Skills and job mobility in the green transition: Evidence from Italy

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Introduction

- **Occupational mobility** is central to labour market adjustment, and skill distance is a key determinant of reallocation.
- Empirically, **skill distance** tends to negatively affects occupational mobility. Whether this is softened or exacerbated in structural transformations remains mostly unexplored.
- **The green transition** provides a rare case of directional structural change, with clearly expanding (green) and contracting (brown) occupations.
- Central for **policy evaluation**. Minimizing gaps between available and required skills is key to an inclusive just transition.

This paper

Research question

What is the role of skill distance in shaping occupational mobility during the green transition?

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- Leverages rich administrative and survey data on job-to-job mobility in Italy (2012–2023).
- Identifies green and brown skills and assesses their degree of overlap.
- Within a gravity model, studies how skill distance shapes mobility within the green transition.
- Profiles the career path of workers coming from green or brown occupations (not today).

Literature Review

1. **Task-based approaches and Green Jobs**
   Autor, Levy, and Murnane (2003); Autor (2013); Vona, Marin, Consoli, and Popp (2018).

2. **Skill Mismatches and Occupational Mobility**
   Ingram and Neumann (2006); Kambourov and Manovskii (2009); Gathmann and Schönberg (2010); Cortes and Gallipoli (2018); Guvenen, Kuruscu, Tanaka, and Wiczer (2020); Macaluso (2024).

3. **Green Jobs, Workforce Reallocation and the Just Transition**
   Bowen (2012); Vona et al. (2018); Saussay, Sato, Vona, and O'Kane (2022); Curtis, O'Kane, and Park (2024).

Data Sources I

- **Comunicazioni Obbligatorie (COB):** details
  - ⋆ A 48-dates sample taken from administrative (MLPS) data. Traces the labour market history of workers.
  - ⋆ Main info on the **initiation** and **termination** of any employment relationship.
  - ⋆ We extract $\sim$ **2.8M** unique workers with $>$ **13M** job transitions.
- **Indagine Campionaria delle Professioni (ICP):** details
  - ⋆ Workers' survey (INAPP, ISTAT) with information on **skills** and knowledge requirements across occupations.
  - ⋆ For each skill, the survey records its **relevance** for the occupation and the **proficiency** required to perform it.
  - ⋆ 796 5-digit occupations characterized in terms of a vector of scores across 255 dimensions (161 used by us).

Data Sources II

- **Greenness/Brownness Measures:**
  - ⋆ Task-based measures of the **greenness** of occupations (Vona et al., 2018). Obtained by crosswalk of O*NET data and the Italian CP2011 classification (via an in-between ISCO crosswalk).
  - ⋆ Industry-exposure measures of the **brownness** of occupations (Vona et al., 2018). Defined by disproportionate employment in highly polluting industries mapped to CP2011 through SOC–ISCO crosswalks.

- **Italian Labour Force Survey (ILFS):**
  - ⋆ Provides employment shares and descriptive statistics (e.g., age, education) at the occupation level.

General Skills - Methodology

We follow the empirical approach outlined by Vona et al. (2018), adopting the **greenness (brownness) indicator as a "search criterion"**.

For each task ℓ in occupation k we estimate the following models:

$$Task\ Rel_k^{\ell} = \beta^{\ell} \times Greenness_k + \phi^{CP_{2D}} + \epsilon_k$$

$$Task\ Rel_k^{\ell} = \beta^{\ell} \times Brownness_k + \phi^{CP_{2D}} + \epsilon_k$$

Skills are labelled as green (brown) when $\hat{\beta}_l$ is positive and statistically significant at the 5% level. ggs-ex gbs

General Green Skills - Results

Engineering & Technical:		
	B10	Engineering and Technology
	B11	Design
	B13	Mechanical
	G05	Estimating the Quantifiable Characteristics of Products and Events
	G21	Drafting, Laying Out, and Specifying Technical Devices and Equipment
Monitoring:		
	B29	Public Safety and Security
	G03	Monitoring Processes, Materials, or Surroundings
	G07	Evaluating Information to Determine Compliance with Standards
Operations Mgmt:		
	B33	Transportation
	G12	Updating and Using Relevant Knowledge
	G20	Operating Vehicles, Mechanized Devices, or Equipment
Science:		
	B15	Physics
	B16	Chemistry
	B17	Biology

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	B17	Biology

Skill Distances Methodology results

Within occupational mobility, a skill distance metric can be interpreted as an assessment of occupational mobility costs (Gathmann & Schönberg, 2010; Cortes & Gallipoli, 2018; Macaluso, 2024).

