The Convergence of Occupations: Evidence from Online Job Posts

Alexis Antoniades
Georgetown University Qatar

Manolis Chatziconstantinou
Georgetown University Qatar

Mohammad Shahmeer Ahmad
Qatar Computing Research Institute

Presented at
ESCoE Conference

May 21, 2025

Motivation: A New Stylized Fact

Over the past decades

1. Wages across occupations were diverging (Fig 1)
2. Mobility was declining (Fig 2)

Fig 1 – Wage variation across occupations

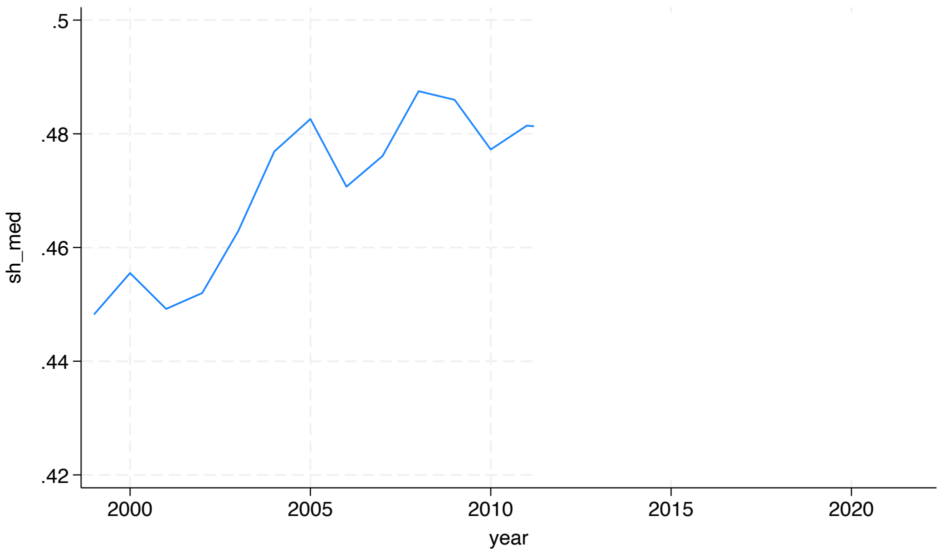
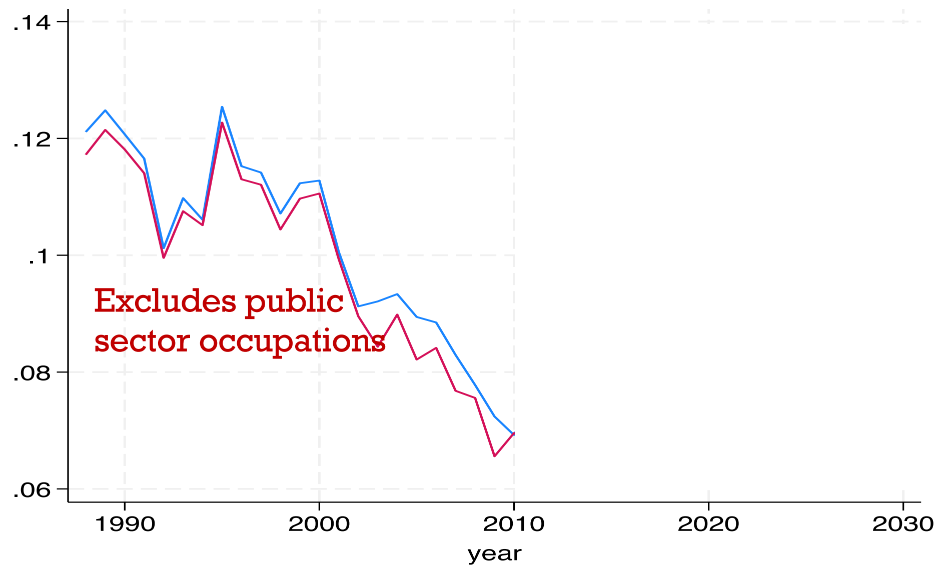


Fig 2 – Mobility across occupations



⟹ *As technical progress has accelerated over the past decades, we should expect the trends to persist.*

Motivation: A New Stylized Fact

However, both trends are reversed:

1. Wages across occupations are <u>converging</u> (Fig 1)
2. Mobility is <u>rising</u> (Fig 2)

Fig 1 – Wage variation across occupations

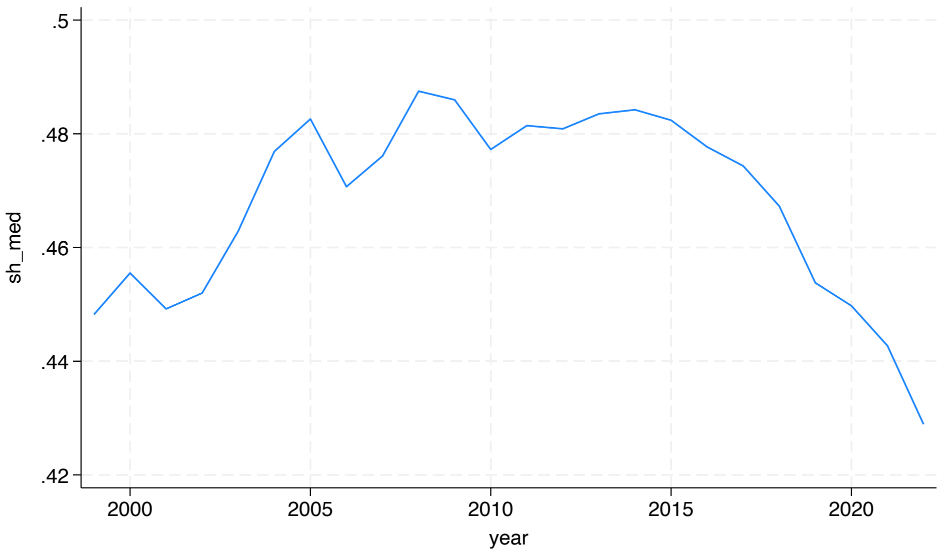
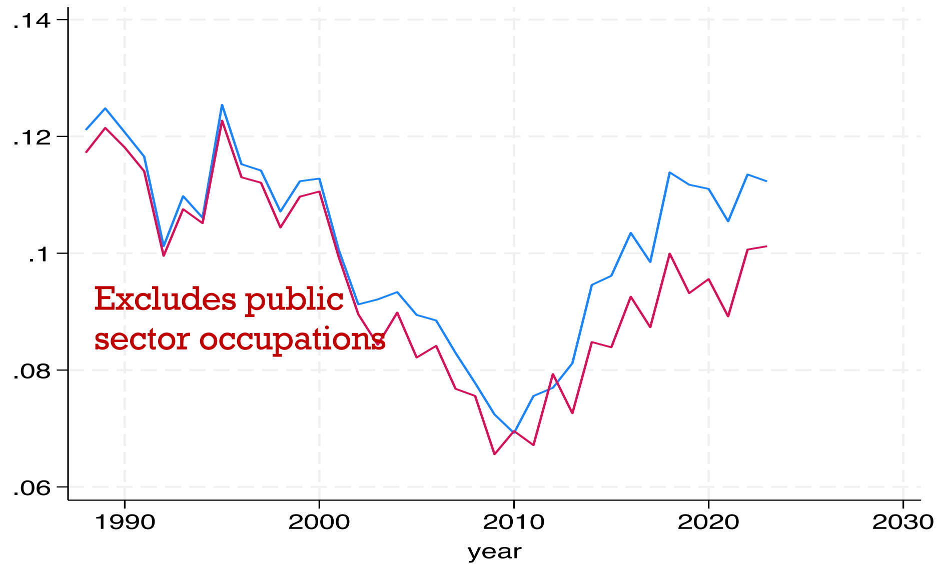


