
Overview

1. Empirical Underpinnings of the Flow Approach to Labor Markets
3. An Interesting Pitfall in Measuring Worker Flows
4. Labor Market Flows in the Cross Section and Over Time
5. Taking Stock: Using Comprehensive Business Databases as a Research Tool
1. Some Empirical Underpinnings of the Flow Approach to Labor Markets

Empirical Regularities

- Gross job flows between employers are remarkably large – in good economic times and bad, in every market economy, in virtually every industry and sector
- Worker flows are larger yet
- Between-sector employment shifts account for a small share of job flows – idiosyncratic factors predominate
- Job and worker flows exhibit pronounced cyclical movements
- Job flows and worker flows trended downward in recent decades (last lecture and this one)
- Worker and job flows are tightly linked in the cross section and over time (Section 4 of the lecture)
Labor Market Flows: Some Definitions

• Job Flows
  – *Job Creation*: employment gains at expanding and new employers (e.g., expanding and new establishments) between two points in time
  – *Job Destruction*: employment losses at employers that contract or exit

• Worker Flows (Employer Side)
  – *Hires*: Flow of new workers hired in a given period
  – *Separations*: Flow of workers who separate from their employers in a given period
    • Quits
    • Layoffs and Discharges for Cause
    • Transfers, Retirements and Deaths

• Worker Flows (Individual or Household Side)
  – *Job-to-Job Flows*: Transitions from one employer to another without a measured non-employment spell
Net Employment Change

≡ Creation - Destruction
≡ Hires - Separations

Job Flows

Worker Flows
A Contracting Firm

Unemployment

Previous Employer

Hires (Inflow)

Out of the Labor Force

Separations (Outflow)

New Employer

Out of the Labor Force

Hires - Separations = Jobs Destroyed
An Expanding Firm

Hires - Separations = Jobs Created

Hires (Inflow) → New Employer

Separations (Outflow) → Unemployment

Previous Employer

Out of the Labor Force

Unemployment

New Employer

Out of the Labor Force
### Job Creation and Destruction Rates in the U.S. Private Sector

#### Table 2

Job and Worker Flows by Selected Industries

<table>
<thead>
<tr>
<th>Industry</th>
<th>Job creation</th>
<th>Job destruction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total private</td>
<td>7.9</td>
<td>7.6</td>
</tr>
<tr>
<td>Construction</td>
<td>14.3</td>
<td>13.9</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>4.9</td>
<td>5.3</td>
</tr>
<tr>
<td>Retail trade</td>
<td>8.1</td>
<td>7.9</td>
</tr>
<tr>
<td>Professional &amp; business services</td>
<td>9.9</td>
<td>9.1</td>
</tr>
<tr>
<td>Leisure &amp; hospitality</td>
<td>10.7</td>
<td>10.2</td>
</tr>
</tbody>
</table>

### Monthly U.S. Worker Flows (Employer Side)

#### B. Average Monthly Worker Flow Rates in JOLTS, December 2000 to January 2005

<table>
<thead>
<tr>
<th></th>
<th>Hires</th>
<th>Separations</th>
<th>Quits</th>
<th>Layoffs</th>
<th>Quit</th>
<th>Destroyed Job</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Nonfarm</td>
<td>3.2</td>
<td>3.1</td>
<td>1.7</td>
<td>1.1</td>
<td>0.7</td>
<td>0.8</td>
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<tr>
<td>Construction</td>
<td>5.3</td>
<td>5.5</td>
<td>2.1</td>
<td>3.2</td>
<td>1.5</td>
<td>1.1</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>2.2</td>
<td>2.7</td>
<td>1.2</td>
<td>1.2</td>
<td>1.1</td>
<td>0.8</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>4.3</td>
<td>4.2</td>
<td>2.6</td>
<td>1.3</td>
<td>0.5</td>
<td>0.7</td>
</tr>
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<td>Professional &amp; Business Services</td>
<td>4.2</td>
<td>3.9</td>
<td>2.0</td>
<td>1.6</td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>Leisure &amp; Hospitality</td>
<td>6.1</td>
<td>5.9</td>
<td>3.9</td>
<td>1.8</td>
<td>0.5</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Notes: Estimates based on authors’ tabulations of BED and JOLTS microdata. Rates are percentages of employment, calculated as described in the text.