We employ a **Manhattan distance**, with two distinct vector characterizations.

(1) Factor Analysis

$$D_{jk} = \frac{1}{F} \sum_{f=1}^{F} |\tilde{\mathbf{R}}_f^j - \tilde{\mathbf{R}}_f^k|,$$

with F being the chosen number of factors (F=4).

(2) General Green Skills

$$D_{jk} = \frac{1}{G} \sum_{g=1}^{G} |\tilde{\mathbf{R}}_f^j - \tilde{\mathbf{R}}_f^k|,$$

with G being the number of general green skills (G=14)

Occupational Mobility

Ultimately our goal is to study **occupational mobility** within the **green transition**.

We collapse the COB data into a **origin and destination dataset** of 4-digit k occupations, measuring mainly the following.

- $Sw_{j,k} \rightarrow$ the number of workers switching occupations from k to j;
- $Sw_{k,k} \rightarrow$ the number of workers staying in occupation k;
- $Green_k \rightarrow$ occupations with a level of greenness > 0.1;
- $Green\ Core_k \rightarrow$ occupations with a level of greenness > 0.3;
- $Brown_k \rightarrow$ occupation with positive brownness.

Occupational Mobility - empirical specification

Drawing from Cortes and Gallipoli (2018)'s occupational choice model, we estimate a Poisson-Pseudo Maximum Likelihood model as follows:

$$Sw_{j,k} = \beta_1 D_{j,k} + \beta_2 Green_{j \in Green,k} + \beta_3 D_{j,k} \times Green_{j \in Green,k} + \tau_k + \alpha_j + \gamma \mathbf{X}'_{\mathbf{j},\mathbf{k}} + \epsilon_{j,k}$$

- $Sw_{j,k}$: count of switchers from origin occupation k to destination occupation j;
- $D_{j,k}$: skill distance measure between k and j;
- $Green_{j \in Green,k}$: whether the destination occupation j is green;
- τ_k, α_j: origin and destination occupation fixed effects;
- $\mathbf{X}'_{\mathbf{j},\mathbf{k}}$: vector of task-different dummies between k and j;

Occupational Mobility - empirical specification

$$
\begin{aligned}
Sw_{j,k} =& \beta_1 D_{j,k} + \beta_2 Green\ Core_{j \in Green\ Core,k} + \beta_3 D_{j,k} \times Green\ Core_{j \in Green\ Core,k} + \\
& \tau_k + \alpha_j + \gamma \mathbf{X'_{j,k}} + \epsilon_{j,k}
\end{aligned}
$$

- We do the same for $Green\ Core_{j \in Green\ Core,k}$.
- **Intuition**: are transitions into green (and green-core) occupations less constrained by skill mismatch?

Occupational Mobility - empirical specification

$$Sw_{j,k} = \beta_1 D_{j,k} + \beta_2 Brown_{j,k \in Brown} + \beta_3 D_{j,k} \times Brown_{j,k \in Brown} + \tau_k + \alpha_j + \gamma \mathbf{X}'_{\mathbf{j,k}} + \epsilon_{j,k}$$

- We do the same for $Brown_{j,k \in Brown}$, i.e., whether the origin occupation k is brown.
- **Intuition**: Are transitions originating from brown occupations less constrained by skill mismatch?