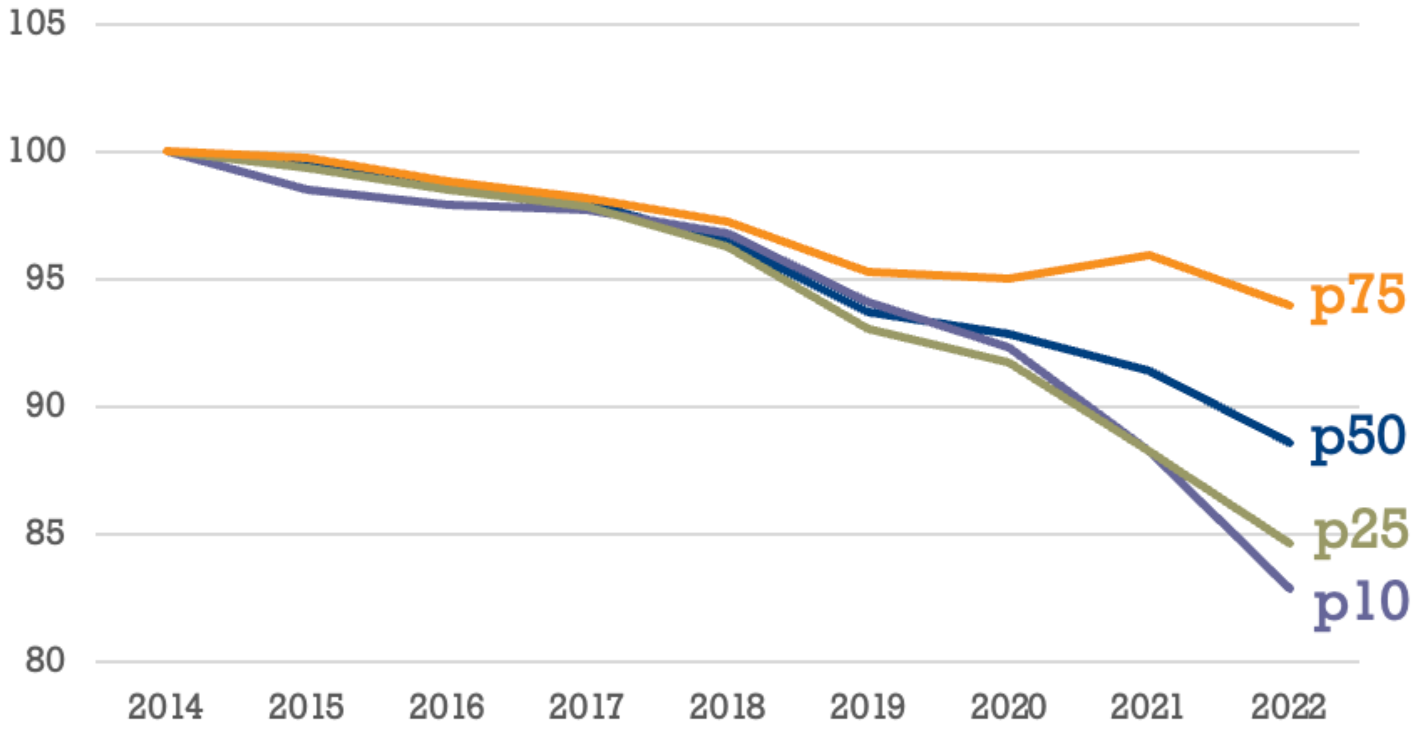
Fig 2 – Mobility across occupations



Motivation: A New Stylized Fact

- The reversal in trend applies to most quantile groups, not just the mean or the median wage

Fig 3 – Wage variation across occupations by wage quantile



Motivation: A New Stylized Fact

GEORGETOWN UNIVERSITY QATAR

A puzzle:

- For the past decade wage inequality has been declining, while mobility has been rising.
- At the same time as SBTC is becoming even more disruptive
- This is in contrast to what our models and intuition would predict

Why?

Explanation: A New Theory

- **Technological progress has not only transformed occupations, but it has also made them more similar (brought them *closer*)**
  - Think of occupations as islands (Lucas and Prescott 1982, Kampourov and Manovski 2008) with workers spread across islands.
  - We hypothesis that these islands have moved closer to one another due to technological progress.
  - **Why? New skills on the block, high in demand and highly transferable across occupations (e.g. data visualization)**
- **As occupations come closer, wages converge and mobility rises**
- ***Caveat:*** *What is distance? How can it be measured?*

1.1 Data

US Data

- Online job vacancy data provided by *Lightcast* (formerly known as BGT)
- Collected daily from 51,000 sources (job boards, company websites, etc).
- NLP techniques used to extract over 70 different elements from every post.
- Includes info on skills (about 16,000), occupation, location, company, education requirements, experience requirements, job responsibilities, qualifications (e.g. CFA, CPA), benefits, etc.

1.1 Data

جامعة جورجتاون قطر
GEORGETOWN UNIVERSITY QATAR

Keyword search: "Plumbing"

Skill	2014	2019	Growth
Plumbing Design	605	1,971	2.3
Mechanical, Electrical, and Plumbing (MEP) Design	1,525	4,357	1.9
Commercial Plumbing	2,382	6,691	1.8
Plumbing Installation	418	1,134	1.7
Plumbing Systems	11,787	30,005	1.6
Plumbing Tools	429	1,082	1.5
Plumbing Fixture Installation	225	536	1.4
Plumbing Maintenance	4,544	10,663	1.4
Plumbing	199,046	445,228	1.2
Plumbing Repairs	11,132	24,334	1.2
Copper Plumbing Installation	1	2	1.0
Industrial Plumbing	377	660	0.8
Residential Plumbing	1,848	3,201	0.7

1.1 Data

Keyword search: “Massage”

Skill	2014	2019	Growth
Sports Massage	267	3,911	13.7
Deep Tissue Massage	1,211	6,142	4.1
Swedish Massage	248	1,014	3.1
Hot Stone Massage	667	2,254	2.4
Chair Massage	449	1,156	1.6
External Cardiac Massage	85	218	1.6
Massage Therapy	16,515	39,535	1.4
Massage	14,447	30,594	1.1
Prenatal Massage	88	186	1.1
Therapeutic Massage	1,487	1,983	0.3
Patient Massage	52	54	0.0

1.1 Data

GEORGETOWN UNIVERSITY QATAR

Keyword search: "Disorder"

