Human Capital and Gender Wage Gaps: What is the Explained Difference?

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  - Presumably, choices reflect some sort of optimization subject to constraints.
  - To what extent are constraints exogenous? Max utility s.t. income, but income depends on previous choices.
  - To what extent are exogenous constraints equitably distributed across gender?

Human Capital as an Explanation for Gender Wage Gaps

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  - Another argument is that observed gender wage gaps measure labor market discrimination (an assumed result).
  - Apparently, there is no need to run a single regression!

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- Measurement of human capital is easier said than done.

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- $$\underset{S}{Max} V = \int_S^\infty Ye^{-it} dt \text{ subject to } Y = F(S, A),$$

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- The model can be equivalently expressed in logs:
  $$\ell n(Y) = \ell n F(S, A).$$
  $$\ell n(V) = \ell n(Y) - iS - \ell n(i).$$

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- The model can be equivalently expressed in logs:
  $$\ell n(Y) = \ell n F(S, A).$$
  $$\ell n(V) = \ell n(Y) - iS - \ell n(i).$$
- Let the marginal rate of return to schooling, r, be defined as
  $$r = \frac{\partial \ell n F(S, A)}{\partial S}.$$

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- An individual's discounting rate of interest, i, is uniquely fixed and does not vary with the level of schooling.
- However, since i can also be interpreted as the marginal opportunity cost of an additional year of school, i can vary across individuals.

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     where S^d is the level of schooling demanded at each discounting rate of interest for an individual with a given (fixed) ability level A.

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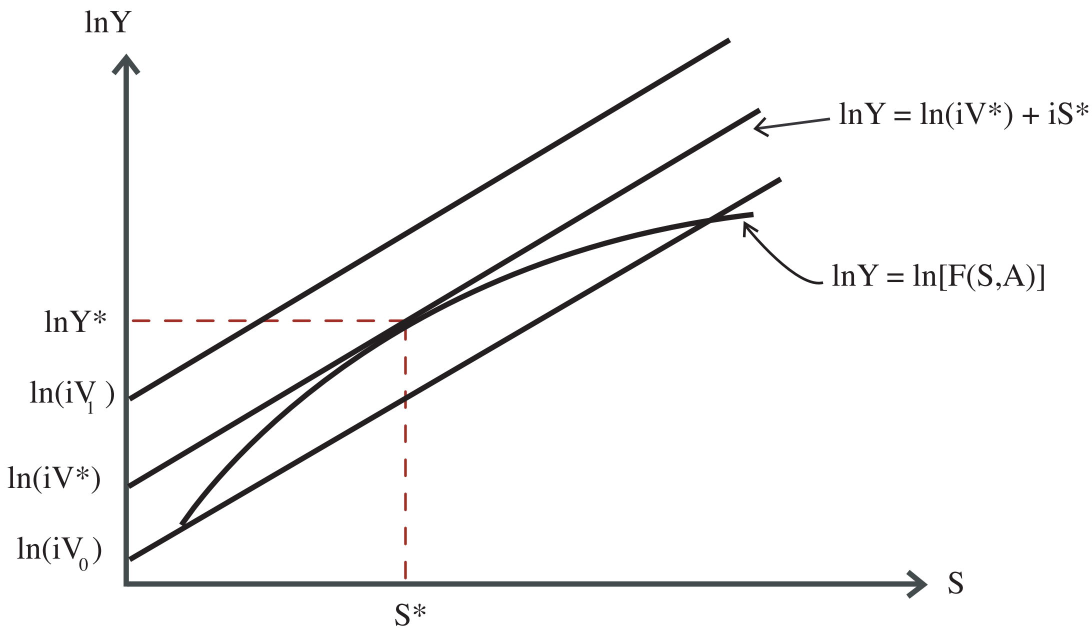
  $$\ell n(Y) = \ell n(iV) + iS.$$
  3. Differentiating the log present value function with respect to S, for a given V, yields i which indexes an individual's supply curve thereby establishing the relationship between the supply of schooling and the discounting rate of interest.

