It Ain't Where You're From, It's Where You're At..

Firm Effects, State Dependence, and the Gender Wage Gap

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October 12, 2019

Abowd, Kramarz, and Margolis (1999)

The AKM model of wage determination

$$y_{it} = \alpha_i + \psi_{j(i,t)} + X'_{it}\beta + \varepsilon_{it}$$

where $j(i,t)$ gives identity of worker i's current employer

Partitions log-wages y_{it} at time t into:

- Time varying covariates X_{it} (age, year, etc)
- Perfectly transferable "person effect"α_i
- Non-transferable "firm effect" $\psi_{j(i,t)}$

Can it be so simple?

AKM loosely motivated by wage posting models (e.g., Burdett and Mortensen, 1998) that feature a stable *wage ladder*

- Wages depend on worker type α and the "rung" ψ of the ladder
- Irrelevant how one gets to that rung

Is there a stable firm wage ladder? Reasons to be skeptical:

- Workers may be willing to take a wage *cut* to move to more productive firms (Postel-Vinay and Robin, 2002)
- Longer run effects of initial conditions (Beaudry and Dinardo, 1991; Von Wachter and Bender, 2006; Oreopolous et al., 2012)

Policy relevance: recent bans on inquiring about past salary

- Concern that gender differences in mobility / bargaining have cumulative effects

A state-dependent ladder

Consider simple dynamic generalization of AKM model (DAKM)

$$y_{it} = \alpha_i + \underbrace{\psi_{j(i,t)}}_{\text{“where you're at”}} + \underbrace{\lambda_{\ell(i,t)}}_{\text{“where you're from”}} + X_{it}'\beta + \varepsilon_{it}$$

where $\ell(i,t)$ gives identity of worker i's *previous* employer or labor force state (e.g., unemployment, NILF)

- $\lambda_{\ell(i,t)}$ is *partially* transferable component
- Interpretations of λ:
  - Reputation effects (Gibbons and Katz, 1992; Gibbons et al., 2005)
  - Implicit contracts (Beaudry and Dinardo, 1991, 1995)
  - Counter-offers / sequential wage bargaining (Postel-Vinay and Robin, 2002; Cahuc et al., 2006)

Some prior estimates of state-dependent models

Random effects: Postel-Vinay and Robin (PVR, 2002); Cahuc et al. (2006); Bagger et al. (2014)

- Joint restrictions across mobility and wage equations
- Assumes 1-factor model:

$$(\psi_j, \lambda_j) = (\psi(p_j), \lambda(p_j))$$

Group fixed effects: Bonhomme, Lamadon, and Manresa (2019)

- 10 firm types identified from clustering on cross-section
- Non-separable contemporaneous + separable lagged effects
- Allow endogenous mobility (including future firm effects)
- Result 1: statistically significant lagged effects
- Result 2: Modest improvement in fit when moving from static model ($R^2 = 74.9\%$) to dynamic model ($R^2 = 77.9\%$)

Today

Assess importance of $\lambda_{\ell(i,t)}$ for "poaching" wages

- Allow each firm to be its own 2-D (ψ, λ) type
- Avoid modeling within-match wage dynamics
- Treat non-employment and N(Y)ILF as separate lagged "firms"
- Discuss conditions under which $\left(\psi_{j(i,t)}, \lambda_{\ell(i,t)}\right)$ separately identified
- Unbiased variance decompositions ala KSS (2018)
- Relate poaching wage from non-employment to Urate

Decomposition of gender gap in hiring wages:

- How much would gender gap shrink if women came *from* the same firms as men?
- How much would gender gap shrink if women were *at* the same firms as men?

Empirical conclusion: It ain't where you're from

It's where you're at..

A motivating framework: PVR (2002)

- Postel-Vinay and Robin (2002, IER) introduced the sequential auction model of worker poaching
- Empirical adaptation in PVR (2002, ECTA)

Model primitives:

- Workers have flow utility over wages $U(w)$
- Worker productivity type ε
- Firm productivity type $p \sim \Gamma(\cdot)$
- Sampling dist is $F(\cdot)$
- Marginal productivity of a match is εp

Market Structure

- Random on the job search ala BM (1998)
- Firms make take it or leave it offers of piece-rate contracts (price per unit of output εp)
- Complete information: firm knows the worker's res wage
  - Reservation wage depends on prod of current employer (if any)
- Incumbent employer can respond which leads to 2nd price auction
  - Worker goes to whichever firm is more productive
- Without heterogeneity, wage would follow a 2-pt distribution:
  - a wage for workers hired from unemployment
  - a wage for those hired from other jobs

Poaching wages

- Value of unemployment: $V_0(\varepsilon)$
- Value of employment: $V(\varepsilon, w, p)$ (p influences wage *growth*)
- Unemployed worker of type ε upon making contact with firm of type p, will be offered monopsony wage $\phi_0(\varepsilon, p)$ obeying:

$$V(\varepsilon, \phi_0(\varepsilon, p), p) = V_0(\varepsilon)$$

- When contacted by outside firm with productivity $p' > p$ will move to new firm and be paid "poaching wage" $\phi\left(\varepsilon, p, p'\right)$ obeying:

$$V\left(\varepsilon, \phi\left(\varepsilon, p, p'\right), p'\right) = V(\varepsilon, \varepsilon p, p)$$

- When contacted by outside firm with productivity $p' < p$ will be paid "retention wage" $\phi\left(\varepsilon, p', p\right)$ provided this does not involve a wage cut

PVR show that:

