginally green occupations, green-specific skills for the most intensely green ones, and brown-specific skills for exits from brown work. These differences are estimated less precisely than the average effect of skill distance: the result for marginally green occupations is the most robust, while the others are more sensitive to the sample used. Nonetheless, they emerge only when distance is measured along the relevant skill dimensions and disappear when all skills are considered together.

The decomposition of the destination fixed effects shows that reallocation across the green–brown spectrum is governed by access costs rather than attractiveness. The high inflows into green and green-core occupations are explained almost entirely by below-average entry barriers, with a modest

attractiveness premium that emerges only when distance is measured over general capabilities. Conversely, the low inflows into brown occupations reflect high access costs, while their attractiveness does not differ from that of other occupations. Together with the absence of an additional distance penalty on exits from brown occupations, this indicates that brown employment declines through reduced inflows rather than accelerated separations, and that green occupations expand because they are easy to enter rather than because they are more rewarding.

The individual-level evidence shows that these margins are crossed unevenly. Distance from the local green skill profile is a strong predictor of green entry. Occupational history matters asymmetrically. Prior green experience increases the probability of entering a green occupation. A brown background lowers this probability for green occupations overall but raises it for green-core ones, a pattern consistent with, though not shown to be caused by, the overlap between green and brown skills. The green-core advantage of brown leavers is nonetheless fragile, since it is no longer detectable once the analysis is restricted to cells in which green-core transitions make up at least 3% of the total. Access is also stratified by gender: conditional on observables, women are 13 percentage points less likely to enter a green occupation and 6 points less likely to enter a green-core one. Workers leaving brown occupations bear a modest but significant transitional cost. They are more likely to be non-employed, less likely to obtain an open-ended contract and considerably more likely to change occupation. Women and less-educated workers also fare worse after leaving their jobs, but this disadvantage is common to all job leavers and is not specific to those exiting brown occupations.

These conclusions are subject to some limitations. Since greenness and skill measures are fixed over the sample period, we capture only reallocation between occupations and not the greening that occurs within them. Worker flows alone cannot distinguish costly entry from costly exit. We adopt the access-cost interpretation, but the estimated access costs, obtained as a residual, may partly reflect differences in occupational growth. Moreover, as the data record employment events rather than stocks, our estimates describe the destinations of job changers rather than the probability of changing job. Finally, the analysis is descriptive and structural rather than causal.

With these caveats in mind, three policy implications emerge. First, skill distance does not appear to trap workers in brown occupations more than other workers, and the brown segment loses ground mainly through fewer entries. This finding concerns the mobility margin only, however: leaving brown work carries a cost in job security, and the data are silent on wages. Second, since the binding skill dimension differs across destinations, retraining focused on green skills in general may miss the relevant margin for some groups of workers. Moreover, given that green occupations already display below-average access costs, the main constraint appears to lie in the supply of skills rather than in access to jobs. Third, the costs and opportunities documented are unevenly distributed across gender, education, occupations and places, and this unevenness is likely to matter for the political sustainability of climate policy (Cavallotti et al. 2025; Vona 2019).

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.
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. Because each communication links a worker to a firm, the CO can be effectively used to reconstruct individual career trajectories, and to hence build a matched employer–employee panel. 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.
Two limitations follow from the design of the archive. Firstly, the CO carries no information on earnings, which is why the paper is silent on the wage consequences of the transitions it studies. Secondly, because it records data only upon contractual events (e.g., hirings, terminations, or contract changes), workers who remain continuously in the same job throughout the sample period may be unobserved. Measures of worker flows are therefore captured reliably, whereas stocks less so.

