

DISCUSSION OF: TASKS, CITIES AND URBAN WAGE PREMIA (ANJA GRUJOVIC)

Federica Daniele¹

OECD

ECB-CEPR 2019 Labour Market Workshop

December 3, 2019

¹The views reported here do not represent the ones of the OECD.

Motivation:

- **urban wage premia vary across occupations**
- consequences of technological change for spatial distribution of economic activity? (e.g., Giannone, 2019)

Contribution:

- **Rich theoretical model of task-based comparative advantage of cities**
⇒ in opposition to traditional view of skill-based comparative advantage (Moretti, 2004)
- **New evidence supporting model predictions based on good data on task-content of occupations**
⇒ realistic occupation production function in the model and good match between testing predictions and data

Ingredients:

- many ex-ante different cities; workers consume final good/housing and choose where to locate (standard)
- tradable final good assembled out of tradable **intermediate “inputs” = occupations supplied by workers** (Costinot and Vogel, 2010)
- occupations assembled out of different tasks according to **task-specific intensities** or shares of individual time spent on each task

Sorting mechanisms:

- ① cities with **higher TFP** have a comparative advantage in production of **abstract occupations**
- ② workers with **higher education** (viewed as costly skill acquisition) have comparative advantage in production **abstract occupations**
- ③ workers with **higher ability** have comparative advantage in acquiring **higher education**

EQM: high-ability workers invest in higher education \Rightarrow perfectly sort into abstract occupations and \Rightarrow (imperfectly) sort into high-TFP cities

Data on task-content of occupations:

- Novel dataset (BIBB QCS): info on time spent on each out of a common set of tasks at the individual level
- Task intensities at occupation level = **average share of individual time spent on each group (A/R/M) of tasks per occupation**

Evidence supporting model predictions:

- 1 Wage premia
 - individual-level regressions
 - **urban wage premium increases in abstractedness of occupation**
- 2 Sorting across cities
 - regressions based on pairwise comparisons across occupations and cities
 - **the ratio between the share of workers located in a given city across any given pair of occupations increases in city size the more the higher is the distance in abstract (manual) task intensity between two occupations**

Model:

- ① Task aggregation: all tasks need to be completed in given proportions in order to have any output but this complementarity (“o-ring” style) is not reflected in the production function

$$q(\sigma, c; \alpha) = e^{\alpha + \int_{\tau \in T} Z(\tau, c) H(\tau, \sigma) d\tau}$$

- ② Assumption on tradable occupations: realistic? The traditional assumption is the opposite
⇒ introduce intermediate input producers (task-based production function as in Haanwinckel, 2019)?

Empirical analysis:

- ❶ does not make the most of “unique” feature of the dataset, i.e., that task intensity varies at individual level
 - why not endogenizing the time allocation to (substitutable) tasks?
 - strengthen evidence that task intensities are invariant to city size
- ❷ distinction from competing occupation-based explanations of the urban wage premium (interactiveness: Michaels et al., 2019; managerial content: Santamaria, 2019; specialization: Daniele, 2018)
- ❸ evidence on sorting across cities
- ❹ are findings compatible with the evolution of relative wages and employment shares over time?
 - How to reconcile with non-monotonic wage growth at the aggregate level across A/R/M?
 - Has sorting increased over time?

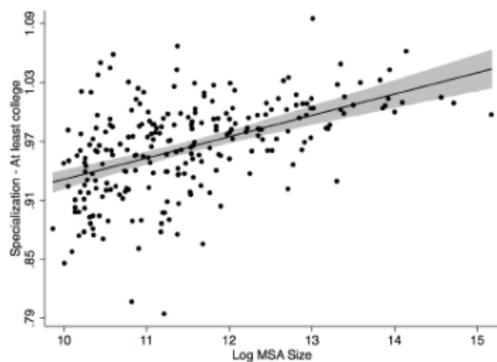
TASK INTENSITIES INVARIANT TO CITY SIZE?

