# It Ain't Where You're From, It's Where You're At:

## Hiring Origins, Firm Heterogeneity, and Wages

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# Wage posting models and wage ladders

Classic wage posting models feature a stable wage hierarchy across firms (a "wage ladder") [Burdett and Mortensen, 1998; Manning, 2011]

- Wages determined by the "rung" of the ladder. Irrelevant how one gets to that rung.
- Workers prefer higher rungs: wage ladder = job ladder
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Problems with traditional posting

- Why let valuable workers go without counter-offers?
- Why not offer lower wages to hires from unemployment?
- Potentially inefficient match formation

# Sequential auction (SA) models

Influential framework, pioneered by Postel-Vinay and Robin (2002a,b), allows firms to tailor wages to worker outside options.

- History dependent wages
- *Dual* wage ladder (DWL) arises, with rungs contingent upon
  - Origin of hire ("where you're from")
  - Destination of hire ("where you're at")
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Concerns

- How much do firms really know about worker outside options?
- Should they / do they act on this information? [Cullen and Pakzad-Hurson, 2019; Caldwell and Harmon, 2019; Jaeger et al, 2020]

# Today

Search for DWL structure in *hiring* wages

Derive linear FE representation of hiring wages from SA model, focusing on Bagger et al (2014) formulation

- FEs for worker, *destination* firm, and *origin* of hire
- Covariance structure of O/D effs provides bounds on worker bargaining strength
- Testable shape restrictions using external productivity measures

Take to Italian administrative data

- Diagnostics on DWL reduced form
- Bias correct variance components using methods in Kline, Saggio, and Sølvsten (2020)

# Empirical findings

Dest effs an order of magnitude more variable than origin effs

- Rationalizing w/ Bagger et al requires implausibly strong worker bargaining strength ($\beta \geq 0.88$)
- And much stronger correlation between O&D effs than is found empirically

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- Violates non-parametric shape restrictions

Origin effs make negligible contribution to evolution of gender wage inequality

# Takeaway: It Ain't Where You're From


*It's where you're at..*

# Preliminaries: coding job transitions

Job histories of workers $i \in \{1, ..., n\}$ across job matches $m \in \{1, ..., M_i\}$.

- $Q_{im} = 1$ iff worker $i$ quits match $m$ ("EE transition")
- *Destination* firm is $j(i, m) \in \{1, ..., J\}$

*Origin* firm/state is

$$h(i,m) = \begin{cases} j(i, m-1), & \text{if } Q_{i,m-1} = 1 \text{ and } m > 1, \\ U, & \text{if } Q_{i,m-1} = 0 \text{ and } m > 1, \\ N, & \text{if } m = 1, \end{cases}$$

- $U$ is "hired from non-employment"
- $N$ is "new labor force entrant."

# Dual Wage Ladder (DWL) specification

The log *hiring* wage for worker $i$ in match $m$ is:

$$y_{im} = \underbrace{\alpha_i}_{\text{worker effect}} + \underbrace{\psi_{j(i,m)}}_{\text{destination effect}} + \underbrace{\lambda_{h(i,m)}}_{\text{origin effect}} + X'_{im}\delta + \varepsilon_{im}.$$

- Similar to AKM model for *mean* wage in a match + "origin effect" for firm/state from which worker was hired
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Treat $\{\alpha_i\}_{i=1}^N, \{\psi_j, \lambda_j\}_{j=1}^J$ as unrestricted fixed effects

- Note: each firm is a separate 2D type!
- SA models traditionally restrict $\psi_j = \psi(p_j)$, $\lambda_j = \lambda(p_j)$ [PVR, 2002a,b; Cahuc et al, 2006; Bagger et al, 2016; Bagger and Lentz, 2019]

# Exogenous mobility

Let $\varepsilon_i = (\varepsilon_{i1}, ..., \varepsilon_{iM_i})'$ and $\mathcal{W}_i = \{j(i,m), h(i,m), X_{im}, \alpha_i\}_{m=1}^{M_i}$

We assume

$$\mathbb{E}[\varepsilon_i | \mathcal{W}_i] = 0.$$

- Rules out selection on time-varying component present at time of hiring.
- Does *not* prohibit selection on $(\psi, \lambda)$
- Implied by standard SA models, which typically assume efficient mobility along stable job-ladder in $p$

# Dynamics: three examples

Career Path #1: two displacements ($Q_{i1} = 0, Q_{i2} = 0$)

$$\mathbb{E}[y_{i3} - y_{i2} \mid Q_{i1} = 0, Q_{i2} = 0] = \psi_{j(i,3)} - \psi_{j(i,2)}$$

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Career path #2: two quits ($Q_{i1} = 1, Q_{i2} = 1$)

$$\mathbb{E}[y_{i3} - y_{i2} \mid Q_{i1} = 1, Q_{i2} = 1] = \psi_{j(i,3)} - \psi_{j(i,2)} + \lambda_{j(i,2)} - \lambda_{j(i,1)}$$

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Career path #3: displacement followed by quit ($Q_{i1} = 0, Q_{i2} = 1$)

$$\mathbb{E}[y_{i3} - y_{i2} \mid Q_{i1} = 0, Q_{i2} = 1] = \psi_{j(i,3)} - \psi_{j(i,2)} + \lambda_{j(i,2)} - \lambda_U$$

Observations:

- Path #1 yields destination based wage growth ala AKM
- Path #2 vs #3: wage penalty of $\lambda_{j(i,1)} - \lambda_U$ for displacement

# Review of SA framework

Postel-Vinay and Robin (2002, IER) pioneered SA framework of wage competition

Empirical adaptation in PVR (2002, ECTA)

Archetype for many dynamic structural models in labor / macro

Model primitives:

- Workers have flow utility over wages $U(w)$
- Worker productivity type $\epsilon$
- Firm productivity type $p \sim \Gamma(\cdot) \in [p_{min}, p_{max}]$
- Sampling dist is $F(\cdot)$
- Marginal productivity of a match is $\epsilon p$

# Rules of the game

- Random on the job search
- Firms make take it or leave it offers of piece-rate contracts (price per unit of output $\epsilon p$)
- Complete information: firm knows the worker's outside option (unemp or other firm)
- Incumbent employer can respond to poaching attempt which leads to 2nd price auction
- Efficient mobility: more productive firm always wins the auction

# Poaching wage

Poaching firm offers wage to match worker's best outside option.