Skill	2014	2019	Growth
Sensory Integration Disorder	48	1,127	22.5
Psychologically Based Disorders	5	103	19.6
Attention Deficit Disorder	83	1,648	18.9
Personality Disorder	97	596	5.1
Anxiety Disorder	81	401	4.0
Post Traumatic Stress Disorder	1,894	7,058	2.7
Social Anxiety Disorder	3	11	2.7
Bipolar Disorder	1,966	5,859	2.0
Generalized Anxiety Disorder	12	33	1.8
Movement Disorders	1,744	4,619	1.7
Attention Deficit Hyperactivity Disorder (ADHD)	3,585	8,565	1.4
Major Depression	313	4,529	13.5

1.1 Data

GEORGETOWN UNIVERSITY QATAR

and a few more

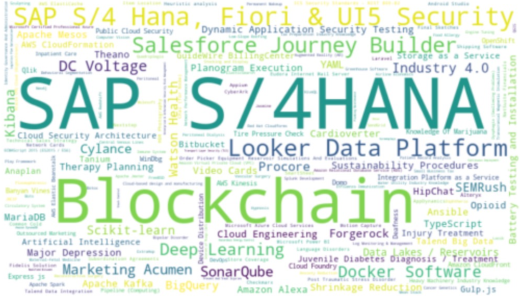
Skill	2014	2019	Growth
3D Printing	2,412	12,263	4.1
AWS	2,254	16,418	6.3
Opioid	895	8,269	8.2
Bitcoin	71	755	9.6
Fintech	819	12,715	14.5
Knowledge Of Marijuana	49	6,324	128.1
Blockchain	9	7,702	854.8

1.1 Data

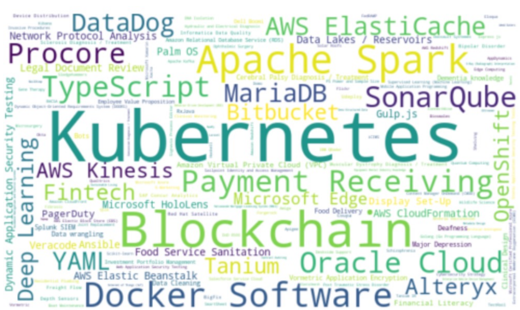
Sample: OJVs for selected occupations (SOC3), 2014-2019

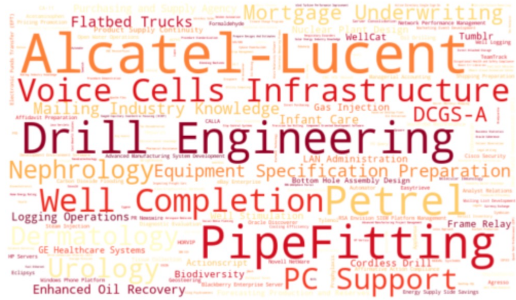
(a) Common | (b) New | (c) Disappearing

Business Operations Specialists (SOC2 131)



Engineers (SOC2 172)





Judges, Lawyers, and Related Workers (SOC2 231)

SOC 2 (1)	SOC2 Name (2)	SOC4 (3)	SOC6 (4)	Online Job Vacancies (in thousands, 000s) 2014 Q1-Q4 (5)	2022 Q1 (6)	Occupational Characteristics High Nonroutine Cognitive (7)	AI Intensity 2014 Q1-Q4 (8)	AI Intensity 2022 Q1 (9)	Data Analytics 2014 Q1-Q4 (10)	Data Analytics 2022 Q1 (11)
	23 Total occupation groups (SOC 2)	98	1,326	24,261	12,595	0.45	0.5%	4.6%	2.3%	8.5%
SOC2 occupation group										
11	Management	4	68	2,694	1,522	0.90	0.4%	1.9%	5.1%	10.6%
13	Business and Financial Operations	2	58	1,506	778	0.78	0.4%	1.4%	8.9%	16.3%
15	Computer and Mathematical	2	33	2,528	1,170	1.00	3.3%	15.8%	19.5%	38.7%
17	Architecture and Engineering	3	57	752	333	0.86	0.8%	4.8%	4.6%	10.2%
19	Life, Physical, and Social Science	5	73	253	134	0.95	0.6%	2.3%	9.1%	16.1%
21	Community and Social Service	2	24	283	169	0.79	0.1%	0.2%	2.9%	3.8%
23	Legal	2	12	203	85	0.71	0.1%	0.6%	1.6%	4.5%
25	Educational Instruction and Library	5	94	610	324	0.93	0.1%	0.4%	1.8%	3.0%
27	Arts, Design, Entertainment, Sports, and Media	4	57	619	277	0.72	0.2%	0.7%	1.7%	3.8%
29	Healthcare Practitioners and Technical	3	99	2,381	1,400	0.73	0.1%	0.1%	1.2%	1.7%
31	Healthcare Support	3	24	511	330	0.13	0.0%	0.1%	0.4%	0.7%
33	Protective Service	4	38	265	160	0.53	0.1%	0.6%	1.4%	2.0%
35	Food Preparation and Serving Related	4	28	1,049	622	0.00	0.0%	0.0%	0.2%	0.4%
37	Building and Grounds Cleaning and Maintenance	3	14	323	264	0.00	0.0%	0.0%	0.3%	0.5%
39	Personal Care and Service	8	52	592	294	0.10	0.0%	0.0%	0.2%	0.5%
41	Sales and Related	5	37	3,031	1,248	0.38	0.1%	1.0%	1.4%	2.3%
43	Office and Administrative Support	7	101	2,567	1,360	0.14	0.1%	0.2%	3.7%	7.7%
45	Farming, Fishing, and Forestry	4	22	21	11	0.00	0.0%	0.2%	0.7%	2.6%
47	Construction and Extraction	5	98	282	159	0.08	0.1%	0.4%	0.5%	0.8%
49	Installation, Maintenance, and Repair	4	70	785	430	0.12	0.4%	0.8%	1.1%	1.9%
51	Production	9	159	755	374	0.10	0.1%	0.3%	0.9%	1.9%
53	Transportation and Material Moving	7	86	1,308	634	0.11	0.0%	0.1%	0.2%	0.7%
55	Military Specific	3	22	29	3	-	0.3%	1.7%	0.7%	5.5%

1.2 Methodology

GEORGETOWN UNIVERSITY QATAR

Step 1:

- Represent each occupation in year *t* as a vector of skills

Step 2:

- Assign weight for each skill (document frequency, df)

Step 3:

- Use Euclidean distance to measure similarity between two vectors (occupations) in year *t*

$$d_{ab} = \sqrt{\sum_{i}^{S} (b_i - a_i)^2}$$

1.3 Estimation

GEORGETOWN UNIVERSITY QATAR

Insight 1: Bilateral distances across occ (SOC6) pairs are falling over time

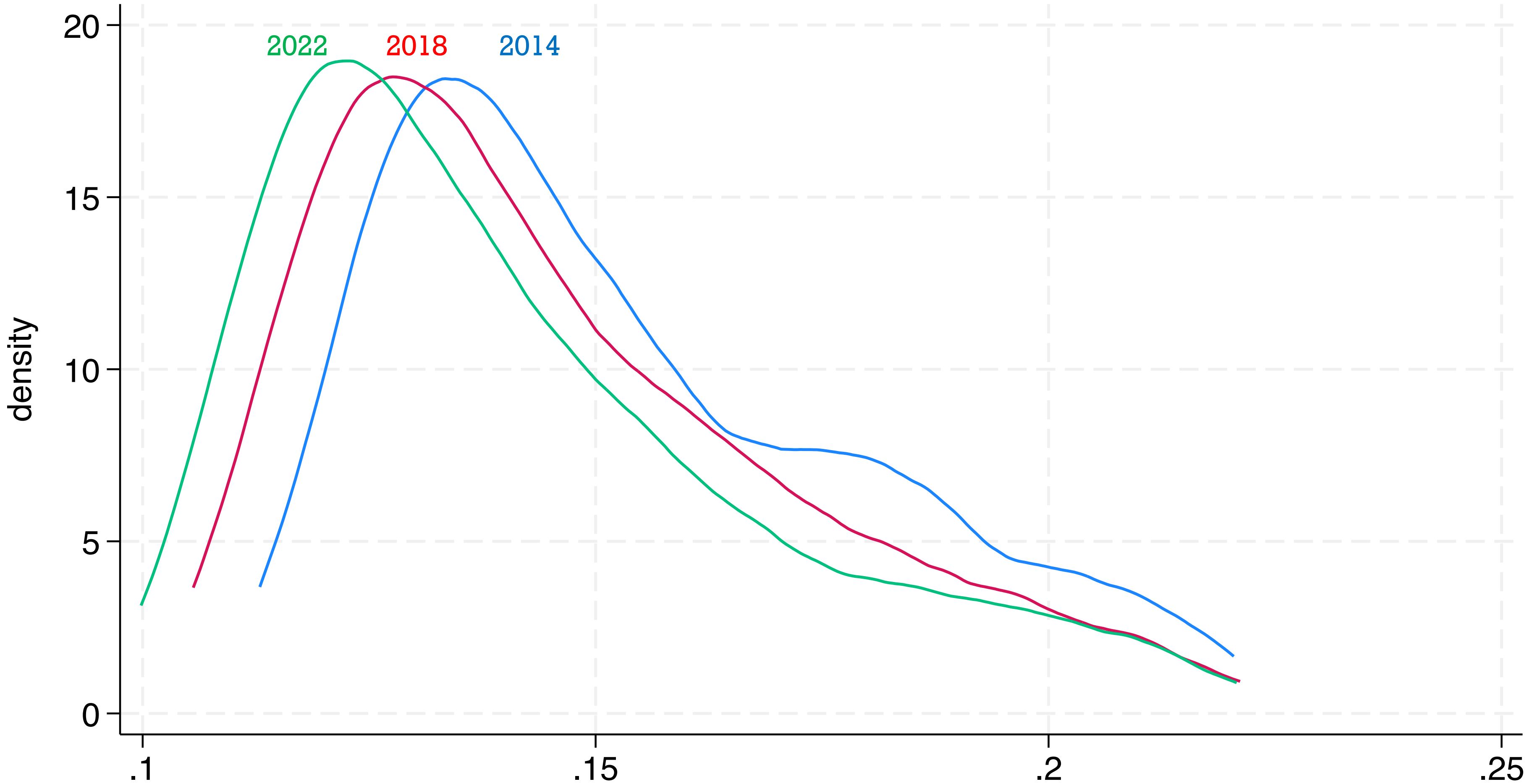


Figure 1 – Distribution of bilateral distances for SOC6 pairs over time

1.3 Estimation

Insight 1: Bilateral distances across occ (SOC4) pairs are falling over time

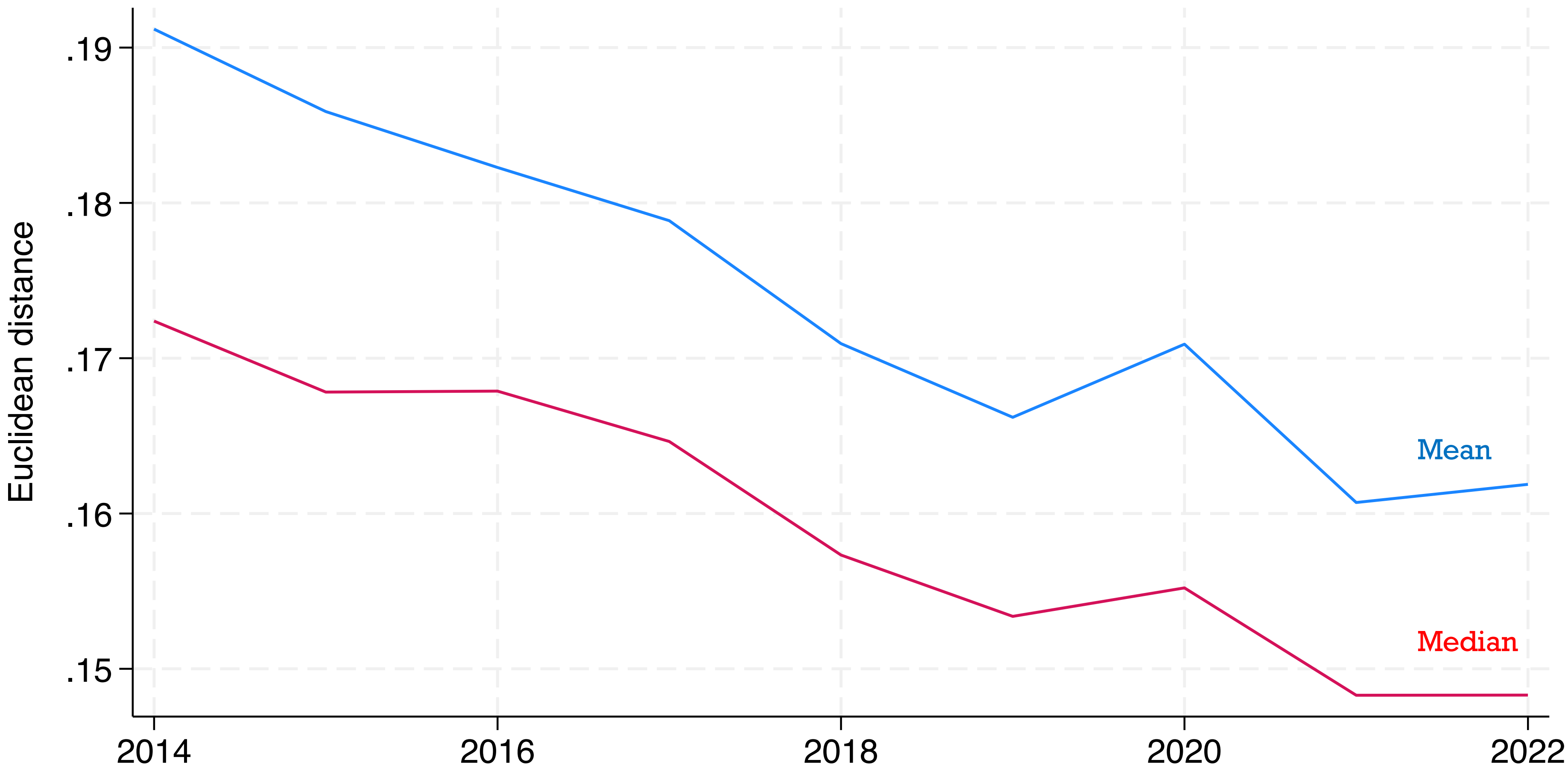


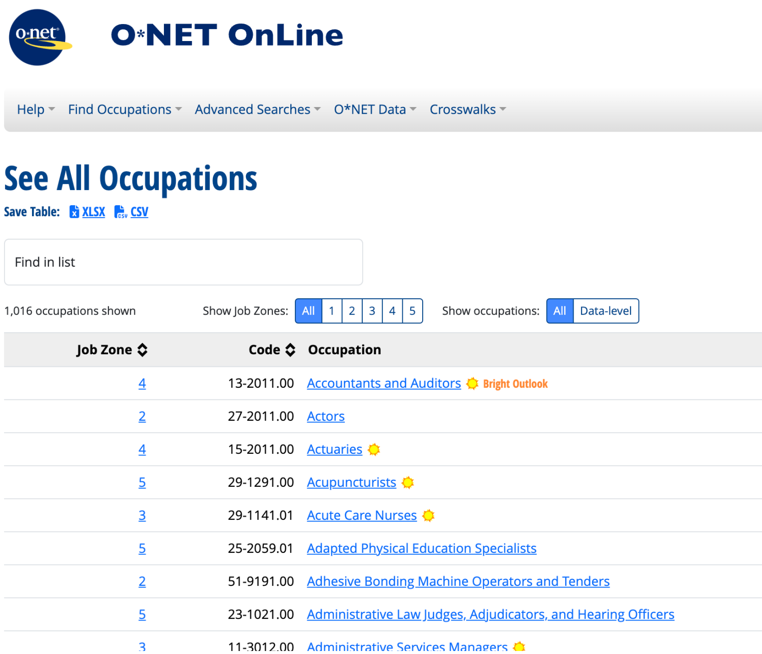
Figure 2 – Average and median Euclidean distance across all occupations by year

1.3 Estimation

جامعة جورجتاون قطر
GEORGETOWN UNIVERSITY QATAR

Insight 3: Can now think of groups as nodes in a network, with distances & edges

