New Evidence on Labor Market Flows and the Hiring Process

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Two Papers


Both with Jason Faberman and John Haltiwanger.
Overview of Part I

1. Examine joint behavior of worker flows and job flows in the cross section (CS) of employer growth rates.
2. Interpret joint behavior in light of search and matching theories.
3. Use statistical models of worker flows in the CS to explain aggregate flows. How much gain?
4. Combine statistical models with administrative data on distribution of establishment growth rates to construct synthetic measures of hires, separations, quits and layoffs.
Two U.S. Data Sets

□ Job Openings and Labor Turnover Survey (JOLTS)

- Monthly sample of 16,000 establishments covering nonfarm economy. Rotating panel design.
- Each establishment reports employment, hires, quits, layoffs, other separations, and (end-of-month) vacancies
- Our micro sample covers Jan-2001 to June-2010 and includes all establishments with data for all three months in a quarter.

□ Business Employment Dynamics Data (BED)

- Quarterly administrative data on nearly all US establishments in the private sector
- Micro Data cover 1990Q1 to 2010Q2
- Micro data are longitudinally linked – allows calculation of establishment-level growth (i.e., job flows)
Quarterly Worker Flows in the Cross Section, United States, Pooled JOLTS Sample, 2001-2010

Employer growth rate measured as
$$g_t = \frac{E_t - E_{t-1}}{(1/2)(E_t + E_{t-1})} \in [-2, 2]$$
Theory Sketch

- Search models in the spirit of Mortensen and Pissarides (1994) but with multi-worker firms
  - “Iron link” of hires to job creation & separations to destruction

- Learning about match quality as in Jovanovic (1979, 1985) and Moscarini (2005)
  - Pries & Rogerson (2005) is a hybrid of MP and learning

- On-the-job search with match-specific productivity and aggregate fluctuations (Barlevy, 2002)
  - Workers are more likely to quit bad matches when aggregate conditions are strong

- Employer search with persistent idiosyncratic firm profitability (Faberman & Nagypal, 2009)
  - Workers are more likely to quit employers with low productivity and slow growth (an “abandon-ship” effect)
Consider an MP model with multi-worker firms

- Cooper-Haltiwanger-Willis (2007, CHW)
- Hires, vacancies and layoffs are endogenously determined subject to fixed and variable costs of posting vacancies and layoffs
- Firms face aggregate and idiosyncratic profit shocks
- Quit rate is exogenous and uniform
- Workers are ex ante homogenous
- Frictional search as in other MP models

Write employer-level growth (hires – separations) as

\[ e_{it} - e_{i,t-1} = h_{it} - l_{it} - \bar{q} e_{i,t-1} \]

\[ = \eta(U_t, V_t) v_{it} - l_{it} - \bar{q} e_{i,t-1} \]

where \( \eta(\cdot) \) is the job-filling rate, which depends on aggregate unemployment \( U_t \) and vacancies \( V_t \)
Movements in aggregate hires and layoffs arise entirely from shifts over time in CS distribution of employer growth rates.

Adjustment costs and shock properties affect the shape and location of growth rate distribution, but not the iron link.
Relaxing the Iron Link

- Simplest extension of CHW model:
  - Quit rate remains exogenous but varies procyclically
    \[ q_t = \bar{q}(G_t) \]
    where \( G_t \) = aggregate employment growth

- Iron link continues to hold in a given cross section, but time variation in \( q_t \) shifts the micro hiring and layoff relations

- Fluctuations in aggregate worker flows now arise from shifts in the growth rate distribution and shifts in the micro-level CS relations
Exogenously Pro-Cyclical Quit Rates

- Quit rate drops when aggregate growth rate falls.
- Inducing rightward shifts in the hiring and layoff relations, including the kink point.
Endogenous Quits, 1
Higher Quit Rate at Weaker Employers

- Faberman-Nagypál (2008) model
  - Employers vary in idiosyncratic component of productivity
  - More productive firms grow faster
  - Employers engage in costly search, contact workers, and make offers
  - Bargained wage rises with employer productivity
  - Because they earn lower wages, workers at less productive employers are more likely to accept outside offers
  - Thus, quit rate declines with employer growth rates in CS
  - Rationalizes positive value and a negative slope in the CS hires relation to the left of zero.

