Presentation: Education, flows and the Great Recession in the United States

John Abowd  
*Cornell University*, John.Abowd@cornell.edu

Lars Vilhuber  
*Cornell University*, lv39@cornell.edu

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Presentation: Education, flows and the Great Recession in the United States

Abstract
Using gross flows of workers into and out of employment, we investigate the composition of flows in non-recessionary periods as well as in the Great Recession of 2008-2009. In particular, we use gross flows at highly detailed geographic and demographic levels to assess whether particular demographic groups are less affected by the sharp changes in gross flows during recessions, and whether such effects are robust across detailed geographic areas.

Following Abowd and Vilhuber (2011), we develop a internally consistent measure of national gross worker and job flows with demographic detail. In particular, we expand on the earlier attempt by providing the first estimate of consistent worker and job flows by age and educational attainment. We provide a comparison to existing job and worker flows derived from several independent sources (CPS, BED, JOLTS). We then identify particular patterns in the national data we develop that highlight certain differential effects. Finally, we assess whether such patterns, observed at the national level, are present in all or only a subset of local labor markets.

We find worker reallocation rates nearly three times as large as job reallocation rates. Workers with less than a high-school diploma have a worker reallocation rate that is nearly twice that of workers with a bachelor’s degree or higher, whereas there is less discrepancy in job reallocation rates. Finally, while these differences are high, excess reallocation rates for different education groups have converged in the last decade. No such convergence is apparent when disaggregating by age.

The national estimates from the QWI are an important enhancement to existing series because they include demographic and industry detail for both worker and job flow data compiled from the same underlying micro-data that have been integrated at the job and establishment levels by the Longitudinal Employer-Household Dynamics Program at the Census Bureau. The estimates presented herein were compiled exclusively from public-use data series and are available for download.

Comments
Suggested Citation

Required Publisher’s Statement
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Education, flows and the Great Recession in the United States

John M. Abowd$^{1,2,3}$ Lars Vilhuber$^{1,2}$

$^1$ Labor Dynamics Institute, ILR, Cornell University

$^2$ U.S. Census Bureau, Center for Economic Studies

$^3$ NBER, IZA, CREST

May 2012, SOLE
Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau.

This is work in progress, some results are very preliminary!
Unemployment by education

Time series of the Unemployment Rate by Education (NSA)

- Recession
- <HS avg
- HS, No College avg
- Some College avg
- BA+ avg

Abowd, Vilhuber
Some elements

- Younger and less educated workers more affected
- By some measures, men more affected
- (lots of other presentations) Reduction in the employment/population ratio
Differences in job market measures across MSAs

Accession (hiring) rates
- Albany-Schenectady-Troy, NY Metropolitan Statistical Area (10580)
- Columbus, OH Metropolitan Statistical Area (18140)
- Dallas-Fort Worth-Arlington, TX Metropolitan Statistical Area (19100)
- Phoenix-Mesa-Glendale, AZ Metropolitan Statistical Area (38060)

Abovd, Vilhuber

Education and flows
Differences in job market measures across MSAs

Worker reallocation rates

- Albany-Schenectady-Troy, NY Metropolitan Statistical Area (10580)
- Columbus, OH Metropolitan Statistical Area (18140)
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Goals in this paper

Explore the local differential effects of education

- We go very local - individual job markets (MSAs)
- Unemployment rates by education only available at the national level
- Use flows (worker and job flows) from integrated data, controlling for national effects, local unemployment, and national unemployment rates for educational groups
Some concepts

Worker reallocation rate

\[ WRR_{egkst} = AR_{egkst} + SR_{egkst} \]

where

\[ AR_{egkst} \equiv \text{accession rate (new hires plus recalls)} \]
\[ SR_{egkst} \equiv \text{separation rate (quits, layoffs, other)} \]

measured for education groups \( e \), gender \( g \), industry \( k \), geography \( s \) and time (quarter) \( t \).
Some concepts

Job Reallocation Rate

Gross job flows are measured in similar fashion using the symmetric Job Reallocation Rate \( (JRR_{egkst}) \)

\[
JRR_{egkst} = JCR_{egkst} + JDR_{egkst}
\]

where

\[
\begin{align*}
JCR_{egkst} & \equiv \text{job creation rate} \\
JDR_{egkst} & \equiv \text{job destruction rate}
\end{align*}
\]
Data
Quarterly Workforce Indicators