- Value of employment: $V(\epsilon, w, p)$ ($p$ influences wage growth)
- Highest wage that a firm of type $p$ can offer is $\epsilon p$
- If worker of type $\epsilon$, employed by firm of type $q$, meets outside firm of type $p > q$, the outside firm hires the worker at "poaching wage" $\phi(\epsilon, p, q)$ implicitly defined by:

$$\underbrace{V(\epsilon, \phi(\epsilon, p, q), p)}_{\text{value of poacher's offer}} = \underbrace{V(\epsilon, \epsilon q, q)}_{\text{best offer of poached firm}}$$

- Unemployment is just a firm with "productivity" $b$, resulting in poaching wage $\phi(\epsilon, p, b)$

# Functional form

PVR show that:

$$U\left(\phi\left(\epsilon, p, q\right)\right) = U\left(\epsilon q\right) - \kappa \int_q^p \bar{F}\left(x\right) U'\left(\epsilon x\right) dx$$

where $\bar{F}\left(x\right) = 1 - F\left(x\right)$ and $\kappa = \frac{\lambda_1}{\rho+\delta+\mu}$ is fn of offer arrival, discount rate, etc.

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If $U\left(x\right) = \ln x$ then poaching wage can be written:

$$\ln \phi\left(\epsilon, p, q\right) = \underbrace{\ln \epsilon}_{\text{worker type}} + \underbrace{\ln q}_{\text{poached firm type}} - \underbrace{\kappa \int_q^p \frac{\bar{F}(x)}{x} dx}_{\text{option val of type upgrade}}$$

- Poaching wage is decreasing in the productivity gap between poaching and poached firms (compensating diff)

# DWL representation

By Fund Thm of Calculus, option value can be written

$$\kappa \int_q^p \frac{\bar{F}(x)}{x} dx = I(q) - I(p), \text{ where}$$

$$I(z) \equiv \kappa \int_z^\infty \frac{\bar{F}(x)}{x} dx \text{ is upgrade from } z \text{ to } p_{max}$$

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Implies poaching wages obey log-linear reduced form:

$$\ln \phi(\epsilon, p, q) = \underbrace{\ln \epsilon}_{=\alpha(\epsilon)} + \underbrace{I(p)}_{=\psi(p)} + \underbrace{\ln q - I(q)}_{=\lambda(q)}$$

- $\psi'(p) < 0$ (comp diff for expected wage growth)
- $\lambda'(q) > 0$ (tougher to poach from more productive firm)
- Exogenous mobility: worker goes to more productive firm

# Properties of O/D effs

$$\ln \phi(\epsilon, p, q) = \underbrace{\ln \epsilon}_{=\alpha(\epsilon)} + \underbrace{I(p)}_{=\psi(p)} + \underbrace{\ln q - I(q)}_{=\lambda(q)}$$

1. Productivity identified from sum of firm's O+D effs:

$$\psi(p) + \lambda(p) = \ln p$$

2. O/D effs are negatively correlated across firms:

$$\mathbb{C}(\psi(p), \lambda(p)) < 0$$

3. Excess variance of O vs D effs:

$$\mathbb{V}[\lambda(p)] > \mathbb{V}[\psi(p)]$$

## Bargaining extension: Bagger et al (2014)

BF-PVR allow workers to extract a share $\beta \in [0, 1]$ of rent.

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Optimal poaching wage becomes:

$$\begin{aligned}\ln \phi(\epsilon, p, q, \mathcal{X}, \mathcal{E} \mid \beta) &= \alpha(\epsilon) + g(\mathcal{X}) + \mathcal{E} \\ &+ \underbrace{\beta \ln p + I(p \mid \beta)}_{=\psi(p)} + \underbrace{(1-\beta)\ln q - I(q \mid \beta)}_{=\lambda(q)},\end{aligned}$$

where $\mathcal{X}$ is labor market experience, $\mathcal{E}$ is a transitory shock to worker productivity, and $I(z \mid \beta) = (1-\beta)^2 \kappa \int_z^\infty \frac{\bar{F}(x)/x}{1+\kappa\beta\bar{F}(x)} dx$ is decreasing in $z$ and $\beta$.

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Observe that:

- As $\beta \to 0$, BF-PVR$\rightarrow$PVR
- As $\beta \to 1$, BF-PVR$\rightarrow$AKM! (no origin effs)

# O/D effs in BF-PVR

$$\begin{aligned} \ln \phi(\epsilon, p, q, \mathcal{X}, \mathcal{E} \mid \beta) &= \alpha(\epsilon) + g(\mathcal{X}) + \mathcal{E} \\ &+ \underbrace{\beta \ln p + I(p \mid \beta)}_{=\psi(p)} + \underbrace{(1-\beta)\ln q - I(q \mid \beta)}_{=\lambda(q)} \end{aligned}$$

- Productivity still identified by $\psi(p) + \lambda(p) = \ln p$
- But large $\beta$ can overcome comp. diff:

$$\beta > 1/2 \Rightarrow \psi'(p) > 0 \Rightarrow \mathbb{C}(\psi(p), \lambda(p)) > 0$$

- Shape restrictions
  1. Origin effs *concave* in $\ln p$: $\frac{d^2}{d(\ln p)^2}\lambda(p) < 0$
  2. Dest effs *convex* in $\ln p$: $\frac{d^2}{d(\ln p)^2}\psi(p) > 0$

# Bounds on worker bargaining power

Consider *firm*-level variance components (firm-size weighted):

$$\mathbb{V}_J[\psi], \quad \mathbb{V}_J[\lambda], \quad \mathbb{C}_J[\psi, \lambda],$$

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$$\beta \geq \frac{1}{2} + \frac{\mathbb{V}_J[\psi] - \mathbb{V}_J[\lambda]}{2\mathbb{V}_J[\psi + \lambda]}.$$

