# 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 facilitate the division of labor among >1 workers (**"team production"**)

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  - classic question *[e.g., Kremer, 1993; Garicano, 2000]* but literature is theoretical & qualitative

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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
- **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:** the firm as an organized collection of heterogeneous workers

  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 optimally assigned...

  $\Rightarrow$ ...team production is advantageous

  $\Rightarrow$ ...production features **coworker talent complementarities** $\rightarrow$ incentives for **talent sorting** $\rightarrow$ firm-level inequality in productivity & wages

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

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

# Today: theory & one application

▸ Literature

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. **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
   - application 2: search frictions lower agg. productivity due to costly coworker mismatch

# 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]*
  - assign $n$ workers to continuum of tasks $\mathcal{T} = [0, 1]$ that get combined into final good *[cf. Acemoglu-Restrepo, 2018]*
- **Heterogeneous workers**: worker $i$ has task-specific skills $\{z_i(\tau)\}_{\tau \in \mathcal{T}}$

$\Rightarrow$ **Analysis:**

1. **microfound tractable firm-level production function** $\leftarrow$ **focus today**
2. integrate into search environment & analyze who is matched with whom

# Environment: firm-level organization of production

- **Final good:** combine **unit continuum of tasks** $\mathcal{T}$ into output

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

- **Task-level aggregation** for task $\tau$ across $n$ workers

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

- **Worker-level task production:** $i$ produces $\tau$ with skill $z_i(\tau)$, given 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 $f$

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

# Firm's optimization problem

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

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

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

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- **FOCs** imply

opportunity cost of $i$'s time

shadow cost of $\tau$

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

$i$'s skill for $\tau$

# Firm's optimization problem

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

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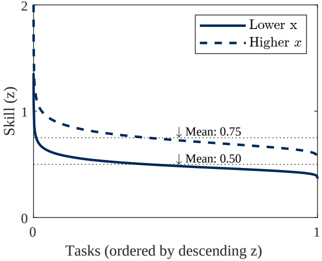
- **FOCs** imply **task assignment by comparative advantage**, complete division of labor

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

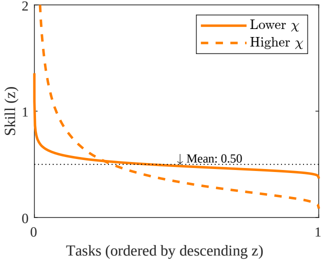
# Parametrized distribution of task-specific skills: "Fréchet-ing things up"

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

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




**(b)** $\chi$: **skill specificity** (1/shape)



# Micro-founded production function

▸ Lemma

**Proposition: Reduced-form production function**

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

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

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

Intuition: task assignment

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

▸ Intuition: task assignment

# Skill specificity implies that productivity is lowered by talent dispersion

**Proposition: Reduced-form production function**

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

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

# Surplus max. determines which teams are formed

▸ Main

- Embed $f(\cdot)$ into search-frictional matching model *[similar to Herkenhoff-Lise-Menzio-Phillips (2024), but with multi-dim. skills and w/o OJS]*
- Joint value of firm with worker $x$, $\Omega_1(x)$, satisfies:

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

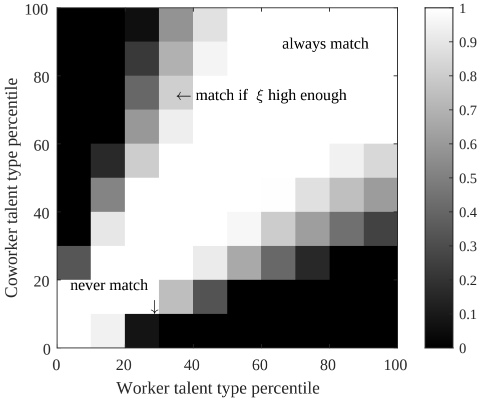
  - $V_u(x)$: value for unemp. worker; $V_{f.0}$: value for vacant firm; $d_u(x)$: density of unemployed workers of type $x$; $u = \int d_u(x)dx$; $\omega$: worker bargaining wgt; $\delta$: sep. rate; $\lambda_{v.u}$: rate of vacancy meeting unmatched worker