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

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

$$\ln\phi\left(\varepsilon,p,p'\right)=\underbrace{\ln\varepsilon}_{\text{person type}}+\underbrace{\ln p}_{\text{poached firm type}}\underbrace{-\kappa\int_{p}^{p'}\bar{F}\left(x\right)\frac{dx}{x}}_{\text{type upgrade}}$$

- Poaching wage is decreasing in the productivity gap between poaching and poached firms (compensating diff)
- Same eq for hires from unemp which is just a “firm” w/ prod b

Link to DAKM

By fundamental theorem of calculus $\int_p^{p'} \bar{F}(x) \frac{dx}{x} = H(p') - H(p)$, where $H(p) = \int_0^p \bar{F}(x) \frac{dx}{x}$. Thus we can write the reduced form

$$\ln \phi\left(\varepsilon, p, p'\right) = \underbrace{\ln \varepsilon}_{=\alpha} + \underbrace{\left(-\kappa H(p')\right)}_{=\psi(p')} + \underbrace{\ln p + \kappa H(p)}_{=\lambda(p)}$$

- Evolution of poaching wages driven by movement along 1-dimensional *productivity ladder*
- Limiting case: $\kappa = 0$ (workers are myopic) starting wages only depend on productivity of previous firm
- Contemporaneous and lagged effects of given firm are *negatively* dependent: $\frac{d\psi(p)}{dp} < 0$ while $\frac{d\lambda(p)}{dp} > 0$.

A Simplified Example

Suppose uniform dist of productivity, so that $\bar{F}(x) = 1 - x$. Hence,

$$\int_p^{p'} \bar{F}(x) \frac{dx}{x} = \ln p' - \ln p - \left(p' - p\right).$$

- Resulting poaching wage is:

$$\ln \phi\left(\varepsilon, p, p'\right) = \underbrace{\ln \varepsilon}_{\alpha} + \underbrace{\kappa \left(p' - \ln p'\right)}_{\psi(p')} + \underbrace{(1+\kappa) \ln p - \kappa p}_{\lambda(p)}$$

- Uniform $\Gamma(\cdot)$ implies $Corr(\psi(p), \lambda(p)) < -.98$!

Dynamics of hiring wages

Suppose we have wage data for n workers who switch jobs at least once

- Let $t \in \{1, 2, 3\}$ index job #
- Y_{it} gives first full-time wage ("poaching wage") at t'th job
- Suppressing covariates X_{it}, DAKM model is:

$$y_{it} = \alpha_i + \psi_{j(i,t)} + \lambda_{\ell(i,t)} + \varepsilon_{it} \qquad (i = 1, \ldots, n,\ t = 1, 2, 3)$$

- Difference across jobs to eliminate worker effects:

$$\begin{aligned} y_{it} - y_{it-1} = \psi_{j(i,t)} - \psi_{j(i,t-1)} + \lambda_{\ell(i,t)} - \lambda_{\ell(i,t-1)} \\ + \varepsilon_{it} - \varepsilon_{it-1} \end{aligned}$$

Three career paths

Let N denote "not yet in LF," J a new full-time job, and U an intervening spell of non-employment. We consider three labor market histories and associated wage changes between last two jobs:

- NJJJ (2 consecutive job-2-job transitions after entry)

$$y_{i3} - y_{i2} = \psi_{j(i,3)} - \psi_{j(i,2)} + \lambda_{j(i,2)} - \lambda_{j(i,1)} + \varepsilon_{i3} - \varepsilon_{i2}$$

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- NJUJJ (1 JUJ + 1 J2J)

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- NJJ- (2 lifetime jobs, 1 J2J)

$$y_{i2} - y_{i1} = \psi_{j(i,2)} - \psi_{j(i,1)} + \lambda_{j(i,1)} - \lambda_{N} + \varepsilon_{i2} - \varepsilon_{i1}$$

Pooled model

Pooling these three cases together, we have a single wage change per individual (growth in hiring wage between last two jobs):

$$\begin{aligned}\Delta y_i &= \Delta\psi_i + \Delta\lambda_i + \Delta\varepsilon_i \\ &= \Delta F_i'\psi + \Delta L_i'\lambda + \Delta\varepsilon_i\end{aligned}$$

Conditioning on employment history $\mathcal{F} = \{(\Delta F_i, \Delta L_i)\}_{i=1}^n$, all uncertainty derives from the independent errors $\{\Delta\varepsilon_i\}_{i=1}^n$ which obey

$$\mathbb{E}[\Delta\varepsilon_i \mid \mathcal{F}] = 0 \qquad \text{(exogenous mobility)}$$

$$\mathbb{E}[\Delta\varepsilon_i^2 \mid \mathcal{F}] = \sigma_i^2 \qquad \text{(heteroscedasticity)}$$

Decomposing wage growth

Under exogenous mobility, a variance decomposition of wage growth is

$$\mathbb{E}\left[\mathbb{V}_n\left[\Delta y_i\right] \mid \mathcal{F}\right] = \underbrace{\mathbb{V}_n[\Delta\psi_i]}_{\Delta\text{dest eff}} + \underbrace{\mathbb{V}_n[\Delta\lambda_i]}_{\Delta\text{origin eff}} + 2\,\underbrace{\mathbb{C}_n[\Delta\psi_i, \Delta\lambda_i]}_{\text{trajectory}} + \mathbb{E}\left[\mathbb{V}_n\left[\Delta\varepsilon_i\right] \mid \mathcal{F}\right]$$

where $\mathbb{V}_n\left[\cdot\right]$ denotes sample variation across *workers*

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$$+\,\mathbb{E}\left[\mathbb{V}_n\left[\Delta\varepsilon_i\right] \mid \mathcal{F}\right]$$

where $\mathbb{V}_n\left[\cdot\right]$ denotes sample variation across *workers*

Also of interest are *firm*-level components:

$$\mathbb{V}_n[\psi_j], \quad \mathbb{V}_n[\lambda_j], \quad \mathbb{C}_n[\psi_j, \lambda_j]$$

