Wage Dynamics and Returns to Unobserved Skill

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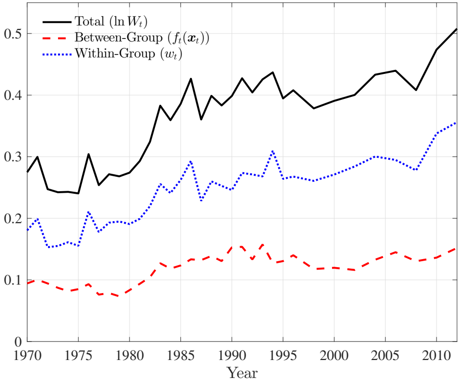
Rising Wage Inequality in the US



- Substantial increase within (education, race, and experience) groups $\Rightarrow$ rising 'residual' wage inequality
- Source: variance of log hourly wages for American men from the Panel Study of Income Dynamics (PSID)

Rising Returns to Unobserved Skill?

- Since Juhn, Murphy & Pierce (1993), many economists have equated rising residual inequality with an increase in the returns to unobserved ability/skill:
  - Let $w_{i,t}$ be the log wage residual of individual i in year t:

$$w_{i,t} = \underbrace{\mu_t}_{\text{return}} \times \underbrace{\theta_i}_{\text{unobserved skill}}$$

- Motivated an influential literature on skill-biased technical change
  - Many studies specifically aimed to explain rising returns to unobserved skill/ability (e.g., Acemoglu 1998, Galor & Moav 2000)
- Still the dominant interpretation within labor economics (e.g., Autor, Katz & Kearney 2008)

Other Interpretations

- Lemieux (2006) argues that some of the increase in residual inequality is explained by an increase in the variance of unobserved skills
  - $\text{Var}(\theta_t)$ increased over time due to an increase in highly educated and older workers who have larger within-group skill dispersion

$$\underbrace{\text{Var}(\theta_t)}_{\text{total var}} = \sum_j \underbrace{p_{j,t}}_{\text{fraction of } j} \underbrace{\text{Var}(\theta_j)}_{\text{var of } j}$$

- Short-term fluctuations in earnings have also increased (Gottschalk & Moffitt 1994)
  - Reflects measurement errors or transitory shocks unrelated to skills:

$$w_{i,t} = \underbrace{\theta_i}_{\text{permanent}} + \underbrace{\varepsilon_{i,t}}_{\text{transitory}}$$

  - Evidence based on panel data (PSID) that $\text{Var}(\varepsilon_t)$ increased over time
  - Motivated a literature on trends in consumption inequality (e.g., Krueger & Perri 2006, Blundell, Pistaferri & Preston 2008)

Identifying the Causes of Rising Residual Inequality

- We show how panel data on wages can be used to separately identify the evolution of:
  - Returns to unobserved skills
  - Distributions of unobserved skills
  - Volatility of transitory wage shocks
- Key idea: 'long' autocovariances of wages identify the evolution of skill returns
  - Transitory shocks do not drive long-term differences in wages across individuals
  - Motives a new Instrumental Variable (IV) estimation strategy for estimating skill returns
    - Requires no assumptions on experience or time effects on variances of skills or shocks

Main Empirical Findings (from PSID)

- Returns to unobserved skill *fell* substantially from mid-1980s through mid-1990s
  - Decline was more dramatic for those who didn't attend college
  - Consistent with falling return to measured cognitive ability (AFQT score) since 1980s (Castex & Dechter 2014)
  - Fundamentally different from returns estimated under assumption of time-invariant skill distributions (e.g., Juhn, Murphy, & Pierce 1993, Moffitt & Gottschalk 2012)
- Rising residual inequality is driven by an increase in the variance of unobserved skill
  - Variance of lifecycle skill growth, not variance of initial skills
  - Not accounted for in composition effects of Lemieux (2006)

Explaining the Falling Returns

- We develop a new quantitative framework to decompose the changes in returns to unobserved skill into changes in demand and supply
  - Based on a job assignment model of Sattinger (1979)
  - Our estimates can be combined with the restrictions implied by the model to recover changes in skill demand and supply
- Decomposition suggests that both supply and demand factors played important roles
  - Decline in skill demand was more important than supply shifts for non-college workers

Modeling Log Wage Residuals

We observe log wage residuals of a large number of individuals for periods $t = \underline{t}, \underline{t}+1, \ldots, \overline{t}$

$$\begin{aligned} w_{i,t} &= \mu_t \theta_{i,t} + \varepsilon_{i,t} \\ \theta_{i,t} &= \theta_{i,t-1} + \nu_{i,t} \end{aligned}$$

- $\theta_{i,t}$ reflects time-varying unobserved skills
- μ_t reflects the labor market returns to unobserved skills
  - Shifts relative wages (log wage differential) between high and low skill
- $\varepsilon_{i,t}$ reflects transitory components of wage
  - Year to year wage fluctuations unrelated to skills (e.g., measurement error, wage dynamics induced by labor market frictions)

Normalizations & Assumptions

$$\begin{aligned} w_{i,t} &= \mu_t \theta_{i,t} + \varepsilon_{i,t} \\ \theta_{i,t} &= \theta_{i,t-1} + \nu_{i,t} \end{aligned}$$

