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 ⇒ 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 $t$:
    \[ w_{i,t} = \mu_t \times \theta_i \]
    - 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.

\[
\text{Var}(\theta_t) = \sum_j p_{j,t} \text{Var}(\theta_j)
\]

- **Short-term fluctuations** in earnings have also increased (Gottschalk & Moffitt 1994).
  - Reflects measurement errors or transitory shocks unrelated to skills:
    \[
    w_{i,t} = \theta_i + \varepsilon_{i,t}
    \]
  - 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 $t = t, t + 1, \ldots, T$

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

- $\theta_{i,t}$ reflects time-varying unobserved skills
- $\mu_t$ 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

\[ w_{i,t} = \mu_t \theta_{i,t} + \varepsilon_{i,t} \]
\[ \theta_{i,t} = \theta_{i,t-1} + \nu_{i,t} \]

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

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

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

- 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, \( \mu_t/\mu_{t-1} \) is identified for all \( t > t + k \)
  - 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 \textit{declining} \( \mu_t \)
- Upward shifting lines suggest \textit{increasing} \( \text{Var}(\theta_b) \)
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 $\mu_t$

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<tbody>
<tr>
<td><strong>A. All men</strong></td>
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<td>-0.044</td>
<td>-0.046</td>
<td>-0.081*</td>
<td>-0.082*</td>
<td>-0.067</td>
<td>-0.075*</td>
<td>-0.039</td>
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<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.034)</td>
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<td>(0.035)</td>
<td>(0.025)</td>
<td>(0.028)</td>
<td>(0.027)</td>
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<td>2,188</td>
<td>2,245</td>
<td>2,189</td>
<td>2,095</td>
<td>2,122</td>
<td>2,129</td>
<td>1,968</td>
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<td>$F$-Stat</td>
<td>163.09</td>
<td>191.61</td>
<td>114.85</td>
<td>209.42</td>
<td>227.13</td>
<td>286.96</td>
<td>369.09</td>
<td>344.25</td>
<td>341.36</td>
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<td><strong>B. All men with 21–40 years of experience (at year $t$)</strong></td>
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<td>-0.052</td>
<td>-0.088*</td>
<td>-0.031</td>
<td>-0.100*</td>
<td>-0.036</td>
<td>-0.104*</td>
<td>-0.084*</td>
<td>-0.040</td>
<td>-0.058</td>
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<td>(0.050)</td>
<td>(0.043)</td>
<td>(0.050)</td>
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<td>(0.045)</td>
<td>(0.030)</td>
<td>(0.032)</td>
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<td>Obs</td>
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<td>1,244</td>
<td>1,211</td>
<td>1,244</td>
<td>1,300</td>
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<td>$F$-Stat</td>
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<td>132.19</td>
<td>66.26</td>
<td>130.53</td>
<td>132.83</td>
<td>201.62</td>
<td>295.75</td>
<td>281.91</td>
<td>267.83</td>
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<td><strong>C. Non-college-educated men (all experience levels)</strong></td>
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<td>-0.075</td>
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<td>(0.061)</td>
<td>(0.056)</td>
<td>(0.060)</td>
<td>(0.050)</td>
<td>(0.058)</td>
<td>(0.054)</td>
<td>(0.043)</td>
<td>(0.047)</td>
<td>(0.075)</td>
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<tr>
<td>Obs</td>
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<td>1,080</td>
<td>997</td>
<td>965</td>
<td>897</td>
<td>851</td>
<td>862</td>
<td>826</td>
<td>615</td>
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<td>85.23</td>
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<td><strong>D. College-educated men (all experience levels)</strong></td>
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<tr>
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<td>-0.034</td>
<td>-0.123*</td>
<td>-0.030</td>
<td>-0.028</td>
<td>-0.097*</td>
<td>-0.074</td>
<td>-0.070*</td>
<td>-0.041</td>
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<td></td>
<td>(0.061)</td>
<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.047)</td>
<td>(0.047)</td>
<td>(0.046)</td>
<td>(0.031)</td>
<td>(0.034)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Obs</td>
<td>508</td>
<td>884</td>
<td>1,046</td>
<td>1,109</td>
<td>1,107</td>
<td>1,242</td>
<td>1,252</td>
<td>1,293</td>
<td>1,141</td>
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<tr>
<td>$F$-Stat</td>
<td>100.95</td>
<td>115.03</td>
<td>123.38</td>
<td>97.29</td>
<td>122.42</td>
<td>208.04</td>
<td>260.47</td>
<td>218.64</td>
<td>229.40</td>
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</table>