Figure 1

Labor Market Flows – International Comparisons

- See Davis & Haltiwanger (1999) for basic international comparisons of job flows
- See Blanchard and Portugal (2001) and Pries and Rogerson (2005) for two insightful analyses of the differences in labor market flows across countries.
Decomposing Total and Excess Job Reallocation into Between-Sector and Within-Sector Components

\[ R_{st} = \sum_{e \in S} |\Delta EMP_{est}| = C_{st} + D_{st}. \]

\[ R_t - |NET_t| = \left( \sum_s |NET_{st}| - |NET_t| \right) + \sum_s \left( R_{st} - |NET_{st}| \right). \]

\[ r_{st} = \frac{R_{st}}{Z_{st}} = \sum_{e \in S} \left( \frac{Z_{est}}{Z_{st}} \right) |g_{est}| = c_{st} + d_{st} \]

\[ x_t = r_t - |g_t| = \left[ \sum_s \left( \frac{Z_{st}}{Z_t} \right) |g_{st}| - |g_t| \right] + \left[ \sum_s \left( \frac{Z_{st}}{Z_t} \right) (r_{st} - |g_{st}|) \right]. \]
Table 5  
Fraction of excess job reallocation accounted for by employment shifts between sectors

<table>
<thead>
<tr>
<th>Country</th>
<th>Period</th>
<th>Classification scheme</th>
<th>Unit of analysis</th>
<th>Number of sectors</th>
<th>Average number of workers per sector (in 000's)</th>
<th>Fraction resulting from shifts between sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>1972–1988</td>
<td>4-Digit SIC manufacturing by state</td>
<td>Plant</td>
<td>448/456</td>
<td>39.1²</td>
<td>0.13</td>
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<tr>
<td>USA</td>
<td>1972–1988</td>
<td>2-Digit SIC manufacturing by state</td>
<td>Plant</td>
<td>980</td>
<td>17.9</td>
<td>0.14</td>
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<tr>
<td>Denmark</td>
<td>1983–1989</td>
<td>1-Digit ISIC private sector</td>
<td>Plant</td>
<td>8</td>
<td>196.1</td>
<td>0.00</td>
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<tr>
<td>Finland</td>
<td>1986–1991</td>
<td>2-Digit ISIC</td>
<td>Plant</td>
<td>27</td>
<td>48.9</td>
<td>0.06</td>
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<tr>
<td>Germany</td>
<td>1983–1990</td>
<td>2-Digit ISIC</td>
<td>Plant</td>
<td>24</td>
<td>1171.2</td>
<td>0.03</td>
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<tr>
<td>Italy</td>
<td>1986–1991</td>
<td>2-Digit ISIC</td>
<td>Firm</td>
<td>28</td>
<td>321.5</td>
<td>0.02</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1979–1993</td>
<td>2-Digit SIC</td>
<td>Firm</td>
<td>18</td>
<td>10.0</td>
<td>0.20</td>
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<tr>
<td>Sweden</td>
<td>1985–1991</td>
<td>2-Digit ISIC</td>
<td>Plant</td>
<td>28</td>
<td>112.4</td>
<td>0.03</td>
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<tr>
<td>Norway</td>
<td>1976–1986</td>
<td>5-Digit ISIC</td>
<td>Plant</td>
<td>142</td>
<td>2.4</td>
<td>0.06</td>
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<tr>
<td>France</td>
<td>1984–1988</td>
<td>NAP private sector</td>
<td>Plant</td>
<td>15</td>
<td>883.3</td>
<td>0.06</td>
</tr>
<tr>
<td>France</td>
<td>1985–1991</td>
<td>Detailed industry</td>
<td>Firm</td>
<td>600</td>
<td>36.6</td>
<td>0.17</td>
</tr>
<tr>
<td>France</td>
<td>1984–1991</td>
<td>NAP</td>
<td>Plant</td>
<td>100</td>
<td></td>
<td>0.12</td>
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<tr>
<td>New Zealand</td>
<td>1987–1992</td>
<td>2-Digit ISIC</td>
<td>Plant</td>
<td>28</td>
<td>27.5</td>
<td>0.01</td>
</tr>
<tr>
<td>Chile</td>
<td>1979–1986</td>
<td>4-Digit manufacturing</td>
<td>Plant</td>
<td>69</td>
<td>3.7</td>
<td>0.12</td>
</tr>
<tr>
<td>Colombia</td>
<td>1977–1991</td>
<td>4-Digit manufacturing</td>
<td>Plant</td>
<td>73</td>
<td>6.31</td>
<td>0.13</td>
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<tr>
<td>Morocco</td>
<td>1984–1989</td>
<td>4-Digit manufacturing</td>
<td>Plant</td>
<td>61</td>
<td>4.0</td>
<td>0.17</td>
</tr>
</tbody>
</table>
Worker Flows and Job Flows in the Cross Section of Establishment Growth Rates

