This lecture draws mainly on two of my papers with Jason Faberman and John Haltiwanger:


It also contains remarks on a few other papers, mainly “Aggregate Recruiting Intensity” by Alessandro Gavazza, Simon Mongey and Giovanni Violante, 2017, forthcoming in the *American Economic Review*. 
The Establishment-Level Behavior of Vacancies and Hiring

Steven J. Davis, Jason Faberman and John Haltiwanger

Quarterly Journal of Economics

May 2013
Overview

• First study of vacancies, hires and vacancy yields at the establishment level in a large sample of U.S. employers

Two key analytical tools for interpreting the data

• Simple model of daily hiring dynamics
  – Identifies the job-filling rate for vacant positions, the employer counterpart to much-studied job-finding rate for unemployed workers.

• Generalized matching function defined over unemployment, vacancies and “recruiting intensity” per vacancy
Motivation

Job vacancies are a key concept in many theoretical models ...

– Random search models (Pissarides, 1986; Mortensen-Pissarides, 1994; Pissarides, 2000)
– On-the-job search (Burdett and Mortensen, 1998)
– Directed search and wage-posting models (Moen, 1997, and Acemoglu and Shimer, 2000)

... and empirical studies ...

– Beveridge Curve studies (Blanchard-Diamond, 1989)
– Matching function estimation (Petrongolo-Pissarides)
– Studies of cyclical dynamics (Shimer, 2005)
Motivation

... Yet, few empirical studies consider job vacancies and their connection to hiring at the level of individual employers.

Even at the aggregate level, our knowledge of vacancy behavior is very thin compared to our knowledge of unemployment behavior

– U.S. studies: HWI, JOLTS at aggregate and industry level, small-scale and one-off data sets – e.g., Abraham (1983, 1987) and Holzer (1994)

– Other countries: Several studies use surveys or centralized registers of job openings – e.g., Van Ours and Ridder (1991), Berman (1997), Yashiv (2000) and Sunde (2007)
Outline of Remarks, 1

• JOLTS micro data on hires and vacancies
• A simple model of daily hiring dynamics to identify the job-filling rate for vacancies
• Big CS variation in job-filling rates. Why?
  – 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.
Outline of Remarks, 2

• JOLTS micro data on hires and vacancies
• A simple model of daily hiring dynamics to identify the job-filling rate for vacancies
• Big CS variation in job-filling rates. Why?
  – 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.
Outline of Remarks, 3

• Generalized matching function (GMF) defined over unemployment, vacancies, and recruiting intensity per vacancy.
  – Combine evidence with GMF to identify the role of recruiting intensity per vacancy in the cross section
  – Build from micro evidence and GMF to construct a time-series index of recruiting intensity per vacancy
  – Interpret recent breakdown of standard matching function (SMF) as resulting, in part, from large movements in recruiting intensity per vacancy (and in search intensity per unemployed)
The GMF outperforms SMF in several ways:

1. GMF accounts for CS behavior of job-filling rates. SMF does not.

2. GMF (as constrained by our recruiting intensity index) better accounts for movements over time in job-finding rates and job-filling rates.

3. GMF yields a more stable Beveridge Curve at national and regional levels.

4. Industry-level changes in fill rates, $v-u$ ratios, and recruiting intensity values during and after the 2008-09 recession satisfy restrictions implied by the GMF. They violate restrictions implied by the SMF.
JOLTS Data

• Sample of ~16,000 establishments per month
  – Employment as of pay period covering 12\(^{th}\) of month
  – *Flow* of hires, separations, layoffs, quits during month
  – *Stock* of vacancies on last business day of month
  – Our micro analysis sample has 577,000 establishment-level observations from January 2001 to December 2006

• Vacancy Definition (Job Openings):
  – “A specific position exists, work could start within 30 days, and [the establishment is] actively seeking workers from outside this location to fill the position.”
  – Broad definition of “actively seeking workers”
## Table 1: Outcomes by Industry, Size and Turnover