Identification in the Simple Schooling Model

- The individual's years of schooling optimization problem is represented in the following figure.


lnY
lnY = ln(iV*) + iS*
lnY = ln[F(S,A)]
lnY*
ln(iV1)
ln(iV*)
ln(iV0)
S
S*

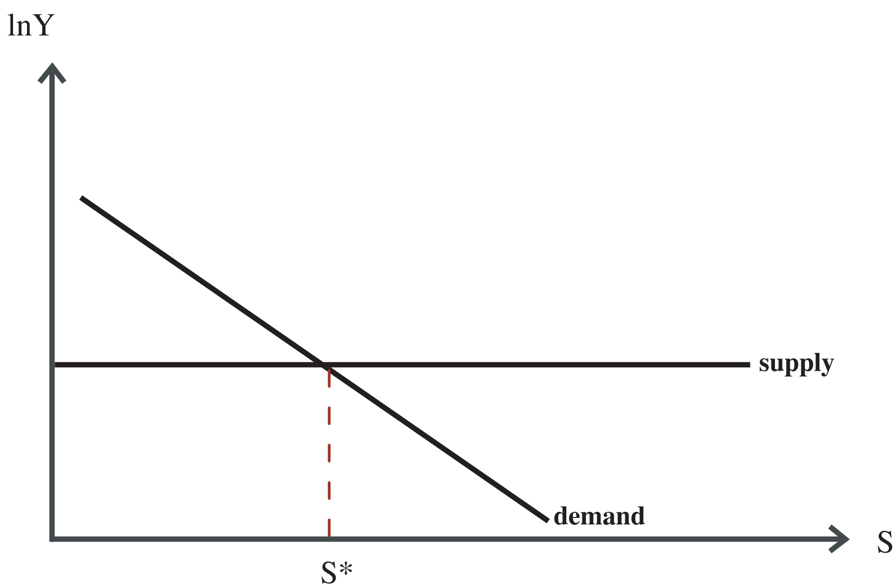

lnY
supply
demand
S
S*

Figure 1

Identification in the Simple Schooling Model

- A labor market with equal opportunity but unequal ability is represented in the following figure.