From this ⬇ to this ➡


O*NET OnLine

Help | Find Occupations | Advanced Searches | O*NET Data | Crosswalks

See All Occupations

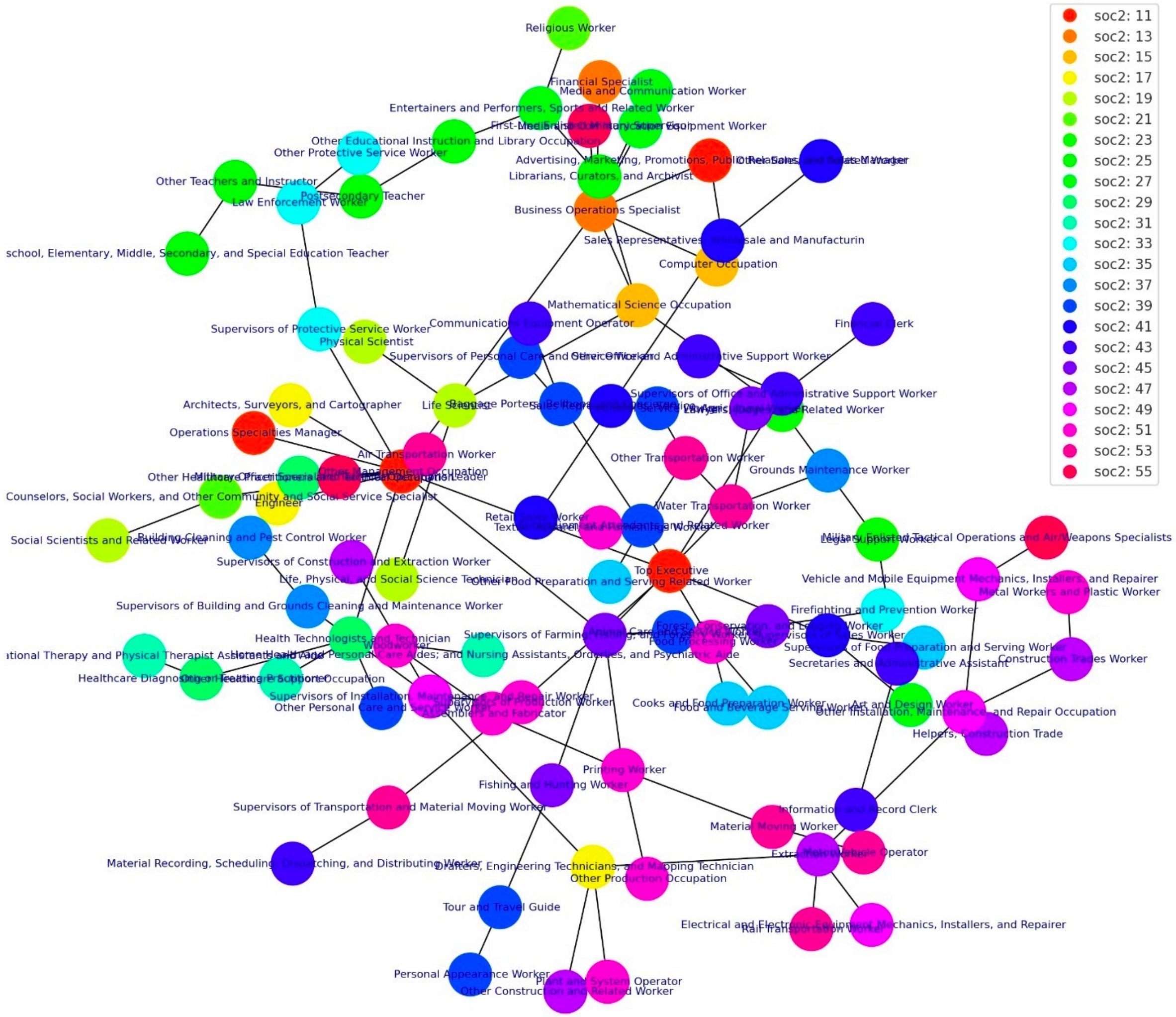
Save Table: XLSX CSV

Find in list

1,016 occupations shown Show Job Zones: All 1 2 3 4 5 Show occupations: All Data-level

Job Zone	Code	Occupation
4	13-2011.00	Accountants and Auditors Bright Outlook
2	27-2011.00	Actors
4	15-2011.00	Actuaries
5	29-1291.00	Acupuncturists
3	29-1141.01	Acute Care Nurses
5	25-2059.01	Adapted Physical Education Specialists
2	51-9191.00	Adhesive Bonding Machine Operators and Tenders
5	23-1021.00	Administrative Law Judges, Adjudicators, and Hearing Officers
3	11-3012.00	Administrative Services Managers

