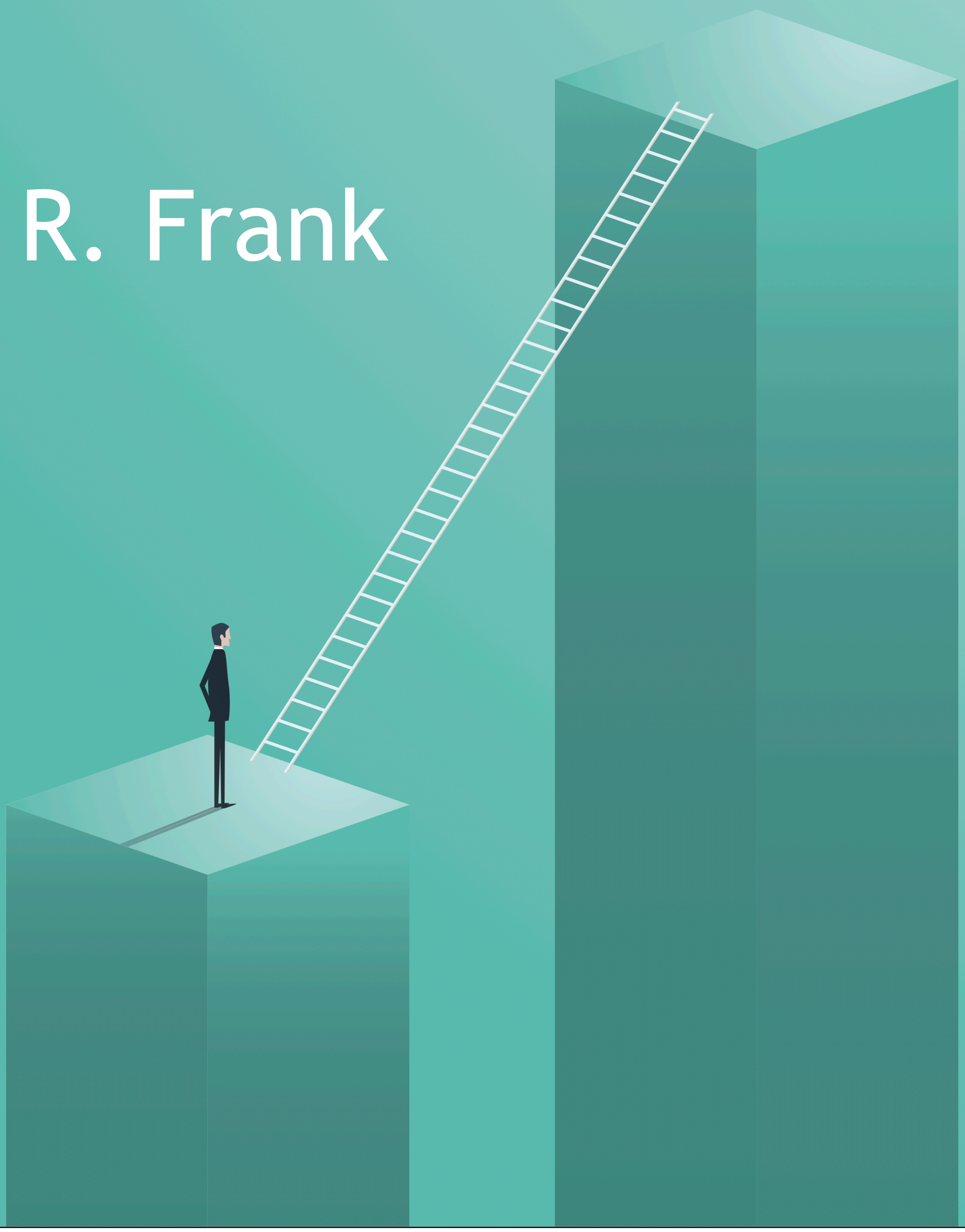
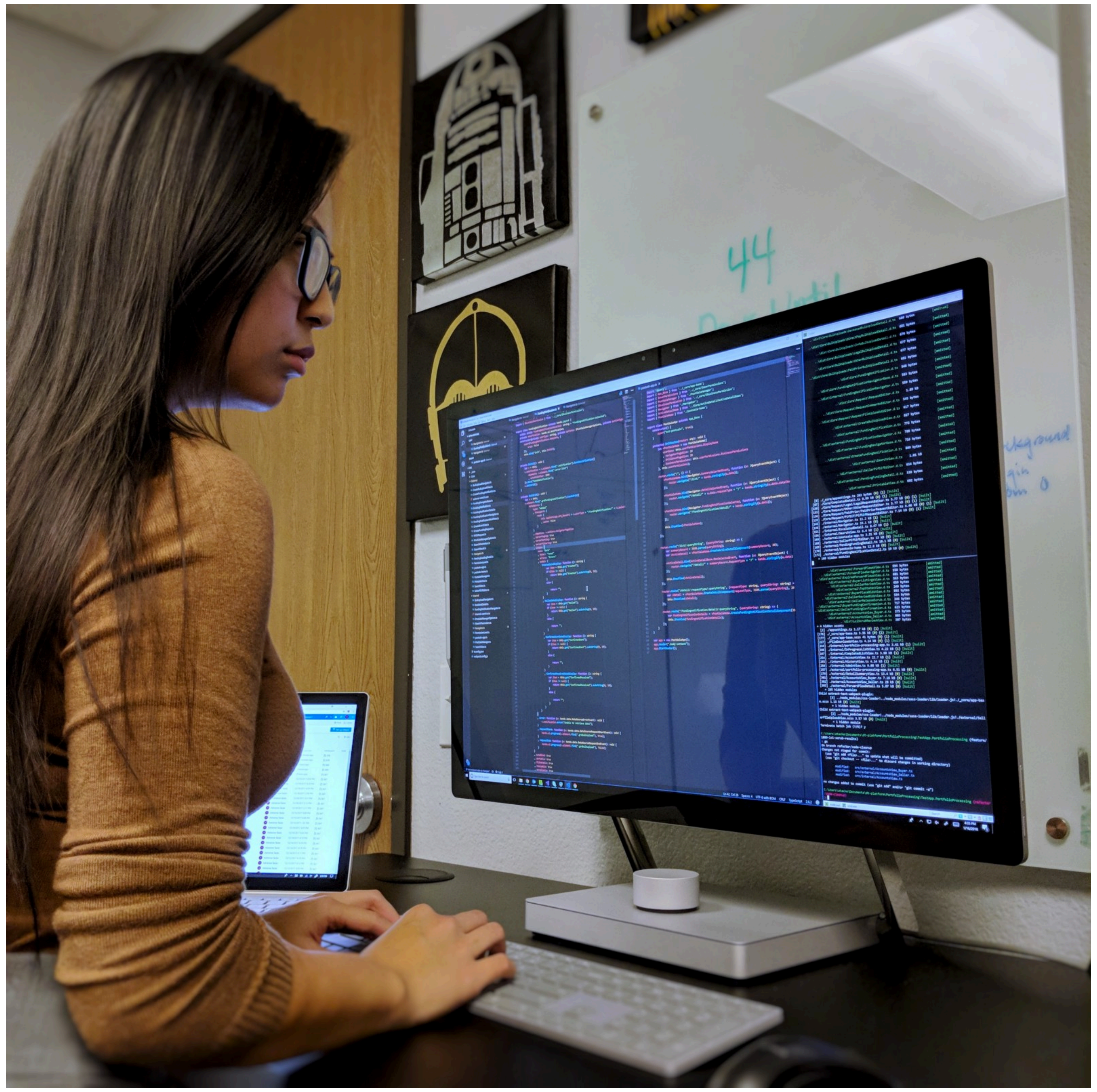
Unpacking complexity in workplace skills

Morgan R. Frank



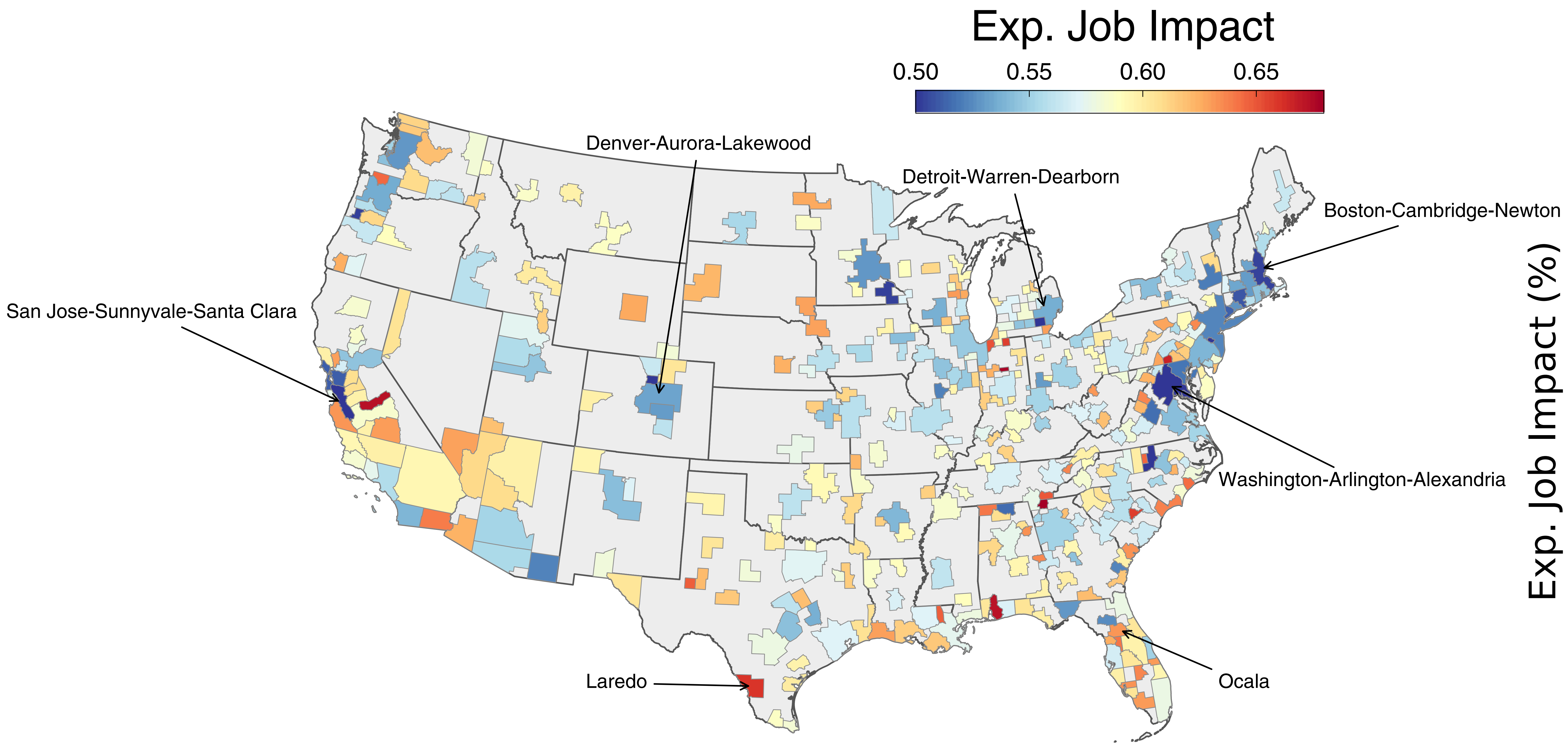
The differential impact of AI

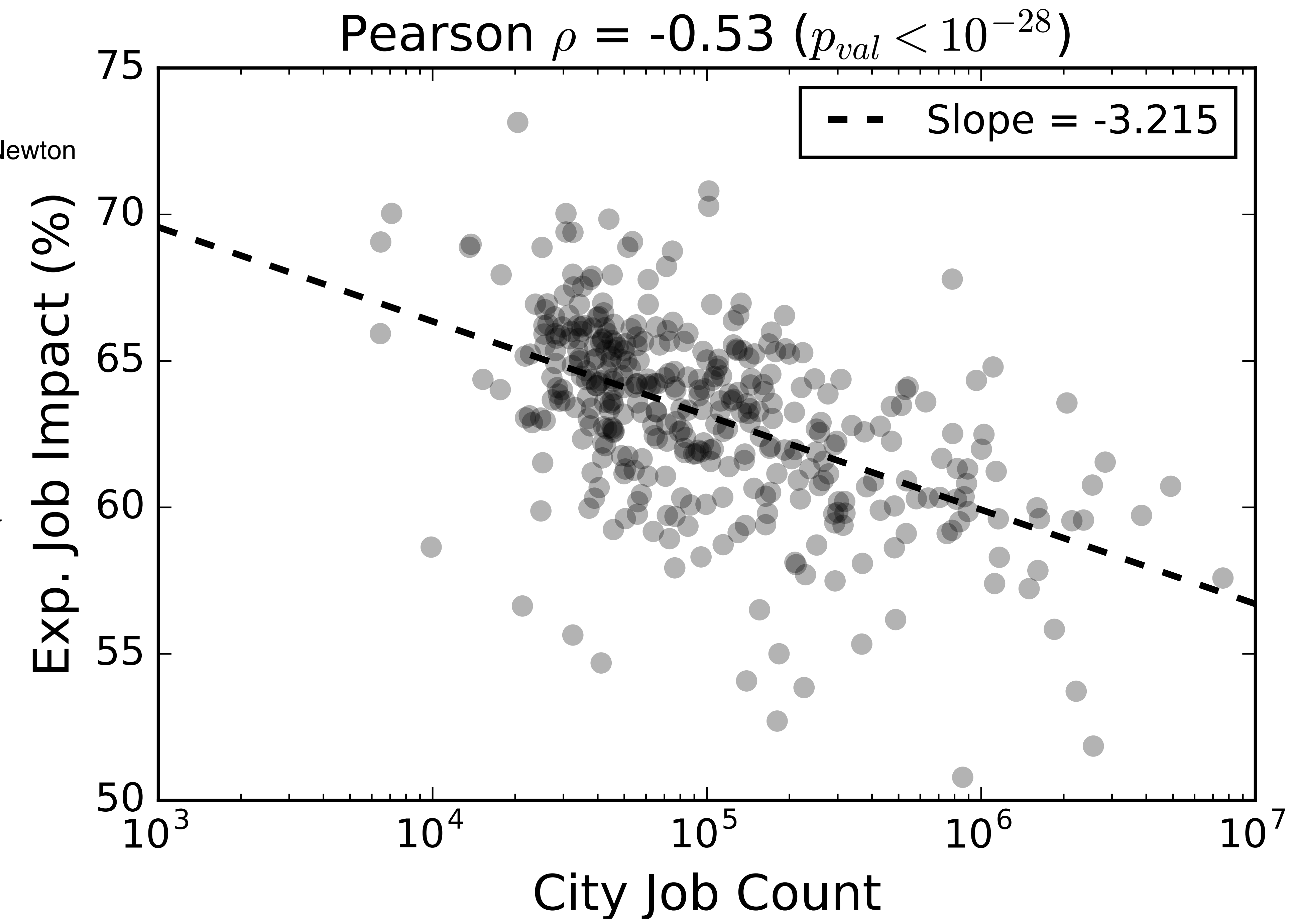
Programmers vs. Machine Learning



Truck Drivers vs. Autonomous Vehicles

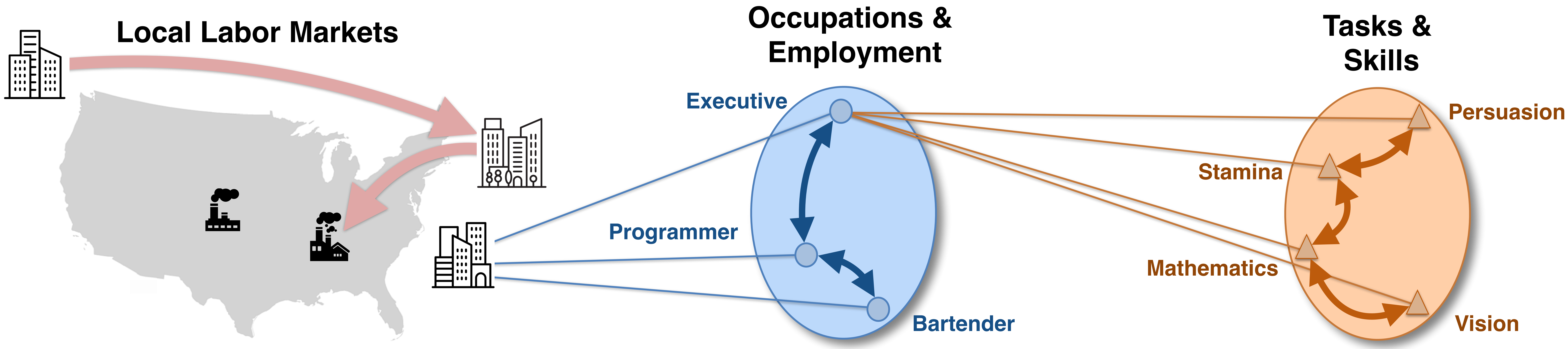
The differential impact of AI





Small cities face greater impact from automation, *J. of the Royal Soc. Interface* (2018)

