Network constraints on cities, careers, and economic resilience

Morgan R. Frank

How do workers' skills shape their mobility?

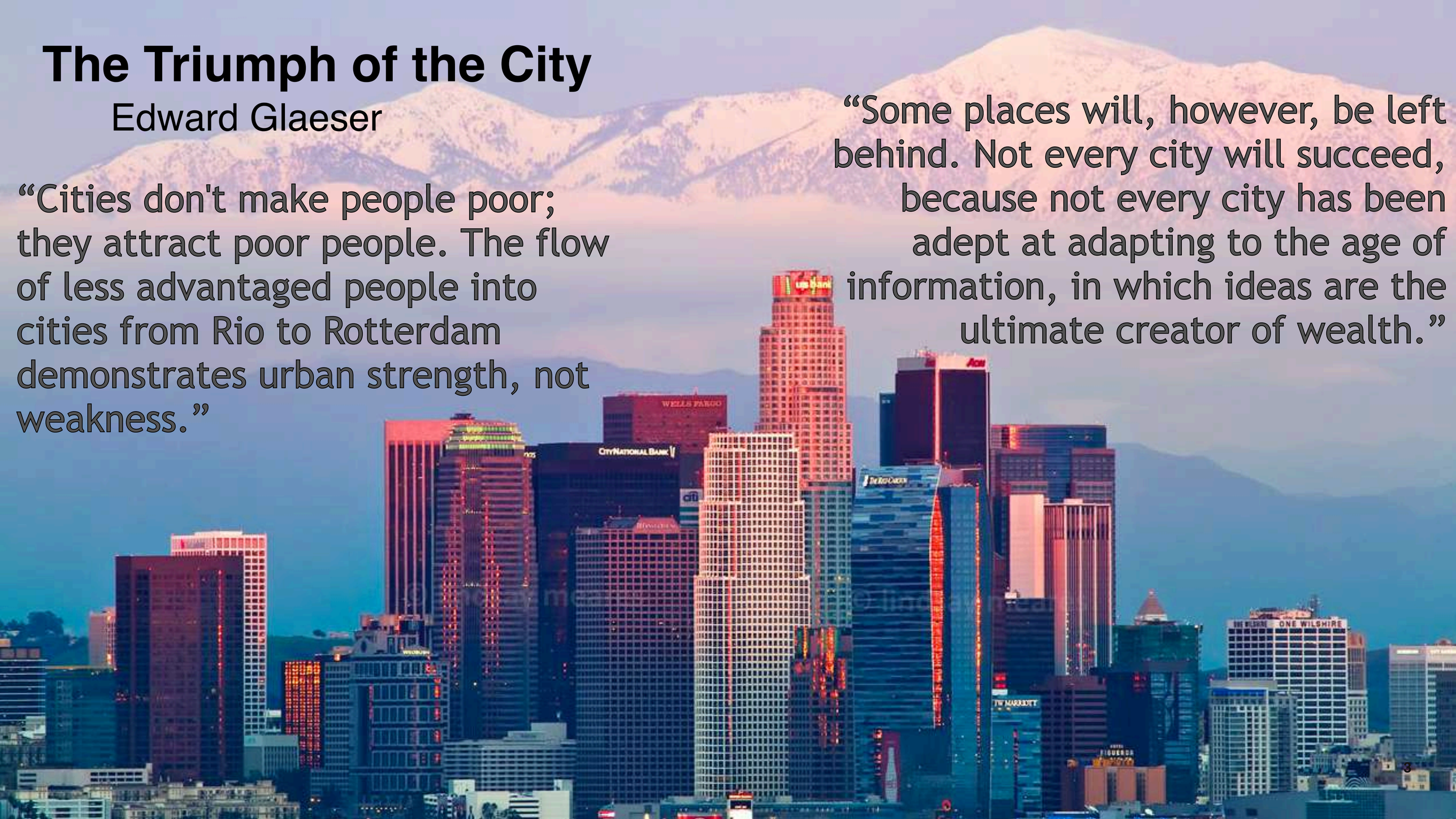
- How do skill requirements shape careers?
- Is labelling an occupation as "cognitive" or "physical" enough?
- How do workers move <u>through</u> urban labor markets?
- What about <u>between</u> urban labor markets?
- Do skills determine the economic resilience of cities?

The Triumph of the City

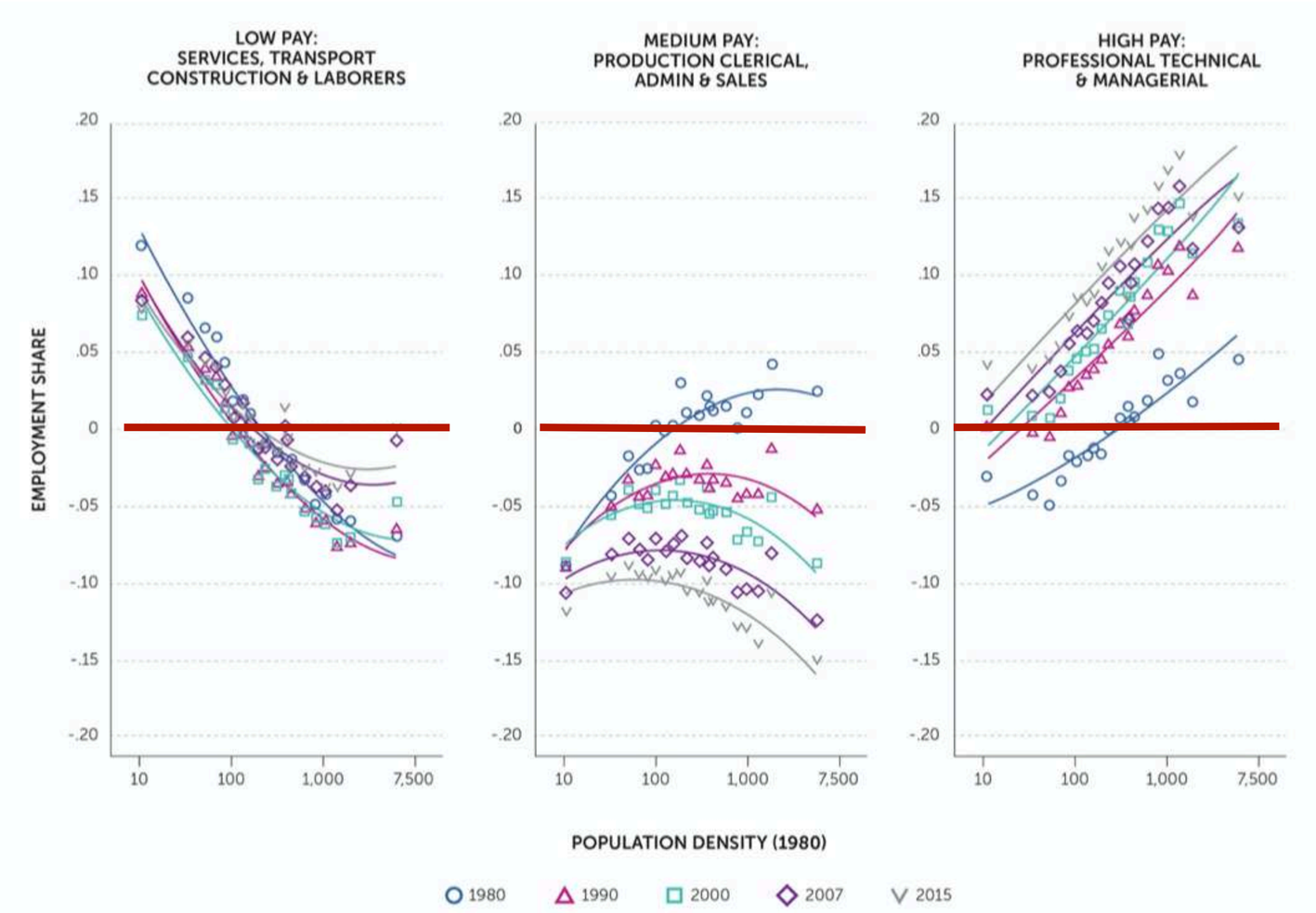
Edward Glaeser

“Cities don't make people poor; they attract poor people. The flow of less advantaged people into cities from Rio to Rotterdam demonstrates urban strength, not weakness.”

“Some places will, however, be left behind. Not every city will succeed, because not every city has been adept at adapting to the age of information, in which ideas are the ultimate creator of wealth.”

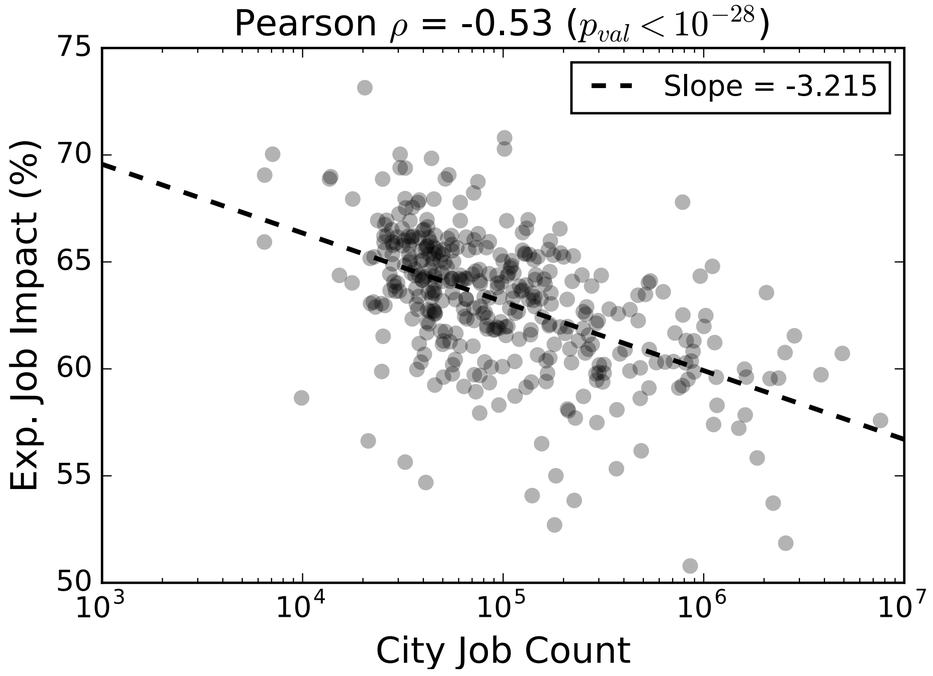


Our reliance on high-skill vs low-skill



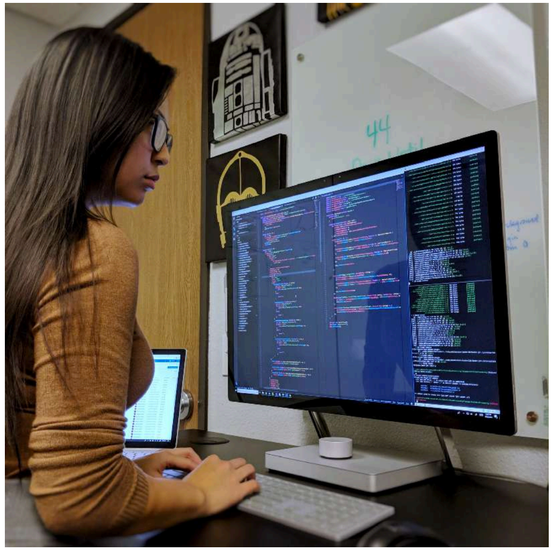
Work of the Past, Work of the Future. David Autor (MIT)

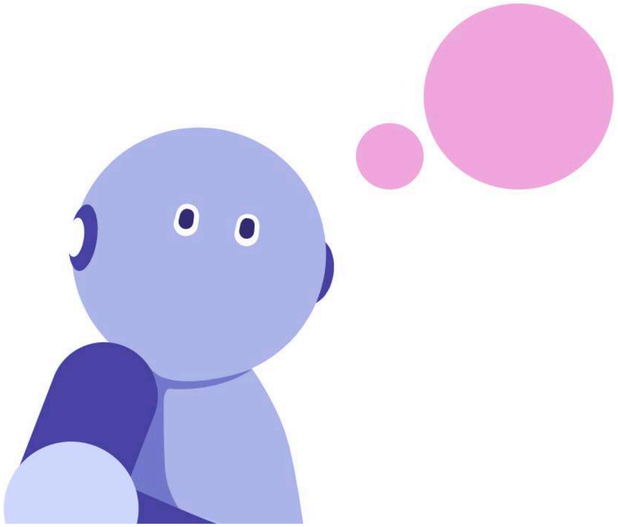
$$impact(c) = \sum_{j \in J} p_{auto}(j) \cdot empShare(j, c)$$



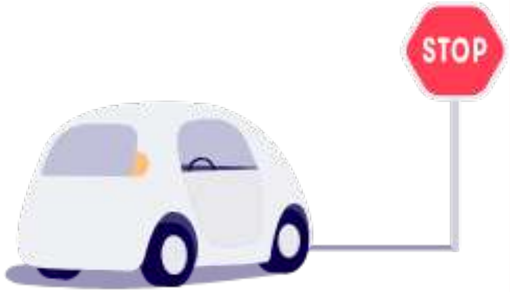
Frank *et al*,
Small cities face greater impact from automation,
Royal. Soc. Int. (2018)