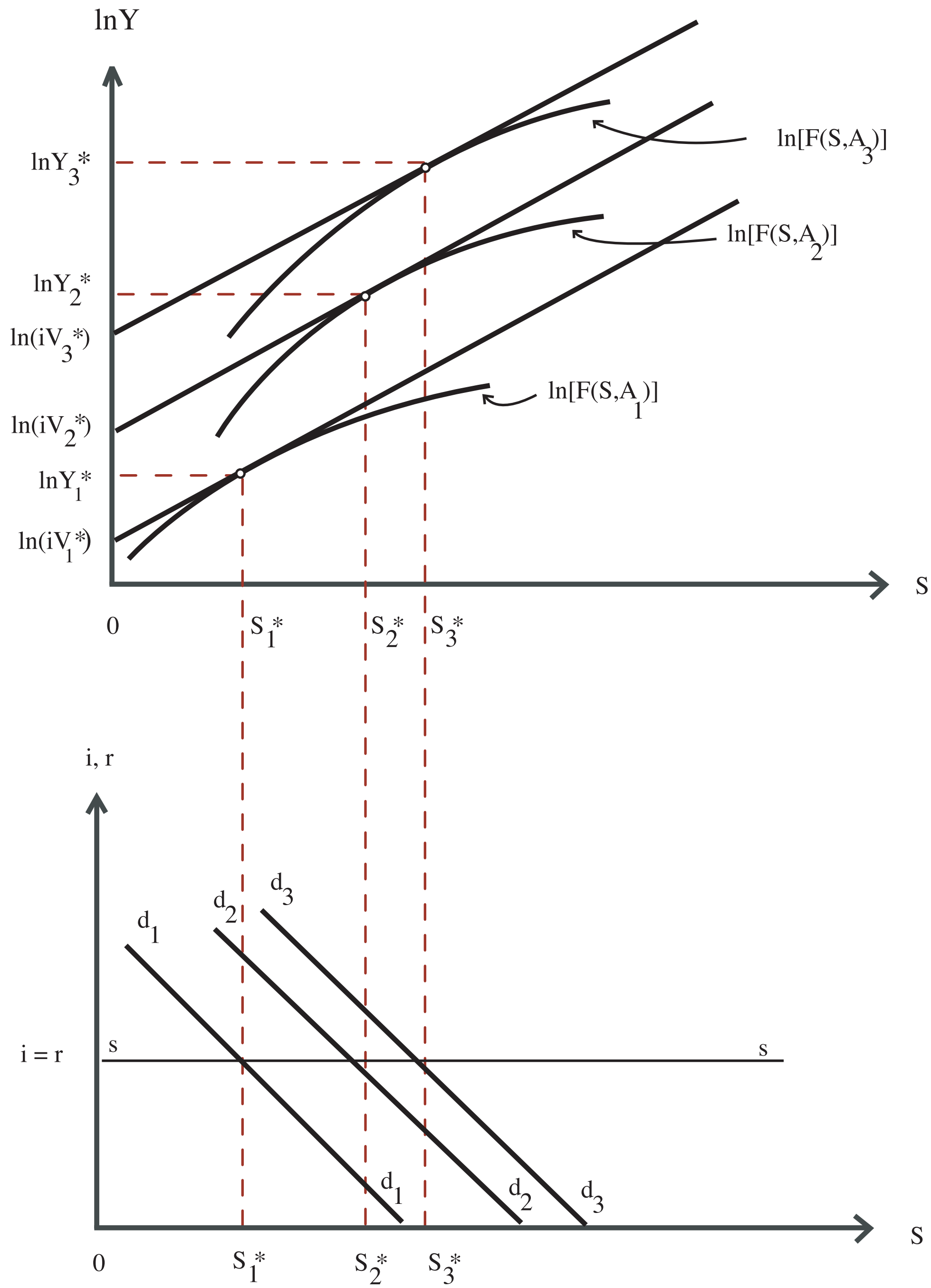
