# Superstar Teams: The Micro Origins and Macro Implications of Coworker Complementarities

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# Motivation: important role of firms in the evolution of wage inequality

▸ Motivating evidence

- **Abundant evidence:** high & $\uparrow$ firm-level wage dispersion

  $\Rightarrow$ wage inequality increasingly a *between-firm* phenomenon

  → canonical theories?

  → "firm-oriented policies"?

# Motivation: important role of firms in the evolution of wage inequality

▸ Motivating evidence

- **Abundant evidence:** high & $\uparrow$ firm-level wage dispersion

  $\Rightarrow$ wage inequality increasingly a *between-firm* phenomenon

- **Scarcity of structural models & explanations**

- **Focus:** competition for talent – who works with whom?

  1. How do firms decide on the talent composition of their workforce?
  2. Driver(s) of $\uparrow$ between-firm wage inequality?

# The main idea of the paper in one slide

- **Framework:** the firm as a "team assembly technology"
    1. workers differ in talent (absolute advantage) & specific tasks they are good at ("specialization")
    2. firms coordinate division of labor
    3. workers & firms meet in search-frictional labor market
- **Key mechanism:** specialization ⇒ coworker complementarity ⇒ coworker sorting

  supermodularity in talent
- **Application:** specialization ↑ ⇒ "firming up" of wage inequality

  shifts in nature of work

  *[e.g., Jones, 2009; Acemoglu-Restrepo, 2018]*

# What I do & find

1. **Theory:** characterize formation of teams and task assignment within teams

   $\Rightarrow$ task-based, analytical microfoundation for coworker complementarity

2. **Empirical tools & results:** develop theory-guided method to measure complementarity & implement using matched employer-employee panel data (DE)

   $\Rightarrow$ coworker complementarity $\approx$ doubled since 1990

   $\Rightarrow$ specialization, complementarity, and sorting are positively related in cross-section

3. **Quantification:** estimate model ($\sim$ '90s + '10s) w/ micro evidence, perform counterfactuals

   $\Rightarrow$ $\approx$ 40% of $\uparrow$ between-firm share of wage inequality in DE due to $\uparrow$ complementarity

   $\Rightarrow$ absent underlying labor market reallocation: $\downarrow \approx$ 2.6% productivity from $\uparrow$ mismatch cost

# Relation & contributions to literature

- **Wage inequality:** structural model of ↑ firm-level inequality due to △ nature of work

  **Nature of work:** *[Autor, Levy & Murnane, 2003; Jones, 2009; Lin, 2011; Acemoglu & Autor, 2012; Deming, 2017; Acemoglu & Restrepo, 2018; Alon, 2018; Neffke, 2019; Jones, 2021; Atalay et al., 2021]*

  **Firms:** *[**Card et al., 2013**; Barth et al., 2016; Alvarez et al., 2018; **Bloom et al., 2019**; Aeppli & Wilmers, 2021; Criscuolo et al. 2021; Hakanson et al., 2021; Sorkin & Wallskog, 2021; Kleinman, 2022]*

- **Firm organization:** task-based microfoundation for coworker compl., frictions, quantification

  *[Lucas, 1978; Rosen, 1982; Becker & Murphy, 1992; **Kremer, 1993**; Kremer & Maskin, 1996; **Garicano, 2000**; **Garicano & Rossi-Hansberg, 2006**; **Acemoglu & Restrepo, 2018**; Bloesch et al., 2022; Kohlhepp, 2022; Kuhn et al., 2022; Minni, 2023]*

- **Teams:** explanation for positively assortative team sorting

  *[Akcigit et al., 2018; Ahmadpoor and Jones, 2019; **Jarosch et al., 2021**; Herkenhoff et al., 2022; Pearce, 2022]*

- **Frictional labor market sorting:** endogenize and measure supermodularity

  *[Shimer & Smith, 2000; Postel-Vinay & Robin, 2002; Cahuc et al., 2006; Eeckhout & Kircher, 2011; Hagedorn et al., 2017; de Melo, 2018; Eeckhout & Kircher, 2018; Chade & Eeckhout, 2020; **Herkenhoff et al., 2022**; Lindenlaub & Postel-Vinay, 2023]*

# Motivating empirics

# Data: DE matched employer-employee panel

▸ SIEED

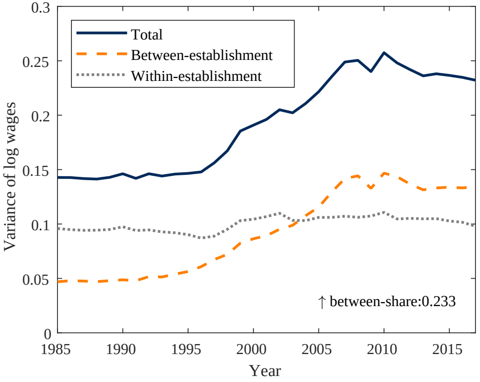
- **Primary data**: SIEED matched-employer employee panel for W Germany, 1985-2017
  - 1.5% sample of establishments + entire biographies of associated workers
  - social security information on employer, daily wage, occupation, demographics
  - work with residualized wages: netting out life-cycle dynamics, tenure and year dummies

# Motivating fact 1: ↑ between-firm share of wage inequality

Back to 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:** ↑ 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.

# Data: DE matched employer-employee panel & FE measure of worker types

▸ Implementation

- **Primary data**: SIEED matched-employer employee panel for W Germany, 1985-2017
- To measure **worker types**, estimate 2-way fixed effect (FE) wage regressions *[Abowd et al., 1999]*
  - implementation: 5 periods; pre-clustering to deal with limited mobility bias *[Bonhomme et al., 2019]*
  - robustness: non-parametric ranking algorithm *[Hagedorn et al., 2017]*

$\Rightarrow$ **Worker "type"** $\hat{x}_i$: percentile rank of worker FE

$\Rightarrow$ **"Representative coworker type"** $\hat{x}_{-it}$: average $\hat{x}_i$ of peers in same establishment-year

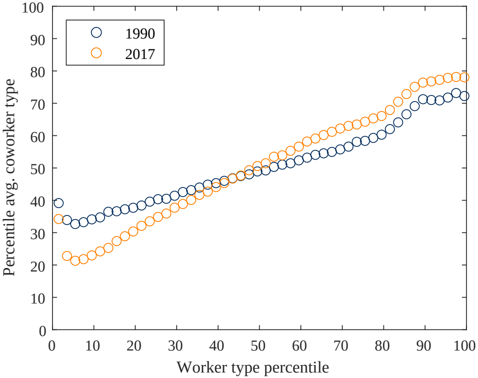
- baseline coworker def.: same establishment-year *[cf. Jarosch et al., 2021]*

# Motivating fact 2: highly capable workers increasingly collaborate among themselves

▸ AKM decomp.

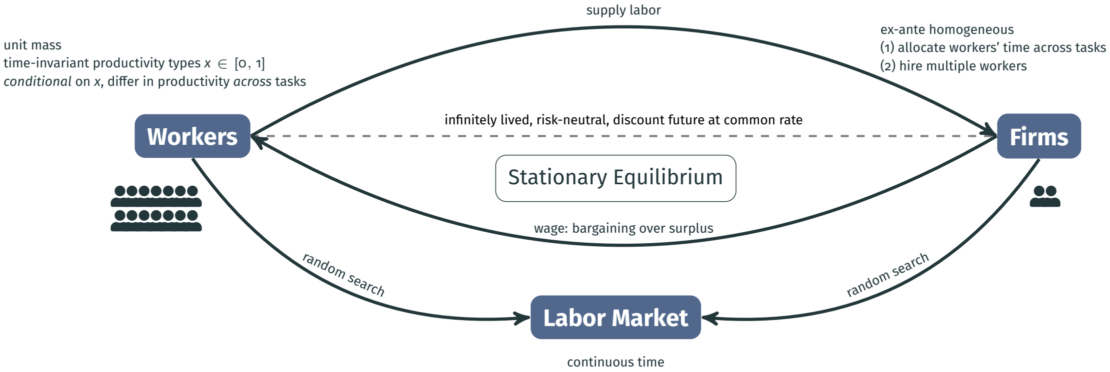
- **Q:** to what extent do "talented workers" tend to be have "talented coworkers"?
- **Fact 2:** + assortative coworker sorting ↑
  - $\rho_{xx}$ = corr($\hat{x}_i$, $\hat{x}_{-it}$): 0.43 ('85-'92) ↗ 0.62 ('10-'17)
- Robust pattern

▸ Table: $\rho_{xx}$ ▸ Within-occ. nonlinear ▸ Mundlak: schooling ▸ Hakanson et al. (2021)



# Theoretical model

# Overview of model environment: firm organization meets labor search




- **Analyze in 2 steps**
  1. task assignment: derive production function for *one* firm, treating workforce as exogenous
  2. competition for talent: equilibrium matching *given* production function

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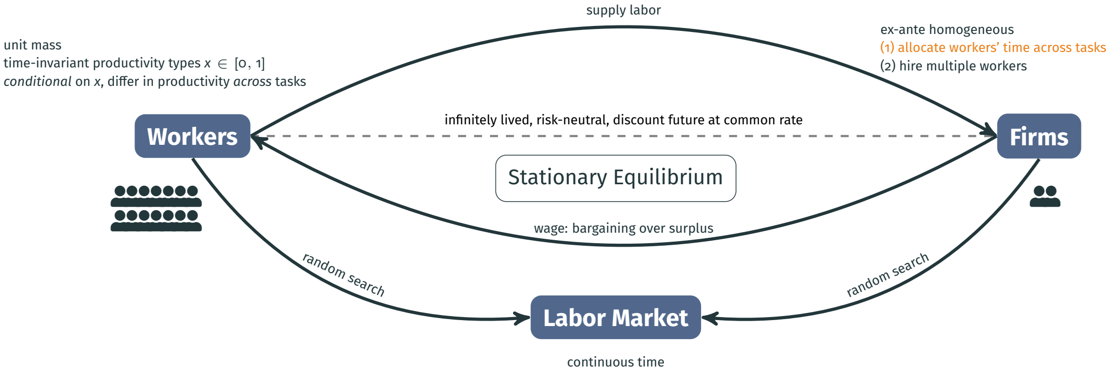


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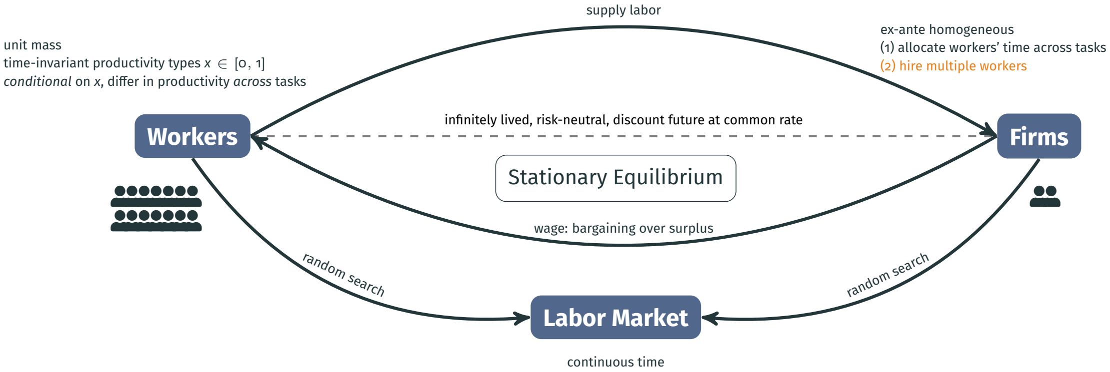



- **Analyze in 2 steps**
  1. task assignment: derive production function for *one* firm, treating workforce as exogenous
  2. competition for talent: equilibrium matching *given* production function

# Step 1: production in a single team of given composition

- Firm with **1 team of $n$ workers** – for now treat $n \in \mathbb{Z}$ & composition as exogenous
- Final output $Y$ is produced from a **unit continuum of tasks** $\tau \in \mathcal{T}$

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

- Each worker can produce any task w/ worker-task specific efficiency $z_i(\tau)$ & s.t. time constraint:

$$y_i(\tau) = z_i(\tau) l_i(\tau) \tag{2}$$

$$1 = \int_{\mathcal{T}} \underbrace{l_i(\tau)}_{\text{time spent on task } \tau \text{ by } i} \, d\tau \tag{3}$$

- **Role of firms**: facilitate **division of labor**

$$q(\tau) = \sum_{i=1}^{n} y_i(\tau) \tag{4}$$

# Organizational optimization problem & tractability

- **Role of firms: coordinate** by solving mini-planner problem ▸ Details

  $\Rightarrow$ Choose $\{q(\tau)\}_{\tau\in\mathcal{T}}$ & $\{\{y_i(\tau)\}_{\tau\in\mathcal{T}}\}_{i=1}^n$ & $\{\{l_i(\tau)\}_{\tau\in\mathcal{T}}\}_{i=1}^n$ to max. $Y$ s.t. (1)-(4)

- To achieve tractability: leverage insight from trade literature *[Eaton-Kortum, 2002]*
  - exploit that Fréchet is max-stable

- **Task-specific efficiencies:** $\{z_i(\tau)\}_{\tau\in\mathcal{T}} \overset{\text{iid}}{\sim}$ **Fréchet** ▸ Illustration

$$G_{Z,i}(z) = \exp\left(-\left(\frac{z}{\iota\, x_i}\right)^{-1/\chi}\right)$$ ; with $\iota$: scaling factor, ignore w.l.o.g.