A.2 Skill data

While we do not process the raw *Indagine Campionaria delle Professioni* (ICP) data directly, we borrow directly from Brunetti et al. (2025) the taxonomies of General Green and Brown Skills (GGS and GBS) and all pairwise skill distance metrics, inheriting the methodological framework developed in that work. The ICP covers 255 items across multiple thematic modules. Following the approach of Vona et al. (2018), Brunetti et al. (2025) focus on Sections B (Knowledge), C (Skills), and G (Work Activities)—comprising 109 items—to identify GGS and GBS – ultimately obtaining a list of 28 General Green Skills and 18 General Brown Skills.
Section D (Abilities, 52 items) is omitted from the identification of GGS and GBS because it records individual characteristics that are, by definition, “relatively stable over time and hard to modify” and are therefore of limited relevance to the retraining and skill adjustment with which the identification of green and brown skills is concerned.
Section D is however combined with sections B, C and G (for a total of 161 skill dimensions) to measure skill distances between pairs of occupations.

A.3 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
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

Table continued on next page

Table A1 (continued)

CP (5D)	Occupation
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
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 equal to or above 0.1. † denotes the green-core occupations, with a greenness score equal to or above 0.3.
Source: Brunetti *et al.* (2025), based on O*NET green task data (Dierdorff *et al.* 2009) mapped to CP2011 via ISCO.

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

Table continued on next page

Table A2 (continued)

CP (5D)	Occupation
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

Note: This table lists the five-digit CP2011 occupations classified as brown.
Source: Brunetti *et al.* (2025)

B. Additional descriptives

Table B1 Origin and destination macrogroup shares of green and brown transitions

Code	Macrogroup	% of origin flows		% of destination flows	
		panel	all	panel	all
Panel A. Into green destinations ($g_j \geq 0.1$) — 97,627 transitions					
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

Table continued on next page

Table B1 (continued)

Panel B. Into green-core destinations ($g_j \geq 0.3$) — 35,476 transitions					
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
Panel C. Out of brown origins — 28,486 transitions					
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

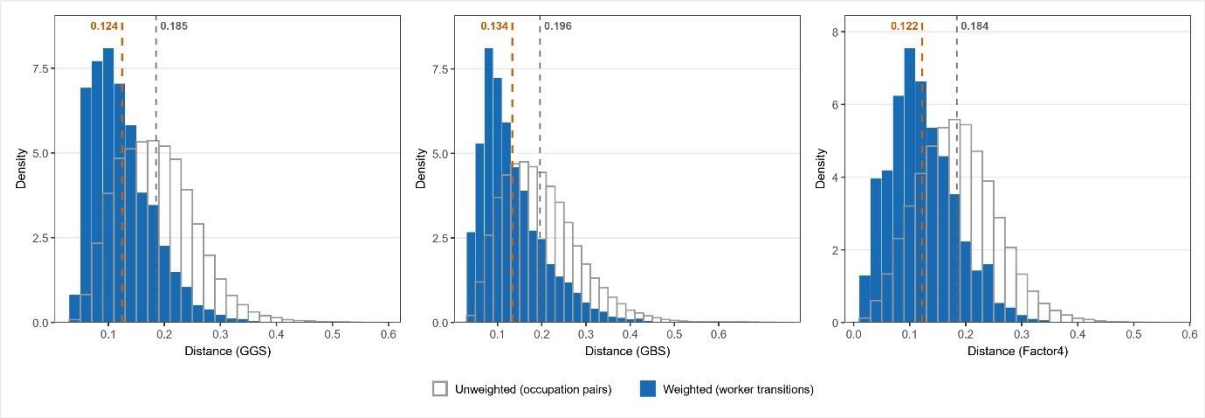
Notes: Share of full-time-weighted flow attributable to each 1-digit CP2011 macrogroup, on the origin side and destination side separately. Each panel restricts the sample to one transition type, and its panel total — $97{,}627$ transitions into green, $35{,}476$ into green-core and $28{,}486$ out of brown, against $1{,}067{,}756$ job-to-job transitions overall — is the denominator of the panel columns, so each sum to 100% within its panel. 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.
Source: Authors' elaborations on CO data 2012-2023

Table B2 Origin and destination macro-group shares of direct brown-to-green transitions

Code	Macro-group	% of origin flows	% of destination flows
Panel A. Brown → green — 2,682 transitions			
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
Panel B. Brown → green-core — 1,020 transitions			
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

