Earnings Equation Estimation

Earnings Equations

We have discussed (and will discuss more) studies that attempt to identify the “factors” that contribute to the earnings gap.

Before evaluating case evidence, we need a short overview of the techniques used to perform an earnings regression.

**Goal:** Determine if there are wage differences between groups after accounting for differences in productivity measures → possible evidence for discrimination.
Explained and Unexplained differences

Recall:

- **Discrimination**: When two individuals with identical observed characteristics besides group membership have systematically different outcomes.

- Unproductive demographic attributes (i.e. gender, race, etc.) are priced in the labor market as if they were a compensating differential.

- Need a way to equalize skill to assess whether the observed wage differences are inconsistent with productivity.
Modeling Earnings

Jacob Mincer’s *Schooling, Experience and Earnings* (1974)

Rationale:
- \( w = MP_L \) = function of skills
- Skill influenced by several factors including education, experience, and tenure

Goals:
- Empirically estimate wages
- Mimic observed empirical regularities in the data

Mincer’s Original Data: Education, Experience, and Earnings

![Figure 2.3 Experience-earnings profiles for white non-farm men by schooling level, 1959. Source: Mincer, 1974, 67](image)
Earnings and education levels

- Holding experience constant, we can evaluate how earnings increase for each education level
- As years of schooling increase, monetary difference increases
Schooling and Income

- Income increasing non-linearly
- $\ln(\text{income})$ appears to be increasing linearly

Estimated Earnings Functions

Nearly universally estimated in log-linear form

Typical Earnings Function:

$$\ln(\text{Wages}) = \beta X + \epsilon$$

where:

- $X$ includes measurable characteristics (education, experience, etc.)
- $\beta$ includes estimated coefficients on variables in $X$
- $\epsilon$ is random error with zero mean
Mincer’s Equation

\[
\ln(W) = \alpha + \beta S + \gamma_1 E + \gamma_2 E^2
\]

where

- S is years of schooling
- E is experience (Age - Ed - 6)

Mincer’s fitted equation:

\[
\ln(W) = 6.20 + 0.107S + 0.081E - 0.0012E^2
\]

- 10.7% return per year of schooling
- Change in wages with respect to experience zero when experience is 33.8 years \( \left( \frac{d\ln(W)}{dE} = 0 \right) \)

Computing Market Discrimination - Simple Regression

Assume unfavored group is paid a constant discount \( D_F \) relative to favored group with the same skills

\[
\ln(Wage) = \beta X + D_F F + \epsilon
\]

where

- F is a dummy variable that equals 1 if the individual is female and 0 otherwise
- \( D_F \) is the coefficient on F that measures the proportional effect of female status on \( \ln(Wage) \)

Similar approach can be done for any group aspect (race, age, etc.)
Empirical Evidence for Basic Regression

Table 11.3  
Determinants of Log Hourly Wages for Men Aged 35 to 42

<table>
<thead>
<tr>
<th></th>
<th>Black</th>
<th>Hispanic</th>
<th>Controlling for Age/10</th>
<th>Controlling for Education</th>
<th>Controlling for AFQT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.37</td>
<td>-0.20</td>
<td>0.17</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.29</td>
<td>-0.11</td>
<td>0.17</td>
<td>0.10</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.12)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-0.11</td>
<td>-0.03</td>
<td>0.07</td>
<td>—</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.13)</td>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>4</td>
<td>-0.17</td>
<td>-0.04</td>
<td>0.13</td>
<td>0.06</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.12)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

Note: See footnote 15 for a reminder about interpretation of logs.

Simple Regression with Dummy Variables

This method is very restrictive:

- Assumes men and women have the same returns to schooling, experience and all other factors included in the equation

This led to the development of the most common method: Oaxaca decomposition
Oaxaca Decomposition

Consider separate regressions for men and women:

\[
\ln(W_M) = \beta_M X_M + \epsilon_M \quad \text{for males}
\]
\[
\ln(W_F) = \beta_F X_F + \epsilon_F \quad \text{for females}
\]

Observed difference: \( \ln(W_M) - \ln(W_F) \)

Decompose observed difference:

\[
\ln(W_M) - \ln(W_F) = (\beta_M X_M + \epsilon_M) - (\beta_F X_F + \epsilon_F) + (\beta_M X_F - \beta_M X_F)
\]
\[
= \beta_M (X_M - X_F) + X_F (\beta_M - \beta_F) + (\epsilon_M - \epsilon_F)
\]

Oaxaca Decomposition

Three reasons for wage differences:

- \( \beta_M (X_M - X_F) \): Explained difference due to gap in skills
  - Holding returns to skill constant, this component is the wage difference due to differing skill levels