<table>
<thead>
<tr>
<th></th>
<th>Hires Rate</th>
<th>Separations Rate</th>
<th>Vacancy Rate</th>
<th>Vacancy Yield</th>
<th>Employment Share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nonfarm Employment</strong></td>
<td>3.4</td>
<td>3.2</td>
<td>2.5</td>
<td>1.3</td>
<td>---</td>
</tr>
<tr>
<td><strong>Selected Industries</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>5.4</td>
<td>5.4</td>
<td>1.7</td>
<td>3.1</td>
<td>5.3</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>2.3</td>
<td>2.6</td>
<td>1.7</td>
<td>1.3</td>
<td>11.3</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>4.5</td>
<td>4.4</td>
<td>2.3</td>
<td>1.9</td>
<td>11.4</td>
</tr>
<tr>
<td>Professional &amp; Business Services</td>
<td>4.6</td>
<td>4.2</td>
<td>3.5</td>
<td>1.3</td>
<td>12.4</td>
</tr>
<tr>
<td>Government</td>
<td>1.6</td>
<td>1.3</td>
<td>1.9</td>
<td>0.8</td>
<td>16.5</td>
</tr>
<tr>
<td><strong>Establishment Size Class</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-9 Employees</td>
<td>3.4</td>
<td>3.3</td>
<td>2.0</td>
<td>1.6</td>
<td>12.1</td>
</tr>
<tr>
<td>10-49 Employees</td>
<td>4.0</td>
<td>4.0</td>
<td>2.3</td>
<td>1.7</td>
<td>23.2</td>
</tr>
<tr>
<td>50-249 Employees</td>
<td>4.0</td>
<td>3.8</td>
<td>2.6</td>
<td>1.5</td>
<td>28.3</td>
</tr>
<tr>
<td>250-999 Employees</td>
<td>3.1</td>
<td>2.9</td>
<td>2.8</td>
<td>1.1</td>
<td>17.1</td>
</tr>
<tr>
<td>1,000-4,999 Employees</td>
<td>2.1</td>
<td>1.9</td>
<td>3.0</td>
<td>0.7</td>
<td>13.0</td>
</tr>
<tr>
<td>5,000+ Employees</td>
<td>1.7</td>
<td>1.5</td>
<td>2.4</td>
<td>0.7</td>
<td>6.4</td>
</tr>
<tr>
<td><strong>Worker Turnover Category</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Turnover</td>
<td>0</td>
<td>0</td>
<td>1.1</td>
<td>0</td>
<td>24.4</td>
</tr>
<tr>
<td>First Quintile</td>
<td>0.5</td>
<td>0.6</td>
<td>1.7</td>
<td>0.3</td>
<td>15.1</td>
</tr>
<tr>
<td>Second Quintile</td>
<td>1.3</td>
<td>1.2</td>
<td>2.6</td>
<td>0.5</td>
<td>15.1</td>
</tr>
<tr>
<td>Third Quintile</td>
<td>2.4</td>
<td>2.2</td>
<td>2.9</td>
<td>0.8</td>
<td>15.1</td>
</tr>
<tr>
<td>Fourth Quintile</td>
<td>4.5</td>
<td>4.3</td>
<td>3.1</td>
<td>1.4</td>
<td>15.1</td>
</tr>
<tr>
<td>Fifth Quintile (highest)</td>
<td>13.5</td>
<td>13.0</td>
<td>4.4</td>
<td>3.1</td>
<td>15.1</td>
</tr>
</tbody>
</table>
Hires

Monthly Hires as a Percent of Employment

- Unconditional
- Controlling for Establishment Fixed Effects

Monthly Employment Growth Rate, Percent
Vacancies

Vacancies as a Percent of Employment

- Unconditional
- Controlling for Establishment Fixed Effects

Monthly Employment Growth Rate, Percent

0.0  5.0  10.0  15.0  20.0  25.0  30.0
-30.0 -25.0 -20.0 -15.0 -10.0 -5.0  0.0  5.0  10.0  15.0  20.0  25.0  30.0
Does this strong positive relationship merely reflect a bigger flow of unobserved vacancies at more rapidly growing establishments?
## Other Summary Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. of Employment at Establishments with No Hires in t</td>
<td>34.8</td>
</tr>
<tr>
<td>Pct. of Employment at Establishments with No Vacancies at the end of ( t-1 )</td>
<td>45.1</td>
</tr>
<tr>
<td>Pct. of Vacancies at the end of ( t ) at Establishments with No Vacancies at the end of ( t-1 )</td>
<td>17.9</td>
</tr>
<tr>
<td>Pct. of Hires in ( t ) at Establishments with No Vacancies at the end of ( t-1 )</td>
<td>41.6</td>
</tr>
</tbody>
</table>
45% of employment is at establishments with no vacancies. Another 7% is at establishments with exactly 1 vacancy.
A Model of Daily Hiring Dynamics

