Superstar Teams

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Motivation: firms form & organize teams of heterogeneous workers

- **Most production processes are too complex for *1* person to perform *all* tasks well**
  - $\rightarrow$ individuals have **heterogeneous, task-specific skills**
  - $\rightarrow$ firms assemble & coordinate the division of labor among >1 workers (**“team”**)

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- **How is production with het. workers organized & what are the macro implications?**
  - classic question *[e.g., Kremer, 1993; Garicano, 2000]* but literature is theoretical & qualitative

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- **This paper:**
  1. **theory** that is tractable
  2. **measurement** with micro data
  3. **quantify macro implications** for agg. productivity & labor market inequality

Intuition: skill specificity $\rightarrow$ complementarities $\rightarrow$ sorting

- **Environment:**
  1. **task-based production**
  2. **multi-dim. skill heterogeneity**
     - $\rightarrow$ talent $\sim$ absolute advantage
     - $\rightarrow$ skill specificity $\sim$ *dispersion* in individual task-specific skills
  3. **teams**
  4. **search**

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- **Mechanism:** when skills are task-specific and tasks are optimally assigned to team members, production features **coworker talent complementarities**

  ⇒ incentives for **talent sorting**: firm-level inequality in productivity & wages

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- **Mechanism:** when skills are task-specific and tasks are optimally assigned to team members, production features **coworker talent complementarities**

  $\Rightarrow$ incentives for **talent sorting**: firm-level inequality in productivity & wages

- **Application:** skill specificity $\uparrow$ can explain the **"firming up of inequality"**

  [cf. Card et al., 2013; Bloom et al., 2019; ...]

This paper: theory - measurement - applications

1. **Develop tractable theory of the firm centered on team production & formation**
   - **microfound task-based production fn. with endogenous coworker complementarities**
   - tractable enough to endogenize team formation via search
2. **Confront theory with data**
   - **identification** with micro panel data on wages+matches $\rightarrow$ estimate & validate model
3. **Main quantitative application**: structural explanation for **"firming up inequality"**
   - $\uparrow$ skill specificity explains $\approx$ 25% of $\uparrow$ between-firm wage inequality share in DE since '85
   - paper: search frictions lower agg. productivity due to costly mismatch

Relation & contributions to literature

- **Firm organization:** **task-based microfoundation for complementarities**

  Firms & teams: *Lucas, 1978; Becker & Murphy, 1992;* ***Kremer, 1993****; Kremer & Maskin, 1996;* ***Garicano, 2000****;* ***Garicano & Rossi-Hansberg, 2006****; Porzio, 2017;* ***Jarosch et al., 2021****; Kuhn et al., 2023*

  Task assignment: *Costinot & Vogel, 2010;* ***Acemoglu & Restrepo, 2018****; Ocampo, 2021*

- **Multi-dim. skill heterogeneity:** **parsimonious parametrization for teams model**

  Gathman-Schoenberg, 2010; Lindenlaub, 2017; Guvenen et al., 2020; Baley et al., 2022; Grigsby, 2024

- **Frictional labor market sorting:** **endogenize & measure complementarities**

  Shimer & Smith, 2000; Cahuc et al., 2006; Eeckhout & Kircher, 2011/2018; Hagedorn et al., 2017; de Melo, 2018; Lindenlaub & Postel-Vinay, 2023; ***Herkenhoff et al., 2024***

- **Wage inequality:** **structural model of ↑ firm-level inequality due to ↑ specialization**

  Technology: *Katz & Murphy, 1992; Krusell et al., 2000; Autor et al., 2003; Acemoglu & Restrepo, 2018*

  Firms: ***Card et al., 2013****; Barth et al., 2016; Alvarez et al., 2018;* ***Bloom et al., 2019****; Sorkin & Wallskog, 2023*

Model environment: high-level overview

- Continuums of workers & firms, infinitely-lived & risk-neutral
- **Ex-ante identical firms**
  - hire $n \in \{0, 1, 2\}$ workers through sequential random search *[cf. HLMP, 2024]*
  - operate task-based production technology, assigning n workers to produce tasks that are combined into final output *[cf. Acemoglu-Restrepo, 2018]*
- **Heterogeneous workers** have task-specific skills

$\Rightarrow$ **Analysis:**

1. microfound tractable firm-level production function
2. integrate into search environment & analyze who is matched with whom

Production with a single team of given composition: task assignment

- Firm employs n workers to produce output from **unit continuum of tasks** $\mathcal{T}$

$$\ln Y = \int_{\mathcal{T}} \ln q(\tau) d\tau \tag{1}$$

- **Task-level aggregation** for task τ:

$$q(\tau) = \sum_{i=1}^{n} y_i(\tau) \tag{2}$$

- **Task production:** i has task-specific skill $z_i(\tau)$, supplies 1 time unit

$$y_i(\tau) = z_i(\tau) l_i(\tau) \tag{3}$$

$$1 = \int_{\mathcal{T}} l_i(\tau)\ d\tau \tag{4}$$

Firm's optimization problem

- **Firm solves mini-planner problem:** $\max_{\mathbf{q},\{\mathbf{y_i}\},\{\mathbf{l_i}\}} Y$ s.t. (1)-(4)

- **Preview:** derive & characterize *reduced-form* team production function f

$$f(\mathbf{z}_1, \ldots, \mathbf{z}_n) = \max Y \quad \text{s.t. (1)-(4)}$$

Firm's optimization problem

- **Firm solves mini-planner problem:** max Y s.t. (1)-(4)

$$\mathcal{L}(\cdot) = Y + \lambda\left[\underbrace{\left(\int_{\mathcal{T}} \ln q(\tau)d\tau\right) - \ln Y}_{\text{tasks} \rightarrow \text{output}}\right] + \int_{\mathcal{T}} \lambda(\tau)\underbrace{\left(\sum_{i=1}^{n} y_i(\tau) - q(\tau)\right)}_{\text{task aggregation}}d\tau$$

$$+ \sum_{i=1}^{n} \lambda_i^L \underbrace{\left(\int_{\mathcal{T}} \frac{y_i(\tau)}{z_i(\tau)}d\tau - 1\right)}_{\text{time constraint + task production}} + \text{non-negativity constraints}$$

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- **FOCs** imply

$$\lambda(\tau) = \min_i \left\{ \frac{\lambda_i^L}{z_i(\tau)} \right\}$$

shadow cost of τ

opportunity cost of i's time

i's skill for τ

Firm's optimization problem

- **Firm solves mini-planner problem:** max Y s.t. (1)-(4)

$$\mathcal{L}(\cdot) = Y + \lambda \underbrace{\left[\left(\int_{\mathcal{T}} \ln q(\tau) d\tau \right) - \ln Y \right]}_{\text{tasks} \rightarrow \text{output}} + \int_{\mathcal{T}} \lambda(\tau) \underbrace{\left(\sum_{i=1}^{n} y_i(\tau) - q(\tau) \right)}_{\text{task aggregation}} d\tau$$

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- **FOCs** imply **task assignment by comparative advantage**

$$\lambda(\tau) = \min_i \left\{ \frac{\lambda_i^L}{z_i(\tau)} \right\}$$

Parametrized distribution of task-specific skills

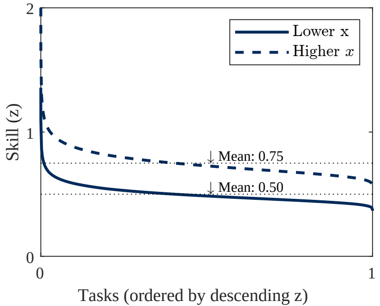
Assumption: Multivariate Fréchet dist.

$$\Pr\left[z_1(\tau) \leq z_1, z_2(\tau) \leq z_2\right] = \exp\left[-\left(\sum_{i=1}^{n=2}\left(\left(\frac{z_i}{\iota X_i}\right)^{-\frac{1}{\chi}}\right)^{\frac{1}{\xi}}\right)^{\xi)}\right]$$