Input data, scope

- Based on quarterly wage record reports from 49 (50,...) states
- Flows, based on longitudinally linked (by employer and employee) Unemployment Insurance Wage Records
- Augmented with person and firm demographics from other data sources
Quarterly Workforce Indicators

Detail

- 30+ indicators on employment dynamics
Quarterly Workforce Indicators

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- Aggregated to detailed time-series by industry x geography x demographics:
Quarterly Workforce Indicators

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  - NAICS sectors, sub-sectors (3-digit), industry groups (4-digit)
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  - Demographics:
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    - Sex x age (8 categories)
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    - Race (6 categories) x ethnicity (hispanicity)
- All levels fully crossed
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Abowd, Vilhuber

Education and flows
Integrated national job and worker flows

Abowd and Vilhuber (CES WP 2010-11; Journal of Econometrics, 2011)

- Addresses the issue of missing historical (and sometimes contemporary) data by using multiple imputation
- First time that person and job flows are computed at a national level from a consistent data source

Lazear and Spletzer (AEA PP, 2012), "Hiring, Churn and the Business Cycle" do a similar exercise with JOLTS data.
Unemployment data

- Source: BLS
- National level: by different demographic categories, from CPS
- Sub-national level: no demographics, but down to large cities/counties/etc, from models (using CES, CPS, etc.)
Unemployment data

Unemployment rate by county

Use this graphic to explore how the unemployment rate around the country has changed over the last year. Click the tabs to see figures since 2007.

National Unemployment Rate:
Jan. 2010: 10.6%
Unemployment rate, 2009Q2, by state
Unemployment rate, 2009Q2, by MSAs

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Education and flows
It did not always look so diverse

Unemployment rate

Abowd, Vilhuber
Categorizing job markets

**Ranking job markets by unemployment rates**

- Classify all metropolitan areas by their unemployment rate in 2009Q2 (trough of recession, but not peak of unemployment rate)
- Consider how labor markets work in MSAs in the bottom 10% (Group 1), middle 80% (Group 2), top 10% (Group 3).
The analysis model
The analysis model

The basic national equation
relating unemployment rates to labor market flows can be expressed as

$$ y_{\circ t} = x_{\circ t} \bar{\beta} + \epsilon_{\circ t} $$ (1)

for any variable $y_{\circ t}$ under study and any vector $x_{\circ t}$ of unemployment rates (possibly by demographic groups) and other aggregate labor market conditions (including an intercept and lags, in our case for 5 quarters without restriction).

The local labor market variable
can be modeled as a composite of national and local effects

$$ y_{jt} = x_{\circ t} \bar{\beta} + (x_{jt} - x_{\circ t}) \beta_j + \epsilon_{\circ t} + \epsilon_{jt}. $$
The analysis model

The purely local equation

\[ y_{jt} - y_{\circ t} = (x_{jt} - x_{\circ t}) \beta_j + \epsilon_{jt} \]  

(2)

where the MSA-specific effect \( \beta_j \) is modeled as a mixed effect.
The analysis model

Relaxing the specification
gives

\[ y_{jt} = \beta_1 y_{ot} + \beta_2 x_{ot} + \beta_3 x_{jt} + \epsilon_{jt}, \]  

(3)

where \( \beta_1 = 1 \) with no MSA-level variation, and \( -\beta_2 = \beta_3 \) if the correct model is equation 2. We then restate equation 3 as a mixed-effects linear model:

\[ y_{jt} = \bar{\beta}_1 y_{ot} + \bar{\beta}_2 x_{ot} + \bar{\beta}_3 x_{jt} \]
\[ + \bar{\nu}_1 y_{ot} + \bar{\nu}_2 x_{ot} + \bar{\nu}_3 x_{jt} + \epsilon_{jt}, \]

where \( \bar{\beta}_1, \bar{\beta}_2 \) and \( \bar{\beta}_3 \) are the fixed national average coefficients, and \( \bar{\nu}_1, \bar{\nu}_2 \) and \( \bar{\nu}_3 \) are the random deviations of MSA-specific coefficients from the national average.
Expanding the specification to account for education