Stylized facts other

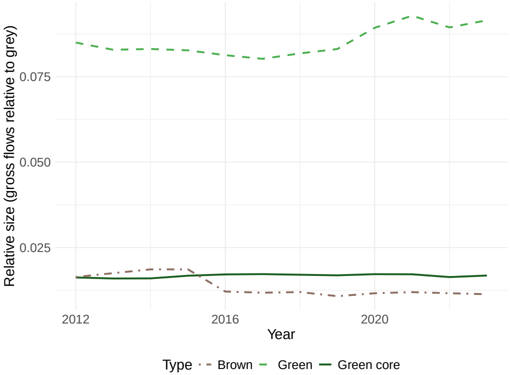


Figure 1: Relative size

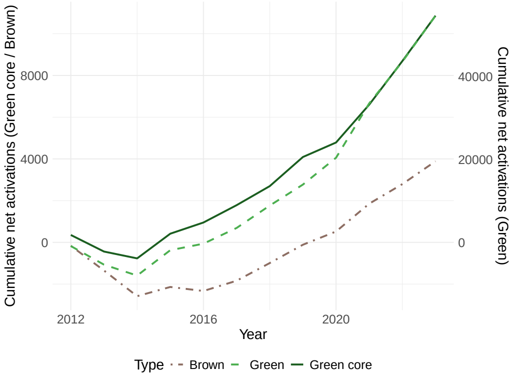


Figure 2: Cumulative net activations

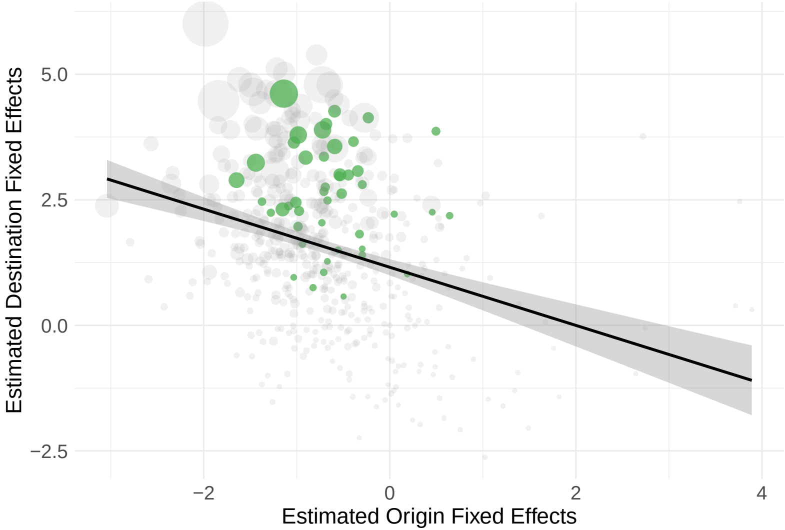
Regression Results factor4

Table 1: Skill distance and job to job transitions.

	(1)	(2)	(3)
$D_{j,k}$	-1.0036***	-0.9808***	-0.9765***
	(0.0480)	(0.0456)	(0.0449)
$D_{j,k} \times Green_{j \in Green,k}$	0.2053**		
	(0.0936)		
$D_{j,k} \times Green\ Core_{j \in Green\ Core,k}$		0.1114	
		(0.0880)	
$D_{j,k} \times Brown_{j,k \in Brown}$			0.0379
			(0.0720)
Num.Obs.	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 occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

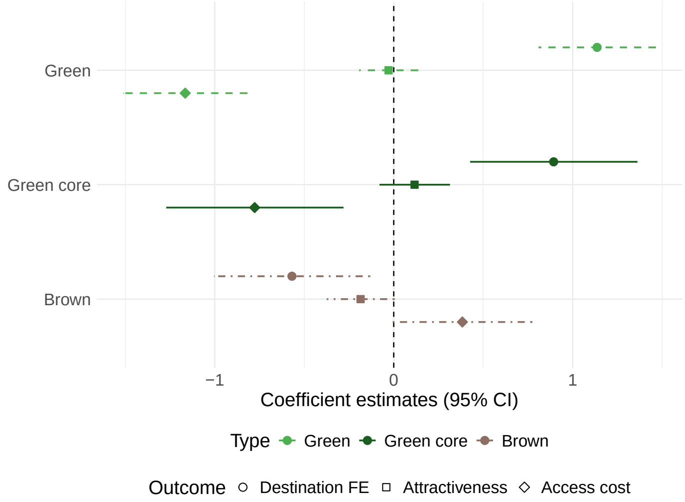
Fixed Effects Analysis I



Fixed Effects Analysis I

Fixed Effects Analysis I

Fixed Effects Analysis II fe-decomp factor4



Conclusions

- Skill distance is a first-order determinant of occupational mobility, but it does not exhaust the sources of reallocation frictions.
- Exploiting the directional nature of the green transition reveals that some expanding occupations attract workers primarily because they are easier to access, not simply because they are closer in skill space.
- Occupations at the core of the transition remain attractive but skill-selective, while declining occupations are characterized mainly by high entry barriers rather than low desirability.
- **Policy implication**: beyond reskilling, reducing occupation-specific access barriers is central to facilitating worker reallocation during episodes of structural change.