Figure 1. The Relationship of Hires and Separations to Establishment Growth

Reproduced from Davis et al. (2010); based on JOLTS micro data.
Quits and Layoffs in the Cross Section of Establishment Growth Rates

Figure 2. The Relationship of Layoffs and Quits to Establishment Growth

Reproduced from Davis et al. (2010); based on JOLTS micro data.
Aggregate Job Creation and Destruction (Quarterly)

Percent of Employment

- Job Creation
- Job Destruction

Reproduced from Davis, Faberman, Haltiwanger (2010b); based on BED
Manufacturing Job Creation and Destruction

Quarterly Job Flows in Manufacturing, 1947-2005

Percent of Employment

Job Destruction Rate

Job Creation Rate

Unemployment Flows with 2 States

• Steady-state approximation:

Unemp. Rate  \equiv \ u_t \approx \frac{S_t}{S_t + f_t} \Rightarrow

d \log u_t \approx (1 - u_t) \left[ d \log s_t - d \log f_t \right]

where s = E\rightarrow U hazard, and f = U\rightarrow E hazard

• Following Elsby, Michaels & Solon (AEJ-Macro, 2009), plot s and f contributions to log change in unemployment rate in each postwar recession.
Decomposition of log unemployment rate rises in postwar U.S. recessions

Courtesy of Mike Elsby.
With corrections for time aggregation.
Decomposition of log unemployment rate rises in postwar U.S. recessions

- $-\text{dlog}(f)$
- $\text{dlog}(s)$

- 2008Q4
- 2009Q3
2. Major U.S. Data Sources on Labor Market Flows, 1

  - Quarterly job flows for U.S. private sector, computed from longitudinal administrative data on establishment-level employment
  - 1992 to present, extended back to 1990 by Jason Faberman
  - Tabulations by Industry, State, Firm Size, Establishment Age

  - Monthly estimates of hires, separations, and vacancies from representative sample of nonfarm establishments
  - December 2000 to present

- **Gross Worker Flows (CPS)**
  - Monthly worker flows across labor market states (E, U, OLF) and between employers, as estimated from short panels of household-level data in the Current Population Survey
  - Many variants are available; Fallick and Fleischman (2004) provide a comprehensive set of gross worker flow estimates from 1994 onwards.
Major U.S. Data Sources on Labor Market Flows, 2

• **Unemployment Inflows and Outflows (CPS)**
  – Unemployment flows can be computed from short overlapping CPS panels (as in Gross Worker Flows above) or by using CPS data on unemployment by duration.
  – Both approaches are widely used. See Davis et al. (AEJ-Macro 2010) for an articulation of the duration-based approach

• **Quarterly Workforce Indicators (QWI)**
  – Worker flows and job flows constructed from administrative records
  – Flows by industry, state, country, demographic characteristics (age and gender)
  – See Abowd and Vilhuber (2010) for details