- PVR implies $\mathbb{C}_n[\psi_j, \lambda_j] \ll 0$ due to forward looking behavior / compensating diffs
- We weight these variances by firm size

Identification

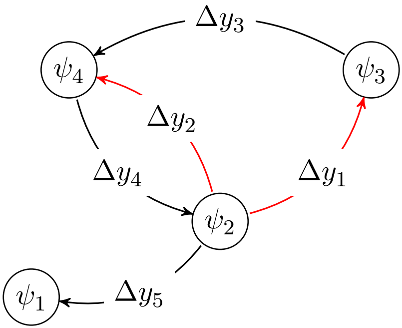
Model of wage growth

$$\Delta y_i = \Delta\psi_i + \Delta\lambda_i + \Delta\varepsilon_i$$

Identification of the variance decomposition requires that $\Delta\psi_i$ and $\Delta\lambda_i$ are separately identified

- Recall that AKM is identified by worker mobility that forms a network of paths between firms
- DAKM involves both contemporaneous and lagged mobility networks
- Identification of DAKM from worker mobility that forms paths on one network and cycles on the other
- Generalization of classic "pairwise differencing" arguments (e.g., Ahn and Powell, 1993)

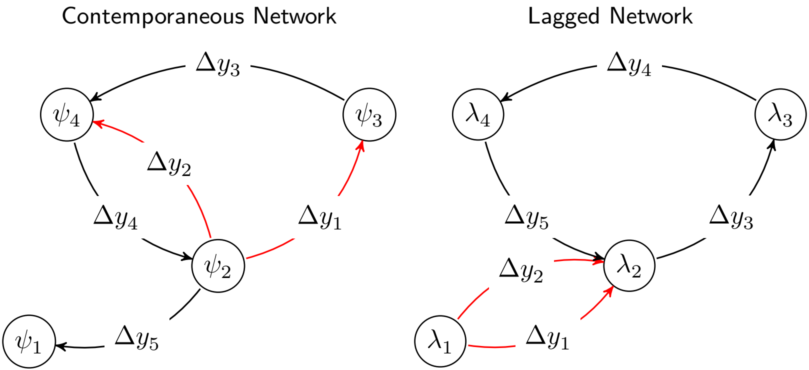
Identification of AKM



The pairwise difference $\Delta y_1 - \Delta y_2$ forms a path from ψ_4 to ψ_3:

$$\begin{aligned} \mathbb{E}[\Delta y_1 - \Delta y_2 \mid \mathcal{F}] &= \psi_3 - \psi_2 - (\psi_4 - \psi_2) \\ &= \psi_3 - \psi_4 \end{aligned}$$

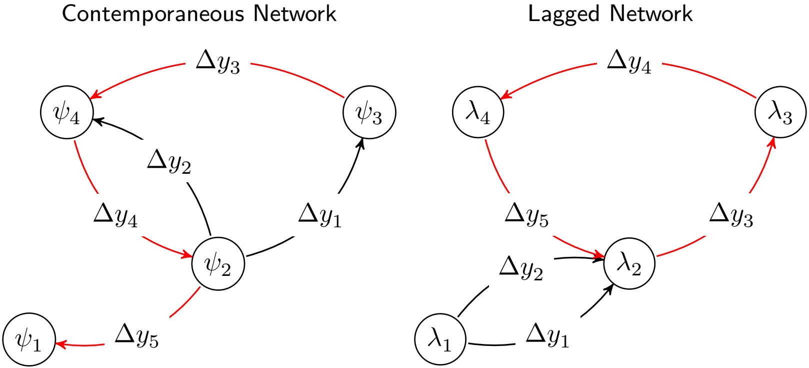
Identification of DAKM



Here, $\Delta y_1 - \Delta y_2$ forms a cycle on the lagged network

$$\begin{aligned}\mathbb{E}[\Delta y_1 - \Delta y_2 \mid \mathcal{F}] &= \underbrace{\psi_3 - \psi_2 - (\psi_4 - \psi_2)}_{\text{Contemporanous diff}} + \underbrace{\lambda_2 - \lambda_1 - (\lambda_2 - \lambda_1)}_{\text{Lagged diff}} \\ &= \psi_3 - \psi_4\end{aligned}$$

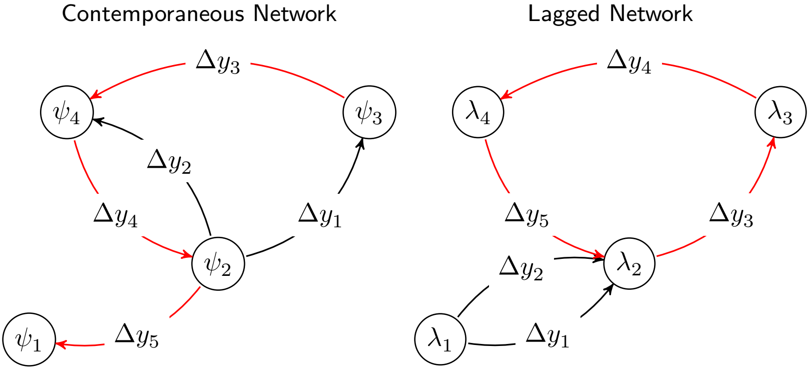
Identification of DAKM



Similarly, $\Delta y_3 + \Delta y_4 + \Delta y_5$ forms a path on the contemporaneous network and a cycle on the lagged one:

$$\mathbb{E}[\Delta y_3 + \Delta y_4 + \Delta y_5 \mid \mathcal{F}] = \psi_1 - \psi_3$$