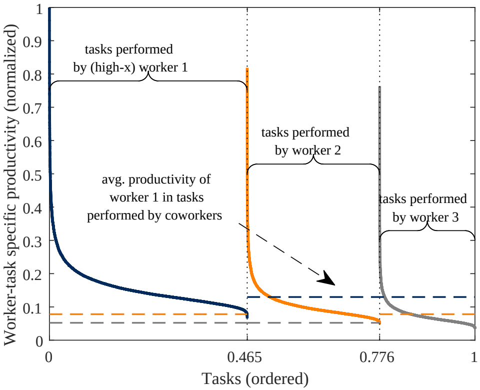
"talent" type $x_i$

**Key parameter** $\chi$ controls importance of task specialization
– dispersion *across* tasks for *given* $i$ & *across* individ's for *given* $\tau$

# Characterization: optimal organization

Extension to communication frictions

- **3 characteristics of optimal organization:**
  1. complete division of labor
     - anyone can perform multiple tasks, no 2 workers perform same task
  2. higher-x workers perform ↑ range of tasks
     - task share of worker $i$: $\left(x_i^{\frac{1}{1+\chi}}\right)\left(\sum_{k=1}^{n}(x_k)^{\frac{1}{1+\chi}}\right)^{-1}$
  3. task assignment by comparative advantage
     - $i$ performs $\tau$ if $i = \arg\min_k \left\{\frac{\lambda_k^L}{z_k(\tau)}\right\}$
- **Integrate over tasks** under optimal assignment




*Notes.* Illustration with $\mathbf{x} = [1, 0.6, 0.4]$ and $\chi = 0.25$. Efficiency draws normalized s.t. $\max_{i,\tau}\{z_i(\tau)\} = 1$. Ordering of tasks and workers on x-axis for illustration only.

# Key result: specialization $\Rightarrow$ coworker complementarity

Taylor approx. Quality & task mismatch

## Proposition: Aggregation result

Team output $Y$ can be written as a function

$$f(x_1, \cdots, x_n) = \underbrace{n^{1+\chi}}_{\text{efficiency gains}} \times \underbrace{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i)^{\frac{1}{1+\chi}}\right)^{1+\chi}}_{\text{team quality}}.$$

1. Standard efficiency gains $\nearrow \chi$
   - no-division-of-labor: $f(x_1, ..., x_n) = n \times (\frac{1}{n}\sum_i^n x_i)$
2. Coworker complementarity $\nearrow \chi$: output more 'vulnerable' to lowest-$x$ member
   - elasticity of complementarity $\gamma = \frac{\chi}{1+\chi}$

# Step 2: production function $\Rightarrow$ equilibrium matching

▸ Equilibrium equations ▸ Extension: $n_{\max} = 3$

- If workers $\neq$ perfect substitutes, composition matters: **hiring** as 2nd aspect of team assembly

  $\Rightarrow$ What are the implications of $\Delta_\chi$ for hiring & wage distribution?

- **Benchmark:** in frictionless labor markets, pure PAM for *any* $\chi > 0$ *[Becker, 1973; Kremer, 1993]*

- **Embed team production fn. into eqm. search model w multi-worker firms** *[Herkenhoff et al., 2022]*
  - tractability restriction to $n_{\max} = 2$, but map to data via "representative coworker"
  - joint worker dist. ($\rightarrow$ sorting) & wage dist. ($\rightarrow \sigma_{\bar{w}}/\sigma_w$) as *structural eqm. objects*
  - equilibrium solved numerically given interaction b/w decisions & distributions

- **Key tradeoff with search frictions**: team match quality vs. cost of searching

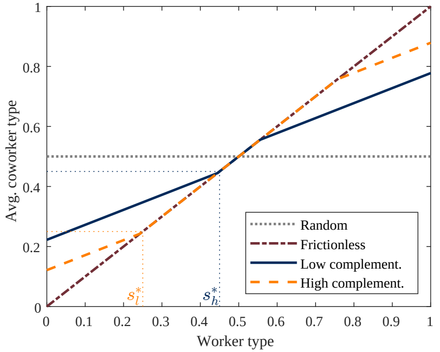
# Intuition: equilibrium outcomes as $\uparrow$ complementarities

▸ Simple model ▸ Lemma ▸ Corollaries

- **Key question:** which type(s) of workers is a firm that already has a worker $x$ willing to hire?

- **Intuition** from analytically tractable, simplified model: firm with type $x$ will hire type $x'$ *if* $|x - x'| < s^*$
  - $s^*$: threshold $\downarrow$ in $\chi$ & $\uparrow$ in search cost

- **Eqm. implications of $\chi \uparrow \Rightarrow s^* \downarrow$**
  1. coworker sorting $\uparrow$
  2. between-firm share of var(wages) $\uparrow$




*Notes.* Analytical results from simplified model. "Kinks" emerge from asymmetries in the matching set at the corners of the type distribution.

# Measuring complementarities

# Overview: empirical analysis of nature of work, complementarities, and sorting

- **Direct evidence for rising worker-task specialization** ($\chi$) ✗ not today

  $\Rightarrow$ Longitudinal survey on task complexity & literature on specialization and teamwork suggest $\uparrow$ worker-task specialization over past 3 decades ▸ Evidence

- **Measurement of coworker complementarities: method & time trends** ✓ focus today

- **Validation of key model mechanisms in the cross-section** ✗ not today

  ✓Across occupations and industries, task complexity predicts coworker complementarity, which in turn is positively associated with coworker sorting ▸ Evidence

# Measuring complementarity in theory: guidance from structural model

▸ Wage equation

- **Aim:** quantify coworker quality complementarity in production, $\frac{\partial^2 f(x,x')}{\partial x \partial x'}$
- **Key:** wage distributions informative about coworker complementarities
- **Theory:** wage level for worker $x$ with coworker $x'$:

$$w(x|x') = \omega \times (f(x,x') - f(x'))$$

$+$ messy function of outside options that depend only on own type

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

  - nb: case w/o OJS; with OJS, $\propto$ not exact, but result qualitatively ✓

# Measuring complementarity in theory: guidance from structural model

- **Aim:** quantify coworker quality complementarity in production, $\frac{\partial^2 f(x,x')}{\partial x \partial x'}$
- **Key:** wage distributions informative about coworker complementarities
- **Theory:**

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

aim to quantify this

- How to approximate $\frac{\partial^2 w(x|x')}{\partial x \partial x'}$
  1. non-parametric FD methods ✗ not today
  2. simple regression approach ✓ focus today

# Measuring complementarity in practice: $\uparrow$ since $\approx$ 1990

FD-approx. Schooling

- **Back to data:** worker & coworker types as before, but using decile bins
  - robustness: types identified with non-parametric ranking algorithm *[Hagedorn et al., 2017]*

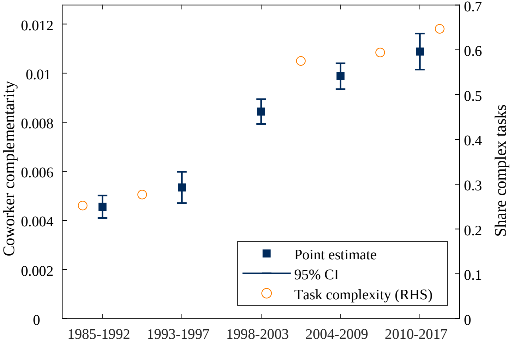
Results

- **Regression:**

coworker complementarity

$$\frac{W_{it}}{\bar{W}_t} = \beta_0 + \beta_1 \hat{x}_i + \beta_2 \hat{x}_{-it} + \beta_c\,(\hat{x}_i \times \hat{x}_{-it})$$
$$+\,\psi_{j(it)} + \nu_{o(i)t} + \xi_{s(i)t} + \epsilon_{it}$$

  - rich set of FEs: employer $\psi_{j(it)}$; occupation-year $\nu_{o(i)t}$; industry-year $\xi_{s(i)t}$
  - wage level on LHS b/c TU & absolute gain matters for sorting



# Quantitative analysis

# Bringing the model to the data: overview of methodology

▸ Details ▸ Identification validation exercises

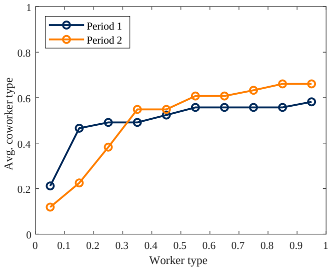
- **Calibrate** the model to the W German economy (2010-2017), at monthly frequency
  1. externally calibrate discount rate, team-benefit, bargaining power
  2. offline estimation of job separation hazard
  3. estimation via indirect inference of meeting rate, unemployment flow benefit, production param's

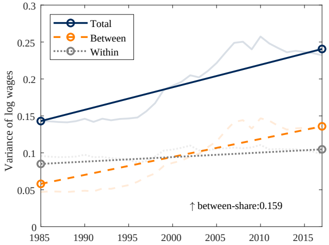
     $\Rightarrow$ production complementarity informed by micro-evidence on wage complementarity ($\hat{\beta}_c$)
     - other targets: wage variance, normalized avg. wage level, official replacement rate, job finding rate
- **Key:** macro moments of interest – coworker sorting, between-firm share – are untargeted!
- **Results:** elasticity of complementarity 0.84; ✓match targeted moments ▸ Jump
- **Validation:** ✓good fit to untargeted coworker sorting patterns in data ▸ Jump

# Re-estimation & validation: model matches empirical wage var decomp.

- **Re-estimate parameters** for '85-'92 (p1)
  - elasticity of complementarity: 0.43 (vs. 0.84 in p2)
  - job arrival & separation rates ↑ from p1 to p2
- Key untargeted moment: wage variance decomp.
- ✓ **Validation:** replicate empirical between-within variance decomp. well
  - 68% of ↑ between-share in data
  - levels adjusted for small-$n$ bias

▸ Details



# Counterfactual: ↑ coworker compl. explains ≈ 40% of empirically observed ↑ in between-share

- **Q:** How much of the ↑ in the between-employer share of wage inequality is due to a strengthening in coworker complementarities (CC)?
- **Counterfactual:** what would the between-employer share have been in 2010s absent ↑ CC
- **A:** ↑ CC accounts for 59% of model-predicted Δ ↔ ≈40% of empirical Δ
  - between-share would have ↑ only by 7ppts instead of 16ppts

| | Δ model | Implied % Δ model due to Δ parameter |
|---|---|---|
| Model 1: baseline | 0.16 | - |
| Cf.: fix period-1 complementarity | 0.065 | 59 |

- **Mechanism:** increased coworker sorting (✓data)

▸ Figure

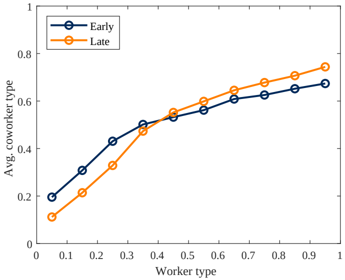
# Overview of extensions, robustness checks, and other implications

- **Extensions and robustness checks**
  - Declining search frictions ▸ Jump
  - Outsourcing & within-occupation analysis ▸ Jump
  - OJS: theoretical & empirical EE patterns ▸ Jump
  - 'Horizontal' complementarity & match-specific shocks ▸ Jump
  - Larger firm size ▸ Jump
- **Implications for overall inequality:** needn't rise due to coworker complementarity ↑ ▸ Jump
- **Implications for aggregate productivity:** reallocation limited rise in mismatch costs ▸ Jump

# Productivity implications of coworker complementarities & sorting

Main

- **Model:** 2-fold effect of ↑ complementarity:
  1. cost of mismatch ↑ for *given* allocation
  2. cost of mismatch ↑ ⇒ labor *re*allocation




*Notes.* Based on model with OJS.