• **Manufacturing Job Flows from the Longitudinal Research Database (LRD)**
  – Annual and quarterly job flows from 1972
  – Breakdowns by industry, state, establishment size and age
  – See Davis, Haltiwanger and Schuh (1996) and Haltiwanger’s website for updates

• **Census Business Dynamics Statistics (BDS)**
  – Annual job flows from 1976 by industry, state, firm size and age
Subtle flaws in sample design can lead to major errors in measurement and inference

- Remark: A sample design suitable for estimating levels can be unsuitable for estimating changes or flows.
- Example: The JOLTS sample design seriously underweights tail mass in the cross-sectional growth rate density. As a result, published JOLTS statistics understate worker flows and job openings, and they misstate the relative amplitude of hires vs. separations and quits vs. layoffs
- A solution: Reweight the sample to ensure that it replicates the growth rates density in, e.g., the BED
Cross-Sectional Densities of Establishment Growth Rates (Employment Weighted)

Reproduced from Davis et al., 2010, “Adjusted Estimates of Worker Flows and Job Openings In JOLTS”
Figure 4: Cross-Sectional Relationships of Worker Flows and Job Openings to Establishment Growth Rates, Monthly JOLTS Data from 2001 to 2006, Full Range of Growth Rates

(a) Hires Rate

(b) Job Openings Rate

(c) Quits Rate

(d) Layoffs Rate
• Our adjusted statistics for hires and separations exceed the published statistics by about one third. The adjusted layoff rate is more than 60 percent greater than the published layoff rate.

• Our adjustments significantly alter time-series properties as well. Aggregate hires are 50 percent more variable than separations in published JOLTS statistics, as measured by the variance of quarterly rates, but 20 percent less variable according to our adjusted statistics. Quarterly quit rates are more than twice as variable as layoffs in published statistics but equally variable according to our adjusted statistics.
4. Labor Market Flows in the Cross-Section and Over Time

Journal of Monetary Economics, Forthcoming

Steven J. Davis, University Of Chicago & NBER
Jason Faberman, Federal Reserve Bank Of Chicago
John Haltiwanger, University Of Maryland & NBER
An Overview of What We Do

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.
Simplest extension of CHW model:

- Quit rate remains exogenous but varies procyclically

\[ q_t = \overline{q}(G_t) \]

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 rises.
☐ 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 \(\rightarrow\) 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 (sulllying 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.
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

<table>
<thead>
<tr>
<th>Hires</th>
<th>Total Separations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layoffs</td>
<td>Quits</td>
</tr>
</tbody>
</table>

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

Quits do not, especially at contracting establishments
Statistical Specifications, cont’d

Baseline

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

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

- \( G_t \) = 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 \( \rightarrow \) Allows shape and location of CS relations to vary with cycle.
**Worker Flows Implied by Statistical Specifications**

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

- **Hires**
- **Separations**
- **Layoffs**
- **Quits**

Graphs showing actual and implied data trends from 2001 to 2010.
Leftward Shift in Growth Rate Distribution And Interaction with the CS Layoff Relation

- Growth Rate Distribution, Expansion Period
- Growth Rate Distribution, Recession Period
- Layoff Rate
## 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></td>
<td>Fixed Cross-Section</td>
</tr>
<tr>
<td>Hiring Rate</td>
<td>0.542</td>
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<tr>
<td>Separation Rate</td>
<td>0.507</td>
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<tr>
<td>Quit Rate</td>
<td>0.159</td>
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<tr>
<td>Layoff Rate</td>
<td>0.463</td>
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<tr>
<td></td>
<td>Augmented Fixed Cross-Section</td>
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<tr>
<td>Hiring Rate</td>
<td>0.543</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>0.509</td>
</tr>
<tr>
<td>Quit Rate</td>
<td>0.162</td>
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<tr>
<td>Layoff Rate</td>
<td>0.466</td>
</tr>
<tr>
<td></td>
<td>Augmented Baseline Specification</td>
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<td>Hiring Rate</td>
<td>0.545</td>
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<tr>
<td>Separation Rate</td>
<td>0.511</td>
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<tr>
<td>Quit Rate</td>
<td>0.170</td>
</tr>
<tr>
<td>Layoff Rate</td>
<td>0.467</td>
</tr>
<tr>
<td></td>
<td>Augmented Flexible Specification</td>
</tr>
<tr>
<td>Hiring Rate</td>
<td>0.588</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>0.556</td>
</tr>
<tr>
<td>Quit Rate</td>
<td>0.239</td>
</tr>
<tr>
<td>Layoff Rate</td>
<td>0.521</td>
</tr>
</tbody>
</table>
Constructing Synthetic JOLTS Data