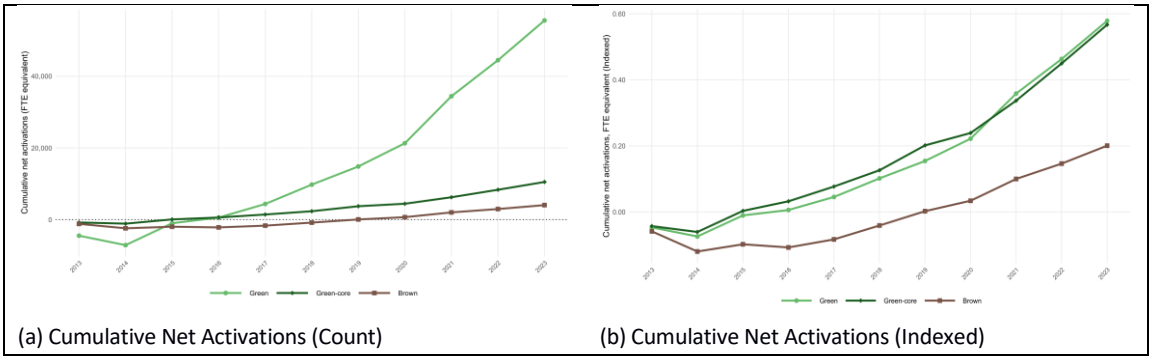
Notes: Share of full-time-weighted flow attributable to each 1-digit CP2011 macro-group, on the origin side and destination side separately. Each panel restricts the sample to one transition type, and its *panel total* — $2{,}682$ brown-to-green transitions and $1{,}020$ brown-to-green-core transitions, 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.
Source: Authors' elaborations on CO data 2012-2023

Figure B1 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.
Source: Authors' elaborations on CO-ICP data 2012-2023

Figure B2 Cumulative Net Activations in Green, Greencore and Brown Occupations



(a) Cumulative Net Activations (Count) (b) Cumulative Net Activations (Indexed)

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: Authors' elaborations on CO data 2012-2023

C. Additional gravity estimates

Table C1 Skill distance and job to job transitions. Aggregation to 2-digit occupations

	GGS	GBS	FACTOR4
$dist_{j,k}$	−0.6734***	−0.4442***	−0.7057***
	(0.0464)	(0.0429)	(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, standardised 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).
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C2 Skill distance and job to job transitions. All skills (161 dimensions) in vector characterisation

	(1)	(2)	(3)	(4)
$dist_{j,k}$	−1.3391***	−1.3435***	−1.3416***	−1.3386***
	(0.0416)	(0.0426)	(0.0424)	(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, standardised on the full estimation sample. The PPML model offsets on the number of stayers in occupation k. 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).
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C3 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***	−1.0544***	−1.0327***	−0.7426***
	(0.0434)	(0.0474)	(0.0452)	(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). The PPML model offsets on the number of stayers in occupation k. 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.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C4 Skill distance and job to job transitions. Factor analysis (4) in vector characterisation. All transitions, no zero-flow restriction

	(1)	(2)	(3)	(4)
$dist_{j,k}$	−0.9701***	−0.9647***	−0.9732***	−0.9714***
	(0.0325)	(0.0341)	(0.0334)	(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, standardised on the full estimation sample. The PPML model offsets on the number of stayers in occupation k. 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.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C5 Skill distance and job to job transitions. Gradual inclusion of FEs 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***	−1.1661***	−0.9754***	−0.9327***	−1.1975***	−1.0036***	−0.9340***	−1.1734***	−0.9808***	−0.7285***	−0.8910***	−0.7064***
	(0.0434)	(0.0414)	(0.0438)	(0.0478)	(0.0447)	(0.0480)	(0.0449)	(0.0428)	(0.0456)	(0.0438)	(0.0455)	(0.0351)
$dist_{j,k} \times Green_j$				−0.1794*	0.2580***	0.2053**						
				(0.1080)	(0.0947)	(0.0936)						
$dist_{j,k} \times Green\ Core_j$							0.0156	0.1719**	0.1114			
							(0.1001)	(0.0873)	(0.0880)			
$dist_{j,k} \times Brown_k$										0.3327***	0.1482**	0.0535
										(0.0737)	(0.0752)	(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). 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.

