

Estimating a Dynamic Adverse-Selection Model: Labor-Force Experience and the Changing Gender Earnings Gap 1968-1997

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Review of Economics Studies, 2012

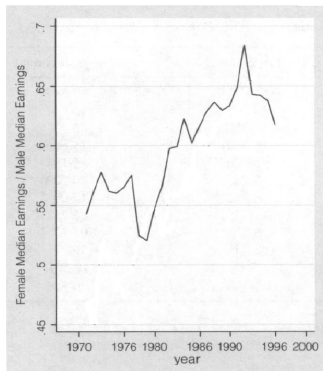
Outline

- 1 Stylized Facts of Gender Gap in Labor Market
- 2 Model Setup
- 3 Equilibrium and Optimality Conditions
- 4 Identification and Estimation
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Gender Gap in Labor Market

Time Trend

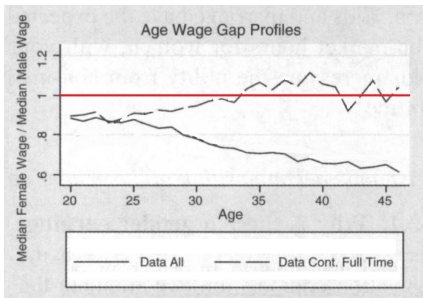
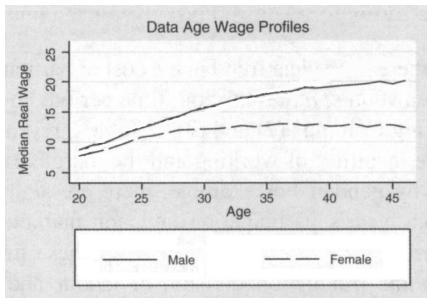
- Significant decline in gender earnings gap between 1970s-1990s



	Labor participation	Hours worked
Male	95% → 92%	2240 → 2270
Female	58% → 78%	1370 → 1850

Gender Gap in Labor Market

Life Cycle Trend



Previous Empirical Attempts

- There is extensive empirical literature on measuring gender earnings gap and its decline (see Altonji and Blank, 1999, for a survey)
- To explain the declining gender earnings gap, some papers specify a fully behavioral model
 - Lee and Wolpin (2010)
 - Greenwood et al. (2005)
- No papers look at *discrimination* in accounting for observed patterns
- This paper incorporates the following into a general equilibrium model with life cycle labor-supply choices
 - private information (i.e. labor participation cost)
 - hiring cost

Model Setup

Worker

- Worker $i \in \{w, m\}$ choose consumption c_t and labor supply decision $a_t = (d_t, \{l_{\tau t}\}_{\tau \in \{P, NP\}}, h_t)$
- i 's current-period utility at t is
$$U_{it} = d_t u_{i0}(z_t, \zeta_t) + u_{i1}(l_t; z_t) + u_{i2}(c_t; x_t, \varepsilon_{2t}) + (1 - d_t)\varepsilon_{0t} + d_t \varepsilon_{1t}$$
where
 - $z_t = (a_0, \dots, a_{t-1}, x_t)$
 - x_t are individual gender-specific characteristics, evolves $F_{i0}(x_{t+1}|z_t)$
 - men and women are allowed to have different labor participation cost
- Worker i then maximize lifetime expected utility

$$\max E_t \left[\sum_{s=t}^T \beta^{s-t} U_{is} | z_t \right]$$

s.t.

$$E_0 \left\{ \sum_{t=0}^T \beta^t \lambda_t [c_{mt} + c_{wt} - \bar{S}_t] \right\} \leq W$$

- Frisch consumption demand $\partial u_{i2}(c_{it}; x_t, \varepsilon_{2t}) / \partial c_{it} = \eta_i \lambda_t$; then
$$u_{i2}(c_{it}; x_t, \varepsilon_{2t}) = \eta_i \lambda_t \sum_{\tau \in \{P, NP\}} l_{\tau t} S_{i\tau t}(h_t, \cdot)$$

Model Setup

Firm

- Firm in each occupation produces $y_{\tau t} = Y_{\tau}(K_{\tau t}, h_t, z_t^P)$
- Occupation-specific hiring cost γ_{τ} for a certain job
- At each t , each firm offer one job with h_t to worker with z_t^P in occupation τ with salary $S_{i\tau t}(h_t, \cdot)$