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

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

- BED data on $f$ + model-based $\hat{w}$ for 1990-2001
- BED data on $f$ + JOLTS-based $w$ for 2001-2010.
Layoffs move with job destruction.
Quits move opposite to both.
Hires tend to move with job creation but are more volatile.

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

Summary of Main Results

- “Iron link” between worker flows and job flows is a prominent feature of the data for hires and, especially, layoffs.
  - Fluctuations in aggregate hires and layoffs reflect movements in CS growth rate density + reasonably stable CS relations to establishment growth.

- In contrast, the CS relationship between quits and employer growth varies greatly over time.
  - Quit rates are higher and more procyclical at contracting establishments
  - Modeling movements in the CS quit relation is essential to account for fluctuations in aggregate quit rate.

- Tracking the CS distribution of employer growth rates substantially improves our ability to account for aggregate worker flows.

- Our statistical models provide a useful tool for constructing synthetic data on worker flows prior to the advent of JOLTS.
A Bit More Detail

- Strong, highly nonlinear relationships of worker flows to establishment growth rates in the CS
  - Strong nonlinearities near the mode of the CS distribution implies nontrivial aggregation from micro to macro.
  - Because of the nonlinearities, tracking the CS distribution greatly improves our ability to account for movements in aggregate worker flows.
  - We demonstrate this point empirically

- The CS relation for layoffs is stable over time – i.e., not very sensitive to aggregate conditions
  - Broadly in line with multi-worker versions of standard Mortensen-Pissarides (MP) search models
Quit rates decline with establishment growth

The CS quit relationship is highly sensitive to aggregate conditions.
- Conditional on own employer growth rate, quit rates rise with aggregate growth
- At odds with workhorse search models and many other models

The nature of the CS quit-growth relation and its cyclical behavior lends empirical support to models with OTJ search and an important role for endogenously determined quits.
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).
5. Taking Stock: Using Comprehensive Business Databases as a Research Tool

1. Building longitudinal research databases on establishments and firms (LBD, ILBD, BED, BDS, QWI)

2. Avoiding extrapolation from non-representative samples (e.g., public vs. private volatility trends in 2006 NBER Macro Annual paper)

3. Backbone source of high-quality longitudinal data on firms and establishments, used in conjunction with rich data from other sources (papers on private equity)

5. Adjusting for biases that arise from flawed sample designs in employer surveys (“Adjusted Estimates of Worker Flows and Job Openings...”)

6. Creating synthetic statistics by combining comprehensive data from administrative sources with richer survey data (“Labor Market Flows in the Cross Section and Over Time”)
Business Volatility, Job Destruction and Unemployment

Steven J. Davis, Jason Faberman, John Haltiwanger, Ron Jarmin and Javier Miranda

American Economic Journal: Macroeconomics, April 2010
Overview

• Trends in Volatility
  – Aggregate Volatility Declining
  – Business (Firm and Establishment) Volatility Declining
    • Volatility for privately held firms declining more rapidly than
      volatility for publicly trading rising (on weighted basis)
  – Unemployment inflow rate exhibits pronounced secular
    decline
    • Relevant for putting current crisis into context

• Causes and Consequences:
  – Reallocation models of growth and cycles
  – This paper focuses on implications for frictional
    unemployment
Overview of our Data Sources

• Longitudinal Business Database (LBD)
  – Annual data from 1976 to 2001
  – All nonfarm business firms and establishments in the U.S. with paid employees