High-skill & low-skill workers



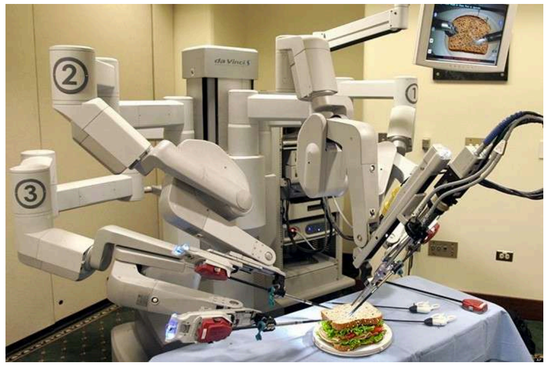


Programmers & Machine Learning



Truck Drivers & Autonomous Vehicles

High-skill & low-skill workers

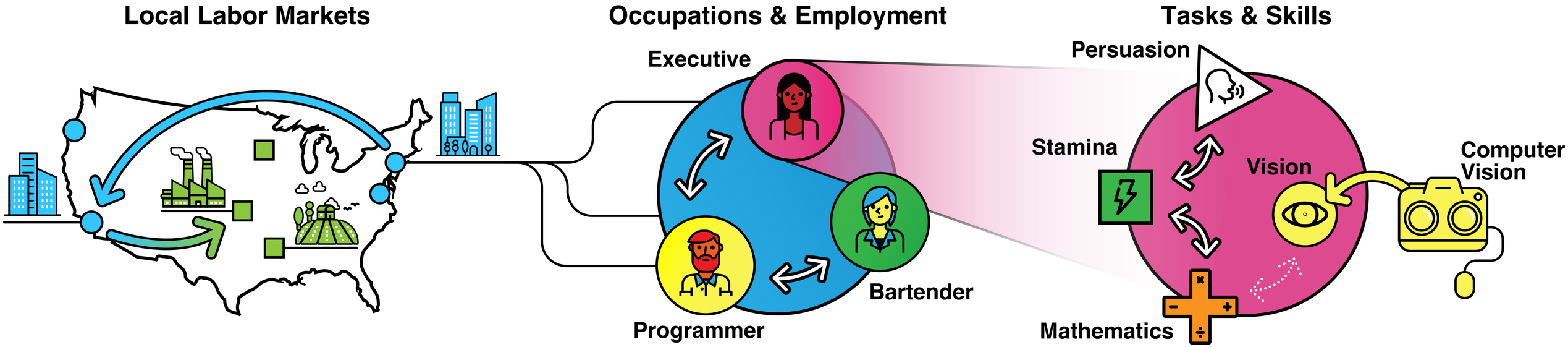



Surgeons & Robotics


Engineers & Drones


Bank Tellers & ATMs

Skills, labor, and cities



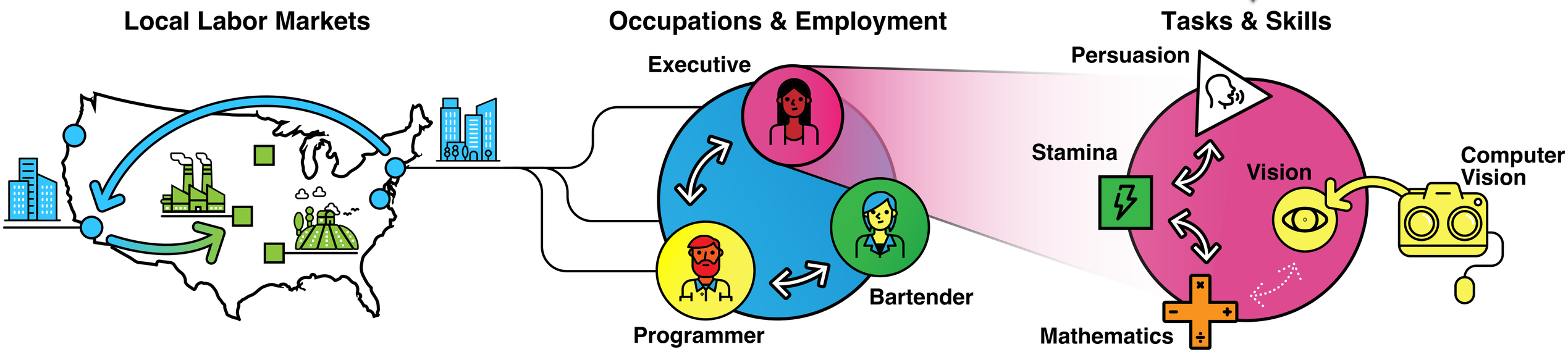
- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education

Frank, et al. *PNAS* (2018)

Unpacking the polarization of workplace skills
Sci. Adv. (2018) (link)



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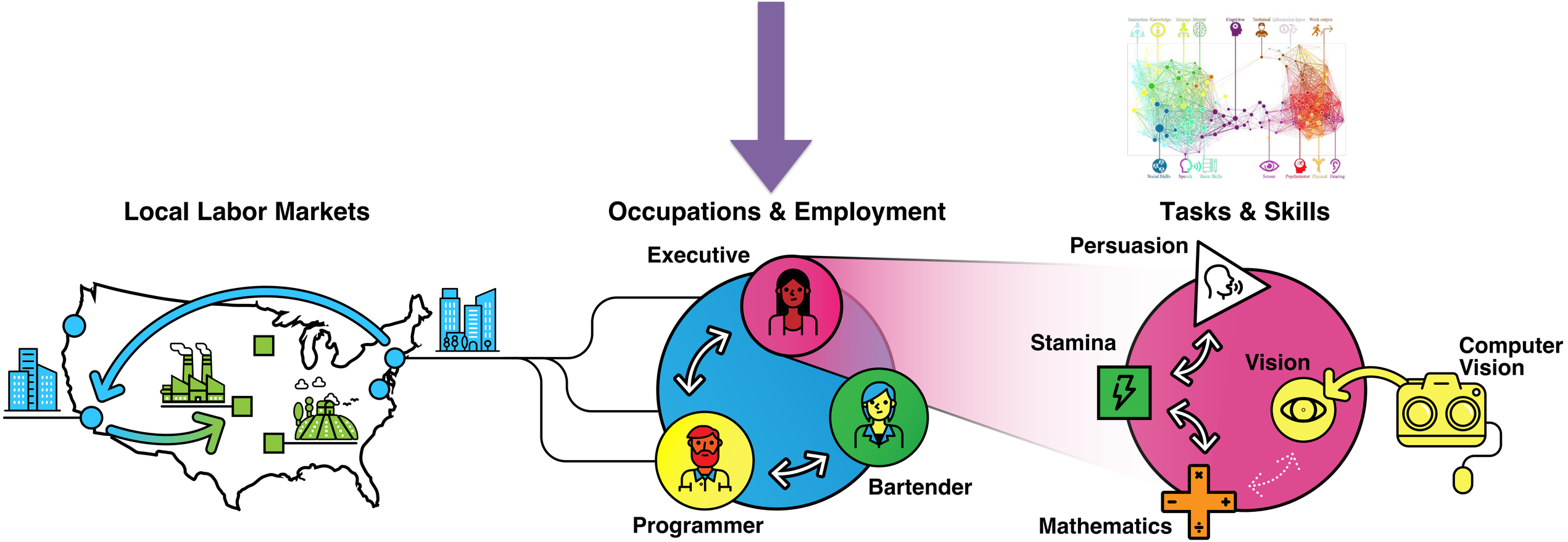

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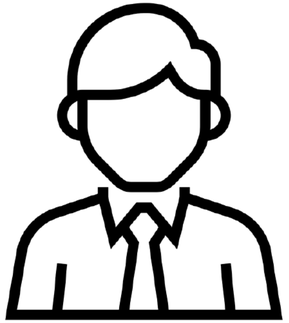
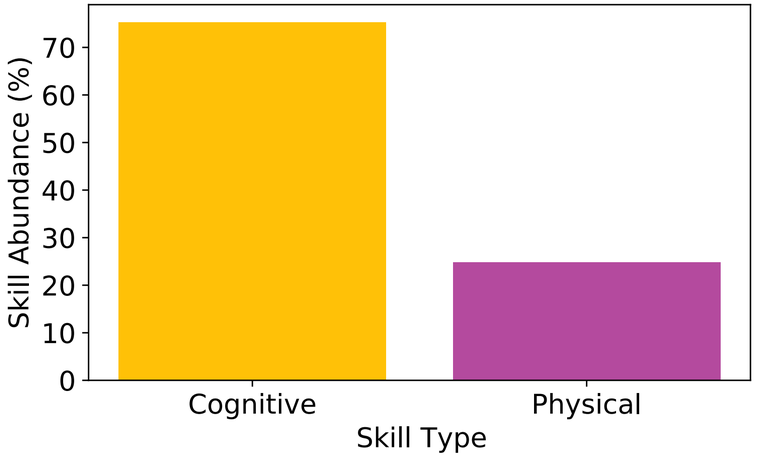
Frank, et al. *PNAS* (2018)

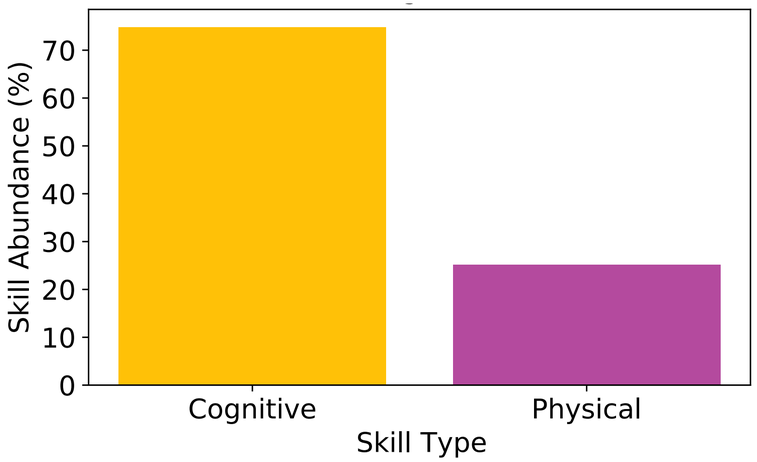
Comparing occupations from skills



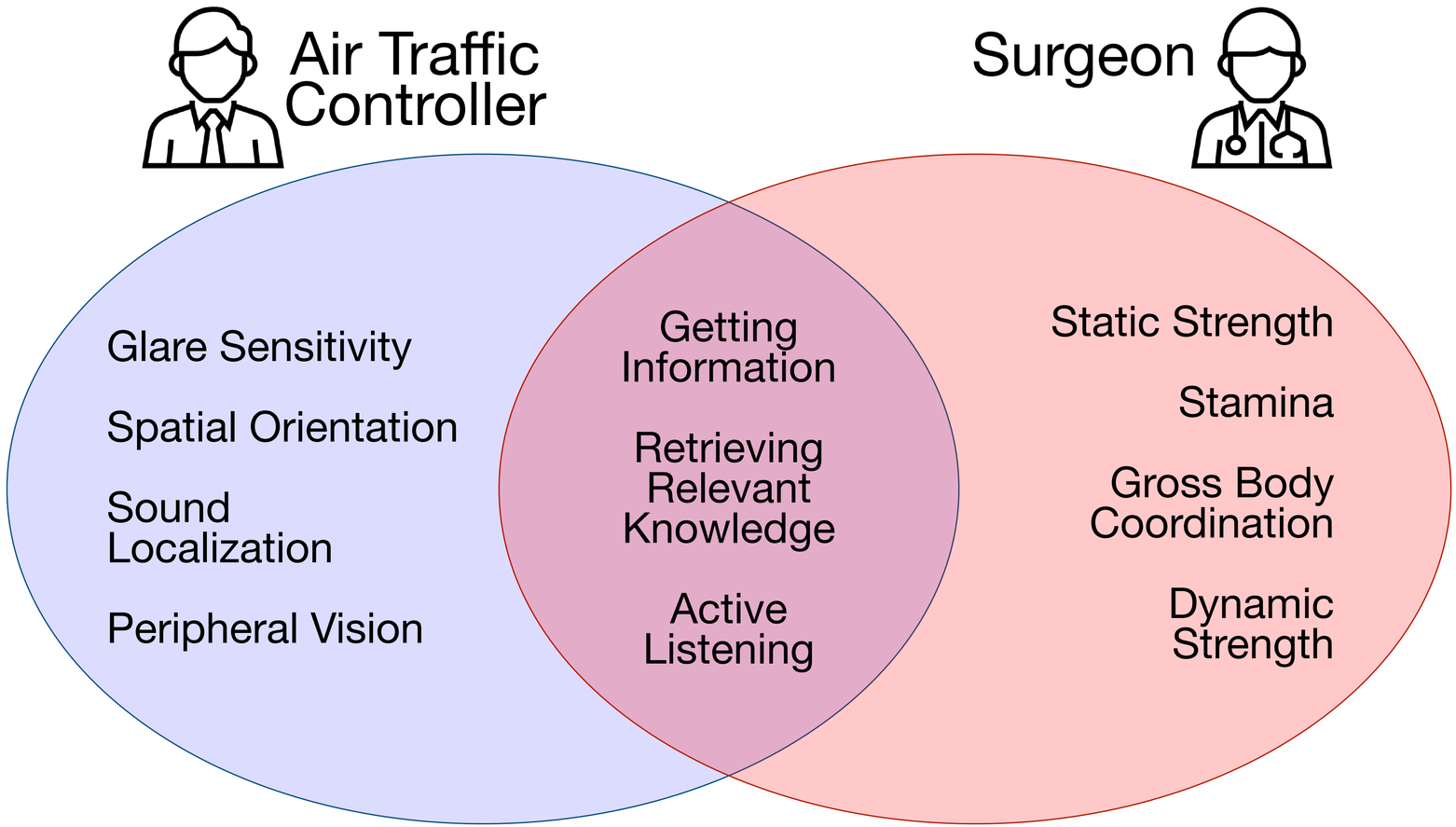
Air Traffic Controller



Surgeon



Comparing occupations from skills



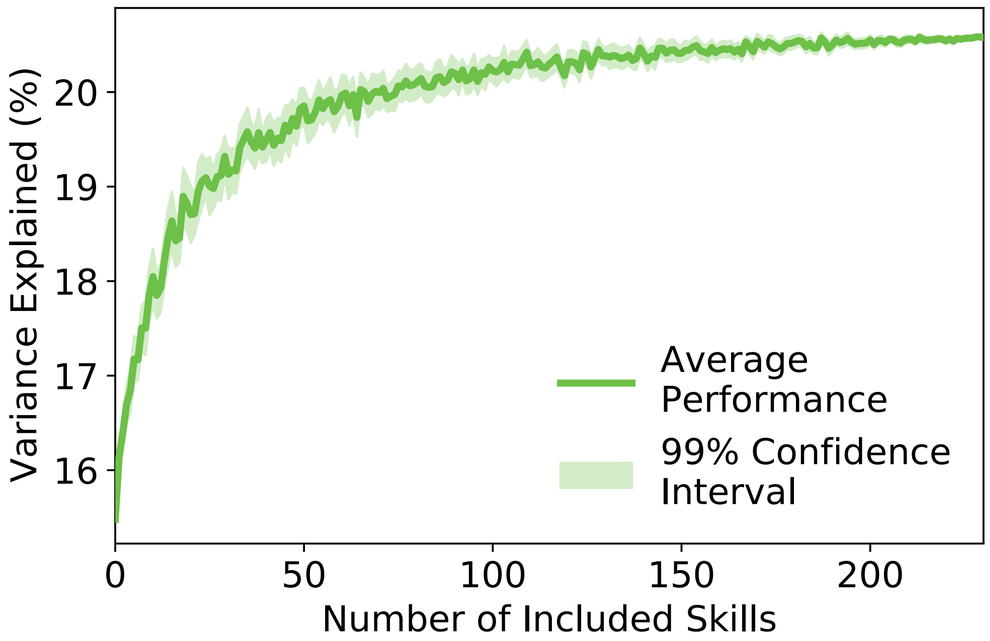
$$skillsim_{j,j'} = \frac{\bigcirc}{\bigcirc}$$

$$= \frac{\sum_s \min(onet(j,s), onet(j',s))}{\sum_s \max(onet(j,s), onet(j',s))}$$

