Reconciling Occupational Mobility in the Current Population Survey

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  - March CPS (retrospective): 1 digit annual mobility 2-4%, trending down
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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

- **Measuring Occupational Mobility**: Moscarini and Vella (2003), Moscarini and Thomsson (2007), Kambourov and Manovskii (2008), Lale (2012), Kamborouv and Manovskii (2013), Molloy et al. (2014), Lale (2017), Forsythe (2018)

- **Addressing Measurement and Misclassification Error**: Aigner (1973), Mathiowetz and Ouncan (1988), Mathiowetz (1992), Kane et al. (1999), Black et al. (2000), Bound, Brown and Mathiowetz (2001)

- **Economics of Occupational Mobility**: Kambourov and Manovskii (2009), Groes et al. (2014), Papageorgiou (2014), Molloy et al. (2014), Gorry et al. (2014), Artuc and Mclaren (2015), Wiczer (2015), Guvenen et al. (2015), Cortes (2016), Huckfeldt (2016), Gervais et al. (2016), Traiberman (2017), Cortes and Gallipoli (2017), Cubas and Silos (2017), Robinson (2018), Xu (2019), Carrillo-Tudela et al. (2019)

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

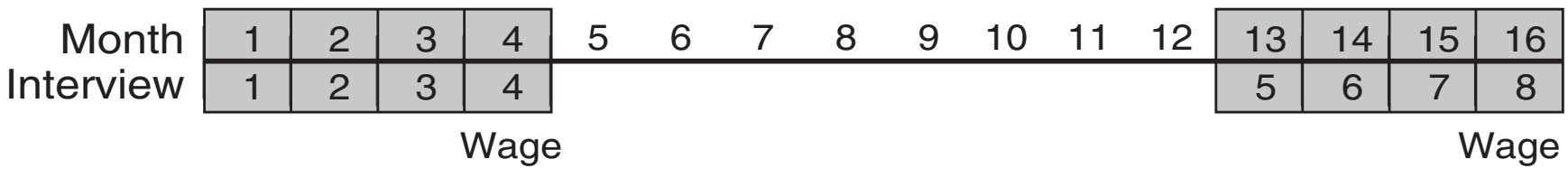


Figure 1, Mueller (2017)

- Additional supplements administered annually – annual socieconomic, 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

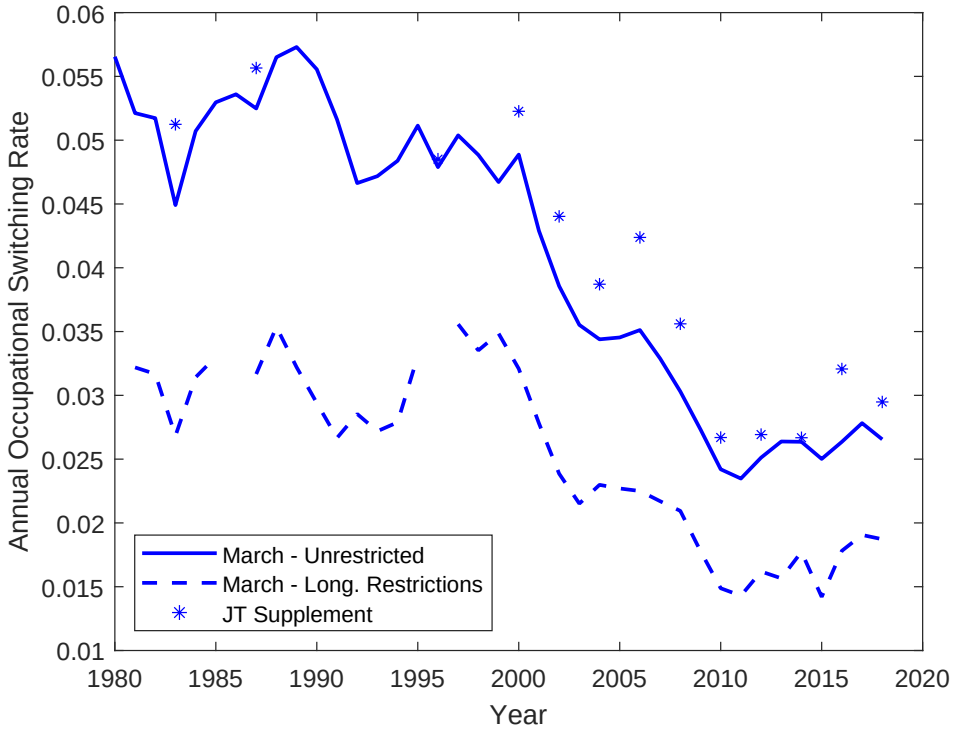
- March CPS asks workers: “What was your longest job during [past year]?” (retrospective measure)
  - Easy, convenient to compute – no linking required
  - Dependently coded – respondent must identify job description has changed
  - Relies on recall, and potentially imprecise timing (timing better in 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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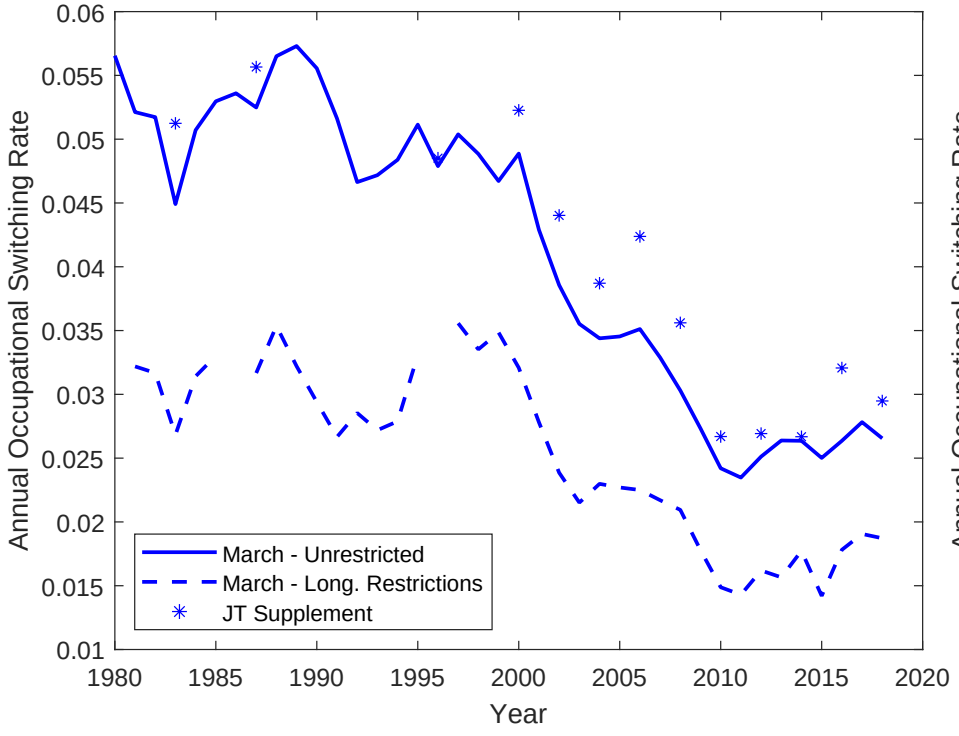

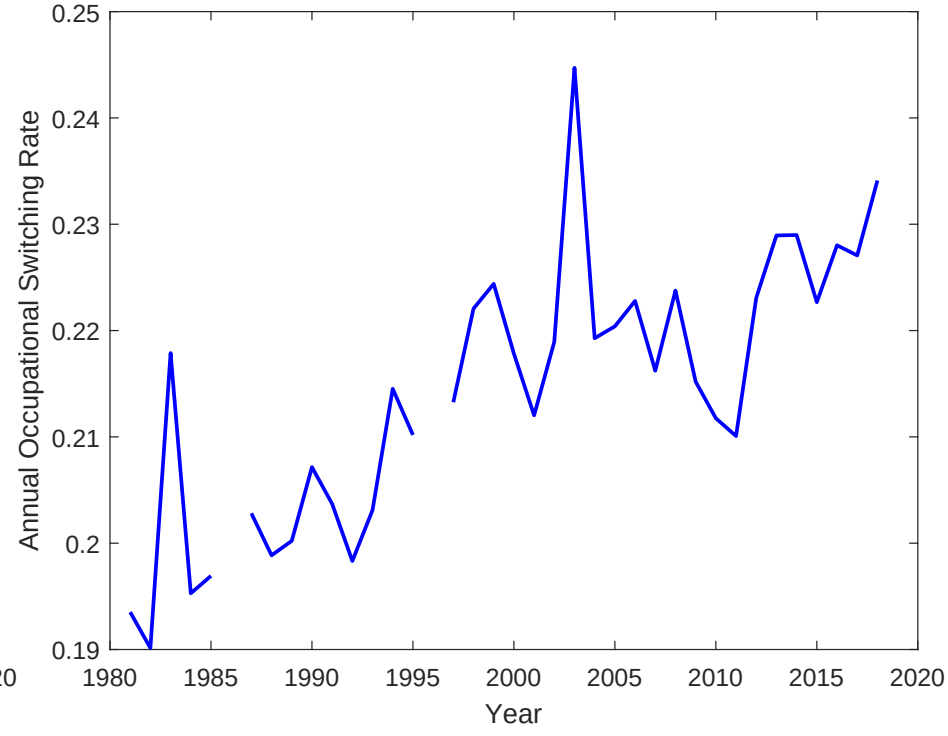

Two and Three Digit

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 $\tilde{SW}^L_{it}$ (longitudinal) and $\tilde{SW}^R_{it}$ (retrospective):

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

- 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 $\tilde{SW}^R_{it} = \tilde{SW}^L_{it} = 1$)

- Estimate parameters year by year via two-stage GMM using moments $\mathbb{E}\left[\tilde{Z}_{it}\right]$, $\mathbb{E}\left[\tilde{Z}_{it} Y_{it}\right]$, $\mathbb{E}\left[\tilde{Z}_{it} X_{it}\right]$, $\mathbb{E}\left[X'_{it} Y_{it}\right]$

- **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:

	All	L=Y,R=Y	L=N,R=N	L=N,R=Y	L=Y,R=N
Switching FT/PT	9.6%	28.0%	8.7%	22.0%	10.8%

- 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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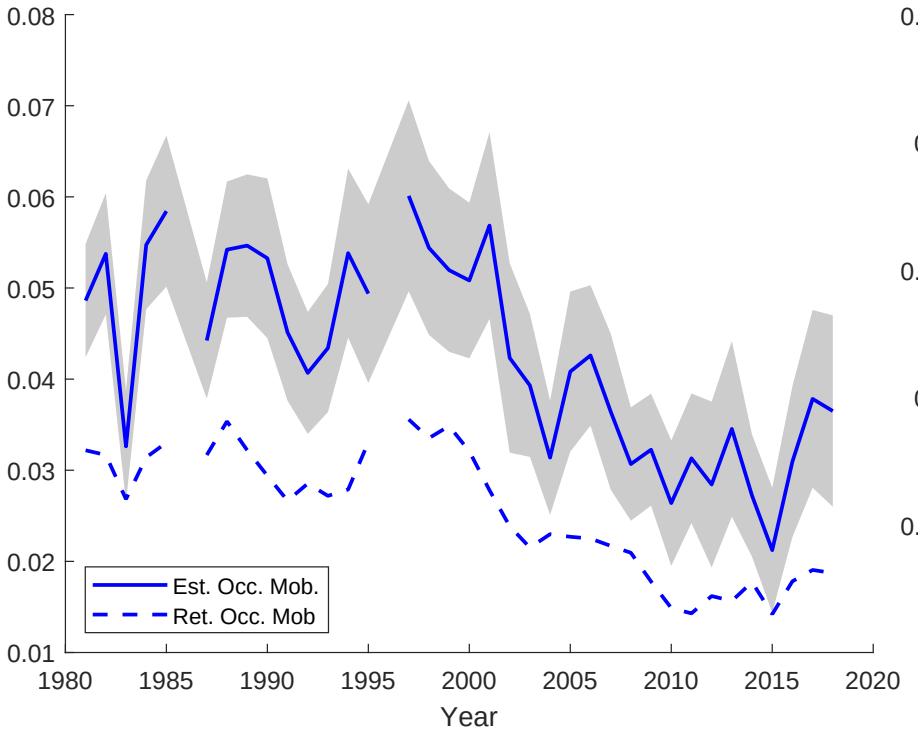
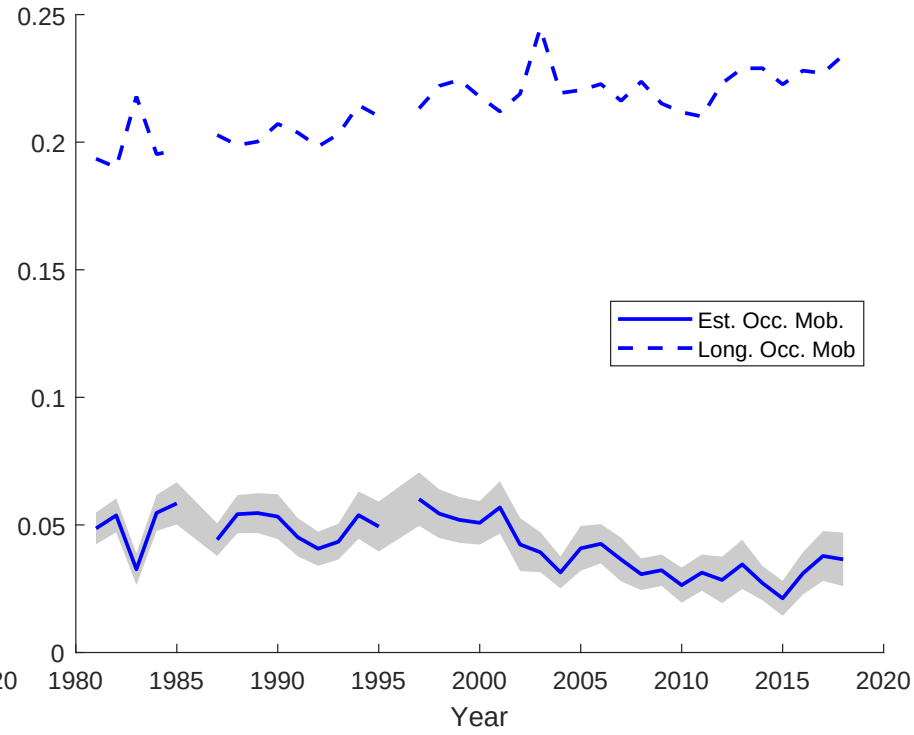
RESULTS

Actual Occupational Mobility

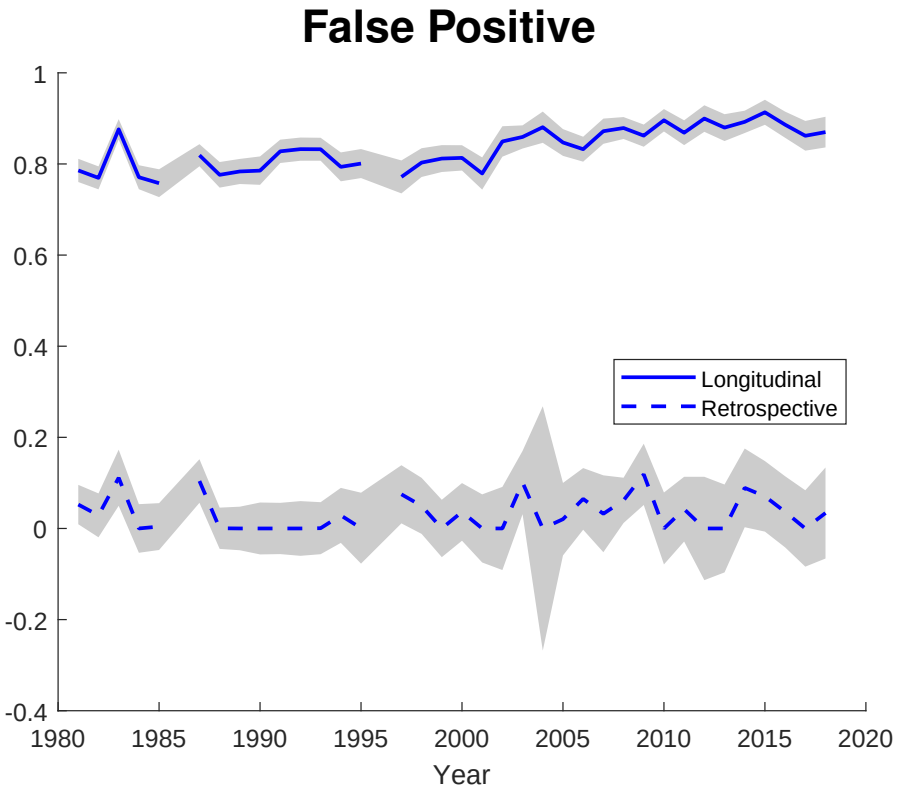


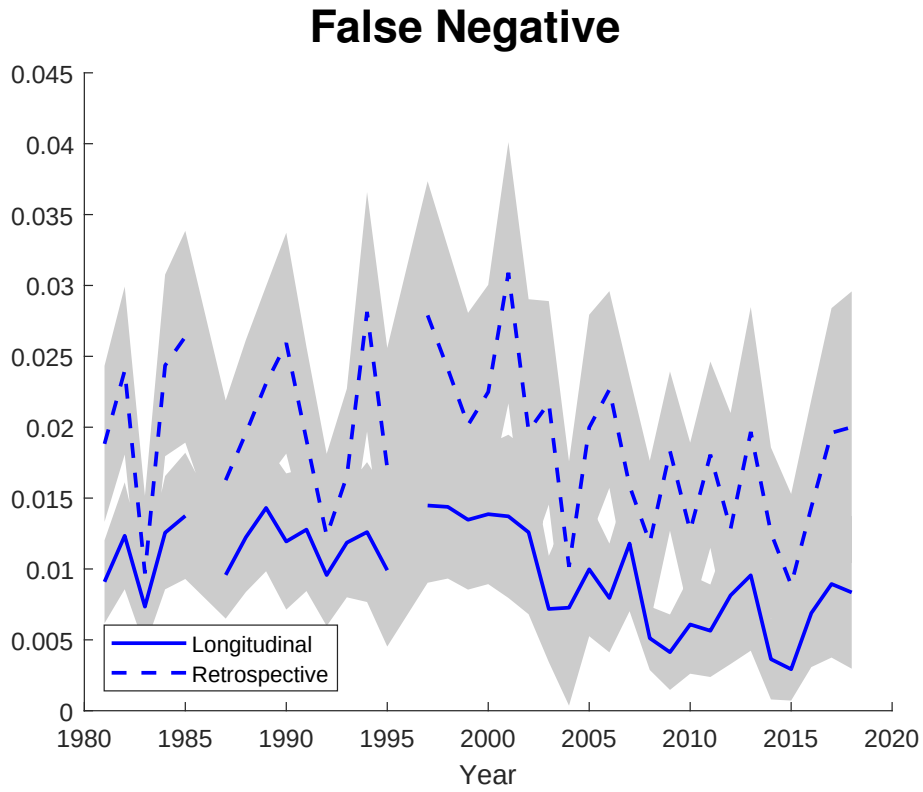


Two and Three Digit

Error Rates

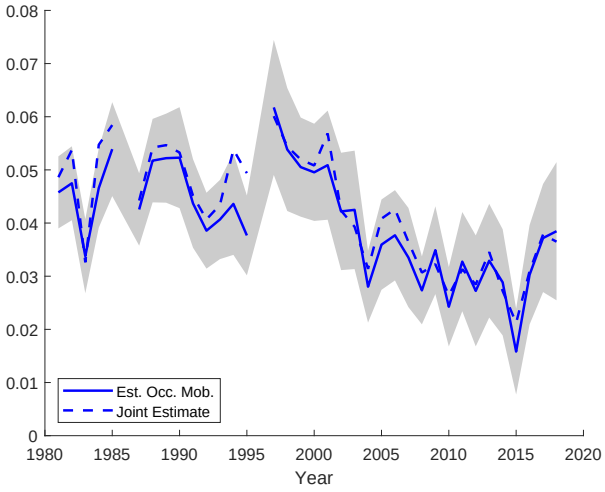
False Positive Rate: $P(SW = 0 \mid \tilde{SW}^j = 1)$; False Negative Rate: $P(SW = 1 \mid \tilde{SW}^j = 0)$