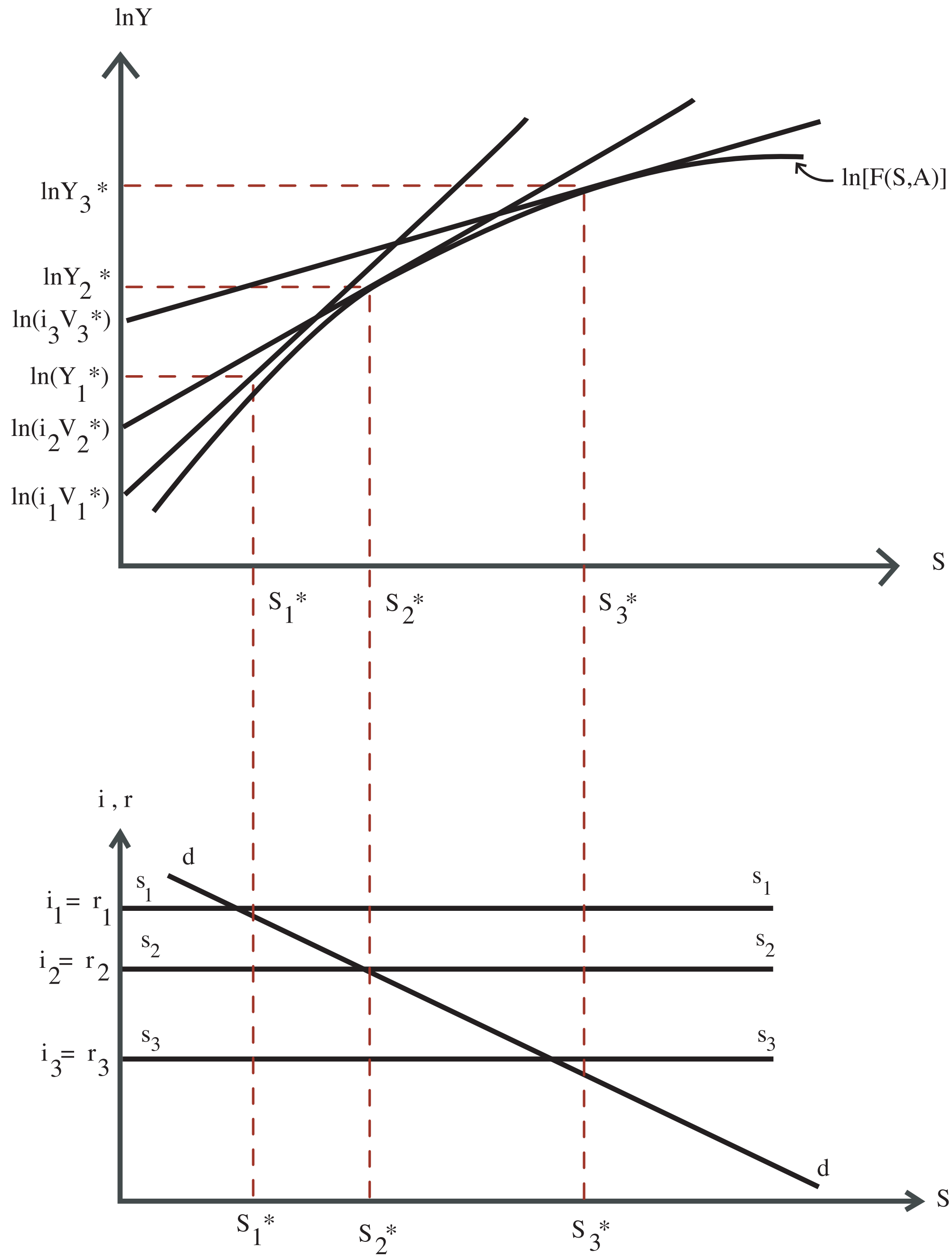