Source: Authors' elaborations on CO-ICP data 2012-2023

Table C6 Skill distance and job to job transitions. Gradual inclusion of fixed effects and controls. Factor analysis (4) in vector characterisation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$dist_{j,k}$	−0.9049***	−1.0851***	−0.9307***	−0.9044***	−1.0847***	−0.9276***	−0.9070***	−1.0900***	−0.9352***	−0.9122***	−1.0890***	−0.9341***
	(0.0421)	(0.0288)	(0.0330)	(0.0461)	(0.0302)	(0.0346)	(0.0437)	(0.0296)	(0.0338)	(0.0433)	(0.0294)	(0.0336)
$dist_{j,k} \times Green_j$				−0.0101	−0.0041	−0.0308						
				(0.0867)	(0.0818)	(0.0821)						
$dist_{j,k} \times Green\ Core_j$							0.0842	0.1346**	0.1128*			
							(0.0795)	(0.0653)	(0.0665)			
$dist_{j,k} \times Brown_k$										0.3687***	0.1547***	0.1317**
										(0.0681)	(0.0576)	(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, standardised on the full estimation sample. 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.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C7 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***	−0.8664***	−0.8583***	−0.6597***
	(0.0100)	(0.0106)	(0.0102)	(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). The negative binomial model offsets on the number of stayers in occupation k. 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).
Source: Authors' elaborations on CO-ICP data 2012-2023

Table C8 Skill distance and job to job transitions. Negative binomial. Factor analysis (4) in vector characterisation

	(1)	(2)	(3)	(4)
$dist_{j,k}$	−0.8309***	−0.8330***	−0.8344***	−0.8323***
	(0.0104)	(0.0109)	(0.0106)	(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, standardised on the full estimation sample. The negative binomial model offsets on the number of stayers in occupation k. 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).
Source: Authors' elaborations on CO-ICP data 2012-2023

C.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.

Table C9 Skill distance: flow scale and implied transition-cost scale

			Implied effect on $d_{j,k}$		
	Coefficient	Flows	$\theta = 3.23$	$\theta = 5.94$	$\theta = 9.00$
Panel A. Green-skill distance (GGS)					
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%	$+28.0\%$	$+14.4\%$	$+9.3\%$
Panel B. Factor-based distance					
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.
Source: Authors' elaborations on CO-ICP data 2012-2023

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.

