Reconciling Occupational Mobility in the Current Population Survey

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QSPS Workshop
September 19, 2019
Motivation

- Occupations provide useful lens for understanding many economic phenomena – inequality, trade, displaced workers, life cycle earnings, etc.
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• QUESTIONS: What is the actual rate of occupational mobility? Is it rising or falling? Implications?
What We Do

- Use linked CPS data with multiple measures of occupational switching and estimate actual rate of mobility using other labor market outcomes
  - Key assumption: Measurement error in each measure of switching is conditionally independent
  - Estimation: overidentified GMM using multiple labor market outcomes
- Also obtain estimates of magnitudes and trends in measurement error and correlated worker characteristics
- Applications:
  - Construct corrected time series of monthly occupational switching
  - Revisit findings in literature on worker level impacts of trade
Findings

- Occupational mobility is *falling* over time, consistent with declining labor market fluidity and migration
  - March CPS: right trend, but estimated actual rate is 70% higher (~2 pp)
  - Linked CPS: wrong trend, measurement error worsening over time

- Measurement error in linked CPS correlated with workers who are male, nonwhite, hispanic, young, and in certain occupations; but observables can’t explain upward measurement error trend

- Trade applications:
  - Workers in tradable occupations less likely to switch occupations (contrary to Ebenstein et al. (2014))
  - Slower worker adjustment implies lower welfare gains and slower transition to steady state in a trade liberalization (vis a vis Artuc, Chaudhuri and Mclaren (2010))
Background Literature


MEASURES OF OCCUPATIONAL MOBILITY
Background on Current Population Survey

- Current Population Survey (CPS): monthly survey of 60,000 households, key source of labor market data
- Households surveyed for four consecutive months, out of sample for next eight months, sampled again for four consecutive months

![Figure 1. CPS Panel Structure by Month and Interview Number](image)

- Additional supplements administered annually – annual socioeconomic, job tenure, occupational mobility, displaced workers, fertility and marriage, voting, etc.
- Large, representative, frequent sample makes it key data source for measuring occupational outcomes
Measuring Occupational Mobility in the CPS

- Occupational mobility: fraction of workers employed presently and employed a year ago who have different occupations

- March CPS asks workers: “What was your longest job during [past year]?” (retrospective measure)
  - Easy, convenient to compute – no linking required
  - Dependent coding – respondent must identify job description has changed
  - Relies on recall, and potentially imprecise timing (timing better in mobility supplement)
  - Forces respondent to filter/decide what constitutes an occupational switch (especially w/in firm)

- Alternatively, longitudinally link individual responses:
  - Point-in-time comparison avoid recall/timing precision concerns
  - No dependent coding – independent coding errors could be large
  - Can’t observe movers; restricted to individuals remaining at same address
  - Can observe wage changes
Measurement Details and Sample Restrictions

- Use responses in March CPS supplements 1980-2018, linked longitudinally (Rivera Drew et al. (2014), Madrian and Lefgren (2000))

- Drop all imputed observations (inc. whole sample) and linked responses responses with inconsistent sex, race, age, educ.

- Must be 18+ and employed this year and last year in non-gov’t industries

- Occupational coding changes over time; apply consistent coding scheme following Dorn (2009) and Autor and Dorn (2013)

- (Talk) Report one digit outcomes (6 occupations); (Paper) Report one, two and three digit outcomes (6, 17, and 325 occupations)
Comparing Occupational Mobility Measures (1 Digit)
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Annual Occupational Switching Rate

- March - Unrestricted
- March - Long. Restrictions
- JT Supplement

Two and Three Digit
ESTIMATION FRAMEWORK
Improving Our Estimates

• GOAL: Use multiple (noisy) signals to improve aggregate estimates

• Linked CPS allows us observation of “conflicting” responses – claim switch longitudinally/retrospectively, but no switch retrospectively/longitudinally

• Use extension of Kane, Rouse and Staiger (1999) – use relationship with other observables to evaluate relative contribution of noise and signal
Simple Regression Framework

- Cond. exp. of labor market outcome $Y_{it}$ for individual $i$ in year $t$, is given by:

$$\mathbb{E} [Y_{it} \mid SW_{it}, X_{it}] = \beta_{0,t} + \beta_{1,t} SW_{it} + X_{it} \beta_{2,t}$$