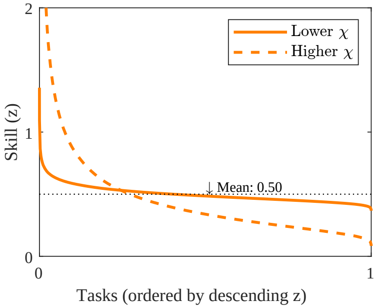
Parametrized distribution of task-specific skills: marginal dist.

$$\mathrm{P}\left[z_i(\tau) \leq z_i\right] = \exp\left(-\left(z_i/(\iota\, x_i)\right)^{-\frac{1}{\chi}} \right)$$

(a) x_i: **talent** (scale)



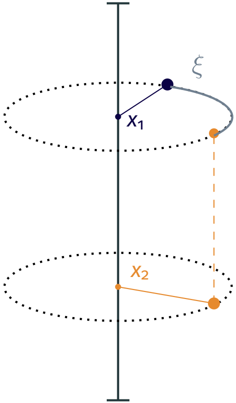
(b) χ: **skill specificity** (inverse shape)



Parametrized distribution of task-specific skills: copula

$$\Pr\left[z_1(\tau) \leq z_1, z_2(\tau) \leq z_2\right] = \exp\left[-\left(\sum_{i=1}^{n=2}\left(\left(\frac{z_i}{\iota x_i}\right)^{-\frac{1}{\chi}}\right)^{\frac{1}{\xi}}\right)^{\xi}\right]$$

team-specific 'distance' between coworkers' task-specific skills: $\xi \in (0, 1]$



Micro-founded production function

Lemma

Proposition: Reduced-form production function

Talent types $\mathbf{x}$ and coworker distance ξ are sufficient statistics for team output Y given parameter χ :

$$Y = f(x_1, \cdots, x_n, \xi; \chi)$$

- Fréchet max-stability property allows closed-form characterization of key objects, e.g. distribution of $\lambda(\tau) \rightarrow$ integrate over *continuum* of tasks

Micro-founded production function

▸ Lemma

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- Fréchet max-stability property allows closed-form characterization of key objects, e.g. distribution of $\lambda(\tau) \rightarrow$ integrate over *continuum* of tasks
- **Benchmark** without division of labor: $Y = n \times \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right)$

Gains from team production are increasing in skill specificity

Proposition: Reduced-form production function

$$f(\mathbf{x}, \xi; \chi) = \underbrace{n^{1+\chi\xi}}_{\text{efficiency gains}} \times \left(\frac{1}{n} \sum_{i=1}^{n} (x_i)^{\frac{1}{1+\chi\xi}} \right)^{1+\chi\xi}$$

1. Value of **team production** increasing in skill specificity (χ)

Intuition

Gains from team production are increasing in skill specificity

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1. Value of **team production** increasing in skill specificity (χ)
   - ***realized* team advantage greater when coworkers are good at different tasks** (ξ)

▸ Intuition

Skill specificity implies that productivity is lowered by talent dispersion

Proposition: Reduced-form production function

$$f(\mathbf{x}, \xi; \chi) = \underbrace{n^{1+\chi\xi}}_{\text{efficiency gains}} \times \underbrace{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i)^{\frac{1}{1+\chi\xi}}\right)^{1+\chi\xi}}_{\text{talent complementarity}},$$

1. Value of team production increasing in skill specificity (χ) ▸ Intuition
   - *realized* team advantage greater when coworkers are good at different tasks (ξ)
2. **Coworker talent complementarities** increasing in skill specificity (χ) ▸ Intuition
   - $\frac{\partial\left(\partial f(\cdot)/\partial x_i \partial x_{-i}\right)}{\partial \chi} > 0$

Roadmap & key takeaways

Theory

1. Under the optimal task assignment, **skill specificity** *endogenously* generates **coworker complementarities** $\rightarrow$ team composition matters
2. Next: **so what teams are formed in equilibrium?**

Endogenous team composition: frictional matching

▸ Details

- Integrate $f(\cdot)$ with search-frictional dynamic matching into teams
- **Main features** of search block: *[similar to Herkenhoff-Lise-Menzio-Phillips, 2024]*
  - random search with multi-worker firms
  - employment states: unemp., employed alone, employed with one coworker
  - Nash wage bargaining with continuous renegotiation
- But introduce **multi-dim. skills** in tractable fashion:
  - microfoundation: if $\chi > 0$, both talent composition $\mathbf{x}$ and differentiation ξ matter for Y
  - ξ is a **match-specific shock** observed by firms + workers before match decision
- **Stationary equilibrium**

▸ Details

Surplus max. determines which teams are formed

- Joint value of firm with worker x, $\Omega_1(x)$, satisfies:

$$\rho\Omega_1(x) = f(x) + \delta\left[-\Omega_1(x) + V_u(x) + V_{f.0}\right]$$
$$+\lambda_{v.u}\int\int\frac{d_u(\tilde{x}')}{u}\max\Big\{\underbrace{-\Omega_1(x) + V_{e.2}(x|\tilde{x}',\tilde{\xi}) + V_{f.2}(x,\tilde{x}',\tilde{\xi})}_{(1-\omega)S(\tilde{x}'|x,\tilde{\xi})}, 0\Big\}dH(\tilde{\xi})d\tilde{x}'$$

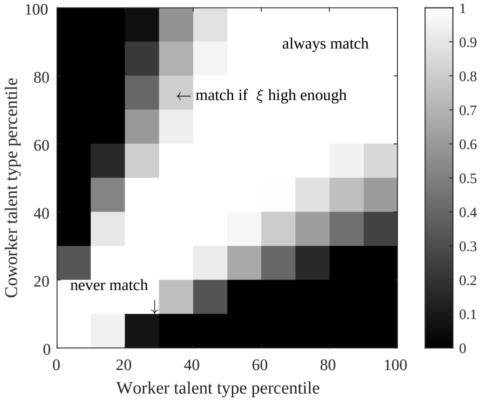
  - $V_u(x)$: value for unemp. worker; $V_{f.0}$: value for vacant firm; $d_u(x)$: density of unemployed workers of type x; $u = \int d_u(x)dx$; ω: worker bargaining wgt; δ: sep. rate; $\lambda_{v.u}$: rate of vacancy meeting unmatched worker

- Surplus $S(x|x',\xi)$ reflects production complementarities

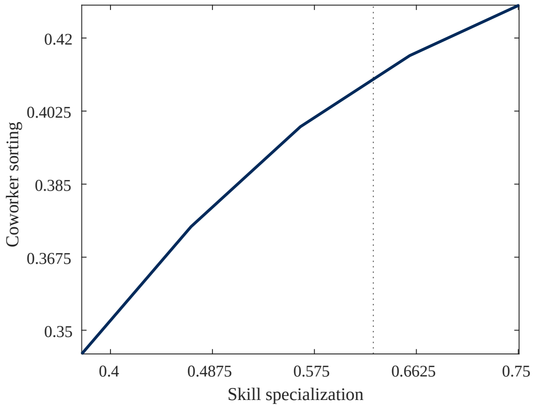
$$S(x|x',\xi)(\rho+2\delta) = f(x,x',\xi) - \rho\big(V_u(x) + V_u(x') + V_{f.0}\big) + \delta S(x) - (\rho+\delta)S(x')$$

Equilibrium properties: conditional matching probabilities for given χ

- Team composition determined by tradeoff between **match quality vs. search costs** $\Rightarrow$ matching probabilities $h(x'|x) = \mathrm{P}\{S(x'|x,\xi) > 0\}$



Comparative 'statics': more positive assortative matching as $\chi \uparrow$



Roadmap & key takeaways

Theory

1. **Skill specificity** *endogenously* generates **coworker complementarities**
2. **Talent complementarities** lead to **positive assortative matching**