- See, also, Trapeznikova (2010)
Endogenous Quits, 2
Higher Quit Rates in Stronger Labor Market

- Barlevy (2002) model with OTJ search
  - Employed workers quit when better offers arrive
  - Vacancies are scarcer and workers have fewer outside options in recessions → lower quit rate
  - Leads to shift and dilation of match quality distribution over business cycle
    - Shift: negative aggregate shock causes dissolution of bad matches (cleansing effect)
    - Dilation: lower outside options cause workers in bad matches to remain in those matches (sullying effect)
  - This model implies that CS quit-growth relation varies with business cycle, shifting up in booms
Endogenous Quits, 3
Separation Rates Decline with Job Tenure

- Learning about match quality as in Jovanovic (1979, 1985), Moscarini (2005), Pries and Rogerson (2005) and many others
  - Stochastic match quality
  - Employer and worker learn about match quality over time
  - Good matches survive, bad ones don’t
  - Separation rate declines with match tenure
  - If growing employers have a larger proportion of young matches, then separation rate rises with employer growth rates in the cross section.
Relating Micro and Macro Behavior

- Express aggregate worker flow rates, $W_t$ (rate of hires, quits, layoffs or separations), as
  
  $$W_t = \sum_g f_t(g) w_t(g)$$

  - Group establishments by employment growth rates, $g$, and calculate the employment-weighted mean rate for each $g$ in period $t$, $w_t(g)$
  - To recover the aggregate flow rate at $t$, weight each growth rate bin by its employment mass in period $t$, $f_t(g)$
  - Obtain $w_t(g)$ from JOLTS and $f_t(g)$ from BED. (See DFHR, 2010.)

- Changes over time in aggregate flow rates arise from:
  1. Changes in average worker flow rates for a given $g$, or
  2. Shifts in the distribution of establishment-level employment growth
  3. Interaction between 1 and 2.
Statistical Specifications for CS Relations

Fixed Cross-Section

- Motivated by time-invariant “iron link” relations in basic multi-worker MP model, but we do not constrain the location of kinks:

\[ w_t(g) = \alpha(g) + \varepsilon_t^D(g) \]

where \( w_t(g) \) is worker flow rate at establishment with growth rate \( g \)

- Estimate this relation on the pooled sample of establishment-level observations from 2001 to 2010Q2.
C-S Relations in Three Periods

Hires

Layoffs show stable “Iron Link” relation to employer growth rates in the CS

Quits

Quits do not, especially at contracting establishments
Baseline

- Allow vertical shifts in CS relation as functions of cycle indicators:

\[ w_t (g) = \alpha (g) + \beta_1 G_t^+ + \beta_2 G_t^- + \beta_3 \Delta G_t + \beta_4 JF_t + \epsilon_t^B (g) \]

- \( G_t \) = aggregate employment growth rate (+, -, change)
- \( JF_t \) = job-finding rate of unemployed workers

Flexible

- Allow for more complex cyclical behavior
- Interact cycle indicators with 5 dummy variables for broad growth rate intervals → Allows shape and location of CS relations to vary with cycle.
Worker Flows Implied by Statistical Specifications

\[ \hat{W}_t = \sum_g f_t(g) \hat{w}_t(g) \]

- **Hires**
  - Actual
  - Implied by Fixed Cross-Section Relation
  - Implied from Baseline Specification

- **Separations**
  - Actual
  - Implied by Fixed Cross-Section Relation
  - Implied from Baseline Specification

- **Layoffs**
  - Actual
  - Implied by Fixed Cross-Section Relation
  - Implied from Baseline Specification

- **Quits**
  - Actual
  - Implied by Fixed Cross-Section Relation
  - Implied from Baseline Specification
## How Much Does Fixed CS Model Improve Fit for Aggregate Flows?