- $SW_{it}$: binary indicator for occupational switching
- $X_{it}$: individual characteristics

- $SW_{it}$ unobserved; only observe two noisy and conditionally independent signals $\tilde{SW}_{it}$ (longitudinal) and $\tilde{SW}_{it}$ (retrospective):

$$P(\tilde{SW}_{it}^R = 1 \mid SW_{it}, \tilde{SW}_{it}^L, X_{it}, Y_{it}) = \alpha_{R,0,t} + \alpha_{R,1,t} SW_{it} + X_{it} \alpha_{R,X,t}$$
$$P(\tilde{SW}_{it}^L = 1 \mid SW_{it}, \tilde{SW}_{it}^R, X_{it}, Y_{it}) = \alpha_{L,0,t} + \alpha_{L,1,t} SW_{it} + X_{it} \alpha_{L,X,t}$$

- Probability of actual switch given by:

$$P(SW_{it} = 1 \mid X_{it}) = \delta_{0,t} + X_{it} \delta_{1,t}$$
Estimation and Identification

- Construct four indicator variables spanning all realizations of both signals
  \[ \tilde{Z}_{it} = [\tilde{Z}_{i,1,t}; \tilde{Z}_{i,2,t}; \tilde{Z}_{i,3,t}; \tilde{Z}_{i,4,t}] \] (ex. \( \tilde{Z}_{i,1,t} = 1 \) if \( \tilde{S}W_{it}^R = \tilde{S}W_{it}^L = 1 \))

- Estimate parameters year by year via two-stage GMM using moments \( \mathbb{E} [\tilde{Z}_{it}] , \mathbb{E} [\tilde{Z}_{it} Y_{it}] , \mathbb{E} [\tilde{Z}_{it} X_{it}] , \mathbb{E} [X_{it} Y_{it}] \)

- Intuition:
  - When both signals indicate switch, estimated relationship with outcome closest to “truth” (independence)
  - When signals disagree, gauge “accuracy” by relative magnitude of relationship with outcome
  - Example:

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>L=Y,R=Y</th>
<th>L=N,R=N</th>
<th>L=N,R=Y</th>
<th>L=Y,R=N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switching FT/PT</td>
<td>9.6%</td>
<td>28.0%</td>
<td>8.7%</td>
<td>22.0%</td>
<td>10.8%</td>
</tr>
</tbody>
</table>

- Note: more moments than parameters – overidentification allows for test of independence assumption
Implementation

• Potentially many outcome variables to choose from; how decide?
• Require the following criteria:
  • Outcome has a priori plausible relationship with occupational switching
  • Outcome available for all samples, 1980-2018
  • Outcome ex ante plausibly uncorrelated with measurement error (exclude related survey outcomes, i.e. industry)
• Jointly estimate using following set of outcome variables
  • Indicator for whether part-time/full-time status differs across responses
  • Indicator for whether responses regarding prior year’s hourly wage differ by 10% or more
  • Indicator for having more than one employer in the prior year
  • Indicator for whether number of weeks worked last year is more than 26 (half-year)
• Controls: age, age squared, sex, white/nonwhite, hispanic, marital status, educational attainment, two digit occ. fixed effects (in 2nd year)
Selecting Variables

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RESULTS
Actual Occupational Mobility

Two and Three Digit
Error Rates

False Positive Rate: $P(SW = 0 \mid \tilde{SW}^j = 1)$; False Negative Rate: $P(SW = 1 \mid \tilde{SW}^j = 0)$
Actual Occupational Mobility by Outcome

**Number of employers in past year > 1**

**Switched full-time/part-time work status**

**Weeks employed between year \( t - 1 \) and \( t > 26 \)**

**% \( \Delta \) hourly wage > 10%**
Correlates with Error and Occupational Switching

- Compare regression coefficients of individual characteristics across measures
Correlates with Error and Occupational Switching (cont’d)

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- Compare regression coefficients of individual characteristics across measures
...But Observables Cannot Explain Upward Trend

- Compute residualized measures of false positive rate for longitudinal occupational switching – observables do not explain trend
Total Occupational Mobility Estimates

- Estimation sample necessarily removes movers; construct total mobility rate with and w/o adjusting mover switching rates