- \( X_F (\beta_M - \beta_F) \): Unexplained difference due to gap in returns to skill
  - Holding skill level constant, this is the wage difference due to differing returns to skill

- \( \epsilon_M - \epsilon_F \): Mean zero error
Oaxaca Decomposition Approach

1. Fit male wage equation to find $\hat{\beta}_M$
   - $\ln(W_M) = X_M \beta_M + \epsilon_M$

2. Predict wage female would earn if she were rewarded like a man
   - $\ln(\tilde{W}_F) = X_F \beta_M$

3. Calculate explained difference (due to skill differences)
   - $\ln(W_M) - \ln(\tilde{W}_F) = \beta_M (X_M - X_F)$

4. Calculate unexplained difference = observed - explained differences
   - $[\ln(W_M) - \ln(W_F)] - [\ln(W_M) - \ln(\tilde{W}_F)] = \ln(\tilde{W}_F) - \ln(W_F)$
   - Measure of discrimination

---

Empirical Results - Oaxaca Decomposition

<table>
<thead>
<tr>
<th>Decomposition of race and gender wage differentials.</th>
<th>Blacks vs whites</th>
<th>Hispanics vs. whites</th>
<th>Females vs males</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification</td>
<td>Partial</td>
<td>Full</td>
<td>Partial</td>
</tr>
<tr>
<td>Part (A) 1979</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (hourly wage) difference</td>
<td>-0.165</td>
<td>-0.126</td>
<td>-0.0457</td>
</tr>
<tr>
<td>Amount due to Characteristics</td>
<td>-0.063</td>
<td>-0.108</td>
<td>-0.086</td>
</tr>
<tr>
<td>Coefficients</td>
<td>-0.102</td>
<td>-0.061</td>
<td>-0.041</td>
</tr>
<tr>
<td>Part (B) 1995</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (hourly wage) difference</td>
<td>-0.211</td>
<td>-0.305</td>
<td>-0.286</td>
</tr>
<tr>
<td>Amount due to Characteristics</td>
<td>-0.082</td>
<td>-0.114</td>
<td>-0.193</td>
</tr>
<tr>
<td>Coefficients</td>
<td>-0.134</td>
<td>-0.098</td>
<td>-0.112</td>
</tr>
</tbody>
</table>

Partial: Controls for Education, Experience, Gender or Race if appropriate, SMSA, Region.

Oaxaca Decomposition Concerns

- Too few elements in X (i.e. missing variables)
  - Undercontrol for skill differences

- Measurement error in experience
  - Potential experience isn’t a perfect measure actual experience

- Use of too many elements in X
  - Include variables that may be subject to discrimination
  - Examples:
    - Black-white school quality differences
    - Men-women access to training and job assignment differences

CASE EVIDENCE: WOMEN
We have discussed several studies that evaluated gender labor market discrepancies

- HH Formation and Production
- Empirical Evidence

Recall:

- Significance of 59 cents per dollar
- Slower convergence in 1990
- Reversal of college gender gap

Blau and Kahn (2000) - “Gender Differences in Pay”

Two (non-exclusive) effects within past 25 years:

1. Gender pay gap narrowed \( \left( \text{i.e. } \frac{\text{female earnings}}{\text{male earnings}} \uparrow \right) \)

2. Women entered traditionally male occupations
Women Blau and Kahn. 2000

Female to Male Earnings Ratio - USA

- 1970s: relative pay for women began to rise
- Mid-1990s: plateaued

Blau and Kahn (2000) - Increase in earnings ratio

2 possible reasons for increase in gender earnings ratio:

1. Entry of new cohorts with better job-related characteristics and facing less discrimination → between cohort differences

2. Upward progression over time in gender ratio within cohorts

Data from the Current Population Survey (CPS) find both between and within cohort effects have played a role in the narrowing of the gender gap.

- Important to consider both the entry to new cohorts AND the earnings growth of older cohorts
Blau and Kahn (2000) - Occupational Choice

- Women used to be concentrated in administrative support and service occupations
  - 1970s: 53% of women workers in and 15% of male workers
  - 1990s: 41% of women workers and 15% of male workers

- Drop in women college graduates who became teachers
  - 1960: Approximately 50%
  - 1990: Less than 10%

- Occupational segregation reduced dramatically in 1980s but reduced slower in 1990s

- Recall: Even if occupational segregation is low, women may be concentrated in lower-paying industries and firms

Blau and Kahn (2000) - Other empirical studies

Blau and Kahn (1997)

- Evaluated the male-female wage differential
  - Raw differential: 27.6%

- Gender differences in education, experience, and race accounted for \( \sim 33\% \) of the total gender gap (i.e. \( \sim 9\% \) of the original gap)
  - Differences in experience were substantial