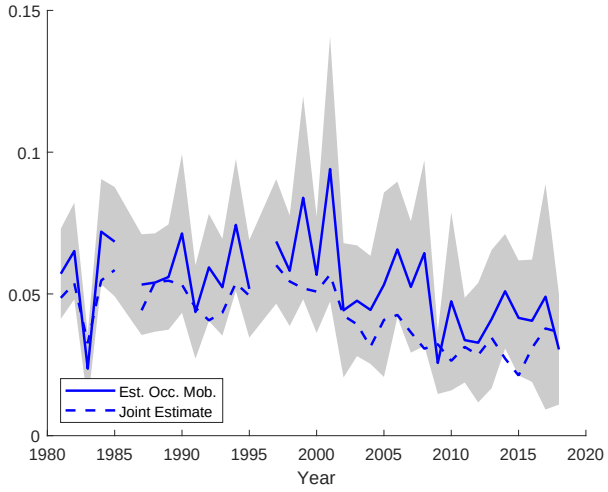


Actual Occupational Mobility by Outcome

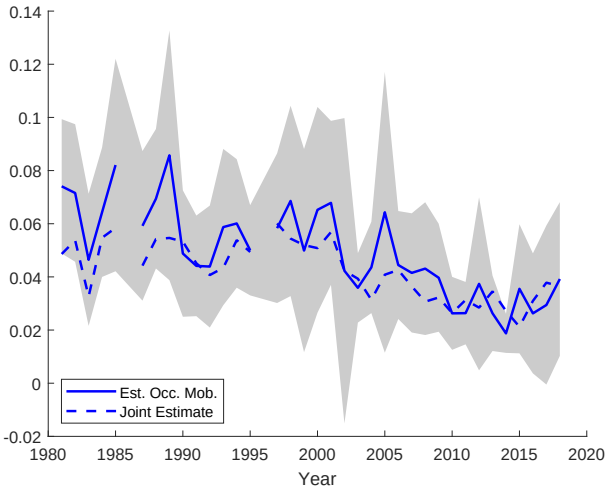
Number of employers in past year > 1



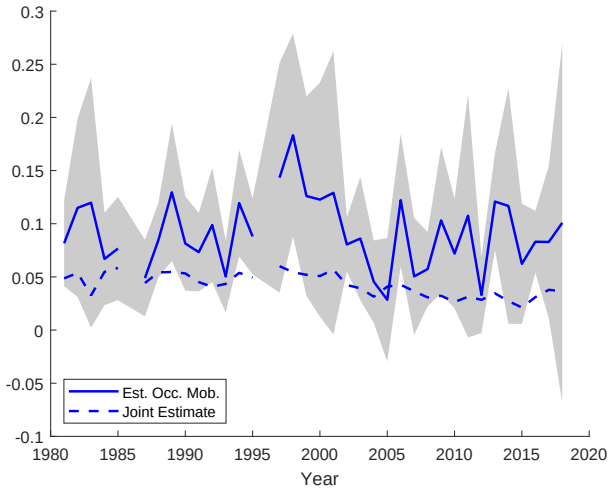
Switched full-time/part-time work status



Weeks employed between year $t-1$ and t > 26

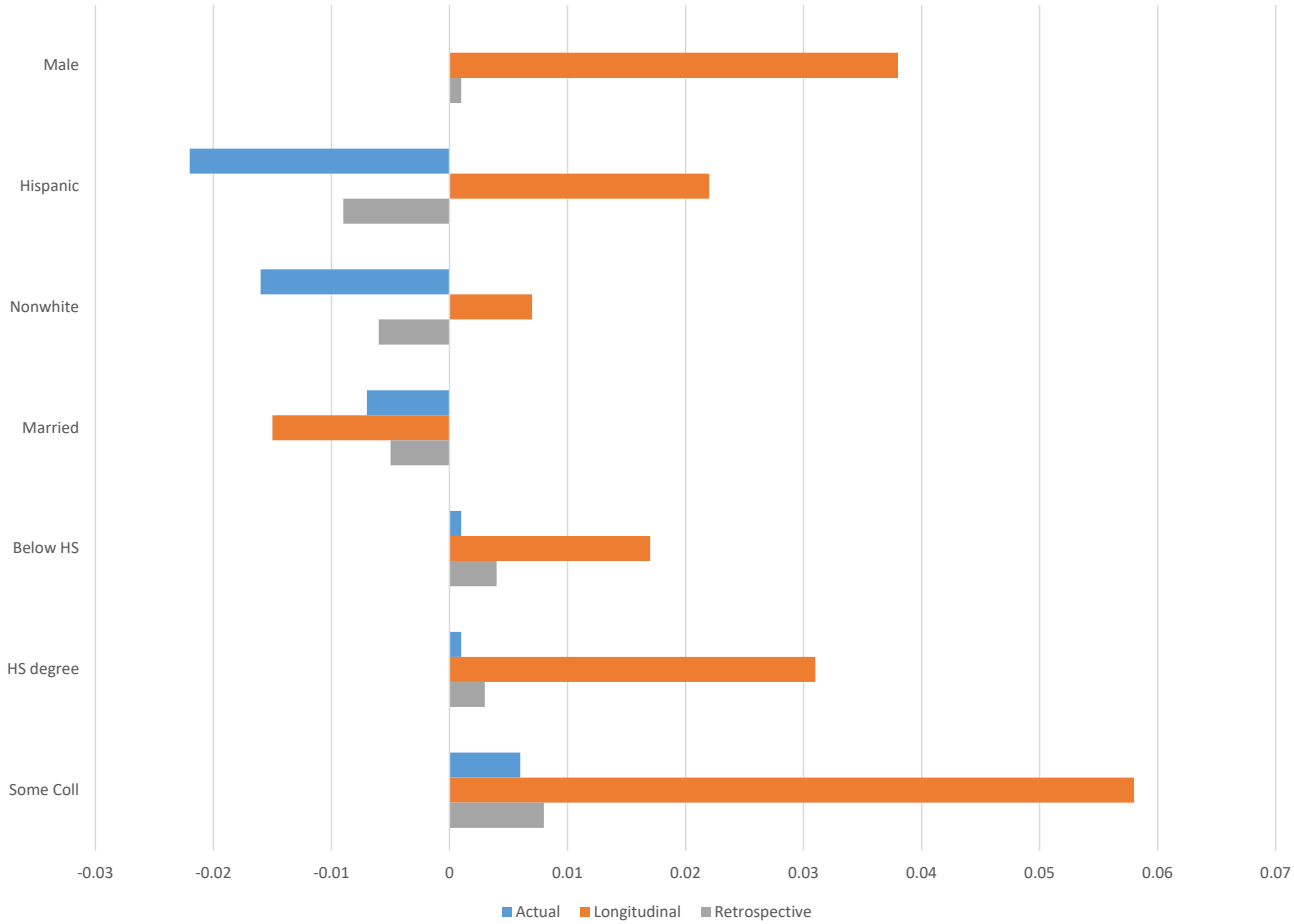


% Δ hourly wage > 10%



Correlates with Error and Occupational Switching

- Compare regression coefficients of individual characteristics across measures



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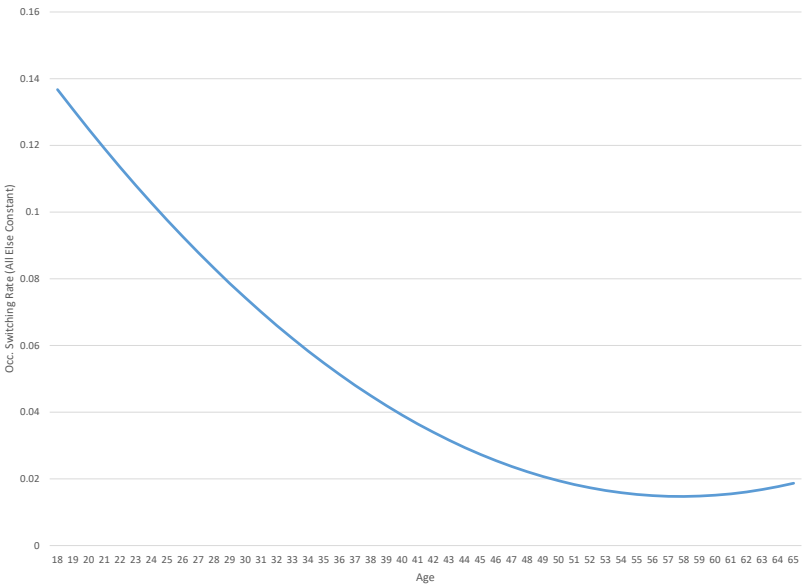