![Graph showing occupational mobility estimates over years]
Robustness

• Findings robust to:
  • Using Job Tenure and Occupational Mobility supplement
  • Including additional outcomes/controls:
    • Outcomes: alternate measures of income/hours changes, changes in employer contributions to health insurance plans
    • Controls: past year FT status, usual hours worked, veteran status, self-employed, state FE, disability status, proxy survey response, multiple job holding, no occ FE
Applications

- Consider applications of our results to other measurement and literature using worker flows in CPS
  - Adjust for error in monthly occupational switching rates
  - Revisit switching patterns and wages changes of workers in tradable jobs (Ebenstein, Harrison, McMillan and Phillips (2014, Restat))
  - Revisit welfare gains from trade in structural discrete choice model (Artuc, Chaudhuri, and Mclaren (2010, AER))
Application 1: Measurement Error in the Monthly CPS

- Monthly occupational transitions subject to same types of measurement error
  - Pre-1994, independent coding (like longitudinal)
  - Post-1994, dependent coding (like retrospective)
Corrected Monthly Occupational Mobility

- Compute predicted probability of switching, given observables $P(SW = 1 \mid X, Y, S\bar{W})$: observe all $X$, only PT/FT switch and number of employers (since 1994)
Corrected Monthly Occupational Mobility

- Compute predicted probability of switching, given observables $P(SW = 1 | X, Y, \tilde{SW})$: observe all $X$, only PT/FT switch and number of employers (since 1994)
- Compare to Moscarini and Thomsson (2007) – rely on judgment calls about reasonable switching patterns
Corrected Monthly Occupational Mobility

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Time Aggregation

- Monthly switching rates only slightly lower than annual – suggests caution in time aggregation
- Example: Assume independent arrival rate of occupational switching shock:
  \[ SW_t^A = 1 - (1 - SW_t^M)^{12} \]
  - Implies annual mobility in the range 20-40%; too large
  - Procedure is sensitive to independence assumption and assumption of minimal heterogeneity in switching rates.
Application 2: Estimates of Trade on Mobility and Wages

• Ebenstein, Harrison, McMillan and Phillips (2014) study empirical measures of trade/offshoring exposure

• Identify losses to occupational displacement with IV regression:
  • Instrument: Tradability of an occupation (based on industry/occupation exposure)
  • Endogenous variable: Longitudinal occupational switching
  • Outcome variable: Log wage changes over time

\[
E \left[ \tilde{SW}_{i,o,t} | Tradable_o, X_{i,o,t} \right] = \eta_0 + \eta_1 Tradable_o + X_{i,o,t} \eta_2
\]

\[
E \left[ \Delta ln(w_{i,o,t}) | \tilde{SW}_{i,o,t}, X_{i,o,t} \right] = \xi_0 + \xi_1 \tilde{SW}_{i,o,t} + X_{i,o,t} \xi_2
\]

• IV won’t correct measurement error (non-classical) and instrument may be correlated with error
Estimates of Mobility and Wages for Tradable Jobs

- Jointly estimate their specification with measurement error model; get opposite results

<table>
<thead>
<tr>
<th>Details</th>
<th>Parameter One Digit Two Digit Three Digit</th>
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<td>-0.119 (0.033)</td>
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First stage, tradable occupation on occupational switching, uncorrected ($\tilde{\eta}^{IV}$) | 0.045 (0.002) | 0.070 (0.002) | 0.091 (0.002) |
| First stage, tradable occupation on occupational switching, corrected ($\hat{\eta}^{IV}$) | -0.013 (0.002) | -0.022 (0.002) | -0.028 (0.003) |
| Difference | 0.058 (0.003) | 0.091 (0.003) | 0.119 (0.003) |
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Application 3: Structural Estimates of Welfare from Trade Liberalization

- Key parameter: cost of switching industries; disciplined by worker mobility rates.
- Acknowledge potential measurement error in retrospective measures and “inflate”
  - Assume that worker switching between industries is independent Poisson shock and correct for time aggregation.
  - Benchmark to annual flows in NLSY.
  - Raises industry mobility rates by 130%.
- Occupational mobility rates suggest that needed correction is half as big.
- Re-estimate parameters of their model with correction consistent with findings for occupational mobility – lower flows imply higher costs of moving.
Welfare Gains/Losses from Trade Liberalization