• Business Employment Dynamics (BED)
  – Quarterly data from 1990 to 2005
  – All nonfarm business establishments in the U.S. with paid employees

• LRD, BED and Manufacturing Turnover Data Integrated

• COMPUSTAT -- Publicly traded firms only
  – We integrate with LBD

• CPS Based Unemployment Flows
Main Findings

• Large secular decline in unemployment inflow rate but not much secular change in escape rate from unemployment (pre 2008)

• Large secular decline in the cross-sectional dispersion of employment growth rates, in the magnitude of within firm volatility, in business turnover rates, in job reallocation rates and in job creation and destruction rates
  – Trend declines pervasive across industries but some industries exhibit much greater declines

• Industries with larger secular decline in business volatility are also those with larger secular decline in unemployment inflows
  – We use this industry-level time variation to identify low-frequency relationship between changes in business volatility and changes in inflows
  – We then consider implications for the evolution of frictional unemployment
Figure 6: Monthly Unemployment Inflow and Escape Rates, 1976Q2 to 2008Q3, CPS Data
Idiosyncratic Shocks and Frictional Unemployment

• Idiosyncratic labor demand shocks drive frictional unemployment: Phelps (1968), Friedman (1968), Hall (1979), ...

• Mortensen-Pissarides (1994)
  – Add aggregate productivity shocks to basic MP model
  – Add endogenous job destruction margin: job productivity is now $p + \sigma \varepsilon$, where $\sigma$ indexes dispersion of idiosyncratic shocks, and new idiosyncratic shocks
  – New idiosyncratic shock value is below reservation value $\Rightarrow$ endogenous job destruction
  – Retain exogenous job destruction as well
MP (1994) in Steady State

Job productivity is $p + \sigma \varepsilon$, where $\sigma$ indexes dispersion of idiosyncratic shocks

SS: Lower $\sigma$ (smaller idiosyncratic shocks)

→ less job destruction

→ fewer workers flowing through the unemployment pool

→ less frictional unemployment
Details of MP (1994) in SS

• Output flow $p + \sigma \varepsilon$, in filled job, where $p$ is a common component of productivity, $\varepsilon$ is an idiosyncratic shock value, and $\sigma$ indexes the average magnitude of idiosyncratic shocks.

• New jobs start at upper support of productivity dist.

• Once filled, productivity evolves exogenously according to Poisson arrival processes for common and idiosyncratic shocks. An idiosyncratic shock brings a new value of $\varepsilon$ drawn from distribution with finite upper support and no mass points. $\varepsilon$ has zero mean and unit variance so that $\sigma$ is the standard deviation of the job-specific productivity component.
But motivation is more general...

- An \( (S,s) \) model of employment dynamics with a decline in the dispersion of idiosyncratic shocks will generate the same implication for dispersion of employment growth rates.

- Then just need the link between dispersion of employment growth rates and separation rates:
  - Models with labor market frictions such as MP deliver this implication, but other models can as well.
  - Empirically, the relationship is tight as seen in our results.
Empirical Specification

• Aggregate evidence suggestive but usual caution about common trends

• Here we exploit pooled sectoral, time series data
  – Focus on low frequency variation
  – Control for common period effects
    • Other factors (e.g., changing workforce composition or changes in adjustment dynamics or changes in wage flexibility)
  – Control for sectoral effects
    • Different labor market dynamics in different industries
  – Use experienced unemployed

• Key identifying assumption:
  – After controlling for industry and year effects, the variation in business volatility measures (e.g., job destruction rate) within industry*year captures variation in the intensity of idiosyncratic shocks.