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

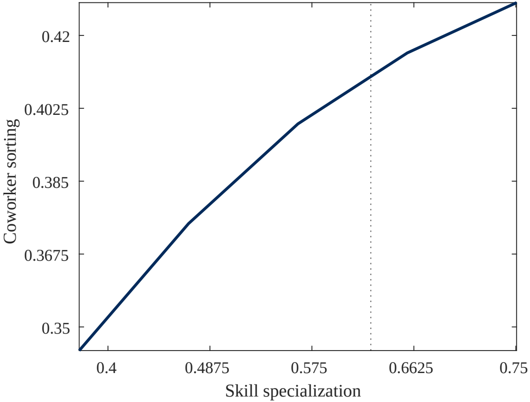
$$S(x|x', \xi)(\rho + 2\delta) = f(x, x', \xi) - \rho\big(V_u(x) + V_u(x') + V_{f.0}\big) + \delta S(x) - (\rho + \delta)S(x')$$

# Equilibrium properties: conditional matching probabilities for given $\chi$

- 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
  - production unit: establishment
- **Approach:**
  - 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 param's from literature (e.g. discount rate $\rho$, bargaining weight $\omega$) or estimated offline (e.g. job separation hazard $\delta$)
  - indirect inference: meeting rate, unemp. flow benefit, production
    - targets: total wage variance, avg. wage level, replacement rate, job finding rate
- **Novel identification strategy:** $\chi$ can be recovered from $\frac{\partial^2 \bar{w}(x|x')}{\partial x \partial x'}$ ▸ Details
- ✓Match untargeted moments like talent sorting ▸ Details
- ✓Extensive validation of core model mechanism ▸ Details

# 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 with DE micro data, endogenously generates large ex-post firm differences

## Next: application(s)

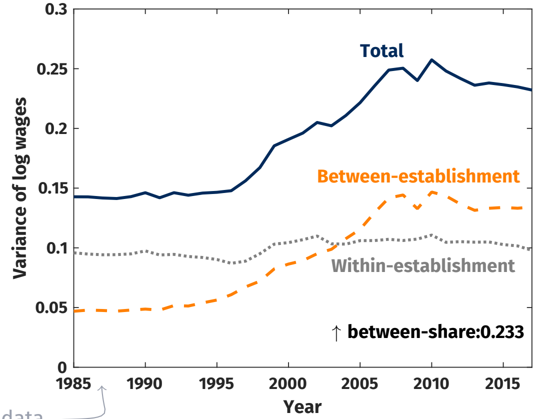
- **Today:** structural explanation for the "firming up of inequality"

# 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]*

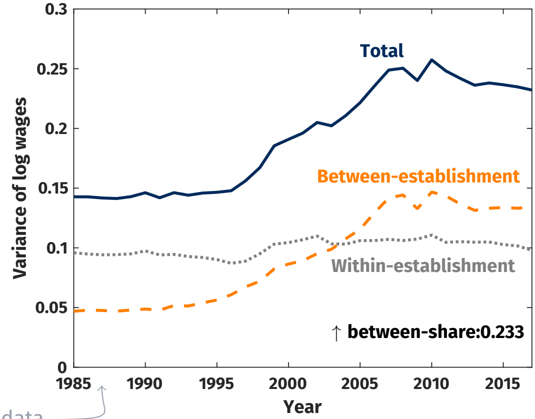



German matched employer-employee data

# Applied question

▸ Details

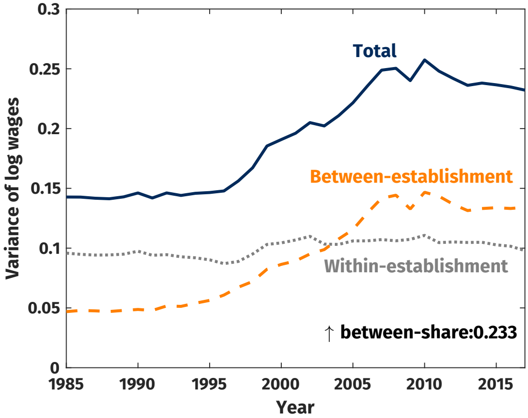
**Applied question:** what is/are the causal driver(s)? implications?