- All components are mean zero:
  $\mathrm{E}[\theta_t] = \mathrm{E}[\varepsilon_t] = \mathrm{E}[\nu_t] = 0$
- Transitory components are uncorrelated with skills:
  $\mathrm{Cov}(\varepsilon_t, \theta_{t'}) = \mathrm{Cov}(\varepsilon_t, \nu_{t'}) = 0, \ \forall (t, t')$
- Serial correlation in transitory component dies out after k periods:
  $\mathrm{Cov}(\varepsilon_t, \varepsilon_{t'}) = 0$ for $|t' - t| \geq k$
- Skill changes are uncorrelated with past skills:
  $\mathrm{Cov}(\nu_t, \theta_{t'}) = 0$ for $t' < t$

Identifying Skill Returns Over Time

Substituting in for $\theta_{i,t-1} = (w_{i,t-1} - \varepsilon_{i,t-1})/\mu_{t-1}$ yields

$$\begin{aligned} w_{i,t} =& \mu_t(\theta_{i,t-1} + \nu_{i,t}) + \varepsilon_{i,t} \\ =& \mu_t \left(\frac{w_{i,t-1} - \varepsilon_{i,t-1}}{\mu_{t-1}} + \nu_{i,t} \right) + \varepsilon_{i,t} \\ =& \frac{\mu_t}{\mu_{t-1}} w_{i,t-1} + \left(\varepsilon_{i,t} - \frac{\mu_t}{\mu_{t-1}} \varepsilon_{i,t-1} + \nu_{i,t} \right) \end{aligned}$$

- OLS is inconsistent because $w_{i,t-1}$ is correlated with $\varepsilon_{i,t-1}$
- *Past* residuals are valid instruments for $w_{i,t-1}$ since $\nu_{i,t}$ is uncorrelated with past skills and serial correlation in $\varepsilon_{i,t}$ dies out after k periods
- Probability limit of the IV estimator is

$$\frac{\text{Cov}(w_t, w_{t'})}{\text{Cov}(w_{t-1}, w_{t'})} = \frac{\mu_t \mu_{t'} \text{Var}(\theta_{t'})}{\mu_{t-1} \mu_{t'} \text{Var}(\theta_{t'})} = \frac{\mu_t}{\mu_{t-1}}, \quad \text{for } t' < t - k$$

- Therefore, μ_t / μ_{t-1} is identified for all $t > \underline{t} + k$ ▸ Identifying Early Returns
  - Normalizing $\mu_{t^*} = 1$ for some t^* sets the units for unobserved skill

Identifying the Rest

Once skill returns have been identified, the rest is identified except for the last k periods

- We can identify $\text{Var}(\theta_t|c)$ (and then $\text{Var}(\nu_t|c)$) from

$$\text{Var}(\theta_t|c) = \frac{\text{Cov}(w_t, w_{t'}|c)}{\mu_t \mu_{t'}} \quad \text{for } t' \geq t + k$$

- Next, we can identify

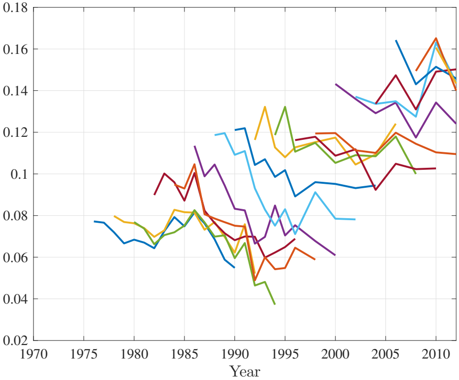
$$\text{Cov}(\varepsilon_t, \varepsilon_{t'}|c) = \text{Cov}(w_t, w_{t'}|c) - \mu_t \mu_{t'} \text{Var}(\theta_t|c) \quad \text{for } t \leq t' \leq t + k$$

PSID Data

- PSID is a longitudinal survey of a representative sample of US individuals and their families
- We use earnings for calendar years 1970-2012
  - Annual up to 1996, biennial thereafter
- Average hourly wages: annual earnings divided by annual hours worked
- Annual earnings: household head's total wages and salaries (excluding farm and business income)
- Select male household heads with ages 16-64 and experiences 1-40
  - Resulting dataset has 3,766 men and 44,547 observations
- To obtain residuals, we run cross-sectional OLS regressions of log wages on regressors including experience, race, and education, separately by year and college attendance status

Long Autocovariances

- $\text{Cov}(w_b, w_t) = \mu_b \mu_t \text{Var}(\theta_b)$ for $t - b \geq k = 6$ plotted



- Negative slopes in late 1980s and 1990s suggest *declining* μ_t
- Upward shifting lines suggest *increasing* $\text{Var}(\theta_b)$ ▸ More

IV Estimation of Changes in Skill Returns

- Recall: for $t' < t - k$,

$$\frac{\text{Cov}(w_t, w_{t'})}{\text{Cov}(w_{t-1}, w_{t'})} = \frac{\mu_t}{\mu_{t-1}}$$