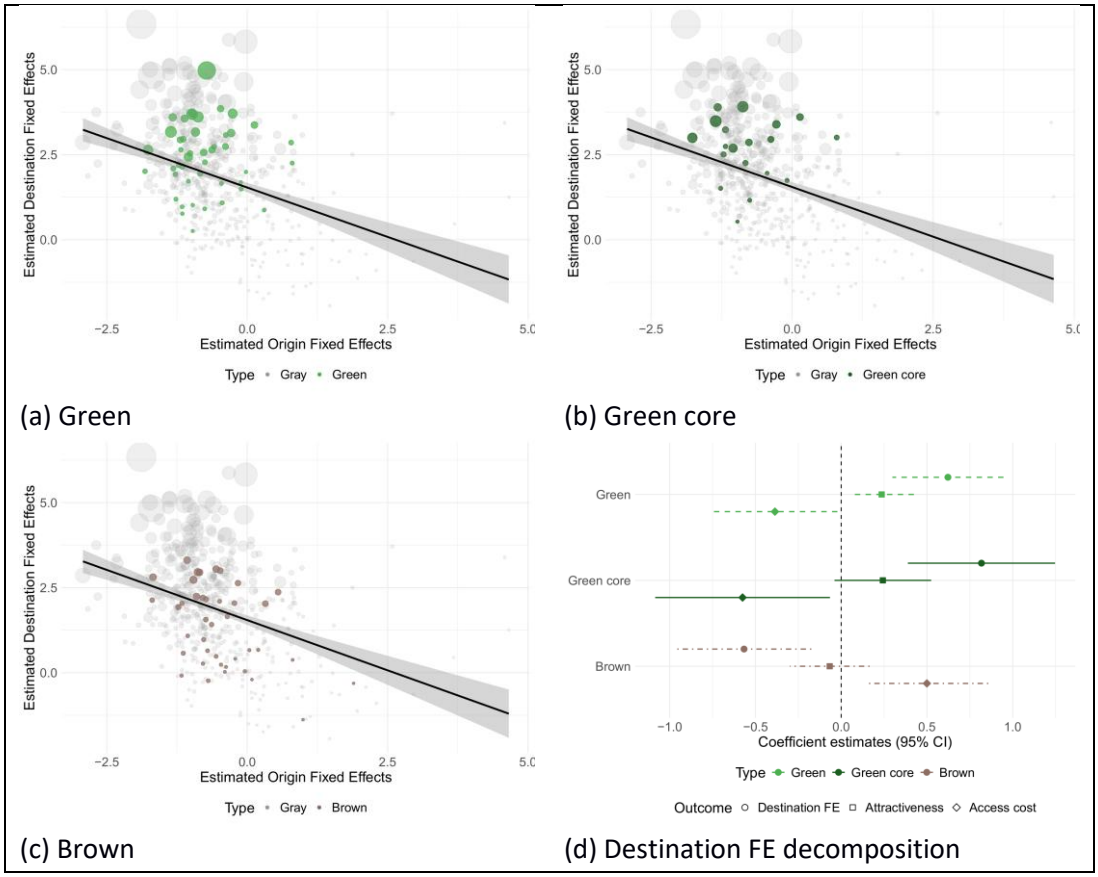
Second, on the differences across occupation types, all three attenuations compress sharply as θ rises. At $\theta = 3.23$ the distance penalty facing green destinations is 8.4 percentage points below that facing non-green ones (28.0% against 36.4%); the green-core gap is 4.6 points and the brown-origin 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.[41] 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.

[41] The 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.

D. Additional gravity estimates

Figure D1 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; grey 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 grey occupations, with 95% confidence intervals. Skill distance measured using factor analysis (F=4). Sample: occupation pairs with positive flows (noflows baseline).
Source: Authors' elaborations on CO-ICP data 2012-2023

E. Additional details on individual analysis

E.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 × region cell, and each separation from a brown occupation to its origin 2-digit occupation × 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 re-estimated at a 3% threshold in Section 5.3 and hold, except the association between a brown origin and green-core entry, which loses significance.

E.2 Local Skill Distances

This section describes the construction of two skill-distance measures used in the individual-level analysis, i.e. $dist_j^{\text{green}}$ and $dist_j^{\text{local}}$. 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 more in detail in Brunetti et al. (2025)), we construct our measures in two steps. Firstly, we compute occupation-specific labour demand shares at the province level. Secondly, we use 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 CO 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, $dist_{jp}^{\text{local}}$ and $dist_{jp}^{\text{green}}$, 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, $dist^{\text{green}}$ 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 $dist_{jp}^{\text{local}}$, 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 Brunetti et al. (2025), 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 mirrors closely the skill-remoteness measure by Macaluso (2025):

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

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:

$$w_{kp}^{\text{G}} = \frac{A_{kp}}{\sum_{\text{o}\in\mathcal{G}} A_{op}}, \qquad k, o \in \mathcal{G}.$$

To further focus on skill dimensions that are most relevant for green transitions, the green-specific local skill distance $dist_{jp}^{\text{green}}$ 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 winsorised at the 95th percentile, to prevent individual high-employment (or high-churn) occupations from dominating the weighted average of specific local markets and then renormalised 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 standardised 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.