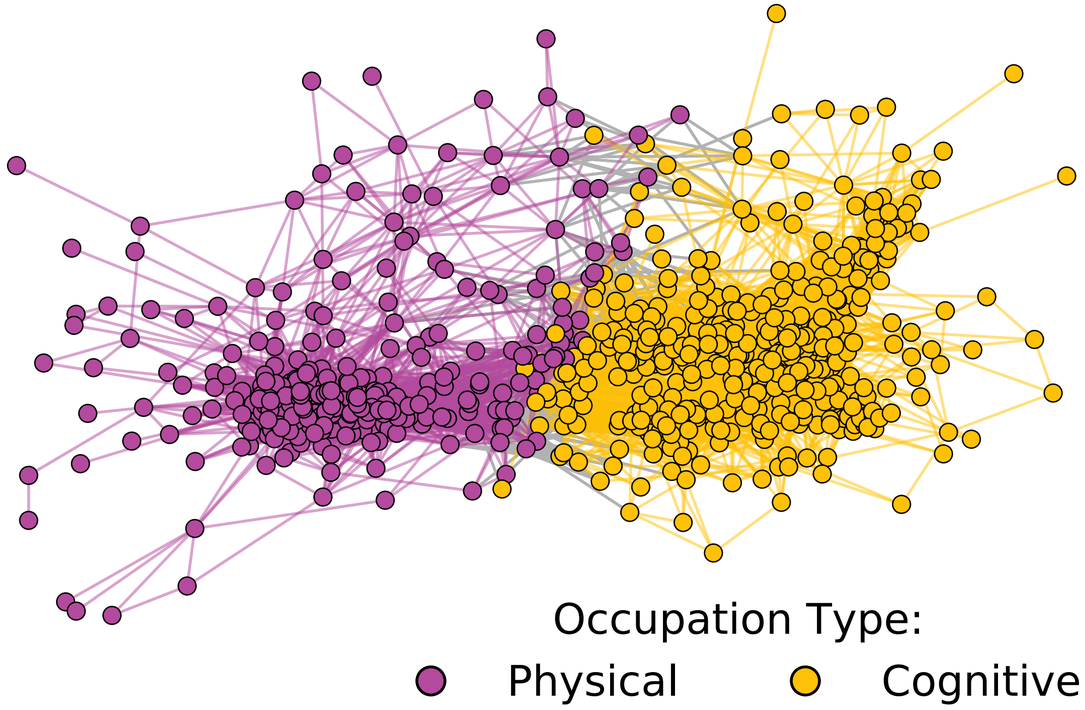
Skill similarity predicts career mobility

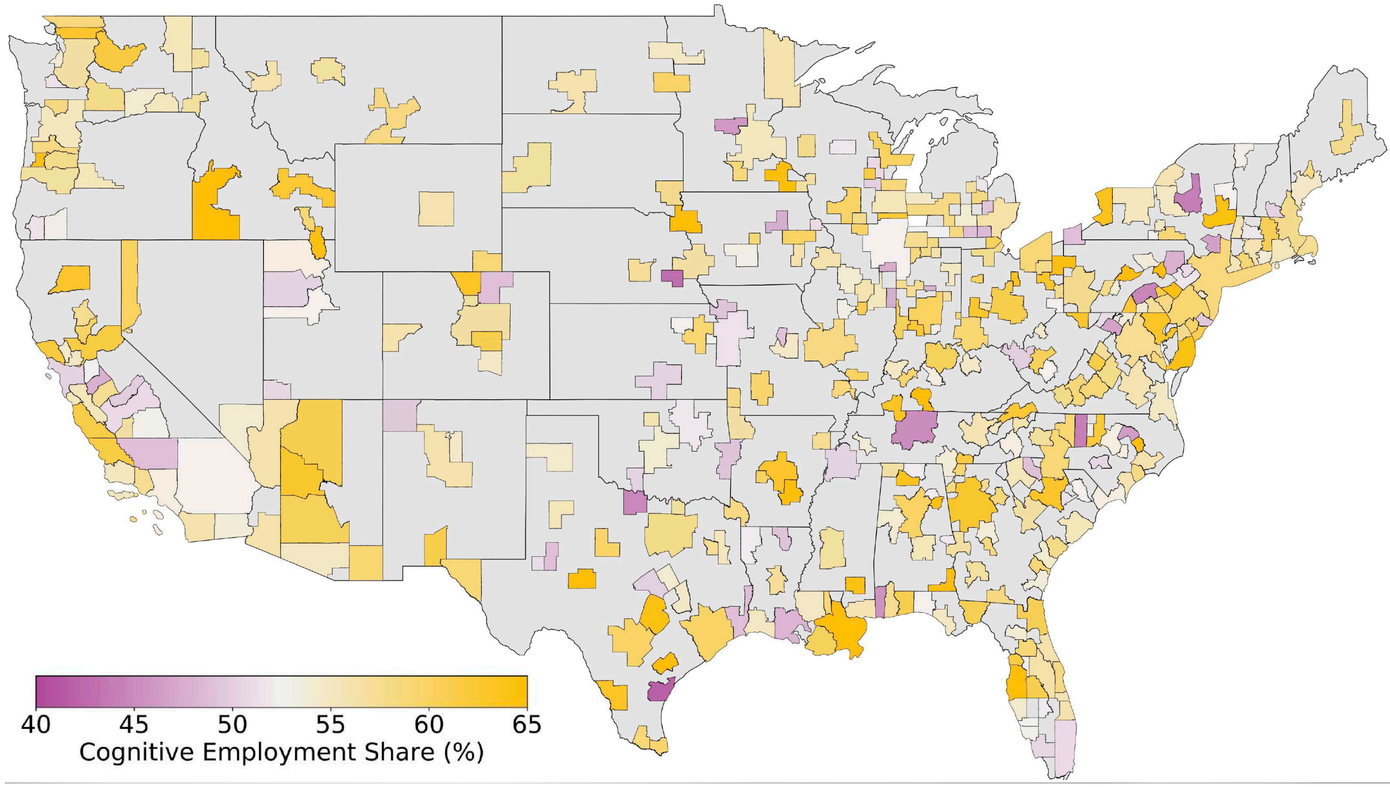
Dependent Variable: Log_{10} Job Transitions				
Variable	Model 1	Model 2	Model 3	Model 4
Skill Similarity ($skillsim_{j,j'}$)			0.271^{***}	0.324^{***}
Total Employment ($\log_{10} N_{j,j'}$)	0.392^{***}	0.403^{***}	0.416^{***}	0.424^{***}
Cognitive/Physical Similarity ($CP_{j,j'}$)		0.172^{***}		-0.005
$skillsim_{j,j'} \times CP_{j,j'}$				0.069^{***}
$skillsim_{j,j'} \times \log_{10} N_{j,j'}$				0.062^{***}
$CP_{j,j'} \times \log_{10} N_{j,j'}$				0.040^{**}
Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.155	0.183	0.219	0.237
adj. R^2	0.154	0.182	0.219	0.237
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

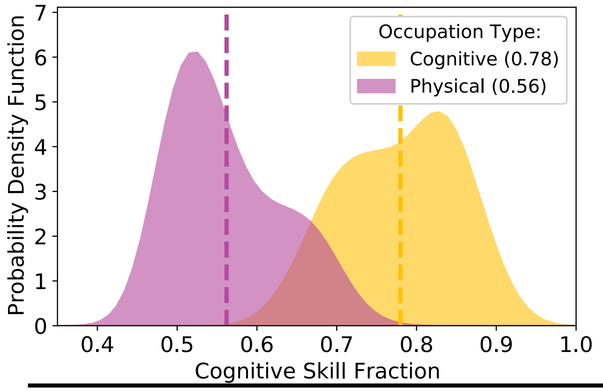
Job transition rates from the Current Population Survey spanning 2012-2018.
Variables are centered and standardized.

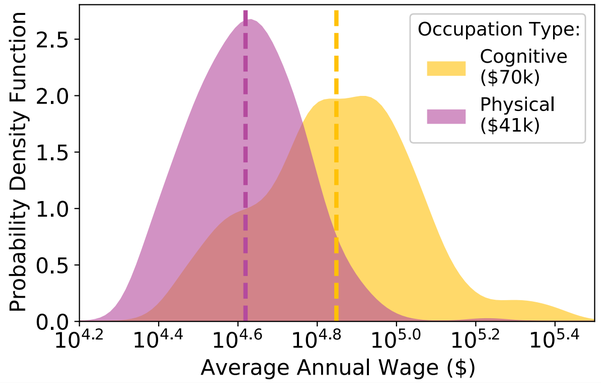


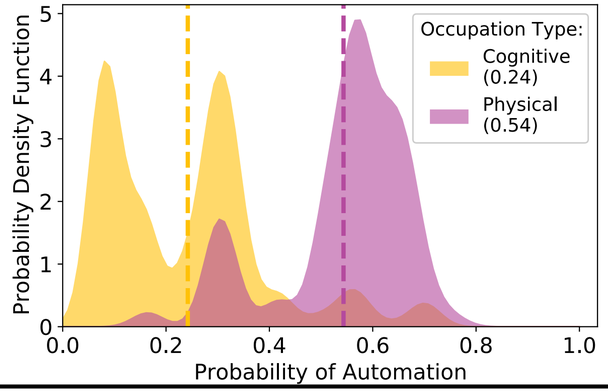
Mapping occupations with skill similarity

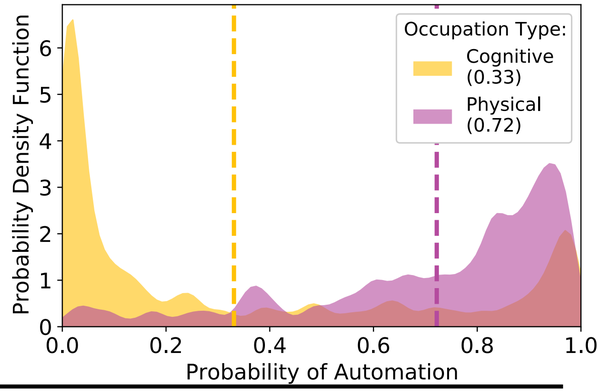












Tracking career trajectories with skill similarity

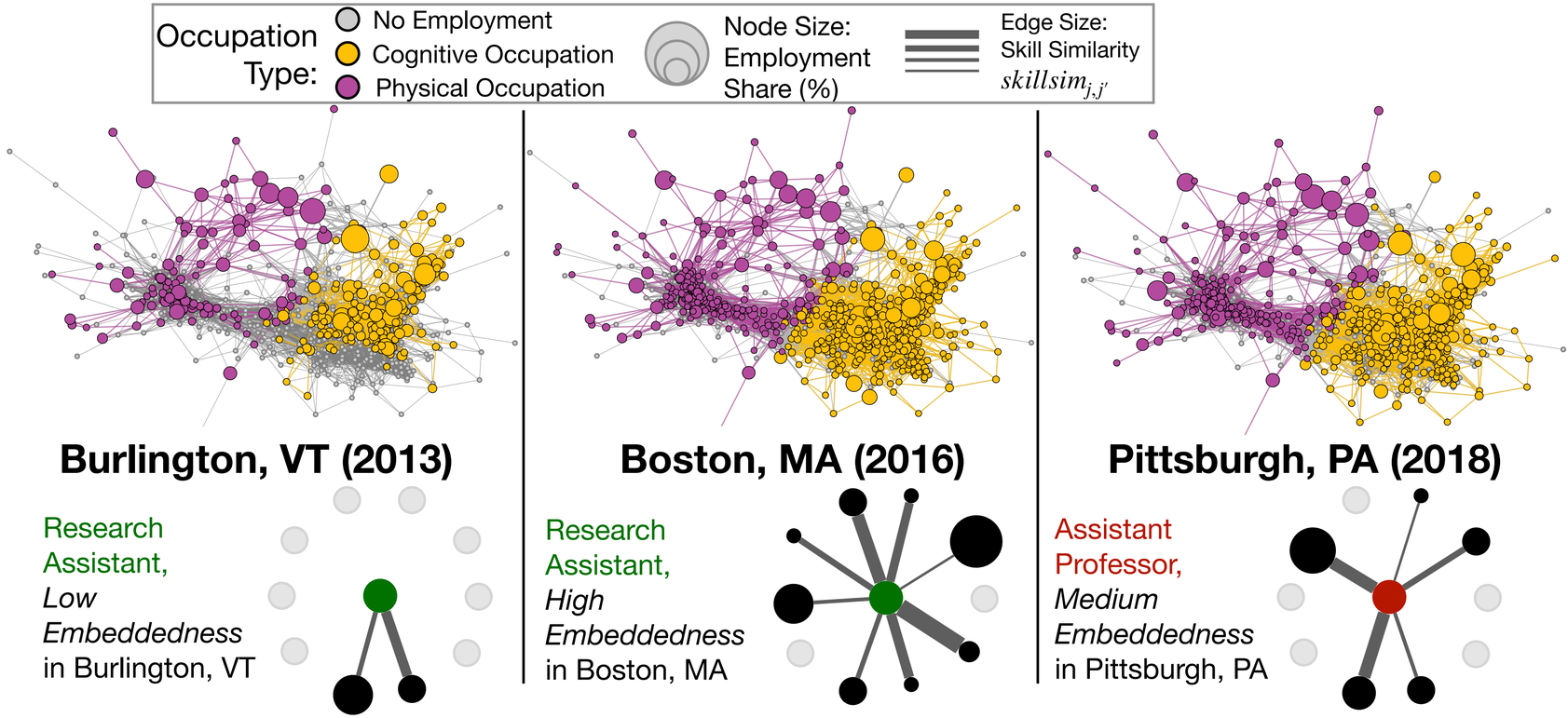
Morgan R. Frank's CV

- Assistant Professor, University of Pittsburgh, Pittsburgh, PA (2020-Present)
- Postdoctoral Researcher, MIT, Boston, MA (2019-2020)
- Research Assistant, MIT, Boston, MA (2014-2019)
- Research Assistant, University of Vermont, Burlington, VT (2012-2014)