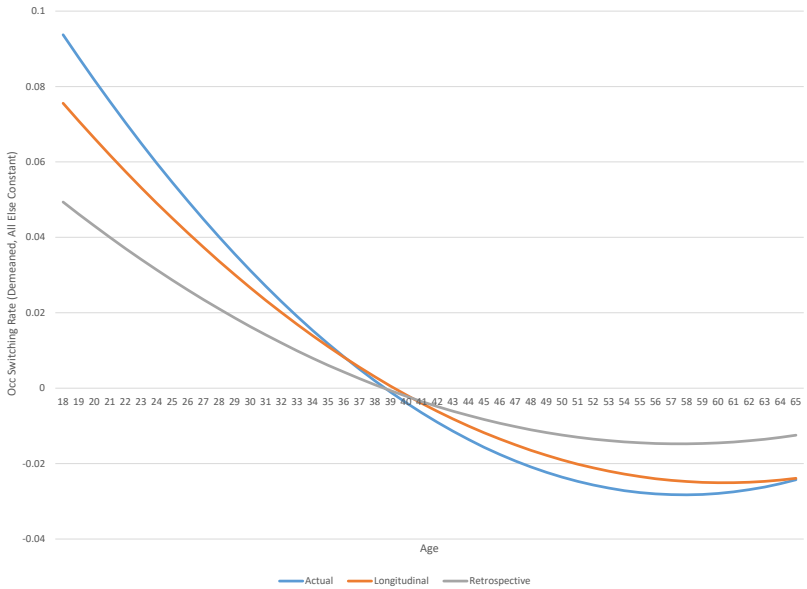

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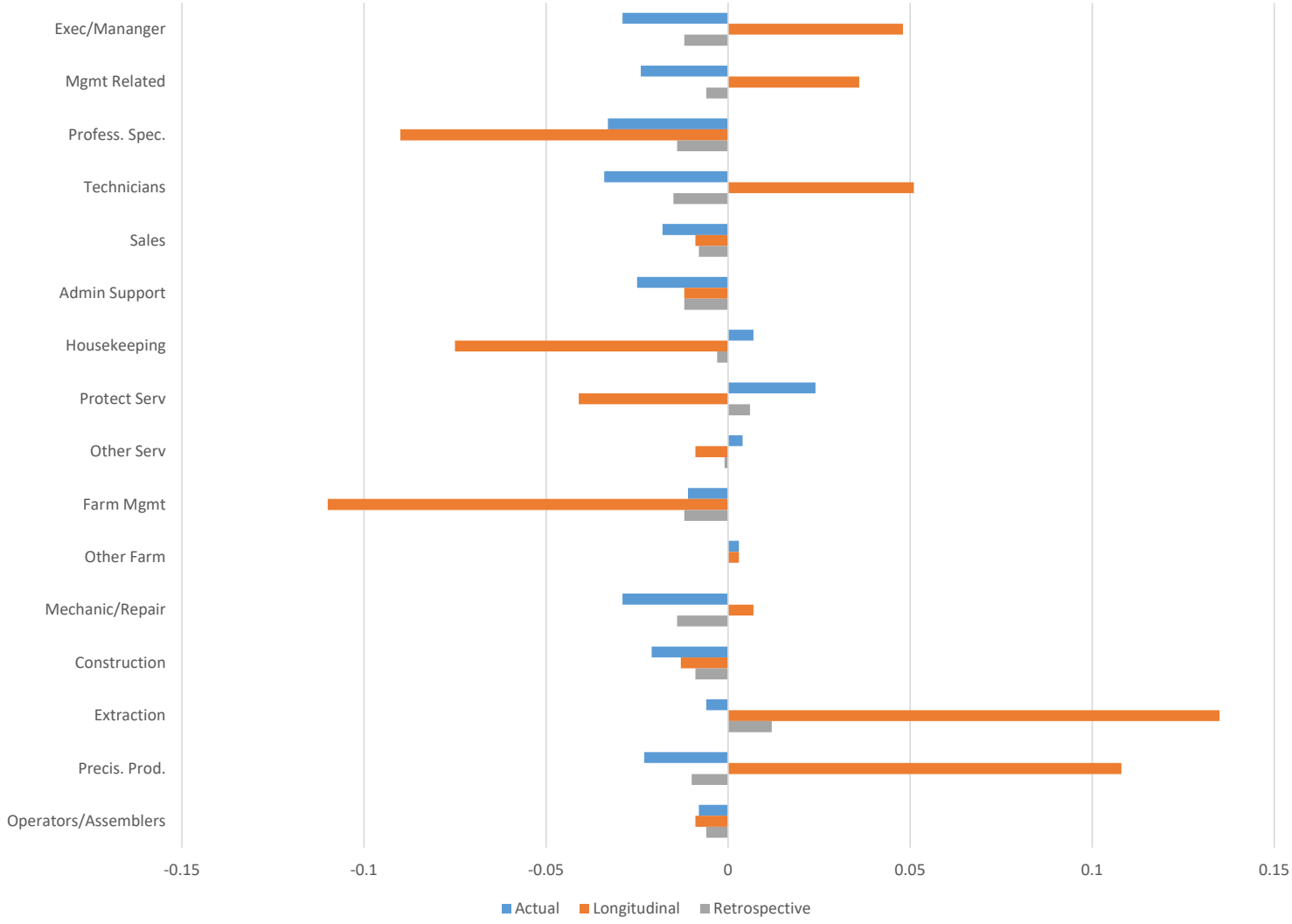
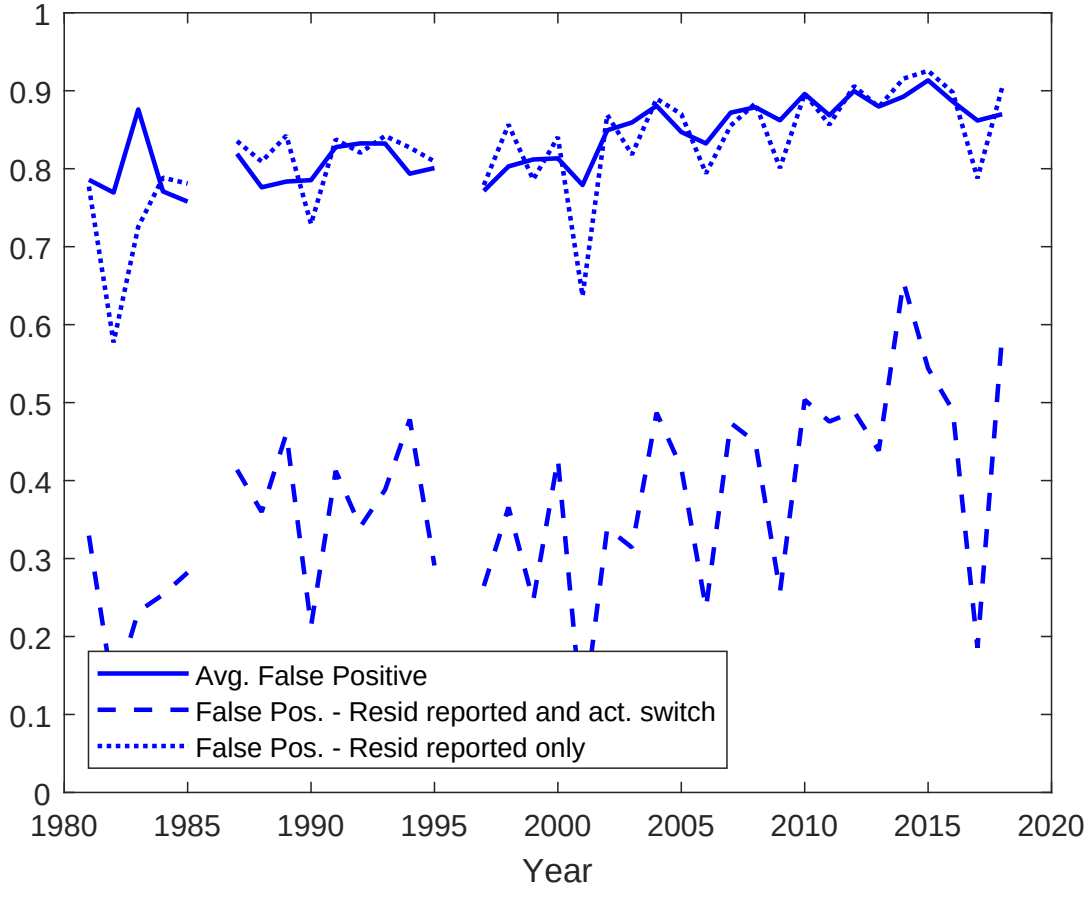


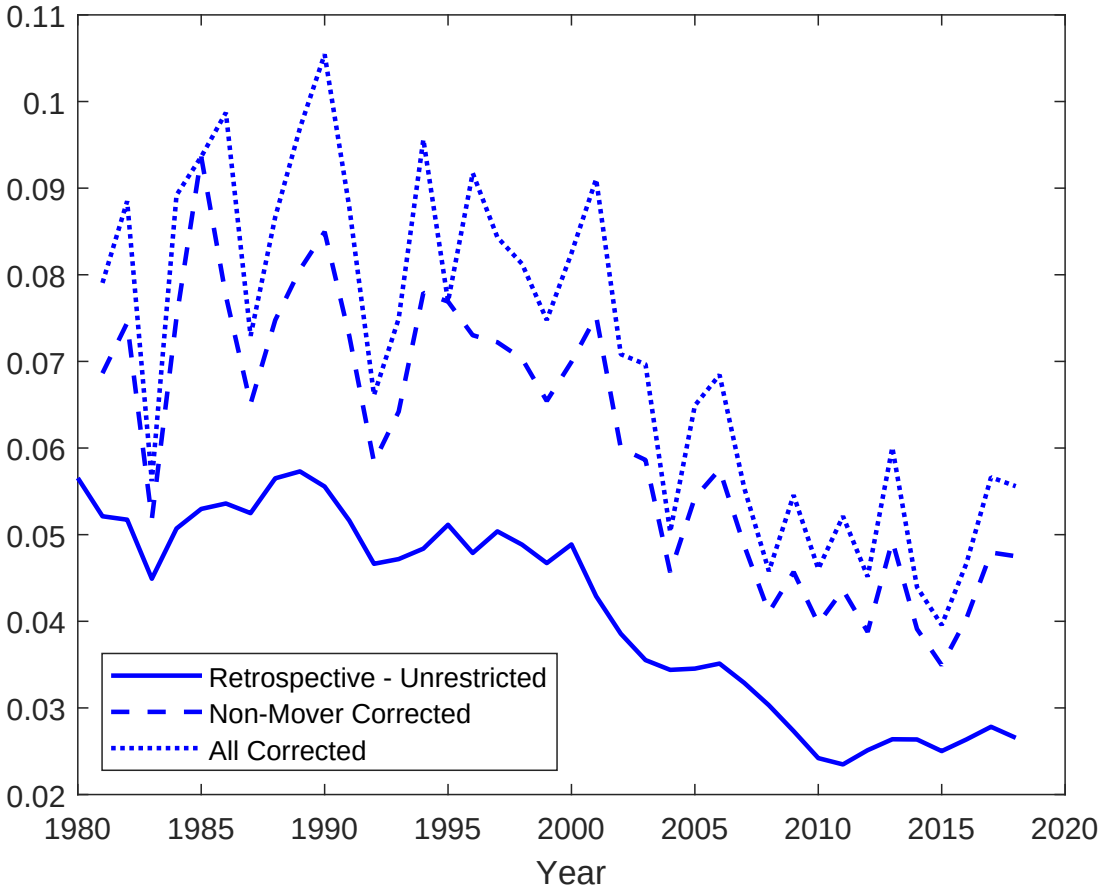
...But Observables Cannot Explain Upward Trend

