New Evidence and New Research Directions in the Macroeconomics Of Labor Markets

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Two Topics

1. Vacancies, Hiring, and Recruiting Intensity
   - “The Establishment-Level Behavior of Vacancies and Hiring.” with Jason Faberman and John Haltiwanger, August 2012

2. Recessions and the Costs of Job Loss
Topic 1: Outline of Remarks

• 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.
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Topic 1: Outline of Remarks

• 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 MF as resulting from large movements in recruiting intensity per vacancy (and in search intensity per unemployed)
• The GMF outperforms standard MF (SMF):
  1. GMF accounts for CS behavior of job-filling rates. SMF does not.
  2. GMF (as augmented and 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 restriction 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\textsuperscript{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”
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).
Vacancy Flows and Job-Filling Rate Relationships to Employer Growth Rates
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)
**Fill Rate and Gross Hires Rate by Growth Rate Bin**

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

\[ y = 0.80x - 0.30 \]
\[ R^2 = 0.80 \]
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.
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, ν_{t-1}</th>
<th>Monthly Vacancy Flow, θ_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>R²</td>
<td>0.779</td>
<td>0.764</td>
</tr>
<tr>
<td>First-stage R²</td>
<td>---</td>
<td>0.996</td>
</tr>
<tr>
<td>Implied γ (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:

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

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.
Recruiting Intensity Index (Micro $q$) Related to Solow Residual Implied by SMF (Macro $q$), Jan 2001 to Dec 2011

Least Squares Fit

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

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

Variation in recruiting intensity is $1/4^{th}$ as large as SMF residual variation.
Beveridge Curve Fits for SMF and GMF, Monthly Data, Jan 2001 to Dec 2011

Regressions of log unemployment rate on log vacancy rate (SMF) or log effective vacancy rate (GMF)

A similar analysis shows the effective tightness ratio (GMF) substantially improves on the $v-u$ ratio (SMF) in explaining movements in the job-finding rate at national and regional levels.

<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>
</table>
Generalized Matching Function: Implications for Industry-Level Changes

- 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:

\[ \frac{\Delta \ln f_{it}}{\Delta \ln (v/u)_{it}} = (1 - \alpha) \frac{\Delta \ln q_{it}}{\Delta \ln (v/u)_{it}} - \alpha. \]
Industry-Level Changes, 1

Job-Filling Rate vs. V-U Ratio

Mild evidence against the equal slope implication of the standard matching function.
Industry-Level Changes, 2

Recruiting Intensity vs. V-U Ratio

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 
\[ \frac{\Delta \ln f}{\Delta \ln (v/u)} = -0.49 \] and \[ \frac{\Delta \ln q}{\Delta \ln (v/u)} = 0.04. \] 
Plugging into 
\[ \frac{\Delta \ln f_{it}}{\Delta \ln (v/u)_{it}} = (1 - \alpha) \frac{\Delta \ln q_{it}}{\Delta \ln (v/u)_{it}} - \alpha \Rightarrow \alpha = 0.51 \]

• For the post-recession, \[ \frac{\Delta \ln q}{\Delta \ln (v/u)} = 0.31 \]: 
Plugging this value into the first equation and evaluating at \( \alpha = 0.51 \) implies a value of -0.35 for \( \frac{\Delta \ln f}{\Delta \ln (v/u)} \), 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

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
  \[ H_t = \mu [s_t U_t]^\alpha [q_t V_t]^{1-\alpha} \]

- 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.

- GMF explains 88% of 2006-2010 change in empirical job-finding rate.
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)
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.
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).
Some Directions for Research

• Assessing performance of GMF in other countries

• Incorporating recruiting intensity into standard theories of labor market flows and unemployment

• Aggregate implications of sectors with atypical frictional characteristics, e.g., outsized role of Construction in recent years

• Hires not mediated through vacancies

• Need for data that supports direct measures of recruiting intensity and recruiting methods – a richer JOLTS
Title: Outline of Remarks on Recessions and the Cost of Job Loss

- Incidence of Job Loss and Job Displacement
- Earnings Losses Associated with Displacement
  - Empirical Specification for Estimating Losses
  - Magnitude of Present Value Losses
  - Sensitivity to Conditions at Time of Displacement
  - Selection Bias?
- Earnings Losses Due to Job Loss in Leading Models of Unemployment Fluctuations
- Directions for Future Research
Fig. 1. Job Loss Indicators, Quarterly, % of Employment

