

# *Vacancy Yields in the Cross-section and Over Time*

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14th CSEF-IGIER Symposium on Economics and Institutions

June 26, 2018

*The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.*

# Unemployment Dynamics



- $u_{t+1} = \delta_t(1 - u_t) - p_t u_t$
- $H_t = \Phi_t V_t^\alpha U_t^{1-\alpha} \rightarrow p_t = \Phi_t \theta_t^\alpha$
- $u_t$ : data     $u_t$ : counterfactual with constant  $\Phi_t$

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Variation in match efficiency is crucial for labor market dynamics

## Looking into the Black Box of $\Phi_t$

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Potential explanations:

- Mismatch btw vacancies and job seekers across sectors ( $\Phi^O$ )
- Job seekers composition and job-search effort ( $\Phi^W$ )

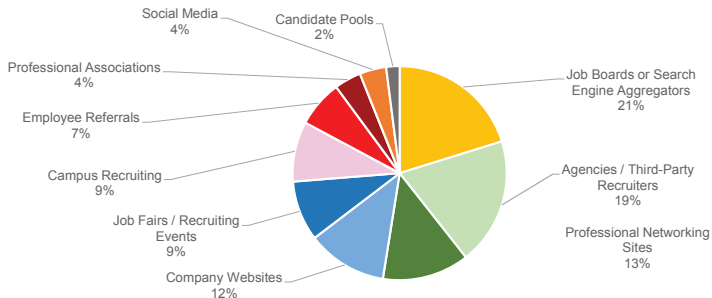
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- Firm recruiting intensity per vacancy ( $\Phi^F$ )
  - ▶ Firms' recruiting expenditures

# Recruiting Expenditures



Average cost per hire (>100 employees): \$3,000-\$4,000

Source: Bersin and Associates (2015)

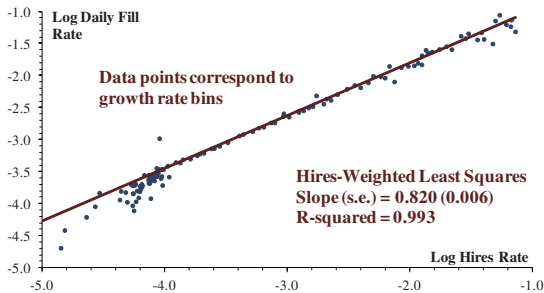
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- **Firm recruiting intensity** per vacancy ( $\Phi^F$ )
  - ▶ Firms' recruiting expenditures
  - ▶ Compensation
  - ▶ Hiring standards

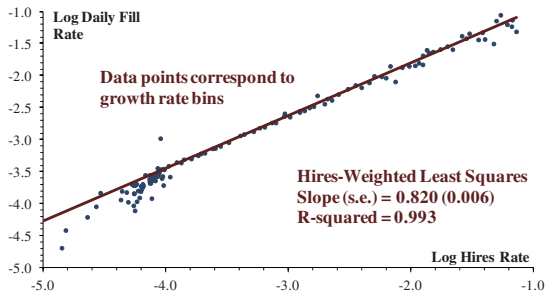
## Vacancy Yields in the Cross-Section



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## Vacancy Yields in the Cross-Section



- Recruiting intensity varies across firms
- Strong **log-linearity** btw recruiting intensity and firm growth rate

## Aggregate match efficiency: Decomposition

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$$H_t = \Phi_t^W \cdot \Phi_t^F \cdot \Phi_t^O \cdot V_t^\alpha U_t^{1-\alpha}$$

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Define:

$$S_t = s_t^U U_t + s_t^N N_t + s_t^E E_t$$

$$V_t^* = \sum_i s_{it}^V(e_{it}, w_{it}, \epsilon_{it}^{\min}) v_{it}$$

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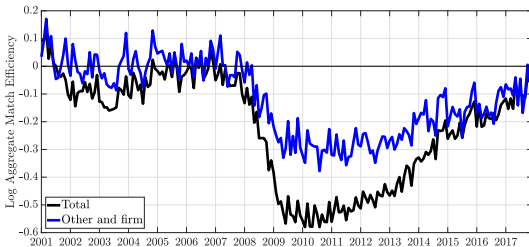
$$V_t^* = \sum_i s_{it}^V (e_{it}, w_{it}, \epsilon_{it}^{\min}) v_{it}$$

Combining:

$$H_t = \underbrace{\left[ 1 + \left( \frac{s_t^N}{s_t^U} \right) \frac{N_t}{U_t} + \left( \frac{s_t^E}{s_t^U} \right) \frac{E_t}{U_t} \right]^{1-\alpha}}_{\Phi_t^W = \left( \frac{S_t}{U_t} \right)^{1-\alpha}} \underbrace{\left[ \sum_i s_{it}^V \frac{v_{it}}{V_t} \right]^\alpha}_{\Phi_t^F = \left( \frac{V_t^*}{V_t} \right)^\alpha} \Phi_t^O V_t^\alpha U_t^{1-\alpha}$$

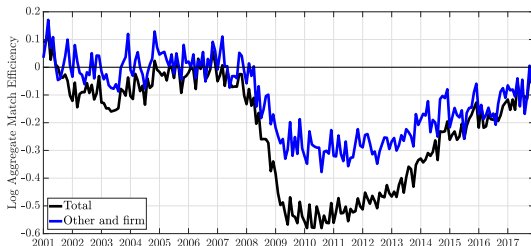
where  $\Phi_t^O$  includes  $s_t^U$ .