Next: confront theory with data

Taking the model to the data: overview

- **Data:** SIEED matched-employer employee panel for W Germany
- **Taking the model to the data: mapping & estimation**
  - worker *i*' s talent type $\hat{x}_i \approx$ rank in wage FE dist. Details
  - "representative coworker type" $\hat{x}_{-it}$: avg. $\hat{x}$ of workers in same estab.-yr. Details
  - some parameters are taken from literature (e.g. discount rate ρ, bargaining weight ω) or estimated offline (e.g. job separation hazard δ)
  - indirect inference: meeting rate, unemp. flow benefit, production
    - targets: total wage variance, avg. wage level, replacement rate, job finding rate
- **Focus today:** structural identification of χ in theory & practice

Measurement: a useful identification result

Identification validation | Monte Carlo

- **Challenge:** skill specialization χ not directly observable
  - literature doesn't offer cardinal measures of specificity *[exception: Grigsby, 2024]*
  - could infer χ from sorting, but v indirect & liable to misattribution
- **Theory guides measurement:** Proposition 1 ties χ to $\frac{\partial^2 f(\cdot)}{\partial x \partial x'}$, which given prior measures of x and x' & accounting for selection on ξ, we can recover from $w(x|x')$

$$\frac{\partial^2 f(x, x', \xi)}{\partial x \partial x'} \propto \frac{\partial^2 w(x|x', \xi)}{\partial x \partial x'}.$$

$$\Rightarrow \frac{\partial^2 \bar{f}(x, x')}{\partial x \partial x'} \underset{\sim}{\propto} \boxed{\frac{\partial^2 \bar{w}(x|x')}{\partial x \partial x'}}$$

can measure this

Proof sketch

Reduced-form regression to identify χ (2010-2017)

Robustness

- Approximate $\frac{\partial^2 \bar{w}(x|x')}{\partial x \partial x'}$ using **regression with interaction term**

$$\frac{w_{it}}{\bar{w}_t} = \beta_0 + \beta_1 \hat{x}_i + \beta_{11} \hat{x}_i^2 + + \beta_2 \hat{X}_{-it} + \beta_{22} \hat{X}^2_{-it} + \beta_c \left(\hat{x}_i \times \hat{X}_{-it} \right) + \psi_{j(it)} + \nu_{o(i)t} + \xi_{s(i)t} + \epsilon_{it}$$

	$\hat{\beta}_c$	Non-parametric FD method
Coworker complementarity	**0.0058*** **	0.0075
Obs. (1000s)	4,410	4,410

Notes. Regressions include FEs for employer; occupation-year; industry-year. Employer-clustered standard errors in parentheses. Observations weighted by the inverse employment share of the respective type and (rounded) coworker type cell. FD: finite differences.

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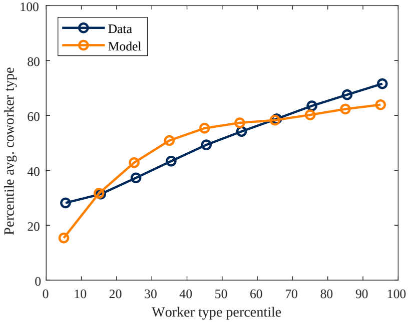
- **Estimation of structural model:** replicate semi-structural regression with model-generated data, infer χ from matching empirical $\hat{\beta}_c$

Quantitative properties of estimated model: untargeted moments

B-S adj. method

Parameter values & discussion

- **✓Match talent sorting patterns**
  - $\rho_{xx} = 0.43$ (vs. 0.62 in data)
- **✓Match between-firm wage inequality**
  - between-share 0.48 (vs. 0.57 in data)



$\Rightarrow$ **Model endogenously generates ex-post firm differences**

Validation of core model mechanisms

- **Team-production functions in science** *[cf. Ahmadpoor-Jones, 2019]* ▸ Details

  ✓talent complementarities stronger *precisely* when teamwork more valuable

- **Cross-sectional variation across occupations/industries** ▸ Details

  ✓task-based proxy for $\chi \uparrow \rightarrow$ estimated talent complementarity $\uparrow$

  ✓estimated talent complementarity $\uparrow \rightarrow$ coworker talent sorting $\uparrow$

- **Direction of EE moves:** non-wage implications of complementarities ▸ Details

  ✓Δ coworker talent positively correlated with own talent

- **Heterogeneous effects of coworker deaths** *[cf. Jaeger-Heining, 2022]* ▸ Details

  ✓wage gains from coworker death *if* coworker specialized in different tasks ($\xi \uparrow$)

Roadmap & key takeaways

Theory

1. Skill specificity *endogenously* generates coworker complementarities
2. Talent complementarities lead to positive assortative matching

Model Meets Data

3. The model, estimated on German micro data, implies large ex-post differences across firms that emerge endogenously

Next: application(s)

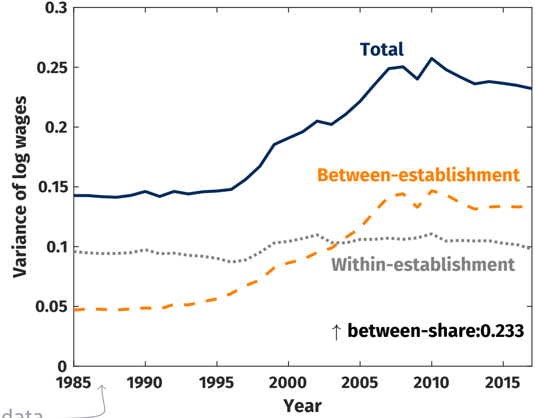
- **Today:** structural explanation for the "firming up of inequality"
  - *caveat:* revision in progress, so numbers are preliminary

Wage inequality has risen – and firms appear to play a key role

▸ Details

"the variance of firm [wages] explains an increasing share of total inequality in a range of countries"

[Song-Price-Guvenen-Bloom-von Wachter, 2019]

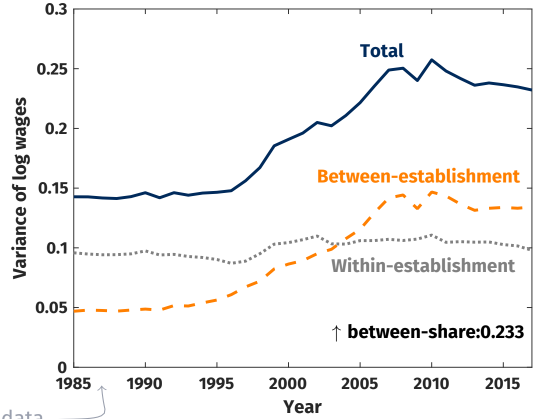


German matched employer-employee data

Applied question

Details

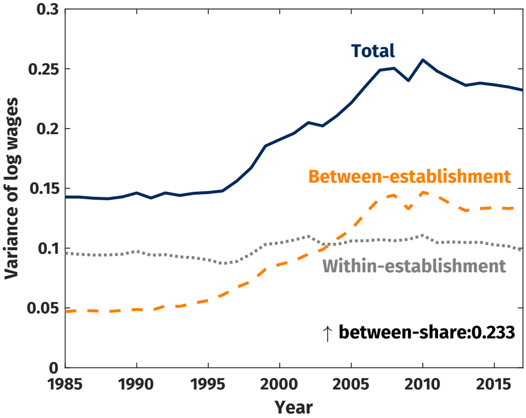
Applied question: what is/are the causal driver(s)? implications?