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

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

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

• 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).
<table>
<thead>
<tr>
<th>Selected Industries</th>
<th>Daily Job-Filling Rate (%)</th>
<th>Monthly Flow of Vacancies (% of Emp.)</th>
<th>Mean Vacancy Duration (Days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonfarm Employment</td>
<td>5.0</td>
<td>3.4</td>
<td>20.0</td>
</tr>
<tr>
<td>Construction</td>
<td>12.1</td>
<td>5.4</td>
<td>8.3</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>7.3</td>
<td>4.5</td>
<td>13.7</td>
</tr>
<tr>
<td>Government</td>
<td>3.2</td>
<td>1.6</td>
<td>31.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of Employees</th>
<th>Daily Job-Filling Rate (%)</th>
<th>Monthly Flow of Vacancies (% of Emp.)</th>
<th>Mean Vacancy Duration (Days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10-49</td>
<td>6.6</td>
<td>4.0</td>
<td>15.2</td>
</tr>
<tr>
<td>250-999</td>
<td>4.1</td>
<td>3.1</td>
<td>24.1</td>
</tr>
<tr>
<td>5,000+</td>
<td>2.6</td>
<td>1.7</td>
<td>38.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Worker Turnover Quintiles (H+S)</th>
<th>Daily Job-Filling Rate (%)</th>
<th>Monthly Flow of Vacancies (% of Emp.)</th>
<th>Mean Vacancy Duration (Days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest</td>
<td>11.4</td>
<td>14.0</td>
<td>8.7</td>
</tr>
<tr>
<td>Middle</td>
<td>3.0</td>
<td>2.4</td>
<td>32.8</td>
</tr>
<tr>
<td>Lowest</td>
<td>1.1</td>
<td>0.4</td>
<td>87.9 ¹⁹</td>
</tr>
<tr>
<td>--------------------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
</tr>
<tr>
<td>Resources</td>
<td>11.9</td>
<td>14.0</td>
<td>14.9</td>
</tr>
<tr>
<td>Construction</td>
<td>7.7</td>
<td>8.7</td>
<td>5.9</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>17.3</td>
<td>20.9</td>
<td>17.6</td>
</tr>
<tr>
<td>Wholesale and Retail Trade</td>
<td>14.2</td>
<td>15.8</td>
<td>14.5</td>
</tr>
<tr>
<td>Warehouse, Transportation and Utilities</td>
<td>18.3</td>
<td>17.3</td>
<td>15.8</td>
</tr>
<tr>
<td>Information</td>
<td>26.7</td>
<td>35.3</td>
<td>29.4</td>
</tr>
<tr>
<td>Financial Services</td>
<td>27.6</td>
<td>32.5</td>
<td>26.2</td>
</tr>
<tr>
<td>Professional &amp; Business Services</td>
<td>18.2</td>
<td>20.1</td>
<td>19.1</td>
</tr>
<tr>
<td>Health and Education</td>
<td>36.8</td>
<td>34.3</td>
<td>31.2</td>
</tr>
<tr>
<td>Leisure and Hospitality</td>
<td>13.8</td>
<td>14.7</td>
<td>12.5</td>
</tr>
<tr>
<td>Other Services</td>
<td>21.8</td>
<td>18.7</td>
<td>21.6</td>
</tr>
<tr>
<td>Total Non-Farm</td>
<td>19.1</td>
<td>20.0</td>
<td>18.8</td>
</tr>
</tbody>
</table>
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
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%.
Is it just the luck effect? No

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)
Note: The figure plots the relationship of the log daily job-filling rate to the log gross hires rate across growth rate bins in [-.3, .3] and the hires-weighted least squares regression fit of the bin-level data. Bin-level fill rates estimated from establishment-level data sorted into bins after removing mean establishment growth rates.
Job-Filling Rate and Gross Hires Rate by Sector