- Job Destruction (BED)
- Unemployment Inflows (CPS)
- Layoffs (JOLTS)
- Initial Claims for UI Benefits (Right Axis)
Job Loss Indicators, Quarterly, % of Employment

- Job Destruction (BED)
- Unemployment Inflows (CPS)
- Layoffs (JOLTS)

~9 million per quarter

~5 million per quarter
Defining Job Displacements in SSA Data

1. A worker separates in year $y$ if he has earnings with the employer in $y-1$ but not in $y$.

2. A worker is displaced in year $y$ if:
   • He separates from his (main) employer in $y$
   • 3+ years of tenure with employer as of $y-1$, and
   • Employer experiences a mass-layoff event in $y$

Employer criteria for a mass-layoff event in $y$:
   • 50+ employees in $y-2$
   • Employment contracts by 30-99% from $y-2$ to $y$
   • Employment in $y-2 < 130\%$ of employment in $y-3$
   • Employment in $y+1 < 90\%$ of employment in $y-2$
Fig. 2. Annual Job Displacement Rates, Percent

Men, 50 and younger, 3+ Years of Prior Job Tenure

Using a 1% R.S. of men with a valid SSA #, then applying age, tenure, firm size & industry criteria

Job Destruction At Firms with 50+ Employees (left axis)
Fig. 2. Annual Job Displacement Rates, Percent

31-36% of men in our SSA data satisfy the age, job tenure and firm size criteria.

20% cumulative displacement from 1980 to 1985 ~ 2.7 million men
The CPS Displaced Worker Supplement uses a less restrictive concept of displacement. It reports 6.9 million persons with 3+ years of prior job tenure were displaced from 2007 to 2009, and another 8.5 million with less tenure were displaced.
Estimating the Dynamic Pattern of Annual Earnings Losses for Workers Displaced in Displacement Year $y$

$$e_{it}^y = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \beta^y X_{it} + \sum_{k=-6}^{20} \delta_k^y D_{it}^k + u_{it}^y$$

- **k** = years since or to job displacement
- **Event**
  - Job displacement in $y$, $y+1$, $y+2$
- **Control Group**
  - Workers not separating from employers in $y$, $y+1$, $y+2$ (same age, tenure and 50+ requirements)
- **Identification Assumption**
  - Evolution of control group earnings is a valid counterfactual for earnings of displaced workers in the absence of job displacement, conditional on controls

Fit to 1974-2008 longitudinal earnings data separately for each displacement year from 1980 to 2005.
Fig. 4B. Average Annual Earnings Losses Before and After Job Displacement Relative to Control Group Earnings, Men 50 or Younger with At Least 3 Years of Job Tenure

We construct these plots by averaging the estimation results over displacement years from 1980 to 2005.

Last year of positive earnings with pre-displacement employer.
Fig. 4C. Average Annual Earnings Losses Before and After Job Displacement Relative to Control Group Earnings, Fraction of Pre-Displacement Annual Earnings, Men 50 or Younger with At Least 3 Years of Job Tenure

Graph showing earnings loss relative to initial earnings, with years before and after job displacement on the x-axis and earnings loss relative to initial earnings on the y-axis. The graph includes two lines: one for Average NBER Recession and another for Average NBER Expansion.
Fig. 5. Annual Earnings Losses in the Third Year of Job Displacement, Men 50 or Younger with at Least 3 Years of Job Tenure Prior to Displacement

Earnings Loss Relative to Pre-Displacement Annual Earnings vs. Unemployment Rate in Displacement Year (Year 1)
Is It Selection Bias?

• Workers displaced from employers with >80% contraction experience similar earnings losses
  – Argues against within-firm selection

• Losses are smaller when controlling for firm-year effects, but they remain large and persistent.
  – Argues against between-firm selection

• Selection does not explain larger losses for workers displaced in worse times, when negative selection effects are likely weaker.

• See VSM (2011) for extensive analysis of selection.
Constructing Estimates of Present Value Earnings Losses

The estimated average annualized log earnings loss between years 6-10 and 11-15, estimated using data for all available displacement years.

\[ PDV_{R}^{\text{Loss}} = \sum_{s=1}^{10} \delta_{s}^{R} \frac{1}{(1 + r)^{s-1}} + \sum_{s=11}^{20} \delta_{10}^{R} \frac{(1 - \lambda)^{s-10}}{(1 + r)^{s-1}} \]