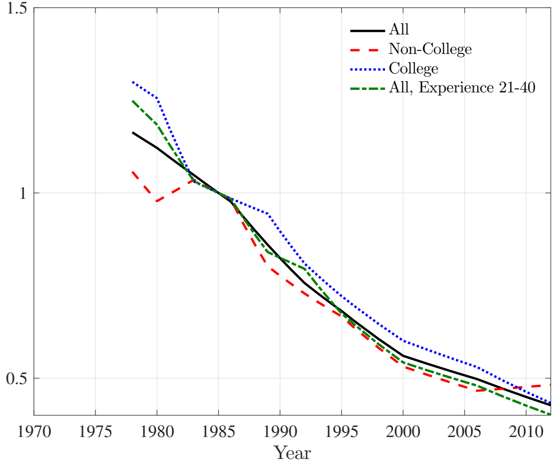
- Assuming $k = 6$, we estimate $(\mu_t - \mu_{t-2})/\mu_{t-2}$ by regressing $w_{i,t} - w_{i,t-2}$ on $w_{i,t-2}$ using the following instruments:
  - $w_{i,t-8}$ and $w_{i,t-9}$ for 1979-1995
  - $w_{i,t-8}$ and $w_{i,t-10}$ for 1996-2012

2SLS Estimates of 2-year Growth Rates of μ_t

	1979-80	1981-83	1984-86	1987-89	1990-92	1993-95	1996-2000	2002-06	2008-12
					A. All men				
	-0.036	-0.044	-0.046	-0.081*	-0.082*	-0.067	-0.075*	-0.039	-0.050
	(0.045)	(0.038)	(0.038)	(0.034)	(0.035)	(0.035)	(0.025)	(0.028)	(0.027)
Obs	1,349	2,077	2,188	2,245	2,189	2,095	2,122	2,129	1,968
F-Stat	163.09	191.61	114.85	209.42	227.13	286.96	369.09	344.25	341.36
					B. All men with 21–40 years of experience (at year t)				
	-0.052	-0.088*	-0.031	-0.100*	-0.036	-0.104*	-0.084*	-0.040	-0.058
	(0.050)	(0.043)	(0.050)	(0.046)	(0.044)	(0.045)	(0.030)	(0.032)	(0.031)
Obs	928	1,323	1,244	1,211	1,244	1,300	1,427	1,591	1,493
F-Stat	117.23	132.19	66.26	130.53	132.83	201.62	295.75	281.91	267.83
					C. Non-college-educated men (all experience levels)				
	-0.075	0.039	-0.035	-0.127*	-0.062	-0.057	-0.087*	-0.043	0.011
	(0.061)	(0.056)	(0.060)	(0.050)	(0.058)	(0.054)	(0.043)	(0.047)	(0.075)
Obs	740	1,080	997	965	897	851	862	826	615
F-Stat	81.85	85.23	39.48	98.34	92.27	91.33	121.44	142.56	104.92
					D. College-educated men (all experience levels)				
	-0.034	-0.123*	-0.030	-0.028	-0.097*	-0.074	-0.070*	-0.041	-0.065*
	(0.061)	(0.048)	(0.049)	(0.047)	(0.047)	(0.046)	(0.031)	(0.034)	(0.029)
Obs	508	884	1,046	1,109	1,107	1,242	1,252	1,293	1,141
F-Stat	100.95	115.03	123.38	97.29	122.42	208.04	260.47	218.64	229.40

Standard errors in parentheses. * Denotes significance at 0.05 level.

μ_t Implied by 2SLS Estimates ($\mu_{1985} = 1$)



- Return to skill declined around 50% from 1985 to 2005

Minimum Distance (MD) Estimation

- We now use all autocovariances of $w_{i,t}$ to estimate all parameters
  - Total 2,824 autocovariances
- MD estimator $\hat{\mathbf{\Lambda}}$ minimizes the distance between the data and model covariances

$$\min_{\mathbf{\Lambda}} \sum_{s,c,t' \leq t} \left\{ \widehat{\text{Cov}}(w_t, w_{t'}|s,c) - \text{Cov}(w_t, w_{t'}|s,c,\mathbf{\Lambda}) \right\}^2$$

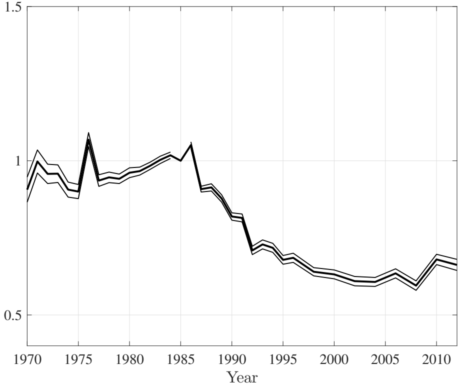
where s is the indicator for college attendance

- For a given $\mathbf{\Lambda}$, we construct model covariances by assuming:

$$\theta_{i,t} = \psi_i + \sum_{j=0}^{t-c_i+1} \nu_{i,t-j}, \quad \varepsilon_{i,t} = \sum_{j=0}^{\min\{5,t-c_i+1\}} \beta_j \xi_{i,t-j}$$