- Results depend on discount factor, report for both $\beta = 0.97$ and $\beta = 0.9$; simulate 30% reduction in tariffs on imported mfg goods
Welfare Gains/Losses from Trade Liberalization

- Results depend on discount factor, report for both $\beta = 0.97$ and $\beta = 0.9$; simulate 30% reduction in tariffs on imported mfg goods

- Welfare gains for exposed workers on impact half as big and convergence much slower

\[
\beta = 0.97 \quad \beta = 0.90
\]
Conclusion

- Estimate actual level of occupational mobility in CPS using GMM approach
  - Occupational mobility trending down over time, but 70% higher than retrospective measures
  - Measurement error in linked responses worsening
- Use estimates of actual occupational mobility in several applications
  - Correcting monthly measures of occupational mobility
  - Worker mobility in response to trade shocks
Comparing Occupational Mobility Measures (2 Digit)
Comparing Occupational Mobility Measures (3 Digit)

- **Annual Occupational Switching Rate**
  - March - Unrestricted
  - March - Long. Restrictions
  - JT Supplement

Year:
- 1980
- 1985
- 1990
- 1995
- 2000
- 2005
- 2010
- 2015
- 2020

Value Range:
- 0.02 to 0.1
- 0.34 to 0.48
Actual Occupational Mobility (2 Digit)
Actual Occupational Mobility (3 Digit)
PSID Comparison

Compare our estimates of occupational mobility to PSID corrections in Kambourov and Manovskii (2009) (PSID has 50% more occupations, count switches among unemployed)
Using Job Tenure and Occupational Mobility Supplement

Utilize biennial (since 2000) job tenure and occupational mobility supplement instead of March CPS; find similar results.
Include additional controls or outcomes; similar results obtain

![Graph showing baseline, alternative hours/income, and incidence of health insurance over years 1980 to 2020. The graphs compare baseline data to additional variables including fixed effects and full sample with restricted sample.]
Details on Predicted Monthly Switching Rates

- Compute monthly prediction of true switching rate as:

\[
P(SW = 1 \mid X, Y, \tilde{SW}) = \frac{P(S\tilde{W}, Y \mid SW = 1, X)P(SW = 1, X)}{P(S\tilde{W}, Y \mid SW = 1, X)P(SW = 1, X) + P(S\tilde{W}, Y \mid SW = 0, X)P(SW = 0, X)}
\]

\[
= \frac{P(S\tilde{W} \mid X, Y, SW = 1)P(Y \mid X, SW = 1)P(SW = 1 \mid X)}{P(S\tilde{W} \mid X, Y, SW = 1)P(Y \mid X, SW = 1)P(SW = 1 \mid X) + P(S\tilde{W} \mid X, Y, SW = 0)P(Y \mid X, SW = 0)P(SW = 0 \mid X)}
\]

Use model estimates from annual switching to represent:

\[
P(SW = 1 \mid X, Y = 1, \tilde{SW} = 1) = \frac{(\alpha_0 + \alpha_1 + X\alpha_X)(\beta_0 + \beta_1 + X\beta_2)(\delta_0 + X\delta_1)}{(\alpha_0 + \alpha_1 + X\alpha_X)(\beta_0 + \beta_1 + X\beta_2)(\delta_0 + X\delta_1) + (\alpha_0 + X\alpha_X)(\beta_0 + X\beta_2)(1 - \delta_0 - X\delta_1)}
\]

- Treat post-1994 switch as retrospective (unless missing data); treat pre-1994 switch as longitudinal (and post-1994 with missing data)
- Use pooled estimates of parameters; robust to using year by year estimates.
- Construct all switching rates as 13 month moving averages.
Details on Trade Estimation

- Adjust our sample and covariates to match those of Ebenstein et al. (2014) – they use outgoing rotation group data
- Estimation robust to how two samples are treated
  - Treating two sample as disjoint (no correlation between parameters)
  - Using non-overlapping samples (literally disjoint)
  - Using strictly comparable sample and allow for correlation between parameter estimates
- Key difference from estimation is the first stage:

  \[
  \hat{\xi}_{IV} = \frac{\tilde{\eta}_1 \xi_{IV}}{\tilde{\eta}_1} = \frac{\alpha_{L,1} \delta_1 (\text{Trad.}) + \alpha_{L,X} (\text{Trad})}{\delta_1 (\text{Trad.})} \xi_{IV}
  \]