Nature or Nurture? Learning and Female Labor Force Dynamics

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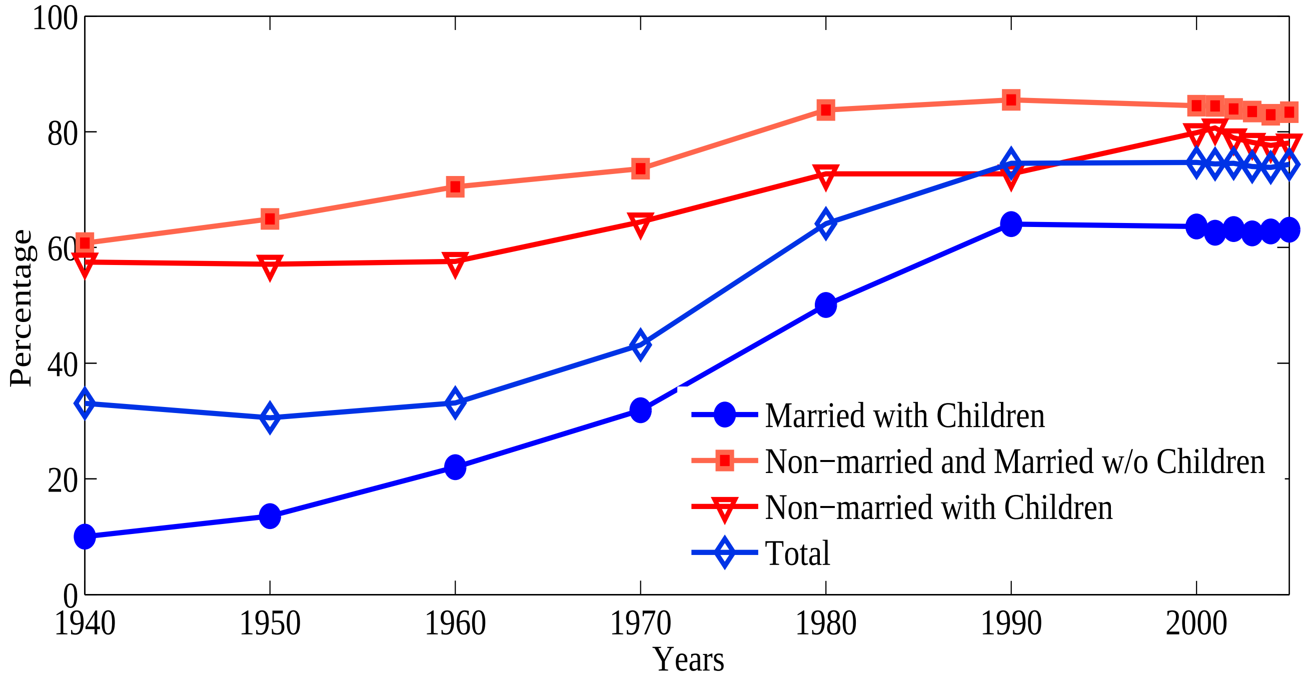
Labor Force Participation

- 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.
   Doepke and Zilibotti (2006), Barro and McCleary (2006)

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

$$U = \frac{c_{it}^{1-\gamma}}{1-\gamma} + \beta \frac{w_{i,t+1}^{1-\gamma}}{1-\gamma} \qquad \gamma > 1$$

- 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 θ.
- 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 $j \epsilon \mathbb{J}_i$.
- Signal variance depends on $(t-1)$ participation:
  $\hat{\sigma}^2_{i,t} = \sigma_a^2 / (\sum_{j\epsilon\mathbb{J}_i} n_{j,t-1})$.
  Update with Bayes' rule: $\sigma^{-2}_{i,t+1} = \sigma^{-2}_{i,t} + \hat{\sigma}^{-2}_{i,t}$,

$$\mu_{i,t+1} = \left(\frac{\sigma^{-2}_{i,t}}{\sigma^{-2}_{i,t+1}}\right)\mu_{i,t} + \left(1 - \frac{\sigma^{-2}_{i,t}}{\sigma^{-2}_{i,t+1}}\right)\sum_{j\epsilon\mathbb{J}_i} \frac{(\log w_{j,t+1} - \mu_a) n_{j,t}}{\sum_{j\epsilon\mathbb{J}_i} n_{j,t-1}}.$$

#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 μ_{it} falls.
   Requires systematically biased beliefs (*Fernandez*).