Log Daily Fill Rate

T = Turnover Quintile
I = Industry
S = Size Class

$y = 0.80x - 0.30$

$R^2 = 0.80$
Key Conclusion: Hires Are Very Far From Proportional to Vacancies in the Cross Section

Three Possible Explanations

• 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.
Key Conclusion: Hires Are Very Far From Proportional to Vacancies in the Cross Section

Three Possible Explanations

• Heterogeneity in the efficiency of search and matching. Cannot explain evidence in slide 24

• Scale economies (or diseconomies) in the hiring technology at the establishment or sectoral level. Analysis and evidence below show this explanation does not take us very far

• Employers use other instruments, in addition to vacancy numbers, to influence the pace of hiring. Supported by analysis and evidence below
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 \( f_{et} = \tilde{f}_{t} v_{et}^{\gamma-1} \tilde{q}(x_{et}) \)

Taking logs and differentiating in the CS \( \Rightarrow \)

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

\[
0.820 = 0 + (\gamma - 1)(0.13) + \frac{d \log(\tilde{q}(x_{et}))}{d \log(H_{et})}
\]

To preclude a role for employer actions on other margins requires a scale economy parameter value of \( \gamma \approx 6.3 \).
Estimating Scale Economies in the Establishment-Level Hiring Technology

- **Basic idea**: Exploit differences in establishment-level 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) per establishment in Industry $i$ and size class $s$

Scale-Economy Parameter: Elasticity of job-filling rate with respect to the (average) number of vacancies per Establishment

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

**Dependent Variable: Log(Job-Filling Rate)**

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Beginning-of-Month Vacancies, $v_{t-1}$</th>
<th>Monthly Vacancy Flow, $\theta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.072</td>
<td>0.227</td>
</tr>
<tr>
<td>(std. error)</td>
<td>(0.082)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.779</td>
<td>0.764</td>
</tr>
<tr>
<td>First-stage $R^2$</td>
<td>---</td>
<td>0.996</td>
</tr>
<tr>
<td>Implied $\gamma$ (Scale Economies)</td>
<td>1.072</td>
<td>1.227</td>
</tr>
</tbody>
</table>

1. Estimated on industry-size class data pooled over the 2001-06 period.
2. N=70 in all regressions. 5 or 6 size classes per industry (12).
3. All regressions include industry and size class fixed effects and the employment growth rate in the industry-size cell.
4. IV is 2SLS using log(Employment Level) as the instrument.
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:

\[ \frac{\Delta \log \bar{q}}{\Delta \log H} = \frac{\Delta \log q_{et}}{\Delta \log H_{et}} = 0.820 \]
Recruiting Intensity Per Vacancy Series Implied by the Working Hypothesis, Jan 2001 to Dec 2011

Effective vacancies equal this index value times the number of measured vacancies.
Aggregate Performance: GMF vs. SMF

1. The GMF, as augmented and constrained by our recruiting intensity index:
   a. Helps explain major recent breakdown in SMF
   b. Yields a more stable Beveridge Curve at national and regional levels than SMF
   c. Better explains movements over time in job-filling rates at national and regional levels than SMF
   d. Better explains movements over time in job-finding rates at national and regional levels than SMF

2. Industry-level changes in fill rates, \( v-u \) ratios, and recruiting intensity values during and after the 2008-09 recession satisfy restriction implied by the GMF. They violate restrictions implied by the SMF.
The GMF accounts for about 30 percent of the gap between empirical and SMF-implied vacancy yield that opens up from 2007 to 2009.
The GMF accounts for about 30 percent of the gap between empirical and SMF-implied vacancy yield that opens up from 2007 to 2009.