gives

\[ y_{jet} = \bar{\beta}_1 y_{ot} + \bar{\beta}_2 x_{ot} + \bar{\beta}_3 x_{jt} + \bar{\beta}_4 x_{oet} + \tilde{\upsilon}_1 y_{ot} + \tilde{\upsilon}_2 x_{ot} + \tilde{\upsilon}_3 x_{jt} + \tilde{\upsilon}_4 x_{oet} + \epsilon_{jet}, \]  

where \( y_{jet} \) is observed flow rate for MSA \( j \) and educational group \( e \) and \( x_{oet} \) are national unemployment rates for educational group \( e \) (and their lags)
Fitted marginal predictor

captures the effects of the overall market conditions and MSA variation in local labor market conditions:

\[ \hat{Y}_{jet} = \hat{\beta}_1 y_{ot} + \hat{\beta}_2 x_{ot} + \hat{\beta}_3 x_{jt} + \hat{\beta}_4 x_{oet}. \]
Predictors

Fitted marginal predictor
captures the effects of the overall market conditions and MSA variation in local labor market conditions:

\[
\hat{Y}_{jet} = \hat{\beta}_1 y_{o}t + \hat{\beta}_2 x_{o}t + \hat{\beta}_3 x_{jt} + \hat{\beta}_4 x_{oet}.
\]

Linear predictor
inclusive of the estimated random effects captures the incremental contribution of the MSA-specific variation in the coefficients:

\[
\hat{\hat{Y}}_{jet} = \hat{Y}_{jt} + \hat{\nu}_1 y_{o}t + \hat{\nu}_2 x_{o}t + \hat{\nu}_3 x_{jt} + \hat{\nu}_4 x_{oet}.
\]
Estimated random effects
\[ \hat{u}_{jet} = \hat{y}_{jet} - \hat{\bar{y}}_{jet} \]
The model is fit for worker flows, job flows by restricted maximum likelihood assuming that the residuals and the random effects have independent normal distributions with zero means and constant variances, with

- $x_{\circ t} = U_{\circ,t=0...-5}, U_{edu}, t=0...-5$
- $x_{jt} = U_{j,t=0...-5}$
- 4 education levels
WRR actual, by group
WRR $\hat{y}_{jet}$, by group
JRR actual, by group
Introduction

Framework

Data

Model structure

Results

Conclusion

JRR $\hat{y}_{jet}$, by group

![Graph showing flow rate over time with shaded areas indicating recessions and lines for different groups.](chart.png)

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Education and flows
JRR $\hat{y}_{jet}$, by group
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WRR, worst decile by unemployment rate 2009Q2

For Group 3

- Recessions
- Avg. Marginal prediction (no RE)
- Avg. Full prediction
- Avg. Actual

Education and flows
## The top (and bottom) 10

### Lowest unemployment rates

<table>
<thead>
<tr>
<th>Rank</th>
<th>Area Description</th>
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<tbody>
<tr>
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Education and flows
Reminder: Unemployment rate, 2009Q2, by MSAs
Geographic distribution of $\hat{u}_{jet}$: WRR

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Education and flows
Geographic distribution of $\tilde{u}_{jet}$: JRR

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For Group 1

- Grey: Recessions
- Blue: Avg. Full prediction
- Red: Avg. Marginal prediction (no RE)
- Black: Avg. Actual

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Education and flows
WRR by education groups

For Group 2

- Recessions
- Avg. Full prediction
- Avg. Marginal prediction (no RE)
- Avg. Actual

Abowd, Vilhuber

Education and flows
WRR by education groups

For Group 3

- Recessions
- Avg. Marginal prediction (no RE)
- Avg. Full prediction
- Avg. Actual

Abowd, Vilhuber

Education and flows
JRR by education groups

For Group 1

- Gray: Recessions
- Blue: Avg. Full prediction
- Red: Avg. Marginal prediction (no RE)
- Black: Avg. Actual
JRR by education groups

For Group 2

- Recessions
- Avg. Full prediction
- Avg. Marginal prediction (no RE)
- Avg. Actual
JRR by education groups