# Aggregate match efficiency: Decomposition



$$\Phi_t = \underbrace{\Phi_t^W}_{\approx 2/5} \cdot \underbrace{\Phi_t^F \cdot \Phi_t^O}_{\approx 3/5}$$

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$$\Phi_t = \underbrace{\Phi_t^W}_{\approx 2/5} \cdot \underbrace{\Phi_t^F \cdot \Phi_t^O}_{\approx 3/5}$$

- What drives fluctuations in recruiting intensity  $\Phi_t^F$ ?
  - ▶ **Composition effect**: changes in the cross-section of hiring firms
  - ▶ **Slackness effect**: firm response to aggregate labor market conditions

## Today

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  - ▶ It extends Gavazza-Mongey-Violante (2018)

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- Assess determinants of recruiting intensity at micro-level
- Relative importance of composition vs slackness effects
- Relative importance of **expenditures, wages**, and selectivity
- Road ahead

## Recruiting Expenditures

Firm's problem:

$$v(n_{it}, z_{it}) = \max_{n_{i,t+1}, v_{it}, e_{it}} \pi(z_{it}, n_{i,t+1}, n_{it}, v_{it}, e_{it}) + \beta \mathbb{E}_t [v(n_{i,t+1}, z_{i,t+1})]$$

*s.t.*

$$\pi_{it} = f(z_{it}, n_{i,t+1}) - W_t n_{i,t+1} - C(n_{it}, v_{it}, e_{it})$$

$$h_{it} := n_{i,t+1} - (1 - \delta) n_{it} = q(\Phi_t, \theta_t) e_{it} v_{it}$$

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- Separability between  $n_{i,t+1}$  and  $(e_{it}, v_{it})$ : **two-stage maximization**
  1. Given  $(n_{it}, z_{it})$ , choose  $h_{it}$
  2. Given  $h_{it}$ , choose  $(e_{it}, v_{it})$

## Choice of vacancies and effort

$$C(h_{it}, n_{it}) = \min_{e_{it}, v_{it}} : \left[ \frac{\kappa_e}{\gamma_e} e_{it}^{\gamma_e} + \frac{\kappa_v}{1 + \gamma_v} \left( \frac{v_{it}}{n_{it}} \right)^{\gamma_v} \right] v_{it}$$

s.t.

$$h_{it} = q(\Phi_t, \theta_t) \underbrace{\mu_{j(i)} e_{it} v_{it}}_{v_{it}^*}$$

where  $\gamma_e > 1$ ,  $\gamma_v > 0$ ,  $q(\Phi_t, \theta_t) = \Phi_t \theta_t^{-(1-\alpha)}$ . Let  $\gamma := \frac{\gamma_v}{\gamma_e + \gamma_v}$

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Choice of functional form dictated by **reverse engineering**

**Optimality:**

$$\log e_{it} = \Omega - \gamma \log q(\Phi_t, \theta_t) - \gamma \log \mu_{j(i)} + \gamma \log \left( \frac{h_{it}}{n_{it}} \right)$$



## Empirical implementation

### Model:

$$\log \left( \frac{h_{it}}{v_{it}} \right) = \log \Omega + (1 - \gamma) \log q(\Phi_t, \theta_t) + (1 - \gamma) \log \mu_{j(i)} + \gamma \log \left( \frac{h_{it}}{n_{it}} \right)$$

### Data:

$$\log \left( \frac{h_{it}}{v_{it}} \right) = \beta_0 + D_t + D_{j(i)} + \beta_1 \log \left( \frac{h_{it}}{n_{it}} \right) + \vartheta_{it}.$$

- $\hat{\beta}_1 = \gamma$
- $\hat{D}_t = (1 - \gamma) \log q(\Phi_t, \theta_t) \rightarrow \log q(\Phi_t, \theta_t)$