lnY
lnY3*
lnY2*
ln(iV3*)
ln(iV2*)
lnY1*
ln(iV1*)
ln[F(S,A3)]
ln[F(S,A2)]
ln[F(S,A1)]
S
0
S1*
S2*
S3*
i, r
d1
d2
d3
i = r
s
s
d1
d2
d3
S
0
S1*
S2*
S3*

Figure 2

Identification in the Simple Schooling Model

- A labor market with equal abilities but unequal opportunity is represented in the following figure.



lnY
lnY3 *
lnY2 *
ln(i3V3*)
ln(Y1*)
ln(i2V2*)
ln(i1V1*)
ln[F(S,A)]
S
S1*
S2*
S3*
i , r
d
s1
s2
s3
i1= r1
i2= r2
i3= r3
d
S
S1*
S2*
S3*

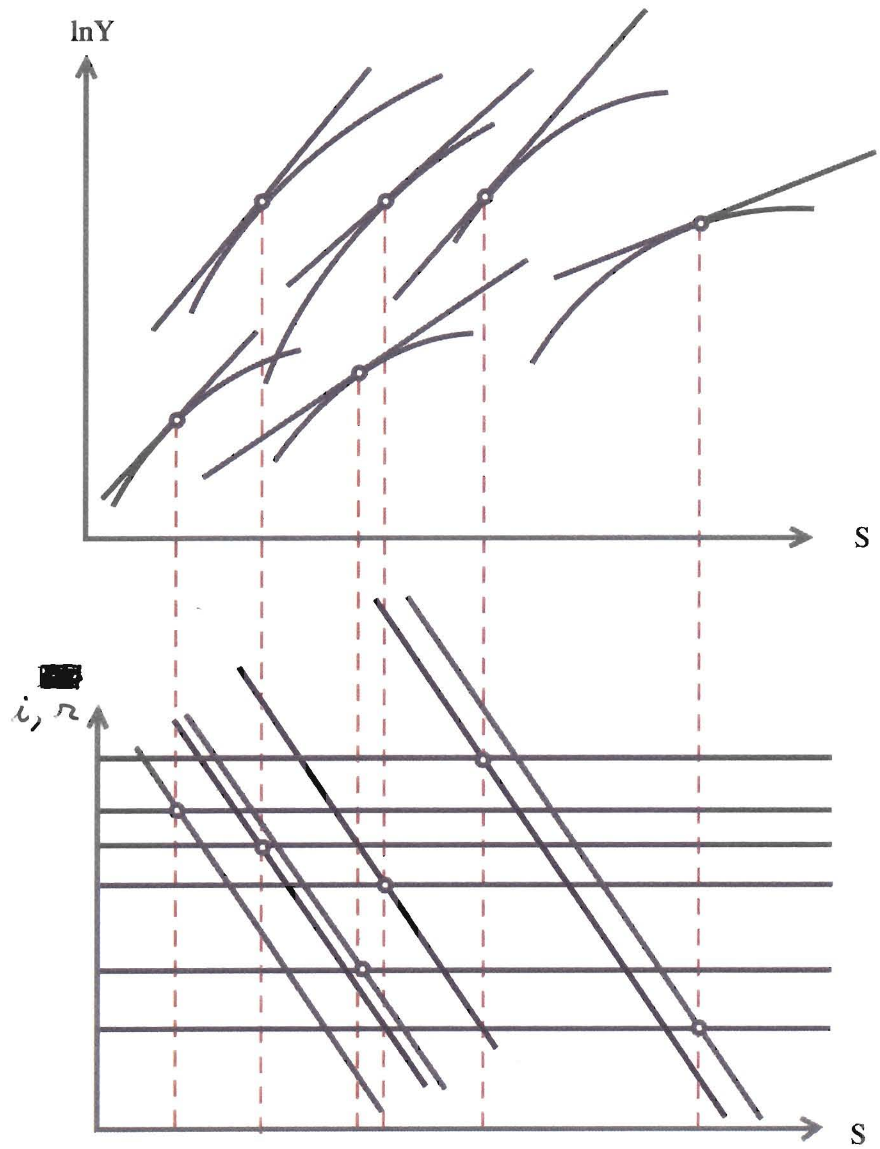
Figure 3

Identification in the Simple Schooling Model

- A labor market with unequal opportunity and unequal abilities is represented in the next figure.
- This figure illustrates why a regression of the form

$$\ell n(Y_i) = \beta_0 + \beta_1 S_i + \varepsilon_i$$

is not identified and why β_1 does not identify r, the marginal rate of return to schooling.



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- Even in this simple model, one can see that gender differences in schooling result from differences in constraints and voluntary choices.

Human Capital and Wage Decompositions

- Standard log wage model

$$\ell n(w_{mi}) = X'_{mi}\beta_m + \varepsilon_{mi}, i = 1, ...N_m$$
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- Wage decomposition assumptions
  - In the absence of discrimination $\beta_m = \beta_f = \beta^*$
  - Endowments (X) are voluntary labor supply side outcomes, though it is generally recognized that pre-labor market discrimination can generate gender differences in X.

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- Standard Wage Decomposition - Blinder (1973), Oaxaca (1973)

$$\bar{Y}_m - \bar{Y}_f = \left(\bar{X}_m' - \bar{X}_f'\right)\hat{\beta}_m + \bar{X}_f'\left(\hat{\beta}_m - \hat{\beta}_f\right).$$

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- $\bar{X}'_f\left(\hat{\beta}_m - \hat{\beta}_f\right)$ can be taken to be an estimate of discrimination but is sometimes referred to as the "unexplained" gap.

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  - Standard wage specifications are used, so why are these equations suddenly misspecified when it is learned that they will be used to estimate discrimination against women?