<table>
<thead>
<tr>
<th>Rate</th>
<th>Aggregate Variables (4 Cycle Indicators)</th>
<th>Adding One Variable: Worker Flow Rate Predicted by Fixed CS Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hiring Rate</td>
<td>0.808</td>
<td>.966 [.000]</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>0.652</td>
<td>.944 [.000]</td>
</tr>
<tr>
<td>Quit Rate</td>
<td>0.929</td>
<td>.961 [.011]</td>
</tr>
<tr>
<td>Layoff Rate</td>
<td>0.525</td>
<td>.880 [.000]</td>
</tr>
</tbody>
</table>

The entry in brackets reports the \( p\)-value of the coefficient on the prediction of the model that imposes a time-invariant cross-sectional relation.
Fit of the Establishment-Level Regressions Used to Estimate the CS Worker Flow Relations

- Table entries show R-squared values for employment-weighted regressions on the indicated statistical models.
  - “Fixed Cross-Section” corresponds to the regression model used to fit the time-invariant CS relations displayed on the previous slides.
  - “Augmented Fixed Cross-Section” relaxes the model slightly to allow for within-bin differences in the worker flow relations.

<table>
<thead>
<tr>
<th>Dependent variable in descriptive CS regression</th>
<th>Model Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hiring Rate</td>
<td>Fixed Cross-Section</td>
</tr>
<tr>
<td></td>
<td>Augmented Fixed Cross-Section</td>
</tr>
<tr>
<td></td>
<td>Augmented Baseline Specification</td>
</tr>
<tr>
<td>Layoff Rate</td>
<td>Augmented Flexible Specification</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Cross-Section</td>
<td>0.542</td>
<td>0.543</td>
<td>0.545</td>
</tr>
<tr>
<td>Augmented Fixed Cross-Section</td>
<td>0.507</td>
<td>0.509</td>
<td>0.511</td>
</tr>
<tr>
<td>Augmented Baseline Specification</td>
<td>0.159</td>
<td>0.162</td>
<td>0.170</td>
</tr>
<tr>
<td>Augmented Flexible Specification</td>
<td>0.463</td>
<td>0.466</td>
<td>0.467</td>
</tr>
</tbody>
</table>
Constructing Synthetic JOLTS Data

- Baseline statistical model + quarterly data on the cross-sectional distribution of establishment-level growth rates ➞ synthetic data for aggregate worker flows

\[ \hat{W}_t = \sum_g f_t(g) \hat{w}_t(g) \]

- BED data on \( f \) + model-based \( \hat{w} \) from 1990 to 2001

- BED data on \( f \) + JOLTS-based \( w \) from 2001 to 2010.
Layoffs move with job destruction.
Quits moves opposite to both.

- Layoffs move with job destruction.
- Quits moves opposite to both.
Hires tend to move with job creation but are more volatile.

Overview of Part II

5. Use a simple model of daily hiring dynamics to identify the job-filling rate for vacancies

   - Heterogeneity in the efficiency of search and matching
   - Scale economies (or diseconomies) in the hiring technology at the establishment or sectoral level
   - Employers use other instruments, in addition to vacancy numbers, to influence the pace of hiring.
5. Use a simple model of daily hiring dynamics to identify the job-filling rate for vacancies.

   - Heterogeneity in the efficiency of search and matching.
   - Scale economies (or diseconomies) in the hiring technology at the establishment and/or sectoral.
   - Employers use other instruments, in addition to vacancy numbers, to influence the pace of hiring.
7. Generalized matching function (GMF) defined over unemployment, vacancies, and other recruiting instruments.