- Estimated earnings loss in year \( s \) from displacement, using average of estimated loss in all or selected displacement years.
- Average annual decay rate of losses in years 11 to 20 after displacement.
- 5% annual discount rate
- Estimated earnings loss in year 10 from displacement
Table 1. Magnitude of PV Earnings Loss at Job Displacement in Mass Layoffs from 1980-2005: Men, 50 or Younger with 3+ Years of Prior Job Tenure

<table>
<thead>
<tr>
<th>Fraction of Years Covered by Row Category</th>
<th>Present Discounted Value (PDV) of Average Loss at Job Displacement</th>
<th>Multiple of Pre-Displacement Annual Earnings</th>
<th>Ratio of PDV of Loss and PDV of Counterfactual Earnings in Absence of Displacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average All Years</td>
<td>–</td>
<td>-77,557</td>
<td>-1.71</td>
</tr>
<tr>
<td>Avg. in NBER Expansion Years</td>
<td>0.88</td>
<td>-72,487</td>
<td>-1.59</td>
</tr>
<tr>
<td>Avg. in NBER Recession Years</td>
<td>0.12</td>
<td>-109,567</td>
<td>-2.50</td>
</tr>
<tr>
<td>Average in Years with:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UR&lt;5%</td>
<td>0.23</td>
<td>-50,953</td>
<td>-1.06</td>
</tr>
<tr>
<td>5%\leq UR&lt;6%</td>
<td>0.35</td>
<td>-71,460</td>
<td>-1.56</td>
</tr>
<tr>
<td>6%\leq UR&lt;7%</td>
<td>0.13</td>
<td>-71,006</td>
<td>-1.58</td>
</tr>
<tr>
<td>7%\leq UR&lt;8%</td>
<td>0.21</td>
<td>-89,792</td>
<td>-2.07</td>
</tr>
<tr>
<td>UR\geq 8%</td>
<td>0.08</td>
<td>-121,982</td>
<td>-2.82</td>
</tr>
</tbody>
</table>
Fig. 6. PV Earnings Losses over 20 Years from Displacement, Men 50 or Younger with 3+ Years of Prior Job Tenure

PV Earnings Loss As a Multiple of Pre-Displacement Annual Earnings

Unemployment Rate in Displacement Year
Table 2. Magnitude of PV Earnings Loss at Job Displacement in Mass Layoffs from 1980-2005: Men, 50 or Younger with 6+ Years of Prior Job Tenure and Women, 50 or Younger with 3+ Years of Tenure

<table>
<thead>
<tr>
<th>Sub-Group</th>
<th>(1) Present Discounted Value (PDV) of Average Loss at Job Displacement</th>
<th>(2) Multiple of Pre-Displacement Annual Earnings</th>
<th>(3) Ratio of PDV of Loss and PDV of Counterfactual Earnings in Absence of Displacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men with 6 or More Years of Job Tenure at Displacement</td>
<td>Average All Years: -106,900</td>
<td>-2.0</td>
<td>-12.9</td>
</tr>
<tr>
<td></td>
<td>Avg. in NBER Expansion Years: -100,543</td>
<td>-1.8</td>
<td>-11.9</td>
</tr>
<tr>
<td></td>
<td>Avg. in NBER Recession Years: -148,400</td>
<td>-3.0</td>
<td>-20.0</td>
</tr>
<tr>
<td>Women with 3 or More Years of Job Tenure at Displacement</td>
<td>Average All Years: -38,033</td>
<td>-1.5</td>
<td>-10.9</td>
</tr>
<tr>
<td></td>
<td>Avg. in NBER Expansion Years: -33,164</td>
<td>-1.3</td>
<td>-9.5</td>
</tr>
<tr>
<td></td>
<td>Avg. in NBER Recession Years: -68,782</td>
<td>-3.3</td>
<td>-20.6</td>
</tr>
</tbody>
</table>
Basic MP Model of Frictional Unemployment

- Homogenous jobs, workers and matches
- Filled jobs/matches blow up at constant rate
- Aggregate productivity, common to all jobs, is exogenous and stochastic
- Hires = M(Unemployed, Vacancies), CRS
- Wage determination: Nash or BRW
- Free entry of employers/vacancies
- The only nontrivial decision in the model is how many vacancies employers create.

\[ q(\theta_i)(P_i - W_i) = c. \]
Table 4. PV Income and Earnings Losses Due to Job Loss in the Basic MP Model

<table>
<thead>
<tr>
<th>Model Version</th>
<th>PV Income Losses, Percent of Employment Asset Value</th>
<th>PV Earnings Losses, Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>MP-Nash Standard</td>
<td>MP-Nash Hall-Milgrom</td>
</tr>
<tr>
<td></td>
<td>MP-Nash Hagedorn-Manovskii</td>
<td>MP-CB Hall-Milgrom</td>
</tr>
</tbody>
</table>