New occupation, New location

New occupation, Same location

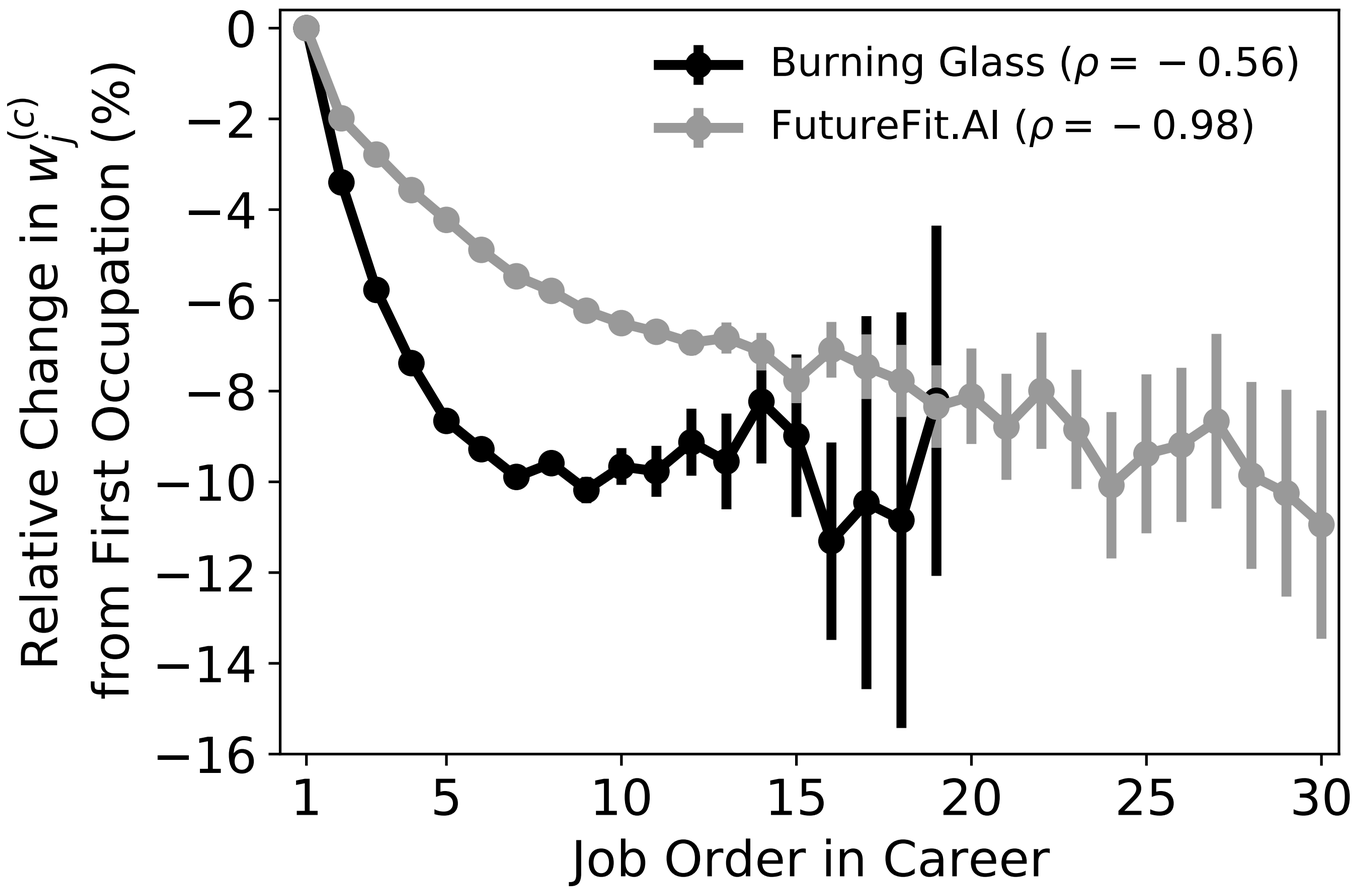
Same occupation, New location



Employment-Weighted Embeddedness: $$w_i^{(c)} = \sum_{j \in Jobs} skillsim_{i,j} \cdot share(c,j)$$

Complementarity or Competition?

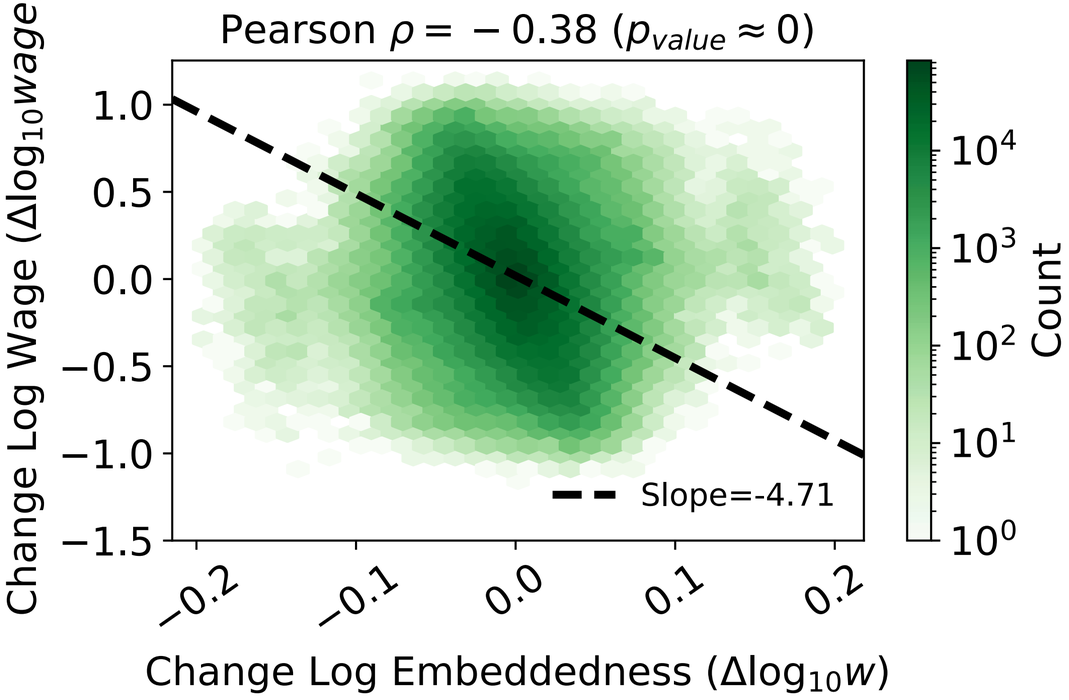
Workers decrease embeddedness over careers

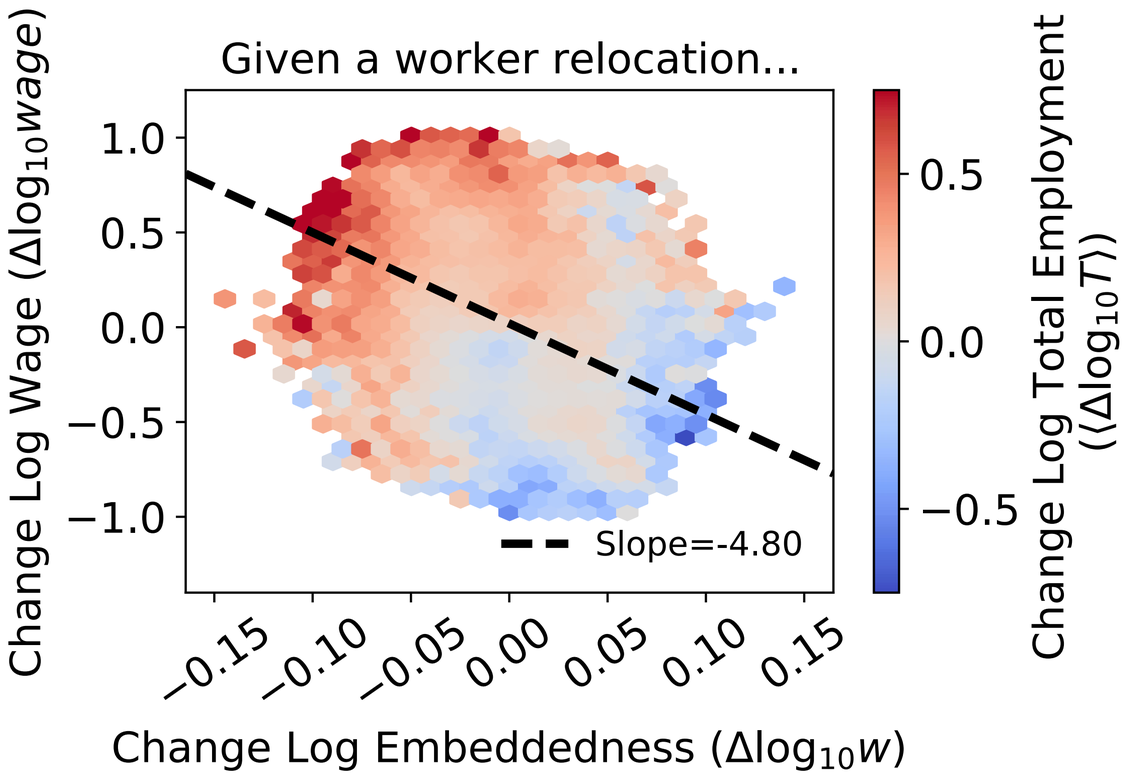


Decreasing embeddedness corresponds to higher wages

Embeddedness Change:

$$\Delta \log_{10} w = \log_{10}\left(w_{i_2}^{(c_2)}\right) - \log_{10}\left(w_{i_1}^{(c_1)}\right)$$





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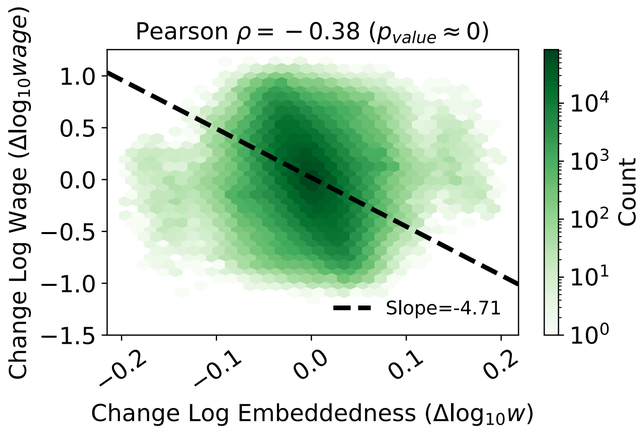
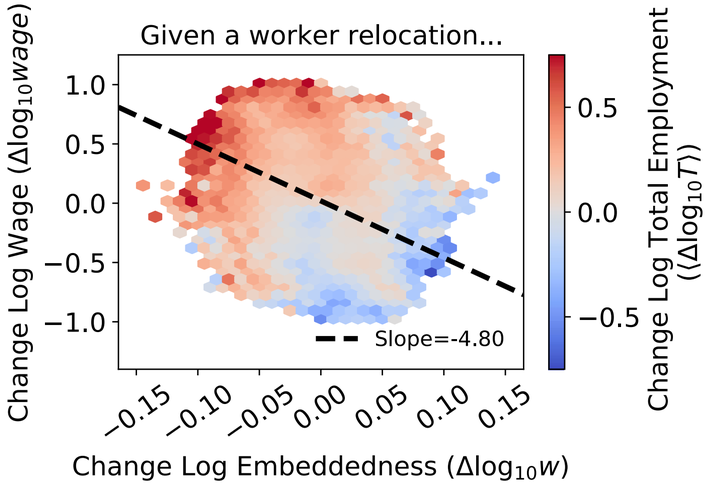




	Dependent Variable: Wage Change ($\Delta \log_{10} wage$)					
	Burning Glass Resumes			FutureFit AI Resumes		
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Occupation Change Dummy (J)	-0.021^{***}	-0.024^{***}	-0.019^{***}	0.019^{***}	0.019^{***}	0.025^{***}
Relocation Dummy ($relocation$)	0.002^{**}	-0.000	-0.017^{***}	-0.001	-0.004^{***}	0.028^{***}
Bachelors Degree Change (ΔB)	0.683^{***}	0.688^{***}	0.534^{***}	0.583^{***}	0.557^{***}	0.462^{***}
$\Delta B \times relocation$	-0.000	0.002^{***}	0.016^{***}	-0.005^{***}	-0.002^{***}	-0.003^{***}
$\Delta B \times J$	0.043^{***}	0.020^{***}	0.019^{***}	-0.016^{***}	-0.011^{***}	0.036^{***}
City Network PageRank Change ($\Delta \log_{10} P$)		0.428^{***}	2.205^{***}		-0.339^{***}	1.094^{***}
$\Delta \log_{10} P \times relocation$		-0.063^{***}	-0.582^{***}		0.055^{***}	-0.415^{***}
$\Delta \log_{10} P \times J$		-0.001	0.005^{***}		0.005^{***}	0.010^{***}
$\Delta \log_{10} P \times \Delta B$		0.001^{*}	-0.002^{**}		0.005^{***}	0.002^{***}
Embeddedness Change ($\Delta \log_{10} e$)			-0.452^{***}			-0.348^{***}
$\Delta \log_{10} e \times relocation$			0.104^{***}			0.068^{***}
$\Delta \log_{10} e \times J$			-0.074^{***}			-0.088^{***}
$\Delta \log_{10} e \times \Delta B$			0.015^{***}			0.022^{***}
$\Delta \log_{10} e \times \Delta \log_{10} P$			-0.000			0.002^{***}
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Source City F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Destination City F.E.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.488	0.496	0.562	0.353	0.357	0.404
adj. R^2	0.487	0.496	0.561	0.353	0.356	0.404
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$						

Variables were centered and standardized.