• Before turning to regressions, take a look at industry-level time series
Figure 7. Quarterly Job Destruction and Unemployment Inflows by Major Industry

- **Bold** = job destruction
- **Light (red)** = U inflow
Industry Trends in Job Destruction and Unemployment Inflows, 2
Figure 8. Annual Job Destruction and Unemployment Inflows by Major Industry

- **Construction**
- **Mining**
- **Durable Goods Manufacturing**
- **Nondurable Goods Manufacturing**
Industry Trends in Job Destruction and Unemployment Inflows, 4

Transportation & Utilities

Wholesale & Retail Trade

FIRE

Services
Estimated Response of Monthly Unemployment Inflow Rate to Job Destruction Rate

<table>
<thead>
<tr>
<th>Using 3-year averages</th>
<th>Dependent Variable: CPS Unemployment Inflow Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BED data, quarterly Job Destruction</td>
</tr>
<tr>
<td></td>
<td>LBD data, annual Job Destruction</td>
</tr>
<tr>
<td>Table 3a</td>
<td>Table 3a (1)</td>
</tr>
<tr>
<td>Table 3b (6)</td>
<td></td>
</tr>
<tr>
<td>0.323 (0.038)</td>
<td>0.278 (0.041)</td>
</tr>
<tr>
<td>0.163 (0.059)</td>
<td>0.101 (0.019)</td>
</tr>
</tbody>
</table>

Industry Effects?       Yes Yes Yes Yes
Period Effects?         No Yes No Yes

Note: Standard errors robust to heteroscedasticity and serial correlation within industries
Figure 10. Job Destruction and Unemployment Inflows by Industry, Three-Year Averages, 1977-2001

Controlling for time and industry fixed effects

Slope coefficient: 0.10
Figure 9. Job Destruction and Unemployment Inflows by Industry, Three-Year Averages, 1990-2005

Slope Coefficient: 0.278

Controlling for Time and Industry Effects
• Multiply observed drop in job destruction rate from 1990 to 2005 (174 basis points) by its estimated effect on unemployment inflow rate (28 basis points)
→ 48 bp decline in unemployment inflow rate:
  -- 55% of observed drop in unemployment inflows
  -- 22% of average unemployment inflow rate

• Analogous calculations using LBD-CPS data show that job destruction accounts for
  -- 28% of observed drop in unemployment inflows from 1982 to 2005
Implications for Unemployment

\[ u_t^{SS} = \frac{l_t}{f_t} \]

Very good approximation to actual unemployment rate – See next slide

\[ \Delta \log u_t = \Delta \log l_t - \Delta \log f_t \]
\[ -0.43 = -0.41 - 0.02 \]

→ Declines in idiosyncratic shock intensity explain about half of secular decline in unemployment rate from 1990 to 2005 and about a quarter from 1982 to 2005.
Validation of Steady State Approximation…
Steady state unemployment would have been substantially higher with average inflow rate from early part of the sample...

Figure 12. Unemployment Rate Implied by Various Inflow Rates

Notes: Each curve shows the steady-state unemployment rate implied by equation (6) for the indicated inflow rate series. The figure plots quarterly averages of monthly values.
The marginal effect of the job-finding rate on unemployment falls from -0.24 to -0.12.

Explains why weak labor markets in 1990s and 2000s involved modest spikes in unemployment compared to recessions in 1970s and 1980s.
Results mixed for escape rates

- Average escape rate is 38 percent
- Aggregate exhibits little trend but cyclicality
- Controlling for only industry effects yields no statistically significant relationship
- Controlling for both period and industry effects, 100 basis point decline in job destruction yields about 135 basis point increase in escape rates.
- Using actual decline between 1990 and 2005, implied increase in escape rate is 230 basis points or about six percent of average escape rate.
- At odds with M&P prediction
  - Industry specific composition effects
  - Flows are based upon experience unemployed
  - Job creation vs. Destruction?
Conclusions

1. Secular fall in idiosyncratic shock intensity:
   A. Drove quarter to half of secular declines in unemployment rate and unemployment flows, depending on time period and data set
   B. Led to big drop in sensitivity of unemployment to movements in job-finding rate

2. Importance of MP mechanism:
   \( \sigma \rightarrow \text{job destruction} \rightarrow \text{unemployment inflow} \)
   A. Big factor in long term unemployment evolution
   B. Secular fall in \( \sigma \) alters shorter term unemployment dynamics
References


• Davis, Steven J., R. Jason Faberman and John Haltiwanger, 2010b, “Labor Market Flows in the Cross Section and Over Time”