- **Model**: reallocation limited rise in mismatch costs
  - productivity gap to pure PAM: 1.75% (period 1) ↗ 2.05% (period 2)
  - no-reallocation counterfactual: productivity gap in period 2 ↗ 4.65%
- "The benefits of the division of labor are limited by the functioning of the labor market"

Details

# Conclusion

# Conclusions: micro-to-macro model, evidence, and quantification

- **What do firms do?** Form and coordinate teams – matters increasingly as work complexity rises
- **3 takeaways:**
  1. division of labor + worker-task specialization $\Rightarrow$ coworker complementarity
  2. $\Delta$ nature of work $\xRightarrow{\uparrow\text{coworker compl.}}$ "firming up" wage inequality via superstar teams
  3. increased sorting helped keep TFP close to potential $\Rightarrow$ matters for agg. productivity
- **Some follow-up research directions:**
  - large-firm dynamics with two-sided heterogeneity
  - sources of firm heterogeneity: org. quality ($\sim$ assignment & hiring) $\uparrow$ important for output as $\chi \uparrow$
  - specialization & collaboration in science: complementarities as challenge for impactful innovation

Thank You & Feedback Very Welcome!

# Extra Slides

# Data sources: short description of main datasets

Main Imputation procedure

- Germany: SIEED linked employer-employee dataset
  - *establishment* and individual data generated in administrative processes
  - built up from a 1.5% sample of all establishments, but includes comprehensive employment biographies of individuals employed at these establishments
  - worker info includes: (real) **daily wage**, occupation and education; establishment info not yet utilized
  - top coding (affects >50% of university-educated men in regular full-time employment) $\rightarrow$ adopt standard imputation methods (Dustmann et al., 2009; CHK, 2013)
  - Much larger sampling frame than more familiar LIAB
- Portugal: Quadros de Pessoal & Relatório Único, 1986-2017
  - $\approx$ universe of private sector firms and workers employed by them
  - annual panel
  - worker information includes: detailed earnings measures (base wage, regular benefits, irregular benefits (performance-pay, bonuses, etc.), overtime pay); no top-coding; also includes information on hours worked within the month (regular and overtime) $\Rightarrow$ (real) total hourly wage
  - firm information includes income and balance sheet data from 2004 onward

# Sample restrictions

- Data cleaning $\Rightarrow$ broadly harmonized samples
- Main restrictions
    - age 20-60
    - full-time employed
    - drop agriculture, public sector, utilities industries
    - firms (and their employees) with at least 10 employees
- DE: West Germany
- PRT: at least. official minimum wage

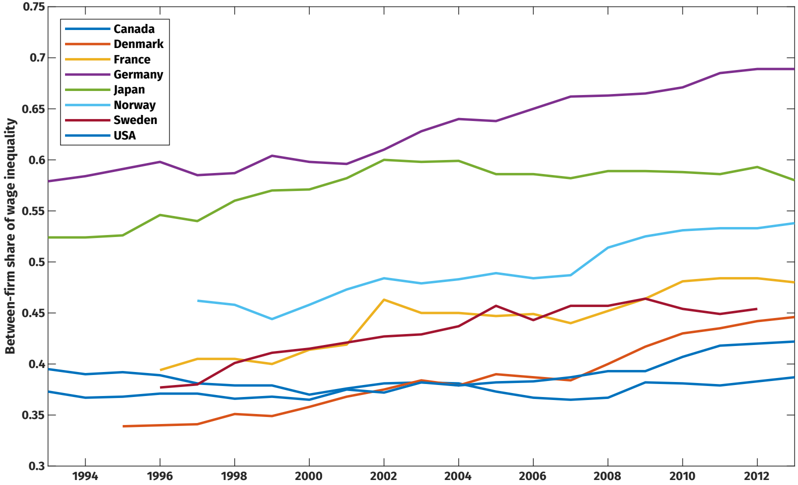
# Wage Imputation procedure

- Follow imputation approach in CHK2013, building on Gartner et al. (2005) and Dustmann et al. (2009)
  1. fit a series of Tobit models to log daily wages
  2. then impute an uncensored value for each censored observation using the estimated parameters of these models and a random draw from the associated (left-censored) distribution

- Currently I fit 16 Tobit models (4 age groups, 4 education groups) *after* having restricted the sample (to include West German men only, in particular) and I follow CHK in the specification of controls by including not only age, firm size, firm size squared and a dummy for firms with more than ten employees, but also the mean log wage of co-workers and fraction of co-workers with censored wages. Finally, following Dauth & Eppselheimer (2020) I limit imputed wages at 10 $\times$ 99th percentile.

# Firming up inequality: cross-country evidence

Main

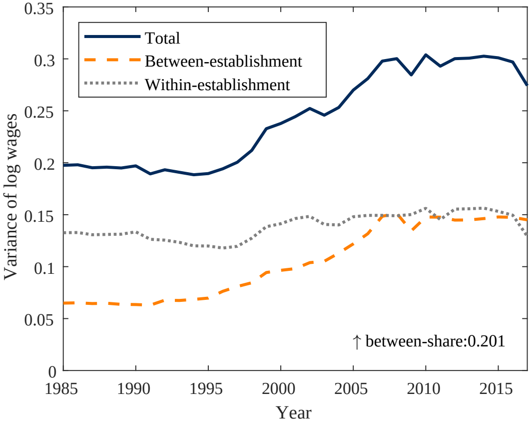



*Notes.* Data from Tomaskovic-Devey et al. (2020). Measures of earnings differ across countries and, for Germany, between T-D et al. and my study based on the SIEED.

# Between-/within-employer wage var decomp. - panel establishments

Main

- Instead of considering *all* employers, restrict attention to “panel establishments”

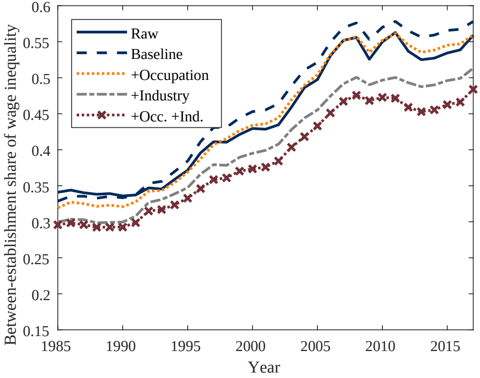



*Notes.* Based on residualized wages, i.e., controlling for age polynomial, tenure polynomial, and year dummies.

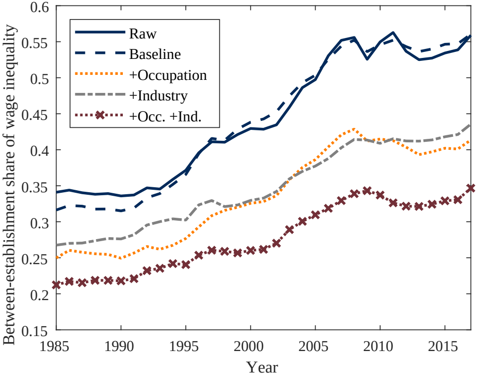
# Between-/within-employer wage var. decomp. - alternative wage residuals

Main

- "With worker FEs": regress $\ln \tilde{w}_{it} = \alpha_i + X_{it}'\hat{\beta} + \epsilon_{it}$, and construct residuals $\ln w_{it} = \ln(\tilde{w}_{it} - X_{it}'\hat{\beta})$.
- "Without worker FEs": regress $\ln \tilde{w}_{it} = \alpha_0 + X_{it}'\hat{\beta} + \epsilon_{it}$, and consider residuals $\epsilon_{it}$




**(a)** With worker FEs

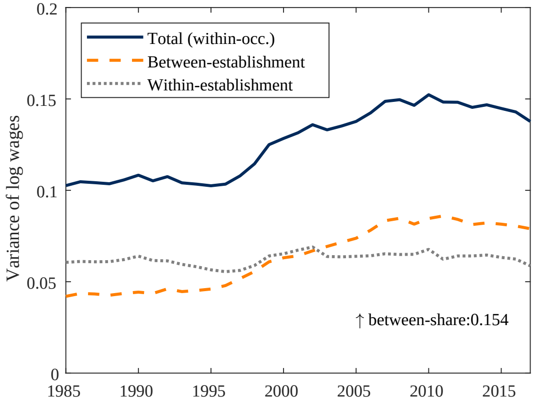



**(b)** Without worker FEs

# Between-/within-employer wage var. decomp. - within-Occupation

Main

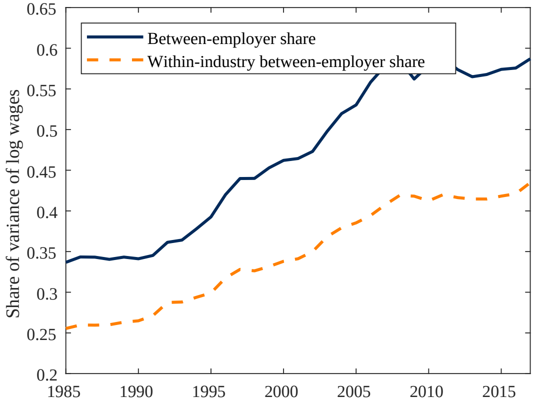
- Decomposition: between-occupation, within-occupation-within-employer, within-occupation-between employer ⇒ within-occupation-between employer/(within-occupation-within-employer + within-occupation-between-employer)



# Between-/within-employer wage var. decomp. - within-Industry

Main

- Decomposition: between-industry ($\rightarrow$ between-employer), within-industry-within-employer, within-industry-between-employer $\Rightarrow$ compare “total” between-employer share (baseline) & within-industry between-employer share



# Evolution of coworker sorting: correlation coefficient

Main

- Estimate $\hat{x}_i$ and $\hat{x}_{-it}$ separately for 5 periods, compute coworker sorting correlation coefficient
- In addition to the baseline, also consider ranking within-occupation

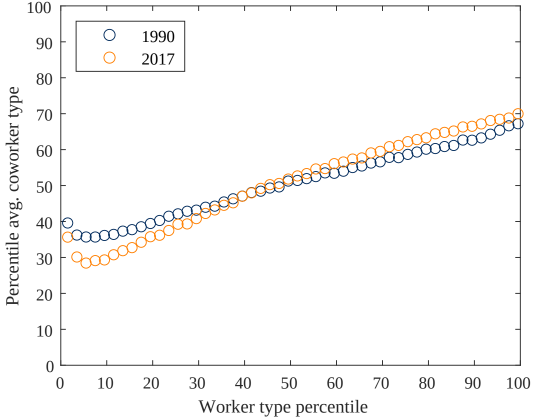
| | Sorting | |
|---|---|---|
| Period | Spec. 1 | Spec. 2 |
| 1985-1992 | 0.427 | 0.423 |
| 1993-1997 | 0.458 | 0.443 |
| 1998-2003 | 0.495 | 0.452 |
| 2004-2009 | 0.547 | 0.470 |
| 2010-2017 | 0.617 | 0.519 |

*Notes.* The column labelled "Sorting" indicates the correlation between a worker's estimated type and that of their average coworker, separately for five sample periods. Under "Spec. 1" workers are ranked economy wide (baseline), while under "Spec. 2" they are ranked within occupations.