German matched employer-employee data

# Preview of argument

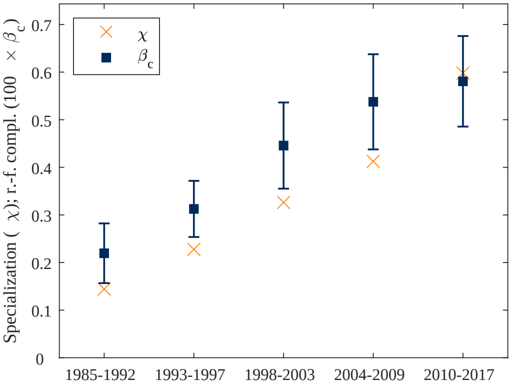
1. The set of tasks any one worker can perform well has narrowed: skill specificity ↑
2. Coworker complementarities ↑
3. Individuals of similar talent increasingly work together
4. This generates greater between-firm wage dispersion



# Estimate model for several periods: skill specialization ↑

▸ Schooling ▸ Peer effect trends

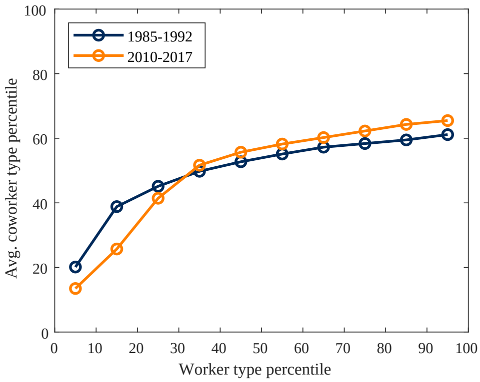
- **Estimate: skill specificity $\chi$ ↑**
- Consistent with independence evidence
  - Grigsby (2024) estimates
  - evidence on Δ task composition: decline in routine ("low-$\chi$") tasks
  - rise of team production in science due to the "burden of knowledge" *[Jones, 2009]* & growing importance of social skills *[Deming, 2017]*



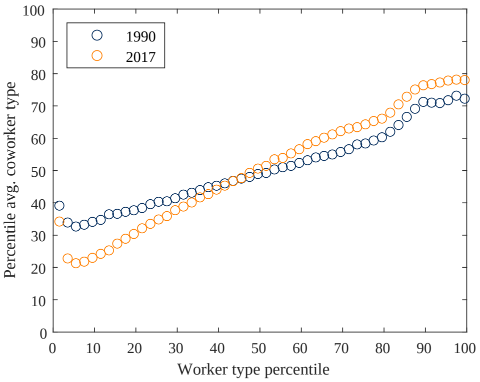
# Talent sorting has intensified: theory & data

Details

**(a)** Theory

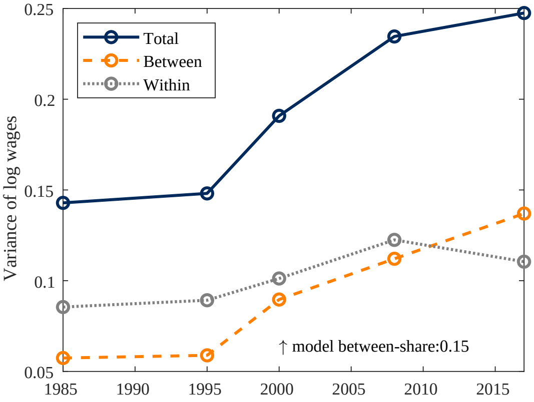



**(b)** Data



# 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)$\to$('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 $\chi \uparrow$?
- **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 $\Delta$**
- **Robustness** exercises: 25-40%

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

# Roadmap & key takeaways

## 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 ↑ between-firm wage inequality share**
5. Enhanced sorting crucial to realize productivity gains from ↑ 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. **theory**: 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

# 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 $\uparrow$ firm-level inequality due to $\uparrow$ 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*

# 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 $\xi$ matter for $Y$
  - $\xi$ is a **match-specific shock** observed by firms + workers before match decision
- **Stationary equilibrium**