2. Uncertainty about the value of nurture σ_{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 $\hat{\sigma}^{-2}_{i,t}$).

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

- *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.

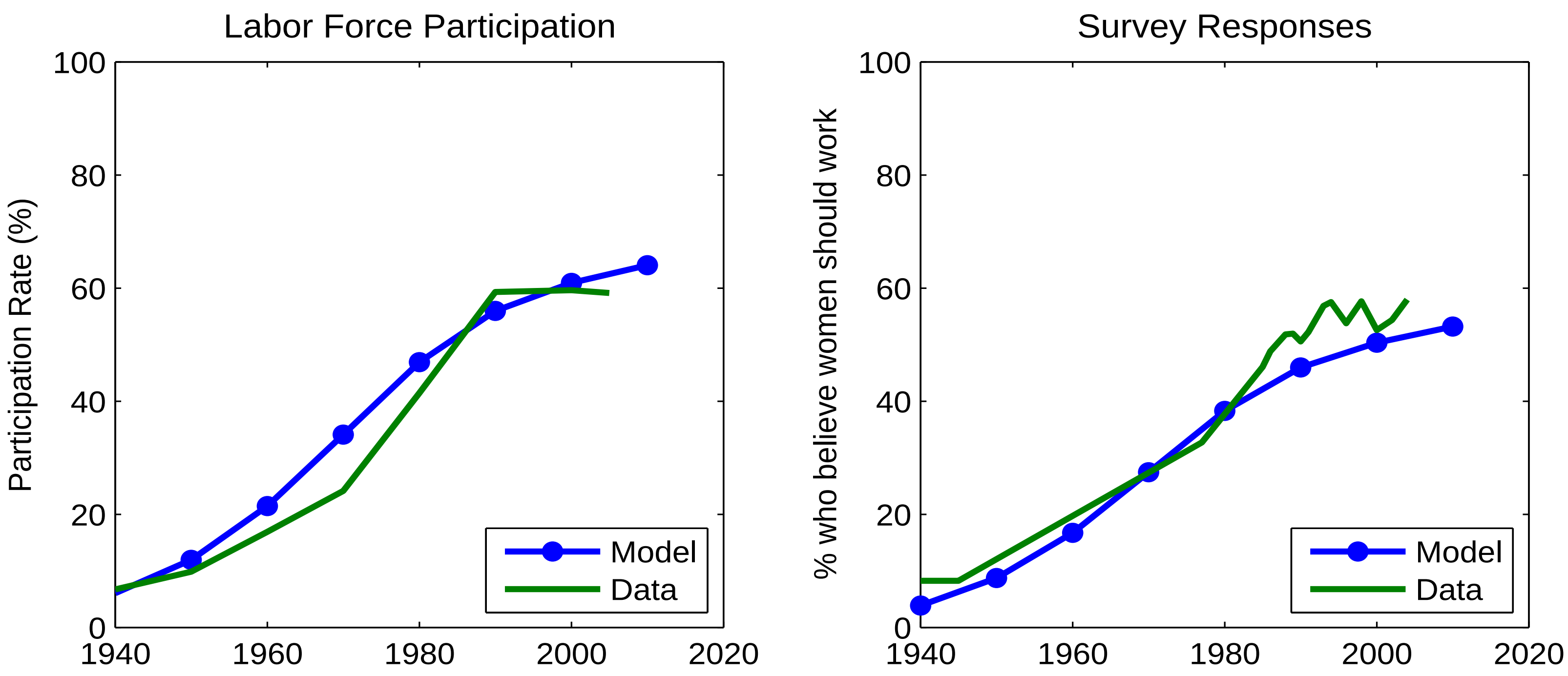
#4 What are women learning about?

- *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.