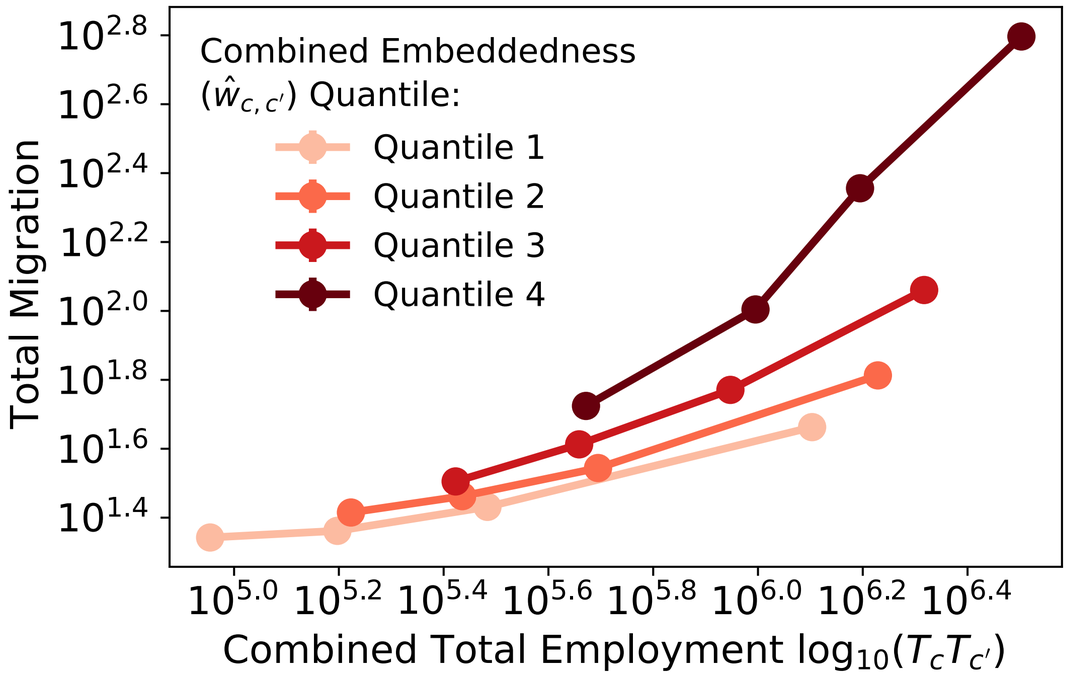
The average combined embeddedness of city pairs predicts spatial mobility

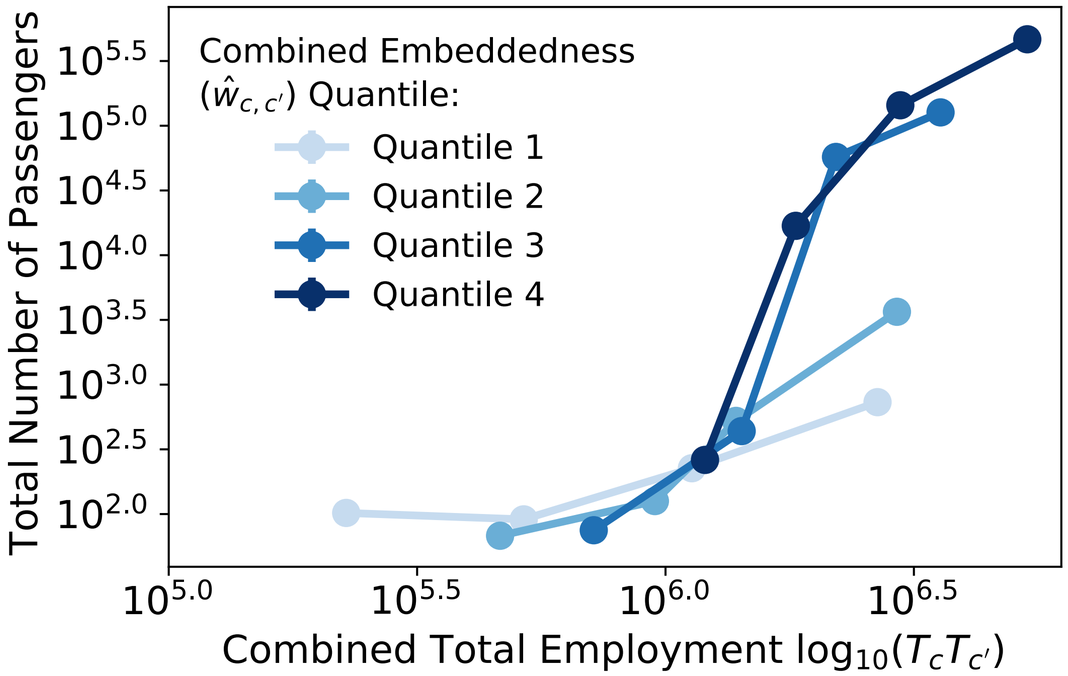
$$\hat{w}_{c,c'} = \sum_{j \in Jobs^{(c)} \cap Jobs^{(c')}} 1/\left(w_j^{(c)} w_j^{(c')}\right)$$

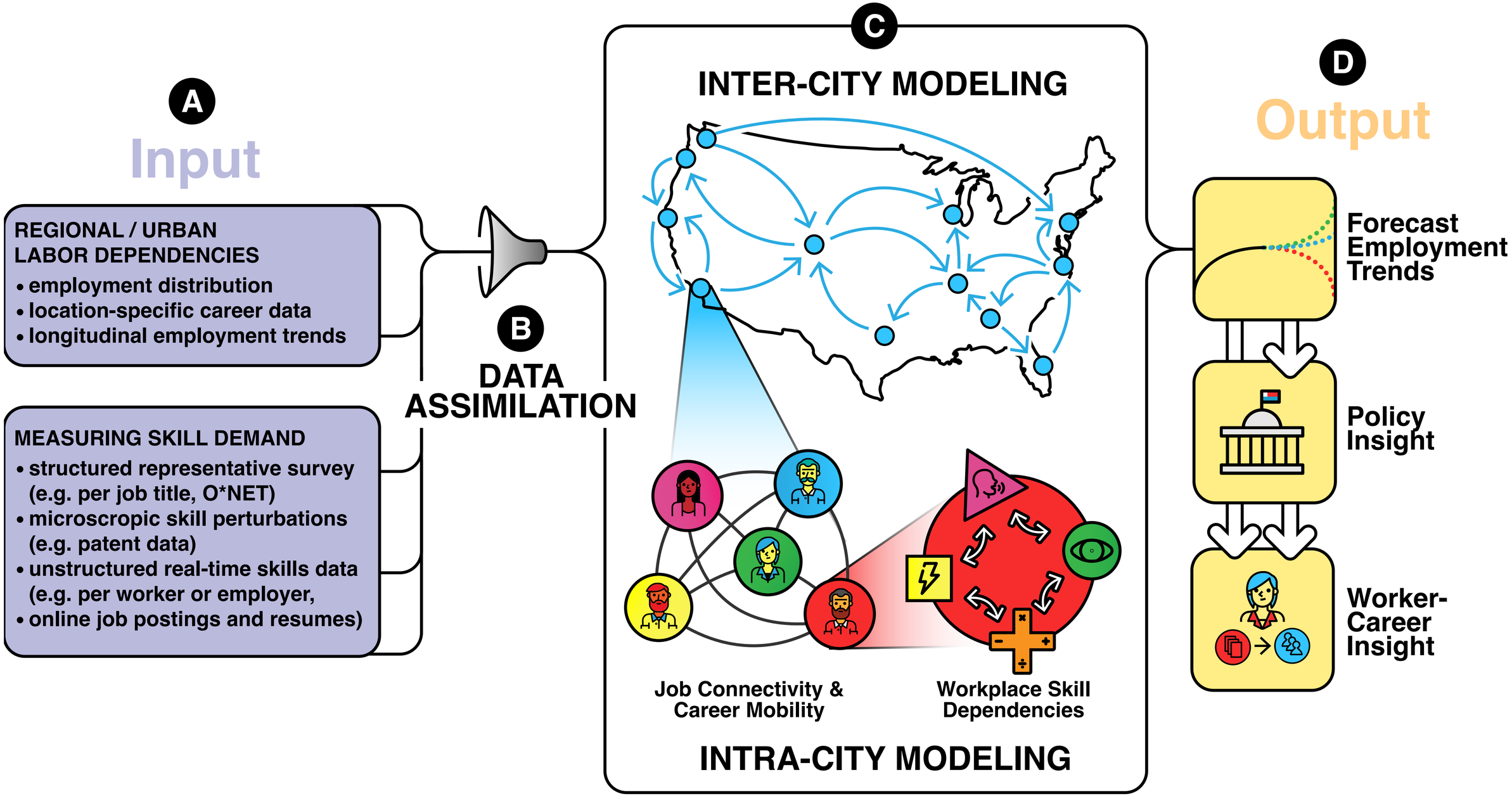
Dependent Variable:	Log_{10} Total Migration			Log_{10} Total Enplaned Passengers		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Total Employment ($\log_{10}(T_c T_{c'})$)	0.517^{***}	0.339^{***}	0.411^{***}	0.578^{***}	0.417^{***}	0.529^{***}
Distance ($\log_{10} D_{c,c'}$)	-0.385^{***}	-0.394^{***}	-0.394^{***}	-0.069^{***}	-0.101^{***}	-0.101^{***}
Embeddedness ($\hat{w}_{c,c'}$)		0.348^{***}	0.223^{***}		0.307^{***}	0.205^{***}
$\hat{w}_{c,c'} \times \log_{10} T_{c,c'}$			0.164^{***}			0.208^{***}
$\hat{w}_{c,c'} \times \log_{10} D_{c,c'}$			-0.022^{***}			0.000
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.358	0.425	0.449	0.326	0.370	0.417
adj. R^2	0.358	0.425	0.449	0.326	0.370	0.416
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$						

Variables were centered and standardized.
US Census Migration Data ($N = 172k$) and Bureau of Transportation Statistics ($N = 25k$) spanning 2013-2018.

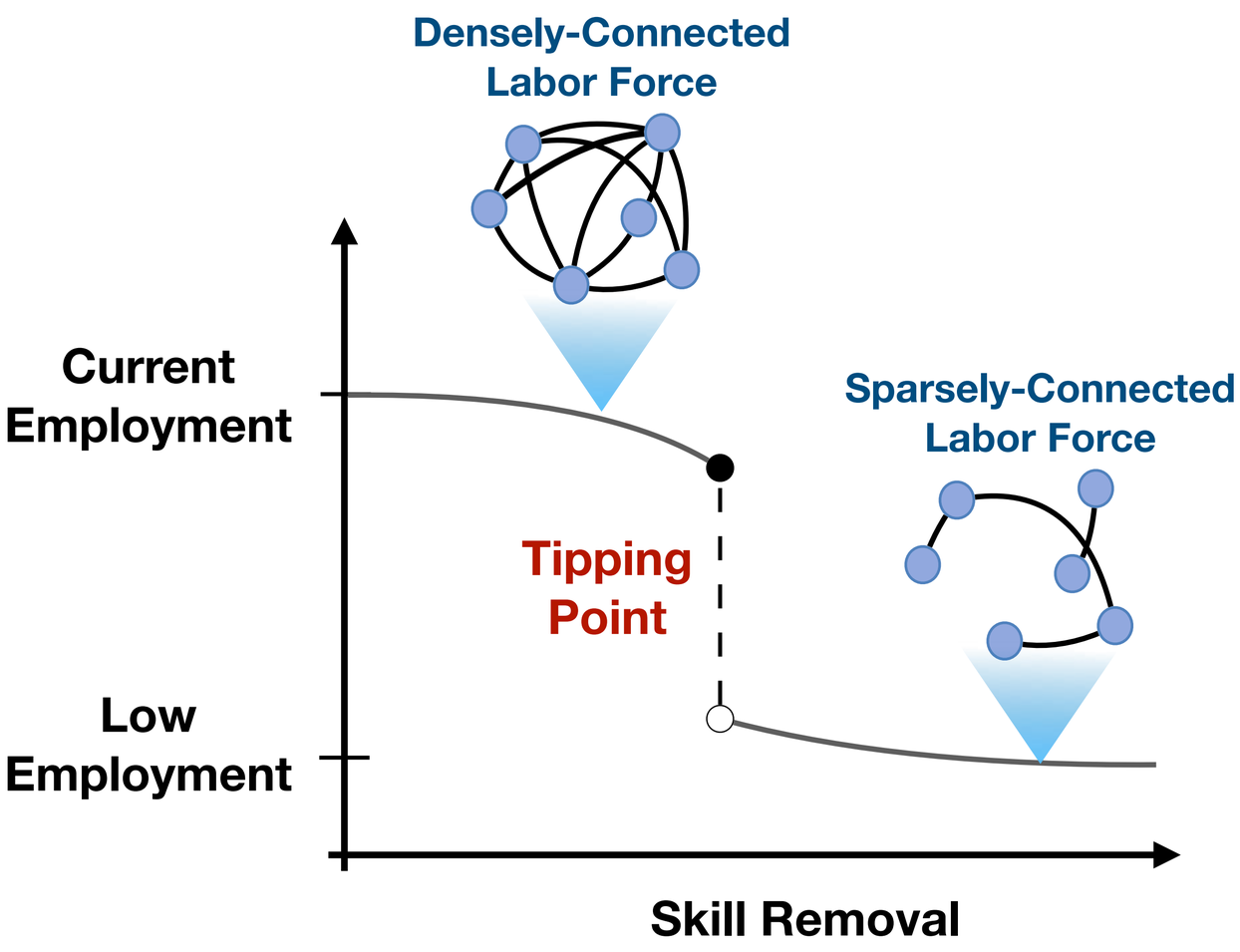
Average combined embeddedness moderates city size in spatial mobility