# Evolution of coworker sorting: within-occupation ranking binscatter

Main

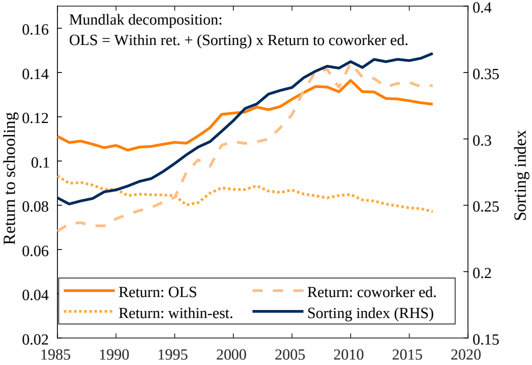
- Reproduce non-linear sorting plot, but now $\hat{x}_i$ is based on *within-occupation* ranking



# Mundlak decomposition of return to schooling

Main

- Years of schooling as non-wage measure of worker skill
- Here show sorting pattern as part of Mundlak decomposition of return to schooling



# AKM-based wage variance decomposition

Main

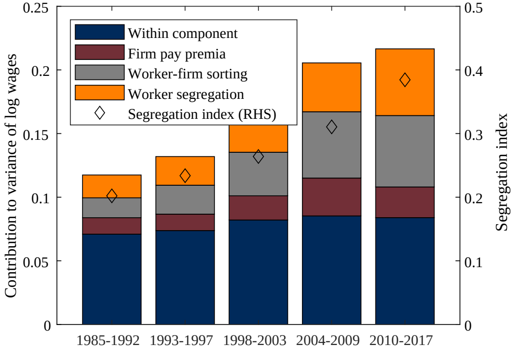
- AKM-based var. decomp. *[Song et al., 2019]*

$$\mathrm{Var}(w_{it}) = \underbrace{\mathrm{Var}(\alpha_i - \bar{\alpha}_{j(i,t)}) + \mathrm{Var}(\epsilon_{i,j})}_{\text{within-component}}$$

$$+ \underbrace{\mathrm{Var}(\psi_{j(it)}) + 2\mathrm{Cov}(\bar{\alpha}_{j(it)}, \psi_{j(it)}) + \mathrm{Var}(\bar{\alpha}_{j(it)})}_{\text{between-component}}$$

  - $\mathrm{Var}(\psi_j)$: firm-specific pay premia
  - $\mathrm{Cov}(\bar{\alpha}_j, \psi_j)$: (worker-firm) sorting
  - $\mathrm{Var}(\bar{\alpha}_j)$: (worker-worker) segregation

- Segregation index *[Kremer-Maskin, 1996]*: $\mathrm{Var}(\bar{\alpha}_{j(it)})/\mathrm{Var}(\alpha_i)$



# Complementarities in Germany: non-parametric approximation

▸ Regression evidence

- Baseline measure suggest $\approx 2\times\uparrow$ in the magnitude of the coefficient
- Alternative: FD-approximation to avg. cross-partial derivative, $\widehat{\frac{\partial w^2(x,x')}{\partial x \partial x'}}$
    - closer to structural model

| | Sorting | | Complementarities | |
|---|---|---|---|---|
| Period | Spec. 1 | Spec. 2 | Spec. 1 | Spec. 2 |
| 1985-1992 | 0.47 | 0.38 | 0.001 | 0.000 |
| 1993-1997 | 0.56 | 0.46 | 0.002 | 0.001 |
| 1998-2003 | 0.60 | 0.48 | 0.004 | 0.002 |
| 2004-2009 | 0.65 | 0.50 | 0.005 | 0.002 |
| 2010-2017 | 0.68 | 0.51 | 0.005 | 0.004 |

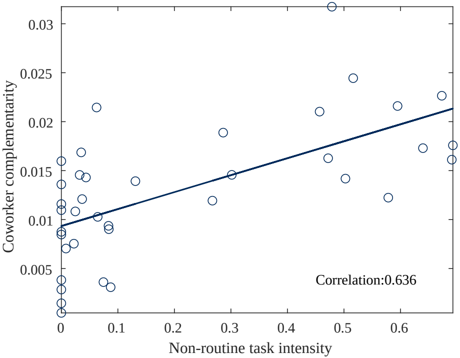
# Cross-sectional analyses: empirical validation tests

Overview of evidence

- **Q: do model-implied relationships also hold in *cross-section*?**
  1. **Prediction #1:** $\uparrow \chi \Rightarrow \uparrow$ coworker complementarity
  2. **Prediction #2:** $\uparrow$ coworker complementarity $\Rightarrow \uparrow$ + assortative matching
- **Test:** variation across occupations & industries
  - caveats: non-causal; treat occupation/industry cells as separate realizations of the model
- **Implementation:** supplement SIEED with rich Portuguese micro data
  - matched employer-employee data for universe of private-sector actors + income statement
  - data processing: analogous to Germany; 2010-2017

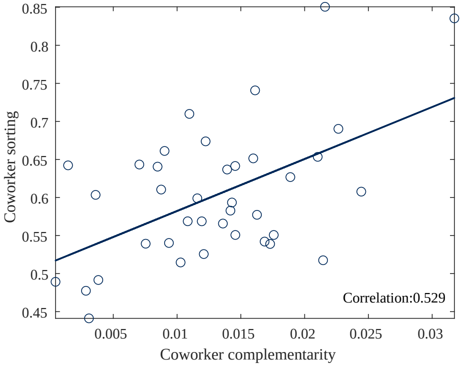
# Occupations: task complexity ⇒ complementarity ⇒ sorting

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




*Notes.* Horizontal axis indicates occupation's reliance on non-routine, abstract (NRA) tasks *[Mihaylov and Tidens, 2019]*. Unweighted ISCO-08 2-digit occupations.

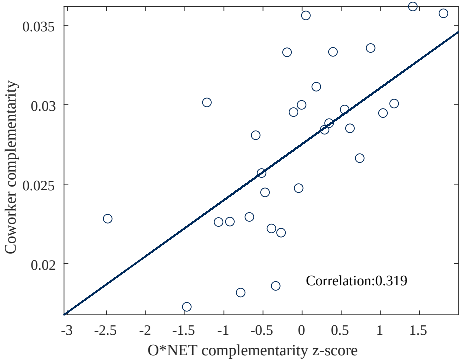
- ↑ Coworker wage complementarity
  ⇒ ↑ coworker sorting




*Notes.* Unweighted ISCO-08 2-digit occupations.

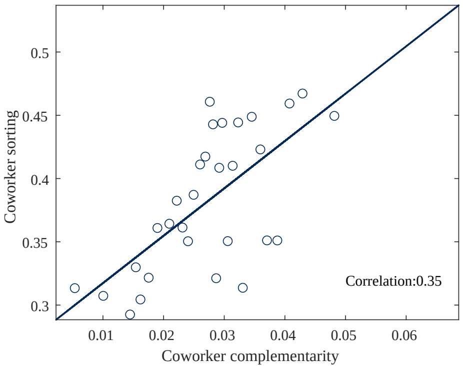
# Industries: team importance ⇒ complementarity ⇒ sorting

- ↑ Team importance *[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: team-work, impact on coworker output, communication, and contact.

- ↑ Coworker wage complementarity ⇒ ↑ coworker sorting

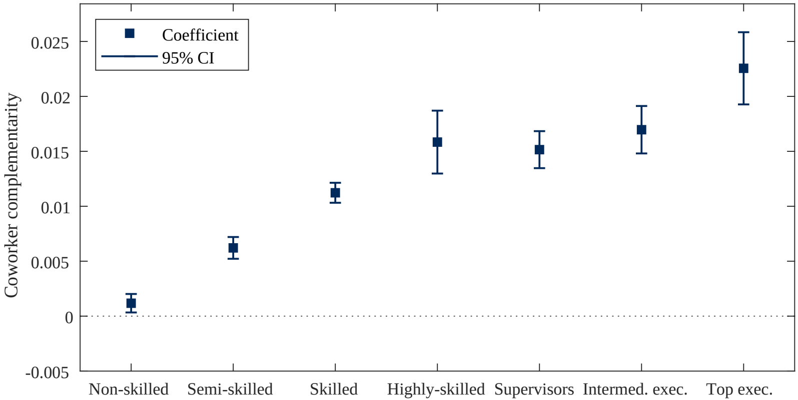



*Notes.* NACE-4-digit industries.

# Result: complexity ⇒ complementarities (hierarchical layers)

▸ Main ▸ Approx. for DE

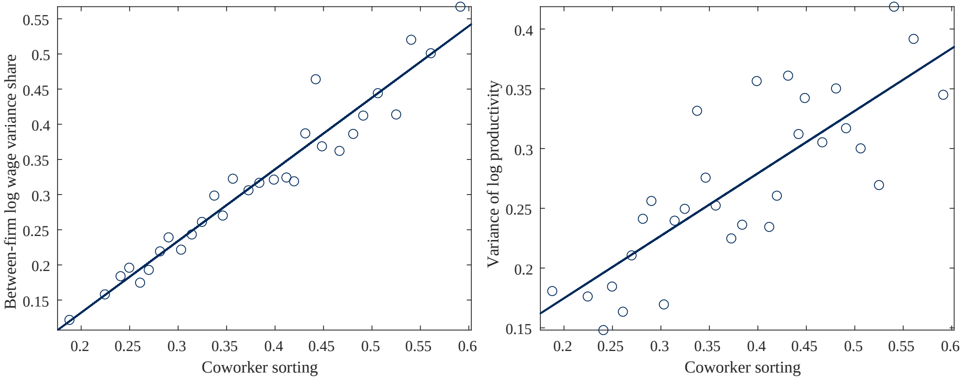
⇒ Coworker wage complementarities are (weakly) monotonically ↑ in the layer of a firm's hierarchy



# Industries: coworker sorting ⇒ between-firm inequality

Main

⇒ Measures of between-firm inequality in productivity and pay are increasing in the degree of coworker sorting at the industry-level.




**(a)** Between-firm share of wage dispersion **(b)** Productivity dispersion

# Results based on non-parametric ranking algorithm

Main

- Instead of ranking workers based on AKM worker FEs, use non-parametric ranking algorithm *[Hagedorn et al., 2017]*

| | Sorting | | Complementarities | |
|---|---|---|---|---|
| Period | Spec. 1 | Spec. 2 | Spec. 1 | Spec. 2 |
| 1985-1992 | 0.47 | 0.38 | 0.001 | 0.000 |
| 1993-1997 | 0.56 | 0.46 | 0.002 | 0.001 |
| 1998-2003 | 0.60 | 0.48 | 0.004 | 0.002 |
| 2004-2009 | 0.65 | 0.50 | 0.005 | 0.002 |
| 2010-2017 | 0.68 | 0.51 | 0.005 | 0.004 |

*Notes.* This table indicates, under the column “Sorting” the correlation between a worker’s estimated type and that of their average coworker, separately for five sample periods. The column “Complementarities” indicates the point estimate of the regression coefficient $\beta_c$. Under “Specification 1” workers are ranked economy wide, while under “Specification 2” they are ranked within two-digit occupations. Worker rankings are based on the non-parametric method.