- Systematic state variables $\omega_t = (z_t, \zeta_t, \eta\lambda_t, K_{Pt}, K_{NPt})$ are separated from $(\varepsilon_{0t}, \varepsilon_{1t})$
- Assume conditional independence of each other

Perfect Bayesian Equilibrium

Worker

- Worker observes $\omega_t = (z_t, \zeta_t, \eta\lambda_t, K_{Pt}, K_{NPt})$ and $(\varepsilon_{0t}, \varepsilon_{1t})$
- Worker's optimal participation decision conditional on ω_t is

$$d_i^o(\omega_t, \varepsilon_{0t}, \varepsilon_{1t}) = \begin{cases} 1 & \text{if } v_{1i}(\omega_t) + \varepsilon_{1t} \geq v_{0i}(\omega_t) + \varepsilon_{0t}, \\ 0 & \text{otherwise} \end{cases}$$

- CCP: probability of participation conditional on ω_t is

$$p_i(\omega_t) = E[d_i^o | \omega_t] = \int_{-\infty}^{v_{1i} - v_{0i}} (\varepsilon_{0t} - \varepsilon_{1t}) dF_1(\varepsilon_{0t}, \varepsilon_{1t}) \equiv Q(\omega_t)$$

- $h_{i\tau t}^*$ can be derived from the first-order condition of Bellman equation
$$v_{1i}(\omega_t) + \varepsilon_{1t} = \max_{h_t; \{l_t\}_\tau} u_{i0}(z_t, \zeta_t) + u_{i1}(l_t, z_t) + \eta\lambda_t \sum_{\tau} l_{\tau t} S_{i\tau t}(h_t, \omega_t) + \beta E_t \{ [p_i(\omega_{t+1}) V_{1i}(\omega_{t+1}) + (1 - p_i(\omega_{t+1})) V_{0i}(\omega_{t+1})] | \omega_t, d_t = 1 \}$$
- Occupation choice $l_{i\tau}^o(\omega_t)$
- $p_{i\tau t+1}(h_t, \omega_t) = \int Q(\omega_{t+1}) l_{i\tau}^o(\omega_{t+1}) f_{i0}(\omega_{t+1} | \omega_t, a_t) d\omega_{t+1}$

Perfect Bayesian Equilibrium

Firm

- Firm only observes $\omega_t^* = (z_t^*, K_{Pt}, K_{NPt})$, where $z_t^* = (a_0, \dots, a_{t-1}, x_t^*)$
- Employer's belief on worker's type
 - Each period, firm forms prior belief $\mu_{it}(\omega_t|\omega_t^*)$
 - After observing a_t , update $\tilde{\mu}_{it}(\omega_t|\omega_t^*, a_t)$ using Bayes' rule
 - Prior in next period $\mu_{it+1}(\omega_{t+1}|\omega_t^*, a_t) = f_{i0}(\omega_{t+1}|\omega_t, a_t)\tilde{\mu}_{it}(\omega_t|\omega_t^*, a_t)$
- Employer's belief on worker's probability of labor participation

$$\tilde{p}_{i\tau t+1}(h_t, \omega_t^*) = \int Q(\omega_{t+1}) I_{i\tau}^o(\omega_{t+1}) \mu_{it+1}(\omega_{t+1}|\omega_t^*, a_t) d\omega_{t+1}$$

- Optimal salary offered

$$S_{i\tau t}(h_t; \omega_t^*) = Y_\tau(K_{\tau t}, h_t, z_t^P) - \gamma_t + \beta \gamma_t \tilde{p}_{i\tau t+1}(h_t, \omega_t^*)$$

Gender Gap in the Model

- Sources of gender gaps in labor market
 - Gender-specific distribution of x_t in ω_t affects $p_{i\tau t}(\omega_t)$, h_t , $S_{i\tau t}(\omega_t)$
 - Hiring cost amplifies the effect
 - Statistical discrimination: women with high $p_{i\tau t+1}$ may receive lower $S_{i\tau t+1}$ than men because $\tilde{p}_{i\tau t+1}$ depends on observables of the whole gender group
- Changes in gender gap due to exogenous factors
 - Hiring cost changes
 - Demographic characteristics (e.g. fertility, education)