▸ Details

# Measurement: a useful identification result

Main | Identification validation | Monte Carlo

- **Challenge:** skill specialization $\chi$ not directly observable
  - literature doesn't offer cardinal measures of specificity *[exception: Grigsby, 2024]*
  - could infer $\chi$ from sorting, but v indirect & liable to misattribution
- **Theory guides measurement:** Proposition 1 ties $\chi$ to $\frac{\partial^2 f(\cdot)}{\partial x \partial x'}$, which given prior measures of $x$ and $x'$ & accounting for selection on $\xi$, 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 $\chi$ (2010-2017)

▸ Robustness ▸ Main

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

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

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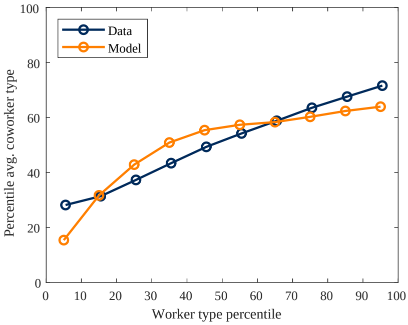
- **Estimation of structural model:** replicate semi-structural regression with model-generated data, infer $\chi$ from matching empirical $\hat{\beta}_c$

# Quantitative properties of estimated model: untargeted moments

▸ B-S adj. method

- ✓**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

Main

- **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

  ✓$\Delta$ 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 ($\xi \uparrow$)

# 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 $\chi$, hence this term co-moves with talent complementarities (and it affects sorting differently)
     - selection effects due to $\xi$: 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

Main

**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 $\chi < \infty$

Low $\chi$

# 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 $\chi$**


$\Rightarrow$ **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 $\xi$ 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 $x'$, $\xi$

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

- 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 $x$

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

- 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

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

# 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.

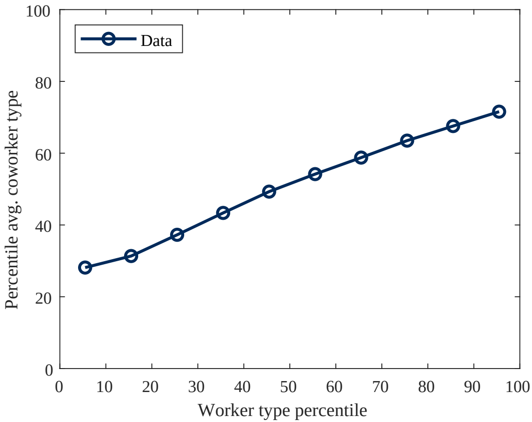
Discussion

# 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 $x'$

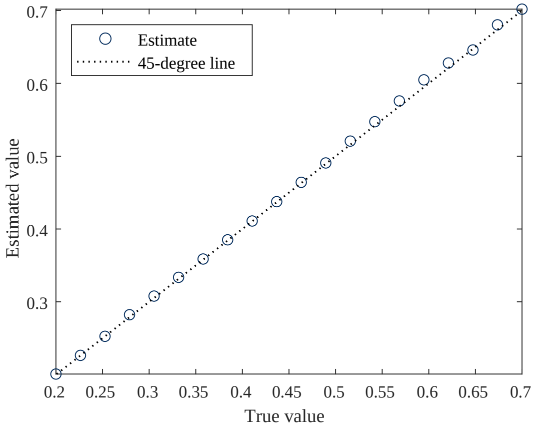
$$w(x|x', \xi) = \omega f(x, x', \xi) + g(x) - h(x')$$