German matched employer-employee data

Preview of argument

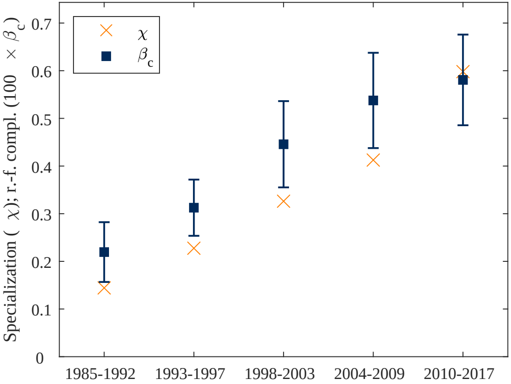
1. The set of tasks any one worker can perform well has narrowed: skill specificity ↑
2. Coworker complementarities ↑
3. Individuals of similar talent increasingly work together
4. This generates greater between-firm wage dispersion



Estimate model for several periods: skill specialization ↑

▸ Schooling ▸ Peer effect trends

- **Method:** estimate reduced-form coefficient β_c for 5 sample periods $\Rightarrow$ re-estimate structural model
- **Estimate:** **skill specificity χ ↑**



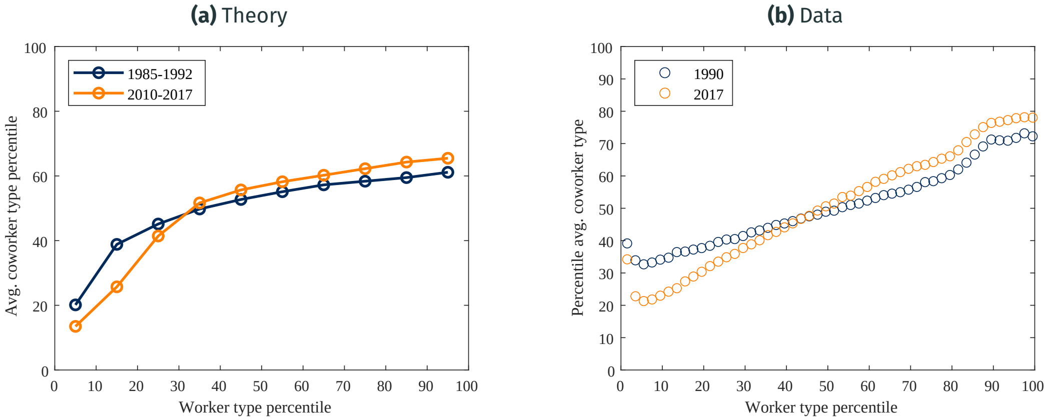
Estimates for $\chi \uparrow$ are consistent with independent evidence

▸ Occ. movements ▸ Case studies

1. **Grigsby (2024) estimates for US:** within-type var. of task-specific skills $\sim$ 50% $\uparrow$ since '80
2. **Evidence on Δ task composition:** fewer routine, more complex tasks ▸ DE evidence
   - routine tasks $\sim$ low-χ
3. **Related trends:** rise of team production in science due to the "burden of knowledge" *[Jones, 2009]* & growing importance of social skills *[Deming, 2017]*

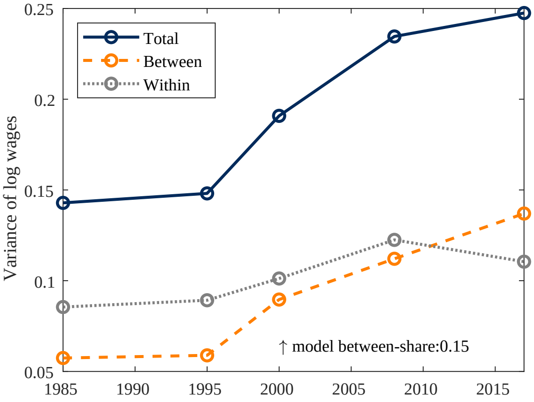
Talent sorting has intensified: theory & data

▸ Details



Model matches *changes* in firm-level wage distribution

- **Model replicates untargeted rise of between-share in data**
  - $\sim$ 2/3 of $\uparrow$ between-share in data, ('85-'92)$\rightarrow$('10-'17)



Skill specificity $\chi \uparrow$ explains $\approx$ 25-40% of observed between-share $\uparrow$

- **Q:** How much of $\uparrow$ between-firm share of wage var. is due to $\chi \uparrow$?

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- **Counterfactual:** between-firm share in 2010s absent $\chi\uparrow$ since '85-'92

Skill specificity $\chi \uparrow$ explains $\approx$ 25-40% of observed between-share $\uparrow$

- **Q:** How much of $\uparrow$ between-firm share of wage var. is due to $\chi \uparrow$?
- **Counterfactual:** between-firm share in 2010s absent $\chi \uparrow$ since '85-'92
- **A:** $\chi \uparrow$ **accounts for 58%** of model-predicted $\Delta \leftrightarrow \approx$ **38% of empirical Δ**
- **Robustness** exercises: 25-40%

	Δ model	Implied % Δ model due to Δ parameter
Model	0.15	
Cf.: $\chi^{'85-'92}$	0.065	58

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Theory

1. Skill specificity *endogenously* generates coworker complementarities
2. Talent complementarities lead to positive assortative matching

Model Meets Data

3. Estimated model endogenously generates realistic ex-post firm heterogeneity

Applications

4. **Increased skill specificity – leading to stronger complementarities and, hence, sorting – explains a substantial share of $\uparrow$ between-firm wage inequality share**
5. Enhanced sorting crucial to realize productivity gains from $\uparrow$ skill specialization

▸ Application: agg. productivity

Conclusion

Conclusion: firms form & organize teams – matters for macro

- **Main idea:** if workers have specialized skills, firms assemble teams of complementary coworkers, with macro implications for productivity & inequality

- **Today:**
  1. **task-based firm-level production fn. with endog. skill complementarities**
     $\Rightarrow$ skill specificity + teams $\rightarrow$ production complementarities
  2. **measurement** combining reduced-form micro evidence with model structure
     $\Rightarrow$ endogenously generated between-firm differences in productivity & pay
  3. **quantitative** application to explain **macro implications**
     $\Rightarrow$ **rising skill specificity** contributed to the **“firming up” of inequality**

Thank You!

Extra Slides

What's the value-added of the micro-founded production function?

- **Concern:** the microfoundation isn't used for measurement — i.e. measure $z_i(\tau)$'s directly and then 'aggregate up' to recover complementarities – so what's the point?
- **Value-added #1**: very tractable formalization of team production with multi-dimensional skills
  - it's not obvious *ex ante* that team production with multi-dim. skills can be represented in this way, nor how this can be incorporated into a search framework
- **Value-added #2**: relative to a reduced-form CES function with talent x (1-dimensional) *[e.g. Herkenhoff et al., 2024]*
  1. offers explanation for why talent complementarities may vary & change over time – in
  2. the two models are not observationally equivalent
     - benefit from team production is also increasing with χ, hence this term co-moves with talent complementarities (and it affects sorting differently)
     - selection effects due to ξ: when we observe low and high x workers together, they are likely to be a good match in terms of their task-specific skills *[cf. Borovickova-Shimer, 2024]*

Lemma

Lemma: Lemma

Implied task share and shadow-cost index equal

$$\pi_i = \frac{\left(x_i/\lambda_i^L\right)^{\frac{1}{\chi\xi}}}{\sum_{k=1}^{n}\left(x_i/\lambda_i^L\right)^{\frac{1}{\chi\xi}}} \quad x;\lambda = \left(\sum_{i=1}^{n}\left(\frac{x_i}{\lambda_i^L}\right)^{\frac{1}{\chi\xi}}\right)^{-\chi\xi}$$

Intuition: features of optimal organization

- **What is the intuition for these properties?**

- Solution of firm's mini-planner problem implies:

1. Complete division of labor, with tasks assigned by comparative advantage
   - i's task set $\mathcal{T}_i = \left\{ \tau \in \mathcal{T} : \frac{z_i(\tau)}{\lambda_i^L} \geq \max_{k \neq i} \frac{z_k(\tau)}{\lambda_k^L} \right\}$
   - classic source of efficiency gains

2. **i's share of tasks $\uparrow$ in i's talent, $\downarrow$ in coworkers' talent**
   - i's task share $\pi_i = \left(x_i^{\frac{1}{1+\chi\xi}}\right) \left(\sum_{k=1}^{n} (x_k)^{\frac{1}{1+\chi\xi}}\right)^{-1}$

Intuition: comparative statics for task shares

Main

- Suppose that $x_i > x_j$. Then
  1. i performs a strictly larger share of tasks than j for $\chi < \infty$