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- $\beta > 1/2 \Rightarrow$inequality restriction on O/D eff correlation:

$$\rho_J(\psi, \lambda) \geq \sqrt{\frac{\mathbb{V}_J[\psi]}{\mathbb{V}_J[\psi + \lambda]}} \left(1 - \frac{3}{10}\sqrt{\frac{\mathbb{V}_J[\lambda]}{\mathbb{V}_J[\psi + \lambda]}}\right)$$

  Intuition: $\beta > 1/2 \Rightarrow$ O/D effs both increasing in $p$

# Estimating variance components

Write as potentially heteroscedastic linear regression:

$$y_\ell = Z_\ell' \gamma + \varepsilon_\ell, \quad \mathbb{E}\left[\varepsilon_\ell^2\right] = \sigma_\ell^2, \quad \text{for } \ell = 1, \ldots, L.$$

- Parameter of interest is quadratic form $\theta = \gamma' A \gamma$
- OLS coeffs $\hat{\gamma} = S_{zz}^{-1} \sum_{\ell=1}^{L} Z_\ell' y_\ell$ unbiased but inconsistent
- "Plug-in" estimator $\hat{\theta}_{\mathrm{PI}} = \hat{\gamma}' A \hat{\gamma}$ exhibits bias of

$$\mathbb{E}[\hat{\theta}_{\mathrm{PI}} \mid \mathcal{W}] - \theta = \operatorname{trace}\left(A \mathbb{V}[\hat{\gamma} \mid \mathcal{W}]\right) = \sum_{\ell=1}^{L} B_{\ell\ell} \sigma_\ell^2,$$

  for $B_{\ell\ell} = Z_\ell' S_{zz}^{-1} A S_{zz}^{-1} Z_\ell$ and $\mathbb{V}[\hat{\gamma} \mid \mathcal{W}]$ var matrix of coeffs
- Tempting to correct by subtracting avg squared "robust" std error ala Krueger and Summers (1988), but fails in high dimensions [Cattaneo et al., 2018]

# KSS (2020) Bias Correction

Leave-out estimator of $\gamma$ is $\hat{\gamma}_{-\ell} = (S_{zz} - Z_\ell Z_\ell')^{-1} \sum_{l \neq \ell} Z_l' y_l$.

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Unbiased "cross-fit" estimator of $\sigma_\ell^2$ is

$$\hat{\sigma}_\ell^2 = y_\ell \left( y_\ell - Z_\ell' \hat{\gamma}_{-\ell} \right) = \frac{y_\ell \left( y_\ell - Z_\ell' \hat{\gamma} \right)}{1 - P_{\ell\ell}},$$

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Use to form bias corrected estimator of $\theta$

$$\hat{\theta}_{\text{KSS}} = \hat{\gamma}' A \hat{\gamma} - \sum_{\ell=1}^{L} B_{\ell\ell} \hat{\sigma}_\ell^2 = \hat{\gamma}' A \hat{\gamma} - \text{trace}\left(A \hat{\mathbb{V}}[\hat{\gamma} \mid \mathcal{W}]\right).$$

- $\hat{\mathbb{V}}[\hat{\gamma} \mid \mathcal{W}]$ is het-*unbiased* not het-consistent [ala White, 1980]
- Primitive conditions for consistency of $\hat{\theta}_{KSS}$ established in KSS
- Stochastic approximation algo for large datasets

# Data: INPS-INVIND

Italian social security records for years 2005–2015

- Private sector workers ever employed at firms sampled by Bank of Italy (INVIND) [Macis and Schivardi, 2016; Daruich et al., 2020]
- Extract individuals w/ 2+ observed jobs
- Earnings, days and months worked at each employer in a given year

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- Extract individuals w/ 2+ observed jobs
- Earnings, days and months worked at each employer in a given year

Measure hiring wage as daily wage in 1st year on job

Likely to provide esp good approximation in Italy because:

- Costly to adjust contract wages in first few months on the job
- When early raise/promotion does occur, new earnings record results (we take the 1st record in the 1st year at employer)

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About 38% of all transitions are resignations / quits

- Close to quit rates in JOLTS during Great Recession (Italian Urate$\approx$ 9% over this period)

# Roughly 13M job matches

**Table 1:** Summary Statistics

| | Pooled | Men | Women |
|---|---|---|---|
| ***Panel (a): Starting Sample*** | | | |
| Number of Person-Job Observations | 13,029,554 | 7,840,247 | 5,189,307 |
| Number of Individuals | 4,895,253 | 2,936,275 | 1,958,978 |
| Share hired from non-employment | 0.59 | 0.58 | 0.60 |
| Share poached from another firm | 0.31 | 0.33 | 0.29 |
| Share new entrants | 0.10 | 0.09 | 0.11 |
| Number of origin fixed effects | 876,395 | 623,478 | 432,317 |
| Number of destination firm effects | 1,493,788 | 1,070,614 | 836,018 |
| Mean Log Hiring Wages | 4.0826 | 4.2044 | 3.8986 |
| Variance Log Hiring Wages | 0.2939 | 0.2427 | 0.3151 |

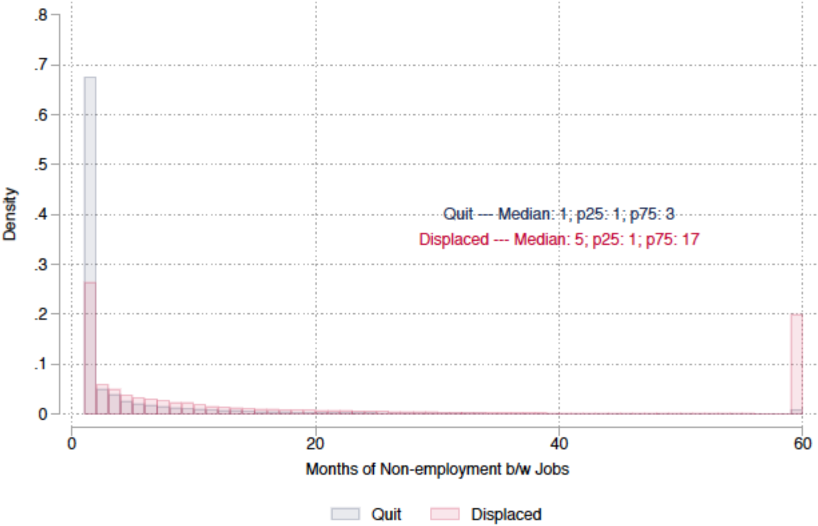
# Pruning for leave-1-out estimability discards small firms