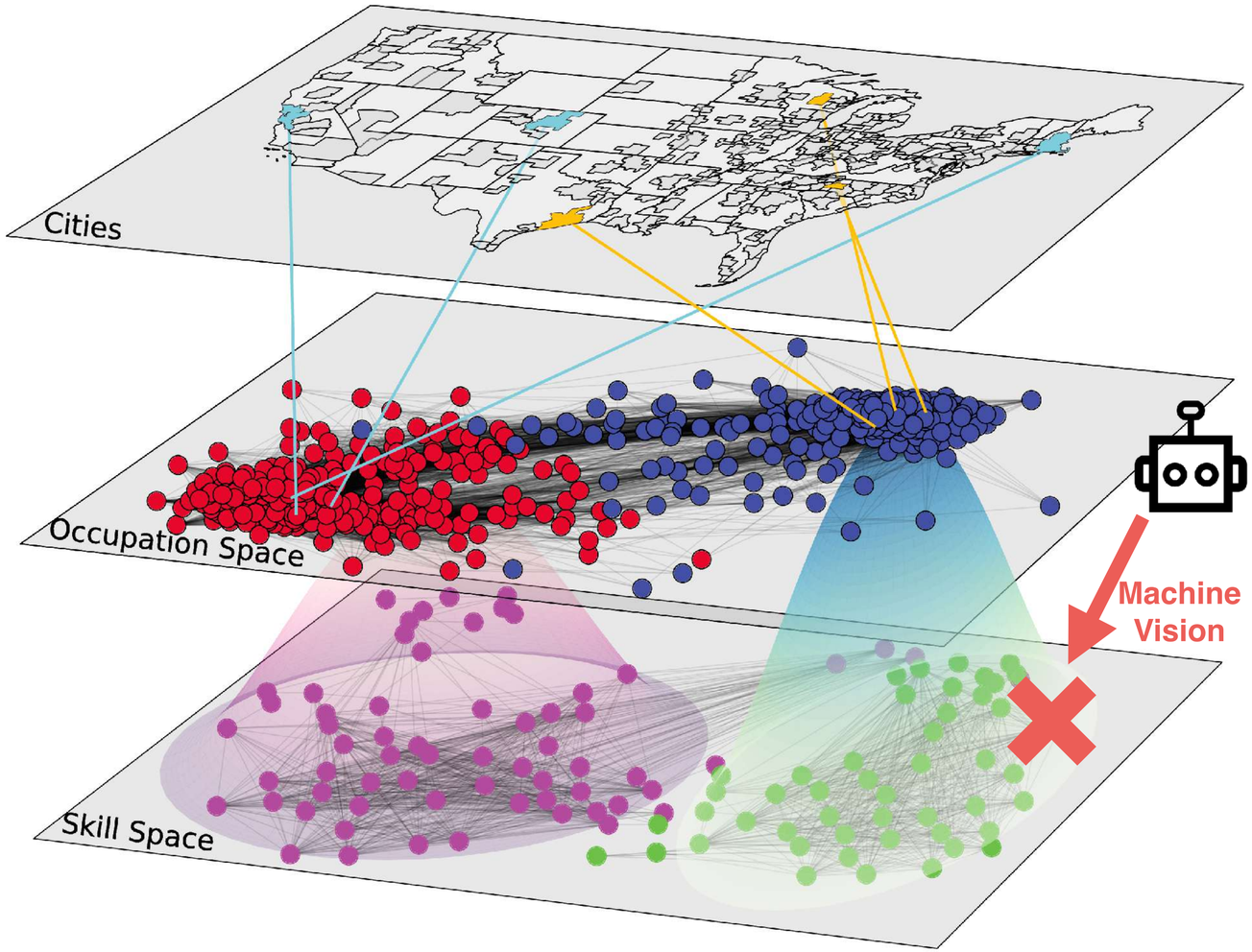




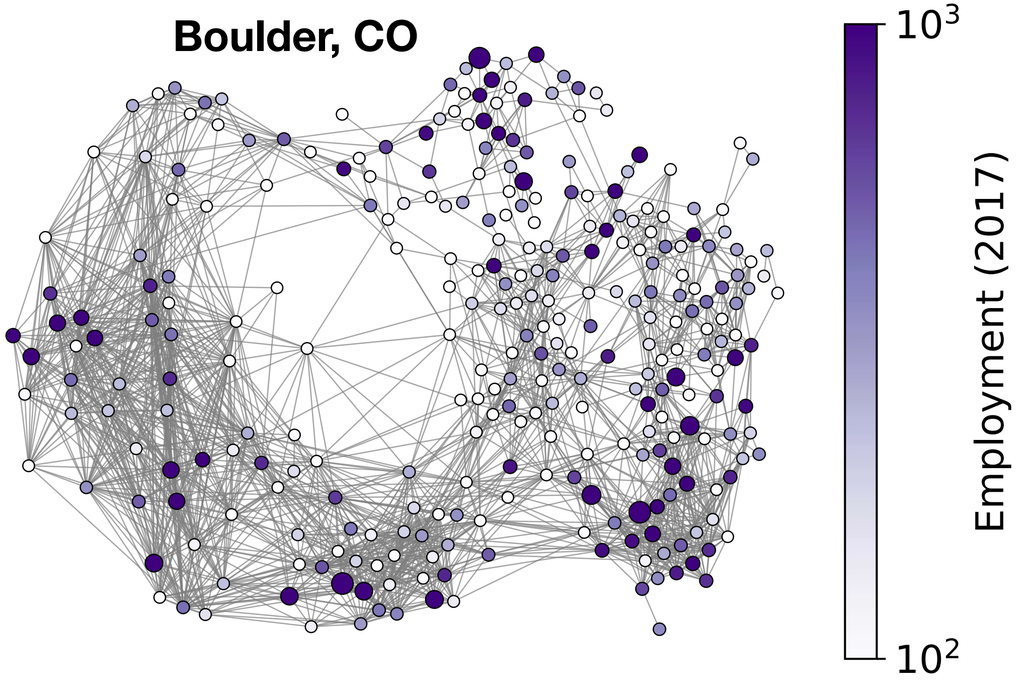

A
Input
REGIONAL / URBAN LABOR DEPENDENCIES
• employment distribution
• location-specific career data
• longitudinal employment trends
MEASURING SKILL DEMAND
• structured representative survey (e.g. per job title, O*NET)
• microscropic skill perturbations (e.g. patent data)
• unstructured real-time skills data (e.g. per worker or employer,
• online job postings and resumes)
B
DATA ASSIMILATION
C
INTER-CITY MODELING
Job Connectivity & Career Mobility
Workplace Skill Dependencies
INTRA-CITY MODELING
D
Output
Forecast Employment Trends
Policy Insight
Worker-Career Insight

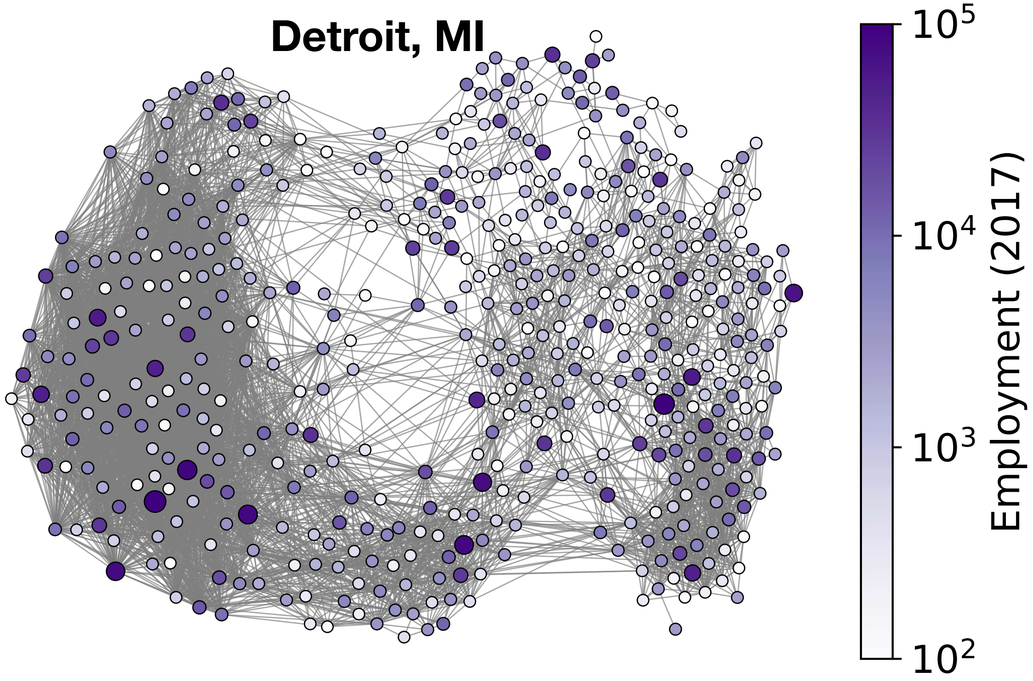
Structural economic resilience





Future Work: Network embeddedness and unemployment risk





Occupational embeddedness: $$w_j^c = \sum_{i \in J} w_{ij}^c$$

Moro*, Frank*, et al. *Nat. Comms* (2021)

How do Workers find Jobs?

2014 Nobel Prize in Economics
for introducing Job Matching

$$\dot{E} = -\lambda U + M(U, V)$$
$$\dot{U} = \lambda E - M(U, V)$$

where $M(U, V) \propto U^{\gamma} V^{1-\gamma}$

for $\gamma \in [0,1]$

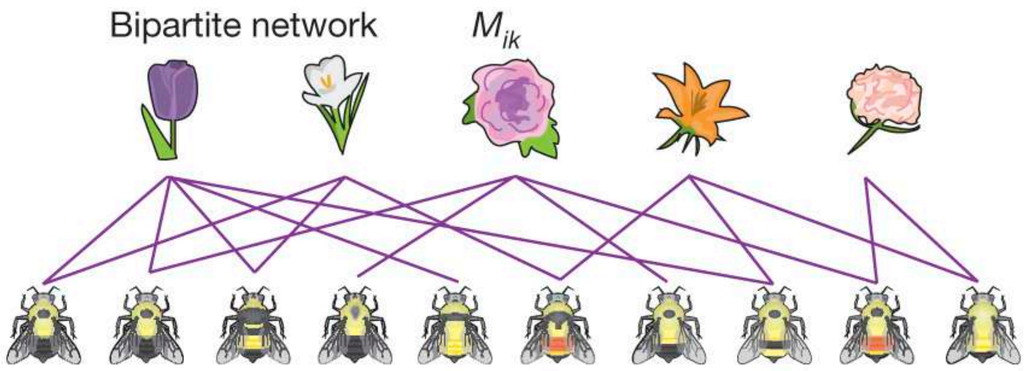
this formulation is
"a reflection at the aggregate level of the complex and varied pattern of hiring"
because it misses the heterogeneous nature of
skill matching

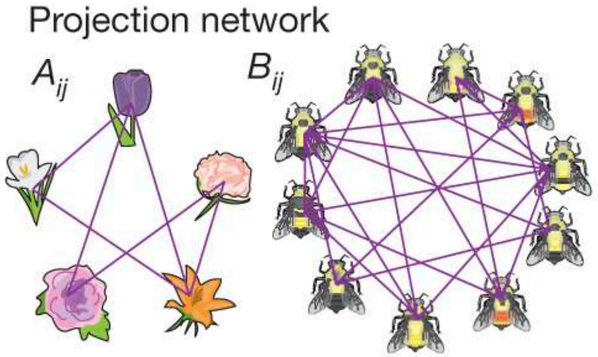
Urban Ecologies of Labor

$$\dot{E}_j = -\lambda E_j + \alpha \sum_{i \in Jobs} w_{i,j} E_j^{\gamma} U_i^{1-\gamma}$$

$$\dot{U}_j = \lambda E_j - \alpha \sum_{i \in Jobs} w_{i,j} E_i^{\gamma} U_j^{1-\gamma}$$

looks like Lotka-Volterra!