E.3 Descriptive Tables

Table E1 To Green and Green-Core vs. Matched Grey Transitions

	To Green Panel		**To Green Core Panel**	
Variable	To Green	To Grey	To Green-Core	To Grey
Sociodemographics				
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%
Labour Market Characteristics				
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%
Transition Dynamics				
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 $N_{To\ Green} = 326{,}101$ and $N_{To\ Grey} = 1{,}567{,}819$ for the Green panel; $N_{To\ Green\text{-}Core} = 92{,}518$ and $N_{To\ Grey} = 1{,}103{,}204$ for the Green-Core panel. The matched pool of transitions is restricted to (region × 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). 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] $N_{Green} = 114{,}470$, $N_{Grey} = 528{,}686$ / $N_{Green\text{-}Core} = 32{,}205$, $N_{Grey} = 387{,}908$ (job-to-job movers with non-missing previous job); [b] $N_{Green} = 100{,}930$, $N_{Grey} = 468{,}667$ / $N_{Green\text{-}Core} = 28{,}584$, $N_{Grey} = 343{,}957$ (job-to-job movers with complete occupation/sector codes).
Source: Authors' elaborations on CO-ICP data 2012-2023

E.4 Regression Results & Robustness Checks

Table E2 Factors Associated with Transitioning to Green and Green-Core Jobs

	To Green			*To Green-Core*		
	Any	OE	FT	Any	OE	FT
	(1)	(2)	(3)	(4)	(5)	(6)
Key Regressors						
Green Occupation ($t-1$)	0.074***	0.049***	0.065***	0.051***	0.028***	0.046***
	(0.008)	(0.005)	(0.008)	(0.003)	(0.002)	(0.002)
Brown Occupation ($t-1$)	−0.041***	−0.012***	−0.037***	0.020***	0.013***	0.022***
	(0.008)	(0.005)	(0.008)	(0.006)	(0.004)	(0.006)
Green Local Distance	−0.033***	−0.013***	−0.031***	−0.009***	−0.004***	−0.008***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Sociodemographics						
Female	−0.134***	−0.084***	−0.114***	−0.063***	−0.036***	−0.049***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Age	0.001**	0.005***	0.001***	0.001**	0.003***	0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(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**	0.007**	0.002	0.013***	0.010***	0.008***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.001)	(0.003)
Upper Secondary Educ.	0.025***	0.031***	0.019***	0.025***	0.020***	0.021***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)
Tertiary Education	0.059***	0.065***	0.054***	0.100***	0.086***	0.096***
	(0.013)	(0.011)	(0.012)	(0.005)	(0.005)	(0.005)
Labour Market History						
Tenure	0.003***	0.001***	0.003***	0.002***	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0. 000)	(0.000)
Full-time	0.038***	0.031***	0.061***	0.006***	0.008***	0.020***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Open-ended	−0.015***	0.040***	−0.007***	−0.009***	0.013***	−0.003**
	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)

Table continued on next page

Table E2 (continued)

From unemployment	0.008***	−0.007***	0.003	0.005***	−0.004***	−0.002
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Involuntary termination	−0.000	−0.009***	−0.001	−0.009***	−0.011***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(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. Variables in the "Labour Market History" panel are measured at t-1, i.e. in the year before the transition. 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 × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table E3 LPM - To Green - Specifications Comparison

	Transition to Green		
	(1)	(2)	(3)
Green Occupation (t-1)	0.122***	0.103***	0.074***
	(0.007)	(0.008)	(0.008)
Brown Occupation (t-1)	0.009	−0.019**	−0.041***
	(0.008)	(0.008)	(0.008)
Green Local Distance		−0.046***	−0.033***
		(0.002)	(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 Probability Model (LPM) estimates where the dependent variable is an indicator for a transition into a green occupation. 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 labour market characteristics (tenure, full-time status, open-ended contract, involuntary termination). The sample is restricted to (region × 2-digit occupation) cells with a share of target-category workers $\geq 1\%$. Standard errors are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table E4 Factors Associated with Transitioning to Green and Green-Core Jobs (3% Threshold on Cell Selection)