**Table 1:** Summary Statistics

| | Pooled | Men | Women |
|---|---|---|---|
| ***Panel (b): Estimation Sample*** | | | |
| Number of Person-Job Observations | 10,100,836 | 5,860,789 | 3,730,985 |
| Number of Individuals | 3,194,370 | 1,849,723 | 1,224,858 |
| Share hired from non-employment | 0.61 | 0.60 | 0.63 |
| Share poached from another firm | 0.28 | 0.29 | 0.24 |
| Share new entrants | 0.12 | 0.11 | 0.13 |
| Number of origin fixed effects | 328,377 | 223,156 | 111,606 |
| Number of destination firm effects | 701,459 | 477,923 | 295,890 |
| Mean Log Hiring Wages | 4.0753 | 4.1978 | 3.9001 |
| Variance Log Hiring Wages | 0.2794 | 0.2215 | 0.3162 |

# Median quit yields job next month

## Median time between jobs for displaced: 5 months



# Nominal wage cuts more common among the displaced

**Table A2: Probability of wage cut by transition and contract type**

| | Hiring wage current job < Hiring wage prev job | Hiring wage current job < avg wage prev job | Hiring wage current job < last wage prev job |
|---|---|---|---|
| **Permanent Contracts** | | | |
| Displacement | 0.31 | 0.37 | 0.38 |
| Quit | 0.23 | 0.29 | 0.31 |
| **Temporary Contracts** | | | |
| Displacement | 0.43 | 0.49 | 0.48 |
| Quit | 0.32 | 0.39 | 0.40 |

# Diagnostic #1: Is there a wage penalty for displacement?

Two workers $i$ and $\ell$ transition between the same firms $j$ and $k$

- Worker $i$ quits 1st job

$$\mathbb{E}[y_{i2} - y_{i1} \mid Q_{i1} = 1] = \psi_k - \psi_j + \lambda_j - \lambda_N$$

- Worker $\ell$ displaced from 1st job

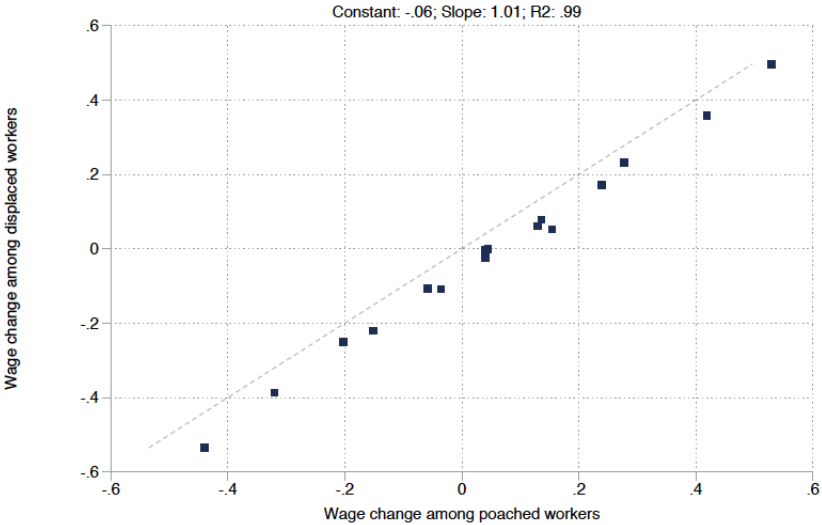
$$\mathbb{E}[y_{\ell 2} - y_{\ell 1} \mid Q_{i1} = 0] = \psi_k - \psi_j + \lambda_U - \lambda_N$$

Displacement wage penalty is

$$\begin{aligned} \lambda_j - \lambda_U &= \mathbb{E}[y_{i2} - y_{i1} \mid Q_{i1} = 1] \\ &- \mathbb{E}[y_{\ell 2} - y_{\ell 1} \mid Q_{i1} = 0] \end{aligned}$$

Rather than exact match on first two employers, group workers by coworker wage quartile at jobs #1 & #2 (16 groups)

# Roughly constant penalty



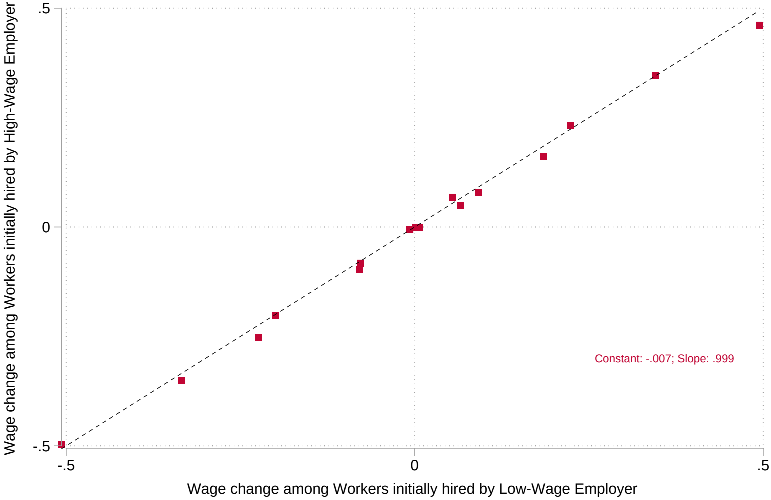
# Diagnostic #2: Does it matter who displaces you?