A. Range of Mean Losses Over Five Aggregate States

|                      | 0.20 - 0.22 | 0.044 - 0.047 | 0.20 - 0.23 |

B. All Aggregate Paths

<table>
<thead>
<tr>
<th></th>
<th>Realized Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Unemployment Rate</td>
<td>0.066</td>
</tr>
<tr>
<td>Monthly Job-Finding Rate</td>
<td>0.43</td>
</tr>
<tr>
<td>Mean PV Losses</td>
<td>0.23</td>
</tr>
<tr>
<td>10th/90th percentile losses</td>
<td>-0.55 / 1.07</td>
</tr>
</tbody>
</table>


MP Model of Burgess and Turon (2010)

- Start with Mortensen and Pissarides (1994)
- Add costly search on the job and other changes

The Model Yields:
- Worker flows apart from job flows
- Heterogeneity in productivity and wages
- A job ladder
- Job loss spikes due to negative aggregate shocks

Idiosyncratic Productivity Thresholds for Job Destruction, Replacement Hiring and Search on the Job
Figure B1. Wage Function and Density of Filled Jobs in the Model of Burgess and Turon for the Table 5 Calibration
Table 5. PV Earnings Losses Due to Job Loss in Model of Burgess and Turon (2010), MP(1994) with Search on the Job

<table>
<thead>
<tr>
<th>Aggregate State</th>
<th>Good</th>
<th>Middle</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Loss</td>
<td>Income</td>
<td>0.39</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>Earnings</td>
<td>2.44</td>
<td>2.54</td>
</tr>
<tr>
<td>B. Quarterly (Monthly) Job Finding Rate</td>
<td>82.5 (44.1)</td>
<td>73.7 (35.9)</td>
<td>64.9 (29.5)</td>
</tr>
</tbody>
</table>

Note: We calibrate the model to match U.S. job-finding rates. Burgess and Turon calibrate their model to match features of the British economy from 1964 to 1999. Using their calibration, which entails much lower job-finding rates for unemployed workers, the Mean PV earnings losses range from 4.4% to 5%. 

<table>
<thead>
<tr>
<th>Aggregate State Transition</th>
<th>Good $\rightarrow$ Middle</th>
<th>Middle $\rightarrow$ Bad</th>
<th>Good $\rightarrow$ Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Present Value Earnings Losses</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>I. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past</strong></td>
<td>2.85</td>
<td>3.08</td>
<td>3.26</td>
</tr>
<tr>
<td><strong>J. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past</strong></td>
<td>2.15</td>
<td>2.57</td>
<td>2.57</td>
</tr>
<tr>
<td><strong>K. Inflow-Weighted Average of Rows I and J</strong></td>
<td>2.81</td>
<td>3.05</td>
<td>3.19</td>
</tr>
<tr>
<td><strong>L. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group</strong></td>
<td>2.54</td>
<td>2.71</td>
<td>2.71</td>
</tr>
<tr>
<td><strong>M. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group</strong></td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>N. Inflow-Weighted Average of Rows L and M</strong></td>
<td>2.39</td>
<td>2.55</td>
<td>2.42</td>
</tr>
</tbody>
</table>
Summary

1. Job displacement brings large PV earnings losses

<table>
<thead>
<tr>
<th>Unemployment Rate in Displacement Year</th>
<th>Mean PV Losses as Multiple of Pre-Displacement Earnings (Men)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 6%</td>
<td>1.4 Years</td>
</tr>
<tr>
<td>More than 8%</td>
<td>2.8 Years</td>
</tr>
<tr>
<td>Full Sample, 1980-2005</td>
<td>1.7 Years</td>
</tr>
</tbody>
</table>

2. Incidence of job loss & displacement rises in recessions and slumps, especially severe ones

3. Job displacement leads to many other negative consequences for workers and their families

4. Job loss is a rather inconsequential event in leading models of unemployment fluctuations
   - MP models do not account for magnitude of PV losses, or the sensitivity to conditions at the time of displacement
   - They miss why workers and policymakers are so concerned about job loss, recessions and unemployment
Directions for Research

• Put specific human capital into DMP models
  – Learning about match quality (Jovanovic, 1979)
  – Learning by doing on the job
  – Investments in job-specific training (Becker, 1962)

• Account for (other sources of) worker rents
  – Pay equity and fairness norms (Akerlof and Yellen, 1982)
  – High pay to deter shirking (Bulow and Summers, 1986)
  – Appropriation of quasi-rents on capital (Grout, 1986)
  – Worker sharing of product market rents
  – Downward stickiness due to contracting and one-sided commitment by firms (Beaudry and DiNardo, 1992)
Directions for Research, 2

• To what extent does the loss of imputed rents account for the estimated PV earnings losses associated with job displacement?
  – Use estimated rent component of industry, employer size, and union wage effects

• Why don’t wages fall (more) at firms that undergo mass layoffs?