# Cluster-based methodology: motivation

▸ Main

- **Standard AKM approach** estimates large number of firm-specific parameters, identified solely off worker mobility $\Rightarrow$ incidental parameters problem $\approx$ limited mobility bias $\Rightarrow$ *var*$(\psi) \uparrow$ & *cov*$(\psi, \alpha) \downarrow$
- **Bonhomme, Lamadon, and Malresa (2019**, Ecma): two-step grouped fixed-effects estimation
  1. Recover firm classes using k-means clustering, based on the similarity of their earnings distribution
  2. Estimate parameters of correlated random effects model by maximum likelihood, conditional on the estimated firm classes
- **Potential advantages**
  1. mitigate limited mobility bias
     – sufficient number of workers who move between any given cluster to identify the cluster fixed effects
  2. allows relaxing sample restrictions ($n$-connected set restriction when estimating group-specific firm/cluster FEs)
  3. *if* also take step 2, can estimate match complementarities between firms and workers (given estimated worker types from step 2)
- Limitation: loss of information by imposing homogeneity within clusters

# Cluster-based methodology: implementation

- Obtain clusters by solving **weighted k-means problem**

$$\min_{k(1),\ldots,k(J),H_1,\ldots,H_K} \sum_{j=1}^{J} n_j \int \left(\hat{F}_j(w) - H_{K_j}(w)\right)^2 d\mu(w),$$

  - $k(1), \ldots, k(J)$: partition of firms into $K$ known classes;
  - $\hat{F}_j$: empirical cdf of log-wages in firm $j$
  - $n_j$: average number of workers of firm $j$ over sample period
  - $H_1, \ldots., H_K$: generic cdf's

- Implementation here:
  - baseline value of $K = 10$, as in BLM, but experiment with $K = 20$ and $K = 100$
  - use firms' cdf's over entire sample period on a grid of 20 percentiles
- "Half-BLM": take step (1), impute class to each worker-year observation, then estimate two-way fixed effect wage regression using cluster effects instead of firm effects:

$$w_{it} = \alpha_i + \sum_{k=1}^{K} \psi_k \mathbb{1}(J(i,t) = k) + \beta X'_{it} + r_{it}$$

# Complementarity estimates using years of schooling

Main

| | Dependent variable: wage | | | | |
|---|---|---|---|---|---|
| | '85-'92 | '93-'97 | '98-'03 | '04-'09 | '10-'17 |
| Own schooling | -0.0382 | -0.0359 | -0.0871 | -0.1099 | -0.1428 |
| | 0.0113 | 0.0102 | 0.0109 | 0.0100 | 0.0116 |
| Coworker schooling | -0.0737 | -0.0604 | -0.1203 | -0.1384 | -0.1726 |
| | 0.0114 | 0.0111 | 0.0107 | 0.0102 | 0.0114 |
| Interaction | 0.0063 | 0.0060 | 0.0099 | 0.0112 | 0.0129 |
| | 0.0008 | 0.0007 | 0.0008 | 0.0007 | 0.0009 |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Obs. (100,000s) | 3,613 | 2,508 | 2,694 | 3,836 | 4,376 |
| $R^2$ | 0.5033 | 0.5451 | 0.5746 | 0.6330 | 0.6425 |

*Notes.* Dependent variable is the wage level over the year-specific average wage. Independent variables are a constant, years of schooling, coworker years of schooling, and the interaction between those two terms. All regressions include industry-year, occupation-year and employer fixed effects. Employer-clustered standard errors are given in parentheses. Observations are unweighted. The sample is unchanged from the main text, except that 96,517 observations with missing years of schooling are dropped. Observation count rounded to 100,000s.

# The firm as team assembly technology: organizational optimization problem

Main

- **Role of firms**: facilitate division of labor & **coordinate**
- **Choose** $\{q(\tau)\}_{\tau\in\mathcal{T}}$ & $\{\{y_i(\tau)\}_{\tau\in\mathcal{T}}\}_{i=1}^n$ & $\{\{l_i(\tau)\}_{\tau\in\mathcal{T}}\}_{i=1}^n$ **to max.** $Y$

$$\mathcal{L}(\cdot) = Y + \lambda\Bigg[\underbrace{\left(\int_{\mathcal{T}} \ln q(\tau) d\tau\right) - Y\Bigg]}_{\text{task aggregation}}$$

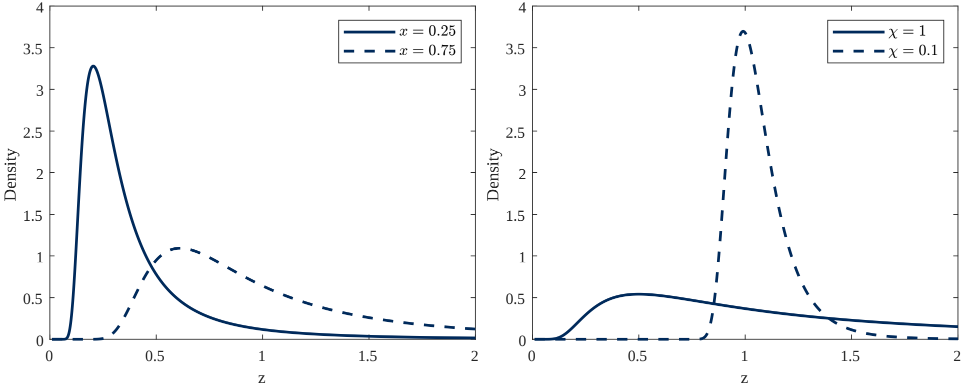
$$+\sum_{i=1}^n \left\{ \int_{\mathcal{T}} \tilde{\lambda}(\tau) \underbrace{\left(\sum_{i=1}^n y_i(\tau) - q(\tau)\right)}_{\text{division of labor}} d\tau + \int_{\mathcal{T}} \lambda_i(\tau) \underbrace{\Big(z_i(\tau) l_i(\tau) - y_i(\tau)\Big)}_{\text{task production}} d\tau + \lambda_i^L \underbrace{\left(1 - \int_{\mathcal{T}} l_i(\tau) d\tau\right)}_{\text{time constraint}} \right\}$$

$+$ non-negativity constraints

- **Solve** mini-planner problem using insight from trade literature
  - key: Fréchet is max-stable

# Illustration: Fréchet distribution

Main




**(a)** Scale parameter **(b)** (Inverse) shape parameter

**Figure 1:** Illustration of properties of Fréchet distribution

## Taylor approximation to CES

Back to team production | Back to stylized model

- Analytically tractable version of the hiring block:

$$f(x_1, x_2) = x_1 + x_2 - \xi(x_1 - x_2)^2$$

  where parameter $\xi$ controls the degree of complementarity

- Justification: CES and link to team production model
  - in the $\kappa = 1$ special case, $\xi$ maps onto $\frac{\chi}{\chi+1}$ (up to scale)

**Remark (Second-order Taylor approximation to CES)**

*The second-order Taylor approximation to $f(x_1, x_2) = (\frac{1}{2}x_1^\gamma + \frac{1}{2}x_2^\gamma)^{1/\gamma}$ around $(\bar{x}, \bar{x})$ with $\bar{x} = \frac{x_1+x_2}{2}$ is*

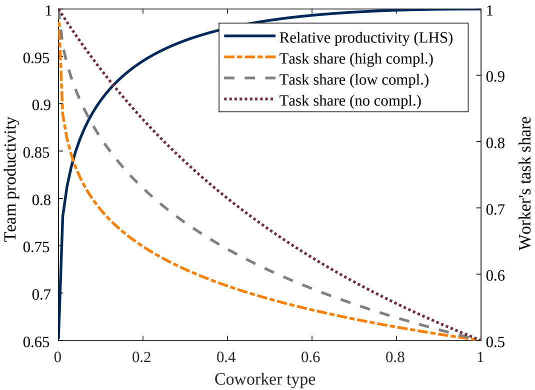
$$\bar{x} - \frac{1}{2}\underbrace{(1-\gamma)}_{\approx\xi}\frac{\sigma_x^2}{\bar{x}},$$

*where $\sigma_x^2 = (\frac{x_1-x_2}{2})^2$.*

# Quality mismatch & task mismatch

▸ Main

- When the high-quality worker is paired with a low-quality worker, she ends up “wasting time” on tasks that she is relatively less efficient in and wouldn’t have to do if teamed up optimally.



# Extension: team production with communication costs

▸ Main

- Assumption till now: division of labor incurs no output losses due to coordination frictions

- But implementing the division of labor may $\downarrow$ time available for task production because of *communication* requirements

  *[Becker & Murphy, 1992; Deming, 2017]*

- **Extension** allowing for such coordination costs shows:

  1. qualitative link between technology & coworker complementarities exists *unless* division of labor is prohibitively costly
  2. $\chi \uparrow \Rightarrow$ importance of organizational quality for productivity $\uparrow$

- Ongoing research: rich microdata from Fortune-100 company to describe communication behavior

# Environment: demographics & preferences & production technology

Main

- **Time**: continuous
- **Agents:** workers & firms
  - unit mass of workers, types uniformly distributed $x \in \mathcal{X} = [0, 1]$
  - $m_f$ mass of firms – ex-ante homogeneous
  - agents indexed by *ranks* of their respective productivity distribution, hence uniform type distribution *[Hagedorn et al., 2017]*
  - all agents are infinitely-lived, risk-neutral, share a common discount rate $\rho$, max. the present value of payoffs
- **Production technology**: firms are vacant or have 1 or 2 workers
  - normalize team size to max. $n = 2 \leftarrow$ key is "existing workforce" & "potential hire"
  - convention: from $x$'s perspective, let $x'$ denote *coworker*
  - team production: $f(x, x') \leftarrow$ see microfoundation
  - 1-worker: $f(x)$, short for $f(x, \emptyset)$

## Environment: random search & wage bargaining

- **Timing** within *dt*-intervals
  1. exogenous separation: Poisson rate $\delta$
  2. random search & matching
  3. production & surplus sharing
- **Meeting process**: unemployed meet *some* firm at Poisson rate $\lambda_u$
  - probability for a firm to be contacted by an(y) unemployed: $\lambda_{v.u} = \lambda_u \times u$
  - baseline: no on-the-job search
- **Matching** decisions based on joint surplus b/w firm & worker(s): privately efficient *[cf. Bilal-Engbom-Mongey-Violante, 2021]*
- **Surplus sharing**: firm bargains with potential new hire, taking into account coworker complementarities; worker bargaining power $\omega$
  - continuous renegotiation, as if each worker is marginal (i.e., outside option: unemployment)

# Key hiring decision

- **Notation:**
  - Value functions for unemployed worker, $V_u(x)$; worker $x$ employed with coworker $x'$, $V_e(x|x')$
  - Value functions for vacant firm, $V_{f.0}$; firm producing with $x$ and $x'$: $V_f(x, x')$
  - $d_u(x)$: density of unemployed workers of type $x$
- **Key question:** which type(s) of workers is a firm that already has one worker willing to hire – trading off match quality vs. cost of searching
- HJB for the **joint value** of a firm with worker $x$, $\Omega(x)$

$$\rho\Omega(x) = f(x) + \delta\big[-\Omega(x) + V_u(x) + V_{f.0}\big]$$
$$+ \lambda_{v.u}\int \frac{d_u(\tilde{x}')}{u} \underbrace{\max\{-\Omega(x) + V_e(x|\tilde{x}') + V_f(x,\tilde{x}'), 0\}}_{=(1-\omega)S(\tilde{x}'|x)^+} d\tilde{x}'$$

$\Rightarrow$ hiring decision based on *marginal surplus*

# Stationary equilibrium

▸ Equilibrium equations

- Remainder of setup is fairly straightforward but lengthy
- Formally, after defining (i.) HJBs for unemployed & vacant & surplus values, and (ii.) Kolmogorov Forward Equations (KFEs) describing the evolution of the distribution of agents across states:

**Definition**

A stationary search equilibrium is a tuple of value functions together with a stationary distribution of agents across states such that (i.) the value functions satisfy the HJB Equations given the distribution; and (ii.) the distribution satisfies the KFEs given the policy functions implied by the value functions.