Gao et al, *Nature* (2016)

Urban Ecologies of Labor

$$W^c = \sum_{i,j \in J^2} w_{ij}^c$$

$$\dot{E}_j = -\lambda E_j + \alpha \sum_{i \in Jobs} w_{i,j} E_j^{\gamma} U_i^{1-\gamma}$$

$$\dot{U}_j = \lambda E_j - \alpha \sum_{i \in Jobs} w_{i,j} E_i^{\gamma} U_j^{1-\gamma}$$

Reduces to...

$$E_{eff}^c = \left(\sum_{j \in Jobs} E_j^c w_j^c \right) / W^c$$

$$U_{eff}^c = \left(\sum_{j \in Jobs} U_j^c w_j^c \right) / W^c$$

$$w_{eff}^c = \left(\sum_{j \in Jobs} (w_j^c)^2 \right) / W^c$$

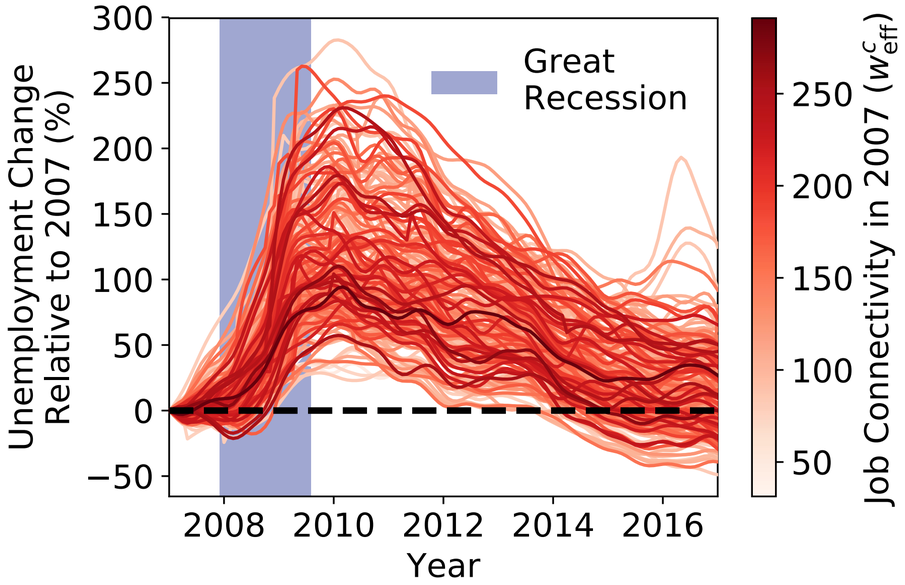
Gao et al, *Nature* (2016)

Future Work: Network embeddedness and unemployment risk

$$w_j^c = \sum_{i \in Jobs} w_{ij}^c$$

$$W^c = \sum_{i,j \in Jobs^2} w_{ij}^c$$

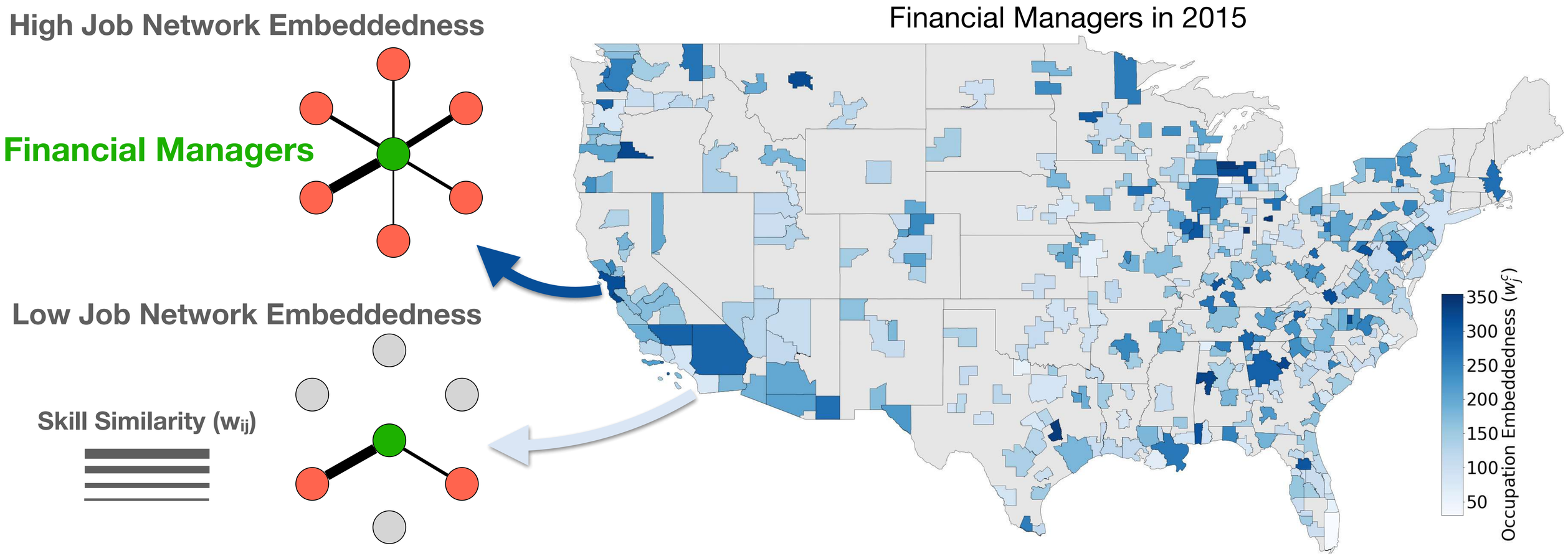
$$w_{eff}^c = \left(\sum_{j \in Jobs} (w_j^c)^2 \right) / W^c$$



Dependent Variable: Peak Unemployment Rate during the Great Recession (R_{GR}^c)						
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\log_{10}$ Total Employment (T^c)	−0.175*	1.132**	−0.005	0.634*	0.458	0.451
Job Connectivity (w_{eff}^c)		−1.399***		−0.637*		−2.481**
2000 Unemployment Rate (R_{2000}^c)			0.703***	0.701***	0.680***	0.695***
Occupation Diversity (N^c)					−0.483	1.979*
Employment Diversity (H^c)					0.008	0.050
$T^c \times R_{2000}^c$			−0.048	−0.355*	−0.072	−0.406*
$w_{\text{eff}}^c \times R_{2000}^c$				0.308		0.362
$w_{\text{eff}}^c \times T^c$		0.093*		−0.004		−0.387
$w_{\text{eff}}^c \times N^c$						0.326
$w_{\text{eff}}^c \times H^c$						0.053
R^2	0.031	0.119	0.535	0.552	0.541	0.565
adj. R^2	0.026	0.105	0.528	0.539	0.530	0.542
$p_{val} < 0.1^*$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$						

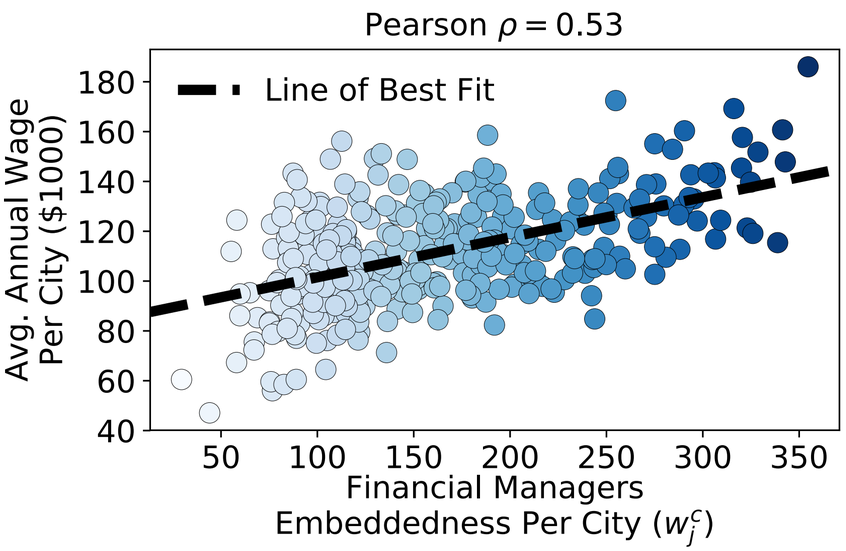
Moro*, Frank*, et al. *Nat. Comms* (2021)

Future Work: Network embeddedness and unemployment risk



Moro*, Frank*, et al. *Nat. Comms* (2021)

Future Work: Network embeddedness and unemployment risk

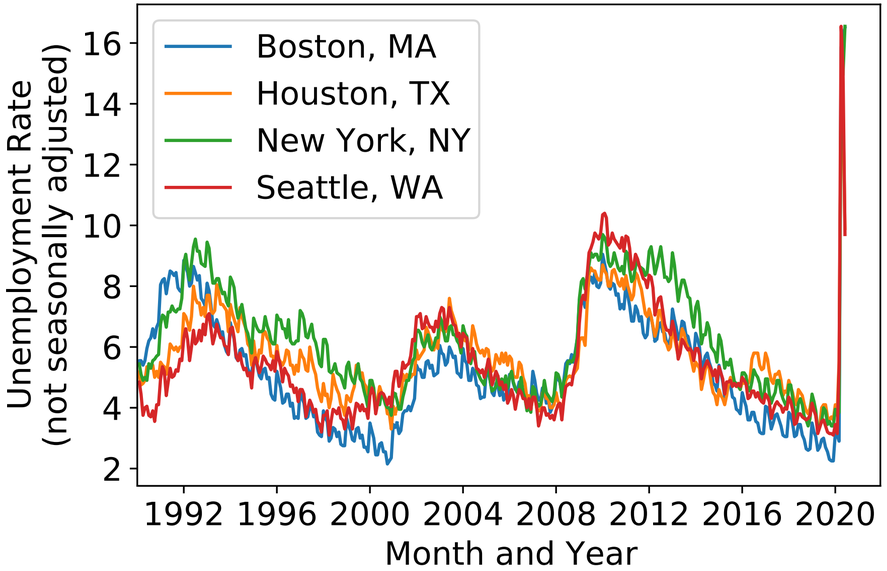


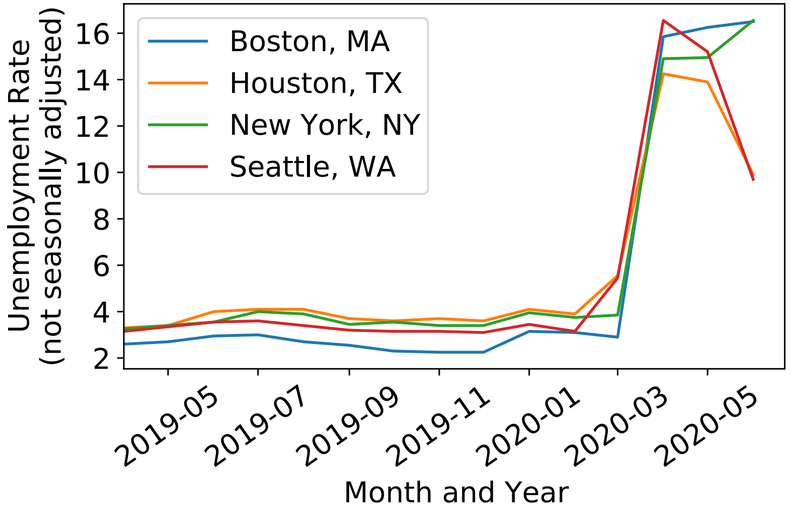
Dependent Variable: Avg. Annual Wage of Occupation i in city c in *year*					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Employment Share in Occ. i in c in *year*	-0.012^{***}			0.009^{***}	0.001
% of Occ. i emp. with Bachelor's in *year*		-0.056^{***}		-0.014^{***}	-0.015^{***}
Embeddedness of Occ. i in c in *year*			0.264^{***}	0.266^{***}	0.258^{***}
(Emp. Share)x(Bachelors)					0.042^{***}
(Emp. Share)x(Embeddedness)					0.010^{***}
(Bachelors)x(Embeddedness)					0.012^{***}
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.252	0.252	0.267	0.267	0.267
adj. R^2	0.251	0.252	0.267	0.267	0.267
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$					

Variables centered and standardized.

Moro*, Frank*, et al. *Nat. Comms* (2021)

Future Work: Network embeddedness and unemployment risk





Dependent Variable: $\log_{10}$ Peak Unemployment by MSA in 2020				
Variable	Model 1	Model 2	Model 3	Model 4
$\log_{10}$ Total Employment (2019)	0.958^{***}		1.329^{***}	1.294^{***}
Job Connectivity (w_{eff}) (2019)		0.936^{***}	-0.376^{***}	-0.358^{***}
interaction				0.018^{*}
R^2	0.917	0.876	0.921	0.922
adj. R^2	0.917	0.875	0.921	0.922
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

All variables centered and standardized.