Embrace Complexity

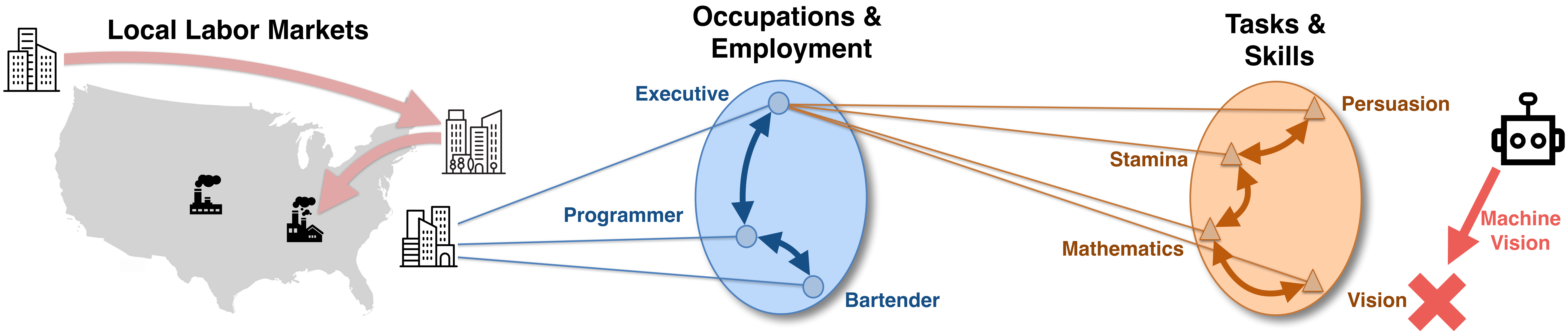


- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education

Embrace Complexity



- differential impact of automation
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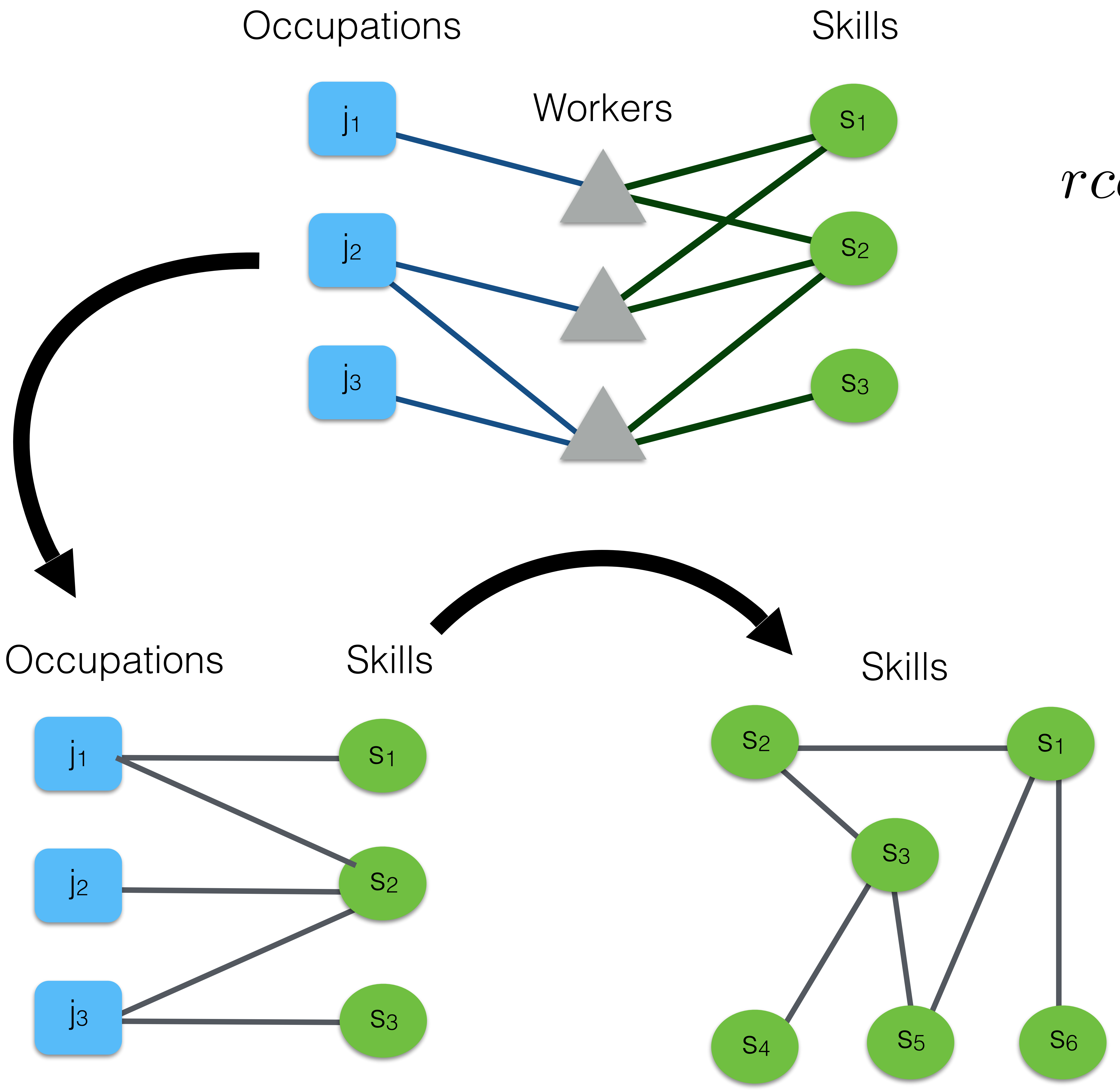
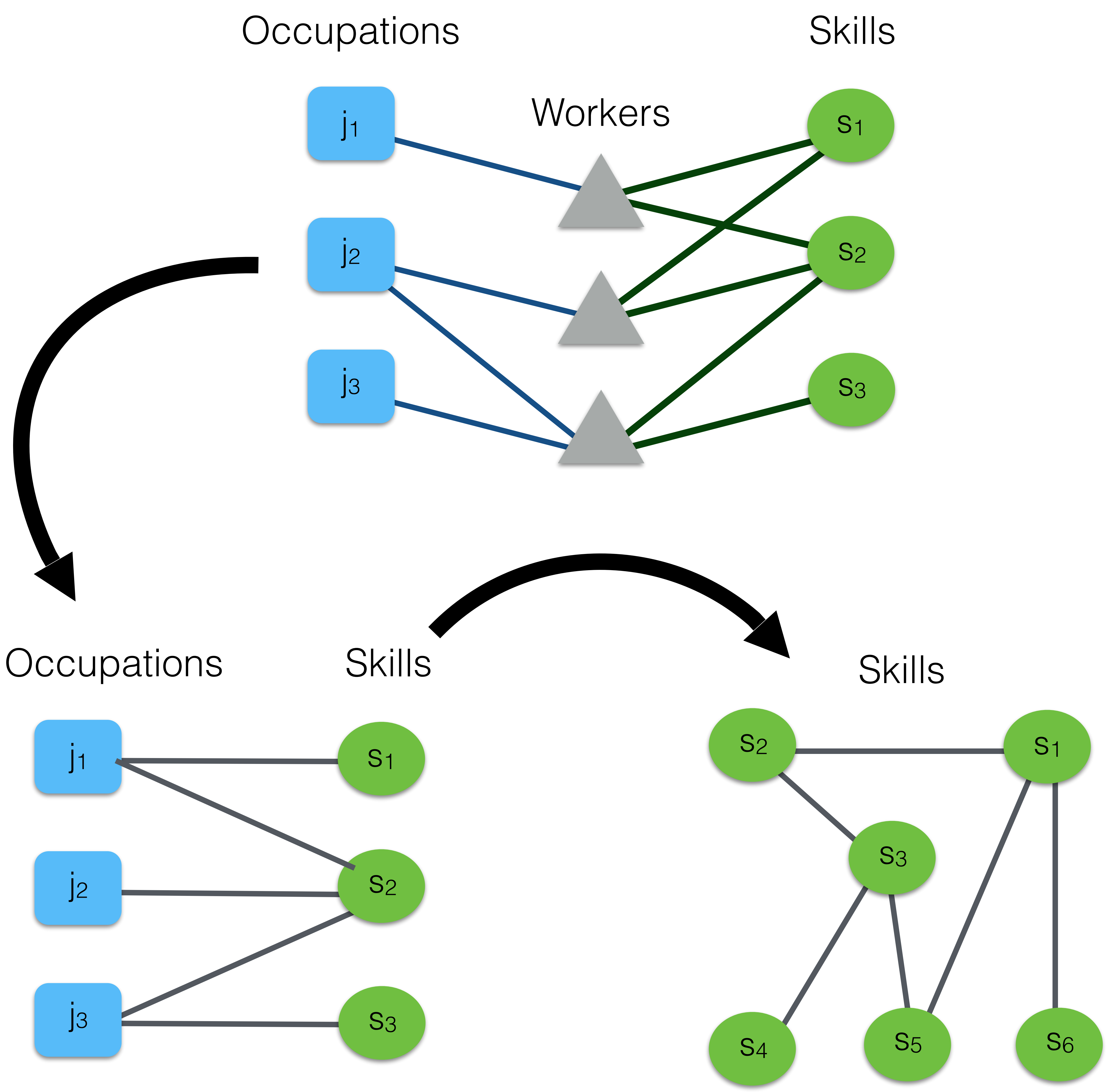
Constructing the Skillscape



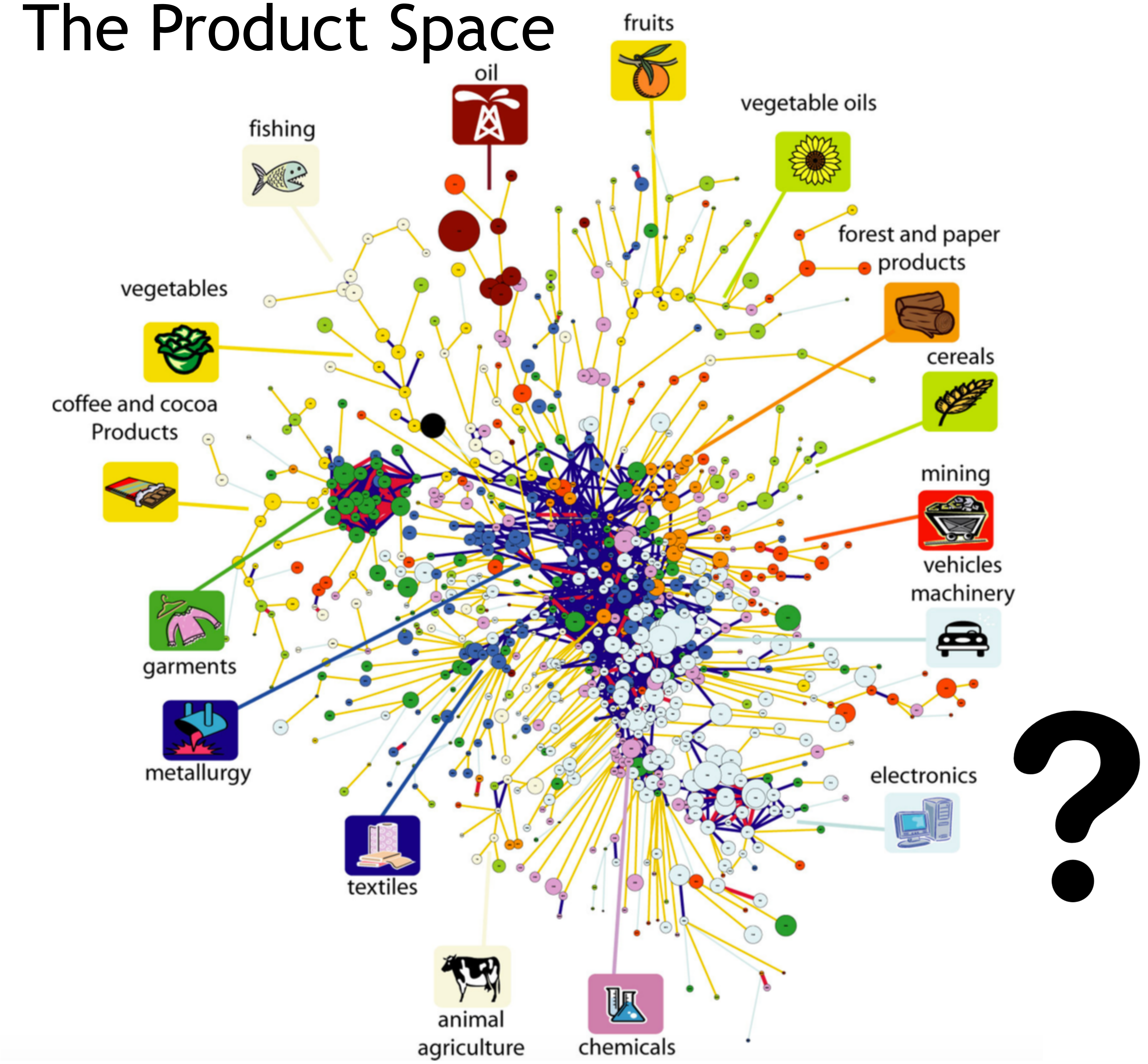
$$rca(i,s) = \frac{onet(i,s) / \sum_{s' \in Skills} onet(i,s')}{\sum_{i' \in Jobs} onet(i',s) / \sum_{s' \in Skills, j' \in Jobs} onet(i',s')}$$

$$I(i,s) = \begin{cases} 1 & \text{if } rca(i,s) > 1, \\ 0 & \text{otherwise.} \end{cases}$$