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*

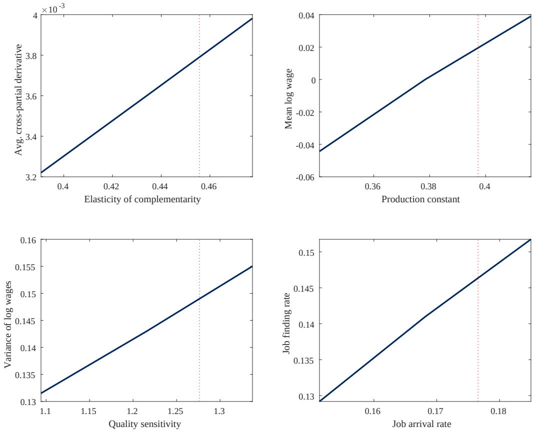
# Monte Carlo study

Main



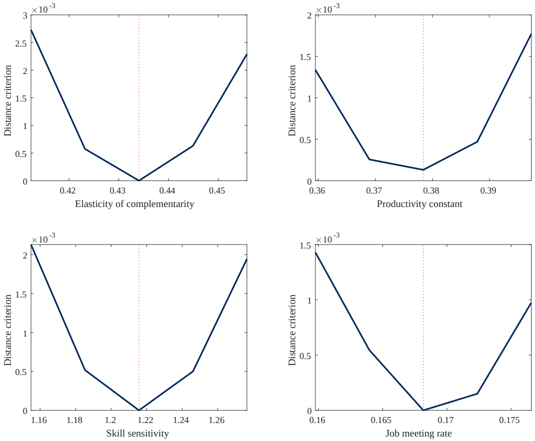
# Identification validation exercise 1

▸ 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 $\psi_i$ around the estimated value $\psi^*_i$. The remaining parameters are allowed to adjust to minimize $\mathcal{G}$.

# Robustness: reduced-form coworker complementarity

Main

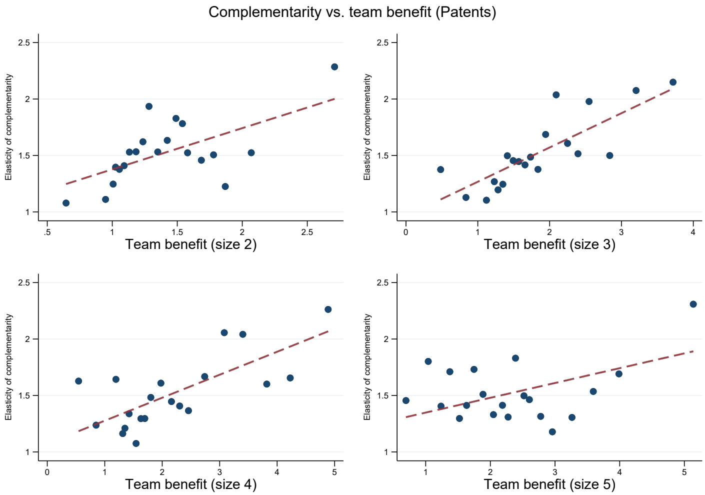
- Types from non-parametric ranking algorithm instead of AKM-based Jump
- Schooling as a non-wage measure of types Jump
- Lagged types Jump
- Small teams Jump
- Movers Jump
- Non-parametric, finite-differences approximation Jump
- Excluding managers Jump
- Log specification Jump

# Estimation results (2010-2017)

| Parameter | Description | Target | Value | $m$ | $\hat{m}$ |
|---|---|---|---|---|---|
| $\chi$ | 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 |
| $\lambda_u$ | Meeting hazard | Job finding rate | 0.22 | 0.162 | 0.162 |
| $\delta$ | Separation hazard | Job loss rate | 0.008 | 0.008 | 0.008 |
| $\omega$ | Worker bargaining weight | External | 0.50 | | |
| $\bar{n}$ | Effective team size | External | 25 | | |

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

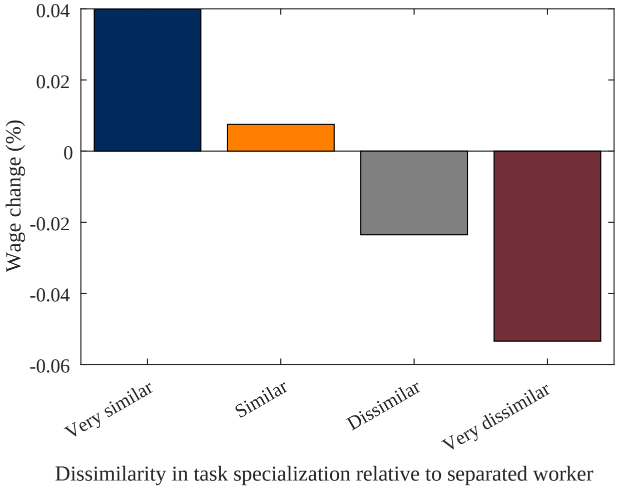
Main




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)