  - We allow for cohort-specific variances $\text{Var}(\psi|c), \text{Var}(\nu_t|c), \text{Var}(\xi_t|c)$

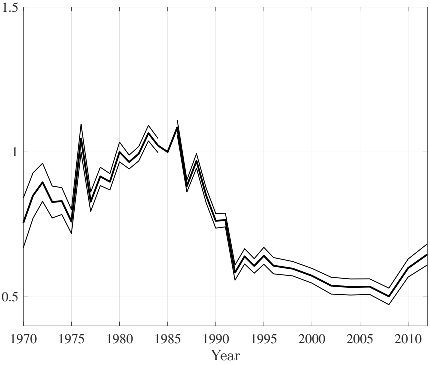
MD Estimates of μ_t: Full Sample ($\mu_{1985} = 1$)



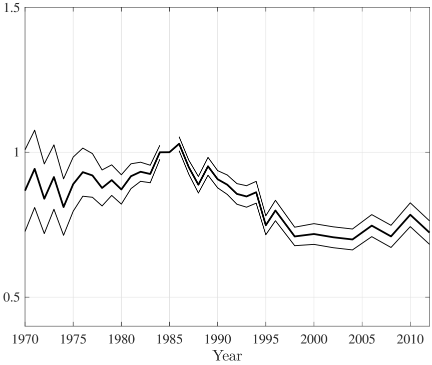
- Substantial decline from 1985 to 2005 consistent with IV estimates

Importance of Time-varying Skill Variance
Accounting for Heterogeneity in Skill Growth

μ_t Estimated Separately by College Attendance



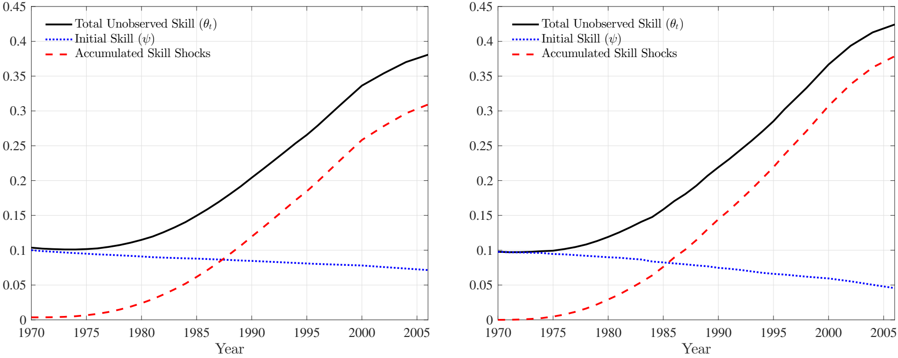
(a) Non-College



(b) College

- Reject the hypothesis of identical returns for two groups
- Stronger decline for non-college workers

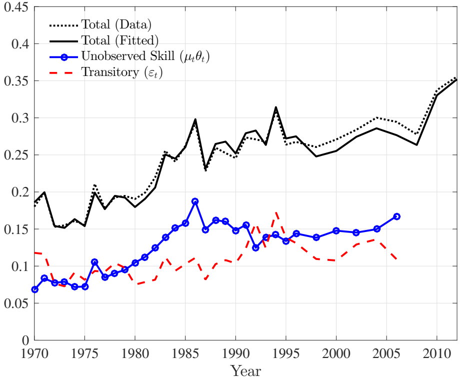
Estimated Variance of Unobserved Skill



(a) Non-College (b) College

- Rising skill variance driven by increasing variance in accumulated skill shocks rather than initial skill

Decomposition of Residual Variance



- Long-run trend in residual variance largely driven by unobserved skill

By College Attendance
Other estimates

Interpreting the Falling Returns

- Why have the returns to skill fallen?
  - Changes in demand or supply?
- We offer a new quantitative framework based on the job assignment model of Sattinger (1979) and Gabaix & Landier (2008)
  - Abstract from transitory wages (i.e., treat as measurement errors)
  - Model gives log wage equation consistent with empirical model
  - Equilibrium conditions can be combined with our estimates to recover changes in demand and supply

Job Assignment Model

- Workers differ by skill $\Theta_t = g_t(\boldsymbol{x}_t) + \theta_t$, normally distributed with mean $\mathrm{E}[\Theta_t]$ and standard deviation $\sigma(\Theta_t)$
- Jobs differ by productivity Z_t, normally distributed with mean $\mathrm{E}[Z_t]$ and standard deviation $\sigma(Z_t)$
- Output is produced through one-to-one matching of workers and jobs

$$\ln Y_t(\Theta_t, Z_t) = \lambda_t \Theta_t + \gamma_t Z_t$$

- Competitive labor market with hedonic wage function $W_t(\Theta_t)$
- Taking $W_t(\Theta_t)$ as given, employer with productivity Z_t solves

$$\max_{\Theta_t} \left\{ Y_t(\Theta_t, Z_t) - W_t(\Theta_t) \right\}$$

  - Let the 'matching function', $\hat{Z}_t(\Theta_t)$, be the inverse of the solution
- Labor market clearing condition:

$$\hat{Z}_t(\Theta_t) = \mathrm{E}[Z_t] + \frac{\sigma(Z_t)}{\sigma(\Theta_t)}(\Theta_t - \mathrm{E}[\Theta_t]),$$