- Estimate scale economies in the employer hiring technology
- Estimate how recruiting intensity varies with hires rate
- Construct a time-series index of recruiting intensity per vacancy
- GMF outperforms standard MF in explaining fluctuations in the job-finding rate and the job-filling rate. GMF also yields a more stable Beveridge Curve.
- GMF accounts for CS behavior of job-filling rates. Standard matching function does not.
A Model of Daily Hiring Dynamics

Daily laws of motion for flow of hires and vacancy stock:

\[ h_{s,t} = f_t \nu_{s-1,t} \]

\[ \nu_{s,t} = \left[ (1 - f_t)(1 - \delta_t) \right] \nu_{s-1,t} + \theta_t \]

- Where \( s \) indexes days, \( f_t \) is the daily job-filling rate in month \( t \), \( \delta_t \) is the rate at which unfilled vacancies lapse, and \( \theta_t \) is the daily flow of new vacancies.
Solving for the job-filling rate and vacancy flows

Use laws of motion to derive two equations relating end-of-month vacancy stock and hires flow during month, both observed, to two unknowns, \( \{ f_t, \theta_t \} \).

\[
v_t = (1 - f_t - \delta_t + \delta_t f_t)^\tau v_{t-1} + \theta_t \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1}
\]

\[
H_t = f_t v_{t-1} \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)(1 - f_t - \delta_t + \delta_t f_t)^{s-1}
\]

Given data on \( \delta_t, v_t, v_{t-1}, H_t \), and a value for \( \tau \), solve numerically for \( f_t \) (daily job-filling rate) and \( \theta_t \) (daily flow of new vacancies).
Vacancy Flows and Job-Filling Rate Relationships to Employer Growth Rates

- Monthly Vacancy Flow Rate (Left Axis)
- Daily Job-Filling Rate (Right Axis)
- Daily Job-Filling Rate, Controlling for Establishment Fixed Effects
Job-Filling Rate and Gross Hires Rate

Data points correspond to growth rate bins

Hires-Weighted Least Squares
Slope (s.e.) = 0.821 (0.006)
R-squared = 0.993
Generalized Matching Function

\[ H_{et} = \mu \left( \frac{v_t'}{u_t} \right)^{-\alpha} q(v_{et}, x_{et}), \text{ where } \sum_e q(v_{et}, x_{et}) = v_t' \]

- Job-filling rate is now \( f_{et} = \tilde{f}_t q(v_{et}, x_{et}) / v_{et} \)
- For \( q(v_{et}, x_{et}) \equiv v_{et} \), aggregation delivers standard Cobb-Douglas matching function
- For \( q(v_{et}, x_{et}) \equiv v_{et} \tilde{q}(x_{et}) \), the hiring function satisfies CRS in vacancies at the micro level, and differences in \( f_{et} \) identify the effects of employer actions on other margins.
Quantifying the Roles of Other Instruments and Scale Economies

Let \( q(v_{et}, x_{et}) \equiv v_{et}^\gamma \tilde{q}(x_{et}) \) so that job-filling rate becomes

\[
f_{et} = \tilde{f}_t v_{et}^{\gamma-1} \tilde{q}(x_{et})
\]

\[
\frac{d \log(f_{et})}{d \log(H_{et})} = \frac{d \log(\tilde{f}_t)}{d \log(H_{et})} + (\gamma - 1) \frac{d \log(v_{et})}{d \log(H_{et})} + \frac{d \log(\tilde{q}(x_{et}))}{d \log(H_{et})}
\]

\[
0.821 = 0 + (\gamma - 1)(0.336) + \frac{d \log(\tilde{q}(x_{et}))}{d \log(H_{et})}
\]

- To preclude a role for employer actions on other margins requires a scale economy parameter value of \( \gamma \approx 3.44 \).
Estimating Scale Economies in the Establishment-Level Hiring Technology

- **Basic idea**: Exploit differences in scale of vacancies and hiring across industry-size cells to estimate returns to scale in employer hiring technology.

- Do **NOT** use time variation, because it is contaminated by the intensity, \( x \). Control for cell-level growth rate for same reason.

- Control for differences in matching efficiency across industries and across employer size classes.