Table 8: Determinants of task intensity

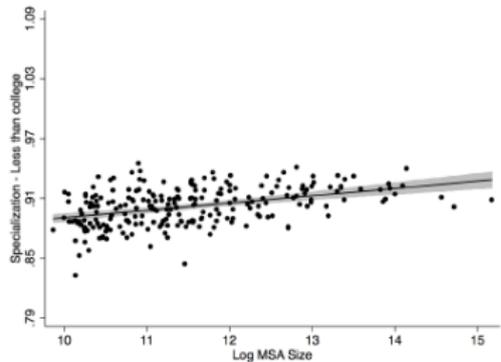
	Abstract		Routine		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
High School	0.0192 (0.002)***	0.0074 (0.0015)***	-0.0048 (0.0015)***	0.0008 (0.0012)	-0.0144 (0.0014)***	-0.0081 (0.0012)***
Further training	0.0562 (0.0028)***	0.0286 (0.0022)***	-0.188 (0.0021)***	-0.068 (0.0017)***	-0.0374 (0.002)***	-0.0218 (0.0017)***
University	0.0979 (0.0021)***	0.0361 (0.0018)***	-0.0439 (0.0016)***	-0.0087 (0.0014)***	-0.0540 (0.0015)***	-0.0274 (0.0014)***
Age	00 (0.0001)	00 (00)	-0.0002 (00)***	-0.0002 (00)***	0.0002 (00)***	0.0001 (00)***
Male	0.0195 (0.0011)***	-0.0044 (0.001)***	-0.0308 (0.0008)***	-0.0033 (0.0008)***	0.0114 (0.0008)***	0.0077 (0.0008)***
Local population:						
2.000 - 4.999	0.0031 (0.0027)	0.0001 (0.002)	-0.0007 (0.002)	0.0018 (0.0016)	-0.0025 (0.002)	-0.0020 (0.0016)
5.000 - 19.999	0.0104 (0.0024)***	0.0033 (0.0018)*	-0.0049 (0.0018)***	0.0002 (0.0014)	-0.0055 (0.0017)***	-0.0035 (0.0014)**
20.000 - 49.999	0.0136 (0.0025)***	0.0036 (0.0019)*	-0.0059 (0.0019)***	0.0002 (0.0015)	-0.0077 (0.0018)***	-0.0037 (0.0015)**
50.000 - 99.999	0.0126 (0.0029)***	0.004 (0.0022)*	-0.0072 (0.0021)***	-0.0014 (0.0017)	-0.0054 (0.0021)***	-0.0025 (0.0017)
100.000 - 499.999	0.0189 (0.0026)***	0.0037 (0.0019)*	-0.0082 (0.0019)***	0.0007 (0.0015)	-0.0107 (0.0018)***	-0.0043 (0.0015)***
≥ 500.000	0.0237 (0.003)***	0.003 (0.0022)	-0.0127 (0.0022)***	-0.0003 (0.0018)	-0.0110 (0.0021)***	-0.0027 (0.0017)

⇒ but is it reasonable to test whether people working as “Managers” specialize in abstract tasks in big cities in the same way as people employed in “Room and household cleaner” occupation?

DISTINGUISHING COMPETING EXPLANATIONS: THE EXAMPLE OF SPECIALIZATION



(e) Census 2000: College



(f) Census 2000: Non-college

Average specialization across US MSA against MSA size by educational group. Specialization = number of tasks per occupation multiplied by their frequency. Source: Daniele (2018).

TABLE 1: Relationship between specialization and other occupational attributes across 325 occupations (Autor and Dorn, 2013)

Abstract	Routine	Manual	Offshorability
0.0029***	-0.0001	0.0009	0.0021**

$\pi(\sigma, c)$ is fraction of workers in occupation σ in city $c \Rightarrow$ supermodular

$$\frac{\pi(\sigma', c')}{\pi(\sigma, c')} > \frac{\pi(\sigma', c)}{\pi(\sigma, c)}$$

for $\sigma' > \sigma$ and $c' > c$

$$\ln \left(\frac{\pi(\sigma', c)}{\pi(\sigma, c)} \right) = \nu_{\sigma} + \nu_{\sigma'} + \sum_{\tau} \theta_{\tau} (h_{\tau\sigma'} - h_{\tau\sigma}) \times \ln \text{density}_c + e_{\sigma\sigma'c}$$

Table 6: Sorting of workers into locations by task intensity

	(1)	(2)
Dependent variable: $\ln \left(\frac{\pi(\sigma', c)}{\pi(\sigma, c)} \right)$	All districts	
Abstract task difference $(h_{A,\sigma'} - h_{A,\sigma}) \times \ln(\text{dens})$	0.126*** (.0002)	
Manual task difference $(h_{M,\sigma'} - h_{M,\sigma}) \times \ln(\text{dens})$		-0.078*** (.0002)
Occupation σ indicators	Yes	Yes
Occupation σ' indicators	Yes	Yes
Observations	23,066,456	23,066,456
Adj. R ²	0.04	0.04

- potential conflict with Eeckhout et al. (2014)
- not clear mapping between testing equation and empirical specification
- add controls (e.g., relative shares across industries)