Identification of DAKM



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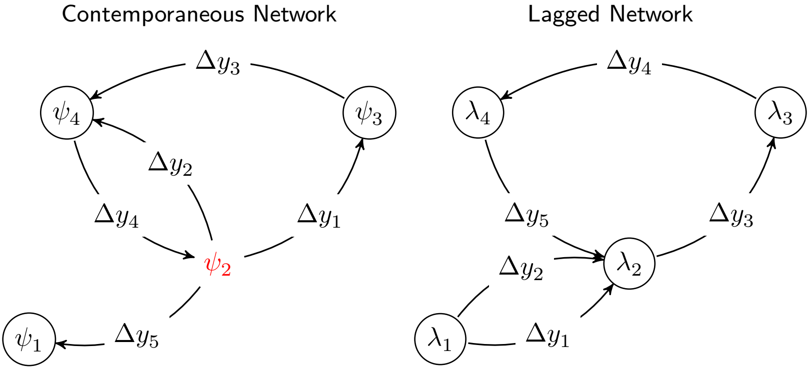
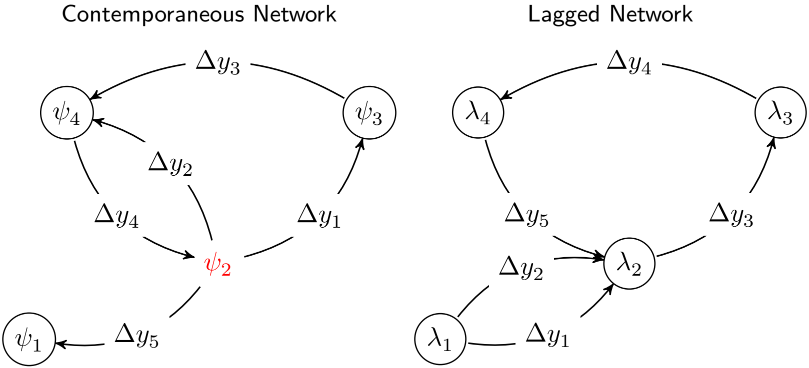
Thus the differences $\{\psi_4 - \psi_1,\ \psi_4 - \psi_3,\ \psi_3 - \psi_1\}$ are identified

Identification of DAKM



- $\psi_2 - \psi_j$ is not identified for $j \in \{1, 3, 4\}$

Identification of DAKM



- $\psi_2 - \psi_j$ is not identified for $j \in \{1, 3, 4\}$
- We refer to $\{\psi_1, \psi_3, \psi_4\}$ as the *largest identified set*
- Same argument for lagged effects

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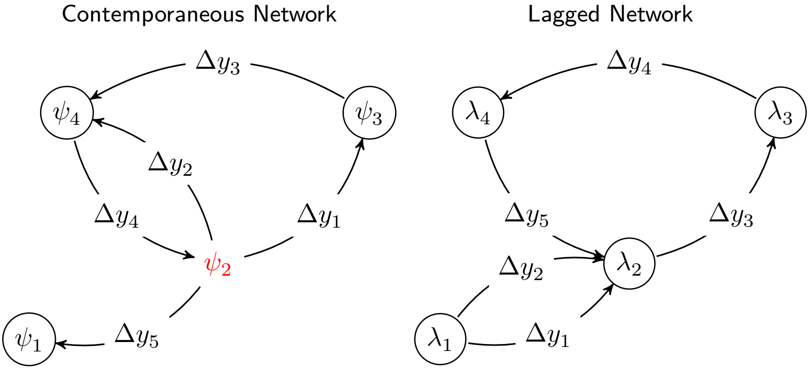

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- Same argument for lagged effects
- Observations with $\Delta\psi_i$ and $\Delta\lambda_i$ in largest identified sets are referred to as the *largest identified sample*

Leave-one-out identification for variance components

KSS (2018) established necessity of *leave-i-out* identification for unbiased variance decomposition under heteroscedasticity:

- Decomposing Δy_i requires identification of unexplained variation:

$$\begin{aligned}\mathbb{E}\left[\mathbb{V}_n\left[\Delta y_i\right] \mid \mathcal{F}\right] = & \mathbb{V}_n[\Delta\psi_i] + \mathbb{V}_n[\Delta\lambda_i] + 2\mathbb{C}_n[\Delta\psi_i, \Delta\lambda_i] \\ & + \underbrace{\mathbb{E}\left[\mathbb{V}_n\left[\Delta\varepsilon_i\right] \mid \mathcal{F}\right]}_{=\frac{n-1}{n^2}\sum_{i=1}^n \sigma_i^2}\end{aligned}$$

- σ_i^2 is identified iff $\Delta\psi_i + \Delta\lambda_i$ is leave-i-out identified

Observations where σ_i^2 is identified are referred to as the *leave-one-out sample*. We use this sample for estimation.