Conclusions

Thank you for you attention!

WP coming soon!

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ICP back

For each skill, the survey records its **relevance for the occupation**, as well as the level at which workers are required to perform it:

D.4	Esprimersi in forma scritta	Attitudine a comunicare informazioni ed idee scrivendo in modo che altri capiscano

A. Quanto è importante questa attitudine nello svolgimento della sua attuale professione?

- Non importante 1|_| → passare all'attitudine successiva
- Appena importante 2|_|
- Importante 3|_|
- Molto importante 4|_|
- Di assoluta importanza 5|_|

B. A quale livello, fra quelli indicati, è necessaria questa attitudine per lo svolgimento della sua attuale professione?

Scrivere un biglietto per ricordare a qualcuno di metter fuori del cibo dal congelatore → 2

Scrivere una nota di raccomandazioni su come fare un lavoro per un collaboratore → 4

Scrivere un libro di economia → 6

1 2 3 4 5 6 7

All 796 occupations at the 5-digit level are characterized in terms of a **vector of scores across 255 dimensions** (out of which we focus on 161, i.e. sections B, C, D and G).

COB back

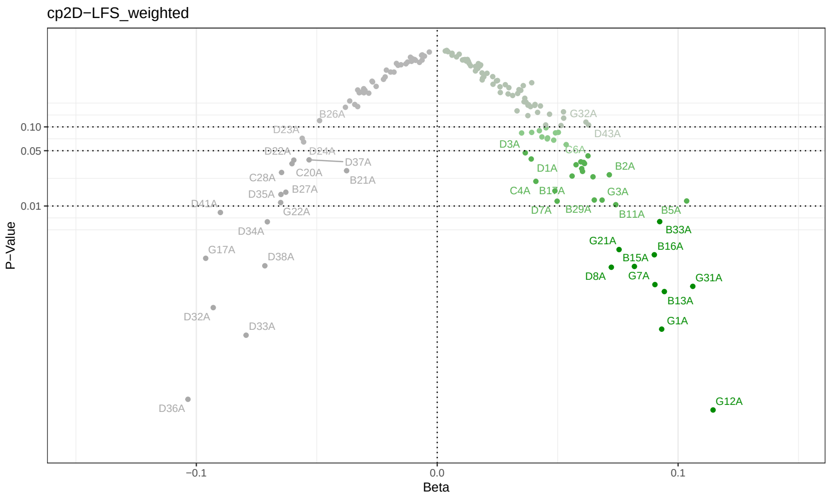
Since 2007, employees are required to submit information (including -notably- the occupation code) about any changes to employment relationships.

This data allows to **trace the labour market history of workers** and is well suited for the **study of job-to-job transitions**.

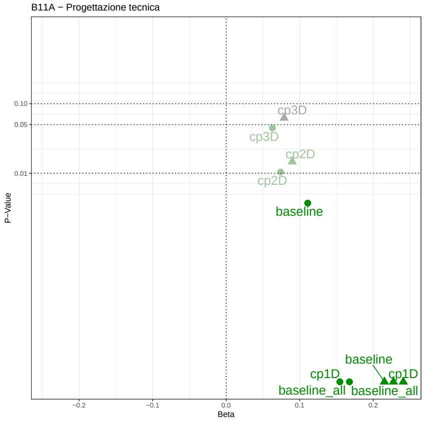
By focusing only the "most relevant" contract within each year, we transform COBs into a **individualized panel dataset** (from 2012 to 2024).