## JOLTS

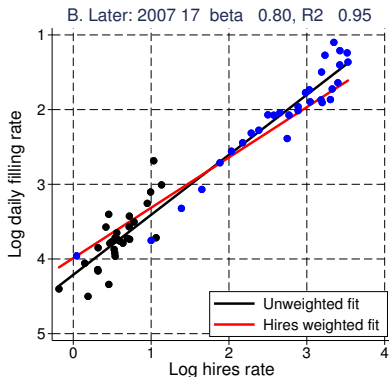
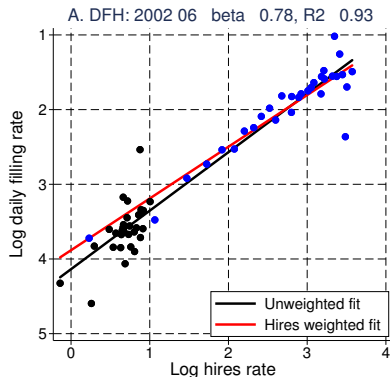
- Job Openings Labor Turnover Survey (since 2001)
- Survey of approximately 16,000 U.S. business establishments collected by the Bureau of Labor Statistics
- Monthly data on employment, vacancies, hires, quits and layoffs

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## Estimation on JOLTS micro data



Notes: Firms binned by (net) growth rates. **Black** points are hires rates at firms with **net negative growth rates**. **Blue** points are hires rates at firms with **net positive growth rates**.

## Aggregation

$$\Phi_t^F := \left( \frac{V_t^*}{V_t} \right)^\alpha = \left[ \sum_i \mu_{j(i)} e_{it} \frac{v_{it}}{V_t} \right]^\alpha$$

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Substituting the optimal effort decision:

$$\Delta \log \Phi_t^F = -\alpha\gamma \Delta \log q(\Phi_t, \theta_t) + \alpha \Delta \log \left[ \sum_i \mu_{j(i)}^{1-\alpha} \left(\frac{h_{it}}{n_{it}}\right)^\gamma \left(\frac{v_{it}}{V_t}\right) \right]$$

$$q(\Phi_t, \theta_t) = \left(\Phi_t^F\right)^{-\left(\frac{1-\alpha}{\alpha}\right)} \cdot q(\Phi_t^W, \theta_t)$$

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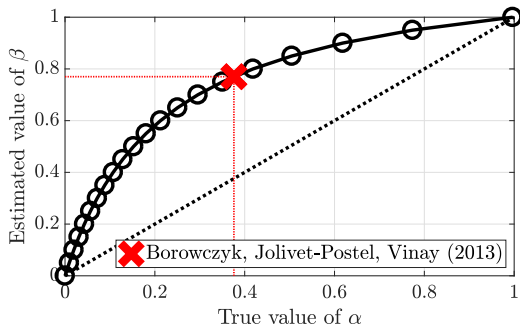
Collecting  $\Phi_t^F$  terms:

$$\Delta \log \Phi_t^F = \underbrace{-\frac{\alpha\gamma}{1-\gamma(1-\alpha)} \Delta \log q(\Phi_t^W, \theta_t)}_{\text{slackness}} + \underbrace{\frac{\alpha}{1-\gamma(1-\alpha)} \Delta \log \left[ \sum_i \mu_{j(i)}^{1-\gamma} \left(\frac{h_{it}}{n_{it}}\right)^\gamma \left(\frac{v_{it}}{V_t}\right) \right]}_{\text{composition}}$$

## Bias in OLS estimates of $\alpha$

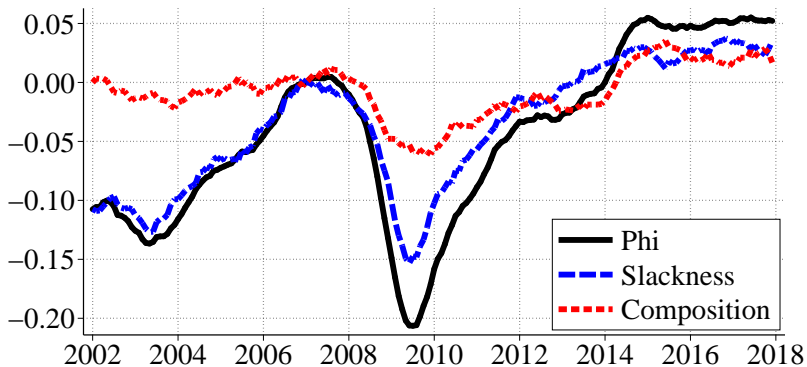
$$\Delta \log \frac{H_t}{U_t} = \alpha \Delta \log \theta_t + \Delta \log \Phi_t$$

$$\Delta \log \frac{H_t}{U_t} = \underbrace{\left[ \frac{\gamma(1-\alpha)\alpha}{1-\gamma(1-\alpha)} + \alpha \right]}_{\beta} \Delta \log \theta_t$$





## Aggregate Recruiting Intensity



- Slackness effect is dominant
- $\Phi_t^F$  explains 80% of variation in  $\Phi_t^F \cdot \Phi_t^O$