Intuition: comparative statics for task shares

- Suppose that $x_i > x_j$. Then
  1. *i* performs a strictly larger share of tasks than *j* for $\chi < \infty$
  2. **the difference in task shares is decreasing in χ**

$\Rightarrow$ **Greater skill specialization implies a larger share of tasks is performed by relatively less talented team members** – more talented coworkers can't easily compensate

Surplus sharing protocol

- The wage of a worker of type x employed alone satisfies

$$(1-\omega)\big(V_{e.1}(x)-V_u(x)\big)=\omega\big(V_{f.1}(x)-V_{f.0}\big), \tag{5}$$

- The wage $w(x|x',\xi)$ of a type-x worker with a coworker of type x' given shock ξ satisfies

$$(1-\omega)\big(V_{e.2}(x|x',\xi)-V_u(x)\big)=\omega\big(V_{e.2}(x'|x,\xi)+V_{f.2}(x,x',\xi)-V_{e.1}(x')-V_{f.1}(x')\big). \tag{6}$$

HJB: unmatched

Main

- Unmatched firm:

$$\rho V_{f.0} = (1-\omega)\lambda_{v.u} \int \frac{d_u(x)}{u} S(x)^+ dx, \tag{7}$$

- Unmatched worker:

$$\rho V_u(x) = b(x) + \lambda_u \omega \left[\frac{d_{f.0}}{v} S(x)^+ + \int \int \frac{d_{m.1}(\tilde{x}')}{v} S(x|\tilde{x}', \tilde{\xi})^+ dH(\tilde{\xi}) d\tilde{x}' \right] \tag{8}$$

Joint values

- Joint value of firm with x and x', ξ

$$\rho\Omega_2(x, x', \xi) = f_2(x, x', \xi) - \delta S(x|x', \xi) - \delta S(x'|x, \xi) \tag{9}$$

- Joint value of firm with x

$$\begin{aligned}\rho\Omega_1(x) &= f_1(x) + \delta\big[-\Omega_1(x) + V_u(x) + V_{f.0}\big] \\ &+ \lambda_{v.u} \int\int \frac{d_u(\tilde{x}')}{u} \big(\underbrace{-\Omega_1(x) + V_{e.2}(x|\tilde{x}', \tilde{\xi}) + V_{f.2}(x, \tilde{x}', \tilde{\xi})}_{(1-\omega)S(\tilde{x}'|x,\tilde{\xi})}\big)^+ dH(\tilde{\xi})d\tilde{x}'.\end{aligned} \tag{10}$$

HJB: surpluses

- Surplus of coalition of firm with worker x

$$\big(\rho+\delta\big)S(x) = f_1(x) - \rho\big(V_u(x) + V_{f.0}\big) + \lambda_{v.u}(1-\omega)\int \frac{d_u(\tilde{x}')}{u} S(\tilde{x}'|x,\tilde{\xi})^+ dH(\tilde{\xi})\tilde{x}'. \quad (11)$$

- Surplus from adding x to x' with xi

$$S(x|x',\xi)\big(\rho+2\delta\big) = f_2(x,x',\xi) - \rho\big(V_u(x) + V_u(x') + V_{f.0}\big) + \delta S(x) - (\rho+\delta)S(x'). \quad (12)$$

KFE: unemployed

$$\delta\left(d_{m.1}(x) + \int d_{m.2}(x,\tilde{x}')d\tilde{x}'\right) = d_u(x)\lambda_u\left(\int \frac{d_{f.0}}{v}h(x,\tilde{y}) + \int \frac{d_{m.2}(\tilde{x}')}{v}h(x|\tilde{x}')d\tilde{x}'\right). \tag{13}$$

KFE: one-worker matches

$$d_{m.1}(x)\left(\delta+\lambda_{v.u}\int\frac{d_u(\tilde{x}')}{u}h(\tilde{x}'|x)d\tilde{x}'\right)=d_u(x)\lambda_u\frac{d_{f.0}}{v}h(x)+\delta\int d_{m.2}(x,\tilde{x}')d\tilde{x}'. \tag{14}$$

KFE: two-worker matches

$$2\delta d_{m.2}(x,x') = d_u(x)\lambda_u \frac{d_{m.1}(x')}{v} h(x|x') + d_u(x')\lambda_u \frac{d_{m.1}(x)}{v} h(x'|x). \tag{15}$$

Matching – stationary equilibrium

Main

- HJ-Bellman equations $\rightarrow$ **values & matching policies** HJBs
- Flows between/**distribution** over types $\times$ employment states KFEs

Definition: Stationary equilibrium

A stationary eqm. consists of a production function, value functions & a distribution of agents, s.t.

1. the production function is consistent with the optimal assignment of tasks;
2. the value functions satisfy the HJB equations given the distribution;
3. the distribution is stationary given the policy fn's implied by the value fn's.

Mapping theory to data: worker & coworker types

Main

- **Theory:** wage monotonically $\uparrow$ in x, so can measure using panel dimension
- **Implementation:** standard methods
  - pragmatic approach: AKM fixed effect (FE) wage regressions *[Abowd et al., 1999]* with pre-est. k-means clustering to address limited mobility bias *[Bonhomme et al., 2019]*
  - theory-consistent: non-param. ranking algo *[Hagedorn et al., 2017]* $\rightarrow$ similar ranking

$\Rightarrow$ **Worker i's talent type $\hat{x}_i$: decile rank of i's FE *within 2d-occupation***

- **"Representative coworker type"** $\hat{x}_{-it}$: avg. $\hat{x}$ of workers in same estab.-yr.

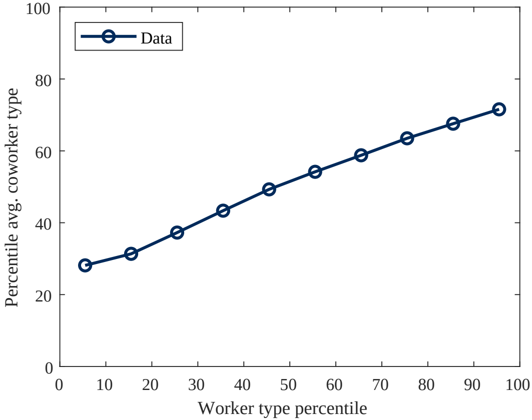
Discussion

Mapping model to data: coworker types

- Defining $S_{-it} = \{k : j(kt) = j(it), k \neq i\}$ as the set of i's coworkers in year t, compute the average type of i's coworkers in year t as $\hat{x}_{-it} = \frac{1}{|S_{-it}|} \sum_{k \in S_{-it}} \hat{x}_k$.
- **Coworker group:**
  - alternative: same establishment-occupation-year cell
  - but CC arise precisely when workers are *differentiated* in their task-specific productivities
- **Averaging step:**
  - equally-weighted averaging ignores non-linearity in coworker aggregation
  - paper: show using non-linear averaging method that baseline results in bias, but it's minor in magnitude
- **Firm size variation:** averaging ensures that a single move will induce a smaller change in the *average* coworker quality in a large team than in a small one

Mapping theory to data: talent sorting in the data

- Measures of $\hat{x}_i$ and $\hat{x}_{-it}$ sufficient to measure empirical talent sorting



Measurement: a useful identification result

Main Non-separable case: scatterplot

- **Q:** How to quantify $\frac{\partial^2 f(x,x')}{\partial x \partial x'}$?
- **Proposition:** production complementarities are proportional to wage compl.
- **Proof sketch:** wage level for worker x with coworker x'