- 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



PSID Comparison

Robustness

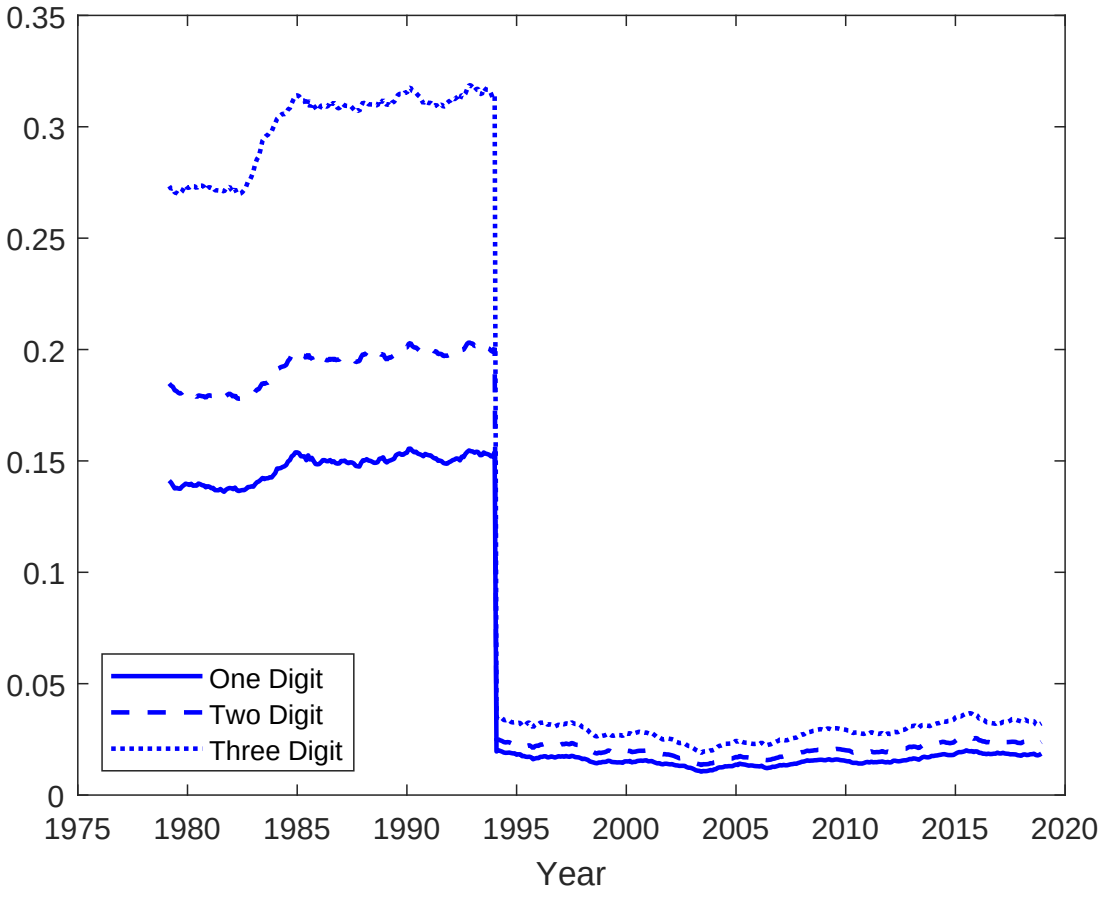
- Findings robust to:
  - Using Job Tenure and Occupational Mobility supplement Results
  - Including additional outcomes/controls: Results
    - Outcomes: alternate measures of income/hours changes, changes in employer contributions to health insurance plans
    - Controls: past year FT status, usual 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 $P(SW = 1 \mid X, Y, \tilde{SW})$: observe all X, only PT/FT switch and number of employers (since 1994) Details

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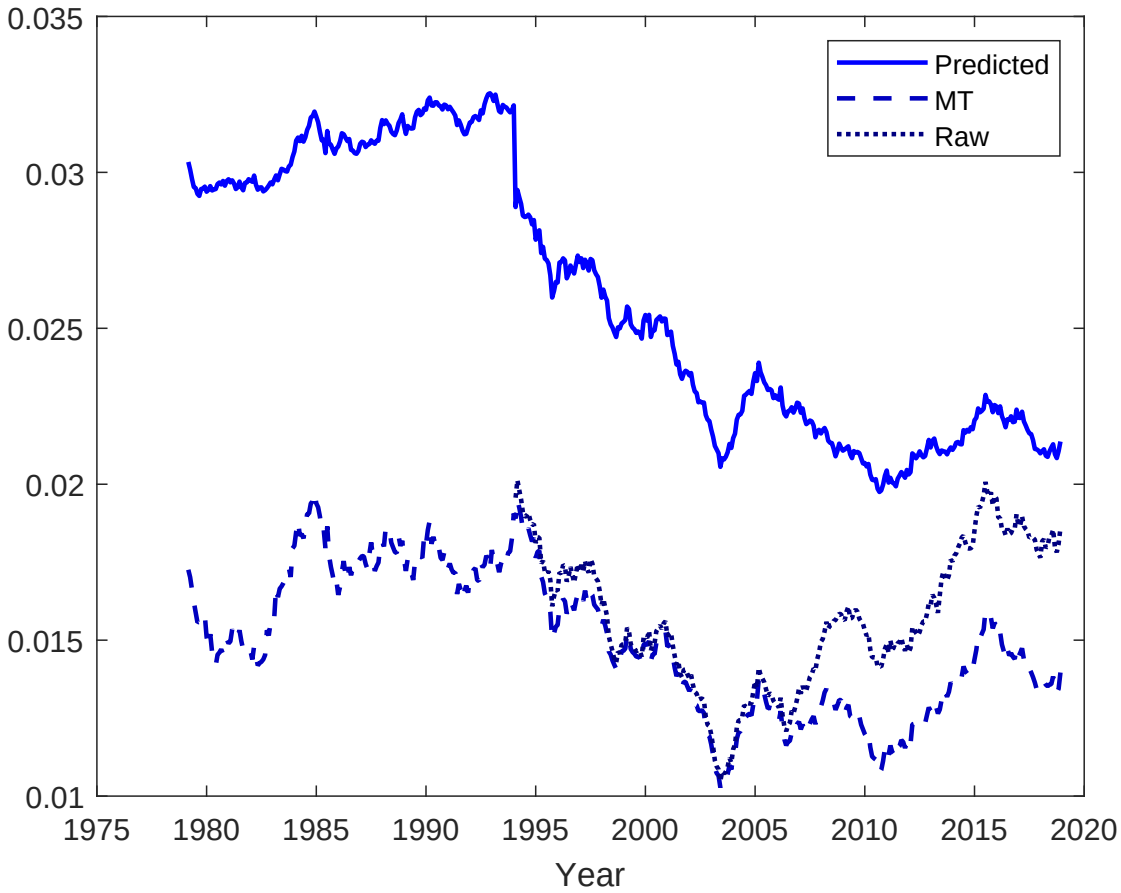

Time Aggregation

- 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

$$\mathbb{E}\left[\tilde{SW}^{L}_{i,o,t} \mid Tradable_o, X_{i,o,t}\right] = \eta_0 + \eta_1 Tradable_o + X_{i,o,t}\eta_2$$

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

- 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

Details

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Details

Parameter	One Digit	Two Digit	Three Digit
IV estimate of occ. switching on wages,	-0.119	-0.173	-0.106
uncorrected ($\tilde{\xi}_1^{IV}$)	(0.033)	(0.022)	(0.016)
IV estimate of occ. switching on wages,	0.403	0.559	0.348
corrected ($\hat{\xi}_1^{IV}$)	(0.117)	(0.075)	(0.055)
Difference	-0.522	-0.732	-0.454
	(0.149)	(0.094)	(0.071)
First stage, tradable occupation on	0.045	0.070	0.091
occupational switching, uncorrected ($\tilde{\eta}_1^{IV}$)	(0.002)	(0.002)	(0.002)
First stage, tradable occupation on	-0.013	-0.022	-0.028
occupational switching, corrected ($\hat{\eta}_1^{IV}$)	(0.002)	(0.002)	(0.003)
Difference	0.058	0.091	0.119
	(0.003)	(0.003)	(0.003)

Application 3: Structural Estimates of Welfare from Trade Liberalization

- Artuc, Chaudhuri and Mclaren (2010) structurally estimate welfare consequences of trade liberalization with worker mobility
- 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

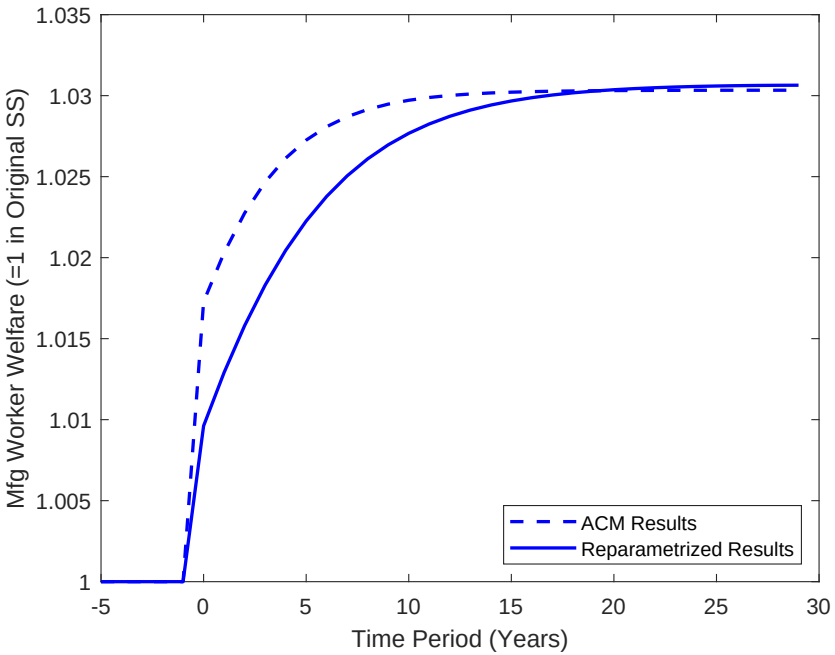
Welfare Gains/Losses from Trade Liberalization