## Allowing for heterogeneity in cost function

Proxy firm-level heterogeneity by observed characteristic  $x_i$

$$\begin{aligned} C(h_{it}, n_{it}) &= \min_{e_{it}, v_{it}} : \left[ \frac{\kappa_e(x_i)}{\gamma_e} e_{it}^{\gamma_e} + \frac{\kappa_v(x_i)}{1 + \gamma_v} \left( \frac{v_{it}}{n_{it}} \right)^{\gamma_v} \right] v_{it} \\ &\text{s.t.} \\ h_{it} &= q(\Phi_t, \theta_t) \underbrace{\mu(x_i) e_{it} v_{it}}_{v_{it}^*} \end{aligned}$$

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Optimality:

$$\log e_{it} = \Omega(x_i) - \gamma \log q(\Phi_t, \theta_t) + \gamma \log \left( \frac{h_{it}}{n_{it}} \right)$$

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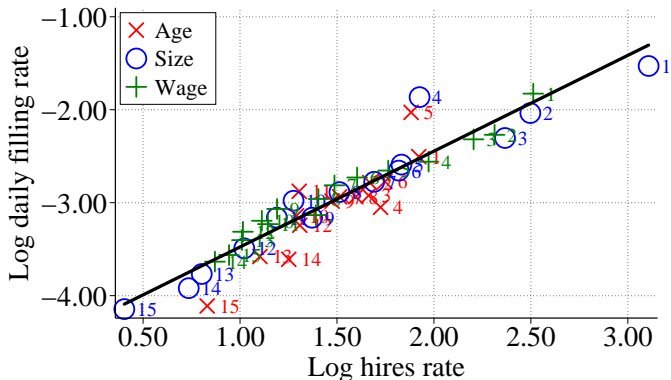
$$\log \left( \frac{h_{it}}{v_{it}} \right) = D(x_i) + D_t + \beta_1 \log \left( \frac{h_{it}}{n_{it}} \right) + \vartheta_{it}.$$

$x_i$ : industry, size, turnover, **age**, **wage**

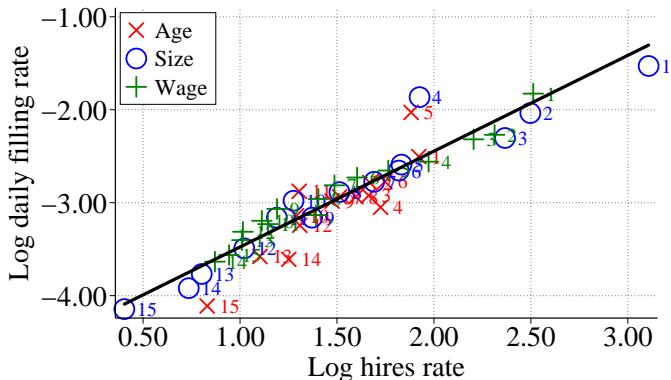
## QCEW

- Quarterly Census of Employment and Wages
- QCEW microdata are a byproduct of the unemployment insurance (UI) accounting system
- BLS receives information on employment and wages from all employers covered under the UI program.
- Matched to JOLTS micro data through EIN
- Obtain: average establishment wage and firm age

## Across Categories - Job Filling Rates



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Heterogeneity in recruiting intensity across firms is revealed to us through differences in hiring rates

## Adding Compensation

$$\begin{aligned} \mathcal{C}(h_{it}, n_{it}) &= \min_{e_{it}, v_{it}, w_{it}} : \frac{w_{it}}{1 - \beta(1 - \delta)} h_{it} + \left[ \frac{\kappa_e}{\gamma_e} e_{it}^{\gamma_e} + \frac{\kappa_v}{1 + \gamma_v} \left( \frac{v_{it}}{n_{it}} \right)^{\gamma_v} \right] v_{it} \\ &\text{s.t.} \\ h_{it} &= q(\Phi_t, \theta_t) \psi(w_{it}) e_{it} v_{it} \\ \psi(w_{it}) &= \bar{\psi} w_{it}^\psi \end{aligned}$$



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**Identification:** 3 estimated coefficients and 3 unknowns ( $\psi, \gamma_e, \gamma_v$ )

## QWI

- Quarterly Workforce Indicators (Census)
- Source data: Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata
- The LEHD data is massive longitudinal database covering over 95% of U.S. private sector jobs
- It contains **wages of new hires**
- Census and BLS do not talk to each other, so we can't merge at firm-level, but can do it by (very disaggregated) cell

## Road Ahead

- Two main results so far:
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  - Slackness > Composition in driving aggregate recruiting intensity
  - Heterogeneity beyond hiring rate does not seem to matter
- Long to-do list:
  - We can incorporate the compensation margin (need to merge in data)
  - Hiring standards as a source of recruiting effort?
  - How do we deal with  $\Phi^O$  component?