- Occupation, industry and unionism accounted for 29% of the total gender gap (i.e. \( \sim 8\% \) of original gap)

- Adjusting for all variables reduced gap to 11.8%

Note: the residual gap may reflect other factors besides discrimination
Blau and Kahn (2000) - Other empirical studies

Wood, Corcoran and Courant (1993)

- 1972-1975 University of Michigan Law School graduates 15 years after graduation
- Pay gap between women and men earnings:
  - Small at beginning of career
  - Women earned only 60% of men 15 years after graduation
- After controlling for other covariates, men had a 13% earnings advantaged

Weinberger (1998)

- Recent college graduates in 1985
- Controlled for educational characteristics
- Unexplained pay gap of 10-15% between men and women

Neumark (1996)

- Hiring “audit” at Philadelphia restaurants
- Female applicants to high priced restaurants were:
  - 40% less likely to get interview
  - 50% less likely to get job offer
Blau and Kahn (2000) - Other empirical studies

Goldin and Rouse (2000)

- Evaluated impact of “blind” auditions for symphony orchestras
  - Used a screen to conceal identity of candidate
- Switch to blind auditions explained 25-46% of the increase in females in the top five U.S. symphony orchestras

Blau and Kahn (2000) - Other factors for wage gap

Recall discussions on:

- Decrease in the size of the unexplained gender gap (wage gap declined despite higher returns for skills)
- Gender differences in college majors
- Marketability of women’s education (lower statistical discrimination)
- Underlying labor market demand shifts
- Technological change (deemphasize physical strength)
- Decreased unionization
- Institutional barriers (glass ceiling)
- Occupational preferences
- Antidiscrimination enforcement (to be discussed later)
### Female/Male Earnings Ratios of Full Time Workers

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.800</td>
<td>0.814</td>
<td>0.868</td>
<td>0.068</td>
</tr>
<tr>
<td>Austria</td>
<td>0.649</td>
<td>0.674</td>
<td>0.692</td>
<td>0.043</td>
</tr>
<tr>
<td>Canada</td>
<td>0.633</td>
<td>0.663</td>
<td>0.698</td>
<td>0.065</td>
</tr>
<tr>
<td>Finland</td>
<td>0.734</td>
<td>0.764</td>
<td>0.799</td>
<td>0.065</td>
</tr>
<tr>
<td>France</td>
<td>0.799</td>
<td>0.847</td>
<td>0.899</td>
<td>0.100</td>
</tr>
<tr>
<td>Germany</td>
<td>0.717</td>
<td>0.737</td>
<td>0.755</td>
<td>0.038</td>
</tr>
<tr>
<td>Japan</td>
<td>0.587</td>
<td>0.590</td>
<td>0.636</td>
<td>0.049</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0.734</td>
<td>0.759</td>
<td>0.814</td>
<td>0.080</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.838</td>
<td>0.788</td>
<td>0.835</td>
<td>-0.003</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>0.626</td>
<td>0.677</td>
<td>0.749</td>
<td>0.123</td>
</tr>
<tr>
<td>United States</td>
<td>0.625</td>
<td>0.706</td>
<td>0.763</td>
<td>0.138</td>
</tr>
<tr>
<td>Non-US Average</td>
<td>0.712</td>
<td>0.746</td>
<td>0.778</td>
<td>0.067</td>
</tr>
</tbody>
</table>

- **1979-1981**: U.S. female/male earnings ratio 9% below the average of all other countries
- **1994-1998**: Marginally below the non-U.S. average
- **Why is U.S. female/male earnings ratio below non-U.S. average?**

**Puzzle:** Mediocre ranking despite the following characteristics

- Do not believe qualifications of women relative to men are lower in U.S. than in other countries
- Do not believe women face more discrimination in U.S.
- U.S. women tend to be relatively more committed to labor force
- Occupational segregation by sex is lower in U.S.
- Women have greater access to traditionally male jobs in U.S.
- Relatively weak entitlement to family leave compared to other countries
- U.S. women's relative qualifications favored in mid-1990s

Possible reasons why U.S. female to male earnings ratio has mediocre ranking:

- U.S. has low rates of collective bargaining coverage

- Minimum wage is lower relative to median wage in U.S. than in most other countries
  - Recall: Women are over-represented in non-standard workforce

- Interindustry and interfirm wage differentials

- Higher level of **wage inequality** in U.S.

Group 4 Presentation

Blau and Kahn (2006) - NOTES
Readings for next sections:

Case Evidence: Blacks
  - Couch and Daly (2002) - GROUP 5

Case Evidence: Hispanics
  - Fry and Lowell (2006)
  - Mora and Davila (2006)

Case Evidence: Immigrants
  - Lubotsky (2007)