Recall that DWL model predicts consecutive displacements $(Q_{i1} = 0, Q_{i2} = 0)$ yield AKM style model of wage changes:

$$\mathbb{E}[y_{i3} - y_{i2} \mid Q_{i1} = 0, Q_{i2} = 0] = \psi_{j(i,3)} - \psi_{j(i,2)}$$

- Identity $j(i, 1)$ of first employer is excludable!
- Test by comparing workers whose first employer was in top / bottom tercile of coworker wages

# 1st job irrelevant for workers displaced twice



# DWL yields <1pp improvement in corrected $R^2$ over AKM

(some evidence of gender diffs)

| | Pooled | Men | Women |
|---|---|---|---|
| AKM | $\boxed{0.7199}$ | 0.7311 | 0.6822 |
| AKM (Gender-Interacted) | 0.7349 | | |
| Origin Effects | 0.5809 | 0.5660 | 0.5452 |
| Origin Effects (Gender-Interacted) | 0.5871 | | |
| DWL | $\boxed{0.7245}$ | 0.7370 | 0.6854 |
| DWL (Gender-Interacted) | $\boxed{0.7427}$ | | |

__Note:__ This table presents the goodness of fit (R2) from various models for the three estimation samples described in Table 1. The model labeled as "Origin effects" corresponds to a DWL model with only origin effects and no destination effects. "DWL (Gender-interacted)" corresponds to a model where both contemporaneous and origin firm effects are interacted with a gender indicator. "AKM (Gender-Interacted)" interacts gender with destination firm effects while "Origin Effects (Gender-Interacted)" interacts gender with origin effects. All reported measures of the goodness fit computed using the leave-out bias correction of Kline, Saggio and Sølvsten (2020). See text for further details.

# Warmup w/ AKM decomp as benchmark

Worker and firm effects make nearly equal contributions to hiring wage!

**Table 3:** Variance Decomposition of Poaching Wages - AKM Model

| | Pooled | Men | Women |
|---|---|---|---|
| Std Dev of Log Hiring Wages | 0.5286 | 0.4706 | 0.5623 |
| ***Bias-Corrected Variance Components*** | | | |
| Std Dev of worker effects | 0.2887 | 0.2558 | 0.2854 |
| Std Dev of firm effects | 0.2578 | 0.2431 | 0.2824 |
| Correlation of worker, firm effects | 0.3135 | 0.2311 | 0.3461 |
| ***Percent of Total Variance Explained by*** | | | |
| Worker effects | $\boxed{29.83\%}$ | $\boxed{29.54\%}$ | $\boxed{25.77\%}$ |
| Firm effects | $\boxed{23.78\%}$ | $\boxed{26.68\%}$ | $\boxed{25.22\%}$ |
| Covariance of worker, firm effects | 16.70% | 12.98% | 17.64% |
| X'δ and associated covariances | 1.69% | 3.91% | -0.41% |
| Residual | 28.01% | 26.89% | 31.78% |

Note: This table reports the variance decomposition after fitting an AKM model to hiring wages only using the estimation sample defined in Table 1, Panel (b). Corrected variance components are calculated using the leave out methodology of KSS (leaving a person-job out). AKM model controls for a cubic in age at hiring and year of hiring fixed effects.

# Large firm eff share due to focus on hiring wage

## Intuition: wages grow more dispersed within match

**Table A3:** Comparing the Contribution of the Variance of Firm Effects

| | DWL Estimation Sample | DWL Estimation Sample restricted to Dominant Jobs | Sample in Column (2) with Hiring and Within-Match Wages | Sample in Column (3) adding Firm-Stayers |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| ***Summary Statistics on Leave-out-Sample*** | | | | |
| Mean Log Wage | 4.0753 | 4.0852 | 4.1765 | 4.3115 |
| Std Dev of Log Wage | 0.5286 | 0.5269 | 0.5443 | 0.5525 |
| Number of Individuals | 3,194,370 | 3,004,100 | 3,004,100 | 6,022,869 |
| Number of firms | 701,459 | 645,011 | 645,011 | 645,011 |
| Number of observations | 10,100,836 | 8,754,197 | 21,609,391 | 41,666,584 |
| ***Contribution of Variance of Firm Effects according to AKM Model*** | | | | |
| Std Dev of firm effects (Bias-Corrected) | 0.2578 | 0.2555 | 0.2399 | 0.2217 |
| Fraction of variance explained by firm effects | 23.78% | 23.52% | 19.42% | 16.10% |

**Note:** This table summarizes how the contribution of firm effects varies across different estimation samples according to an AKM model. Sample in Column 1 corresponds to our pooled estimation sample described in Table 1, Panel (b). Our dependent variable there is therefore represented by hiring wages. In Column 2, we take our estimation sample of Column 1 but we restrict only to dominant jobs in the year. That is, we only retain person-job observations that correspond to the highest paying job of an individual in a particular year. Our dependent variable in Column 2 is still represented by hiring wages. In Column 3, we retain the worker-firm matches used in Column 2 but instead of looking at hiring wages we look at both hiring and within-match wages. Column 4 adds to the sample of Column 3 firm-stayers, i.e. individuals that remained always during the period 2005-2015 with one of the 645,011 employers characterizing the sample of Column 3. All summary statistics refer to the leave-out connected sample. All reported variance components are weighted by the number of observations present in each sample.

# Roughly 3% penalty for hiring from non-employment

(Note: we have normalized $\lambda_N = 0$)

**Table 5:** DWL variance decomposition of hiring wages among job movers

| | Pooled | Men | Women |
|---|---|---|---|
| Std Dev of log hiring wages | 0.5286 | 0.4706 | 0.5623 |
| Mean $\lambda_{j(i,m-1)}$ among displaced workers | 0.0414 | 0.0536 | 0.0687 |
| Mean $\lambda_{j(i,m-1)}$ among poached workers | 0.0508 | 0.0543 | 0.0690 |
| Origin effect when hired from non-employment ($\lambda_U$) | 0.0163 | 0.0136 | 0.0220 |
| ***Bias-Corrected Variance Components*** | | | |
| Std Dev of worker effects | 0.2823 | 0.2479 | 0.2798 |
| Std Dev of destination firm effects | 0.2580 | 0.2434 | 0.2828 |
| Std Dev of origin effects | 0.0439 | 0.0454 | 0.0431 |
| Std Dev of origin effects (among poached workers) | 0.0761 | 0.0782 | 0.0798 |
| Correlation of worker, destination firm effects | 0.3157 | 0.2351 | 0.3441 |
| Correlation of worker, origin effects | 0.1200 | 0.1629 | 0.0757 |
| Correlation of destination firm, origin effects | 0.0316 | 0.0308 | 0.0000 |
| ***Percent of Total Variance Explained by*** | | | |
| Worker effects | 28.52% | 27.75% | 24.77% |
| Destination firm effects | 23.81% | 26.74% | 25.29% |
| Origin effects | 0.69% | 0.93% | 0.59% |
| Covariance of worker, destination | 16.46% | 12.81% | 17.23% |
| Covariance of worker, origin | 1.06% | 1.66% | 0.58% |