- Instrument using level of employment to deal with potential division bias.
Scale-Economy Regressions

$$\ln f_{is} = \ln \tilde{f} + (\gamma - 1) \ln v_{is} + \ln q(x_{is}) + \epsilon_{is}$$

Mean Job-Filling Rate in Industry $i$ and size class $s$

Average Time Effect

Mean Number of Vacancies (Stock) in Industry $i$ and size class $s$

Scale-Economy Parameter: Elasticity of Job-Filling Rate with Respect to the Number of Vacancies

Sectoral differences in matching efficiency and average recruiting intensity: include industry and size fixed effects and industry-size mean employment growth rates.
### Scale Economies Regressions

**Dependent Variable:** $\log(\text{Job-Filling Rate})$

<table>
<thead>
<tr>
<th>Explanatory Variable $\rightarrow$</th>
<th>Log Beginning-of-Month Vacancies (Level)</th>
<th>Log Monthly Vacancy Flow (Level)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Estimation Method $\rightarrow$</strong></td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>Coefficient (std. error)</td>
<td>-.059 (.049)</td>
<td>.001 (.051)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.779</td>
<td>.772</td>
</tr>
<tr>
<td>First-stage $R^2$</td>
<td>---</td>
<td>.985</td>
</tr>
<tr>
<td>Implied $\gamma$</td>
<td>0.941</td>
<td>1.001</td>
</tr>
</tbody>
</table>

1. N=70 in all regressions. 5 or 6 size classes per industry (12).
2. All regressions include industry and size class fixed effects and the employment growth rate in the industry-size cell.
3. IV is two-stage LS regression using $\log(\text{Employment Level})$ as the instrument. N=70 in all regressions.
Aggregate Implications

GMF with CRS at the employer-level implies:

\[ H_t = \sum_e H_{et} = \mu \left( \frac{v'_t}{u_t} \right)^{-\alpha} \sum_e v_{et} \tilde{q}(x_{et}) = \mu \left( \frac{v'_t}{u_t} \right)^{-\alpha} v'_t = \mu v_t^{1-\alpha} u_t^\alpha \bar{q}_t^{1-\alpha}, \]

where \( \bar{q}_t = \sum_e (v_{et} / v_t) \tilde{q}(x_{et}) \) and \( v'_t = v_t \bar{q}_t \).

\[ \Delta \log H = \alpha \Delta \log u + (1 - \alpha) \Delta \log v + (1 - \alpha) \Delta \log \bar{q} \]

Working Hypothesis:

\[ \frac{\Delta \log \bar{q}}{\Delta \log H} = \frac{\Delta \log q_{et}}{\Delta \log H_{et}} = 0.821 \]
Effective vacancies equal this index value times the number of measured vacancies.

January 2001 to December 2010
Market Tightness and the Role of Recruiting Intensity Per Vacancy

The drop in recruiting intensity accounts for one-fourth of the gap that emerges between these two measures from 2007 to 2009.

Davis (2011) draws on Krueger and Mueller (2011) to develop evidence that a drop in search intensity per unemployed also accounts for a sizable share of the gap that emerges after 2007.
Testing Performance of Standard vs. GMF In Time-Series Regressions

<table>
<thead>
<tr>
<th>Specification</th>
<th>Std. Deviation, Dependent Variable</th>
<th>RMSE Using Standard Matching Function</th>
<th>Percent Drop in RMSE, Generalized MF</th>
<th>Non-Nested Test of Added Predictive Ability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$p$-value, $H_0 = $ Standard Model</td>
</tr>
<tr>
<td><strong>Job-finding rate (Unemployment Escape Rate) Regressed on Tightness Ratio ($v'/u$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National Data</td>
<td>0.19</td>
<td>0.05</td>
<td>-2.4</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Job-finding rate (Hires Per Unemployed) Regressed on Tightness Ratio ($v'/u$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National Data</td>
<td>0.38</td>
<td>0.07</td>
<td>-19.8</td>
<td>0.00</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.34</td>
<td>0.13</td>
<td>-46.1</td>
<td>0.00</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.39</td>
<td>0.08</td>
<td>-31.2</td>
<td>0.00</td>
</tr>
<tr>
<td>South</td>
<td>0.41</td>
<td>0.12</td>
<td>-19.2</td>
<td>0.00</td>
</tr>
<tr>
<td>West</td>
<td>0.45</td>
<td>0.12</td>
<td>-31.9</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Unemployment Rate Regressed on Effective Vacancy Rate ($v^\uparrow$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National Data</td>
<td>0.28</td>
<td>0.11</td>
<td>-17.6</td>
<td>0.00</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.25</td>
<td>0.16</td>
<td>-10.4</td>
<td>0.00</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.27</td>
<td>0.10</td>
<td>-8.0</td>
<td>0.00</td>
</tr>
<tr>
<td>South</td>
<td>0.28</td>
<td>0.15</td>
<td>-17.3</td>
<td>0.00</td>
</tr>
<tr>
<td>West</td>
<td>0.32</td>
<td>0.16</td>
<td>-24.3</td>
<td>0.00</td>
</tr>
</tbody>
</table>
A Summary: Tools and Methods