Recruiting intensity accounts for about 30% of gap that opens up between empirical & SMF-implied vacancy yield from 2007-2009.
Recruiting Intensity Index (Micro $q$) Related to Solow Residual Implied by SMF (Macro $q$), Jan 2001 to Dec 2011

Least Squares Fit

$q^{micro} = 0.01 + 0.24q^{macro}$

s.e. = 0.03, $R^2 = 0.91$

Variation in recruiting intensity is $\frac{1}{4}$ as large as SMF residual variation.
Regressions of log unemployment rate on log vacancy rate (SMF) or log effective vacancy rate (GMF)

<table>
<thead>
<tr>
<th>Aggregation Level of Unemployment and Vacancy Data</th>
<th>Time-Series Standard Deviation, Log Unemployment Rate</th>
<th>RMSE of Residuals in Regression on Log Vacancy Rate, Standard Matching Function</th>
<th>Percent Reduction in RMSE Using Log Effective Vacancy Rate, Generalized Matching Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Data</td>
<td>0.30</td>
<td>0.13</td>
<td>20.7</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.27</td>
<td>0.17</td>
<td>17.2</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.28</td>
<td>0.14</td>
<td>13.0</td>
</tr>
<tr>
<td>South</td>
<td>0.30</td>
<td>0.16</td>
<td>18.4</td>
</tr>
<tr>
<td>West</td>
<td>0.34</td>
<td>0.19</td>
<td>23.8</td>
</tr>
</tbody>
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A similar analysis shows the effective tightness ratio (GMF) substantially improves on the \( \nu-u \) ratio (SMF) in explaining movements in the job-finding rate at national and regional levels.
Our generalized matching function yields the following expression for the job-filling rate:

\[ f_t = \mu (v/u)_t^{-\alpha} q_t^{1-\alpha} \]

Given a uniform elasticity, this expression yields the following restriction across the industry-level changes in fill rates, \( v-u \) ratios, and recruiting intensities:

\[ \frac{\Delta \ln f_{it}}{\Delta \ln (v/u)_{it}} = (1 - \alpha) \frac{\Delta \ln q_{it}}{\Delta \ln (v/u)_{it}} - \alpha. \]
Mild evidence against the equal slope implication of the standard matching function.
Strong evidence against the flat slope implication of the standard matching function in the post-recession period.
Evaluating the Restriction Implied by the Generalized Matching Function:

• For the recession period, the figures above give
  \[ \Delta \ln f / \Delta \ln (v/u) = -0.49 \text{ and } \Delta \ln q / \Delta \ln (v/u) = 0.04. \]
  Plugging into
  \[
  \frac{\Delta \ln f_{it}}{\Delta \ln (v/u)_{it}} = (1 - \alpha) \frac{\Delta \ln q_{it}}{\Delta \ln (v/u)_{it}} - \alpha \quad \Rightarrow \quad \alpha = 0.51
  \]

• For the post-recession, \( \Delta \ln q / \Delta \ln (v/u) = 0.31 \):
  Plugging this value into the first equation and evaluating at \( \alpha = 0.51 \) implies a value of -0.35 for \( \Delta \ln f / \Delta \ln (v/u) \), close to actual value of -0.28.

• So the data satisfy the GMF-implied restriction.
Contributions to Changes in Job-Filling Rates and Recruiting Intensity During and After the Great Recession

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</thead>
<tbody>
<tr>
<td>Percent Change, Relative to 2007Q4</td>
<td>39.0</td>
<td>-22.0</td>
<td>-21.8</td>
<td>5.9</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Selected Industry</th>
<th>Contribution to National Change, Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Construction</td>
<td>4.7</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>9.0</td>
</tr>
<tr>
<td>Professional &amp; Business Services</td>
<td>12.6</td>
</tr>
<tr>
<td>Leisure &amp; Hospitality</td>
<td>10.1</td>
</tr>
<tr>
<td>Health and Education</td>
<td>14.6</td>
</tr>
<tr>
<td>Government</td>
<td>17.4</td>
</tr>
</tbody>
</table>

Mean vacancy duration in Construction: 8 days prior to the recession, 3 days at the trough.
Further Extending the GMF

- My remarks on Krueger and Mueller (2011 BPEA) consider a GMF of the form
  \[ H_t = \mu \left[ s_t U_t \right]^\alpha \left[ q_t V_t \right]^{1-\alpha} \]

- Using evidence from their paper on how search time varies with unemployment spell duration and CPS time-series data on mean unemployment spell duration, I construct an index of average search intensity per unemployed person.