Future Work: Network embeddedness and unemployment risk

Boulder, CO

Using the month of UI data in which each city experienced peak UI

$$P_{state}(ui\,|\,soc) = \frac{P_{state}(2soc\,|\,ui)\cdot P_{state}(ui)}{P_{state}(soc)}$$

N=93,000

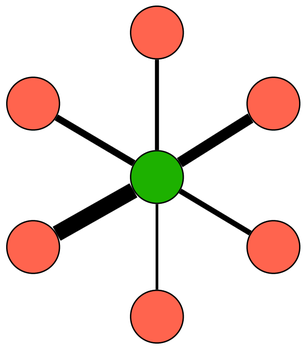
Dependent Variable: $\log_{10} P_{state}(ui\|soc)$				
Variable	Model 1	Model 2	Model 3	Model 4
$\log_{10}$ Avg. Wage			-0.041^{***}	-0.010^{***}
$\log_{10}$ Total Employment		-0.577^{***}		-0.576^{***}
Occ. Embeddedness	-0.279^{***}	-0.027^{**}	-0.265^{***}	-0.024^{**}
City F.E.	Yes	Yes	Yes	Yes
2-Digit SOC F.E.	Yes	Yes	Yes	Yes
R^2	0.675	0.889	0.677	0.889
adj. R^2	0.674	0.889	0.675	0.889
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

$$P_{city}(ui\,|\,soc) = \frac{P_{state}(2soc\,|\,ui)\cdot P_{city}(ui)}{P_{city}(soc)}$$

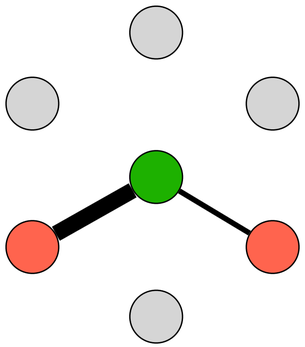
Dependent Variable: $\log_{10} P_{city}(ui\|soc)$				
Variable	Model 1	Model 2	Model 3	Model 4
$\log_{10}$ Avg. Wage			-0.032^{***}	0.001^{*}
$\log_{10}$ Total Employment		-0.637^{***}		-0.638^{***}
Occ. Embeddedness	-0.288^{***}	-0.009^{*}	-0.276^{***}	-0.009^{*}
City F.E.	Yes	Yes	Yes	Yes
2-Digit SOC F.E.	Yes	Yes	Yes	Yes
R^2	0.697	0.958	0.698	0.958
adj. R^2	0.696	0.958	0.697	0.958
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

Financial Managers

High Embeddedness

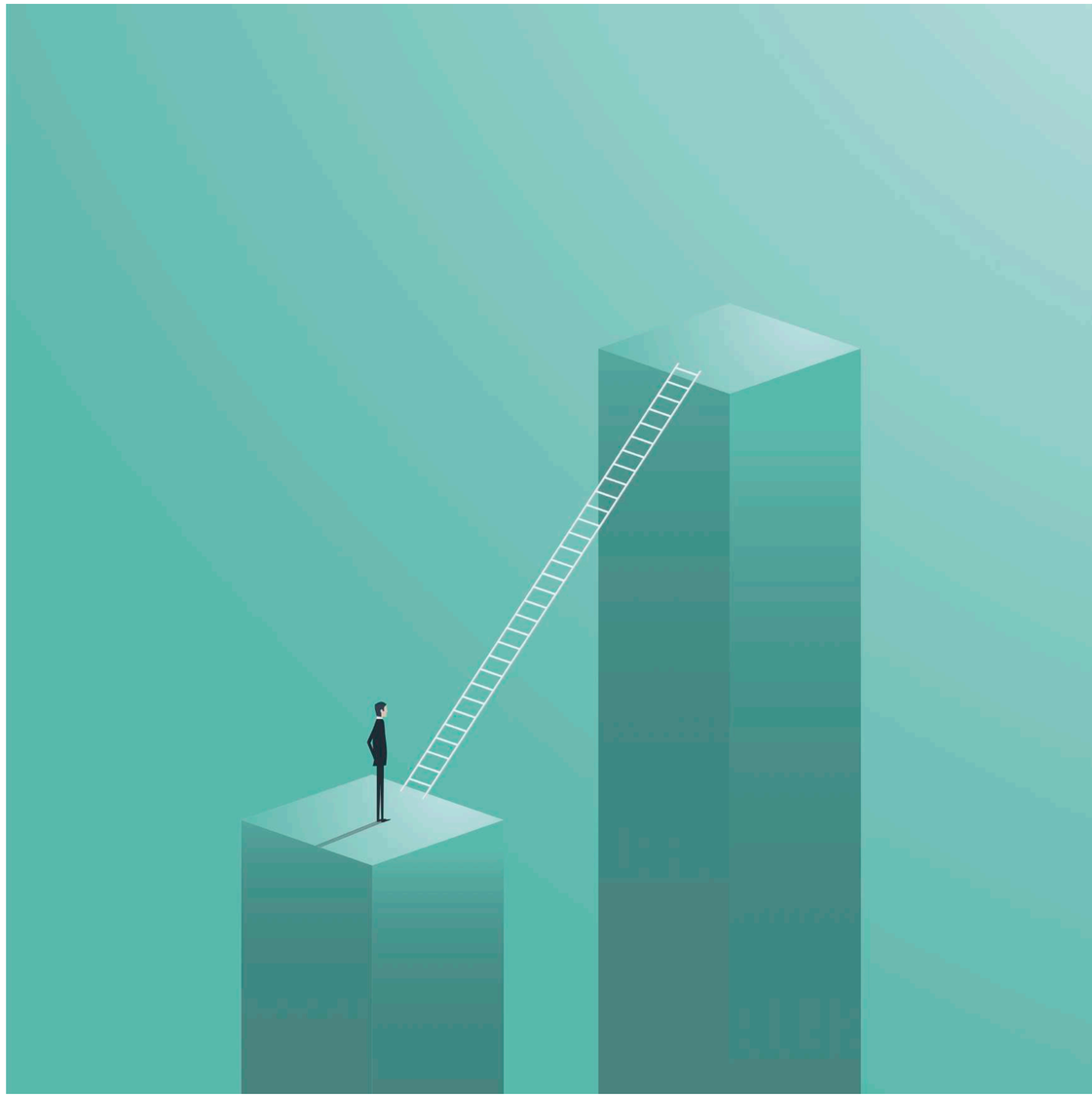


Low Embeddedness



Summary

- Use empirical skill profiles for US occupations to relate occupations and predict job transitions.
- Modeling US cities as occupation networks, we find that workers tend to decrease their employment-weighted embeddedness over their career
- City pairs with large average combined embeddedness exhibit greater flows of spatial mobility.
- Using a similar idea to occupation embeddedness, cities with high job connectivity were more resilient during the Great Recession.



Related Reading

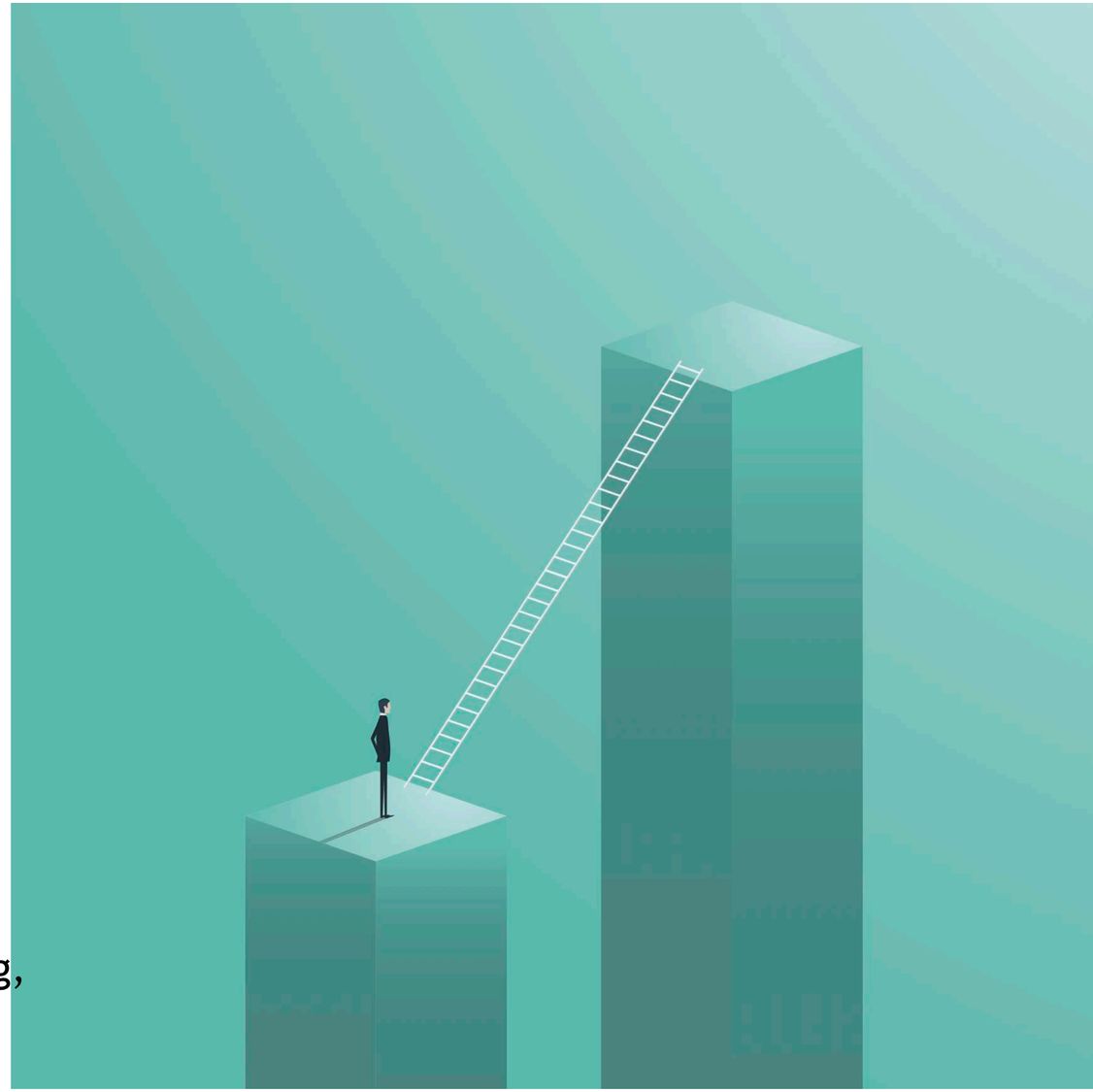
- Small cities face greater impact from automation
  M.R. Frank, L. Sun, M. Cebrian, H. Youn, I. Rahwan
  Journal of the Royal Society Interface, 2018

- Unpacking the polarization of workplace skills
  A. Alabdulkareem*, M.R. Frank*, L. Sun, B. AlShebli, C. Hidalgo, I. Rahwan
  *joint first author
  Science Advances, 2018

- Universal resilience patterns in labor markets
  E. Moro*, M.R. Frank*, A. Pentlan, A. Rutherford, M. Cebrian, I. Rahwan
  Nature Communications, 2021

- Network constraints on worker mobility: how workplace skills determine a worker's next move
  M.R. Frank, E. Moro, A. Rutherford, I. Rahwan
  (under review at ***Nature Communications***)

- Towards Understanding the Impact of AI on Labor
  M.R. Frank, D. Autor, J.E. Bessen, E. Brynjolfsson, M. Cebrian, D.J. Deming, M. Feldman, M. Groh, J. Lobo, E. Moro, D. Wang, H. Youn, I. Rahwan
  Proceedings of the National Academy of Science, 2019



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Lots of data

- Occupational skill profiles: US Bureau of Labor Statistics (BLS) O*NET database from 2010-2018

- Urban Employment by Occupation: BLS Occupation employment statistics from 2010-2018

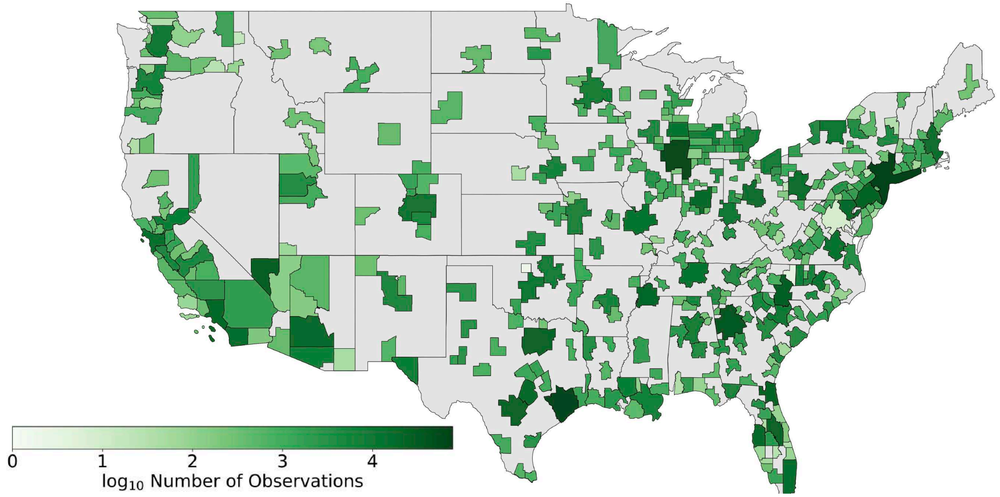
- Workers' Career Trajectories:
  - US Census Current Population Survey
    - nationally-representative, but only sparsely samples the space of occupation pairs
  - millions of worker resumes from two sources: Burning Glass Technologies and FutureFit AI
    - good coverage for a biased sample of industries

- Spatial Mobility between US cities:
  - US Census migration from 2013-2018
  - US Bureau of Transportation Statistics enplaned passenger data spanning 2013-2018

Skill similarity improves models of individual career mobility

Dependent Variable: $\log_{10}$ Job Transitions				
Variable	Model 1	Model 2	Model 3	Model 4
$skillsim(j,j')$			0.266^{***}	0.366^{***}
Log-10 Total Employment ($T(j,j')$)	0.479^{***}	0.484^{***}	0.511^{***}	0.517^{***}
Cognitive/Physical Similarity ($CP(j,j')$)		0.135^{***}		-0.125^{***}
$skillsim(j,j') \times CP(j,j')$				0.019^{***}
$skillsim(j,j') \times T(j,j')$				0.062^{***}
$CP(j,j') \times T(j,j')$				0.008^{*}
Year F.E.	Yes	Yes	Yes	Yes
R^2	0.238	0.255	0.300	0.312
adj. R^2	0.238	0.255	0.300	0.312
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

Job transition rates from the Burning Glass Technologies resume data (1.2 million career moves).Variables are centered and standardized.



Dependent Variable: $\log_{10}$ Job Transitions				
Variable	Model 1	Model 2	Model 3	Model 4
$skillsim(j,j')$			0.203^{***}	0.319^{***}
Log-10 Total Employment ($T(j,j')$)	0.198^{***}	0.196^{***}	0.189^{***}	0.186^{***}
Cognitive/Physical Similarity ($CP(j,j')$)		0.090^{***}		-0.138^{***}
$skillsim(j,j') \times CP(j,j')$				0.035^{***}
$skillsim(j,j') \times T(j,j')$				0.094^{***}
$CP(j,j') \times T(j,j')$				-0.049^{***}
Year F.E.	Yes	Yes	Yes	Yes
R^2	0.045	0.053	0.082	0.098
adj. R^2	0.045	0.053	0.082	0.098
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$				

Job transition rates from the FutureFit.Ai resume data (3.2 million career moves). Variables are centered and standardized.