Nature or Nurture? Learning and Female Labor Force Dynamics

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• Mothers of children < 5: 6% participated in 1940, 60% today.

• Why did the participation gap between married women with young children and all women close?
Why Learning?

Other theories also explain labor force participation:
Wages, child care, the pill, dishwashers, preferences.
Why add learning?

1. Cultural change is economically important.

2. A theory of beliefs is already present in existing models. We should examine unstated assumptions.

3. Learning reconciles a broad set of facts that others don’t: participation dynamics, labor supply elasticity, reported beliefs, and cross-sectional participation differences due to ethnicity, wealth, ability, geography, marital status and motherhood.
Outline

1. The model - Focus on 4 differences with Fernandez (2007)
   - Do we learn from research or from our peers?
   - Are women uncertain or just wrong?
   - Where does the S-shape come from?
   - What is it that women are learning about?

2. Quantitative predictions
   - Calibrate using wage distributions and 1940 participation.
   - Compare model to participation, wage, wealth and survey data.

3. Additional evidence and alternative theories
Model

- Discrete infinite time. OLG economy. Large finite number of agents. Period 1: Agent is nurtured or not. Period 2: Agent works, has child and consumes.

- Preferences: over consumption and kids’ wage

\[ U = \frac{c_{it}^{1-\gamma}}{1-\gamma} + \beta \frac{w_{i,t+1}^{1-\gamma}}{1-\gamma}, \quad \gamma > 1 \]

- Budget constrains consumption \( c_{it} \in \mathbb{R}_+ \), labor \( n_{it} \in \{0, 1\} \).

\[ c_{it} = n_{it} w_{it} + \omega_{it} \]

- Wage depends on nature \( a_{i,t} \sim N(\mu_a, \sigma_a^2) \) and nurture \( n_{i,t-1} \):

\[ w_{i,t} = \exp(a_{i,t} - n_{i,t-1} \theta) . \]
Information and Beliefs

- Learn about $\theta$.
- Priors inherited from parents: $\theta_{i,0} \sim N(\mu_0, \sigma_0^2)$.
- Observe $J$ signals: $(w_{it}, n_{i,t-1})$ and $(w_{jt}, n_{j,t-1})$ for $j \in J_i$.
- Signal variance depends on $(t - 1)$ participation:
  \[
  \hat{\sigma}_{i,t}^2 = \sigma_a^2 / (\sum_{j \in J_i} n_{j,t-1}).
  \]
  Update with Bayes’ rule:
  \[
  \sigma_{i,t+1}^2 = \sigma_{i,t}^2 + \hat{\sigma}_{i,t}^2,
  \]
  \[
  \mu_{i,t+1} = \left( \frac{\sigma_{i,t}^{-2}}{\sigma_{i,t+1}^{-2}} \right) \mu_{i,t} + \left( 1 - \frac{\sigma_{i,t}^{-2}}{\sigma_{i,t+1}^{-2}} \right) \sum_{j \in J_i} \frac{(\log w_{j,t+1} - \mu_a)n_{j,t}}{\sum_{j \in J_i} n_{j,t-1}}.
  \]
#1 **Do we learn from research or from our peers?**

- The key challenge: Bayesian learning converges quickly. LFP grows over a century. Models need frictions to make learning slow.

- **Fogli-Veldkamp**: Information is decentralized. It is generated when women work. Low participation makes information scarce. Explains geographic concentration of LFP.

- **Fernandez**: Centralized signals with large idiosyncratic noise. > 40% chance that women believe LFP is negative initially. Aggregate LFP is extremely volatile.
#2 Are women uncertain or pessimistic?

Participate if $EUO < EUW$:

$$EUO_{it} = \frac{(\omega_{it})^{1-\gamma}}{1-\gamma} + \frac{\beta}{1-\gamma} \exp \left( \mu_a (1-\gamma) + \frac{1}{2} \sigma_a^2 (1-\gamma)^2 \right).$$

$$EUW_{it} = \frac{(w_{it} + \omega_{it})^{1-\gamma}}{1-\gamma} + \frac{\beta}{1-\gamma} \exp \left( (\mu_a - \mu_{i,t}) (1-\gamma) + \frac{1}{2} (\sigma_a^2 + \sigma_{i,t}^2)(1-\gamma)^2 \right).$$

The probability that a woman will participate rises if...

1. The expected value of nurture $\mu_{it}$ falls.
   Requires systematically biased beliefs (*Fernandez*).

2. Uncertainty about the value of nurture $\sigma_{it}$ falls.
   No bias (*Fogli-Veldkamp*).
#3 Where does the S-shape come from?

- Changes in LFP follow changes in beliefs. Normal beliefs change more when priors are uncertain (high $\sigma^2_{i,t-1}$) or signals are accurate (high $\hat{\sigma}_{i,t}^{-2}$).

$$\text{var}(\mu_{i,t}|\mu_{i,t-1}) = \sigma^2_{i,t-1} - \frac{1}{\sigma^{-2}_{i,t-1} + \hat{\sigma}^{-2}_{i,t}}$$

- **Fogli-Veldkamp**: Signals are less accurate initially because few women work.