- Needs to be computed **numerically**
  - agents' expectations & decisions must conform w/ population dynamics to which they give rise; as distribution evolves, so do agents' expectations
  - mean-field game

# Environment: firm & worker states

- Distribution across states for a **worker** type $x$:

$$d_w(x) = d_u(x) + d_{m.1}(x) + \int d_{m.2}(x, \tilde{x}')d\tilde{x}'$$

  - $d_u(x)$: 'density' of unemployed of type $x$
  - $d_m(x)$, shorthand for $d_m(x, \emptyset)$: 'density' of matches w/ $x$ as only worker
  - $d_m(x, x')$: 'density' of "team matches" b/w $x$ and $x'$

- Distribution across states for a **firm** type $y$:

$$d_f = d_{f.0} + \int d_{m.1}(x)dx + \frac{1}{2}\int\int d_{m.2}(x, x')dxdx'.$$

  - $\frac{1}{2}$: account for 1 firm having 2 workers

- **Aggregates** can be backed out, e.g.

$$u = \int d_u(x)dx$$

# Environment: surplus sharing

- **Desiderata:**
  1. hiring decisions are based on the joint value to all parties affected and, thus, constrained Pareto efficiency in allocations
  2. order of hiring does not matter
  3. wages continuously renegotiated

- **One-worker firm:**

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

**Two-worker firm**

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

# 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:

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

# HJB: surpluses

- Surplus of coalition of firm with worker $x$

$$(\rho+\delta)S(x) = f_1(x) - \rho\big(V_u(x) + V_{f.0}\big) + \lambda_{v.u}(1-\omega)\int \frac{d_u(\tilde{x}')}{u} S(\tilde{x}'|x)^+ d\tilde{x}' \tag{9}$$

- Surplus from adding $x$ to $x'$

$$S(x|x')\big(\rho+2\delta\big) = f_2(x,x') - \rho\big(V_u(x) + V_u(x') + V_{f.0}\big) + \delta S(x) - (\rho+\delta)S(x') \tag{10}$$

# KFE: unemployed

$$\delta\left(d_{m.1}(x) + \int d_{m.2}(x, \tilde{x}')d\tilde{x}'\right) = d_u(x)\lambda_u\left(\int \frac{d_{f.0}}{v}h(x, \tilde{y}) + \int \frac{d_{m.2}(\tilde{x}')}{v}h(x|\tilde{x}')d\tilde{x}'\right). \tag{11}$$

# KFE: one-worker matches

$$d_{m.1}(x)\left(\delta + \lambda_{v.u}\int \frac{d_u(\tilde{x}')}{u} h(\tilde{x}'|x)d\tilde{x}'\right) = d_u(x)\lambda_u \frac{d_{f.0}}{v} h(x) + \delta \int d_{m.2}(x,\tilde{x}')d\tilde{x}'. \tag{12}$$

# KFE: two-worker matches

$$2\delta d_{m.2}(x, x') = d_u(x)\lambda_u \frac{d_{m.1}(x')}{v} h(x|x') + d_u(x')\lambda_u \frac{d_{m.1}(x)}{v} h(x'|x). \tag{13}$$

# Lemma: monotonicity of unemployment value and wage in $x$

▶ Main

**Lemma**

*Assume that $\frac{f_1(x)}{\partial x} > 0$, $\frac{\partial f_2(x,x')}{\partial x} > 0$, and $\omega > 0$. Then: (i) The value of unemployment $V_u(x)$ is monotonically increasing in x, and (ii) so is the wage function $w(x|x')$.*

**Proof.**

See paper appendix. Key: surplus representation. □

# Wage equation

Main

- NB: here allow for ex-ante firm heterogeneity $\Rightarrow$ measurement result extends

$$\begin{aligned}
w(x|y,x') &= \rho V_u(x) + \omega\Big[f(x,y,x') - \rho\left(V_u(x) + V_u(x') + V_{f.o}(y)\right) \\
&\quad + \delta S(x|y) - (\rho+\delta)S(x'|y)\Big] - \delta\omega S(x|y) \\
&= \omega\big(f(x,y,x') - f(x',y)\big) + (1-\omega)\rho V_u(x) \\
&\quad - \omega(1-\omega)\lambda_{v.u}\int \frac{d_u(\tilde{x}'')}{u} S(\tilde{x}''|y,x')^+ d\tilde{x}''.
\end{aligned}$$

# Characterization using a stylized model: setup

Main

Intuition for how coworker complementarities shape matching can be gained from a stylized model $\rightarrow$ closed-form solutions

- **Simplified setup:**
  - no ex-ante firm heterogeneity; mass of firms $m_f = \frac{1}{2}$
  - production fn.: $f(x, x') = x + x' - \xi(x - x')^2$, where $\xi$ controls complementarity (cost of mismatch)
    Approx. of microfounded team prod. fn.
  - no production with 1 employee & abstract from team production benefits
  - firm has no bargaining power, workers each receive their outside option plus half the surplus
- **Explicit search costs**: no discounting, guaranteed match ($M_u = M_f = 1$); but type-invariant worker search costs $c$
  - supermodularity in $f$ suffices for PAM *[Atakan, 2006]*
- **Stylized** timing & specification of final stage $\downarrow$ *[cf. Eeckhout & Kircher, 2011]*

# Characterization using a stylized model: timing

Frictionless stage-2 outcome

0. Each firm is randomly paired with one worker $x' \in \mathcal{X}$
   - remaining: mass $\frac{1}{2}$ of uniformly distributed workers; mass $\frac{1}{2}$ of firms with one employee

1. Each (firm + $x'$) unit is randomly paired with a worker $x \in \mathcal{X} \to$ decision:
   a. match: form a team
      + produce & share production value
      – no further actions and zero payoff in stage 2
      *or*
   b. search: don't form a team
      – workers pay search cost $c$
      + all have opportunity to re-match in stage 2, s.t.

2. frictionless matching b/w unmatched firms & workers; production
   - pure PAM: $x$ works with $x$ ($\leftarrow$ deterministic coupling $\mu(x) = x$)
   - payoffs *given* pure PAM: $w^*(x) = x$ and $v^* = 0$

# Characterization using a stylized model: stage-1 matching decision

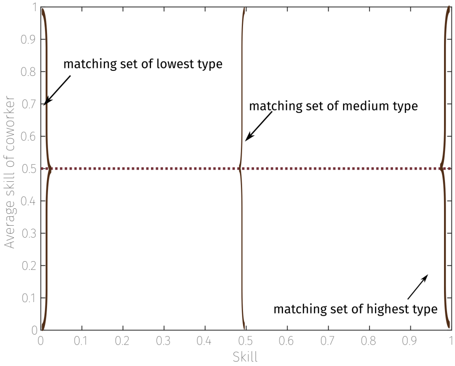
- A firm with employee $x'$ that meets a worker of type $x \in \mathcal{X}$ decides to hire her, i.e. $h(x,x') = 1$, if

$$\underbrace{\overbrace{f(x,x')}^{\text{match}} - \overbrace{\left[w^*(x) + w^*(x') + v^* - 2c^w\right]}^{\text{search}}}_{\equiv S(x,x')} > 0$$

- Threshold distance $s^*$ s.t. $h(x,x') = 1 \Leftrightarrow |x' - x| < s^*$
- Threshold distance satifies: $s^* = \sqrt{2c/\xi}$
  - greater complementarities ($\xi$) render the matching set *narrower*
  - greater search costs ($c$) render the matching set *wider*

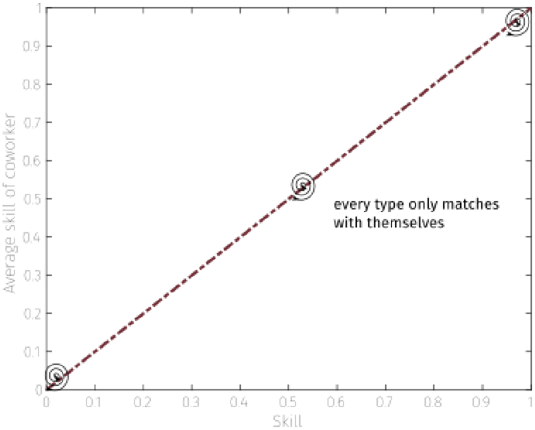
# Characterization using a stylized model: matching decisions

- Random matching ($s^* = 1$)



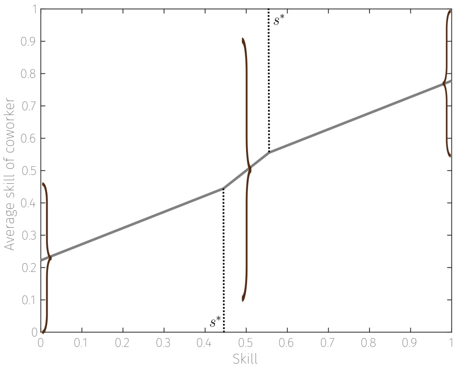
# Characterization using a stylized model: matching decisions

- Perfectly assortative matching (PAM; $s^* = 0$)



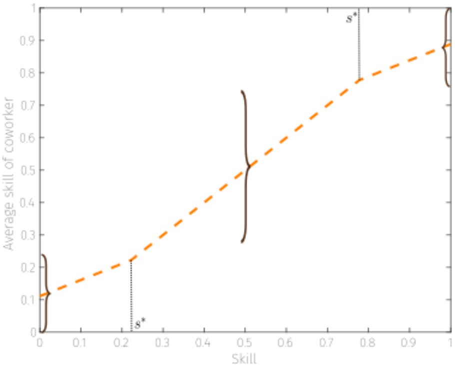
# Characterization using a stylized model: matching decisions

- Matching under weak complementarities ($s^* = 0.45$)



# Characterization using a stylized model: matching decisions

- Matching under stronger complementarities ($s^* = 0.225$)



# Characterization using a stylized model: corollary

Main

**Corollary (Stylized model)**

*For a given threshold s, which is decreasing in $\chi$:*

1. *the coworker correlation is:* $\rho_{xx} = (2s+1)(s^2-1)^2$;
2. *the average coworker type is*

$$\hat{\mu}(x) = \begin{cases} \frac{x+s^*}{2} & \textit{for} \quad x \in [0, s^*) \\ x & \textit{for} \quad x \in [s^*, 1-s^*] \\ \frac{1+x-s^*}{2} & \textit{for} \quad x \in (1-s^*, 1]. \end{cases}$$

3. *the between-firm share of the variance of wages is decreasing in s*

# Frictionless matching: assignment and payoffs

Main

- Working backwards, let's first pin down the frictionless payoffs that determine the outside option
- The equilibrium of the frictionless model can be derived in many ways
- Equilibrium assignment and payoffs:
  - PAM: $\mu(x) = x$ *given supermodular* $f(x_1, x_2)$
  - wage schedule obtained from integrating over FOC
  $$w^*(x) = \int_0^x f_x(\tilde{x}, \mu(\tilde{x}))d\tilde{x}$$
  where integration constant is zero due to $f(0, 0) = 0$
  - firm payoffs in this formulation are 0
- Given $f(x_1, x_2) = x_1 + x_2 - \gamma(x_1 - x_2)^2$, with $\gamma > 0$, we have

$$\mu(x) = x$$

$$w^*(x) = x \quad \text{and } v^* = 0$$

# Characterization results: conditional distribution

Main

**Lemma (Conditional type distribution)**

*Given a threshold distance s, the conditional distribution of coworkers for $x \in \mathcal{X}$ is*

$$\Phi(x'|x) = \begin{cases} 0 & \textit{for } x' < \sup\{0, x - s\} \\ \frac{x - \sup\{0, x-s\}}{\inf\{x+s,1\} - \sup\{0,x+s\}} & \textit{for } x' \in [\sup\{0, x - s, \}, \inf\{x + s, 1\}] \\ 1 & \textit{for } x' > \inf\{x + s, 1\} \end{cases}$$

# Characterization results: between-share of wage variance

Main

**Corollary**

*Given a threshold distance s and a value of $\gamma$, the between-firm share of the variance of wages is equal to*

$$\frac{-\frac{13\,\gamma^2\,s^5}{2400}+\frac{\gamma^2\,s^4}{80}+\frac{5\,s^3}{36}-\frac{s^2}{6}+\frac{1}{12}}{\frac{\gamma^2\,s^4}{45}-\frac{4897\,\gamma^2\,s^5}{10800}-\frac{\gamma^2\,s^6}{324}+\frac{19\,\gamma^2\,s^5\,\ln(2)}{30}+\frac{1}{12}}.$$

# Parameterization, including estimation results

Main

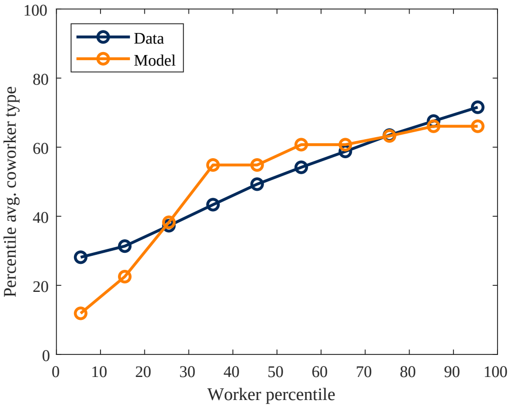
| Parameter | Description | Targeted moment | Value | $m$ | $\hat{m}$ |
|---|---|---|---|---|---|
| $\gamma$ | Elasticity of complementarity | $\hat{\beta}_c$ | 0.837 | 0.0091 | 0.0091 |
| $a_0$ | Production, constant | Avg. wage (norm.) | 0.239 | 1 | 1 |
| $a_1$ | Production, scale | Var. log wage | 1.557 | 0.241 | 0.241 |
| $b_1$ | Replacement rate, scale | Replacement rate | 0.664 | 0.63 | 0.63 |
| $\delta$ | Separation hazard | Job loss rate | 0.008 | 0.008 | 0.008 |
| $\lambda_u$ | Meeting hazard | Job finding rate | 0.230 | 0.162 | 0.162 |
| $\rho$ | Discount rate | External | 0.008 | | |
| $\omega$ | Worker bargaining weight | External | 0.50 | | |
| $a_2$ | Production, team advantage | External | 1.10 | | |

*Notes.* This table lists for each of the estimated parameters, the targeted moment, the estimated value, and moment values in data ($\hat{m}$) and model ($m$). In the quantitative model, the production function includes a constant ($a_2$) and a scale/proportionality factor ($a_1$). The elasticity of complementarity is $\gamma = \frac{\chi}{1+\chi}$. Sources: SIEED, LIAB.