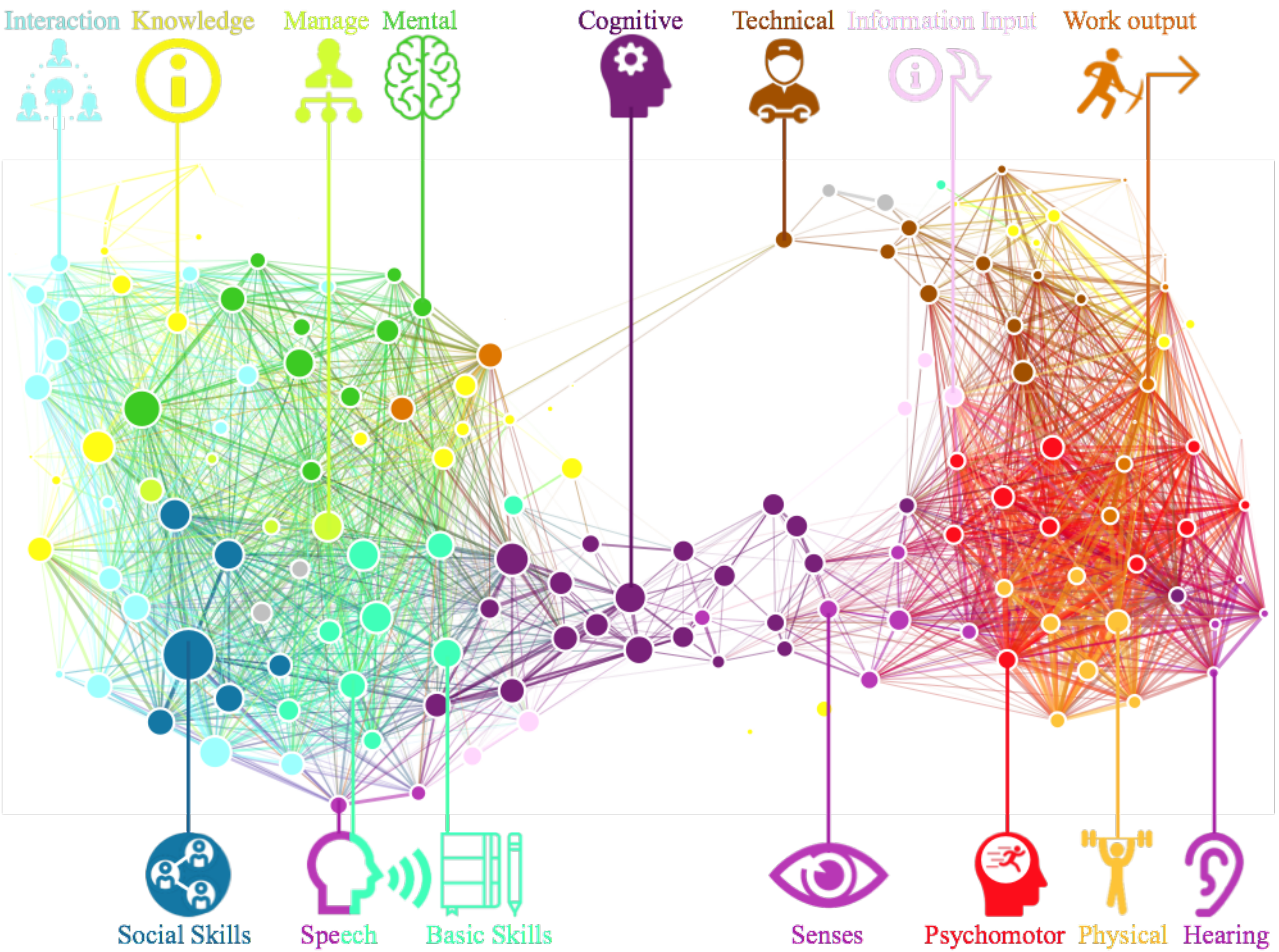
Constructing the Skillscape



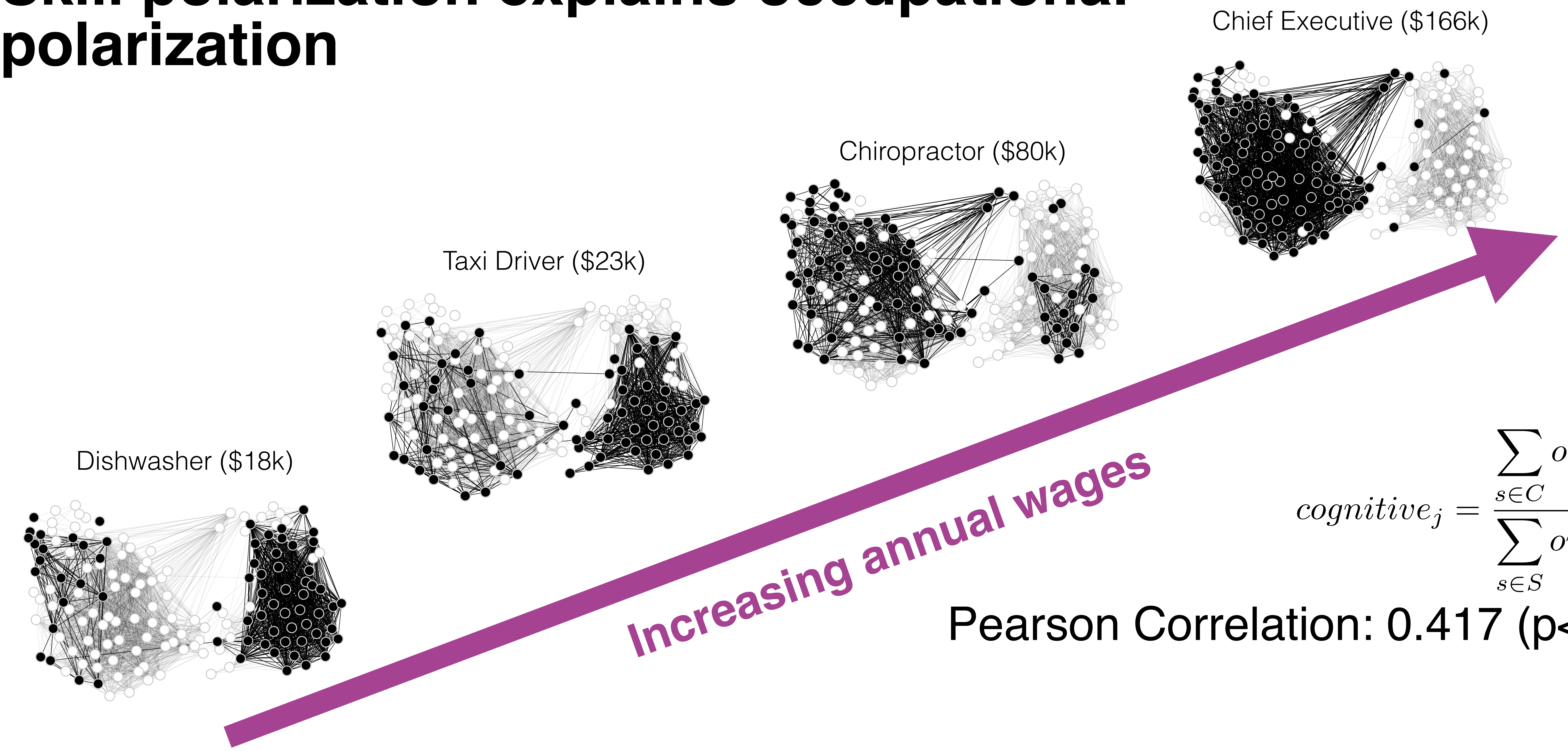
The Product Space



Unpacking the polarization of workplace skills



Skill polarization explains occupational polarization



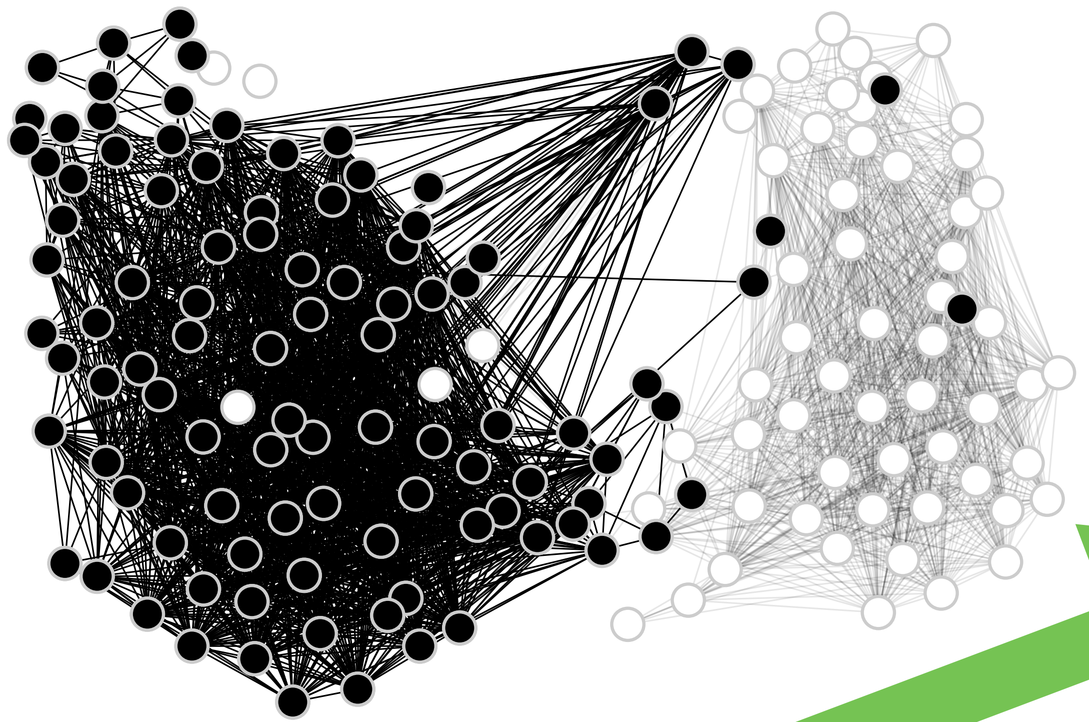
$$cognitive_j = \frac{\sum_{s \in C} onet(j,s)}{\sum_{s \in S} onet(j,s)}$$

Pearson Correlation: 0.417 ($p<10^{-26}$)

Unpacking the polarization of workplace skills, *Science Advances* (2018)

Skill polarization and economic well-being

New York, NY ($67k)



Detroit, MI ($52k)

Yuma, AZ ($41k)

Increasing median household income

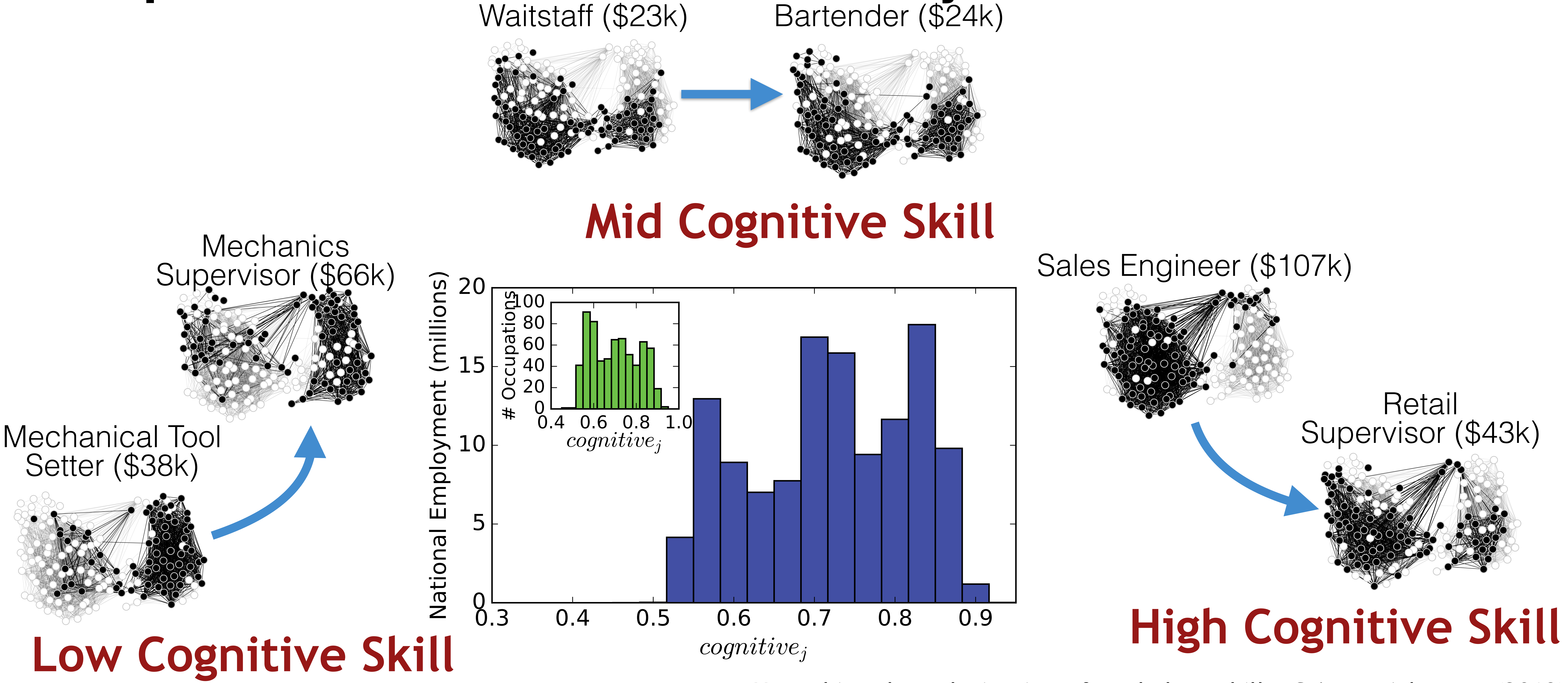
(also population)

$$cognitive_j = \frac{\sum_{s \in C} onet(j,s)}{\sum_{s \in S} onet(j,s)}$$

Pearson Correlation: 0.254 ($p<10^{-4}$)

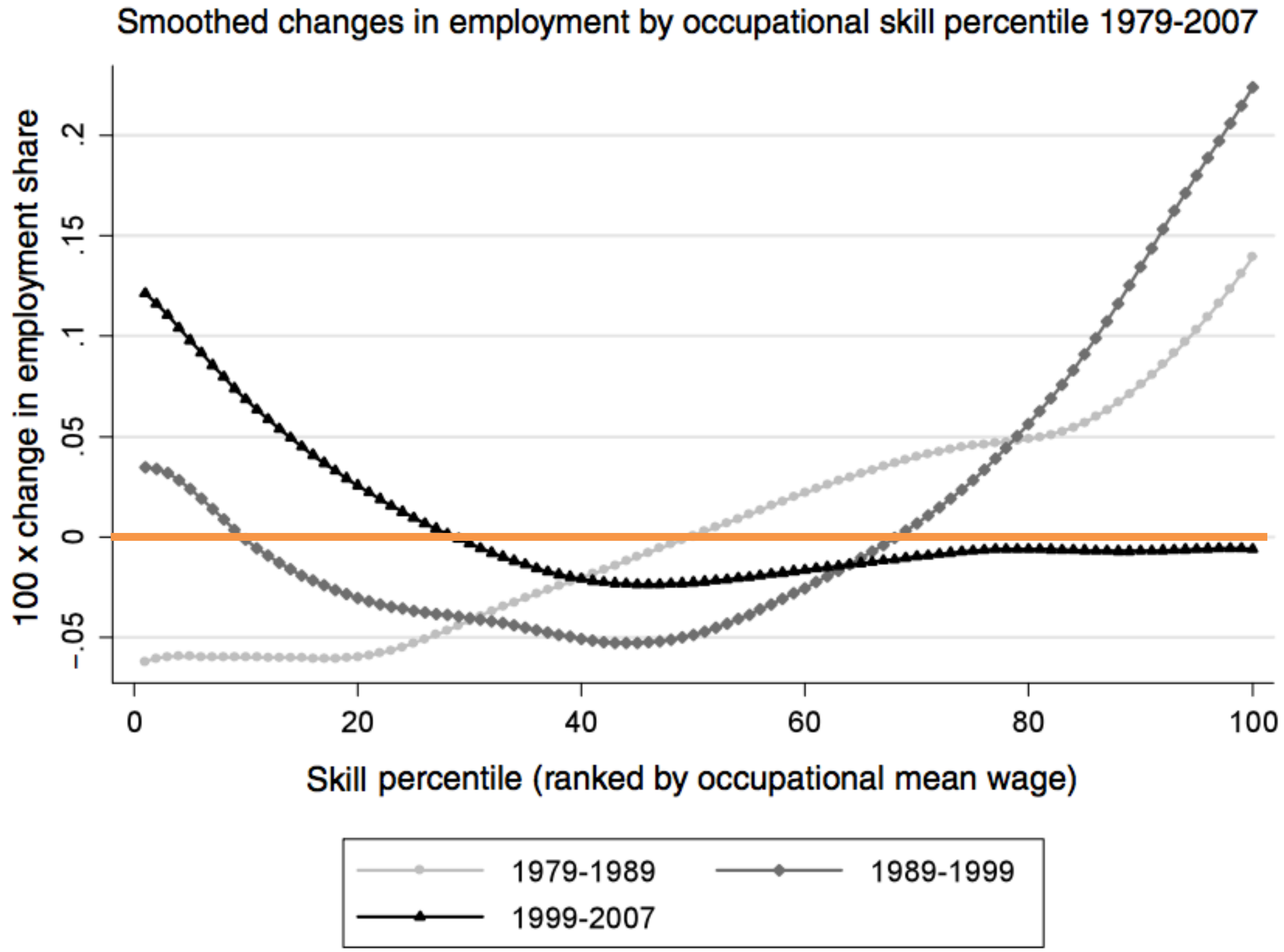
Unpacking the polarization of workplace skills, *Science Advances* (2018)

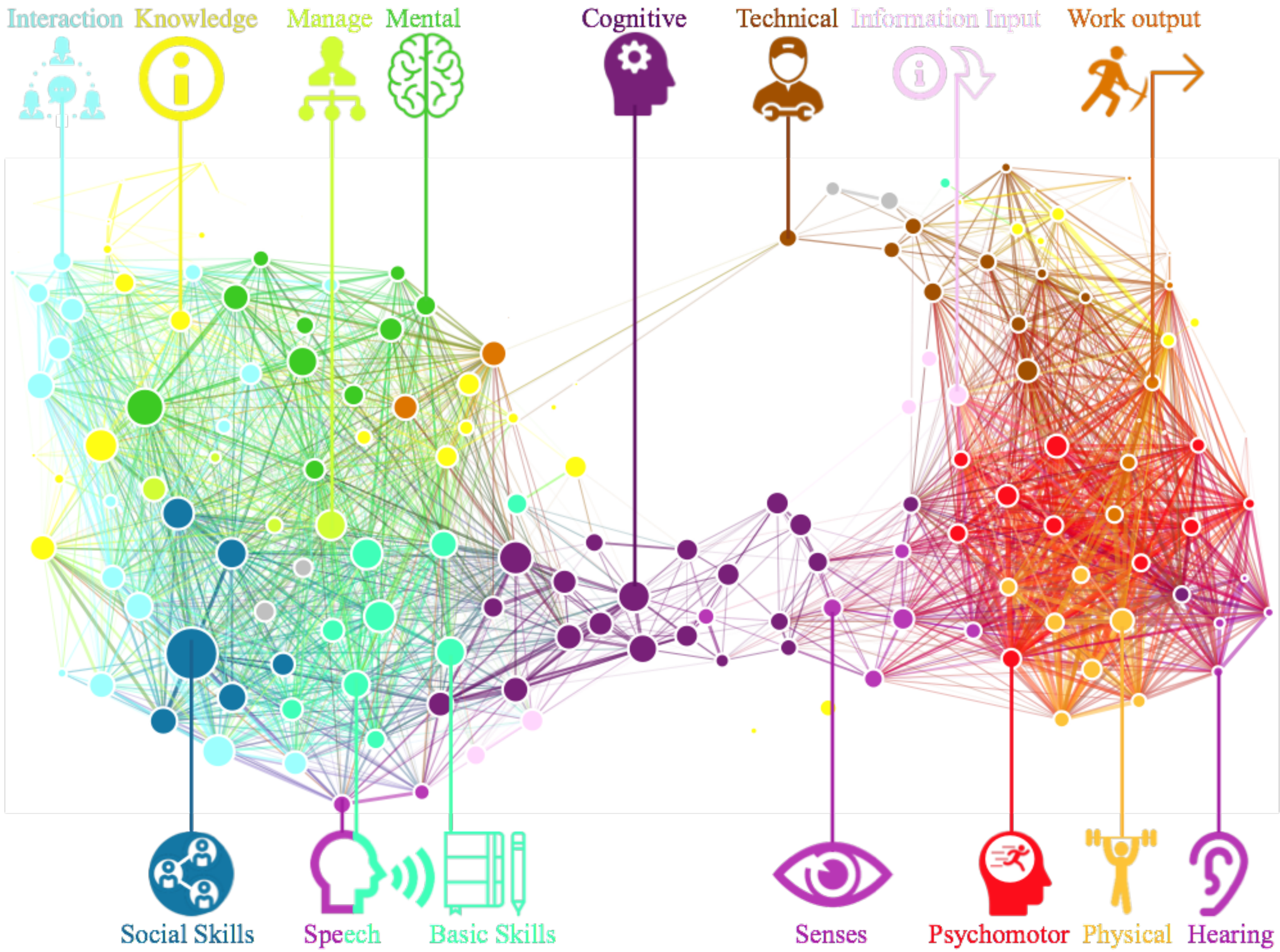
Skill polarization and career mobility



Unpacking the polarization of workplace skills, *Science Advances* (2018)

Explaining low- and high-skill employment

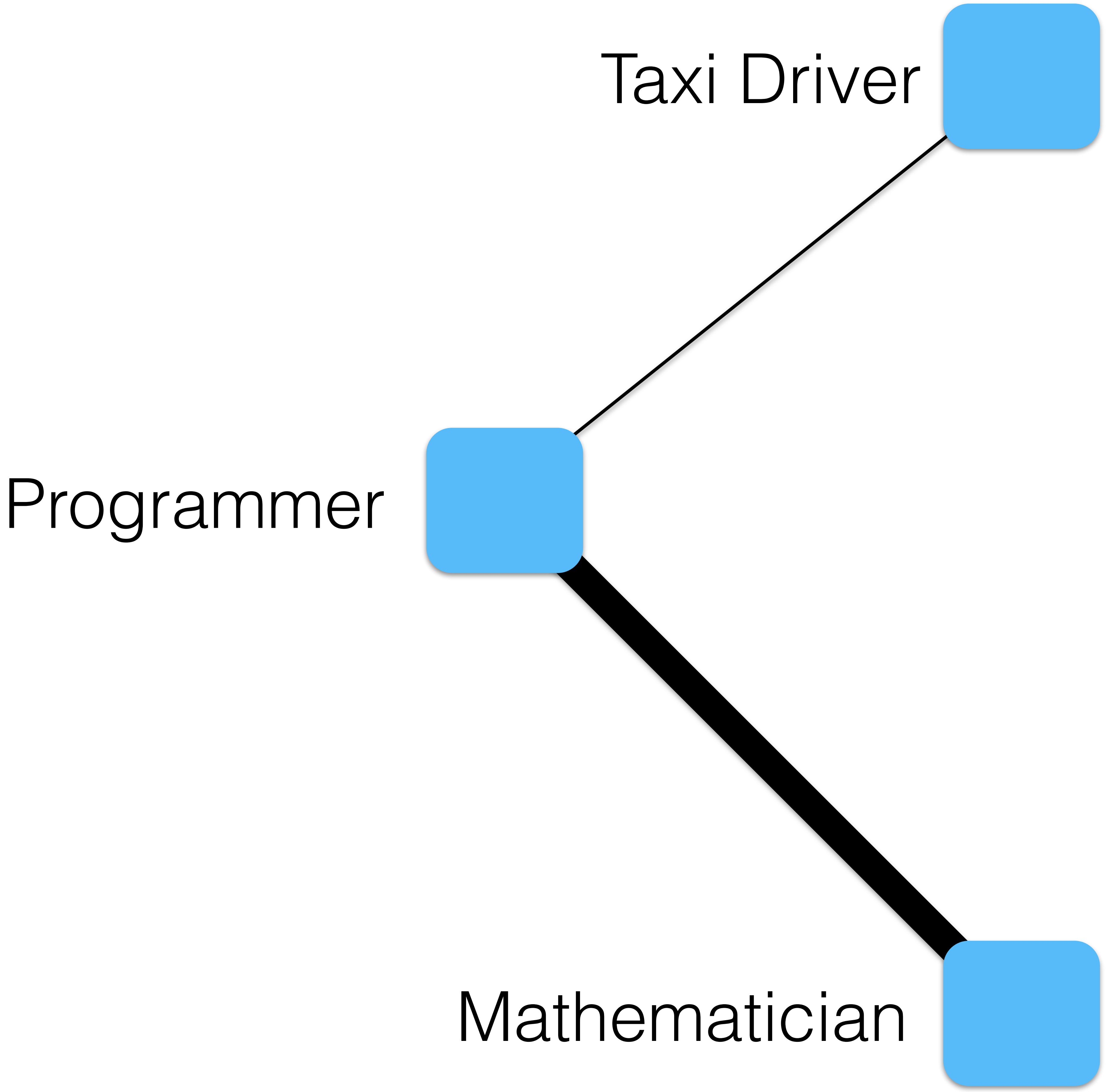




Unpacking the polarization of workplace skills, *Science Advances* (2018)