Closed Form Formula for the Return to Skill

Recall: $\ln Y_t(\Theta_t, Z_t) = \lambda_t \Theta_t + \gamma_t Z_t$

$$\frac{d \ln W_t(\Theta_t)}{d\Theta_t} = \underbrace{\lambda_t}_{\text{direct}} + \underbrace{\gamma_t \frac{d\hat{Z}_t(\Theta_t)}{d\Theta_t}}_{\text{sorting}} = \lambda_t + \gamma_t \frac{\sigma(Z_t)}{\sigma(\Theta_t)}$$

- More skilled workers receive higher wages because
  - They produce more at any given job (λ_t)
  - They also work at more productive jobs ($\gamma_t \sigma(Z_t)/\sigma(\Theta_t)$)
- Sorting effect depends on the slope of the matching function $\sigma(Z_t)/\sigma(\Theta_t)$
  - Small if everyone works at the same job ($\sigma(Z_t) \approx 0$)
  - Large if everyone has the same skill ($\sigma(\Theta_t) \approx 0$)

Recovering Demand and Supply Factors

- Equating the estimated return with its theoretical counterpart:

$$\mu_t = \lambda_t + \gamma_t \frac{\sigma(Z_t)}{\sigma(\Theta_t)}$$

- We also derive the formula for the labor share:

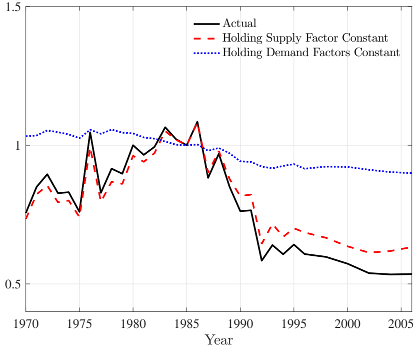
$$\frac{W_t(\Theta_t)}{Y_t(\Theta_t, \hat{Z}_t(\Theta_t))} = \frac{\lambda_t}{\lambda_t + \gamma_t \frac{\sigma(Z_t)}{\sigma(\Theta_t)}} \Rightarrow \lambda_t = \mu_t \times \text{labor share}$$

- Variance of skill:

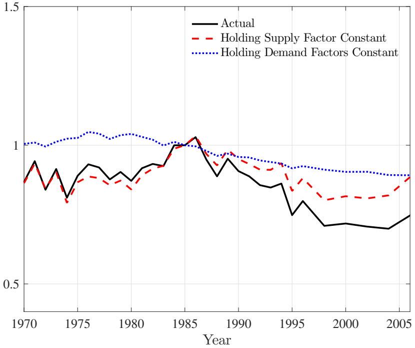
$$\sigma(\Theta_t)^2 = \frac{\text{Var}(\ln W_t) - \text{Var}(\varepsilon_t)}{\mu_t^2}$$

- Finally, $\gamma_t \sigma(Z_t) = (\mu_t - \lambda_t)\sigma(\Theta_t)$

Effects of Demand and Supply Factors on Skill Returns



(a) Non-College



(b) College

- Falling skill returns driven mostly by demand factors for non-college workers
- Both supply and demand forces driving decline for college workers

Implications for the Nature of Technical Changes

Demand-driven fall in skill returns after the mid-1980s

- Challenges the skill-biased technical change hypothesis
  - New technologies complement skilled labor and raise its relative demand
  - Skilled workers are also better at adopting new technologies ('Nelson-Phelps hypothesis')
- Consistent with Schumpeterian growth through creative destruction
  - Innovations involve radically new techniques rather than improvements in existing methods
  - Some skills become obsolete, while new set of skills are required
    - Workers who are equally productive today might become differentiated tomorrow $\Rightarrow$ large skill changes
  - Similar to 'turbulence' by Ljungqvist & Sargent (1998, 2008)

Conclusions

- We use panel data to separately identify changes in skill returns from changes in the distributions of labor market skills
  - Simple IV strategy can identify changes in the return to skill
- Using the PSID, we show that
  - Skill returns have *declined* substantially since the mid-1980s
    - Stronger declines for non-college men
  - Variance of unobserved skills increased markedly
    - Driven by increase in variances of skill growth shocks
- Develop an equilibrium framework to interpret the falling returns
  - Driven by both demand and supply factors
  - Fall in demand is more important for non-college workers

Thank You!