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

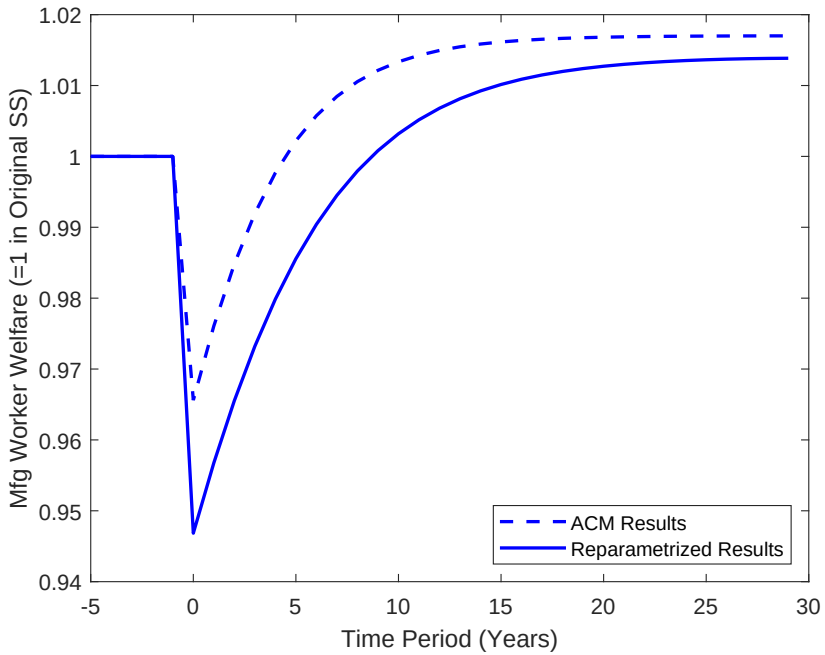
Welfare Gains/Losses from Trade Liberalization

- 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

$\beta = 0.97$



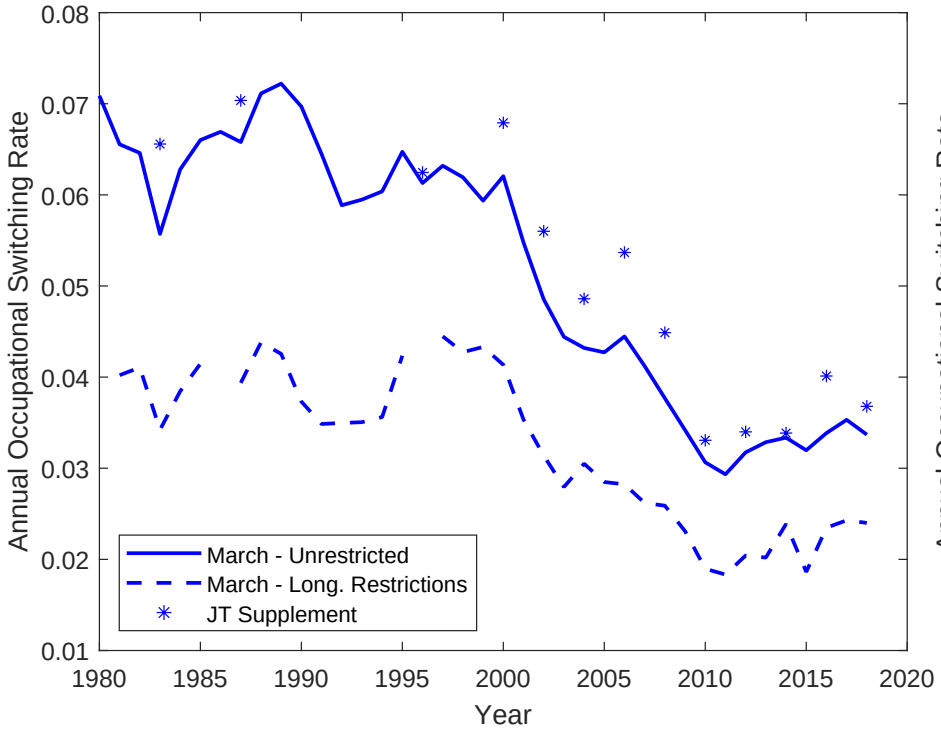
$\beta = 0.90$

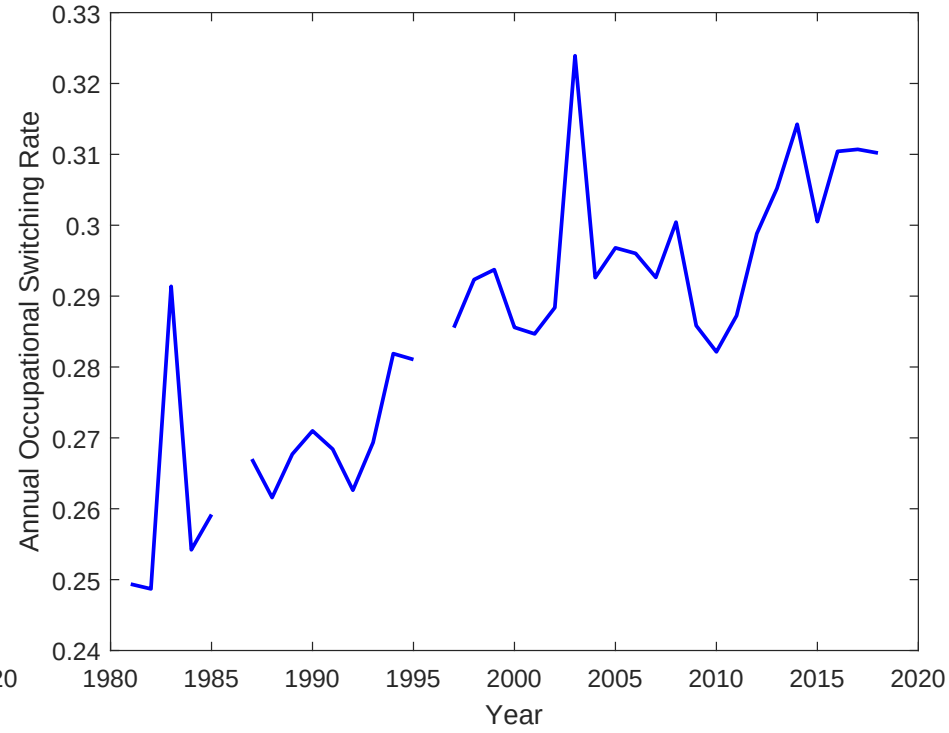


Conclusion

- 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)





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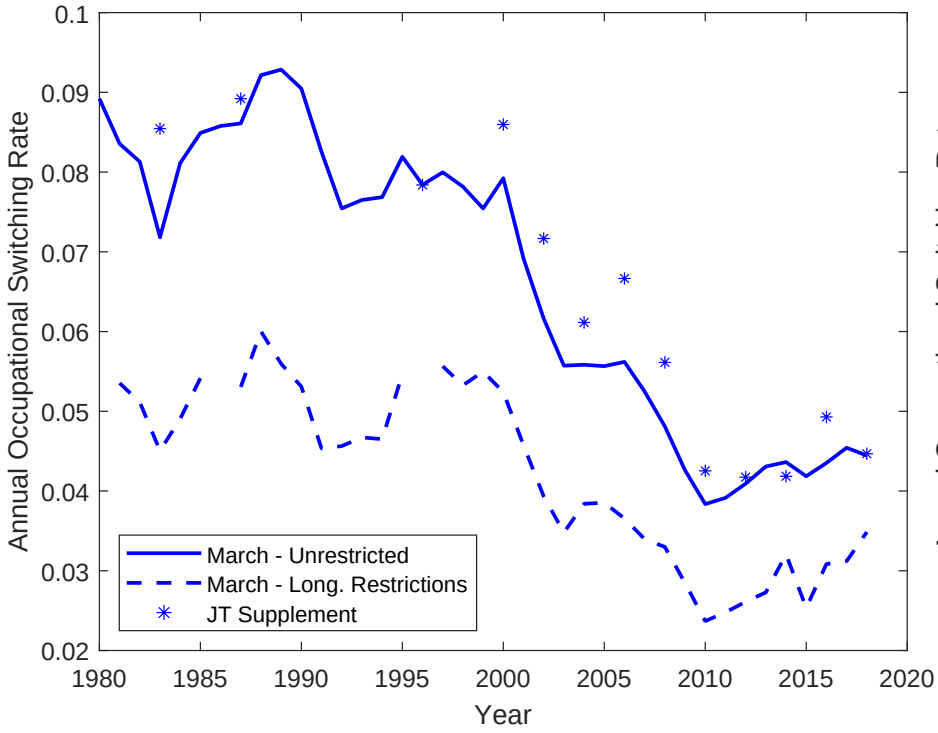
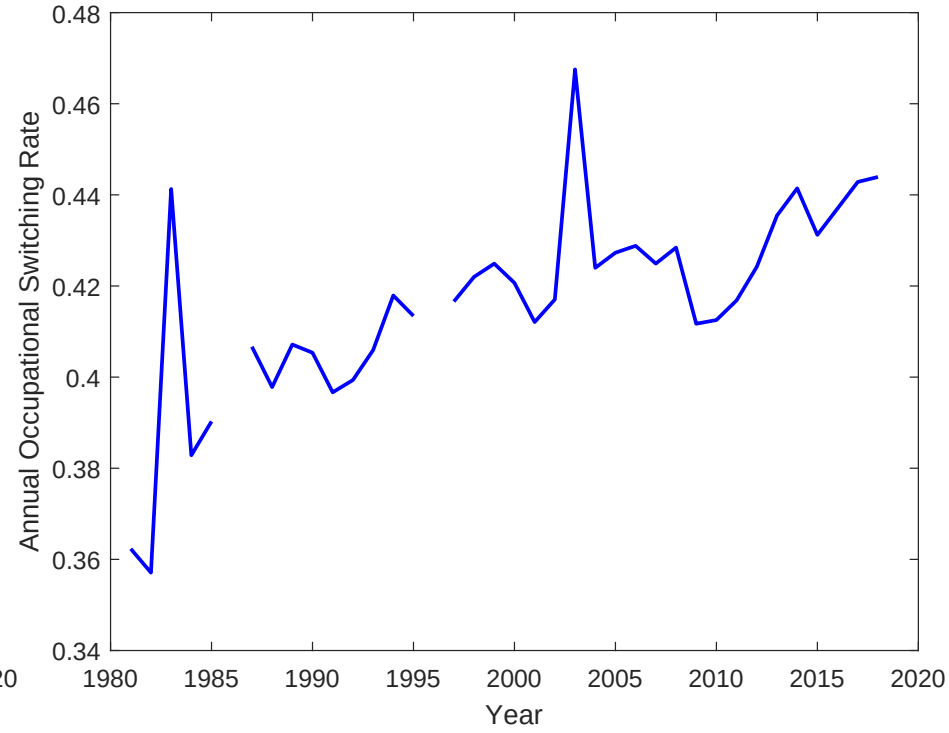
Comparing Occupational Mobility Measures (3 Digit)