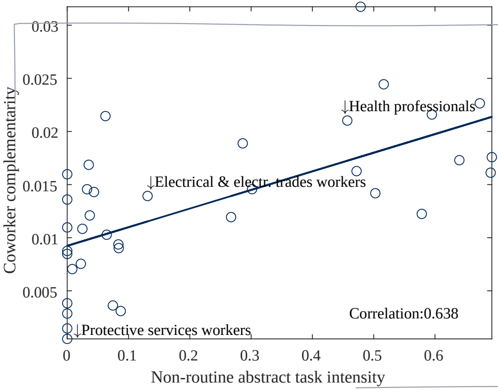
Main



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

▸ Main

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



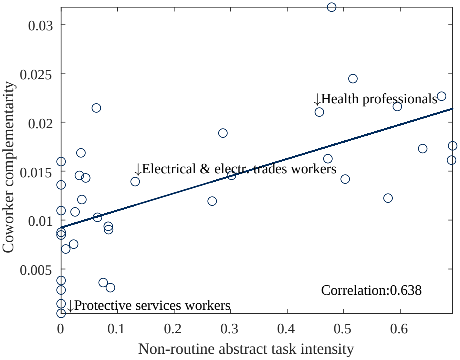

$\hat{\beta}_c$ estimated separately for each occupation

Non-routine abstract task intensity: proxy for $\chi$

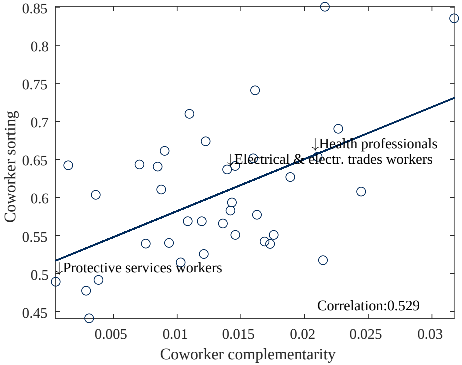
*Notes.* Quadros de Pessoal microdata. Analysis at ISCO-08-2d level.

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

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



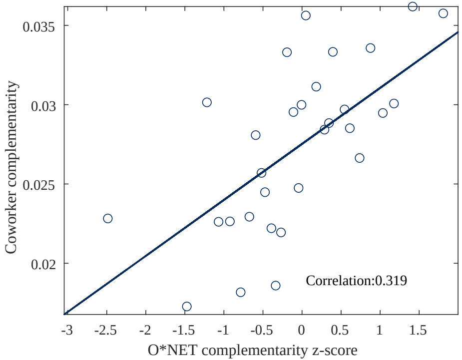

- **↑ Coworker talent complementarity ⇒ ↑ coworker sorting**



# Industries: coworker importance ⇒ complementarity ⇒ sorting

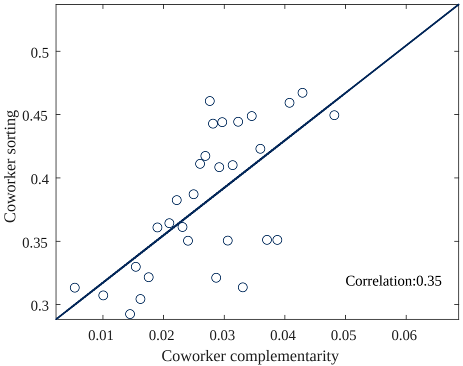
▸ Main

- ↑ **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

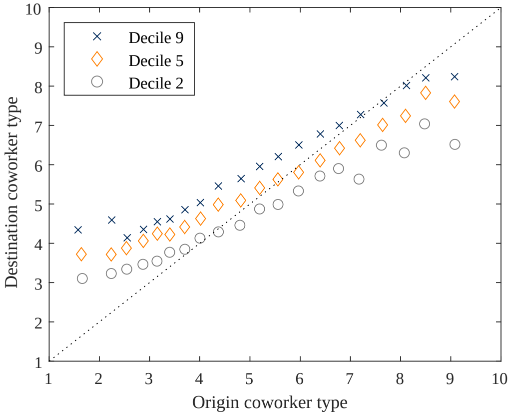
- **Theoretical prediction:** EE transitions move workers in surplus-maximizing direction $\Rightarrow \Delta\hat{x}_{-it} = \hat{x}_{-i,t} - \hat{x}_{-i,t-1}$ should be *positively* correlated with $\hat{x}_i$
  - $h_{2.1}(x, x''|x') = 1$ – worker $x$ in a two-worker firm with coworker $x''$ would move 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. $\sigma_\Delta$ 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 | $\infty$ | $\infty$ |
| adj. $R^2$ | 0.284 | 0.204 | | |