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- $\hat{\beta}^*$ is an estimate of a nondiscriminatory standard obtained from estimating a pooled wage regression for the combined sample of males and females.
- $\left(\bar{X}_m' - \bar{X}_f'\right)\hat{\beta}^*$ is the endowment effect or "explained" gap (human capital?).
- $\bar{X}_m' \ \left(\hat{\beta}_m - \hat{\beta}^*\right)$ is an estimate of favoritism toward males.
- $\bar{X}_f' \ \left(\hat{\beta}^* - \hat{\beta}_f\right)$ is an estimate of pure discrimination against women.
- $\bar{X}_m' \ \left(\hat{\beta}_m - \hat{\beta}^*\right) + \bar{X}_f' \ \left(\hat{\beta}^* - \hat{\beta}_f\right)$ is an estimate of overall discrimination against women.

Human Capital and Wage Decompositions

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  - In the broader labor market what might statistically appear to be pure wage discrimination probably reflects the incidence of women being employed in lower wage firms.
- Much of the gender disparity in wages is associated with gender disparity in job titles/occupational categories.

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Human Capital and Wage Decompositions

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- Consider the Mincer-type, post-schooling investment model:
- $$\ell n(E_t) = \ell n(E_0) + \tilde{r} \sum_{\tau=0}^{t-1} k_\tau - \delta t$$

  where E_t is earnings capacity in period t, E_0 is earnings capacity in the initial period of work following the completion of schooling, $\tilde{r}$ is the rate of return to post-schooling investments (OJT), k_τ is the fraction of time or time-equivalent invested in OJT in each period prior to t, and δ is the depreciation rate on post schooling human capital.

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- Generally, earnings capacity is not observed. What is observed is earnings net of current human capital investment (Y_t):
- $$\begin{aligned} \ell n(Y_t) &= \ell n(E_t) - k_t \\ &= \ell n(Y_0) + \bar{r}S + \tilde{r}\sum_{\tau=0}^{t-1} k_\tau - \delta t - k_t \end{aligned} \qquad (1)$$

Human Capital and Wage Decompositions

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- $$\sum_{\tau=0}^{t-1} k_\tau = \sum_{\tau=0}^{t-1} k_0 \left(1 - \frac{\tau}{T}\right) \approx k_0 t - \frac{k_0 t^2}{2T}$$

Human Capital and Wage Decompositions

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- $$\ell n(Y_t) = [\ell n(Y_0) - k_0] + \bar{r}S + \left(\tilde{r}k_0 + \frac{k_0}{T} - \delta\right) t - \frac{\tilde{r}k_0 t^2}{2T} \quad (4)$$

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- The interpretation of the parameters according to our formulation of the Mincer model are given by
- $$\begin{aligned} \beta_0 &= \ell n(Y_0) - k_0 \\ \beta_1 &= \bar{r} > 0 \\ \beta_2 &= \tilde{r} k_0 + \frac{k_0}{T} - \delta > 0 \text{ (since } \tilde{r} k_0 > \delta) \\ \beta_3 &= -\frac{\tilde{r} k_0}{2T} < 0 \end{aligned}$$

Human Capital and Wage Decompositions

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Human Capital and Wage Decompositions

- In the light of the Mincer model, should gender differences in the β coefficients from the standard human capital earnings model be interpreted as part of the unexplained wage gap?
- How should gender differences in the constituent human capital parameters $Y_0, k_0, \bar{r}, \tilde{r}, \delta$, and T be regarded in terms of discrimination/unexplained versus explained/human capital components?

Human Capital and Wage Decompositions

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$$L_i^* = H_i'\gamma + \varepsilon_i,$$
$$\ell n(w_i) = X_i'\beta + u_i$$

where L_i^* is a latent variable associated with being employed, H_i', is a vector of determinants of employment, w_i is the market wage, X_i' is a vector of determinants of market wages, γ and β are the associated parameter vectors, and ε_i and u_i are $i.i.d$ error terms that follow a bivariate normal distribution $(0, 0, 1, \sigma_u, \rho)$.