Estimator

$$\Delta y_i = \Delta\psi_i + \Delta\lambda_i + \underbrace{\Delta X_i'\beta}_{\text{age + yr effects}} + \Delta\varepsilon_i$$
$$= Z_i'\gamma + \Delta\varepsilon_i$$

where $Z_i = (\Delta F_i', \Delta L_i', \Delta X_i')'$ and $\gamma = (\psi', \lambda', \beta')$

- Write any variance component θ of interest as quadratic form:

$$\theta = \gamma' A \gamma$$

- When decomposing $\mathbb{E}\left[\mathbb{V}_n\left[\Delta y_i\right] \mid \mathcal{F}\right]$, A considers individuals where both $\Delta F_i'\psi$ and $\Delta L_i'\lambda$ are in largest identified set
- For employer-centric variance components, A considers firms where both ψ_j and λ_j are in largest identified set

Plug-in Estimator (aka OLS)

Letting $S_{zz} = \sum_{i=1}^{n} Z_i Z_i'$, the OLS estimator of γ is:

$$\hat{\gamma} = S_{zz}^{\dagger} \sum_{i=1}^{n} Z_i' \Delta y_i$$

where $\dagger$ is MP-inverse (spit out by CG-routine when singular)

- "Plug-in" estimator of variance component is:

$$\hat{\theta}_{\mathsf{PI}} = \hat{\gamma}' A \hat{\gamma}.$$

- Easy to show that $\hat{\theta}_{\mathsf{PI}}$ is biased:

$$\mathbb{E}[\hat{\theta}_{\mathsf{PI}} \mid \mathcal{F}] = \theta + \operatorname{trace}\left(A \mathbb{V}[\hat{\gamma} \mid \mathcal{F}]\right) = \theta + \sum_{i=1}^{n} B_{ii} \sigma_i^2$$

  where $B_{ii} = Z_i' S_{zz}^{\dagger} A S_{zz}^{\dagger} Z_i$

KSS (2018) Estimator

$$\mathbb{E}[\hat{\theta}_{\mathsf{PI}} \mid \mathcal{F}] = \theta + \sum_{i=1}^{n} B_{ii}\sigma_i^2$$

- Let leave-i-out estimator of γ be $\hat{\gamma}_{-i} = \left(S_{zz} - Z_i Z_i'\right)^{\dagger} \sum_{l \neq i} Z_l \Delta y_l$
- Key idea in KSS: unbiased estimator of σ_i^2 is

$$\hat{\sigma}_i^2 = \Delta y_i \left(\Delta y_i - Z_i' \hat{\gamma}_{-i}\right)$$

- KSS estimator of variance component is:

$$\hat{\theta}_{\mathsf{KSS}} = \hat{\gamma}' A \hat{\gamma} - \sum_{i=1}^{n} B_{ii}\hat{\sigma}_i^2$$

Data: Veneto Work History File

Administrative social security records for Italian region of Veneto years 1984–2001

- Panel of annual earnings, weeks worked, employer ids in that year
- Extract individuals w/ career paths: NJJJ, NJUJJ, or NJJ-
- Non-employment "gap" (U) when worked < 37 weeks in year
- NILF (N) before first observed job
- "Poaching wage" is average daily earnings in first year w/ ≥ 37 weeks that employer earnings record is dominant
- For each worker, extract a single *change* in poaching wages between last two jobs

Restricting the Sample

Iterative algorithm restricts to workers in leave-one-out sample and characterizes largest identified set for contemporaneous and lagged firm effects

- Drop observations where σ_i^2 is not identified: Drop observations with statistical leverage $P_{ii} = Z_i' S_{zz}^{\dagger} Z_i$ equal to 1
- Characterize largest identified set for ψ: For $\tilde{\gamma} = S_{zz}^{\dagger} S_{zz} \gamma$, $\mathcal{J}_\psi$ is the largest set of firms such that $j \in \mathcal{J}_\psi$ if and only if

  $$\tilde{\psi}_j - \tilde{\psi}_{j'} = \psi_j - \psi_{j'}$$

  for all $j' \in \mathcal{J}_\psi$ and any γ. Same for λ yields $\mathcal{J}_\lambda$.
- Largest identified sample are individuals whose employment history is contained in $\mathcal{J}_\psi$ and $\mathcal{J}_\lambda$.

Table 1: Summary Statistics

	All Workers	Male Workers	Female Workers
Starting Sample			
Number of individuals	$572,421$	$366,810$	$205,611$
Number of firms	$167,453$	$117,632$	$104,044$
Average wage growth	0.1031	0.1177	0.0771
Variance of wage growth	0.0670	0.0611	0.0765
Leave-one-out Sample			
Number of individuals	$465,336$	$288,677$	$130,970$
Number of firms	$86,104$	$57,093$	$35,623$
Average wage growth	0.1088	0.1263	0.0766
Variance of wage growth	0.0636	0.0594	0.0662
Largest Identified Sample			
Number of individuals	$392,731$	$241,501$	$89,841$
Number of firms	$58,527$	$38,945$	$18,515$
Average wage growth	0.1091	0.1280	0.0676
Variance of wage growth	0.0640	0.0605	0.0664

DAKM explains 2% more wage growth variance than AKM

(But coefficients vary substantially by gender..)

Table 2: Explained Variance of Wage Growth

	All Workers	Male Workers	Female Workers
Variance of wage growth	0.0636	0.0594	0.0662
Explained variance, R^2 (Plug-in)			
Lagged model, $\Delta\lambda_i$	0.3894	0.4547	0.3781
AKM model, $\Delta\psi_i$	0.5190	0.6029	0.4860
DAKM, $\Delta\psi_i + \Delta\lambda_i$	0.5926	0.6692	0.5642
DAKM by gender, $\Delta\psi_i^g + \Delta\lambda_i^g$	0.6741		
Explained variance, R^2 (KSS)			
Lagged model, $\Delta\lambda_i$	0.2908	0.3620	0.2353
AKM model, $\Delta\psi_i$	0.4215	0.5197	0.3303
DAKM, $\Delta\psi_i + \Delta\lambda_i$	0.4460	0.5417	0.3520
DAKM by gender, $\Delta\psi_i^g + \Delta\lambda_i^g$	0.5275		

"Where you're at" explains 4–$5\times$ "where you're from"