?
NEW YORKER

Connecting Occupations

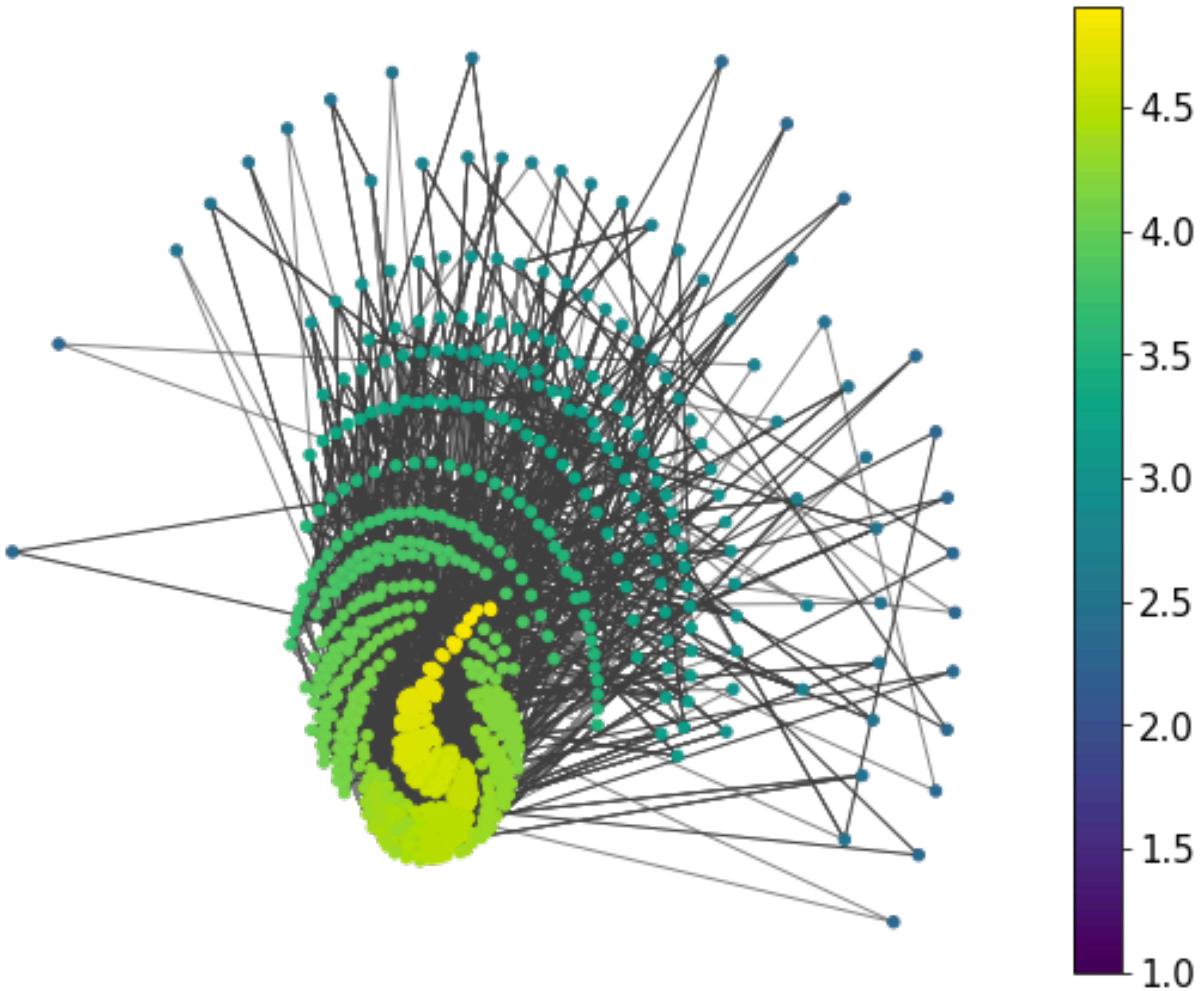


$$rca(i,s) = \frac{onet(i,s) / \sum_{s' \in Skills} onet(i,s')}{\sum_{i' \in Jobs} onet(i',s) / \sum_{s' \in Skills, j' \in Jobs} onet(i',s')}$$

$$I(i,s) = \begin{cases} 1 & \text{if } rca(i,s) > 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$skillsim(i,j) = \sum_{s \in Skills} w_s \frac{I(i,s) + I(j,s)}{2}$$

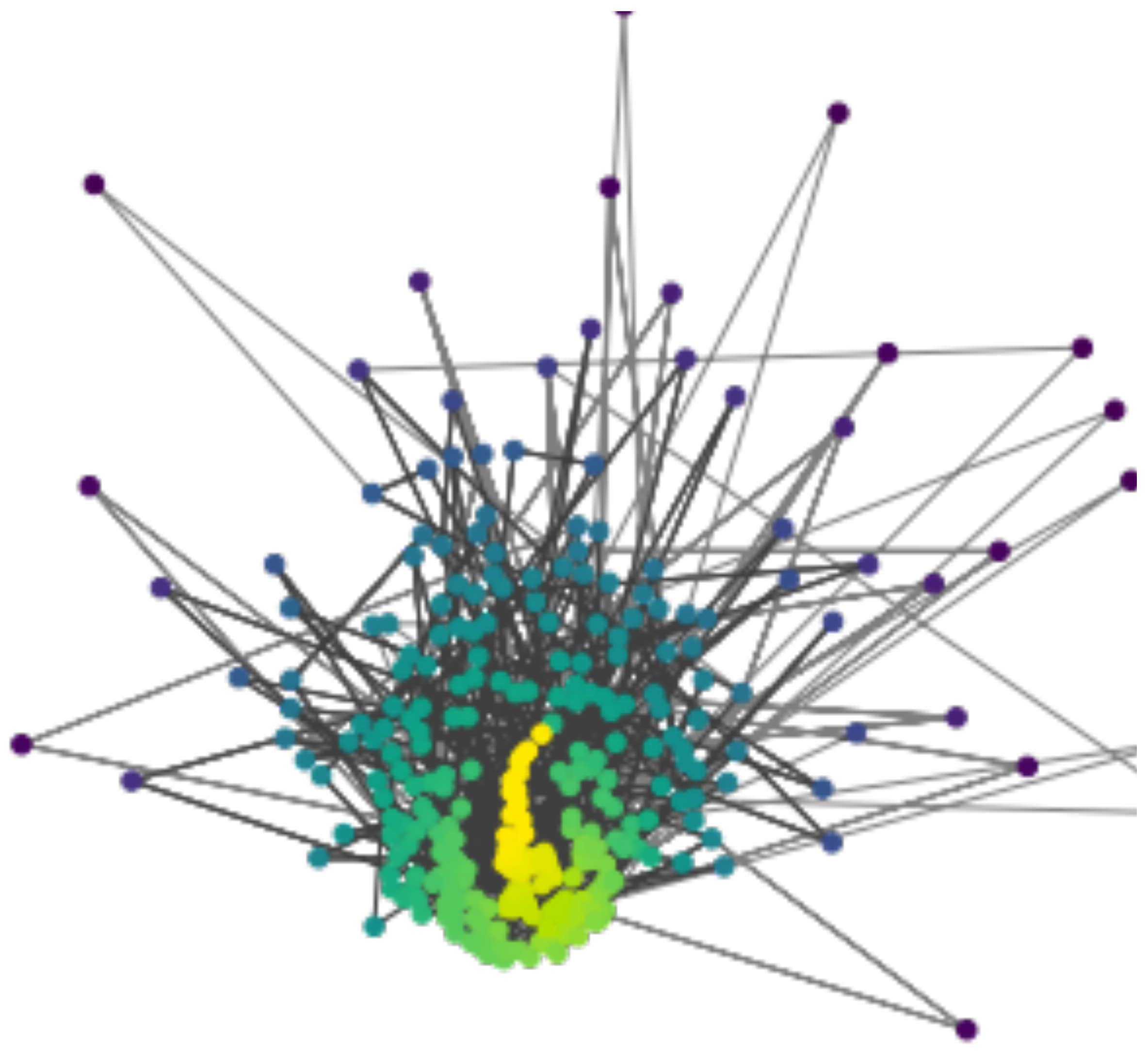
Connecting Occupations



$$\text{Total Skill Similarity}(i) = \sum_{j \in Jobs, j \neq i} skillsim(i, j)$$

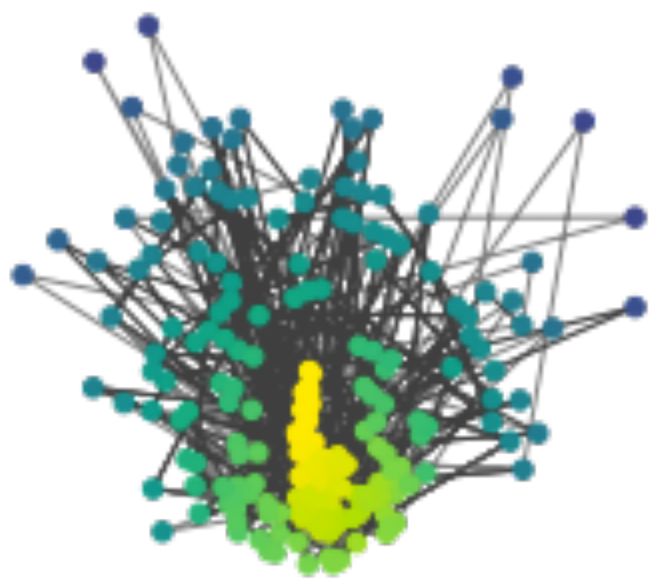
Connecting urban workforces

Chicago, IL



$\cap$

Orlando, FL



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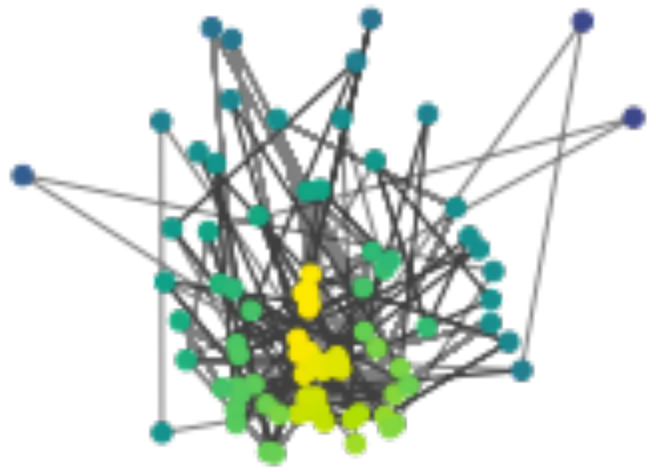
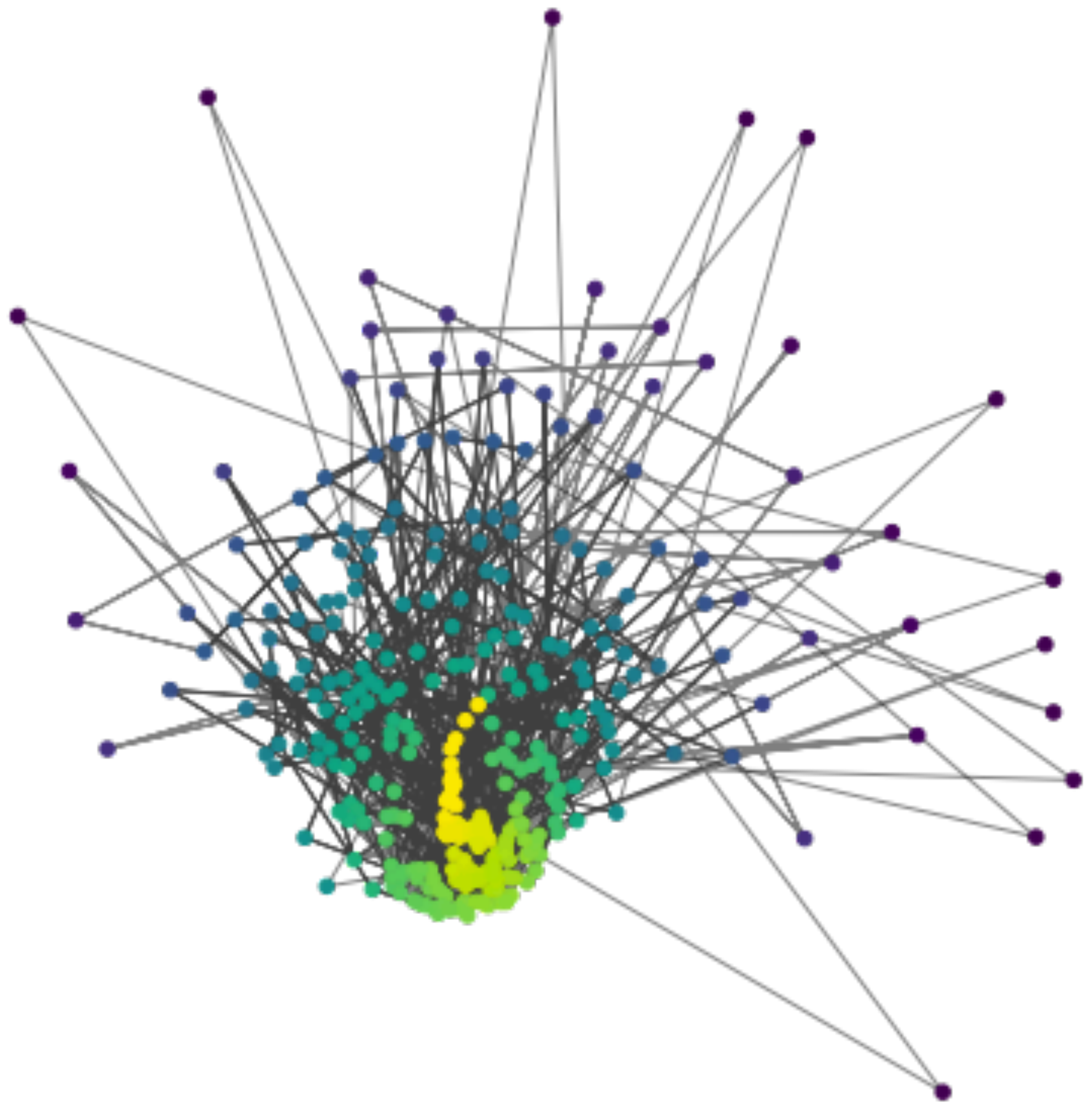
Chicago-Orlando
Employment Overlap



Connecting urban workforces

Boston, MA



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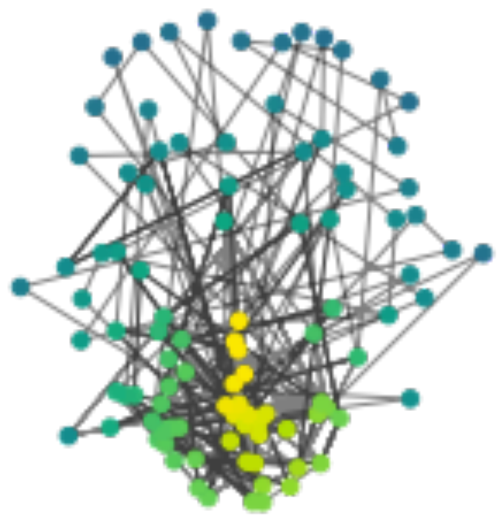
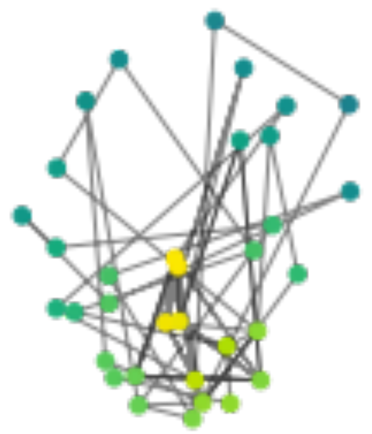
Napa, CA



$=$

Boston-Napa
Employment Overlap



$$\vec{c}_a = [\ldots, I(a,j), \ldots]_{j \in Jobs}$$

$$\text{job tightness}(a,b) = \frac{\langle JJ \cdot (\vec{c}_a + \vec{c}_b) \rangle}{\langle JJ \rangle}$$

Connecting skills to *spatial* mobility

Two Types of Intercity Mobility:

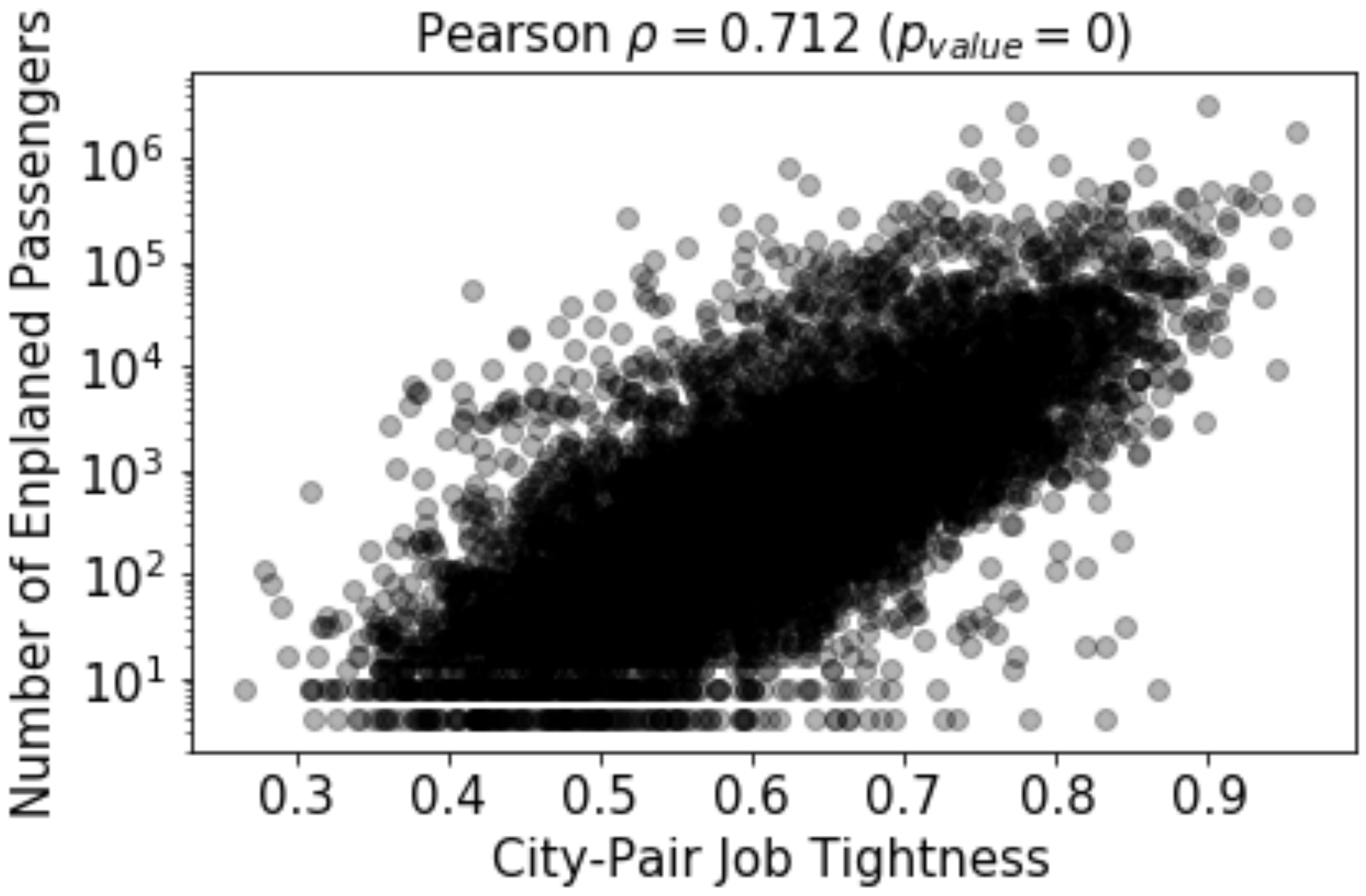
Enplaned Passengers

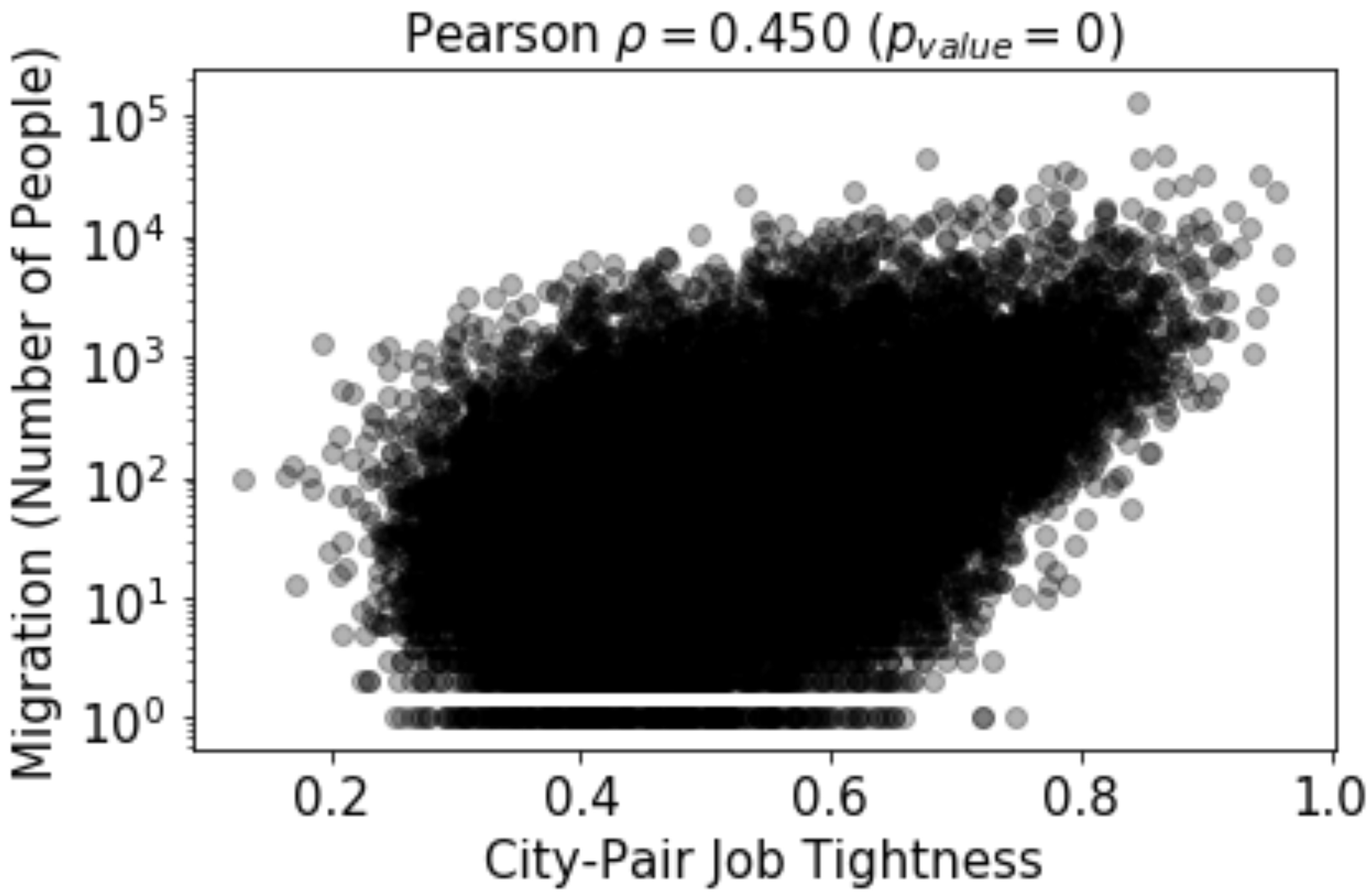
Migration

Connecting skills to *spatial* mobility

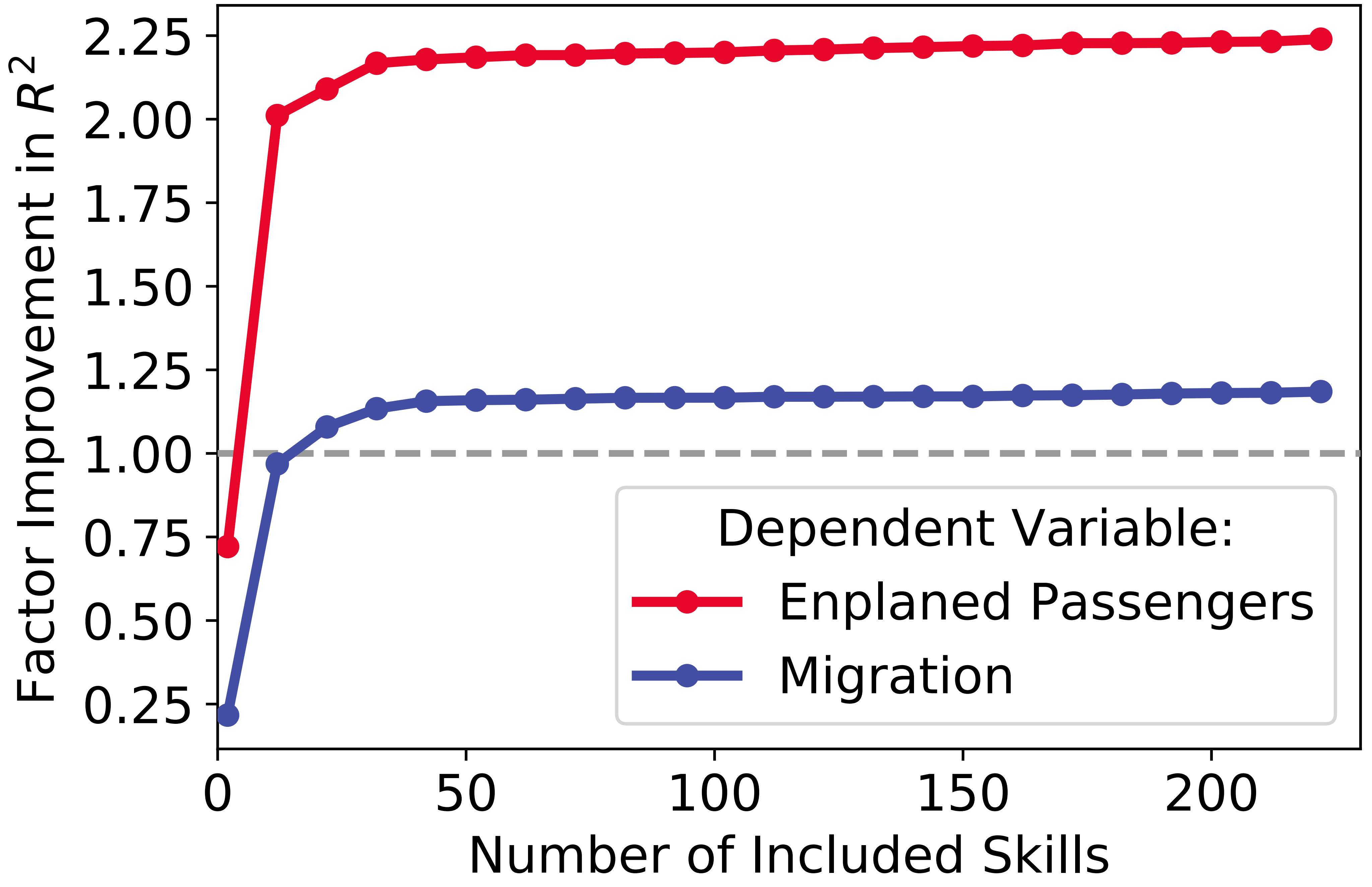
$$\vec{c}_a = [\ldots, I(a,j), \ldots]_{j \in Jobs}$$

$$\text{job tightness}(a,b) = \frac{\langle JJ \cdot (\vec{c}_a + \vec{c}_b) \rangle}{\langle JJ \rangle}$$





Not all skills are equal



Use supervised CMA-ES to learn skill weights (w_s)

Connecting skills to spatial mobility

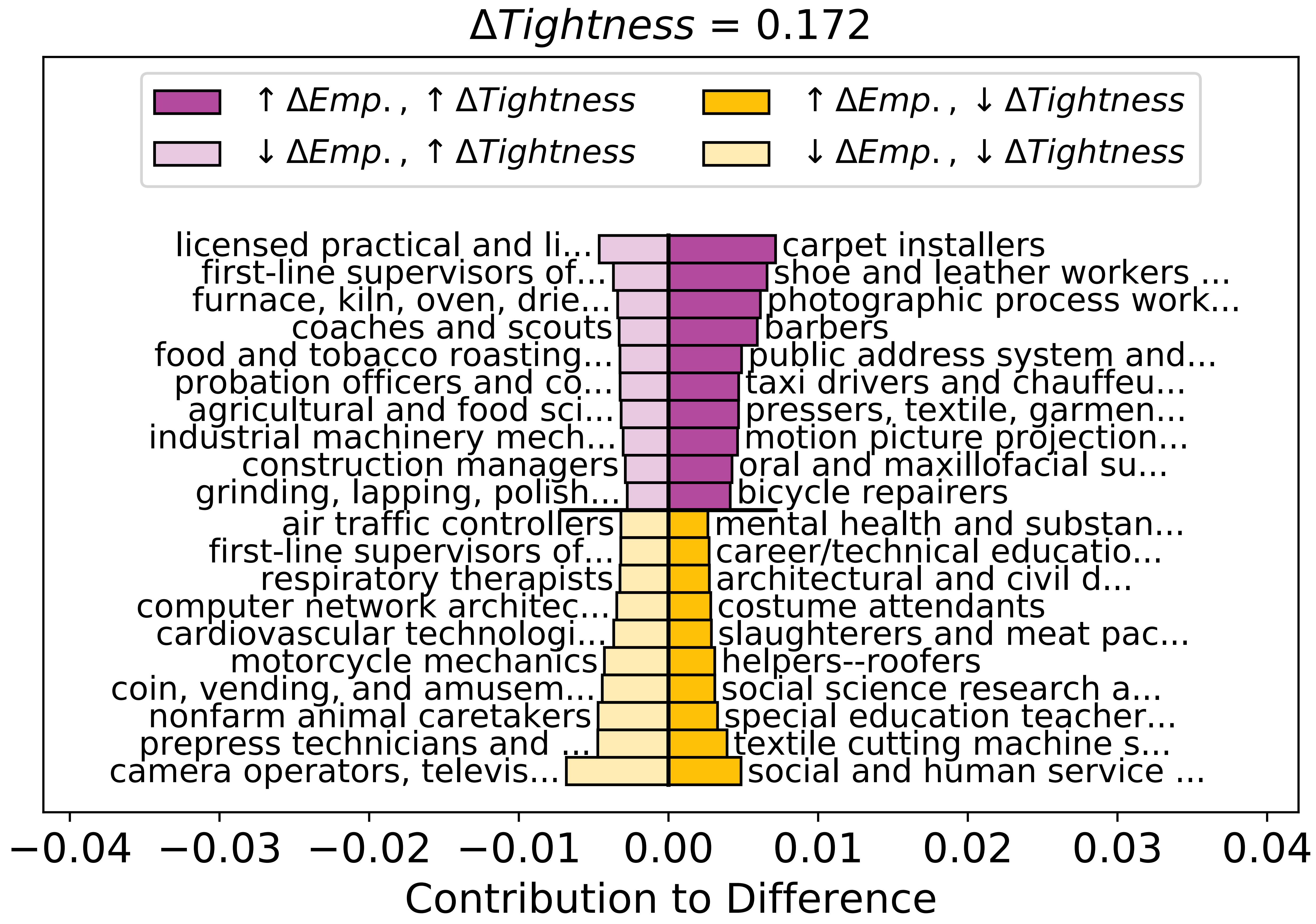
Dependent Variable: $\log_{10}(\text{enplaned passengers}_{a,b})$					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Weighted Job Tightness	0.867^{***}		0.815^{***}		0.841^{***}
Log Employment		0.560^{***}	0.085^{***}	0.203^{***}	0.091^{***}
Log Distance		0.095^{***}	0.016^{**}	0.097^{***}	0.013^{*}
Characteristic Job Overlap				0.585^{***}	-0.035^{***}
R^2	0.752	0.330	0.757	0.545	0.757
adj. R^2	0.752	0.330	0.757	0.545	0.757
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$					