Identification and Estimation

Beliefs

- Model estimated using PSID 1968-1997
- Employer's belief $\tilde{p}_{in\tau t+1}$
 - computed as a non-linear regression of $d_{nt+1} \times I_{n\tau t+1}$ on ω_{nt}^* and h_{nt} , conditional on working today in occupation τ
 - beliefs restricted to last 3 periods of labor history to reduce state space
 - estimated nonparametrically using the kernel estimator
- Worker's CCP p_{int} , given optimal occupation choice τ^*
 - computed as a non-linear regression of d_{nt} on all ω_{nt}
 - ω_{nt} includes
 - gender, age, edu
 - family size, no. of kids, marital status, MU_{wealth} , spouse income and edu
 - estimated nonparametrically using the kernel estimator

Identification and Estimation

Earnings Equation

- Earnings $S_{i\tau t}(h_{nt}, \omega_{nt}) = Y_{\tau}(K_{\tau t}, h_{nt}, z_{nt}^P) - \gamma_t + \beta\gamma_t \tilde{p}_{in\tau t+1}$

where

$$Y_{\tau}(K_{\tau t}, h_{nt}, z_{nt}^P) = K_{\tau t} + b_{\tau 1} h_{nt} + b_{\tau 2} h_{nt}^2 + \sum_{r=1}^{\rho} b_{\tau 3r} h_{nt-r} + \sum_{r=1}^{\rho} b_{\tau 4r} d_{nt-r} \\ + b_{\tau 5} \text{age}_{nt} + b_{\tau 6} \text{age}_{nt}^2 + b_{\tau 7} \text{age}_{nt} \times \text{edu}_n + v_n$$

- Hiring cost γ_t is identified through the coefficient of $\tilde{p}_{in\tau t+1}$
 - by salary variation across τ , i , patterns of labor supply, age and education
 - estimated by standard panel data estimation

Identification and Estimation

Utility Functions

- Assume $(\varepsilon_{0t}, \varepsilon_{1t})$ Type-I extreme value

- $$u_{i0}(z_t, \zeta_t) = \zeta_t + \sum_{s=1}^2 \kappa_{is} d_{t-s} + x_t' B_{i1}$$

- $$u_{i1}(l_t; z_t) = x_t' l_t B_{i2} + \theta_{i0} l_t^2 + \sum_{s=1}^2 \theta_{is} l_t l_{t-s}$$

- Applying inversion and representation

$$m_{i0t} \equiv \eta \lambda_t \sum_{\tau} l_{i\tau t}^o S_{i\tau t}^o + \sigma \sum_{s=1}^3 \beta^s \ln\left(\frac{1-p_{1it}^{(s)}}{1-p_{0it}^{(s)}}\right) - \sigma \ln\left[\frac{p_{it}}{1-p_{it}}\right] + \zeta_t + \sum_{s=1}^2 \kappa_{is} d_{t-s} \\ + x_t' B_{i1} - x_t' h_t B_{i2} - \theta_{0i}(1-l_t^2) - \sum_{s=1}^2 \theta_{si} h_t(l_{t-s} + \beta^s)$$

$$m_{i1t} \equiv \eta \lambda_t \sum_{\tau} l_{i\tau t}^o \frac{\partial S_{i\tau t}^o}{\partial h_t} + \sigma \sum_{s=1}^3 \beta^s (1-p_{1it}^{(s)})^{-1} \frac{\partial p_{1it}^{(s)}}{\partial h_t} - x_t' B_{i2} - 2\theta_{0i} l_t + \sum_{s=1}^2 \theta_{si} (l_{t-s} + \beta^s)$$

- The model is then estimated by GMM, as the final-step estimation
 - using identified consumption, beliefs and CCP (pre-estimation)

Empirical Results

Why Gender Gaps Exist

- Simulate the model with no hiring cost or with no private information
- Compare to observed data
 - Observed gender earnings gap will decrease by 70% (44%) under no hiring cost
 - or 48% (13%) under symmetric information
 - in professional (nonprofessional) occupation

Empirical Results

Changes in Gender Gap

- Decline in work experience gender gap nearly entirely explains decline in gender earnings gap over time
 - work experience measured by $h_{nt} + h_{nt}^2 + \sum_{r=1}^p h_{nt-r} + \sum_{r=1}^p d_{nt-r}$ in earnings equation
- Decomposition of the decline in work experience gender gap

	Professional	Non-professional
Hiring cost	37.5	29.5
Demographics	26.5	38.5
Private information	12.5	13.5

- Explained the evolution of gender earnings gap over time and life cycle
- Particularly, showed asymmetric information is significant in labor markets
- As econometricians, they are able to
 - recover worker's private information from data
 - show that it's quantitatively important in explaining the gender earnings gap