Standard errors in parentheses. * Denotes significance at 0.05 level.
\( \mu_t \) 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 $\hat{\Lambda}$ minimizes the distance between the data and model covariances
  \[
  \min_{\Lambda} \sum_{s,c,t' \leq t} \left\{ \text{Cov}(w_t, w_{t'}|s, c) - \text{Cov}(w_t, w_{t'}|s, c, \Lambda) \right\}^2
  \]
  where $s$ is the indicator for college attendance
- For a given $\Lambda$, we construct model covariances by assuming:
  \[
  \theta_{i,t} = \psi_i + \sum_{j=0}^{t-c_i+1} \nu_{i,t-j}, \quad \varepsilon_{i,t} = \min\{5, t-c_i+1\} \beta_j \xi_{i,t-j}
  \]
  - We allow for cohort-specific variances $\text{Var}(\psi|c), \text{Var}(\nu_t|c), \text{Var}(\xi_t|c)$
MD Estimates of $\mu_t$: 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
\( \mu_t \) Estimated Separately by College Attendance

- Reject the hypothesis of identical returns for two groups
- Stronger decline for non-college workers
Rising skill variance driven by increasing variance in accumulated skill shocks rather than initial skill
• Long-run trend in residual variance largely driven by unobserved skill
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 $\Theta_t = g_t(x_t) + \theta_t$, normally distributed with mean $E[\Theta_t]$ and standard deviation $\sigma(\Theta_t)$
- Jobs differ by productivity $Z_t$, normally distributed with mean $E[Z_t]$ 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

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

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

$\hat{Z}_t(\Theta_t) = E[Z_t] + \frac{\sigma(Z_t)}{\sigma(\Theta_t)} (\Theta_t - E[\Theta_t])$,
Closed Form Formula for the Return to Skill

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

\[
\frac{d \ln W_t(\Theta_t)}{d \Theta_t} = \lambda_t + \gamma_t \frac{d \hat{Z}_t(\Theta_t)}{d \Theta_t} = \lambda_t + \gamma_t \frac{\sigma(Z_t)}{\sigma(\Theta_t)}
\]

- More skilled workers receive higher wages because
  - They produce more at any given job (\( \lambda_t \))
  - 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

- 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 ⇒ 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 \( \mu_t / \mu_{t-1} \) is identified for all \( t \) if \( \bar{t} - t \geq 2k \)
16-30 Years of Experience
1-15 Years of Experience
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))
Cohort Trends in Initial Skill Variances

(a) Non-College

(b) College
Experience Trends in Skill Shock Variances

(a) Non-College

(b) College
Time Trends in Transitory Shock Variances

(a) Non-College

(b) College
Experience Trends in Transitory Shock Variances

(a) Non-College

(b) College
$\chi_t$
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 $\mu_t$
- 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 $\mu_t$
Estimated $\mu_t$ 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 $\text{Var}(\psi|c)$
  - Very similar to Haider (2001) and Moffitt and Gottschalk (2012)
Labor Share

- Challenge: we need sector-specific labor shares
- We use industry-specific labor shares weighted by fraction of workers by education type
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:

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

- \( \delta_i \) is a mean zero individual-specific growth rate
  - Uncorrelated with all shocks, but may be correlated with \( \psi \)
  - Assume no cohort trend in Var(\( \delta \)) and 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 \( \mu_t \)
- \( \chi_t \) allows for time-varying differences in systematic skill growth
  - Assume cubic polynomial in time
Estimates with HIP: Full Sample

(a) $\mu_t$

(b) Skill Variance Decomposition

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