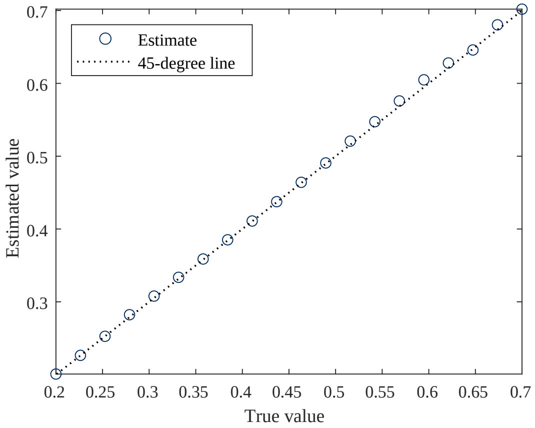
$$w(x|x',\xi) = \omega f(x,x',\xi) + g(x) - h(x')$$

where $g : [0,1] \to \mathbb{R}$ and $h : [0,1] \to \mathbb{R}$ are strictly increasing

$\Rightarrow$ *outside options* are *separable*: affect *level* of wage but not the *cross-partial*

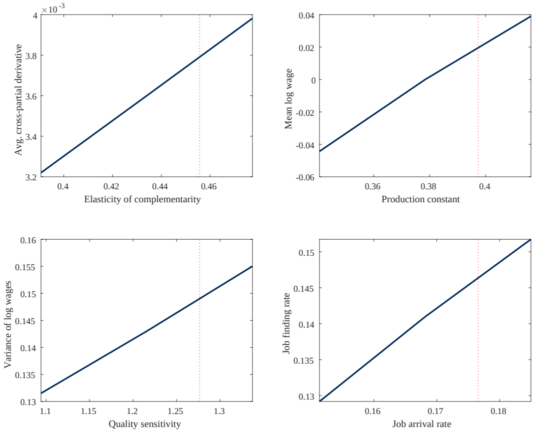
Monte Carlo study

▸ Main



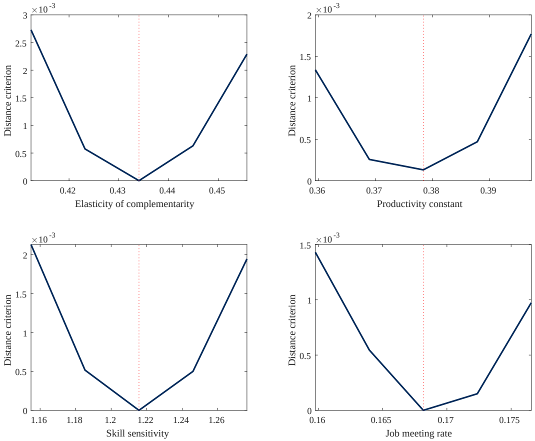
Identification validation exercise 1

Main



Notes. This figure plots the targeted moment against the relevant parameter, holding constant all other parameters.

Identification validation exercise 2



Notes. This figure plots the distance function $\mathcal{G}(\psi_i, \psi^*_{-i})$ when varying a given parameter ψ_i around the estimated value ψ_i^*. The remaining parameters are allowed to adjust to minimize $\mathcal{G}$.

Robustness: reduced-form coworker complementarity

Main

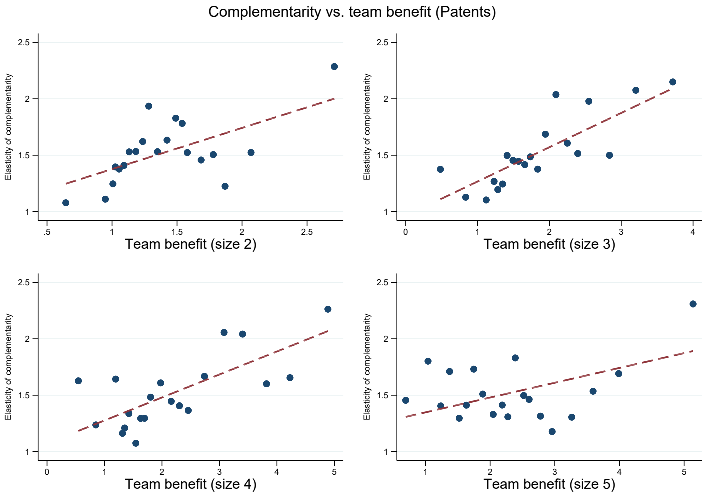
- Types from non-parametric ranking algorithm instead of AKM-based Jump
- Schooling as a non-wage measure of types Jump
- Lagged types Jump
- Small teams Jump
- Movers Jump
- Non-parametric, finite-differences approximation Jump
- Excluding managers Jump
- Log specification Jump

Estimation results (2010-2017)

Parameter	Description	Target	Value	m	$\hat{m}$
χ	Specialization	$\hat{\beta}_c$	**0.67**	0.0058	0.0058
a_0	Production, constant	Avg. wage (norm.)	0.29	1	1
a_1	Production, scale	Var. log wage	1.71	0.241	0.241
b_1	Replacement rate, scale	Replacement rate	0.60	0.63	0.63
λ_u	Meeting hazard	Job finding rate	0.22	0.162	0.162
δ	Separation hazard	Job loss rate	0.008	0.008	0.008
ω	Worker bargaining weight	External	0.50		
$\bar{n}$	Effective team size	External	25		

Validation: Production functions estimated by Ahmadpoor-Jones (2019)

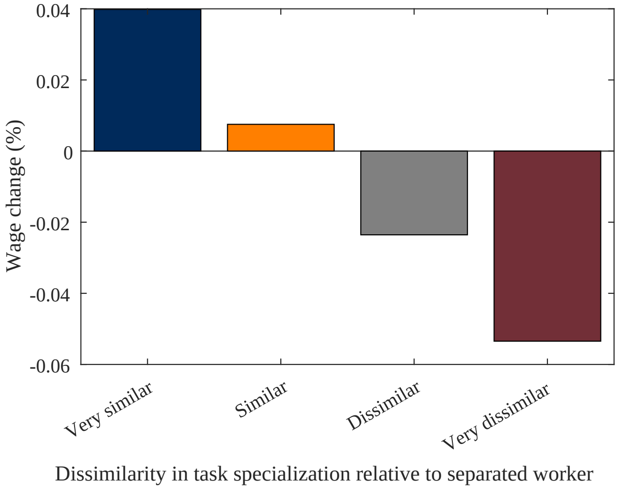
Main



Notes. Source data from Ahmadpoor and Jones (2019, PNAS). Own calculations. Binscatter plot for subsample with complementarity <= 5.

Validation: Structural interpretation of Jaeger-Heining (2022)

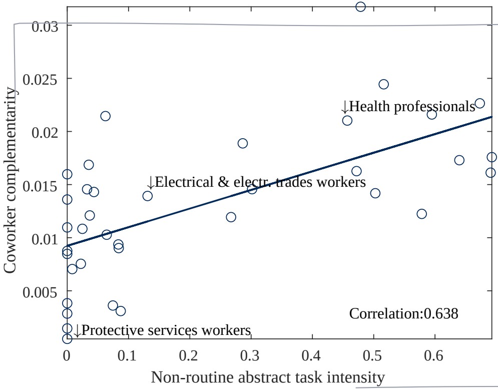
Main



X-sectional validation (occ's): tasks $\Rightarrow$ complementarity

▸ Main

- **$\uparrow$ Non-routine abstract task intensity $\Rightarrow \uparrow$ coworker talent complementarity**



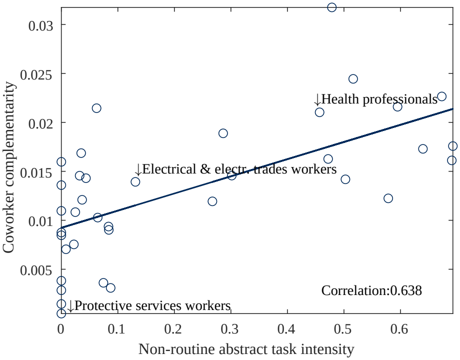
$\hat{\beta}_c$ estimated separately for each occupation

Non-routine abstract task intensity: proxy for χ

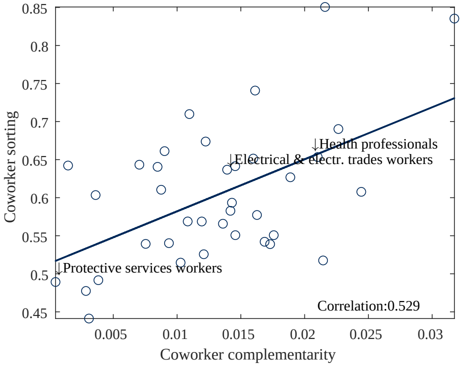
Notes. Quadros de Pessoal microdata. Analysis at ISCO-08-2d level.