- Movements in search intensity per unemployed and recruiting intensity per vacancy explain 70% of the gap between empirical and SMF-implied job-finding rate and that opens up from 2006 to 2010.
Figure 3. Indexes of Search Intensity per Unemployed Worker and Recruiting Intensity per Vacancy, January 2001–February 2011.

- Recruiting intensity per vacancy (right scale)
- Search intensity per unemployed worker for $\beta = 1.54$ (left scale)
See Veracierto (2011) and Hall and Schulhofer-Wohl (2018) for fuller efforts to construct better measures of the jobseeker input (U) to the matching function. They start from the first-order fact that most new hires are NOT from the pool of unemployed workers.
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 recruiting intensity at aggregate level.
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 19 and 22 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 (2015).
Are All Hires Mediated through Vacancies? A Specification 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.
27.4/41.6 = 66% \rightarrow \text{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.}
Quick Look at a Few Indicators Of U.S. Labor Market Conditions

The recruiting intensity and vacancy duration measures displayed on the next two slides are also available by industry, Census region, firm size and establishment size on my website at http://faculty.chicagobooth.edu/steven.davis/.

Scroll down to DHI Hiring Indicators and click on ”Latest Data Release.”
Source: DHI Hiring Indicators using JOLTS data and methods in Davis et al. (2013 QJE)
DHI-DFH Measure of Mean Vacancy Duration, January 2001 to November 2017

Source: DHI Hiring Indicators using JOLTS data and methods in Davis et al. (2013 QJE)
Notes: Short Term Unemployment is the number of persons unemployed 26 weeks or less. The Quit Rate is rescaled to have the same mean and variance as the Vacancy-Unemployment Ratio from January 2001 to date. Non-Employment + PTER, an index developed by Hornstein, Kudlyak and Lange, reflects all persons who are not employed (weighted by labor force attachment) plus persons working part time for economic reasons who would prefer full-time work full. Here, their index is multiplied by minus one and then rescaled to have the standard deviation as the Vacancy-Unemployment Ratio from January 2001 to date.
Aggregate Recruiting Intensity

By Alessandro Gavazza, Simon Mongey and Giovanni L. Violante

Forthcoming in the *American Economic Review*
Overview, 1

A very well-crafted paper that incorporates a recruiting intensity margin, decreasing returns in production at the employer level, and collateral constraints into an equilibrium model with frictional hiring and rich employer-level dynamics.

• The recruiting technology maps neatly to evidence on the micro behavior of employment growth, vacancies and hiring. The authors use this mapping and evidence to discipline the choice of key parameter values.

• The analysis delivers a coherent interpretation of prominent patterns in the micro data, and it shows how aggregate shocks drive fluctuations in matching “efficiency” through their effects on average recruiting intensity. In turn, matching efficiency affects job-finding rates, job-filling rates and hiring.
Overview, 2

The analysis quantifies three mechanisms whereby aggregate shocks drive (average) recruiting intensity:

- **Slackness effect**: Average recruiting intensity (RI) falls when job seekers per vacancy rise. The main quantitative force behind RI fluctuations, according to the authors.

- **Composition effect**: A negative aggregate shift causes a leftward shift in the distribution of employer growth rates, including a decline in entry and young-employer expansion, reducing average RI. A small force.

- **Sectoral mix effect**: Matching efficiency is very high in the Construction sector. So a cyclical shift away from Construction lowers the economy-wide average matching efficiency (equivalent to an RI drop, given Cobb-Douglas). An important force in certain episodes.
New Testable Implications

The GMV model also has rich implications for how recruiting intensity varies by employer age and how the cross-sectional distribution of vacancies, hiring and recruiting intensities respond to financial shocks and to common productivity shocks.

We currently have little evidence that speaks directly and powerfully to these implications. It’s a good topic for future empirical work that integrates JOLTS micro data with data on the production and financial characteristics of individual employers.
GMV: “The robust finding of DFH is that firms that grow raster fill their vacancies at a faster rate.”

My restatement: Looking across sectors and employers, and looking over time for a given employer, the vacancy-filling rate rises with the gross hires rate.