Appendix

Identifying Early Skill Returns

- Using future residuals as instruments would allow us to identify growth in early returns, but these are biased: for $t' \geq t + k$,

$$\frac{\text{Cov}(w_t, w_{t'})}{\text{Cov}(w_{t-1}, w_{t'})} = \frac{\mu_t \mu_{t'} \text{Var}(\theta_t)}{\mu_{t-1}\mu_{t'} \text{Var}(\theta_{t-1})} = \frac{\mu_t}{\mu_{t-1}} \left(\frac{\text{Var}(\theta_{t-1}) + \text{Var}(\nu_t)}{\text{Var}(\theta_{t-1})} \right)$$

- Can difference this out if we have two cohorts such that $\text{Var}(\nu_t | c) = \text{Var}(\nu_t | c')$
  - Satisfied with U-shaped variance in age/experience (Baker & Solon 2003, Blundell, Graber & Mogstad 2015)
- For $t' \geq t + k$,

$$\frac{\text{Cov}(w_t, w_{t'}|c) - \text{Cov}(w_t, w_{t'}|c')}{\text{Cov}(w_{t-1}, w_{t'}|c) - \text{Cov}(w_{t-1}, w_{t'}|c')} = \frac{\mu_t}{\mu_{t-1}}$$

- So μ_t/μ_{t-1} is identified for all t if $\overline{t} - \underline{t} \geq 2k$

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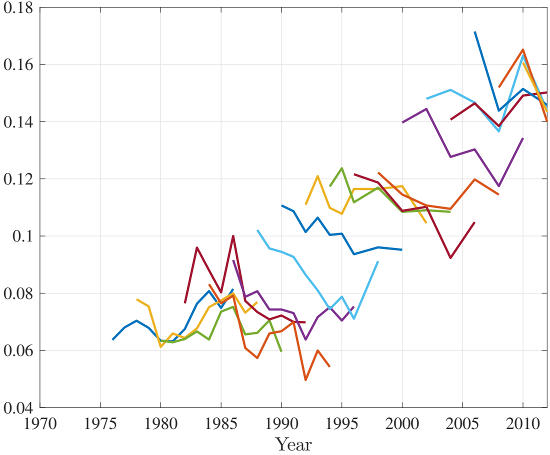
'Balanced' Sample



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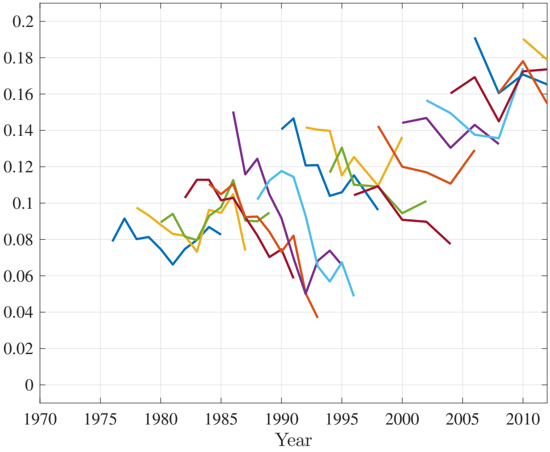
16-30 Years of Experience



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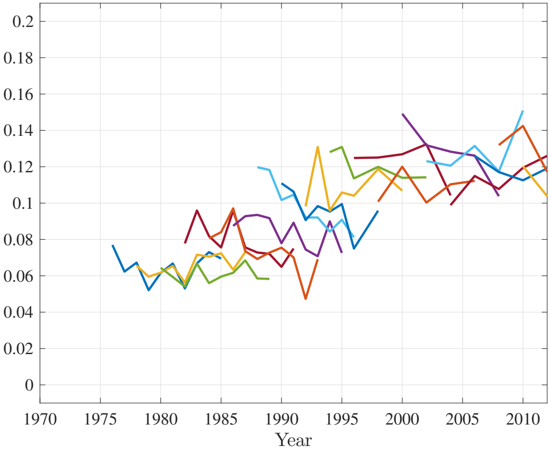
1-15 Years of Experience



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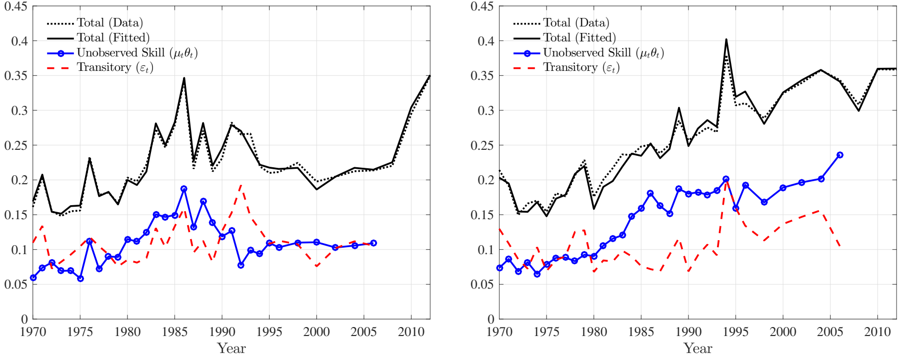
Variance Decomposition: Estimated by College Attendance



(a) Non-College

(b) College

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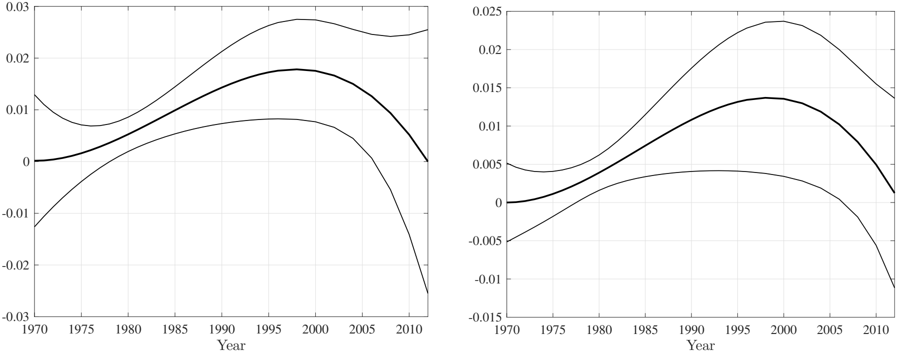
Time Trends in Skill Shock Variances ($\pi(t)$)