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

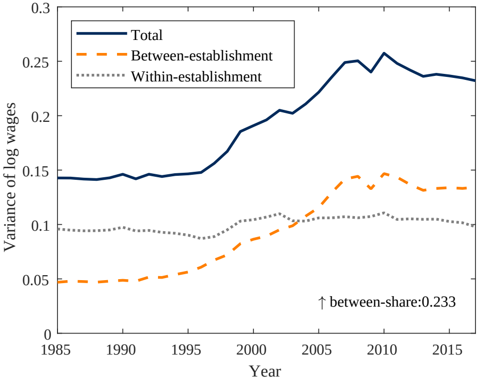
*Notes.* For the data columns, individual-level clustered standard errors are given in parentheses. Model counterparts are computed simulation-free in population. Dependent variable is scaled throughout by the standard deviation of the change in coworker type.

# 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

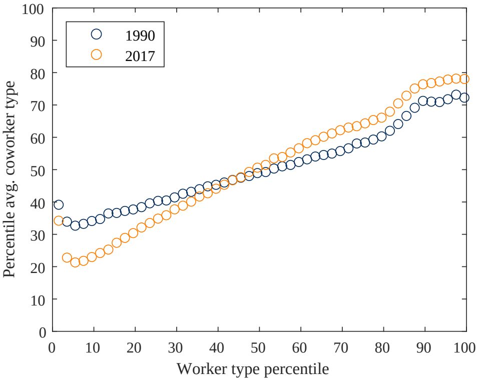
- To what extent do talented workers tend to have talented coworkers?

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

- Robust pattern

▸ Table ▸ Within-occ. nonlinear

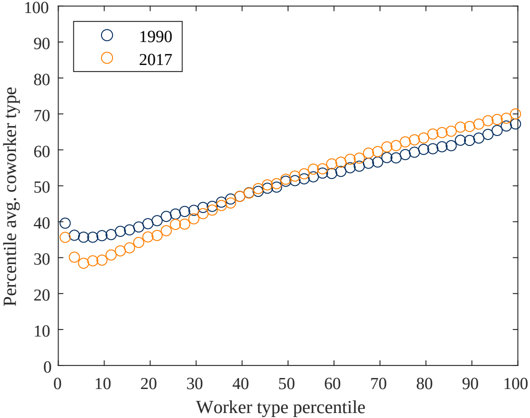
▸ Hakanson et al. (2021)



# Evolution of coworker sorting: within-occupation ranking

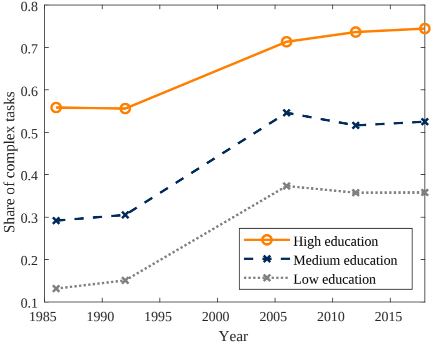
Main

- 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 $\chi$
  - DE longitudinal task survey ▸ BIBB
  - "complex": cognitive non-routine (e.g., organizing, researching)

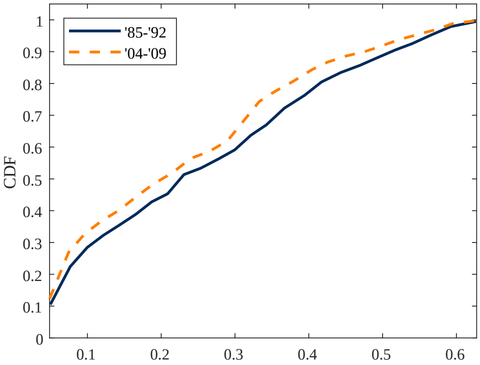


# Workers increasingly tend to perform similar tasks across different jobs

▸ 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?