The two statements are equivalent only in a world with no replacement hiring.
I prefer my restatement for several reasons:

- Replacement hiring is huge: worker flows are at least twice as large as job flows.
- Worker and job flows exhibit distinct patterns of variation in the C-S and over time.
- The matching function aggregates gross hires over employers, not gross job creation.
- Accordingly, the key elasticity that DFH estimate from JOLTS micro data – and to which GMV calibrate their recruiting technology – derives from the empirical relationship between vacancy-filling rates and gross hires rates.
GMV consider an extended model with on-the-job search, quits and replacement hiring. The extension posits an exogenous quit rate that is invariant in the C-S and over time. Empirically, the quit rate varies systematically in the C-S of employer growth rates. Moreover, the quit rate is highly sensitive to the cycle *conditional* on an employer’s growth rate, and this sensitivity varies a lot with the employer growth rate. The next slide illustrates these facts. See DFH (2012 JME) for more.
Quarterly Quit Rates in the C-S & Over Time

Reproduced from Figure 8.d in Davis, Faberman and Haltiwanger, *Journal of Monetary Economics*, 2012
1. Relative to their employment, young employers make up a disproportionate share of gross job creation. They are also cyclically sensitive. The authors account for these facts in quantifying their composition effect.

2. But the young-employer share of gross hires is even greater than their share of gross job creation.
   - Why? Because all workers at young employers have short job tenures, and separation rates fall with tenure. Thus, young employers have higher rates of replacement hiring.
   - Thus, their composition analysis understates the cyclical shift in the young-employer share of gross hires.

So, yes, I think they understate the “composition” effect. Is this a big deal quantitatively? Probably not. But there are other composition effects as well.
Davis, Faberman and Haltiwanger (2013)

Strengths
• Captures all shifts in distribution of vacancies and hires across (a) employers that differ in recruiting intensities and (b) sectors that differ in matching efficiencies
• Readily disaggregates into market segments defined in observable employer characteristics (industry, size, turnover rates, etc.)
• Circumvents need to measure the effective number (and search intensities) of jobseekers

Weaknesses
• Neglects the slackness effect
Gavazza, Mongey and Violante (2016)

Strengths

• Incorporates the slackness effect
• Augmented version captures some changes in sectoral mix

Weaknesses

• Tied to a particular measure of jobseekers (the number of unemployed in GMV), a nettlesome matter
• Neglects distinction between gross job creation and gross hires
• Only captures explicitly modelled shifts across (a) employers that differ in recruiting intensities and (b) sectors that differ in matching efficiencies
In short, the DFH and GMV recruiting intensity measures have very different sets of strengths and weaknesses.

Both measures advance our understanding of the hiring process, matching efficiency, job-filling rates, etc. Both have material limitations.

Downstream users may want to try both measures, recognizing that one of them may be more suitable for certain applications.

– When capturing the slackness effect is essential, the GMV measure is clearly more suitable.
– When it’s desirable to disaggregate by employer characteristics or capture a broad range of composition effects, the DFH measure is better.
Help Wanted: We Need Direct Measures of Recruiting Intensity

1. Both DFH and GMV develop clever(!) methods for extracting information about recruiting intensity from data sources that contain no direct measures of RI.

2. We need direct measures of recruiting intensity. An expanded JOLTS questionnaire is a natural vehicle for obtaining direct evidence on recruiting intensity (and many other poorly understood aspects of hiring behavior).

3. Davis (2014) offers several concrete suggestions for improving the JOLTS, including a suggested question on recruiting intensity.
Some Directions for Research

• Assessing performance of GMF in other countries
• Incorporating recruiting intensity into theories of labor market flows, unemployment and aggregate fluctuations.
  – In addition to Gavazza, Mongey and Violante (2017), see Kaas and Kircher (2013), Baydur (2017) and Leduc and Liu (2016).
• Better measures of the jobseeker input to matching
  – E.g., Veracierto (2011), Hall & Schulhofer-Wohl (2018), and Mukoyama, Patterson and Sahin (2013)
• Aggregate implications of sectors with atypical frictional characteristics.
• Hires not mediated through vacancies
• Need for data that supports direct measures of recruiting intensity and recruiting methods – e.g., a richer JOLTS
References, 1


Extra Slides