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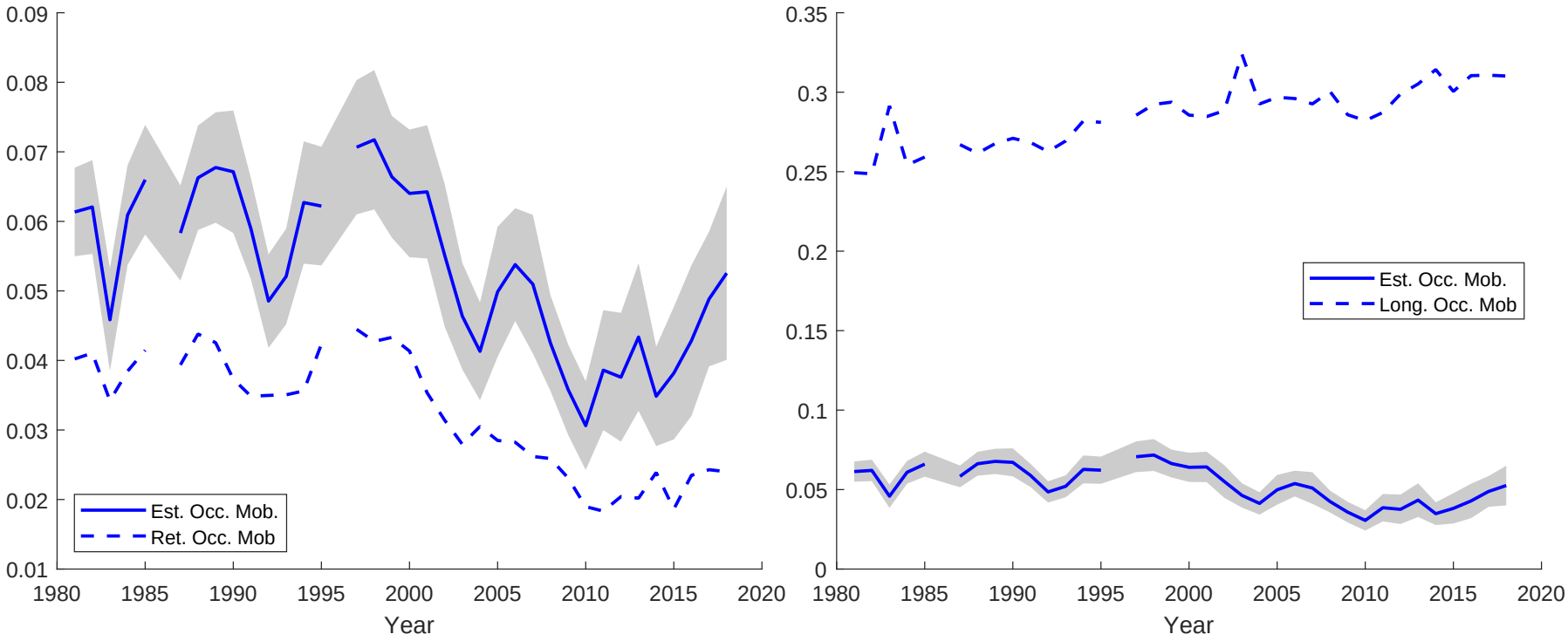
Actual Occupational Mobility (2 Digit)



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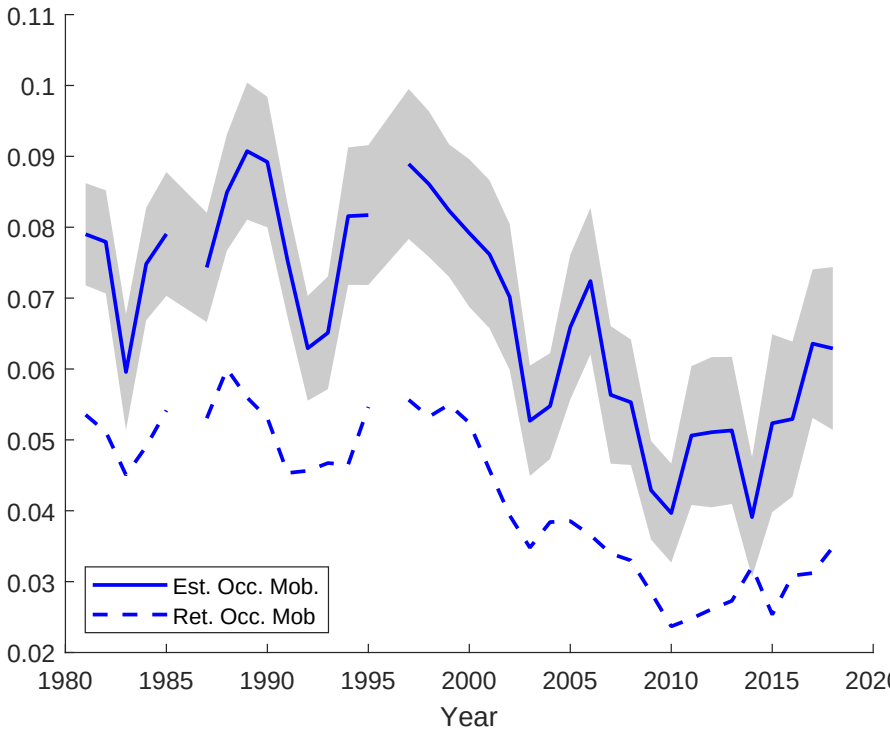
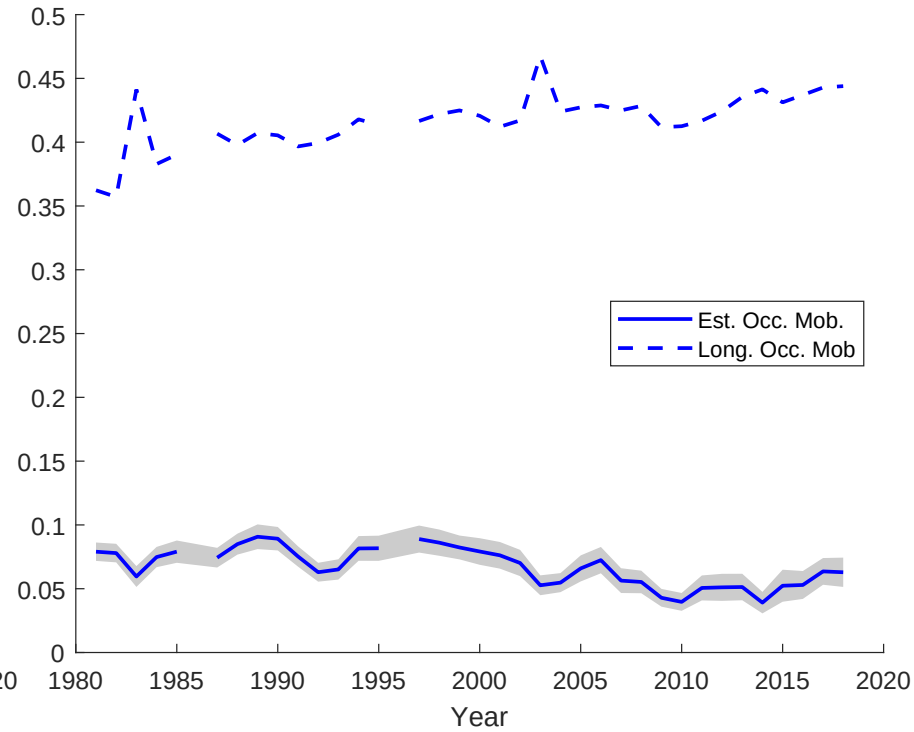
Actual Occupational Mobility (3 Digit)