# Validation: model reproduces empirical coworker sorting patterns

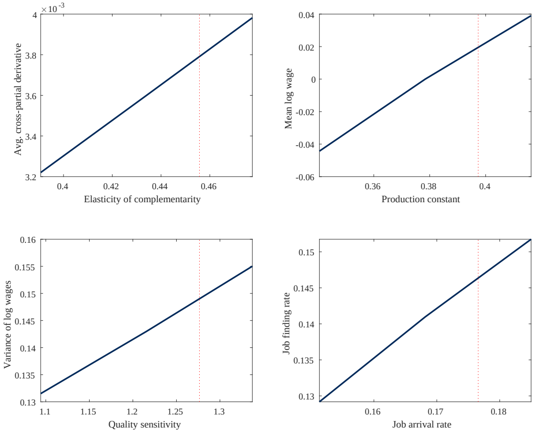
Main

- Key untargeted moment (1): coworker sorting patterns
- Coworker correlation matches data well, $\rho_{xx} = 0.53$ (vs. 0.62 in the data)
- Model slightly underestimates the quality of coworkers at both bottom and top
  - OJS will help



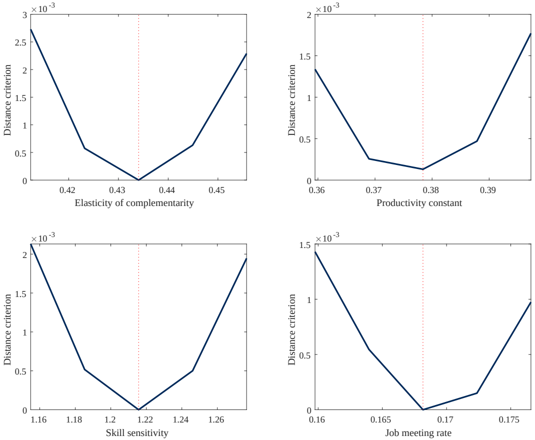
# Identification validation exercise 1

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 $\mathcal{G}$.

# Between-share adjustment procedure (1)

Main

- **Problem.** For any degree of coworker sorting less than unity, i.e. $\rho_{xx} < 1$, the level of the between-share in a model with team size $m = 2$ will be biased upward relative to the case of $m > 2$ and, in particular, $m \to \infty$ (LLN...)
  - implication 1: upward bias in level
  - implication 2: downward bias in estimated $\uparrow$ between-share as sorting increases

- **Propose** statistical adjustment method

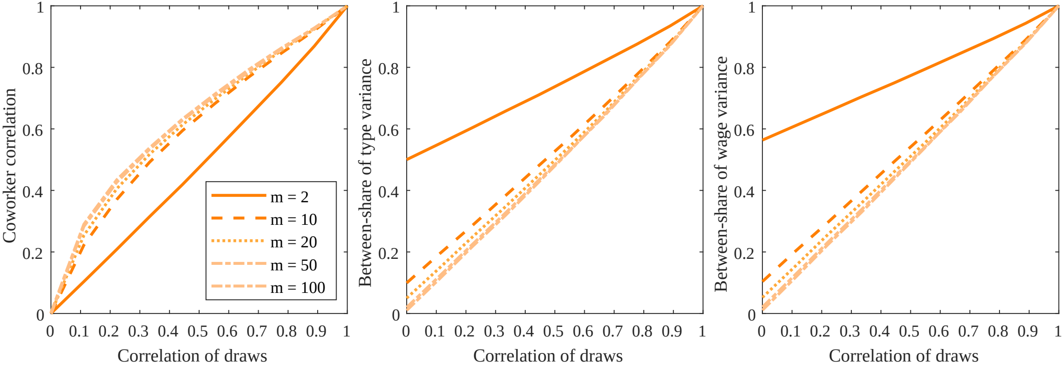
- Consider a random vector $X = (X_1, X_2, \ldots, X_m)'$ whose distribution is described by a Gaussian copula over the unit hypercube $[0,1]^m$, with an $m \times m$ dimensional correlation matrix $\Sigma(\rho^c)$, which contains ones on the diagonal and the off-diagonal elements are all equal to $\rho_c$

- Interpretation. Each vector of observations drawn from the distributions of $X$, $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})'$, describes the types of workers in team of size $m$, indexed by $j$

# Between-share adjustment procedure (2)

- Since the marginals of the Gaussian copula are simply continuous uniforms defined over the unit interval, the variance of the union of all draws is just $\frac{1}{12}$
- The mean of the elements of $X$ is itself a random variable, $\bar{X}$. That is, for some realization $x_j$, we can define $\bar{x}_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}$
- The variance of $\bar{X}$ will be $\frac{1}{m^2}\left(\frac{m}{12} + m(m-1)(\frac{\rho_c}{12})\right)$
- So $\sigma^2_{x,\text{between-share}}(\rho_c, m) = \frac{1}{m}\left(1 + (m-1)\rho_c\right)$
- Correction-factor $= \frac{1}{2}\left(1+\rho_c\right) - \frac{1}{\hat{m}}\left(1 + (\hat{m}-1)\rho_c\right)$ where the empirical average size is $\hat{m}$

# Between-share adjustment procedure (3)




**(a)** Coworker sorting **(b)** Between-share of type var. **(c)** Between-share of wage var.

# The effect of declining search frictions

Main

- **Model-based concern:** reduction in search frictions could also explain ↑ coworker sorting
- Yes: job arrival & separation rates estimated to ↑ from p1 to p2
- **Counterfactual analysis:** explains 6% of empirically observed ↑ in between-employer share of wage variance

| | Δ model | Implied % Δ model due to Δ parameter |
|---|---|---|
| Model 1: baseline | 0.159 | - |
| Cf. a: fix period-1 complementarity | 0.065 | 59 |
| Cf. b: fix period-1 search frictions | 0.150 | 6 |

# Outsourcing & within-occupation ranking analysis

▸ Main

- **Concern:** confounding shifts in labor boundary of firm, e.g. outsourcing
- **Address this concern in multiple steps:**
  1. empirically rank workers *within* occupation ("good engineer vs. mediocre engineer")
  2. empirically re-estimate coworker sorting & complementarity (lower but similar ↑)
  3. re-estimate model for both periods & re-do counterfactual exercises
- **Result:** qualitatively & quantitatively similar findings

| | Δ model | Implied % Δ model due to Δ parameter |
|---|---|---|
| Model 2: within-occ. ranking | 0.198 | - |
| Cf. a: fix period-1 complementarity | 0.076 | 61.47 |

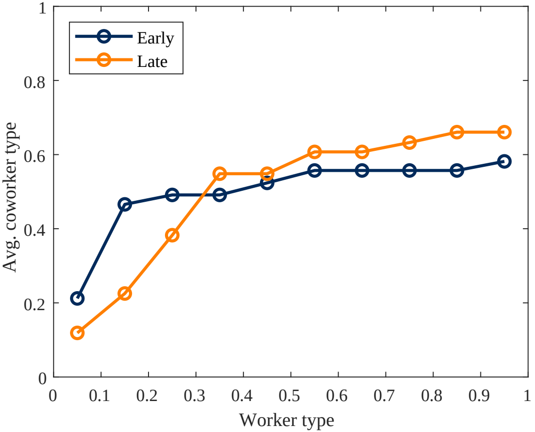
# Extension: model with OJS

Main

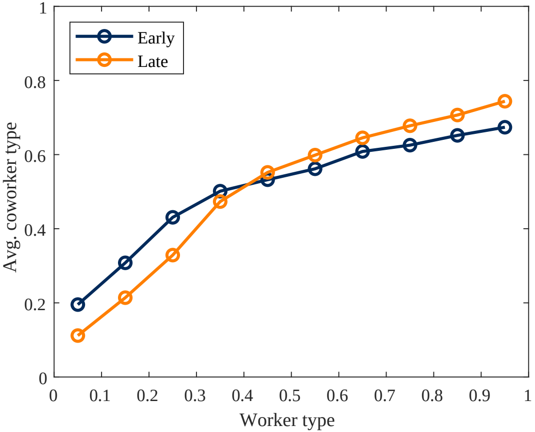
- Baseline model omitted OJS $\Rightarrow$ now suppose that employed worker may meet vacancies at Poisson rate $\lambda_e$
  - wages both off and on the job are continuously renegotiated under Nash bargaining, with unemployment serving as the outside option *[cf. di Addario et al., 2021]*
- Tradeoff in the "cross-section":
  - + better job at capturing empirical coworker sorting patterns
  - + additional predictions for EE transitions ✓match data
  - - over-predicts the *level* of the between-share
  - - mapping between production and wage complementarities less transparent, based on v forward-looking wage setting of questionable empirical relevance
- Future research: wage-setting with partial insulation from outside options; match-specific shocks to capture vast gross EE flows

# Model-implied coworker sorting (change): without and with OJS

Main




**(a)** Baseline




**(b)** OJS

# Additional validation exercise w/ OJS: predictions for EE transition

- **Theoretical prediction:** EE transitions ought to 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 $\mathbf{1}\{S(x|x') - S(x|x'') > 0\}$
- **Empirical analysis**: use SIEED *spell* data to create worker-originMonth-destinationMonth-originJob-destinationJob panel, with information on characteristics of origin and destination job (e.g., coworker quality)
  - subsample period 2008-2013 (huge panel at monthly frequency!)
  - count as "EE" if employer change between two adjacent months
- **Regression analysis in model & data:** regress $\Delta\hat{x}_{-it}$, scaled by Std. $\sigma_\Delta$ of coworker quality changes, on *own* type and *origin* coworker type

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

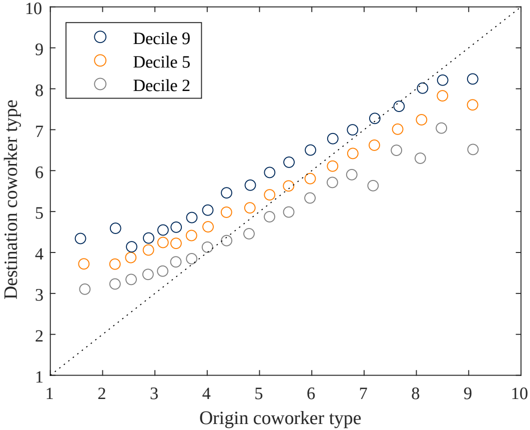
- **Result:** $\hat{\beta}_1 = 0.11 > 0$, s.s. at 1% ✓

# Regression result

| | |
|---|---|
| $\hat{x}_i$ | 0.1125*** |
| | (0.0008314) |
| $\hat{x}_{-it}$ | -0.2741*** |
| | (0.0011517) |
| Constant | 0.9785*** |
| | (0.004854) |
| Number of obs. | 227,148 |
| R-squared | 0.2022 |
| Adj R-squared | 0.2022 |
| Root MSE | 0.8932 |

*Notes.* *** $p<0.001$, ** $p<0.01$, * $p<0.05$. .