Table 3: Variance Decomposition of Wage Growth

	All Workers	Male Workers	Female Workers
Variance of wage growth	0.0640	0.0605	0.0664
Variance decomposition (Plug-in)			
$\mathbb{V}_n[\Delta\lambda_i]$	0.0176	0.0160	0.0270
$\mathbb{V}_n[\Delta\psi_i]$	0.0317	0.0310	0.0413
$2\mathbb{C}_n[\Delta\psi_i, \Delta\lambda_i]$	-0.0209	-0.0189	-0.0366

$$\mathbb{E}\left[\mathbb{V}_n\left[\Delta y_i\right] \mid \mathcal{F}\right] = \mathbb{V}_n[\Delta\psi_i] + \mathbb{V}_n[\Delta\lambda_i] + 2\mathbb{C}_n[\Delta\psi_i, \Delta\lambda_i] + \mathbb{E}\left[\mathbb{V}_n\left[\Delta\varepsilon_i\right] \mid \mathcal{F}\right]$$

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Variance decomposition (KSS)			
$\mathbb{V}_n[\Delta\lambda_i]$	0.0039	0.0039	0.0046
$\mathbb{V}_n[\Delta\psi_i]$	0.0165	0.0177	0.0165
$2\mathbb{C}_n[\Delta\psi_i, \Delta\lambda_i]$	-0.0019	-0.0022	-0.0028

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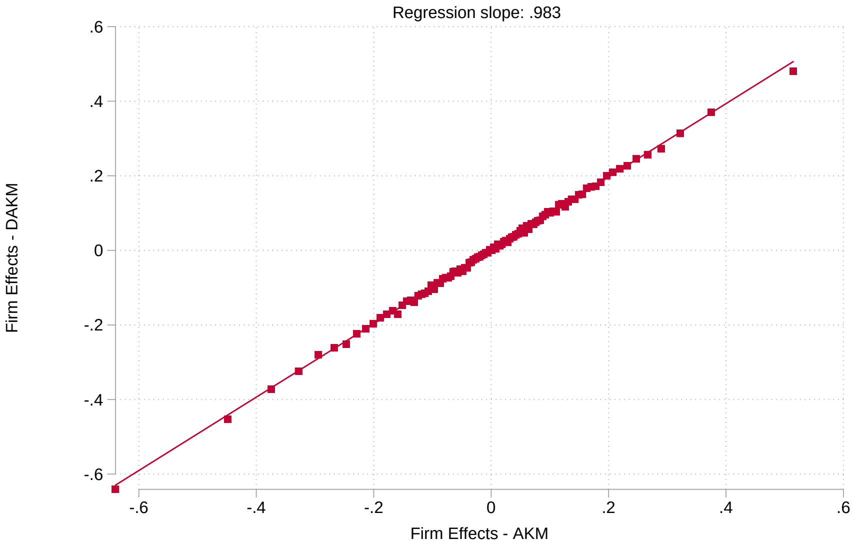
Lagged and contemporaneous effects positively correlated!

Table 4: Moments of Firm Effects (Person Weighted)

	All Workers	Male Workers	Female Workers
Firms in leave-one-out sample	$86,104$	$57,093$	$35,623$
Firms with identified ψ_j and λ_j	$40,946$	$26,477$	$11,777$
Covariances (KSS)			
$\mathbb{V}_n[\lambda_j]$	0.0039	0.0037	0.0053
$\mathbb{V}_n[\psi_j]$	0.0172	0.0172	0.0212
$\mathbb{C}_n[\psi_j, \lambda_j]$	0.0036	0.0027	0.0045
Correlation	0.4433	0.3430	0.4249

Ignoring lags has no effect on estimates of ψ

Figure 1: Estimated Contemporaneous Effects in DAKM and AKM



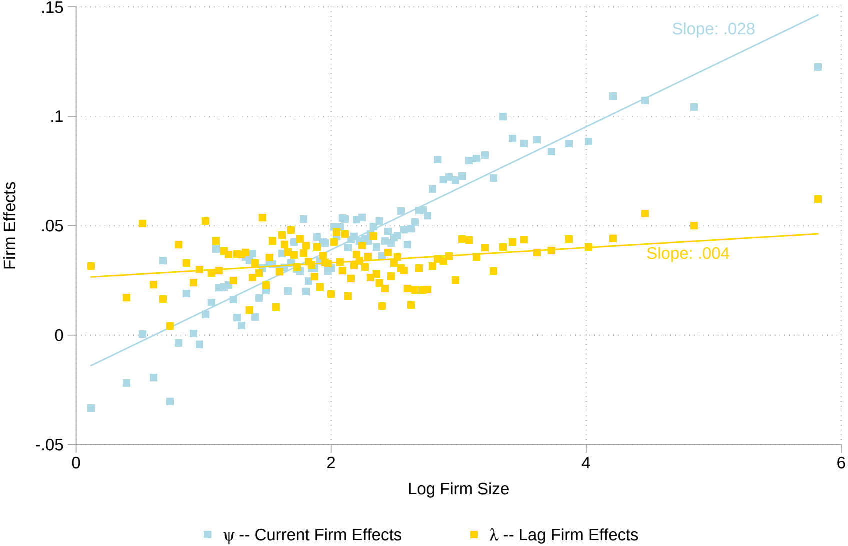
Some Normalizations

Useful to impose some normalizations on (ψ_j, λ_ℓ) to study differences in mean firm effects across groups:

1. Impose $\lambda_N = 0$
   - Effect of lagged state measured relative to N(Y)ILF
2. Set $\mathbb{E}_n[\psi_j|\text{firm size in bottom vingtile}] = 0$
   - Firm size measured as average number of workers for whom firm is dominant employer across years the firm is alive
   - For gender-specific estimates impose normalization among firms in each gender's leave-out-sample ala Card, Cardoso, and Kline (2016)