1. A useful descriptive tool: Relate worker flows and job-filling rates to growth rates in the CS.
   - Yields empirical objects for assessing, calibrating and developing theory
   - Highlights the importance of nonlinear aggregation in labor market fluctuations

2. How to combine CS statistical models with administrative data on employer growth rates to construct synthetic data.

3. A simple model + moment-fitting method that identifies job-filling rates from periodic data on the stock of vacancies and the flow of hires
A Summary: Tools and Methods

4. A generalized matching function (GMF):
   - How to estimate the degree of scale economies (or diseconomies) in the employer hiring technology
   - How to identify the elasticity of recruiting intensity per vacancy with respect to the hires rate
   - A time-series index for recruiting intensity per vacancy
   - An aggregate time-series index for effective vacancies that outperforms the standard measure of vacancies in accounting for fluctuations in job-finding rates and job-filling rates, and that yields a more stable Beveridge Curve.


ADDITIONAL SLIDES

TO BE DISCUSSED AS TIME PERMITS
## U.S. Employment Growth Rate Distribution, Selected Periods, BED Data

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Establishments with Contractions &gt; 10%, including Closings</td>
<td>16.0</td>
<td>14.0</td>
<td>14.5</td>
<td>12.6</td>
<td>14.0</td>
</tr>
<tr>
<td>Establishments with Contractions &gt;= 10%</td>
<td>27.4</td>
<td>26.9</td>
<td>29.3</td>
<td>28.0</td>
<td>30.8</td>
</tr>
<tr>
<td>Establishments with No Net Change in Employment</td>
<td>14.3</td>
<td>13.9</td>
<td>14.8</td>
<td>15.5</td>
<td>16.1</td>
</tr>
<tr>
<td>Establishments with Expansions &lt; 10%</td>
<td>27.4</td>
<td>30.0</td>
<td>28.0</td>
<td>30.7</td>
<td>27.4</td>
</tr>
<tr>
<td>Establishments with Expansions &gt;=10%, including Openings</td>
<td>14.8</td>
<td>15.2</td>
<td>13.4</td>
<td>13.2</td>
<td>11.6</td>
</tr>
</tbody>
</table>
Layoff Rates Compared to Other Job Loss Data

- Job Destruction (left axis)
- Layoffs (Left Axis)
- Unemployment Inflows, CPS (Left Axis)
- Initial UI Claims (Right Axis)

Percent of Employment

- 1990
- 1991
- 1992
- 1993
- 1994
- 1995
- 1996
- 1997
- 1998
- 1999
- 2000
- 2001
- 2002
- 2003
- 2004
- 2005
- 2006
- 2007
- 2008
- 2009
- 2010
Job-Filling Rate and Gross Hires Rate

Log Daily Fill Rate

T = Turnover Quintile
I = Industry
S = Size Class

y = 0.80x - 0.30
R² = 0.80
Is It Just “Lucky” Employers Growing Faster?

Stochastic nature of job filling induces a positive relationship between realized employment growth and job-filling rates at the establishment level.

• “Lucky” employers fill jobs faster and, as a result, grow faster.

• To quantify this effect, we simulate hires and employment growth at the establishment level for fitted values of $f$, $\theta$, $\delta$, and the distribution of vacancies, allowing parameters and vacancy distributions to vary freely by employer size class.