• Turning the displaced worker literature upside-down: What’s the impact on PV earnings of (early) attachment to a firm that experiences rapid, sustained growth?
• Incorporating lessons from research on graduating in a recession
  – Workers who enter the labor market when conditions are slack suffer persistent negative effects on future earnings (Kahn, 2010)
  – Lasting declines in employer quality and lasting effects of low starting wages on wage growth within firms (Oreopolous, von Wachter and Heisz, 2010)
  – These results suggest that weak conditions at the time of labor market entry (or displacement) slow the accumulation of rents and specific human capital for many years thereafter.
Directions for Research, 4

• Who recovers from displacement events and who doesn’t?
  – How much explanatory power from “standard” measures of skills, education and cognitive ability?
  – Is there an important role for social networks (size and character) in recovery from displacement?
  – Do personality traits matter and, if so, how much?
    • Resilience, optimism, perseverance, sociability, organizational skills and practices, propensity to plan, attitudes, etc.
Additional Slides – Not for Prepared Remarks
### 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 as a Percent of Employment

Unconditional

Controlling for Establishment Fixed Effects
Vacancy Yields and Establishment Growth Rates in the Cross Section

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.
Table 3: Selected Results by Industry, Size, Turnover

<table>
<thead>
<tr>
<th></th>
<th>Daily Job-Filling Rate, $f_i$</th>
<th>Monthly Vacancy Flow Rate, $\overline{\lambda} \overline{\lambda} \overline{\lambda}_i$ (pct. of empl.)</th>
<th>Mean Vacancy Duration, $1/f_i$ (in days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonfarm Employment</td>
<td>0.050</td>
<td>3.4</td>
<td>20.0</td>
</tr>
<tr>
<td><strong>Selected Industries</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>0.121</td>
<td>5.4</td>
<td>8.3</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.052</td>
<td>2.3</td>
<td>19.3</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>0.073</td>
<td>4.5</td>
<td>13.7</td>
</tr>
<tr>
<td>Professional &amp; Business Services</td>
<td>0.049</td>
<td>4.6</td>
<td>20.4</td>
</tr>
<tr>
<td>Government</td>
<td>0.032</td>
<td>1.6</td>
<td>31.4</td>
</tr>
<tr>
<td><strong>Establishment Size Class</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-9 Employees</td>
<td>0.061</td>
<td>3.3</td>
<td>16.5</td>
</tr>
<tr>
<td>10-49 Employees</td>
<td>0.066</td>
<td>4.0</td>
<td>15.2</td>
</tr>
<tr>
<td>50-249 Employees</td>
<td>0.059</td>
<td>4.0</td>
<td>17.1</td>
</tr>
<tr>
<td>250-999 Employees</td>
<td>0.041</td>
<td>3.1</td>
<td>24.1</td>
</tr>
<tr>
<td>1,000-4,999 Employees</td>
<td>0.026</td>
<td>2.1</td>
<td>37.9</td>
</tr>
<tr>
<td>5,000+ Employees</td>
<td>0.026</td>
<td>1.7</td>
<td>38.9</td>
</tr>
<tr>
<td><strong>Worker Turnover Category</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First Quintile (lowest turnover)</td>
<td>0.011</td>
<td>0.4</td>
<td>87.9</td>
</tr>
<tr>
<td>Second Quintile</td>
<td>0.019</td>
<td>1.3</td>
<td>52.8</td>
</tr>
<tr>
<td>Third Quintile</td>
<td>0.030</td>
<td>2.4</td>
<td>32.8</td>
</tr>
<tr>
<td>Fourth Quintile</td>
<td>0.054</td>
<td>4.6</td>
<td>18.4</td>
</tr>
<tr>
<td>Fifth Quintile (highest turnover)</td>
<td>0.114</td>
<td>14.0</td>
<td>8.7</td>
</tr>
</tbody>
</table>
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:

$$E_t^{NoVac} H_t^{NEW} / H_t$$

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>
</tr>
</thead>
<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.