(a) Non-College (b) College

- Rising variance of permanent shocks not purely a composition effect (as in Lemieux (2006))

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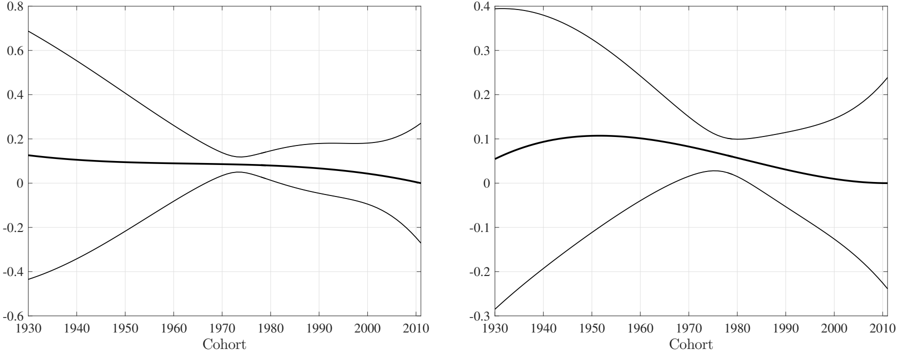
Cohort Trends in Initial Skill Variances



(a) Non-College (b) College

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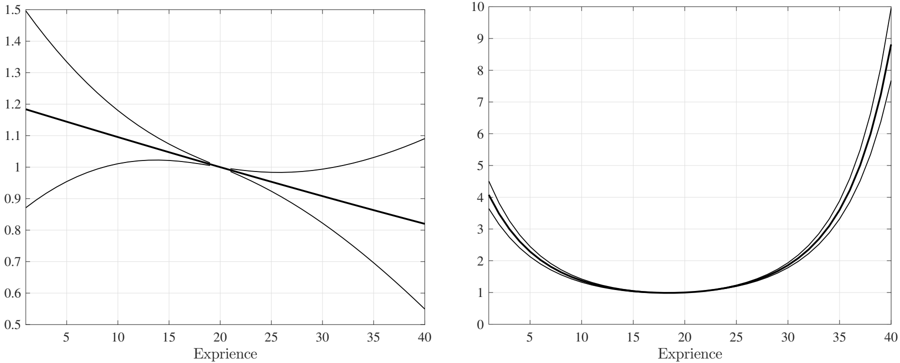
Experience Trends in Skill Shock Variances



(a) Non-College (b) College

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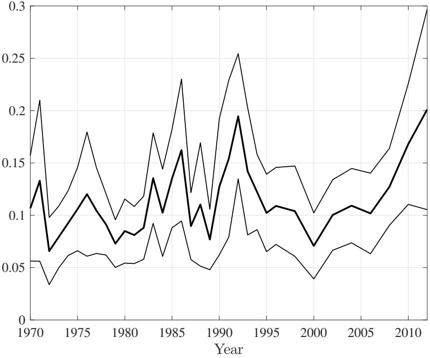
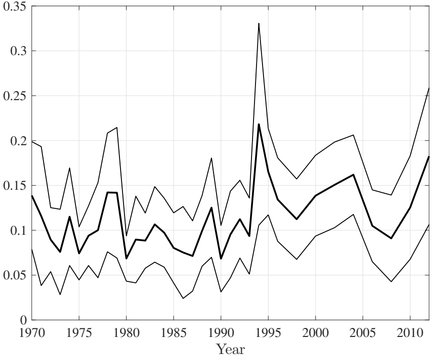
Time Trends in Transitory Shock Variances



(a) Non-College



(b) College

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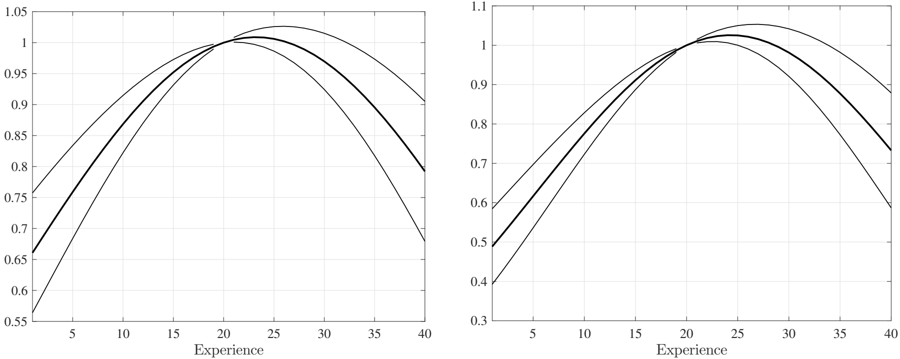
Experience Trends in Transitory Shock Variances