# It ain't where you're from..

**Table 5:** DWL variance decomposition of hiring wages among job movers

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| Std Dev of log hiring wages | 0.5286 | 0.4706 | 0.5623 |
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| Origin effect when hired from non-employment ($\lambda_U$) | 0.0163 | 0.0136 | 0.0220 |
| ***Bias-Corrected Variance Components*** | | | |
| Std Dev of worker effects | 0.2823 | 0.2479 | 0.2798 |
| Std Dev of destination firm effects | 0.2580 | 0.2434 | 0.2828 |
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| Correlation of worker, destination firm effects | 0.3157 | 0.2351 | 0.3441 |
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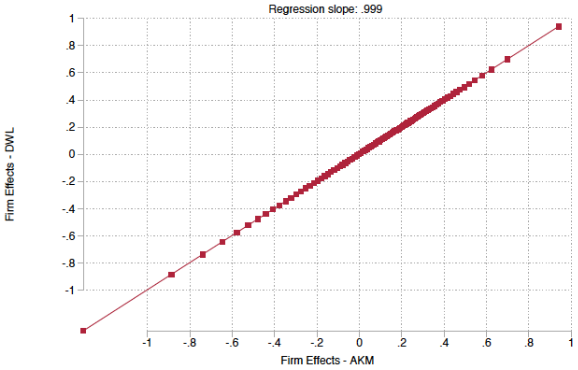
| Covariance of worker, destination | 16.46% | 12.81% | 17.23% |
| Covariance of worker, origin | 1.06% | 1.66% | 0.58% |
| Covariance of destination, origin | 0.26% | 0.31% | 0.00% |
| X'δ and associated covariances | 1.66% | 3.51% | 0.09% |
| Residual | 27.55% | 26.30% | 31.46% |

# OVB from origin effs not much of a concern in practice..

Figure 3: AKM firm effects vs. DWL firm effects




**Note:** For each firm we have an estimated firm effect according to either the AKM model or the DWL model. We then take centiles of the firm effects estimated from the AKM model. Within each centile of the AKM effects, we average the AKM effects and the corresponding DWL destination effects. The figure then shows these two means and we report the corresponding regression slope obtained from the micro-level regression. Both set of effects have been normalized to have mean zero in the lowest vingtile of the firm-size weighted distribution of mean value added per worker.

# Dest effs $\approx 14\times$ as variable as orig effs across firms

**Table 5:** Variance Decomposition across Firms

| | Pooled | Men | Women |
|---|---|---|---|
| # of firms with identified destination and origin effect | 297,865 | 201,080 | 99,508 |
| ***Bias-Corrected Variance Components*** | | | |
| Std of Destination Effects | $\boxed{0.2590}$ | 0.2449 | 0.2724 |
| Std of Origin Effects | $\boxed{0.0707}$ | 0.0721 | 0.0510 |
| Correlation of destination, origin | 0.2511 | 0.2491 | 0.3168 |
| Std of Destination + Origin Effects | 0.2851 | 0.2720 | 0.2926 |
| Lower Bound on Bargaining Power | 0.8819 | 0.8703 | 0.9182 |
| Lower Bound on Correlation of Destination, Origin Effects | 0.8409 | 0.8288 | 0.8824 |

**Note**: Here we report the variance decomposition across firms where each firm has an identified origin and destination firm effect. Variance components are weighted by average firm-size over 2005-2015 as recorded by official INPS records collected in the dataset *Anagrafica* , see text for details. Variance components corrected using the leave-out bias correction of Kline, Saggio and Sølvsten (2020). The lower bounds on the barganing power and correlation of destination and origin firm effects are based upon equation (5)-(6), see text for details.

# Implied std dev of log productivity=.28

## Compare to std log VA/L≈0.8

**Table 5:** Variance Decomposition across Firms

| | Pooled | Men | Women |
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| # of firms with identified destination and origin effect | 297,865 | 201,080 | 99,508 |
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# Need $\beta > .88$ to explain excess orig eff var

Which would require O/D corr $> .84$, but empirical corr is only .25..

**Table 5:** Variance Decomposition across Firms

| | Pooled | Men | Women |
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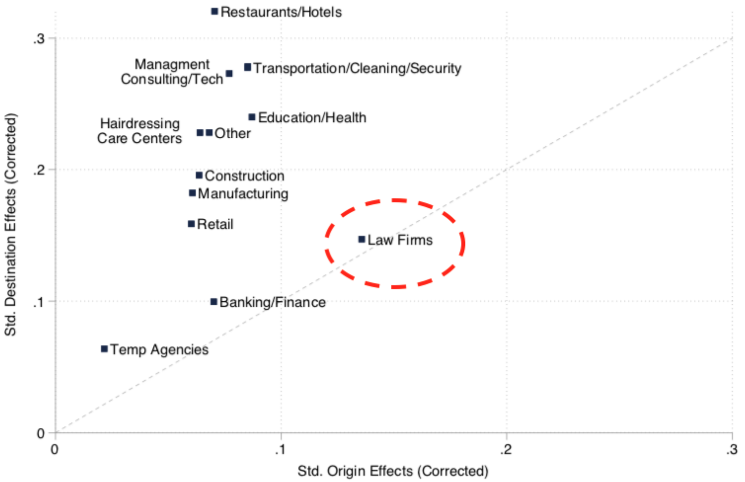
# Heterogeneity: law firms have important origin effs

Figure 4: Variability of origin and destination effects by sector




**Note:** This figure reports leave-out corrected standard deviations of destination and origin firm effects for selected sectors of the Italian economy (2-Digit 2007 Ateco codes). All variance components are firm-size weighted. The dashed line is the 45 degree line.