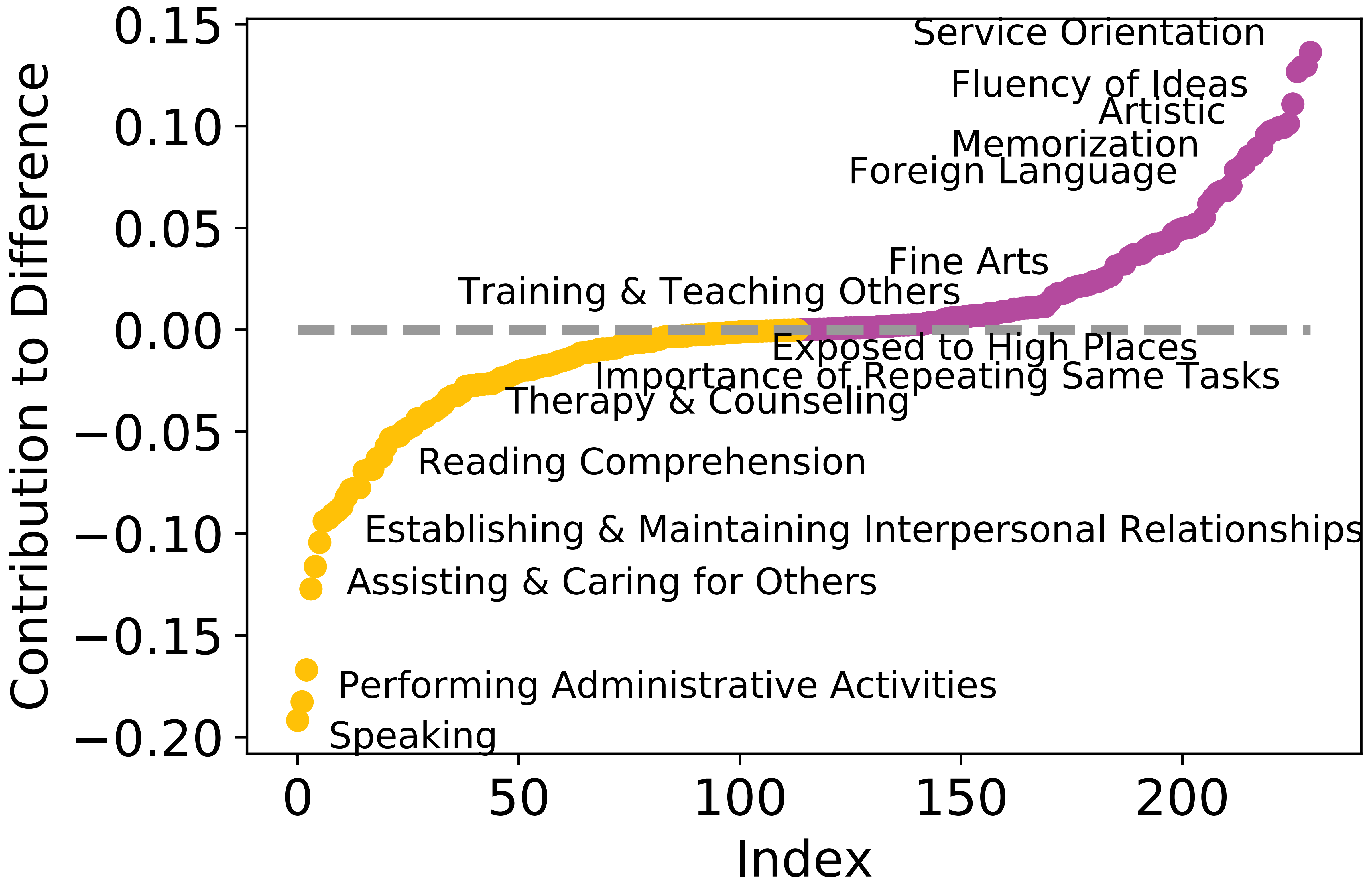
Dependent Variable: $\log_{10}(\text{migration}_{a,b})$					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Weighted Job Tightness	0.520^{***}		0.548^{***}		0.631^{***}
Log Employment		0.404^{***}	0.114^{***}	0.155^{***}	0.132^{***}
Log Distance		-0.306^{***}	-0.395^{***}	-0.357^{***}	-0.395^{***}
Characteristic Job Overlap				0.427^{***}	-0.105^{***}
R^2	0.271	0.225	0.427	0.340	0.429
adj. R^2	0.271	0.225	0.427	0.339	0.429
$p_{val} < 0.1^{*}$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$					

Explaining Job Tightness

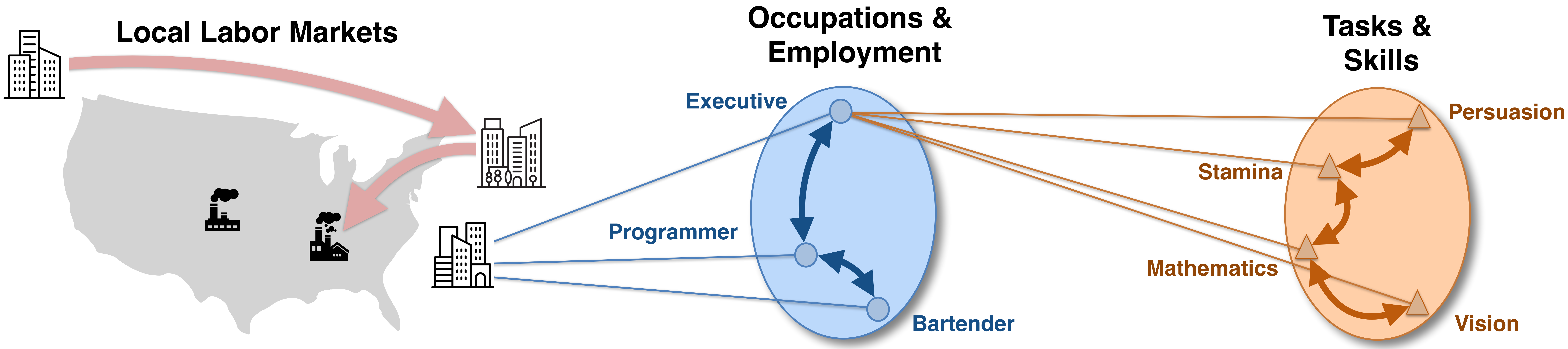
$$tightness(\text{Chicago}, \text{New York}) = 0.98$$

$$tightness(\text{Chicago}, \text{Indianapolis}) = 0.81$$





Unifying Perspectives



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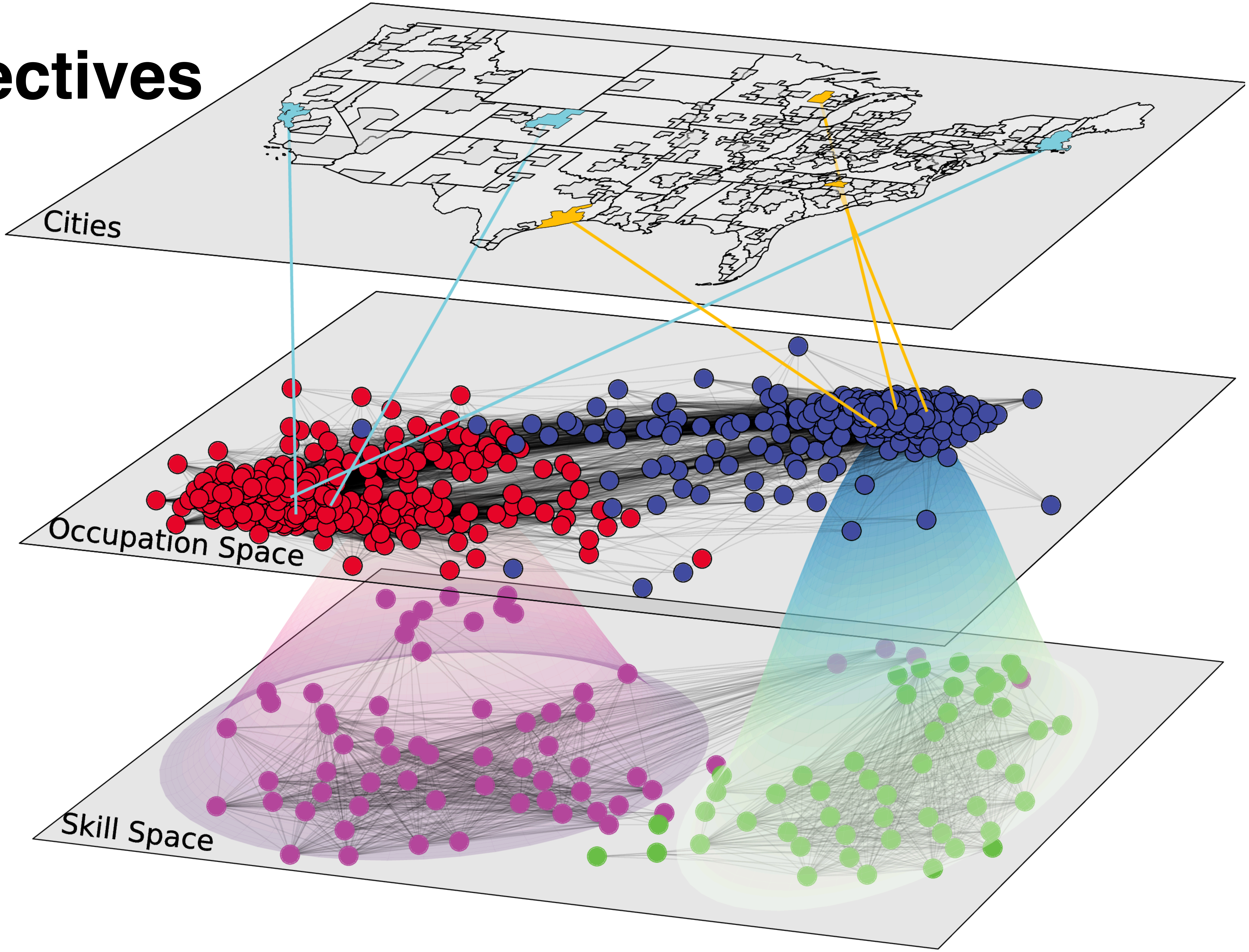
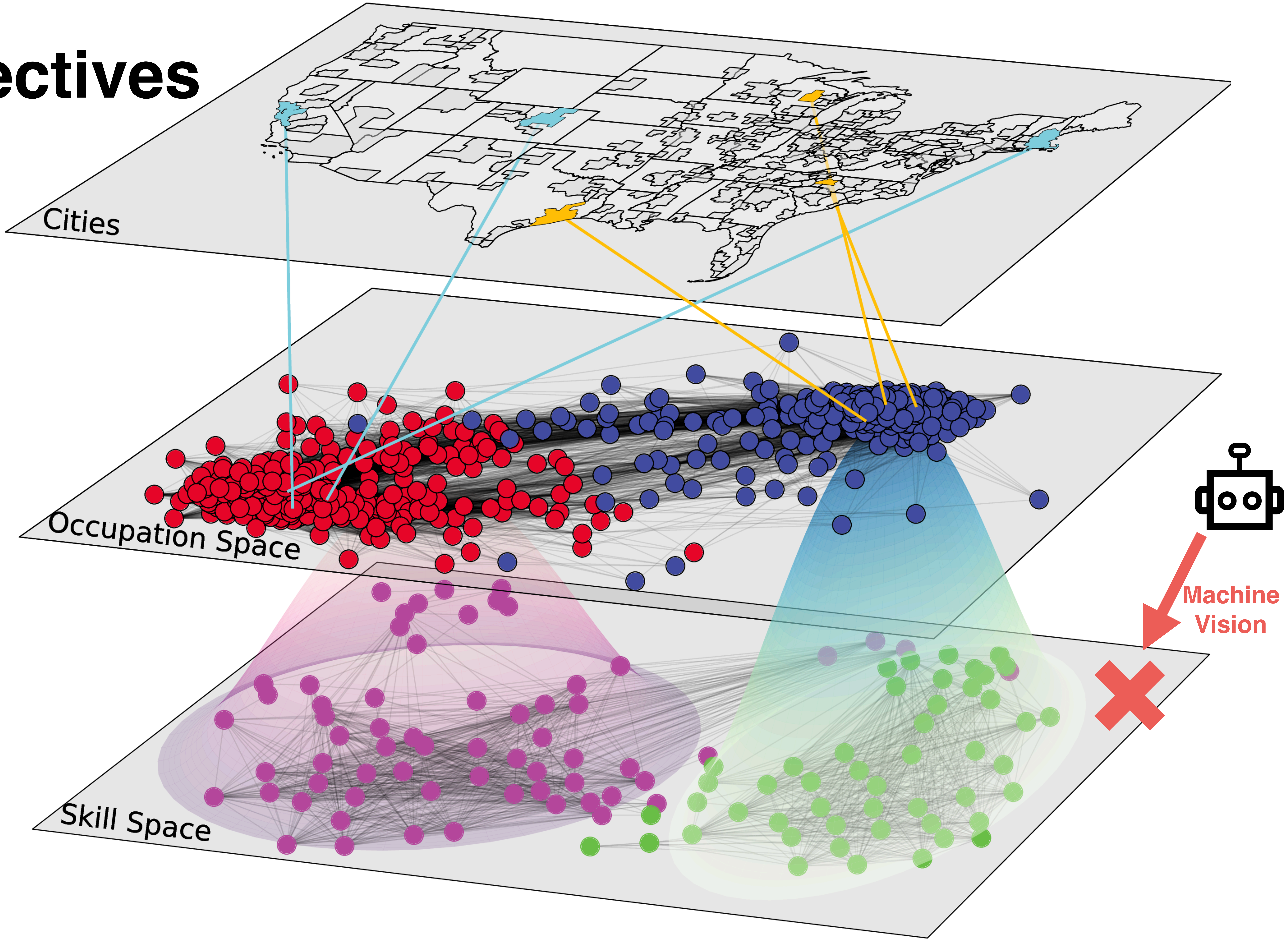
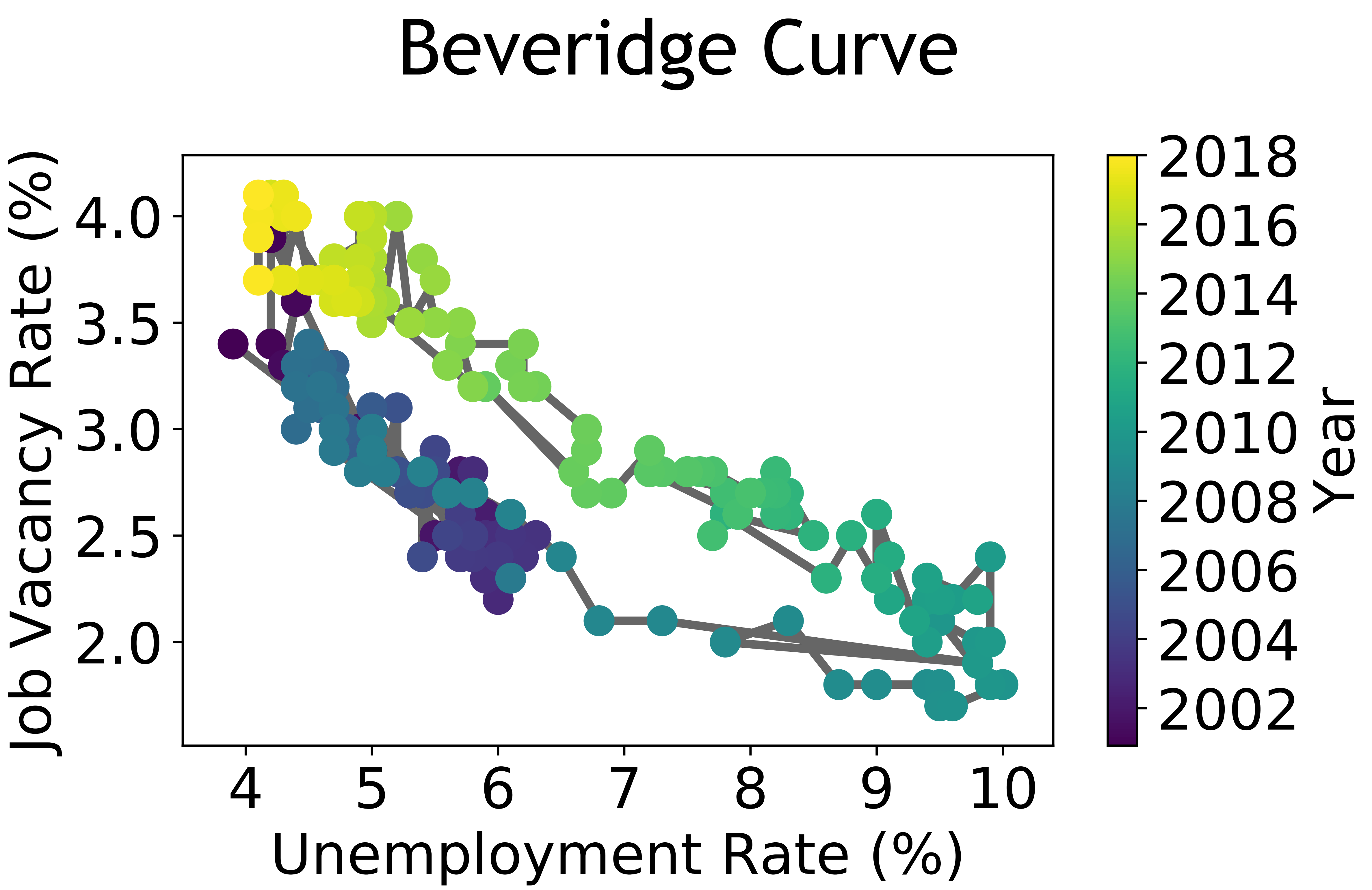
Unifying Perspectives