X-sectional validation (occ's): tasks ⇒ complementarity ⇒ sorting

- ↑ Non-routine abstract task intensity ⇒ ↑ coworker talent complementarity



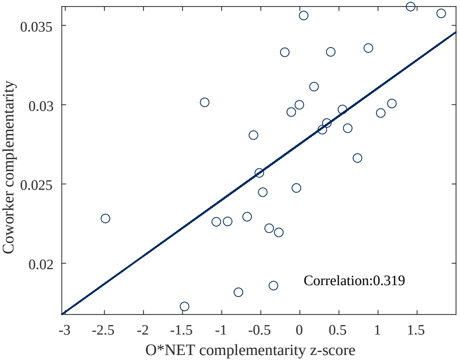
- **↑ Coworker talent complementarity ⇒ ↑ coworker sorting**



Industries: coworker importance ⇒ complementarity ⇒ sorting

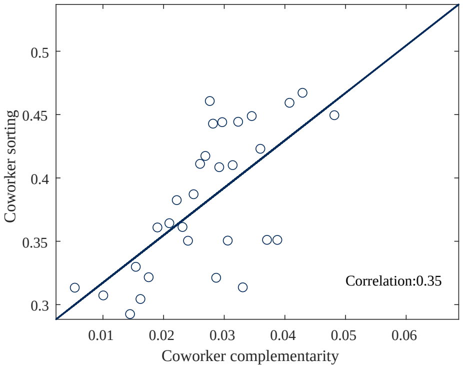
Main

- ↑ **Teamwork** *[Bombardini et al., 2012]* ⇒ ↑ **coworker wage complementarity**



Notes. Horizontal axis measures the industry-level weighted mean score of an occupation-level index constructed from O*NET measuring the importance of: teamwork, impact on coworker output, communication, and contact.

- ↑ **Coworker wage complementarity** ⇒ ↑ **coworker sorting**



Notes. NACE-4-digit industries.

EE transitions in theory and data

Main

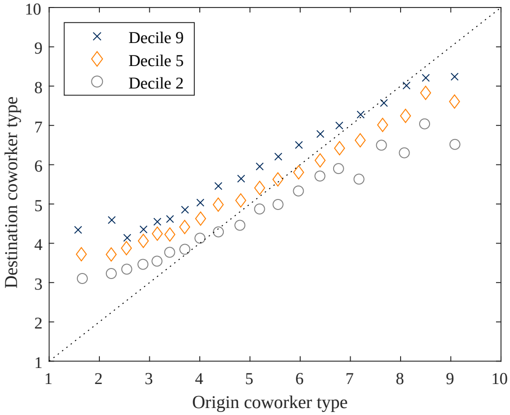
- **Theoretical prediction:** EE transitions move workers in surplus-maximizing direction $\Rightarrow \Delta\hat{x}_{-it} = \hat{x}_{-i,t} - \hat{x}_{-i,t-1}$ should be *positively* correlated with $\hat{x}_i$
    - $h_{2.1}(x, x''|x') = 1$ – worker x in a two-worker firm with coworker x'' would move to an employer that currently has one employee of type x' – if $S(x|x') - S(x|x'') > 0$
- **Empirical analysis**: use SIEED *spell* data to create worker-originMonth-destinationMonth-originJob-destinationJob panel, with information on characteristics of origin and destination job
    - subsample period 2008-2013 (huge panel at monthly frequency)
    - count as “EE” if employer change between two adjacent months
- **Regression analysis:** regress $\Delta\hat{x}_{-it}$, scaled by std. σ_Δ of coworker quality changes, on *own* type and *origin* coworker type

$$\frac{\Delta\hat{x}_{-it}}{\sigma_\Delta} = \beta_0 + \beta_1\hat{x}_i + \beta_2\hat{x}_{-i,t-1} + \epsilon_{it}$$

Empirical coworker sorting changes due to EE moves

Main

- **EE transitions push toward greater coworker sorting:** for given origin, higher *x*-workers move to places with better coworkers than lower-*x* workers do
- Limitation: empirically, EE transitions "move up" low types more than theory predicts
- "**Coworker job ladder**" with both absolute and type-specific dimension?
- **Next:** change in the job ladder *[e.g., Haltiwanger-Spetzler, 2021]*



Evidence that EE *increasingly* reallocate toward PAM: in data & model

	Data		Model	
Change in coworker type	'85-'92	'10-'17	Period-1	Period-2
Own type	**0.0883*****	**0.118*****	**0.214**	**0.270**
	(0.000799)	(0.000918)		
Controls	Year FEs, Origin	Year FEs, Origin	Origin	Origin
N	196,098	282,718	∞	∞
adj. R^2	0.284	0.204		

Table 1: Change in coworker type due to EE moves positively related to own type – increasingly so

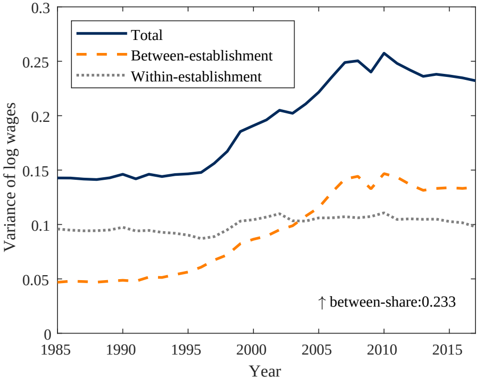
Notes. For the data columns, individual-level clustered standard errors are given in parentheses. Model counterparts are computed simulation-free in population. Dependent variable is scaled throughout by the standard deviation of the change in coworker type.

Fact #1: ↑ between-firm share of wage inequality

Intro Intro

- Large empirical literature: "firming up inequality" *[e.g., Card et al., 2013; Song et al., 2019]*
  - "superstar firms" *[e.g., Autor et al., 2020]*
- **Fact 1: ↑ wage inequality primarily due to between-component**
- Robust pattern

Cross-country Panel est. Wage resid. alternatives
Within-occ Within-ind



Notes. Model-free statistical decomposition, where the "between" component corresponds to the person-weighted variance of est.-level avg. log wage.

Fact #2: talented workers increasingly collaborate

▸ Intro ▸ Main ▸ Var. decomp. ▸ Fact #3

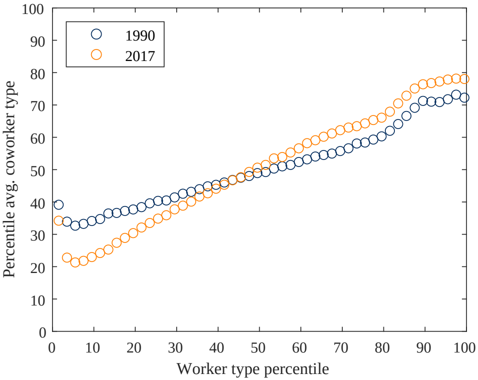
- To what extent do talented workers tend to have talented coworkers?