# But even among law firms O/D correlation too low

**Table 8:** Variability of Origin and Destination Effects by Sector

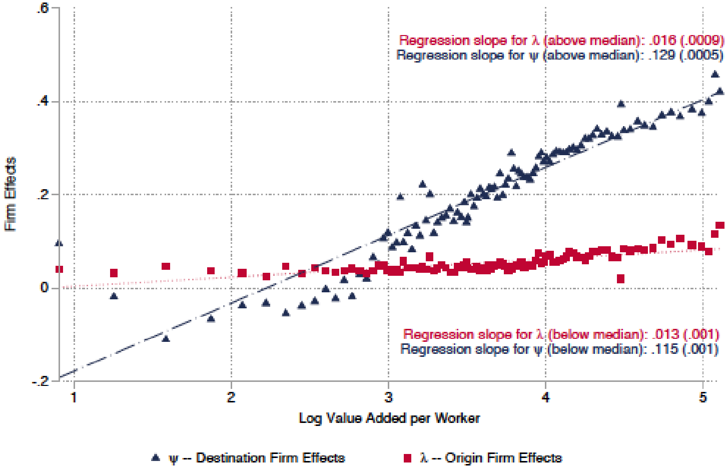
| | SD of Destination Effects | SD of Origin Effects | Correlation of Origin, Destination Effects | Lower Bound on Bargaining Power | Lower Bound on Correlation |
|---|---|---|---|---|---|
| Retail | 0.1587 | 0.0602 | 0.2291 | 0.8249 | 0.7849 |
| Construction | 0.1957 | 0.0636 | -0.0714 | 0.9222 | 0.8796 |
| Restaurants / Hotels | 0.3206 | 0.0705 | 0.0669 | 0.9415 | 0.9020 |
| Hairdressing / Care Centers | 0.2283 | 0.0640 | 0.1450 | 0.8972 | 0.8560 |
| Law Firms | 0.1471 | 0.1357 | 0.0636 | 0.5378 | 0.5721 |
| Manufacturing | 0.1823 | 0.0607 | 0.2641 | 0.8455 | 0.8040 |
| Transportation | 0.2786 | 0.0852 | 0.1022 | 0.8921 | 0.8507 |
| Cleaning / Security | 0.2777 | 0.0851 | 0.0892 | 0.8944 | 0.8530 |
| Temp Agencies | 0.0638 | 0.0216 | 0.1569 | 0.8628 | 0.8221 |
| Management / Consulting / Tech | 0.2732 | 0.0770 | 0.3737 | 0.8568 | 0.8149 |
| Banking/Finance | 0.0995 | 0.0701 | $\boxed{0.5476}$ | 0.6111 | $\boxed{0.5709}$ |
| Education/Health | 0.2401 | 0.0871 | 0.0170 | 0.8796 | 0.8399 |
| Other | 0.2284 | 0.0681 | 0.2879 | 0.8613 | 0.8196 |

Note: This table reports leave-out corrected standard deviations of destination and origin firm effects within selected sectors of the Italian economy (2-Digit 2007 Ateco codes). All variance components are firm-size weighted. The lower bounds on the barganing power and correlation of destination and origin firm effects are based upon equation (5)-(6), see text for details.

# O/D effs both increasing in VA

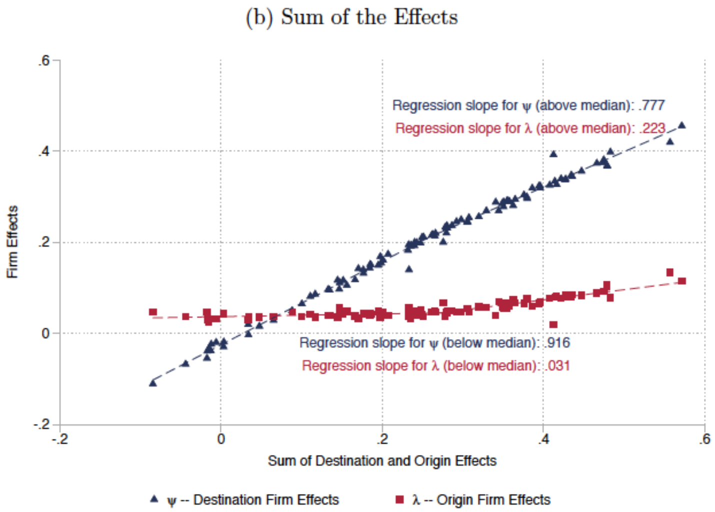
Figure 5: Origin and destination effects by value added

(a) Value Added per Worker



# O/D effs violate shape restrictions

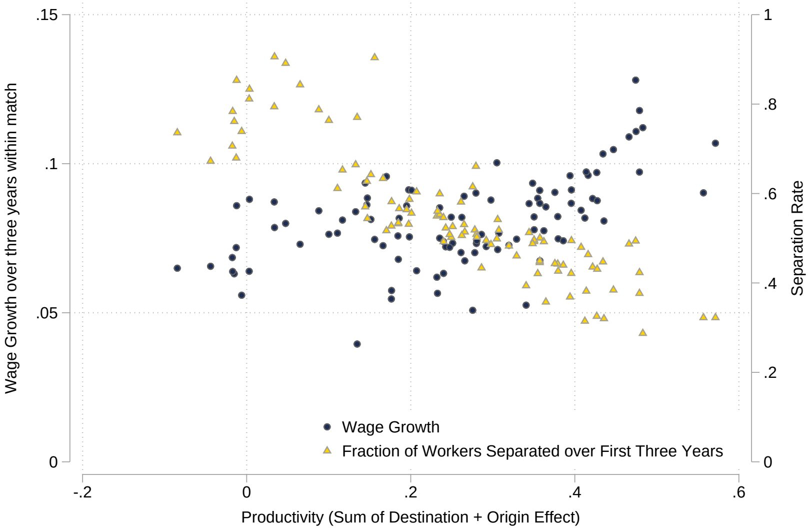
Also: BF-PVR requires $\beta > \max_{p'} d\psi(p')/d\ln p \approx 0.92$!