Lags more weakly correlated with firm size

Figure 2: Contemporaneous and lagged firm effects by size



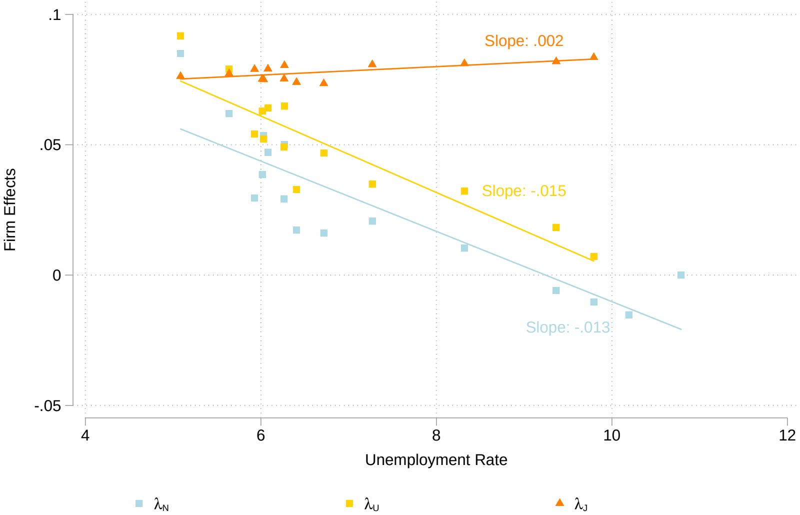
Time varying state-dependence

Figure 3: Urate, λ_U, and λ_N by year

Note: This model allows (λ_U, λ_N) to vary by calendar year. λ_N is normalized to 0 in 1984.

Better to enter LF or be hired from U when urate is low

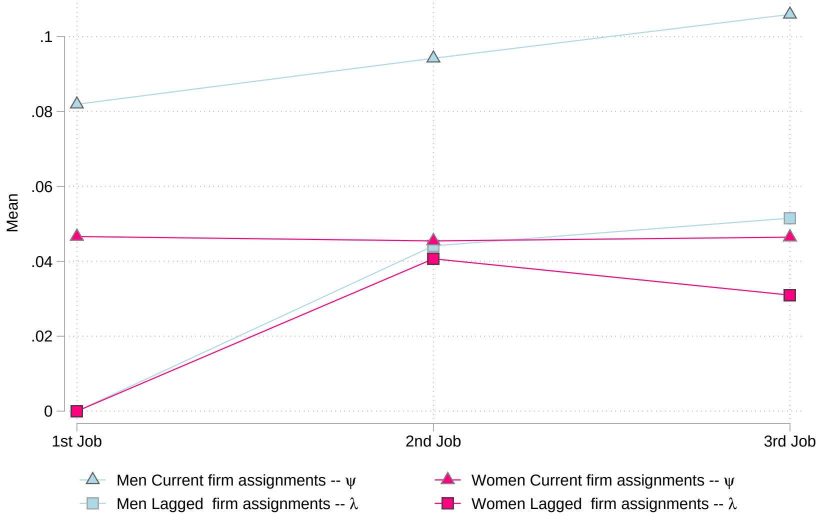
Figure 4: Employment weighted mean of ψ and (λ_N, λ_U) by Urate



Note: This model allows (λ_U, λ_N) to vary by calendar year. λ_N is normalized to 0 in 1984.

Men start out ahead, and climb, while women fall behind..

Figure 5: Mean of firm effects and lagged states by job # (NJJJ sample)



Note: ψ_j normalized to have mean zero among firms in bottom firm size vingtile. λ_j normalized relative to λ_N.

Gender Wage Decomposition (Pooled Model)

Hiring wage equation at job $t \in \{1, 2, 3\}$:

$$y_{it} - X_{it}'\beta = \alpha_i + F_{it}'\psi + L_{it}'\lambda + \varepsilon_{it}$$

Mean wages by gender $G_i \in \{m, f\}$ at job j:

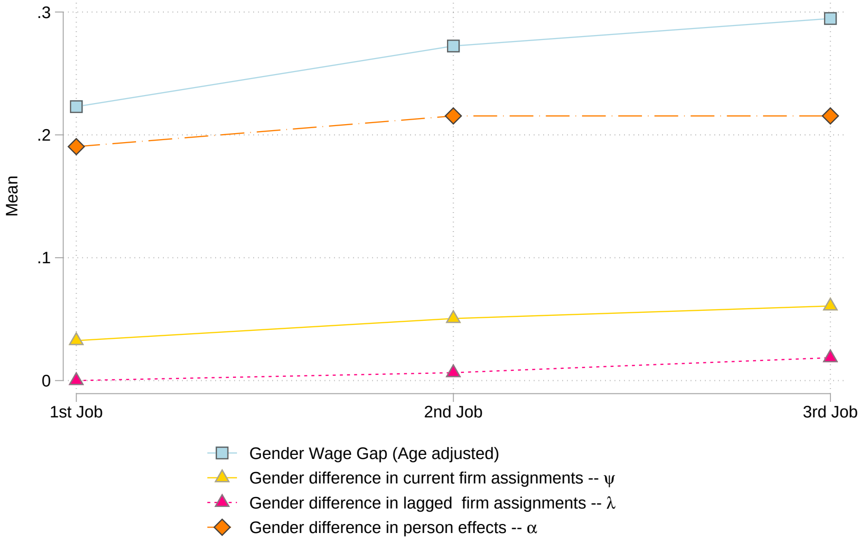
$$\mathbb{E}_n\left[y_{it} - X_{it}'\beta \mid G_i = g\right] = \bar{\alpha}_g + \bar{F}_{gt}'\psi + \bar{L}_{gt}'\lambda$$