Minimum Spanning Tree of Distances, 2014



1.4 Validity

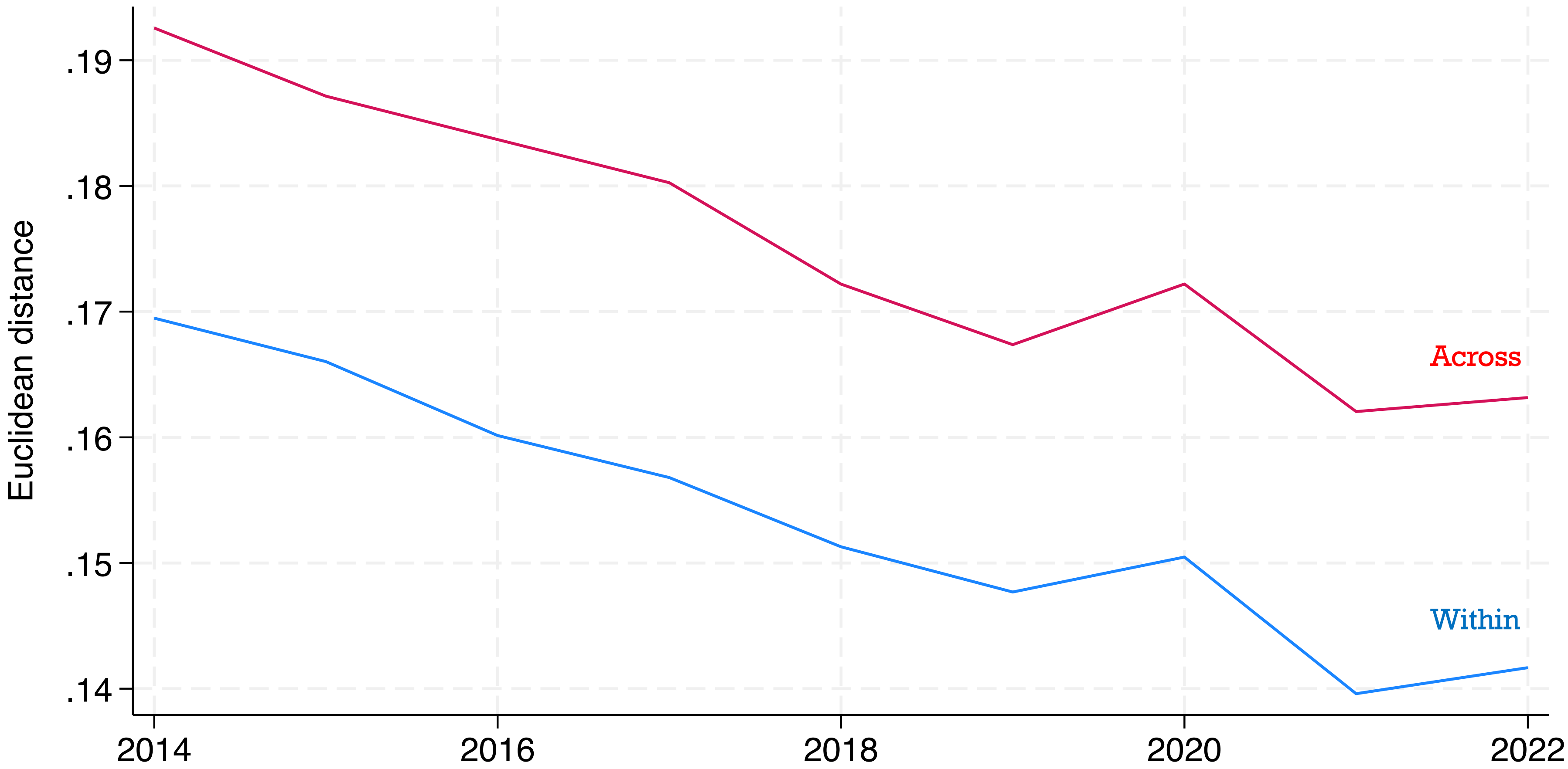
- **Is our measured distance a good measure of …distance (i.e similarity)?**
  1. Distance within vs across occupation groups
  2. Occupations with the highest similarity
  3. Mobility

1.4 Validity

GEORGETOWN UNIVERSITY QATAR

1. Within group occupations are closer than across group

Figure 3 – Median Euclidean distance across and within SOC2 groups



1.4 Validity

جامعة جورجتاون قطر
GEORGETOWN UNIVERSITY QATAR

2. Closest across-group occupations have identical names

Rank	Occ 1	Occ 2	Occupation 1 Name	Occupation 2 Name
1	11-3061	13-1022	Purchasing Managers	Wholesale and Retail Buyers, Except Farm Products
2	17-3026	49-9041	Industrial Engineering Technologists and Technicians	Industrial Machinery Mechanics
3	25-4031	43-4121	Library Technicians	Library Assistants, Clerical
4	13-1151	11-3131	Training and Development Specialists	Training and Development Managers
5	43-4041	13-2041	Credit Authorizers, Checkers, and Clerks	Credit Analysts
6	11-9033	21-1012	Education Administrators, Postsecondary	Educational, Guidance, and Career Counselors and Advisors
7	11-9151	21-1093	Social and Community Service Managers	Social and Human Service Assistants
8	13-1141	11-3111	Compensation, Benefits, and Job Analysis Specialists	Compensation and Benefits Managers

SOC2 occupation group

11	Management
13	Business and Financial Operations
15	Computer and Mathematical
17	Architecture and Engineering
19	Life, Physical, and Social Science
21	Community and Social Service
23	Legal
25	Educational Instruction and Library
27	Arts, Design, Entertainment, Sports, and Media
29	Healthcare Practitioners and Technical
31	Healthcare Support
33	Protective Service
35	Food Preparation and Serving Related
37	Building and Grounds Cleaning and Maintenance
39	Personal Care and Service
41	Sales and Related
43	Office and Administrative Support
45	Farming, Fishing, and Forestry
47	Construction and Extraction
49	Installation, Maintenance, and Repair
51	Production
53	Transportation and Material Moving
55	Military Specific