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- Wages are observed for those for whom $L_i^* > 0$, so that the expected wage of an employed individual is determined according to

  $$\begin{aligned} E\left(\ell n(w_i) \mid L_i^* > 0\right) &= X_i'\,\beta + E\left(u_i \mid \varepsilon_i > -H_i'\gamma\right) \\ &= X_i'\,\beta + \theta\,\lambda_i, \end{aligned}$$

  where $\theta = \rho\sigma_{u_j},\ \lambda_i = \phi(H_i'\,\gamma)/\Phi(H_i'\,\gamma)$, and $\phi\,(\cdot)$ is the standard normal density function.

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  where $\theta = \rho\sigma_{u_j},\ \lambda_i = \phi(H_i'\,\gamma)/\Phi(H_i'\,\gamma)$, and $\phi\,(\cdot)$ is the standard normal density function.
- The estimating equation for employed individuals may be expressed as

$$\ell n(w_i) \mid L_i^* > 0\ = X_i'\,\beta + \theta\,\lambda_i + error.$$

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where $\widehat{\lambda}_f^0 = \sum_{i=1}^{N_{1f}} \widehat{\lambda}_{if}^0 / N_f$, and $\widehat{\lambda}_{if}^0 = \phi(H_{if}' \widehat{\gamma}_m) / \Phi(H_{if}' \widehat{\gamma}_m)$.

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- The term $\widehat{\lambda}_f^0$ is the mean value of the IMR if females faced the same selection equation that the men face.

Human Capital and Wage Decompositions

- The term $\widehat{\theta}_m\,(\widehat{\lambda}_f^0 - \widehat{\lambda}_f)$ measures the effects of gender differences in the parameters of the probit selectivity equation on the male/female wage differential.

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- Given that $\hat{\theta} = \hat{\rho}\hat{\sigma}_u$ and that the parameters $\hat{\rho}$ and $\hat{\sigma}_u$ are identified, further decomposition of $\widehat{\theta}_m - \widehat{\theta}_f$ is possible:

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- How do we treat gender differences in the parameters of the selection process? Explained (human capital)? Unexplained (discrimination)?

Human Capital and Wage Decompositions

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- $$\bar{w} = exp(\bar{X}\hat{\beta} + \hat{\theta}),$$

  where $\hat{\theta} = \ell n\left(N\bar{w}\right) - \ell n\left\{\sum_{i=1}^{N_j}\left[exp(X'\hat{\beta})\right]\right\}$

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  - Accordingly, $\theta = 0.5\alpha^2\sigma_\nu^2$.

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  where $\hat{w}_f^0 = \frac{\sum_{i=1}^{N_f} exp(\bar{X}_f \hat{\beta}_m + \hat{\theta}_m)}{N_f}$ or $\frac{\sum_{i=1}^{N_f} exp(\bar{X}_f \hat{\beta}_m + \hat{\theta}_f)}{N_f}$.
- $\hat{\theta}$ measures the value of unobserved skills.
- Let the log wage residual $\varepsilon = \alpha\nu$,where α is the return to unobserved skills and ν is an index of unobserved skills such that $\nu \sim N(0, \sigma_\nu^2)$.
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Human Capital and Wage Decompositions

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  - It is not obvious whether to use $\hat{\theta}_m$ or $\hat{\theta}_f$ to predict the mean female wage in the absence of discrimination.

Specification Error in Earnings/Experience Profiles

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\begin{aligned}
Y_i &= \beta_0 + \beta_1 S_i + \beta_2 X_i^* + \beta_3 X_i^{*2} + \sum_{i=1}^{K} \alpha_i H_i + \varepsilon_i, \ \ i = 1, ..., N, \\
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where Y is the natural log of the hourly wage, S is the schooling level, X^* is actual work experience, H is a set of K other control variables, ε is a random error term, i indexes the individual, and N represents the sample size.