For Group 3

- Recessions
- Avg. Full prediction
- Avg. Marginal prediction (no RE)
- Avg. Actual
Preliminary conclusions

MSAs that have had a (locally) worse reaction in labor markets are distinctly different over several dimensions.
Preliminary conclusions

- MSAs that have had a (locally) worse reaction in labor markets are distinctly different over several dimensions
- Local effects matter quite a bit
Preliminary conclusions

- MSAs that have had a (locally) worse reaction in labor markets are distinctly different over several dimensions
- Local effects matter quite a bit
- Education does not seem to have a differential effect - is primarily a national effect
Caveats, Outlook

- Not yet estimated with a more flexible (time-varying) random effect
- Effect on average wages, rather than on employment-based measures
Thank you.
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Further links

- Labor Dynamics Institute
- VirtualRDC @ Cornell
- Center for Economic Studies, U.S. Census Bureau
Quarterly Workforce Indicators

Definitions

- **Beginning-of-quarter** employed if wage record with earnings > $1.00 in quarters $t - 1$ and $t$ ($B$)
- **End-of-quarter** employed if wage record with earnings > $1.00 in quarters $t$ and $t + 1$ ($E$)
- **Accession** if wage record in $t$ but not $t - 1$ ($A$)
- **Separation** if wage record in $t$ but not $t + 1$ ($S$)
- **Job creation** if establishment has positive employment change from beginning to end of quarter ($JC$)
- **Job destruction** if establishment has negative employment change from beginning to end of quarter ($JD$), always stated as absolute value of change
Some concepts

Accession rates

\[ AR_{egkst} = \frac{A_{egkst}}{(B_{egkst} + E_{egkst})/2} \]

where

\[ B_{egkst} \equiv \text{beginning-of-quarter employment} \]
\[ E_{egkst} \equiv \text{end-of-quarter employment}. \]

Separation rates

\[ SR_{egkst} = \frac{S_{egkst}}{(B_{egkst} + E_{egkst})/2}. \]
Some concepts

Gross job flow measures are defined at an establishment, not job, level.

\[
JC_{egjt} \equiv \max (E_{egjt} - B_{egjt}, 0)
\]

\[
JD_{egjt} \equiv \max (B_{egjt} - E_{egjt}, 0)
\]

(Davis and Haltiwanger, 1992)

Gross job flow rates

\[
JCR_{egkst} = \frac{JC_{egkst}}{(B_{egkst} + E_{egkst}) / 2}
\]

and

\[
JDR_{egkst} = \frac{JD_{egkst}}{(B_{egkst} + E_{egkst}) / 2}.
\]
Alternate sources

- Business Employment Dynamics (BED)
- Job Openings and Labor Turnover Survey (JOLTS)
- Current Population Survey (CPS) with adjustments (Fallick-Fleischman, Abowd-Zellner)
Stacking them up

Fraction of employment

1995q1  2000q1  2005q1  2010q1

Seasonally adjusted WRR  CPS WRR (seas adj)  JOLTS: WRR adjusted

Abowd, Vilhuber  Education and flows
Extra slides

Different sources, same analysis?

Abowd, Vilhuber

Education and flows
Alternative sources

Business Employment Dynamics (BED)

- Source: BLS
- Derived from establishment-level data (same basic universe as QWI)
- Gross job gains (job creations) and gross job losses (job destructions)
- Detail: state-level, NAICS sector (collapsed)
Job Openings and Labor Turnover Survey (JOLTS)

- Source: BLS
- Monthly survey of continuing establishments
- Accessions, Separations (split into quits, layoffs, discharges, and other reasons)
- Timely information, and only source for reasons of separations
- Detail: National data only, NAICS sectors
Current Population Survey (CPS)

- Source: BLS/Census
- For flows, only measures (change in) labor market states, some measurement of job change
- BLS-provided flows series: Accessions measures as change from un-/non-employed to employed, corrected for margin changes (but not classification errors!)
- Fallick-Fleischman: also include job-to-job changes
- Detail: Nationally representative, no industry, gender available in published series, age+ education if computing from micro-data (Fallick-Fleischman)
Distorted maps