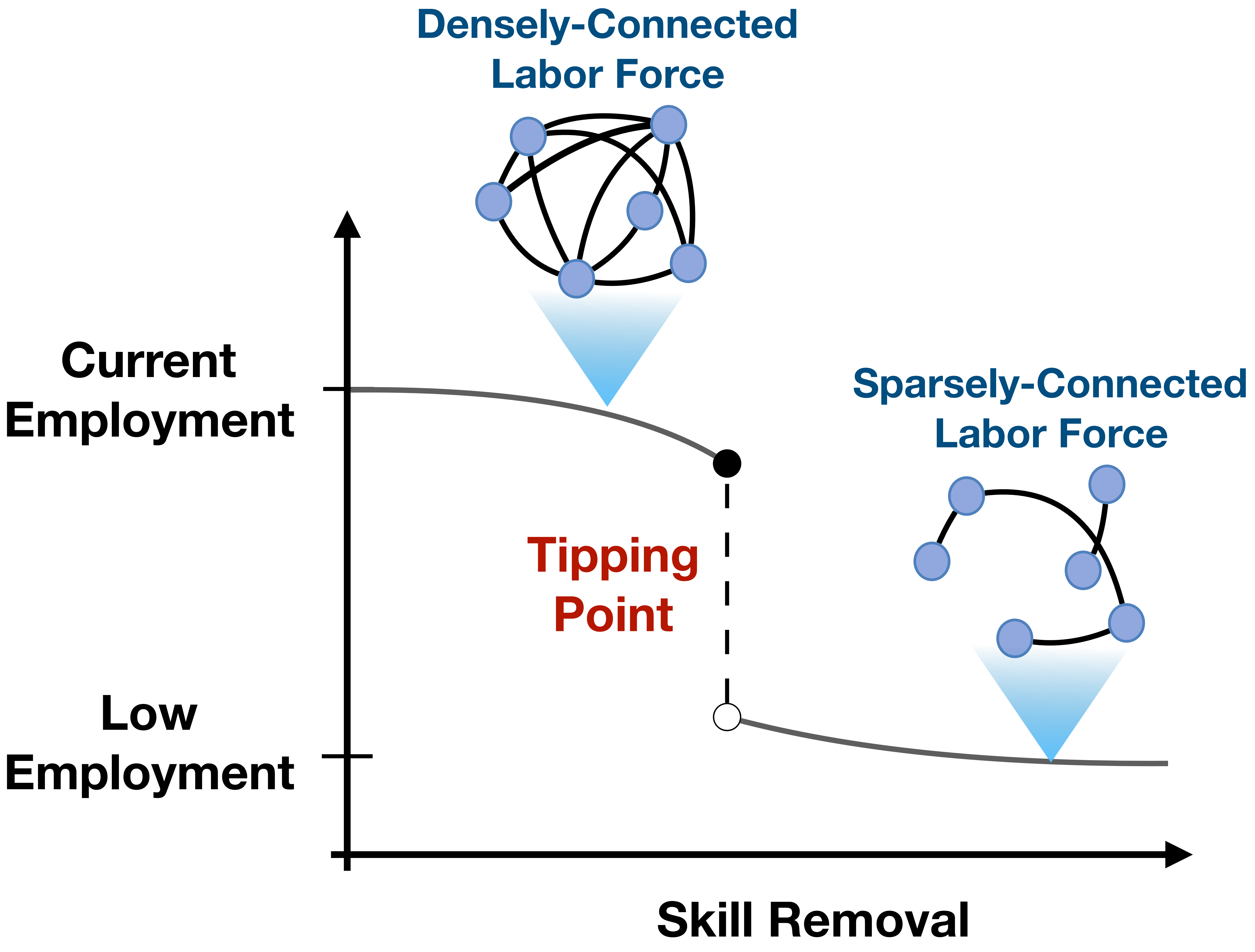


Unifying Perspectives



The structural resilience of urban labor markets



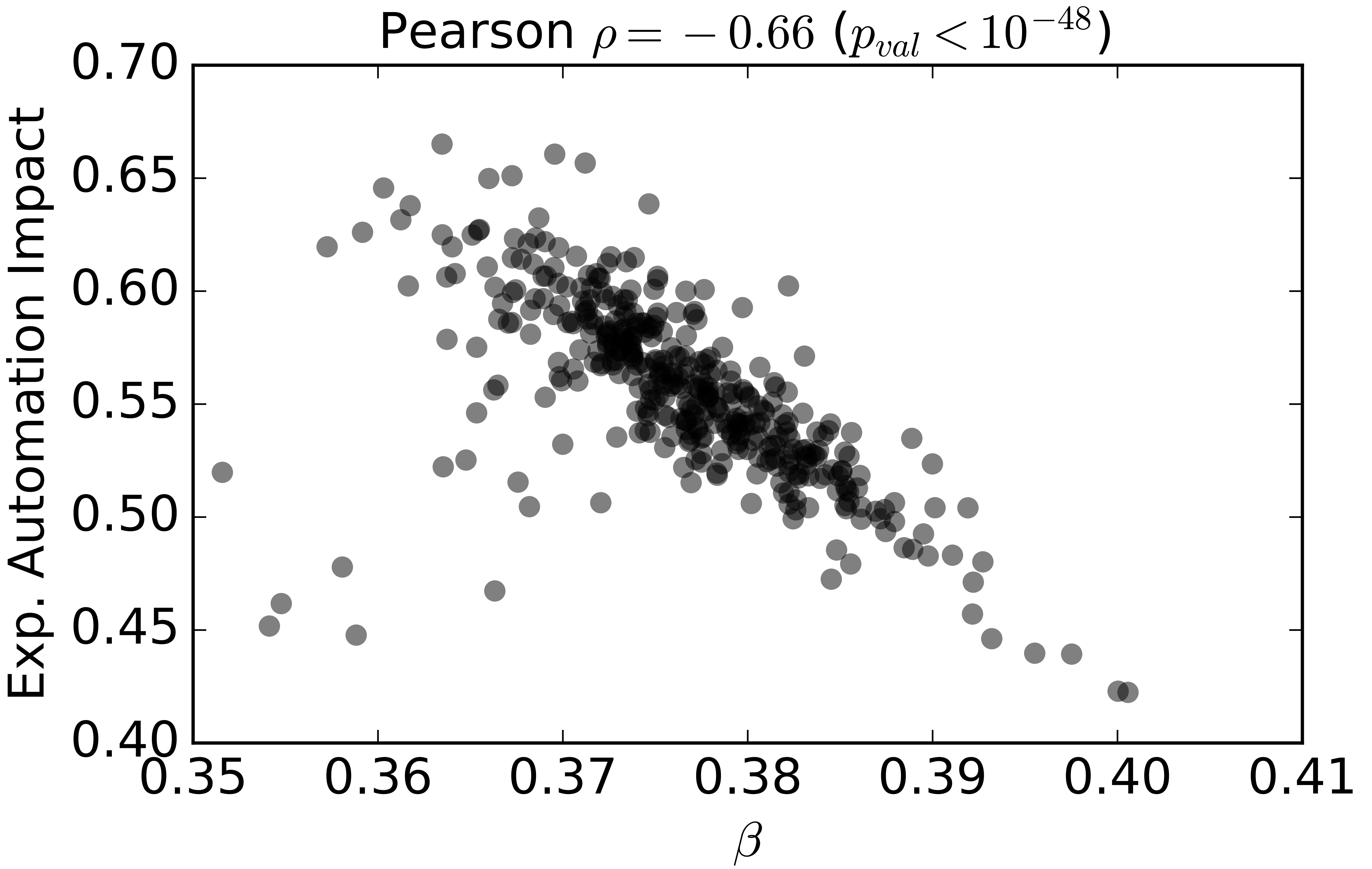


The structural resilience of urban labor markets

- Jianxi Gao, Baruch Barzel, & Alberto-Laszlo Barabasi. *Universal resilience patterns in complex networks*. Nature (2016)

- occupations -> animals,
  skills -> plants,
  cities -> ecosystems

- exp. impact from automation strongly correlates with structural resilience measure from ecology



Pearson: -0.86 without outliers

Fellow Laborers (to name a few):

Lijun Sun

Iyad Rahwan

Esteban Moro

Manuel Cebrian

César Hidalgo

Alex Rutherford

Hyejin Youn

Ahmad Alabdulkareem

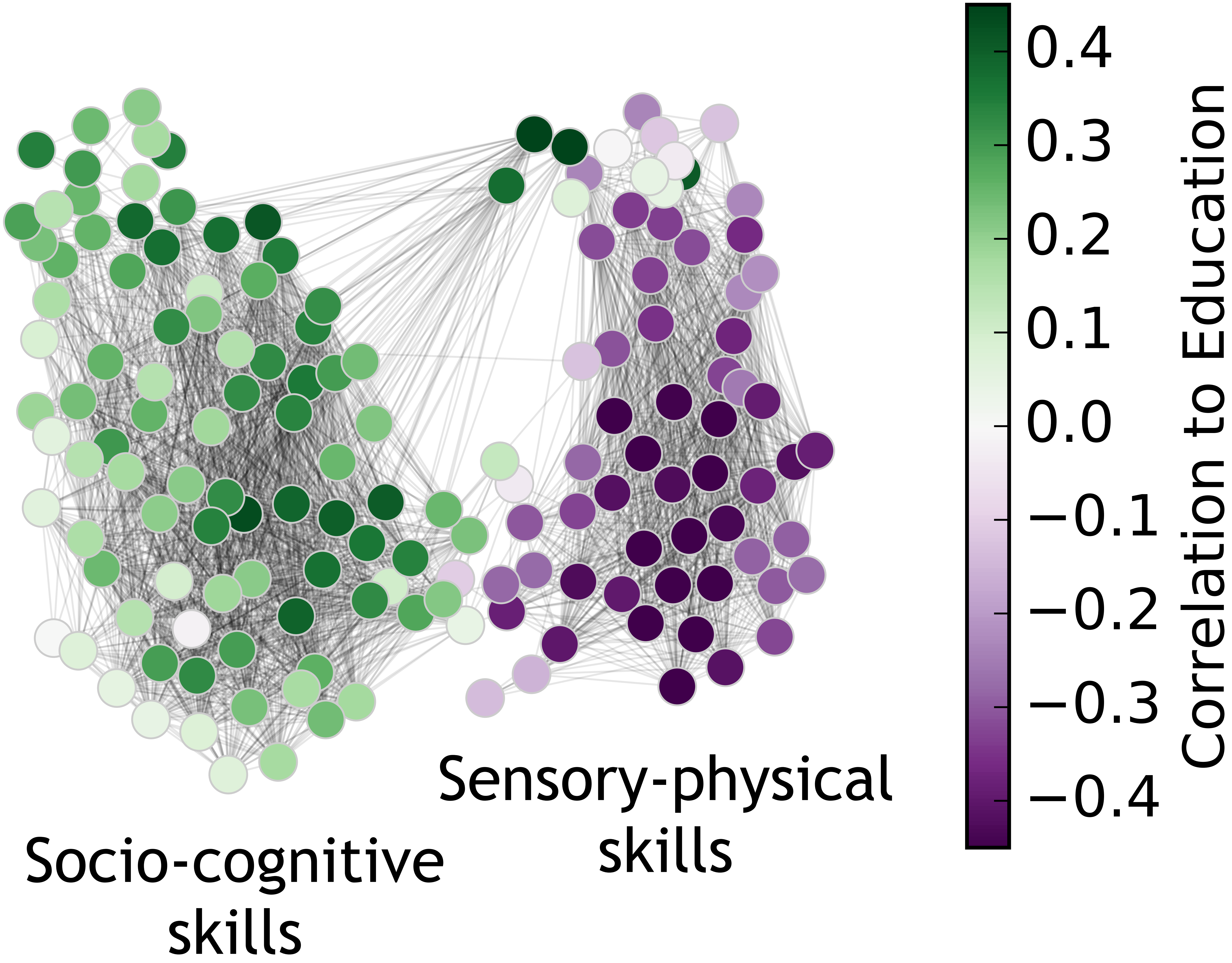
Inho Hong

Erik Brynjolfsson

Daniel Rock

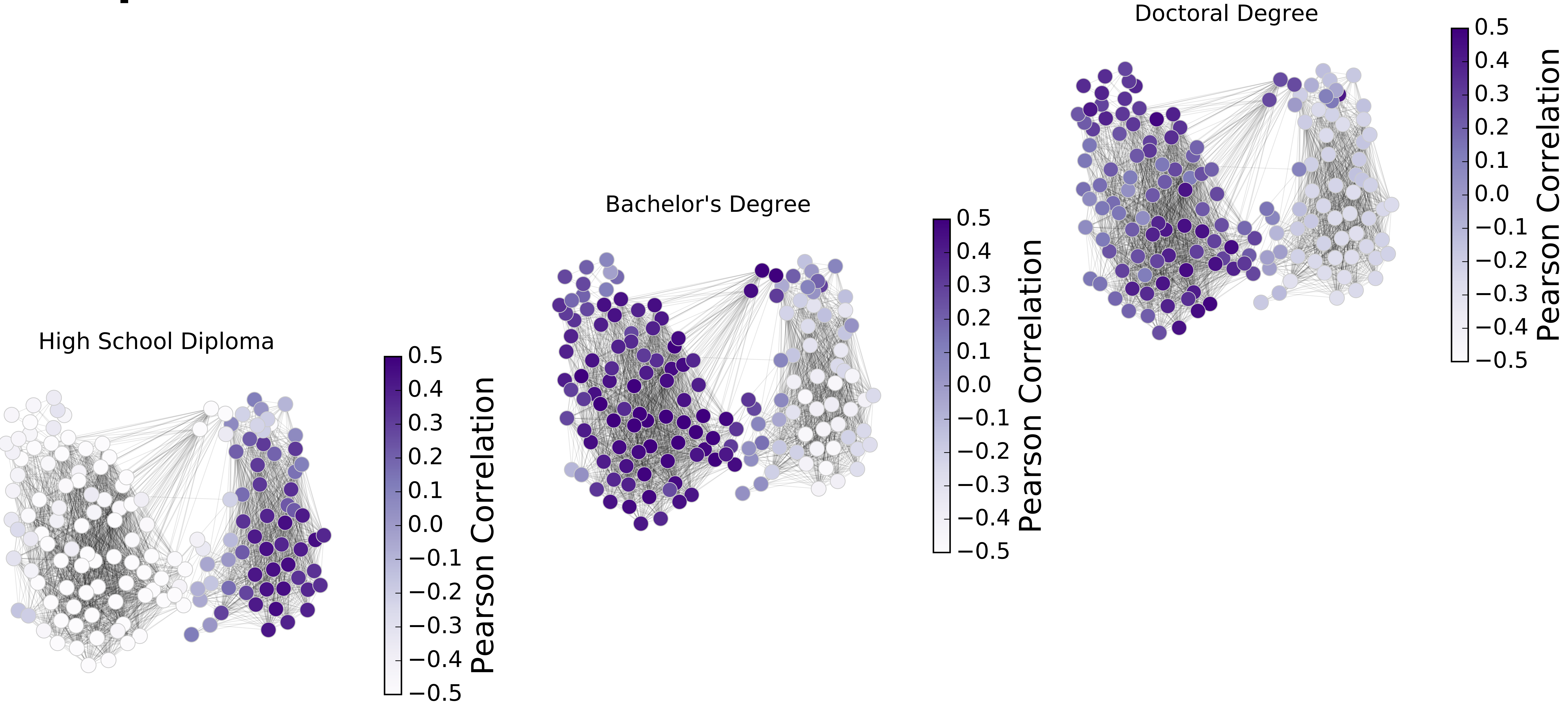
Dashun Wang

Skill polarization and education



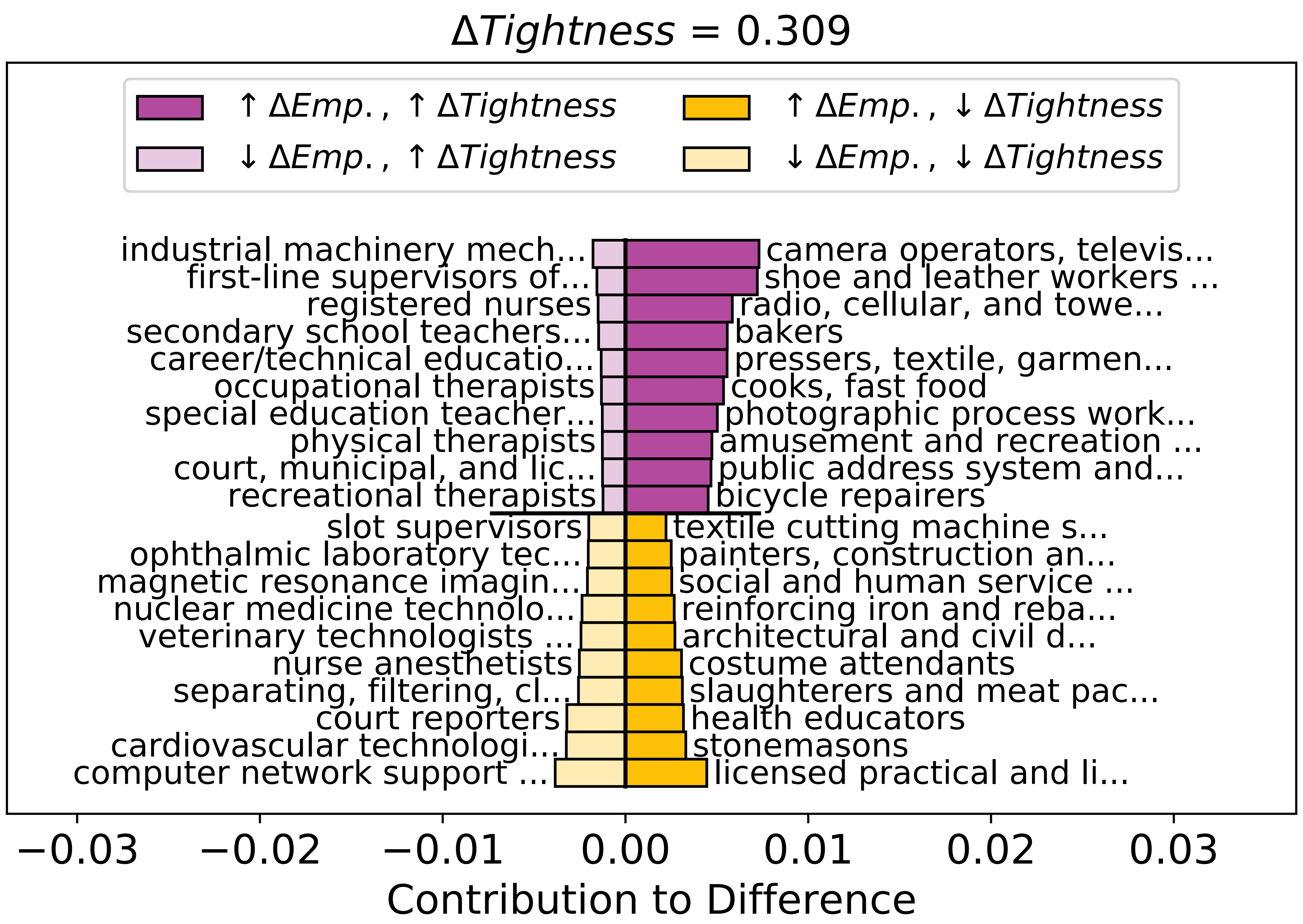
Unpacking the polarization of workplace skills, *Science Advances* (2018)