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- Taking the probability limit of the OLS estimator yields,

$$plim(\widehat{\gamma}) = \gamma + \Sigma_{W^* W^*}^{-1} \Sigma_{W^* \varepsilon},$$

which is consistent only if $plim(N^{-1} W^{*'} \varepsilon) = \Sigma_{W^* \varepsilon} = 0$.

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- where $\varepsilon_i^* = \varepsilon_i - \beta_2 v_i - 2\beta_3 X_i^* v_i - \beta_3 v_i^2$.

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- The probability limit of the OLS estimator of γ in the misspecified model can be shown to be,
- $$plim(\widehat{\gamma}) = \gamma - \Sigma_{WW}^{-1}\Sigma_{Wv}\beta_2 - 2\Sigma_{WW}^{-1}\Sigma_{W,X^*\odot v}\beta_3 - \Sigma_{WW}^{-1}\Sigma_{W,v\odot v}\beta_3,$$
  assuming $\Sigma_{WW}^{-1}\Sigma_{W\varepsilon} = 0$.

Specification Error in Earnings/Experience Profiles

- Consider the standard decomposition of gender wage gaps:

$$\bar{Y}_m - \bar{Y}_f = \left(\bar{X}^{m,a} - \bar{X}^{f,a}\right)\widehat{\beta}^{m,a} + \bar{X}^{f,a}\left(\widehat{\beta}^{m,a} - \widehat{\beta}^{f,a}\right)$$
$$= \left(\bar{X}^{m,j} - \bar{X}^{f,j}\right)\widehat{\beta}^{m,j} + \bar{X}^{f,j}\left(\widehat{\beta}^{m,j} - \widehat{\beta}^{f,j}\right),$$

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  where a denotes the specification with actual experience and j denotes the specification with potential experience.
- The effects of experience specification bias on the endowment (explained) component of the wage decomposition can be decomposed into parameter bias and mean experience measure bias:

$$\left(\bar{X}^{m,a} - \bar{X}^{f,a}\right)\widehat{\beta}^{m,a} - \left(\bar{X}^{m,j} - \bar{X}^{f,j}\right)\widehat{\beta}^{m,j} =$$

$$\left(\bar{X}^{m,a} - \bar{X}^{f,a}\right)\left(\widehat{\beta}^{m,a} - \widehat{\beta}^{m,j}\right)$$
$$+ \left[\left(\bar{X}^{m,a} - \bar{X}^{f,a}\right) - \left(\bar{X}^{m,j} - \bar{X}^{f,j}\right)\right]\widehat{\beta}^{m,j}.$$

Specification Error in Earnings/Experience Profiles

- The effects of experience specification bias on the discrimination (unexplained) component of the wage decomposition can also be decomposed into parameter bias and mean experience measure bias:

$$\bar{X}^{f,a}\left(\widehat{\beta}^{m,a}-\widehat{\beta}^{f,a}\right)-\bar{X}^{f,j}\left(\widehat{\beta}^{m,j}-\widehat{\beta}^{f,j}\right)=$$

$$\bar{X}^{f,j}\left[\left(\widehat{\beta}^{m,a}-\widehat{\beta}^{f,a}\right)-\left(\widehat{\beta}^{m,j}-\widehat{\beta}^{f,j}\right)\right]$$
$$+\left(\bar{X}^{f,a}-\bar{X}^{f,j}\right)\left(\widehat{\beta}^{m,a}-\widehat{\beta}^{f,a}\right).$$

Concluding remarks

- Explained differences in labor market outcomes are not synonymous with mean differences in covariates.

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Concluding remarks

- Explained differences in labor market outcomes are not synonymous with mean differences in covariates.
  - Gender/racial/ethnic differences in wage equation parameters are not necessarily indicative of discrimination.
  - Gender/racial/ethnic differences in acquired human capital may reflect optimization subject to unequal constraints.
- Possible quality differences in acquired human capital may be related to unequal constraints faced by men and women.