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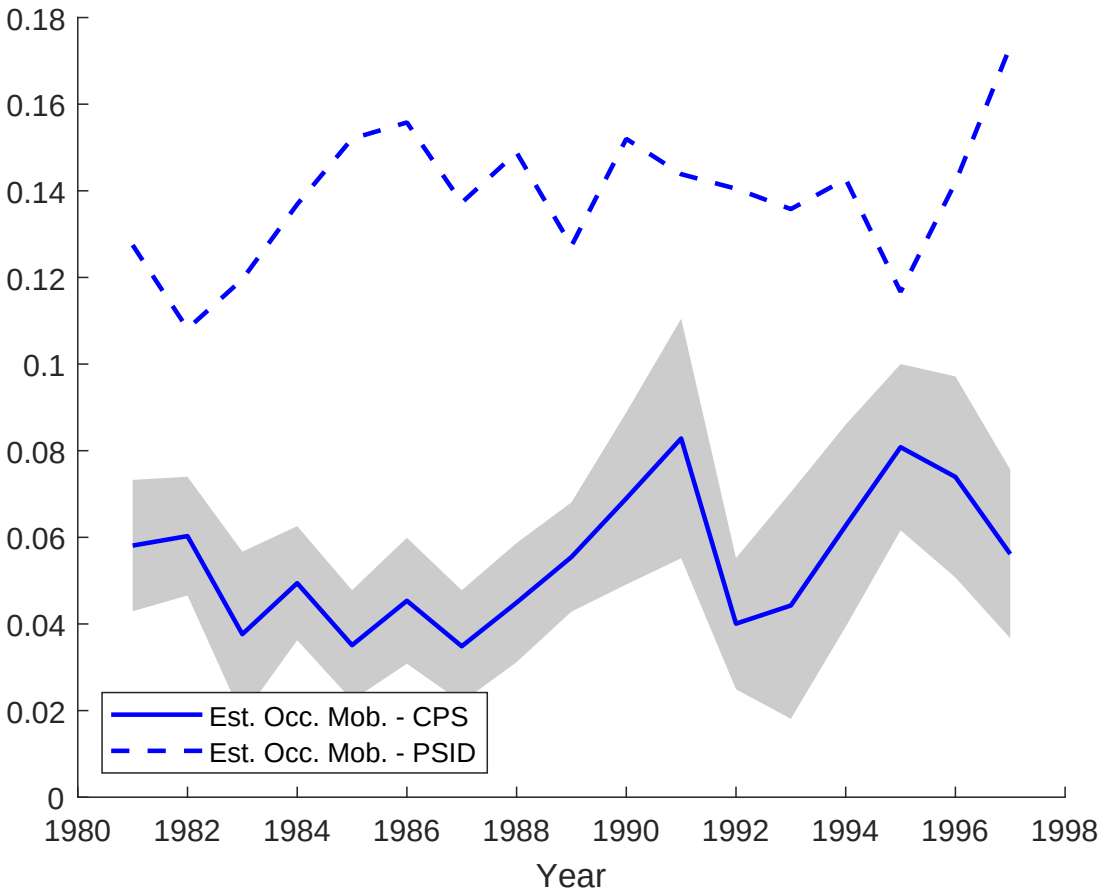
PSID Comparison

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



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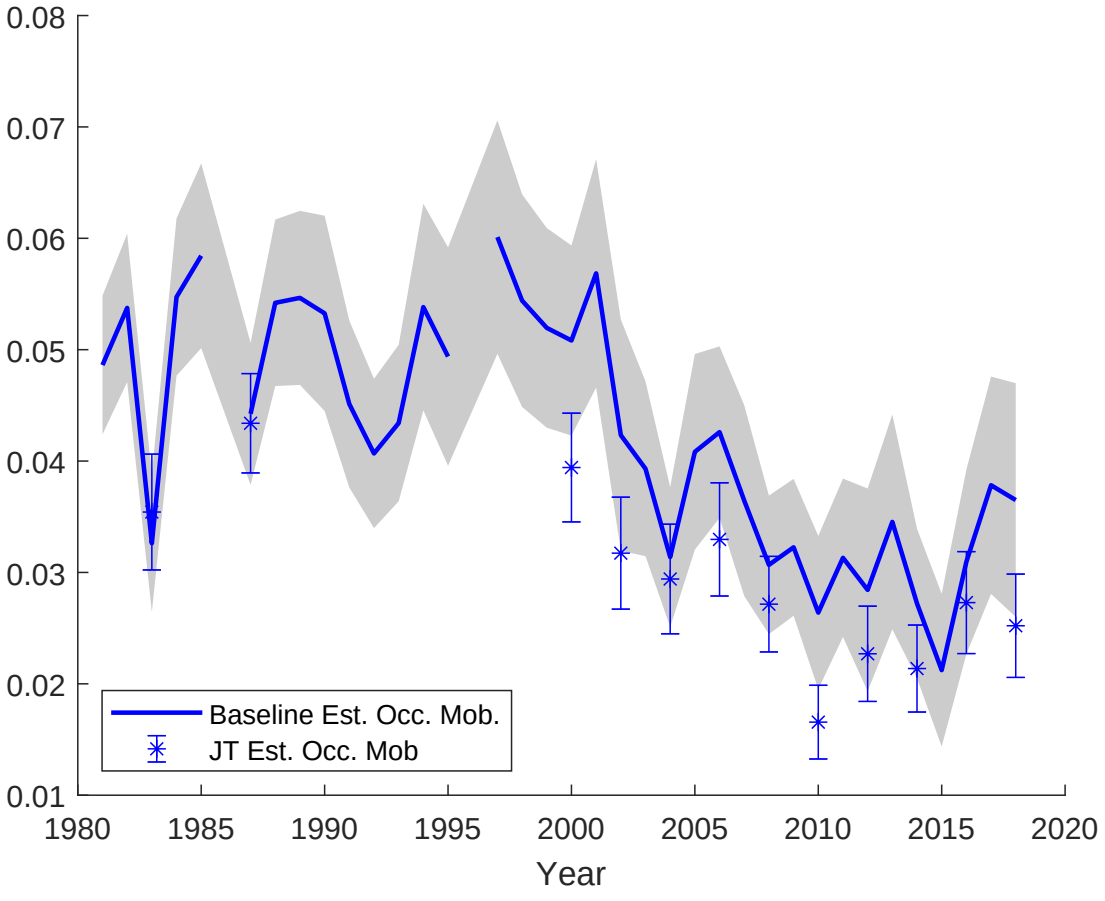
Using Job Tenure and Occupational Mobility Supplement

Utilize biennial (since 2000) job tenure and occupational mobility supplement instead of March CPS; find similar results.



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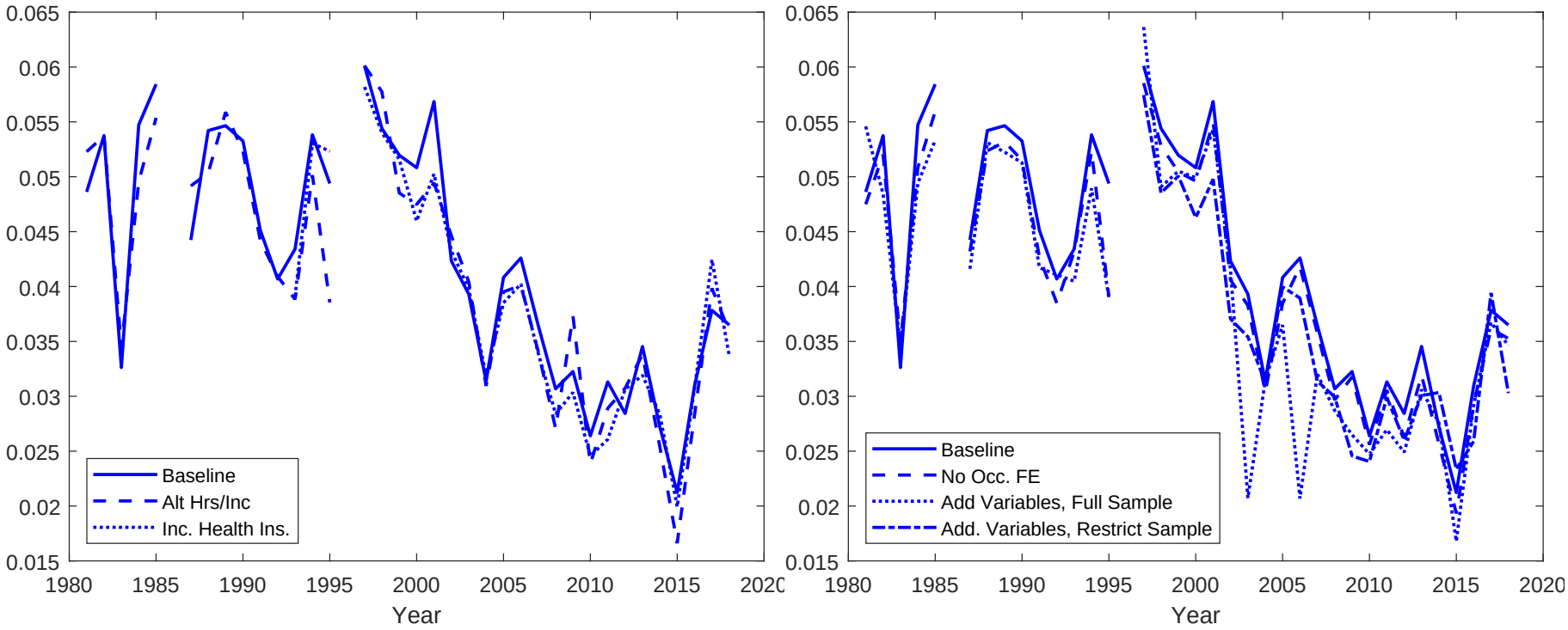
Alternate Variable Combinations

Include additional controls or outcomes; similar results obtain



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Details on Predicted Monthly Switching Rates

- Compute monthly prediction of true switching rate as:

$$
\begin{aligned}
&P(SW = 1 \mid X, Y, \tilde{SW}) \\
&\quad = \frac{P(\tilde{SW}, Y \mid SW = 1, X) P(SW = 1, X)}{P(\tilde{SW}, Y \mid SW = 1, X) P(SW = 1, X) + P(\tilde{SW}, Y \mid SW = 0, X) P(SW = 0, X)} \\
&= \frac{P(\tilde{SW} \mid X, Y, SW = 1) P(Y \mid X, SW = 1) P(SW = 1 \mid X)}{P(\tilde{SW} \mid X, Y, SW = 1) P(Y \mid X, SW = 1) P(SW = 1 \mid X) + P(\tilde{SW} \mid X, Y, SW = 0) P(Y \mid X, SW = 0) P(SW = 0 \mid X)}
\end{aligned}
$$

Use model estimates from annual switching to represent:

$$
\begin{aligned}
&P(SW = 1 \mid X, Y = 1, \tilde{SW} = 1) \\
&\quad = \frac{(\alpha_0 + \alpha_1 + X\alpha_X)(\beta_0 + \beta_1 + X\beta_2)(\delta_0 + X\delta_1)}{(\alpha_0 + \alpha_1 + X\alpha_X)(\beta_0 + \beta_1 + X\beta_2)(\delta_0 + X\delta_1) + (\alpha_0 + X\alpha_X)(\beta_0 + X\beta_2)(1 - \delta_0 - X\delta_1)}
\end{aligned}
$$

- 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.

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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:

$$\hat{\xi}_1^{IV} = \frac{\tilde{\eta}_1}{\hat{\eta}_1}\tilde{\xi}_1^{IV} = \frac{\alpha_{L,1}\delta_1(Trad.) + \alpha_{L,X}(Trad)}{\delta_1(Trad.)}\tilde{\xi}_1^{IV}$$

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