(a) Non-College (b) College

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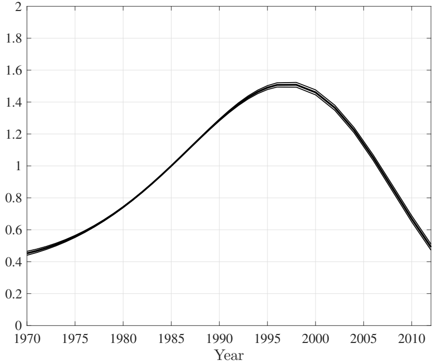
χ_t



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1995
2000
2005
2010
Year

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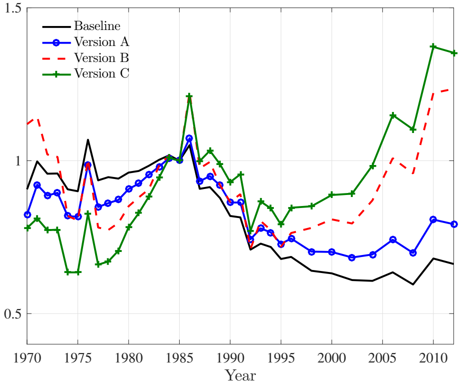
Importance of Accounting for Time-Varying Skill Variance

- Haider (2001) and Moffitt and Gottschalk (2012) estimated similar models using PSID, but they reached different conclusions about μ_t
- We argue that the difference is due to the time-invariant skill distribution assumed in the previous MD estimates
  - Initial skill variances are identical across cohorts and skill shock variances are constant over time
- Without time-varying skill variances, the model is 'forced' to explain the increase in residual variance via increasing μ_t

Estimated μ_t under Different Restrictions: Full Sample



- Version A: ARMA(1,1) transitory component (rather than MA(5))
- Version B: Version A+no time trend in skill shock variance $\pi(t)$
- Version C: Version B+cohort-invariant initial skill variance $\mathrm{Var}(\psi|c)$
    - Very similar to Haider (2001) and Moffitt and Gottschalk (2012)

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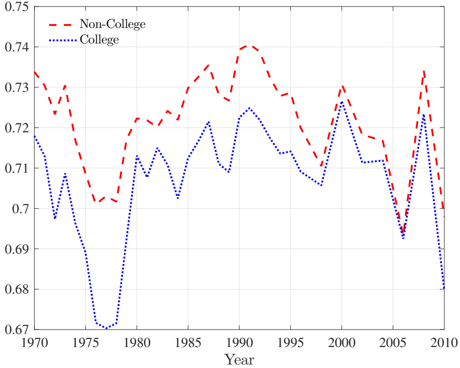
Labor Share

- Challenge: we need sector-specific labor shares
- We use industry-specific labor shares weighted by fraction of workers by education type
- KLEMS data for US, 1970-2010 (Jorgenson, et al. 2012)



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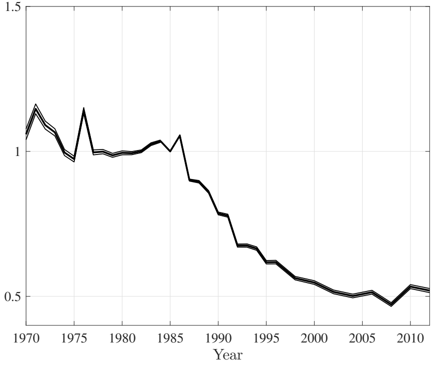
Accounting for Heterogeneous Skill Growth

- Rising skill variance may reflect systematic growth rather than shocks
  - 'Heterogeneous income profile': e.g., Baker (1997), Guvenen (2009)
- Consider general HIP process:

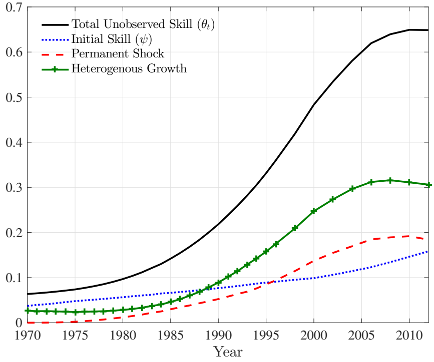
$$\theta_{i,t} = \theta_{i,t-1} + \chi_t \eta(e_{i,t})\delta_i + \nu_{i,t}$$

  - δ_i is a mean zero individual-specific growth rate
    - Uncorrelated with all shocks, but may be correlated with ψ
    - Assume no cohort trend in $\text{Var}(\delta)$ and $\text{Cov}(\delta, \psi)$
  - $\eta(e) = \max\{1 - e/30, 0\}$ accounts for diminishing growth rates
    - No systematic growth after 30 years of experience$\Rightarrow$ helps identify μ_t
  - χ_t allows for time-varying differences in systematic skill growth
    - Assume cubic polynomial in time

Estimates with HIP: Full Sample



(a) μ_t



(b) Skill Variance Decomposition

- Systematic skill growth is important for rising skill variance
- But time pattern of μ_t is robust to the HIP process

▸ χ_t ◂ Back