Note: each dot is mean within a VA bin (same as previous fig)

# Wage growth of stayers weakly increasing in productivity

## (Separations decreasing in productivity)




Note: each dot is mean within a VA bin (same as previous fig)

# Gender differences

Past work suggests firm effects differ by gender [Card et al, 2015; Casarico and Lattanzio, 2019]

Gender differences in mobility patterns also well documented [Loprest, 1992; Hospido, 2009; Del Bono and Vuri, 2011]

- Women less likely to move to higher paying firms
- Showed earlier that women slightly less likely to be "poached"

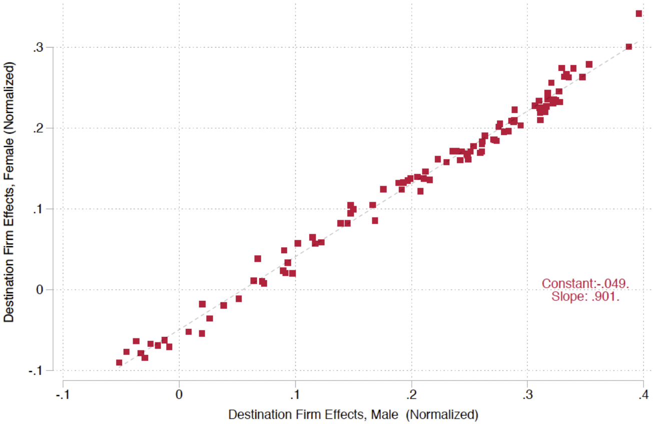
SA models suggest temporary slip down job ladder could have lasting effects on gender gap

- Not much prior work on gender gap in *hiring* wages
- Is this a quantitatively important phenomenon?

# Female dest effs less sensitive to VA

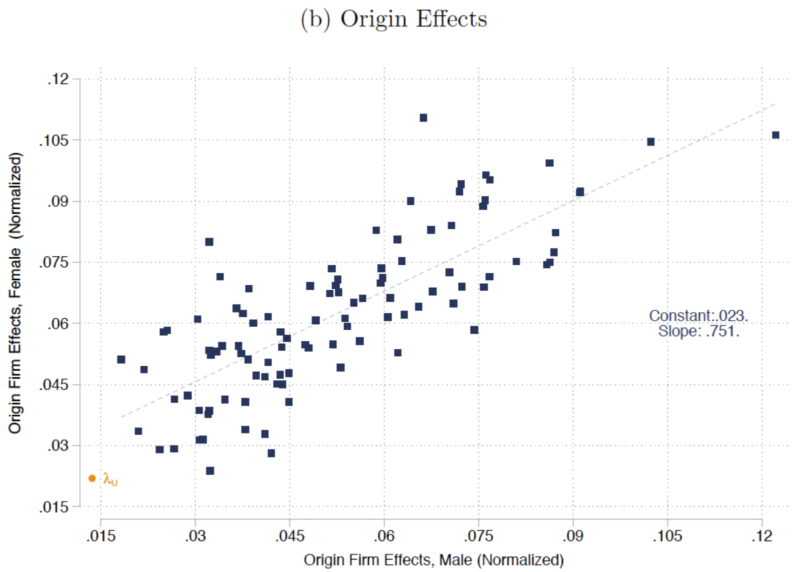
Figure 7: Origin and Destination Effects by Gender and Value Added

(a) Destination Effects




Same slope as found in Portugal [Card, Cardoso, Kline, 2015]

# Same for orig effs but female suffer greater penalty for EUE

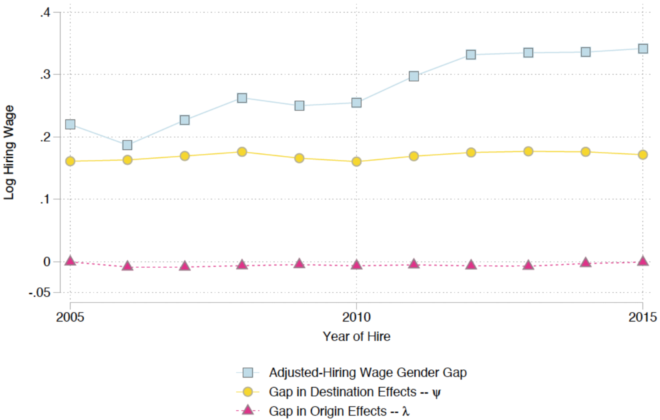


# Where you're from irrelevant for gender gap

## Initially explained by where you're at. Evolution due to other factors.

Figure 8: Gender Wage Gap and the DWL Model

(a) Entered Labor Market in 2005



# Wrapping up

There is a clear penalty for hiring from non-employment

But dest effs order of magnitude more variable than origin effs

- Difficult to rationalize w/ traditional SA models
- Orig effs more important in skilled markets with clear hierarchy (i.e., law firms / finance)

Potentially important fact for future models to match..

# Ways forward

Foundations for relative importance of where you're at:

- Heterogeneity in wage strategies (posting vs negotiating) [Postel-Vinay and Robin, 2004; Hall and Krueger, 2012; Brenzel et al, 2014; Flinn et al., 2017; Caldwell and Harmon, 2019]
  - Surveys as "ground truth"?
  - Can we reliably infer firm-level conduct from wages and hiring?
- Firm amenities contribute to dest effs [Sorkin, 2018; Card et al, 2018; Lindenlaub and Postel-Vinay, 2016; Lamadon et al, 2019]
- Limited information about outside options [Jaeger et al, 2021]
- Horizontal equity / morale concerns [Card et al., 2012; Breza et al., 2018; Mas, 2017; Cullen and Pakzad-Hurson, 2019]