- **Fernandez**: Slow increase arises also because priors are very precise and become less precise over time. Some of the effect relies on a binomial state.
#4 What are women learning about?

- **Fogli-Veldkamp**: the effect of maternal employment on children’s future earnings.
  - Why are mothers so different?
  - We use research from Bernal-Keane (2006) and Goldin-Katz (1999) to calibrate true cost.

- **Fernandez**: a preference parameter.
  Not all parameters can be calibrated because the true cost is not pinned down.
### Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean log ability</td>
<td>$\mu_a$ -0.88</td>
</tr>
<tr>
<td>std log ability</td>
<td>$\sigma_a$ 0.57</td>
</tr>
<tr>
<td>mean log endowment</td>
<td>$\mu_\omega$ -0.28</td>
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<tr>
<td>std log endowment</td>
<td>$\sigma_\omega$ 0.75</td>
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<tr>
<td>outcomes observed</td>
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<tr>
<td>prior mean $\theta$</td>
<td>$\mu_0$ 0.04</td>
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<tr>
<td>prior std $\theta$</td>
<td>$\sigma_0$ 1.38</td>
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<tr>
<td>true value of nurture</td>
<td>$\theta$ 0.04</td>
</tr>
<tr>
<td>intertemporal substitution</td>
<td>$\gamma$ 2</td>
</tr>
</tbody>
</table>

- women’s earnings distribution
- average endowment = 1
- men’s earnings distribution
- $\text{Prob}(n_{i,t} = n_{i,t-1})_{1970 - 2000}$
- unbiased beliefs
- 1940 LFP
- children’s test scores (NLSY)
- commonly used
S-shaped dynamics

Labor Force Participation

Survey Responses

% who believe women should work

Model
Data

Model
Data

Fogli and Veldkamp
• Wages decline because of a selection effect (O’Neill, 1984).
• Solution: Career choice - high or low intensity careers.
Nature or Nurture?

Occupation Choice Model

- Add a high-intensity career with a wage premium,
  \[ c_{i,t} = n_{i,t} w_{i,t} + h_{i,t} \tilde{w}_{i,t} + \omega_{i,t} \]
  but a higher expected toll on kids,
  \[ w_{i,t+1} = \exp(a_{i,t+1} - n_{i,t} \theta - h_{i,t} \tilde{\theta}) \]

- High initial uncertainty makes \( h_{i,t} \) low. High-intensity participation rises later, in the 1970’s and 80’s.

- More high-wage work raises the average wage at the end of the century.
Wage Elasticity of Labor Supply

- In the data, female wage elasticity declined 50% 1980-2000 (Blau and Kahn, 2005).

- Proposition 5: Falling uncertainty lowers elasticity.

- Measurement problem dampens effect: Decrease in unmeasured heterogeneity from falling dispersion in beliefs. Wages and participation become more correlated. This increases measured elasticity.

- In occupation choice model, elasticity falls 22%.
The Smoking Gun: Geographic Diffusion

- Labor force participation spreads geographically. Looks like the spread of information through a network. Nearby counties’ participation rates matter, even after controlling for economic and demographic factors.

- Suppose agents’ indices represented spatial location. Signals from nearby locations have higher probability. Participation spreads from areas of initial high participation.

- This distinguishes learning from neighbors and learning from research. Also challenges technology or policy-based theories.
Conclusion: What we add to existing theories

- Rising wages (Goldin, 1990)
  - Why the decline in labor supply elasticity?
  - Why did married mothers join faster?

- Child care and new technologies (Greenwood, Seshadri, Yorukoglu, 2001)
  - Why did poor women work first?
  - How does culture regulate the adoption of new technologies?

- Preferences changed
  - Why lower elasticity? S-shape?

- Learning from public signals
  - Geography facts, smooth LFP, unbiased beliefs.
Learning from decisions of others

- We cannot solve that model exactly because signals have many sources of noise.
- We solve an approximate model. Approximate signals are normal with the same signal-to-noise ratio as true signals.
- Results are almost indistinguishable because the extra signals have high noise.
Extra-information model

LFP

Survey Response

Std Mean of Beliefs

Avg Std of beliefs
Sensitivity analysis

Panel A: Number of signals $j$

Panel B: Distribution prior beliefs $\mu_\theta, \sigma_\theta$

Panel C: Distribution of ability $\mu_a$

Panel D: Cost of maternal employment $\theta$

Benchmark

$\mu_\theta = 0.2, \sigma_\theta = 1.2$
$\mu_\theta = 0.5, \sigma_\theta = 0.8$
$\mu_a = 0.24$
$\mu_a = 0.73$
$\mu_a = w_t$

$\theta = 0.02$
$\theta = 0.06$
Qualitative Evidence: Uncertainty Declines

- From 1977-2004, we have richer survey data. With 1-4 scale of agree/disagree, we can calculate belief dispersion.

- Dispersion in beliefs declines by 2.5% from 1977 to 2004.

- Ratio of less certain to more certain replies falls 5%.

- Model belief dispersion and uncertainty fall during this time as well.