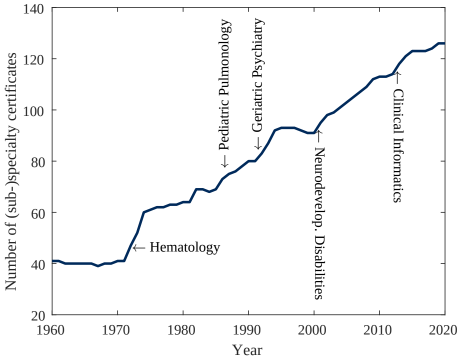
- **Yes:** distribution of moves in ('04-'09) is stochastically dominated by that in ('85-'92)
  - uncond. average: 0.253 → 0.227: 10% decline
- Robust in regression design
  - quantile regressions: ✓at different quantiles



# Examples: rising specialization

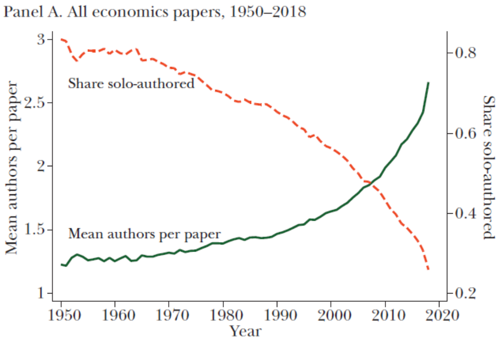
Main

- **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

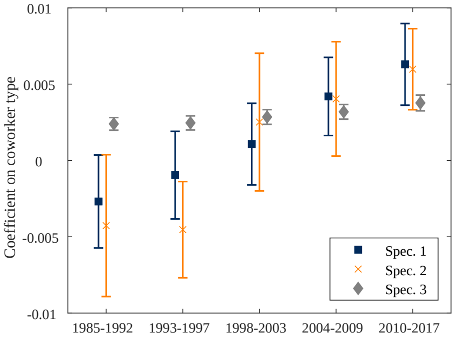
- Declining search frictions ▸ Jump
- Within-industry calibration ▸ Jump
- Economy-wide vs. within-occupation analysis ▸ Jump
- OJS ▸ Jump
- Increased talent dispersion ▸ Jump

# Coworker effects: log wage regression

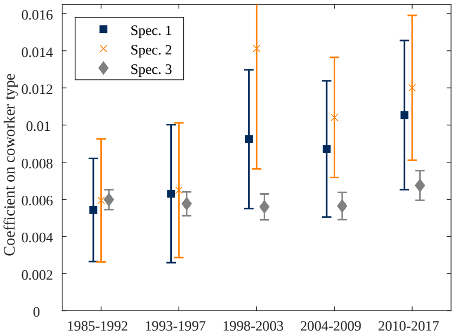
▸ Back: cross-section ▸ Back: time series

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

**(a)** AKM types




**(b)** NP types




*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**

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- **Quantify** mismatch costs: compare eqm outcome to productivity under pure talent-PAM and different values of $\xi$ – given param's for 2010s

# Implications for aggregate productivity

▸ Conclusion

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

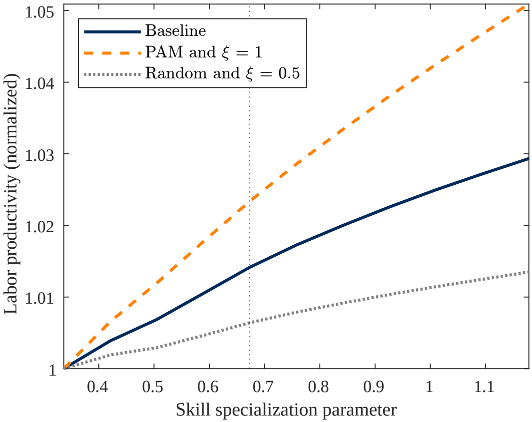
- **Quantify** mismatch costs: compare eqm outcome to productivity under pure talent-PAM and different values of $\xi$ – given param's for 2010s

| | 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. Enhanced talent sorting is crucial to realize the productivity gains from deepening skill specialization