• Result: Luck effect is much too small to explain the observed C-S relationship between job-filling rate and growth rate:
  – Luck alone $\rightarrow$ job-filling rate rises by 2 percentage points in moving from 0% to 10% monthly growth rate.
  – It rises by another 1 point in moving from 10 to 30%.
Simulated and Empirical Job-Filling Rates Compared

Fill Rate

- **Empirical Job-Filling Rate**
- **Simulated Rate, New Vacancies Allotted in Proportion to Establishment Vacancies**
- **Simulated Rate, New Vacancies Allotted in Proportion to Establishment Employment**

Monthly Employment Growth Rate (Percent)
Closely Related Work in Progress

- Apply the same statistical approach to the analysis of vacancies:
  - Assess theoretical models
  - Construct synthetic JOLTS-like vacancy measures back to 1990
  - Construct highly disaggregated vacancy measures by region, industry, employer size, etc. (with the intention to overcome small-sample problems in disaggregated vacancy measures calculated directly from JOLTS).
Textbook Equilibrium Search Model

• No role for “recruiting intensity” per vacancy
• Pissarides (2000, chapter 5) extends standard model to incorporate variable recruiting intensity per vacancy
  – Costs per vacancy are increasing and convex in intensity
  – His hiring technology and matching function are consistent with our generalized matching function (micro CRS case)
• Optimal recruiting intensity is insensitive to aggregate conditions and same for all employers in the cross-section. Why? Employers use vacancies to vary hires, and choose intensity to minimize cost per vacancy.
• Rejected by our CS evidence, specifically positive relationship of job-filling rates to employer growth and hires rate.
• Cannot explain role of other instruments for aggregate hires.
Additional Theoretical Implications

- A major role for recruiting intensity per vacancy is not fatal to standard equilibrium search models with random matching, but it calls for re-evaluation of widely used building blocks in the standard model.
  - Dropping the standard free-entry condition for new jobs (and dispensing with the convenient result that equilibrium vacancy value is 0) leads to a meaningful role for recruiting intensity per vacancy. See Davis (2001), “Quality Distribution of Jobs …”
- The CS evidence on slides is hard to square with the basic mechanism stressed by mismatch models.
- Directed search models are readily compatible with the CS evidence, because these models come built-in with an extra recruiting margin, typically in the form of posted offer wages. See Kass and Kircher (2010).
Are All Hires Mediated through Vacancies? A Test

- Number of hires in month $t$ accounted for by the flow of new vacancies in $t$:

$$H_{t}^{NEW} = f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)(1 - f_t - \delta_t + \delta_t f_t)^{s-1}$$

- So, according to the model, the percent of hires in $t$ accounted for by establishments with no vacancies at start of month is:

$$E_t^{NoVac} \frac{H_{t}^{NEW}}{H_t}$$

where the first variable is the employment share at establishments with no vacancies at start of month.
## Model Specification Test Results

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
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<tbody>
<tr>
<td>Percent of Hires in $t$ by Establishments with No Vacancies at end of $t-1$</td>
<td>41.6</td>
</tr>
<tr>
<td>Percent Implied by Model for Alternative Sectoral Breakdowns</td>
<td></td>
</tr>
<tr>
<td>Size Class (6) by Worker Turnover Rate (6) – 36 cells</td>
<td>27.0</td>
</tr>
<tr>
<td>Industry (12) by Size Class (2) by Worker Turnover (6) Rate – 144 cells</td>
<td>26.7</td>
</tr>
<tr>
<td>Industry (2) by Size Class (6) by Worker Turnover Rate (15) – 180 cells</td>
<td>27.4</td>
</tr>
</tbody>
</table>

$27.4/41.6 = 66\% \rightarrow$ Our model of daily hiring accounts for about 2/3 of hires at establishments with no vacancies at start of month. So a big share of hires are not mediated through vacancies.
Figure B.5: Scatter Plot of the Log Vacancy Rate against the Log Hires Rate across Growth Rate Bins and Hires-Weighted Least Squares Regression Results

Hires-Weighted Least Squares
Slope (s.e.) = 0.336 (0.011)
R-squared = 0.876

Data points correspond to growth rate bins