The final analysis sample consists of **2,793,904 unique workers**. In total we observe $>$ **13M job-to-job transitions.**

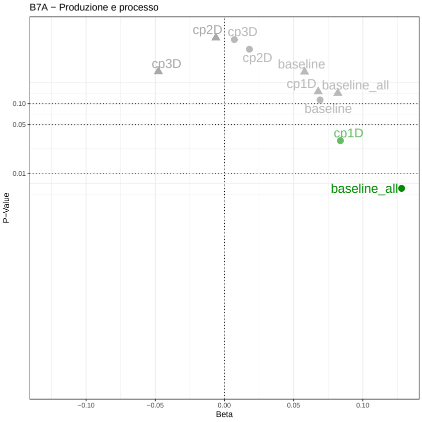
General Green Skills - Results



General Green Skills - Selected examples - back



B11 - Design



B7 - Production and Processing

Brown Skills

back

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

Skill Distances - Results - back

Most Similar Pairs

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

Skill Distances - Results - back

Most Different Pairs

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

Correlation between Skill Distance Measures

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

Factor 4 loadings

Table 2: Factor Analysis - Skills with Highest Loadings

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

Additional stylized facts back

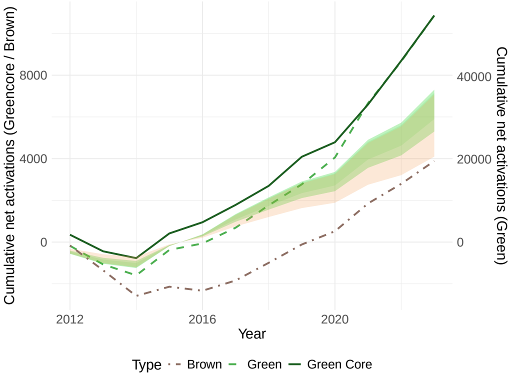


Figure 3: Cumulative net activations and balanced growth path

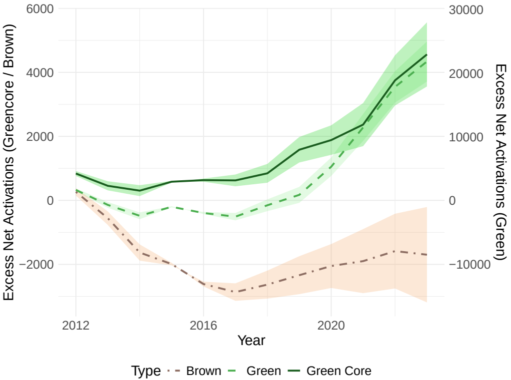


Figure 4: Excess net activations

Regression Results - Factor 4 back

Table 3: Skill distance and job to job transitions.

	(1)	(2)	(3)
$D_{j,k}$	-0.9276***	-0.9352***	-0.9341***
	(0.0346)	(0.0338)	(0.0336)
$D_{j,k} \times Green_{j \in Green,k}$	-0.0308		
	(0.0821)		
$D_{j,k} \times Green\ Core_{j \in Green\ Core,k}$		0.1128*	
		(0.0665)	
$D_{j,k} \times Brown_{j,k \in Brown}$			0.1317**
			(0.0575)
Num.Obs.	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 occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Fixed effects decomposition back

Cortes and Gallipoli (2018)'s main equation is the following

$$\ln\left(\frac{sw_{kj}}{sw_{kk}}\right) = D_j - S_k - \theta\beta_1 \text{dist}_{kj} - \theta\beta_2\lambda_{kj}^{NC} - \theta\beta_3\lambda_{kj}^{RC} - \theta\beta_4\lambda_{kj}^{RM} - \theta\beta_5\lambda_{kj}^{NM} - \theta\epsilon_{kj}.$$

where D_j and S_k are, respectively, destination and origin fixed effects.