- **Fact 2: + assortative coworker sorting ↑**
  - ρ_{xx} = corr($\hat{x}_i$, $\hat{x}_{-it}$): 0.43 ('85-'92) ↗ 0.62 ('10-'17)

- Robust pattern

▸ Table ▸ Within-occ. nonlinear

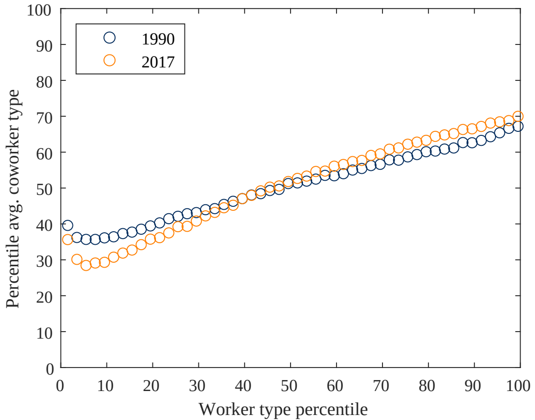
▸ Hakanson et al. (2021)



Evolution of coworker sorting: within-occupation ranking

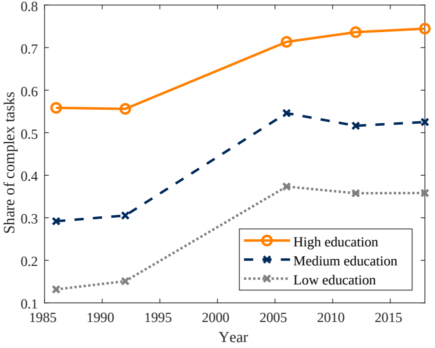
▸ Main

- The most talented within each occupation – the best engineer, PA, economist, manager, ... – tend to work together, and increasingly so



Task composition changes

- **Task complexity** ↑:
  “extensive margin” of χ
  - DE longitudinal task survey ▸ BIBB
  - “complex”: cognitive non-routine (e.g., organizing, researching)

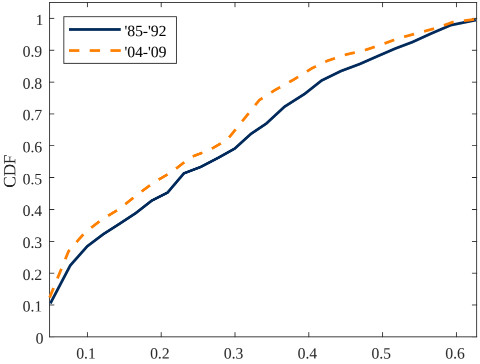


Workers increasingly tend to perform similar tasks across different jobs

▸ Back

- ✓Workers move to jobs with similar tasks, rather than randomly ▸ Comparison
- **Q:** are workers becoming *more* likely to perform similar tasks across jobs, over time?

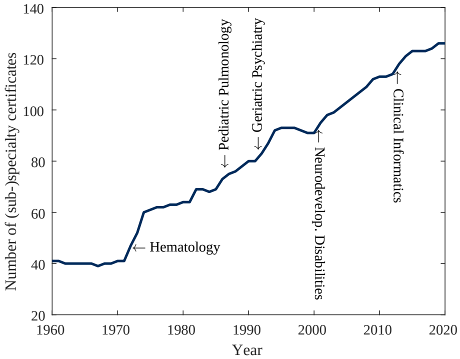
- **Yes:** distribution of moves in ('04-'09) is stochastically dominated by that in ('85-'92)
  - uncond. average: 0.253 → 0.227: 10% decline
- Robust in regression design
  - quantile regressions: ✓at different quantiles



Examples: rising specialization

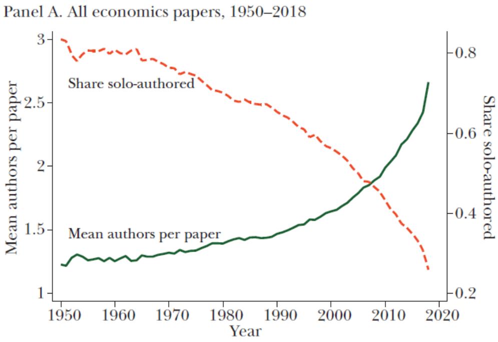
Main

- **Deepening medical specialization**



Notes. Data from American Board of Medical Specialities. For each year, it shows the number of unique speciality or sub-speciality certificates that have been approved and issued at least once by that year and which are are still being issued.

- **Rise of research teams** *[Jones, 2021]*



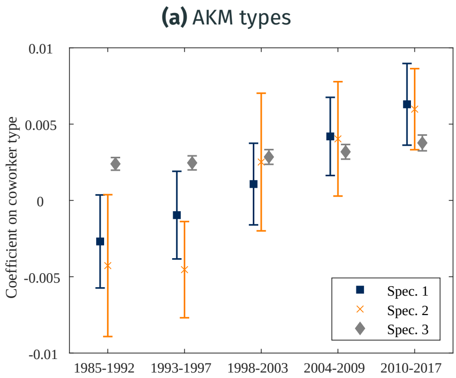
Overview of model robustness checks

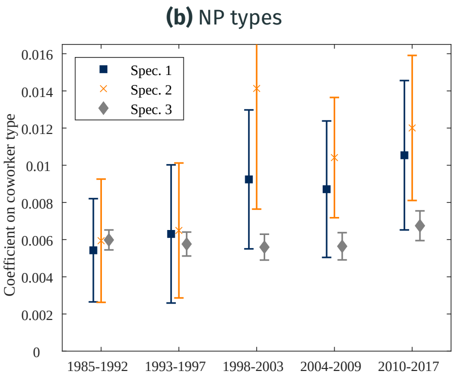
- Declining search frictions Jump
- Within-industry calibration Jump
- Economy-wide vs. within-occupation analysis Jump
- OJS Jump
- Increased talent dispersion Jump

Coworker effects: log wage regression

Back: cross-section Back: time series

$$\ln w_{it} = \beta_0 + \beta_1 \hat{x}_i + \beta_2 \hat{x}_{-it} + \psi_{j(it)} + \nu_{o(i)t} + \xi_{s(i)t} + \epsilon_{it}$$





Notes. Specifications vary by ranking method – within-economy (spec. 1) vs. within-occupation (spec. 2/spec.3) and coworker group definition – establishment-year (spec. 1/spec.2) vs. establishment-occupation-year (spec.3).

Implications for aggregate productivity

▸ Conclusion

- **Production complementarities imply sorting matters for agg productivity, but search frictions induce misallocation**

Implications for aggregate productivity

Conclusion

- **Production complementarities imply sorting matters for agg productivity, but search frictions induce misallocation**
- **Quantify** mismatch costs: compare eqm outcome to productivity under pure talent-PAM and different values of ξ – given param's for 2010s

Implications for aggregate productivity

Conclusion

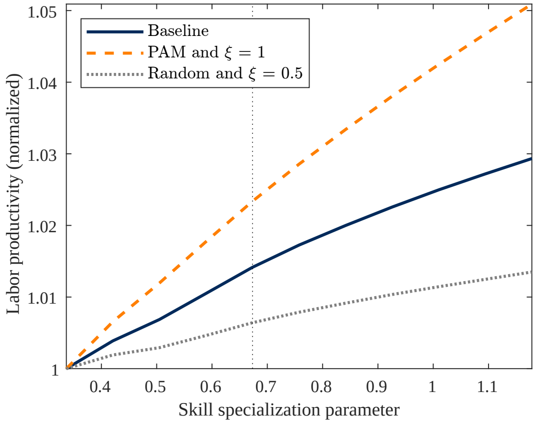
- **Production complementarities imply sorting matters for agg productivity, but search frictions induce misallocation**
- **Quantify** mismatch costs: compare eqm outcome to productivity under pure talent-PAM and different values of ξ – given param's for 2010s

	Labor productivity
Baseline (norm.)	100
PAM + $\xi = 1$	102.6
PAM	101.1
$\xi = 1$	101.4

- Eliminating mismatch would yield **productivity gains** but of **limited magnitude**

Reaping benefits of specialization requires well-functioning labor markets

“The benefits of the division of labor are limited by the functioning of the labor market”



Key takeaways

1. Skill specialization endogenously generates coworker talent complementarities
2. Talent complementarities lead to + assortative coworker matching
3. This fosters ex-post heterogeneity across firms
4. Deepening specialization – leading to intensified complementarities and, hence, sorting – explains a substantial share of $\uparrow$ between-firm wage inequality share
5. Enhanced talent sorting is crucial to realize the productivity gains from deepening skill specialization