Hence, we have the decomposition

$$\begin{aligned}
&\mathbb{E}_n\left[y_{it} - X_{it}'\beta \mid G_i = m\right] - \mathbb{E}_n\left[y_{it} - X_{it}'\beta \mid G_i = f\right] \\
&= \bar{\alpha}_m - \bar{\alpha}_f + \underbrace{\left(\bar{F}_{mt} - \bar{F}_{ft}\right)'\psi}_{\text{Move women to same firms as men}} + \underbrace{\left(\bar{L}_{mt} - \bar{L}_{ft}\right)'\lambda}_{\text{Move women to same lagged states as men}}
\end{aligned}$$

“Where you’re from” negligible for gender gap

Figure 6: Mean gender gap and firm effect contribution by job #
(all groups pooled)



Oaxaca Decomposition

Hiring wage equation at job $t \in \{1, 2, 3\}$:

$$y_{it} - X_{it}'\beta = \alpha_i + F_{it}'\psi^{G_i} + L_{it}'\lambda^{G_i} + \varepsilon_{it}$$

Mean wages by gender at job j:

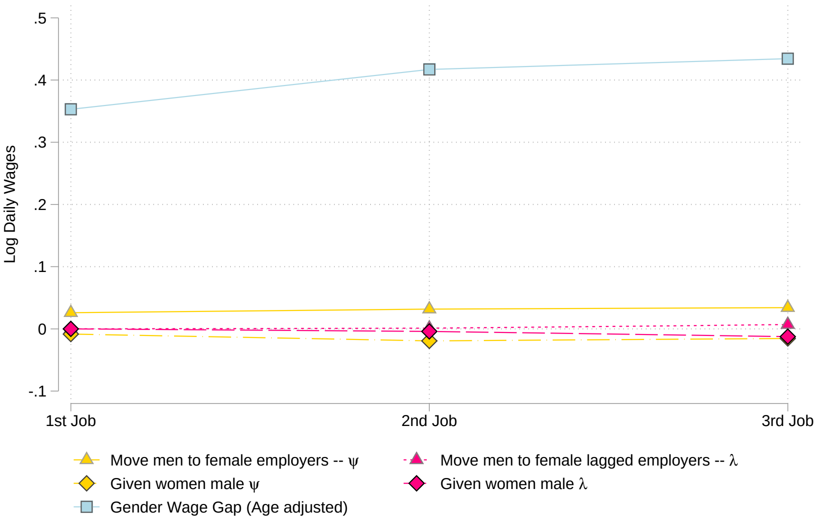
$$\mathbb{E}_n \left[y_{it} - X_{it}'\beta \mid G_i = g \right] = \bar{\alpha}_g + \bar{F}_{gt}'\psi^g + \bar{L}_{gt}'\lambda^g$$

Hence, we have the decomposition:

$$\begin{aligned}
&\mathbb{E}_n \left[y_{it} - X_{it}'\beta \mid G_i = m \right] - \mathbb{E}_n \left[y_{it} - X_{it}'\beta \mid G_i = f \right] \\
&\quad = \bar{\alpha}_m - \bar{\alpha}_f - \underbrace{\left(\bar{F}_{ft} - \bar{F}_{mt} \right)' \psi^m}_{\textbf{Move \textit{men} to same firms}} - \underbrace{\left(\bar{L}_{ft} - \bar{L}_{mt} \right)' \lambda^m}_{\textbf{Move \textit{men} to same states}} \\
&\qquad + \underbrace{\bar{F}_{ft}' \left(\psi^m - \psi^f \right)}_{\textbf{Give \textit{women} male } \psi\textbf{'s}} + \underbrace{\bar{L}_{ft}' \left(\lambda^m - \lambda^f \right)}_{\textbf{Give \textit{women} male } \lambda\textbf{'s}} \qquad \text{(normalization dependent)}
\end{aligned}$$

Oaxaca: it's still where you're at

Figure 7: Mean gender gap and firm effect contribution by job #
(all groups pooled)



Conclusions

Modest state dependence in job ladder (consistent w/ BLM)

- Roughly 4% premium on average for poached vs. N(Y)ILF
- Negligible bias in ψ estimates from omitting lagged states
- Positive correlation between ψ_j and λ_j inconsistent w/ PVR
- Firm size more strongly correlated with ψ_j than λ_j
  - ψ a better proxy of rents?
- Strong correlation of (λ_U, λ_N) with Urate
  - Consistent w/ many models: sequential auctions / Nash Bargaining / implicit contracts.
  - But potentially at odds with reduced form findings of Jäger et al (2019) that hiring wages insensitive to UI benefits

Conclusions

Stark gender differences in sorting

- Men start out at higher paying firms
- Male advantage intensifies by (slowly) climbing the ladder, while women fail to climb when moving
- NJJ- women initially move to firms that are worse to be from!

Conclusions

Stark gender differences in sorting

- Men start out at higher paying firms
- Male advantage intensifies by (slowly) climbing the ladder, while women fail to climb when moving
- NJJ- women initially move to firms that are worse to be from!

But $\lambda_{\ell(i,t)}$ quantitatively unimportant for gender gap in hiring wages..

- 13–20% of gender gap attributable to where workers "are at"
- $\leq 1\%$ due to differences in where "they're from"
- Prediction: salary non-disclosure laws unlikely to substantially alter gender gap (consistent w/ Agan et al, 2019)