# Origin-Destination Plot



# The implications of "horizontal" complementarity

▸ Main

- **Baseline:** only "vertical" complementarity *due to* horizontal differentiation
- **Concern:** but couldn't it better to match a high-type (A) with a low-type (L) coworker than a high-type coworker (H) if A & L are specialized in *different* tasks while A & H are specialized in the *same* tasks?
  - through lens of model: correlation between $\mathbf{z}_A$ and $\mathbf{z}_L$ or $\mathbf{z}_H$ vs. baseline: assume *iid* draws
  - ofc correlation could be *endogenous*: if task-specific skills "persistent," they may be observable upon matching ("inspection") or afterwards ("experience") $\rightarrow$ shape formation or separation probabilities
- **Important & requires careful consideration**
  - conceptual/theoretical: 3 cases (no specialization; baseline with iid draws; case with correlated draws) $\Rightarrow$ conditional on correlation, $\chi \uparrow$ leads to increase 'vertical' complementarity
  - empirical: within-occupation ranking, so focus on matching *conditional* on occupational specialization
  - extension: match-specific shocks $\rightarrow$ consider next

# Match-specific shocks

- Suppose that $f(x, x', \zeta) = \zeta f(x, x')$, where $\ln \zeta \sim G$
  - in progress: micro-foundation for $\zeta$ through multi-variate Fréchet: interpretation in terms of negative correlation of **z** vectors
- Sketch of solution approach to extended model
  - define

$$h(x|x') = 1 - G\left(\bar{\zeta}(x|x')\right)$$
$$p(k) = 1 - G(k)$$
$$\zeta^*(k) = \frac{\int_k^\infty \zeta dG(\zeta)}{1 - G(k)} \text{ if } G(k) < 1 \text{ and } \zeta^*(k) = k \text{ otherwise}$$

where $\bar{\zeta}(x|x')$ solves $S(x|x', \zeta) = 0$

  - then, e.g., value of unemployment for type $x$ satisfies

$$\rho V_u(x) = b(x) + \lambda_u \omega \left[ \int \frac{d_{f.0}}{v} S(x)^+ + \int \frac{d_{m.1}(\tilde{x}')}{v} p\left(\bar{z}\left(x|\tilde{x}'\right)\right) \times S\left(x|\tilde{x}', \zeta^*\left(\bar{\zeta}\left(x|\tilde{x}'\right)\right)\right) d\tilde{x}' \right]$$

# Match-specific shocks

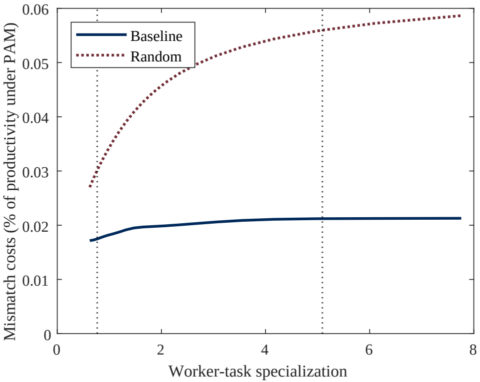
- **Quantitative** evaluation: *in progress*
- **Initial findings:**
  - much better fit to coworker sorting patterns
  - much better fit to wage functions
  - precise calibration of $\sigma_\zeta$ not easy: within-$(x, x')$ wage dispersion captures also e.g. measurement error
  - main prediction of $\uparrow$ between-share as $\gamma \uparrow$: *robust*

# Productivity costs of complementarity & labor market functioning

▸ Main

"The benefits of the division of labor are limited by the functioning of the labor market"

- Recall microfoundation: $\uparrow \chi \Rightarrow \uparrow$ direct efficiency *gains* from teamwork *and* $\uparrow$ mismatch *costs*
- **Q:** how does the gap to potential vary depending on labor markets?
- **A:** under random sorting, the productivity gap due to suboptimal sorting $\uparrow$ more sharply as $\chi \uparrow$

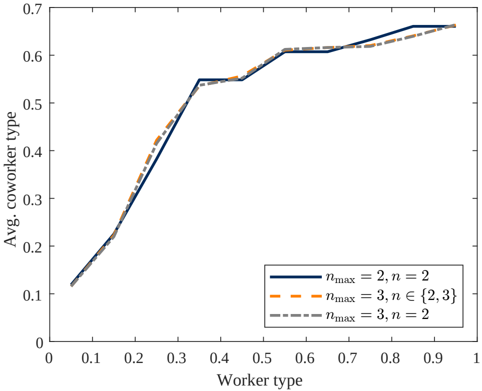


# Extension to $n_{max=3}$

▸ Main

- Baseline model imposes $n_{\max} = 2$ for reasons of (i) tractability and (ii) transparency

- Can extend to $n_{\max} = 3$ (or $n_{\max} = 4$) & find that results are robust



# Implications for overall inequality?

Main

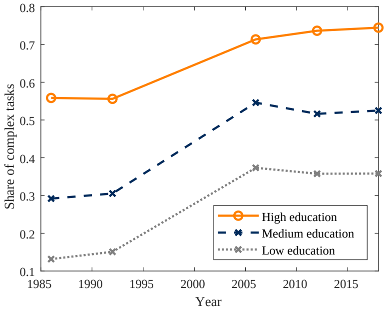
- Coworker complementarities do not necessarily $\uparrow$ variance of person-level wages
    - (un-)surprising? AKM-variance decomposition perspective vs. common intuition/question
    - counterfactual: variance of log wages 0.2166 in 2010 under 1990-complementarities vs. 0.210
    - mechanisms: (i) reallocation effect, (ii) valuation effect, (iii) outside option effect
- Importance of within-firm wage compression: if high, then $\uparrow$ coworker sorting also pushes up *overall* inequality (currently conjecture only!)
- Other caveats: coworker learning *[Jarosch-Oberfield-RossiHansberg, 2021]*, increasing returns to labor quality *[Kremer, 1993]*, sharing in monopoly rents, ... $\Rightarrow$ future research
- Not straightforward to analyze formally: alternative bargaining setup with coalition of workers bargaining with firm $\rightarrow$ lack of tractability when hiring decisions are not privately efficient (incumbent workers...)

# Direct evidence on $\chi$: $\Delta\uparrow$ complex tasks, specialization, team collaboration

▸ Back to overview ▸ BIBB

- **Large empirical literature:** $\Delta$ nature of work *[e.g., Acemoglu-Restrepo, 2018]*

- **Fact:** $\uparrow$ % of complex tasks $\Rightarrow$ "extensive margin" of $\chi$
  - BIBB longitudinal task survey microdata
  - "complex": cognitive/interactive non-routine (e.g., organizing, teaching)




- **Related evidence:**
  - Grigsby (2023): workers have become more specialized since 1980s & transferability of skills has declined amongst occupations requiring high/social/manual skills
  - rise of teams *[Jones, 2009, 2021]*: $\uparrow$ cumulativeness of knowledge + $\downarrow$ communication costs $\Rightarrow$ specialization *[Garicano, 2000; Neffke, 2019]*
  - Jovanovic and Rousseau (2008): proliferation of occupation codes

# Evolution of the German task structure

Main

- Employment Surveys (ES) carried out by the German Federal Institute for Vocational Training (BIBB)
    - detailed information on tasks performed at work
    - individual-level, with consistent occupation codes
    - repeated cross-sections ranging from 1985/86 to 2018
    - large sample sizes (20,000-30,000 per wave)
- Methodology to study evolution of task content of production follows Spitz-Oener (2006), Antonczyk et al. (2009), Rohrbach-Schmidt & Tiemann (2013)
    - task classification
    - sample harmonization (West Germany, aged 15 to 65, employed)

# Task classification

- Focus on $\Delta$ in usage of abstract/complex (non-routine, non-manual) tasks vs. "rest" (manual & routine)

  *[Autor and Handel, 2009; Acemoglu & Autor, 2011; Rohrbach-Schmidt & Tiemann, 2013]*

- Index capturing the usage of abstract/complex tasks for worker $i$ in period $t$ *[Antonczyk et al., 2009]*

$$T_{it}^{\text{complex}} = \frac{\text{number of activities performed by } i \text{ in task category "complex" in sample year } t}{\text{total number of activities performed by } i \text{ in sample year } t}$$

| Task classification | Task name | Description |
|---|---|---|
| Complex | investigating<br>organizing<br>researching<br>programming<br>teaching<br>consulting<br>promoting | gathering information, investigating, documenting<br>organizing, making plans, working out operations, decision making<br>researching, evaluating, developing, constructing<br>working with computers, programming<br>teaching, training, educating<br>consulting, advising<br>promoting, consulting, advising |
| Other | repairing, buying, accommodating, caring, cleaning, protecting, measuring, operating, manufacturing, storing, writing, calculating | |

# Increase in aggregate task complexity, driven by within-occupation ↑

- Aggregate task intensity & decompose period-by-period change into:
  1. between component: Δ occupational employment shares
  2. within component: Δ task content within occupations

| | Total | Between | Within | Within-share |
|---|---|---|---|---|
| 1986 level | 0.252 | | | |
| 1986-1992 | 0.025 | 0.002 | 0.022 | 0.906 |
| 1992-2006 | 0.298 | 0.057 | 0.241 | 0.809 |
| 2006-2012 | 0.019 | 0.002 | 0.017 | 0.890 |
| 2012-2018 | 0.053 | 0.028 | 0.025 | 0.476 |
| Total change | 0.395 | 0.089 | 0.306 | 0.775 |

*Notes.* Decompose changes in the usage of abstract tasks between periods $t$ and $t-1$ according to $\Delta\bar{T}_t^{\text{abstract}} = \sum_o \omega_{o,t-1}(\bar{T}_{t,o}^{\text{abstract}} - \bar{T}_{t-1,o}^{\text{abstract}}) + \sum_o(\omega_{o,t} - \omega_{o,t-1})\bar{T}_{t,o}^{\text{abstract}}$ where $\bar{T}_{t,o}^{\text{abstract}}$ measures the average usage of abstract tasks by members of occupation $o$ in period $t$ and $\omega_{o,t}$ is the period- $t$ employment share of occupation.

# Large variation in task complexity across occupations

- Aggregate individual responses to 2-d occupation level, using 2012 & 2018 waves
  - 2012 & 2018: ← ISCO-08 codes available

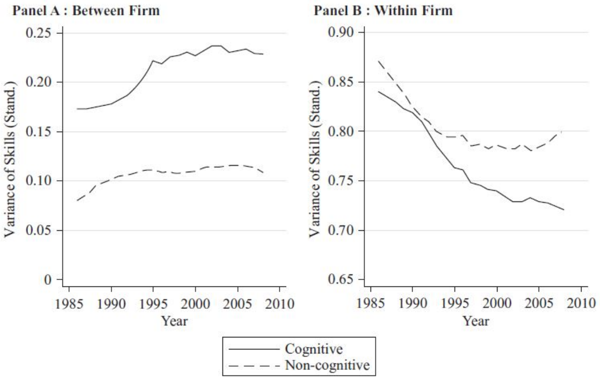
| Occupation | $\bar{T}_o^{\text{complex}}$ |
|---|---|
| Business and administration professionals | 0.859 |
| Legal, social and cultural professionals | 0.830 |
| Business and administration associate professionals | 0.827 |
| Administrative and commercial managers | 0.820 |
| Teaching professionals | 0.807 |
| ... | ... |
| Drivers and mobile plant operators | 0.214 |
| Agricultural, forestry and fishery labourers | 0.193 |
| Market-oriented skilled forestry, fishery and hunting workers | 0.168 |
| Food preparation assistants | 0.131 |
| Cleaners and helpers | 0.124 |

*Notes.* Top-5 and bottom-5 ISCO-08 2-digit occupations when ranked by $\bar{T}_o^{\text{abstract}}$ in pooled 2012 & 2018 waves.

# Evidence from the literature: Hakanson et al. (2021)

▸ Main

- *Direct* measures of cognitive and non-cognitive skills across Swedish firms during 1986–2008, using test data from military enlistment




*Notes.* Sample includes men 30–35 years old employed at private firms with at least ten employees.