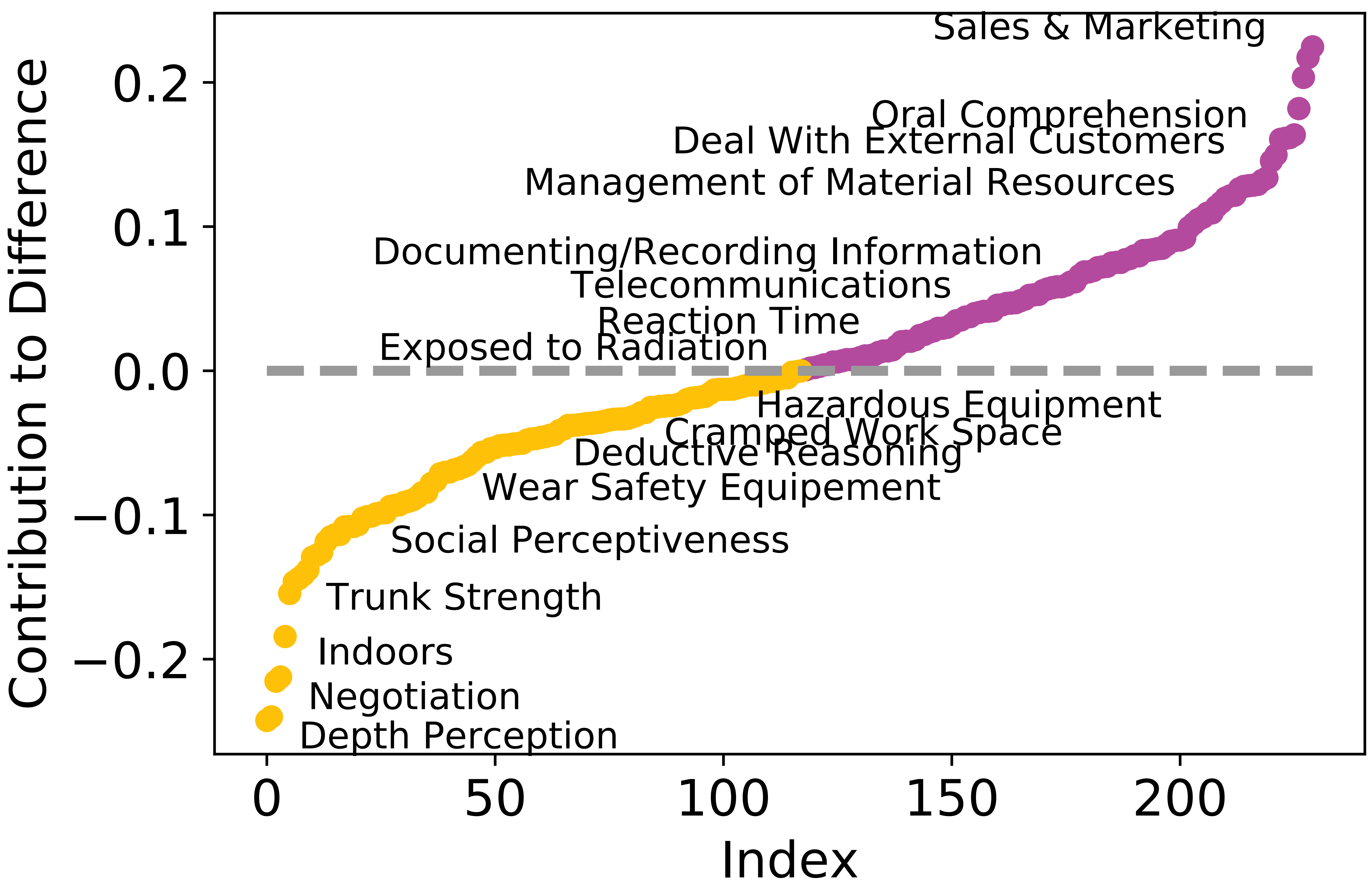
Skill polarization and Education



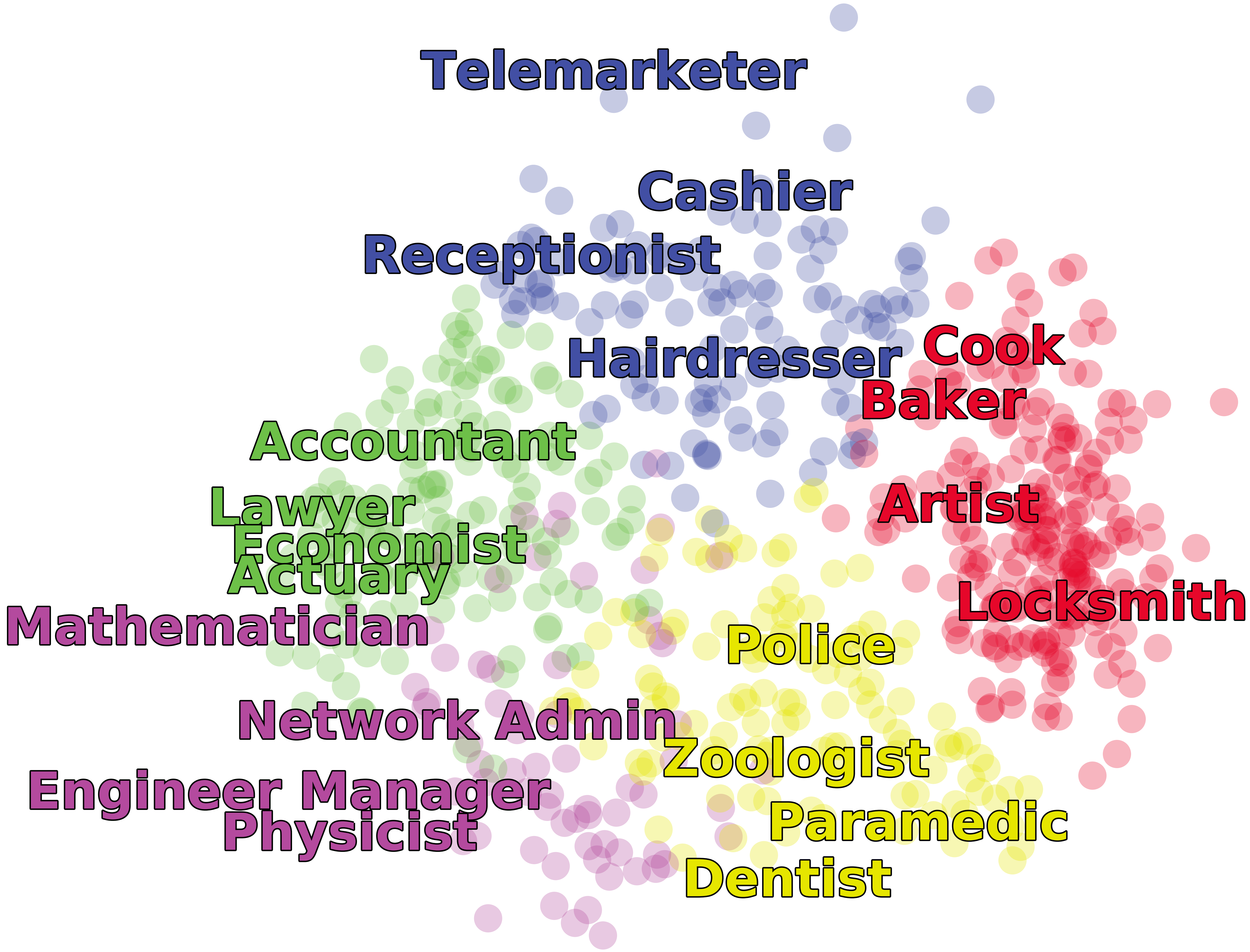
Explaining Job Tightness

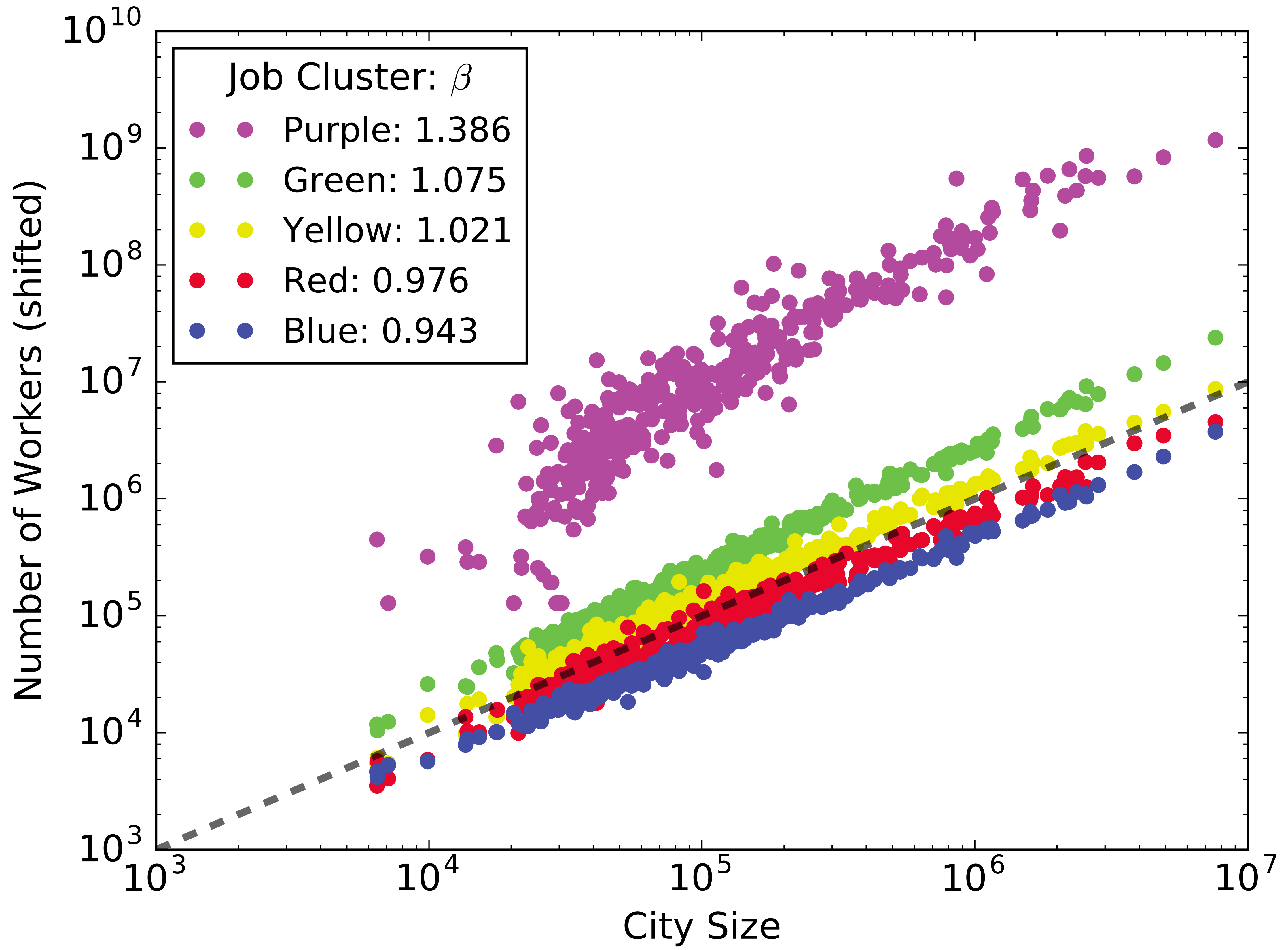
20 Least Tight City Pairs vs. 20 Most Tight City Pairs





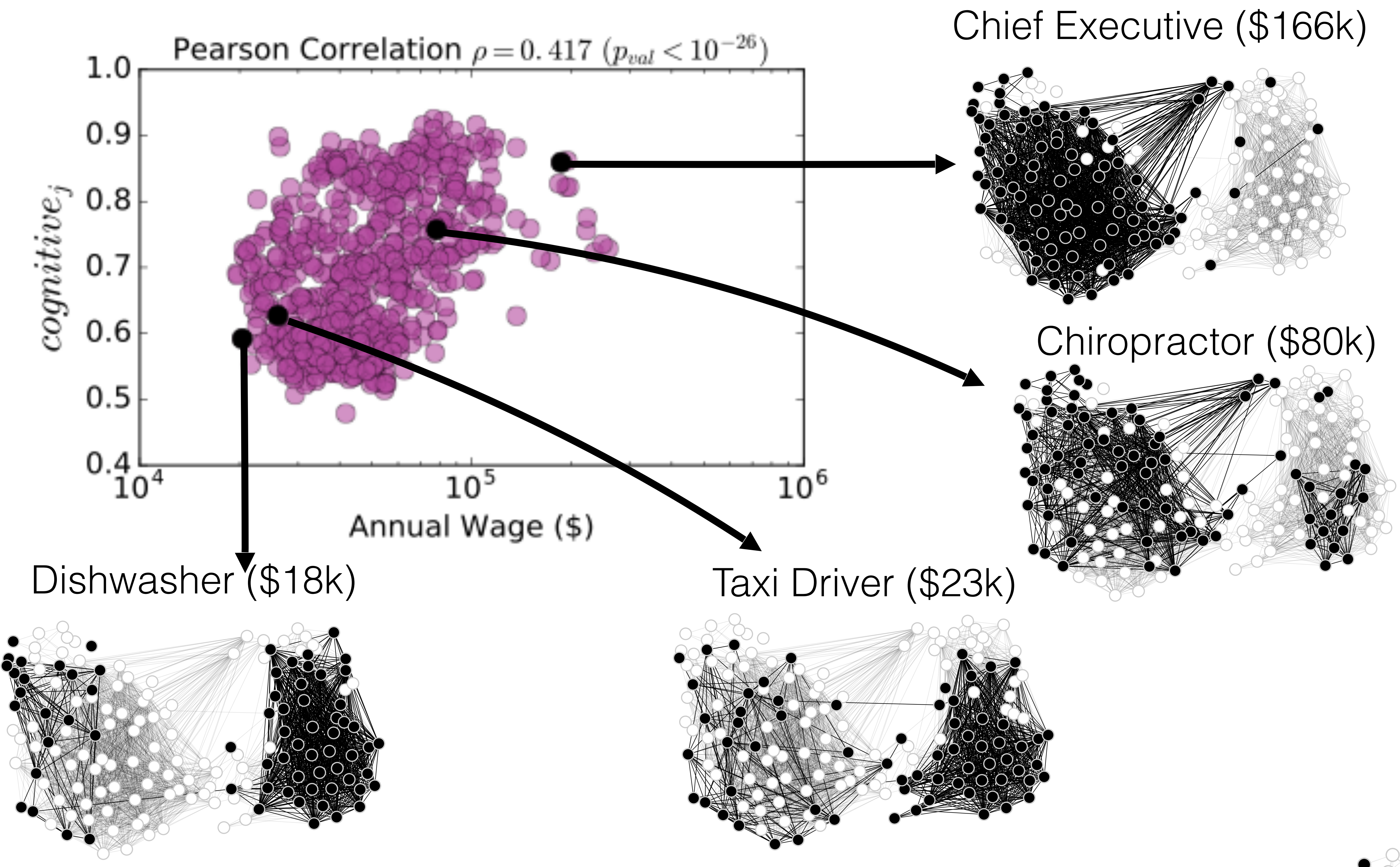
Cities race with the machines

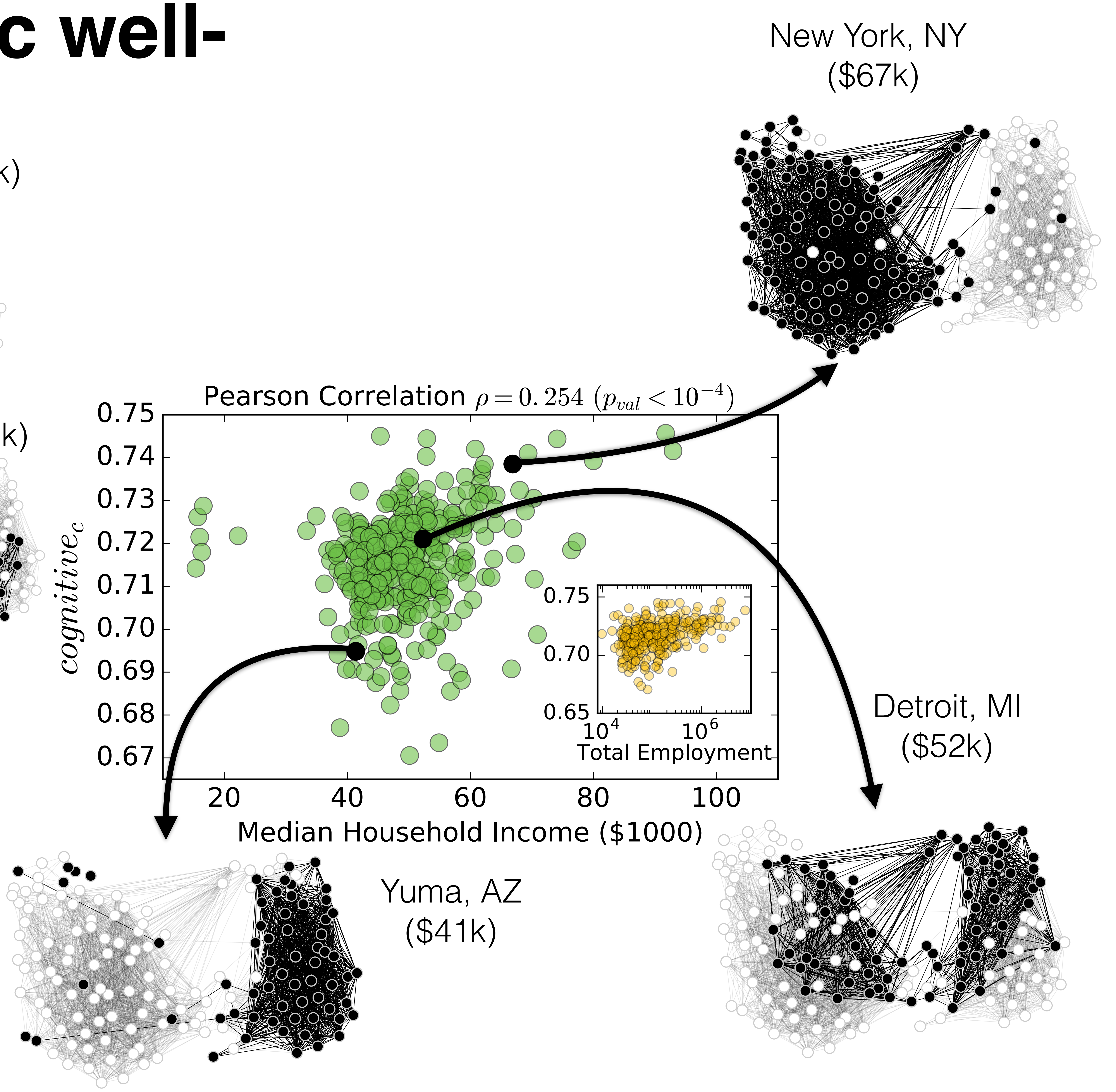




Small cities face greater impact from automation, *J. of the Royal Soc. Interface* (2018)

Skill polarization and economic well-being





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