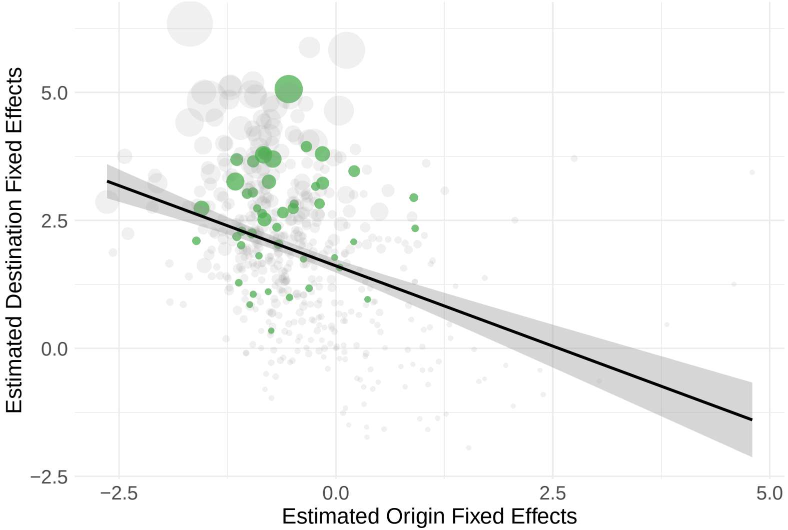
Within their model is possible to decompose D_j as

$$D_j \equiv S_j - \theta m_j$$

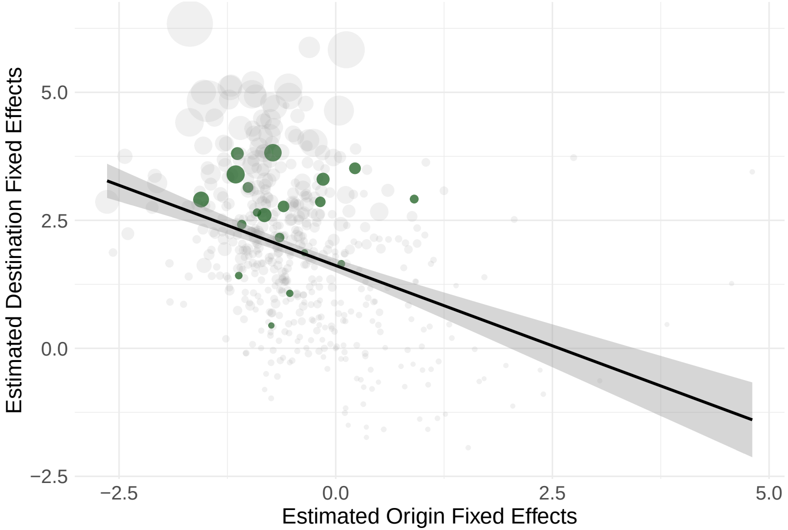
where S_j can be interpreted as a measure of **attractiveness** of occupation j, and θm_j as a measure of **access costs** of occupation j.

Fixed Effects Analysis I - Factor 4

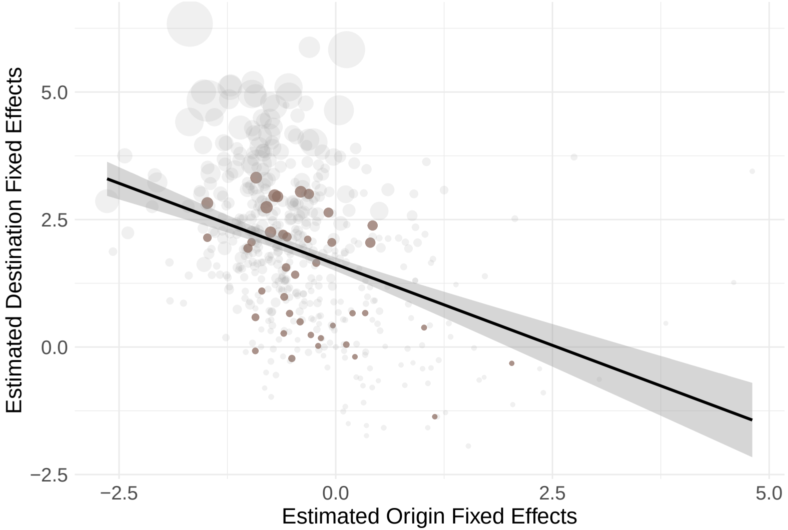
back



Fixed Effects Analysis I - Factor 4 back



Fixed Effects Analysis I - Factor 4 back



Fixed Effects Analysis II - Factor 4 back