	To Green			*To Green-Core*		
	Any	OE	FT	Any	OE	FT
	(1)	(2)	(3)	(4)	(5)	(6)
Green Occupation (t − 1)	0.063***	0.042***	0.055***	0.045***	0.023***	0.041***
	(0.007)	(0.005)	(0.006)	(0.004)	(0.003)	(0.003)
Brown Occupation (t − 1)	−0.067***	−0.025***	−0.061***	−0.009	−0.000	−0.003
	(0.008)	(0.005)	(0.008)	(0.006)	(0.005)	(0.006)
Green Local Distance	−0.038***	−0.013***	−0.036***	−0.018***	−0.007***	−0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls & FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	499,406	499,398	499,406	221,928	221,920	221,928
Mean dep. var	0.220	0.122	0.197	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 × 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 labour market history controls, as well as year and region fixed effects. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table E5 Factors Associated with Transitioning to Green and Green-Core Jobs (Probit Coefficients)

	To Green			*To Green-Core*		
	Any	OE	FT	Any	OE	FT
	(1)	(2)	(3)	(4)	(5)	(6)
Green Occupation (t − 1)	0.246***	0.225***	0.225***	0.282***	0.246***	0.284***
	(0.024)	(0.021)	(0.025)	(0.014)	(0.017)	(0.015)
Brown Occupation (t − 1)	−0.153***	−0.066**	−0.147***	0.129***	0.129***	0.153***
	(0.031)	(0.026)	(0.032)	(0.036)	(0.030)	(0.039)
Green Local Distance	−0.145***	−0.082***	−0.144***	−0.074***	−0.047***	−0.070***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(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 × 2-digit occupation) cells with a share of green (or green-core) workers $\geq 1\%$. All specifications include the full set of sociodemographic and labour market history controls, as well as year and region fixed effects. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table E6 Factors Linked to Post-Brown Job Outcomes

	Not Employed (1)	Open-Ended (2)	FT + Open-Ended (3)	Sector Change (4)	Occupation Change (5)
Key Regressors					
Brown (t-1)	0.007**	−0.032***	−0.012***	0.006	0.113***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)
Local Skill Distance	0.031***	−0.026***	−0.008***	0.033***	0.062***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)
Sociodemographics					
Female	0.082***	−0.075***	−0.118***	0.007	0.097***
	(0.008)	(0.007)	(0.005)	(0.007)	(0.005)
Age	−0.026***	0.036***	0.032***	−0.001	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(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 Second. Educ.	0.002	−0.031***	0.035***	0.012	0.009
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Upper Secondary Education	−0.057***	0.028***	0.096***	0.025***	0.068***
	(0.007)	(0.009)	(0.006)	(0.009)	(0.005)
Tertiary Education	−0.107***	0.141***	0.229***	0.045***	0.105***
	(0.012)	(0.007)	(0.007)	(0.011)	(0.012)
Labour Market History					
Tenure (t-1)	0.029***	−0.017***	−0.009***	0.010***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Full-time (t-1)	−0.056***	0.040***	0.231***	−0.030***	−0.036***
	(0.004)	(0.006)	(0.005)	(0.007)	(0.009)
Open ended (t-1)	−0.097***	0.224***	0.169***	−0.031***	−0.141***
	(0.003)	(0.005)	(0.006)	(0.004)	(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 labour market history ($t-1$ tenure, full-time status, open-ended contract status). The analysis is restricted to (region × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' elaborations on CO-ICP data 2012-2023

Table E7 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)
Brown Occ. ($t-1$)	0.010**	−0.036***	−0.020***	0.010	0.109***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)
Local Skill Distance	0.029***	−0.022***	−0.005	0.030***	0.052***
	(0.005)	(0.004)	(0.003)	(0.005)	(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 labour-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 × 2-digit occupation) cells with a percentage of previously brown workers $\geq 3\%$. All specifications cluster standard errors at the province level (in $t-1$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

Table E8 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)
Brown Occ. ($t-1$)	0.034***	−0.091***	−0.040***	0.015	0.325***
	(0.011)	(0.013)	(0.013)	(0.019)	(0.017)
Local Skill Distance	0.085***	−0.065***	−0.022**	0.082***	0.167***
	(0.013)	(0.013)	(0.009)	(0.012)	(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 labour-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 × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' elaborations on CO-ICP data 2012-2023

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INAPP
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