1.4 Validity

3. Closer occupations have higher mobility

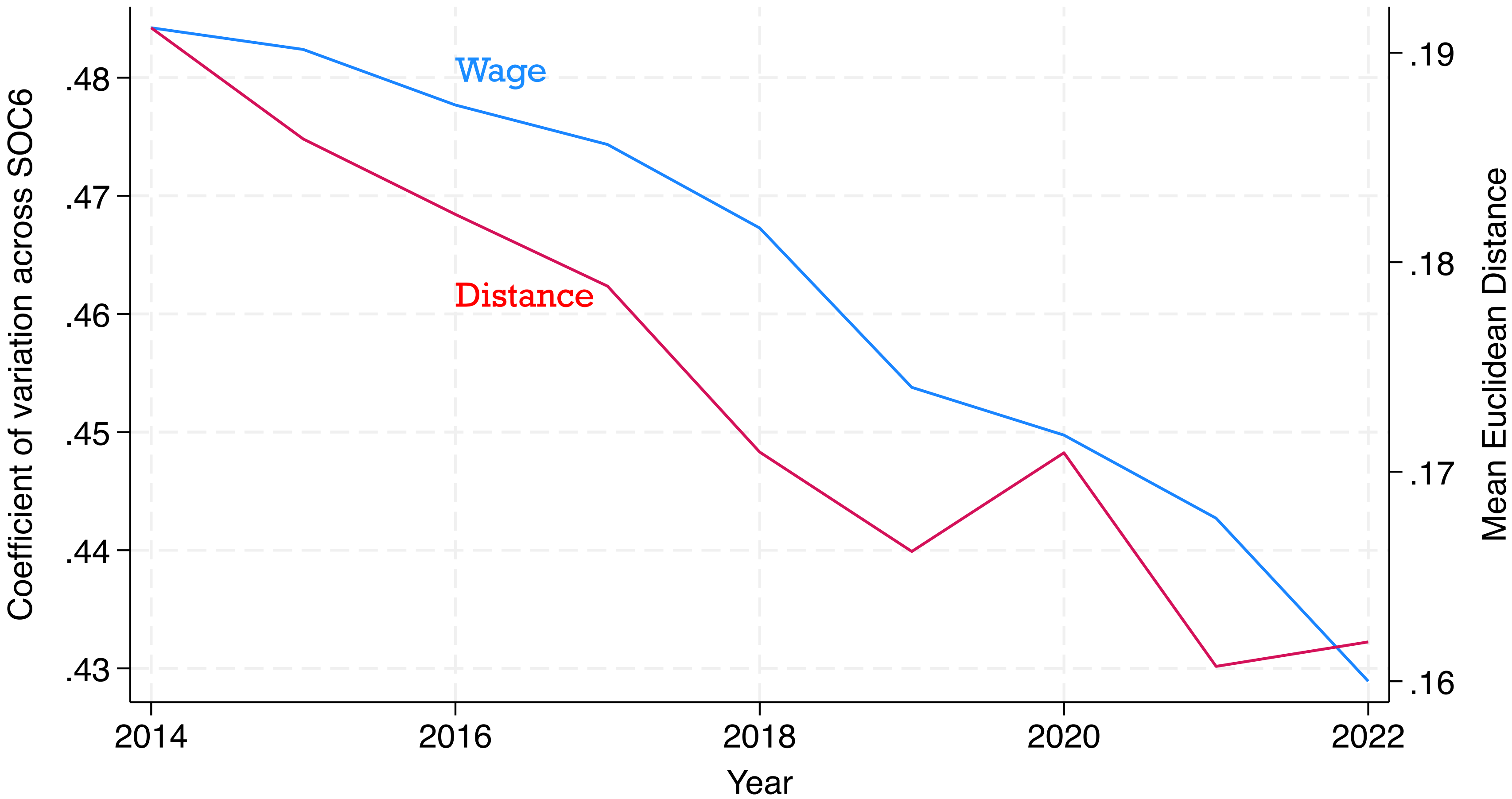
	Dependent Variable: Transition shares between Occ I and Occ j				
	(1)	(2)	(3)	(4)	(5)
Distance	-0.0607***	-0.0533***	-0.0595***	-0.1055***	-0.0324***
	(0.0016)	(0.0015)	(0.0016)	(0.0034)	(0.0036)
Same		0.0033***	0.0036***	0.0053***	0.0025***
		(0.0002)	(0.0003)	(0.0004)	(0.0005)
Distance * Same		-0.0151***	-0.0168***	-0.0266***	-0.0052**
		(0.0012)	(0.0014)	(0.0029)	(0.0023)
Occupation 1 FE	Yes	Yes	Yes	Yes	Yes
Occupation 2 FE	Yes	Yes	Yes	Yes	Yes
Exclude 0s				Yes	
Data			Schubert et al (2024)		CPS
Observations	696,390	696,390	666,672	275,733	93,025
R2	0.32601	0.32931	0.34109	0.37861	0.06697

Robust standard errors clustered by occupation 1 in parenthesis, *** p<0.01, ** p<0.05, * p<0.1

2.1 Implications: Wages

Hypotheses 1:

As occupations become more similar, do wages converge?



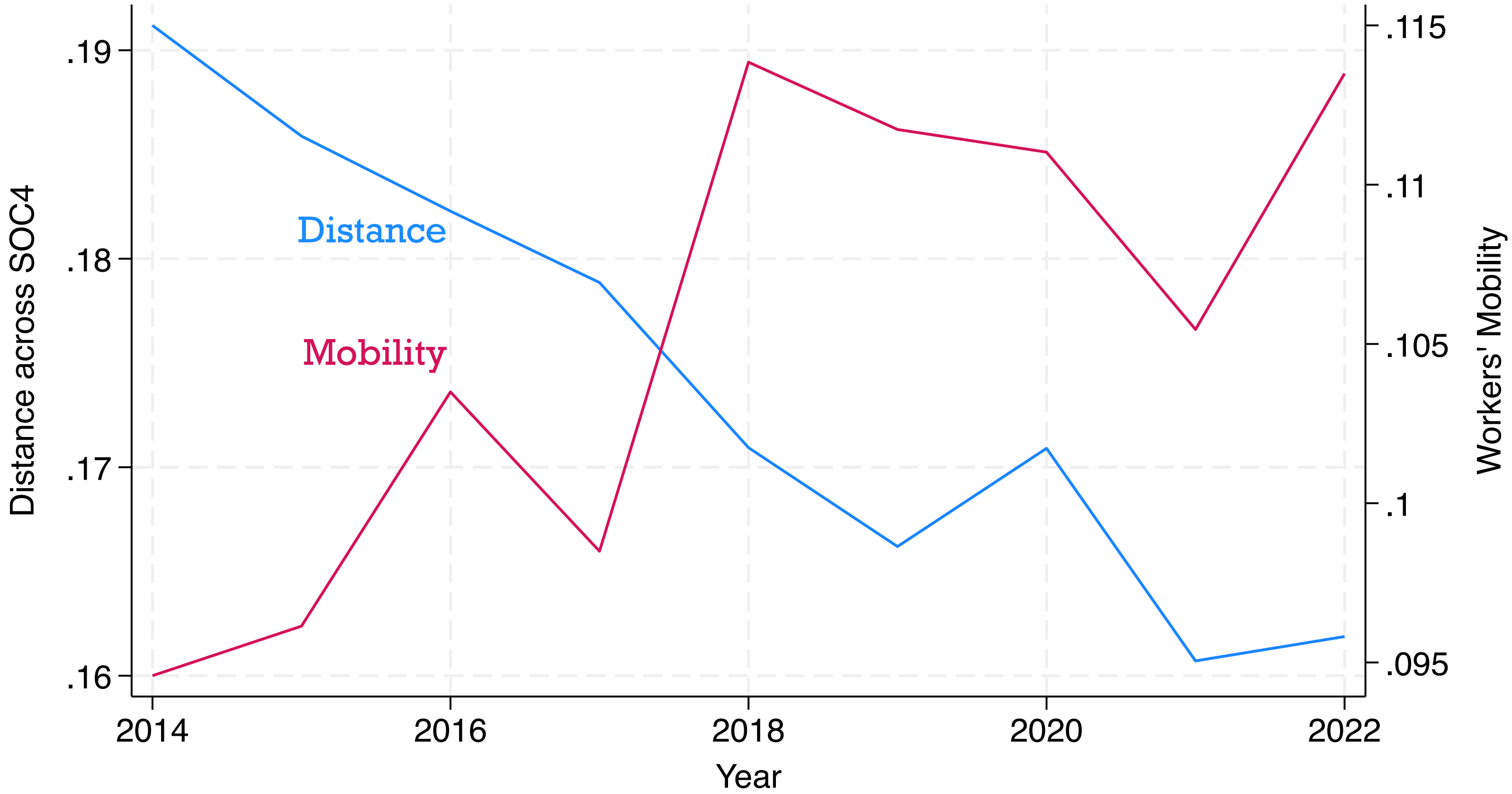
	(1)	(2)	(3)	(4)
wage gap 2014	-0.101***	-0.101***	-0.102***	-0.109***
	(0.000489)	(0.000489)	(0.000503)	(0.000789)
Δdist	0.0819***	0.0781***	0.0813***	0.0112***
	(0.00123)	(0.00126)	(0.00126)	(0.00250)
Self Distance		-0.0190***		
		(0.00134)		
Same			-0.00479***	
			(0.000563)	
Same * wage gap 2014			0.0207***	
			(0.00268)	
same * Δdist			0.00872	
			(0.00558)	
Low NR-C				-0.00830***
				(0.000327)
Low NR-C * wage gap 2014				0.00652***
				(0.00106)
Low NR-C * Δdist				0.0774***
				(0.00320)
Constant	0.0100***	0.0113***	0.0104***	0.0143***
	(0.000148)	(0.000174)	(0.000155)	(0.000249)
Observations	497,730	497,730	497,730	419,475
R-squared	0.088	0.088	0.088	0.092

Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1

2.2 Implications: Mobility

Hypotheses 2:

As occupations become more similar, does mobility rise?



2.2 Implications: Mobility

GEORGETOWN UNIVERSITY QATAR

Hypotheses 2:

As occupations become more similar, does mobility rise?

	Dependent Variable: Change in Transition shares between Occ I and Occ j		
	(1)	(2)	(3)
Change in Distance	-0.1504***	-0.1213**	-0.1172**
	(0.0575)	(0.0579)	(0.0556)
Same		-0.0127	-0.0111
		(0.0137)	(0.0132)
Change in Distance* Same		-0.0464	-0.0430
		(0.0338)	(0.0330)
Occupation 1*Year FE	Yes	Yes	Yes
Occupation 2*Year FE	Yes	Yes	Yes
Occupation 1*Occupation 2 FE	Yes	Yes	Yes
Weighted by log employment	No	No	Yes
Observations	24,159	24,159	24,159
R2	0.78044	0.78052	0.77131

Source CPS. Robust standard errors clustered by occupation 1 in parenthesis, *** p<0.01, ** p<0.05, * p<0.1

2.3 Additional results

GEORGETOWN UNIVERSITY QATAR

❖ Self-distance (between 2014 and 2022):

Occupations that have transformed the most have experienced:

1. Bigger declines in *within* occupation wage inequality
2. Higher increase in wage growth between 2014 and 2022

2.4 Robustness

- **Minimum Wage:**
  - We exclude counties with changes in min-wage.
  - Results do not change
- **Market tightness:**
  - We control for market tightness (interact with change in Eucl. distance)
  - Results do not change
- **Extending the results backward in time**
  - We replicate our methodology using data from 1980 (from newspapers)
  - Consistently with the literature, we find that between 1980 and 2000 the distance has been rising.

VI Conclusion

- We make a theoretical, methodological, and empirical contribution in furthering our understanding of labor market dynamics:
  - **Theoretical**: we introduce a puzzle on wages and mobility and offer a new theory to explain it
  - **Methodological**: we introduce a skill-based measure of distance using OJVs
  - **Empirical**: we show that occupations are converging, and as they converge mobility rises and wages converge.
- This is part of a series of papers on AI, Skills, and the Future of Work.

APPENDIX

3 Application:

جامعة جورجتاون قطر
GEORGETOWN UNIVERSITY QATAR

❖ Are cities converging?

❑ United States

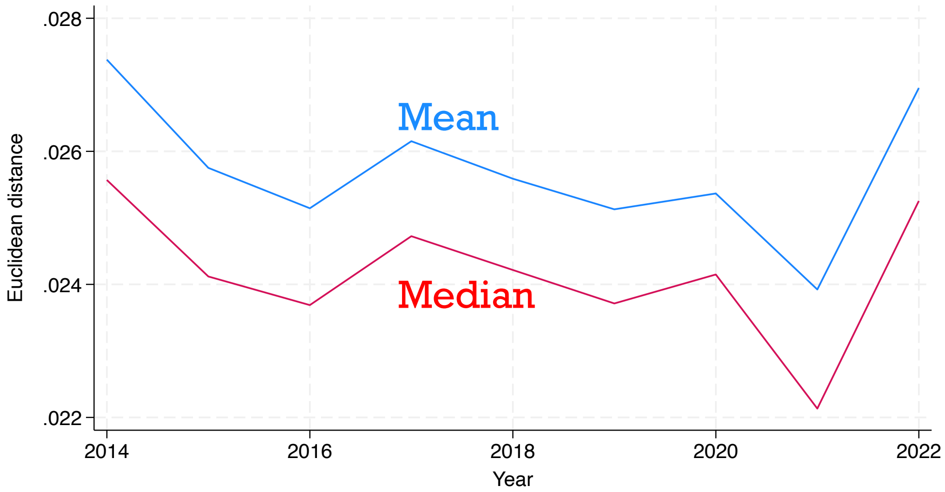


Fig 1 - Bilateral distanced across US cities

❑ China

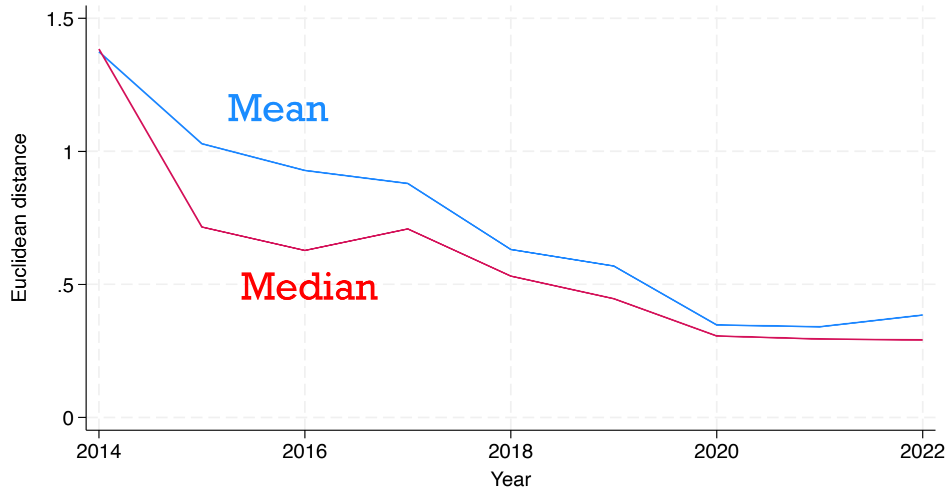


Fig 2 - Bilateral distanced across Chinese cities

3 Application:

GEORGETOWN UNIVERSITY QATAR

❖ Are US and China drifting apart of converging?

- ❑ Compare distance between US cities (MSAs) and Chinese cities

Beijing	San Jose-Sunnyvale-Santa Clara San Francisco-Oakland-Hayward
Wuhan	Seattle-Tacoma-Bellevue Chicago-Naperville-Elgin
Shanghai	San Francisco-Oakland-Hayward Boston-Cambridge-Newton
Foreign	Reno Las Vegas-Henderson-Paradise

1.3 Estimation

❖ A note on the choice of vector size:

Kernel density functions of bilateral occupation distances (Year = 2014) for various skill-vector sizes.