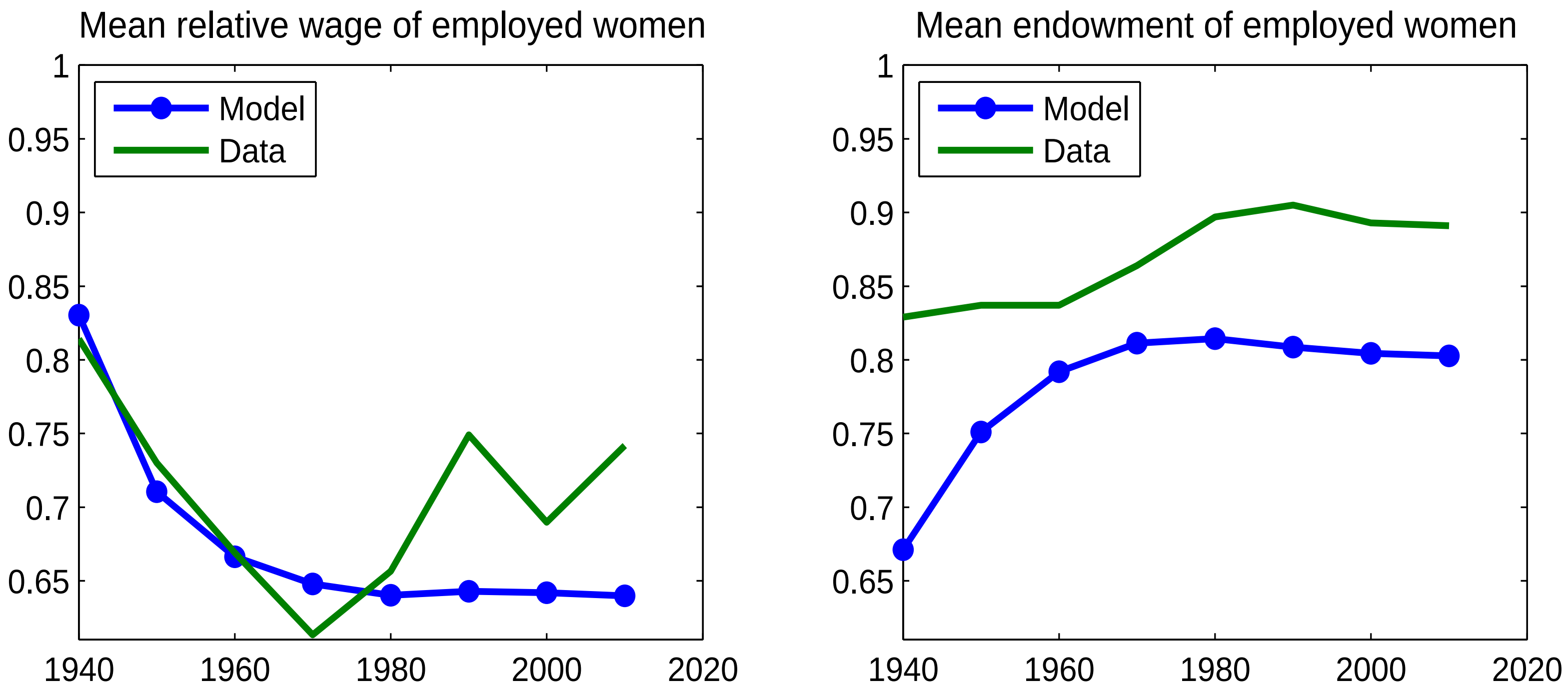
Calibration

mean log ability	μ_a	-0.88	women's earnings distribution
std log ability	σ_a	0.57	women's earnings distribution
mean log endowment	μ_ω	-0.28	average endowment $= 1$
std log endowment	σ_ω	0.75	men's earnings distribution
outcomes observed	J	3	Prob$(n_{i,t} = n_{i,t-1})1970 - 2000$
prior mean θ	μ_0	0.04	unbiased beliefs
prior std θ	σ_0	1.38	1940 LFP
true value of nurture	θ	0.04	children's test scores (NLSY)
intertemporal substitution	γ	2	commonly used

S-shaped dynamics



Wages and Endowments



- Wages decline because of a selection effect (O'Neill, 1984).
- Solution: Career choice - high or low intensity careers.

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,

$$w_{i,t+1} = \exp(a_{i,t+1} - n_{i,t}\theta - h_{i,t}\tilde{\theta}).$$

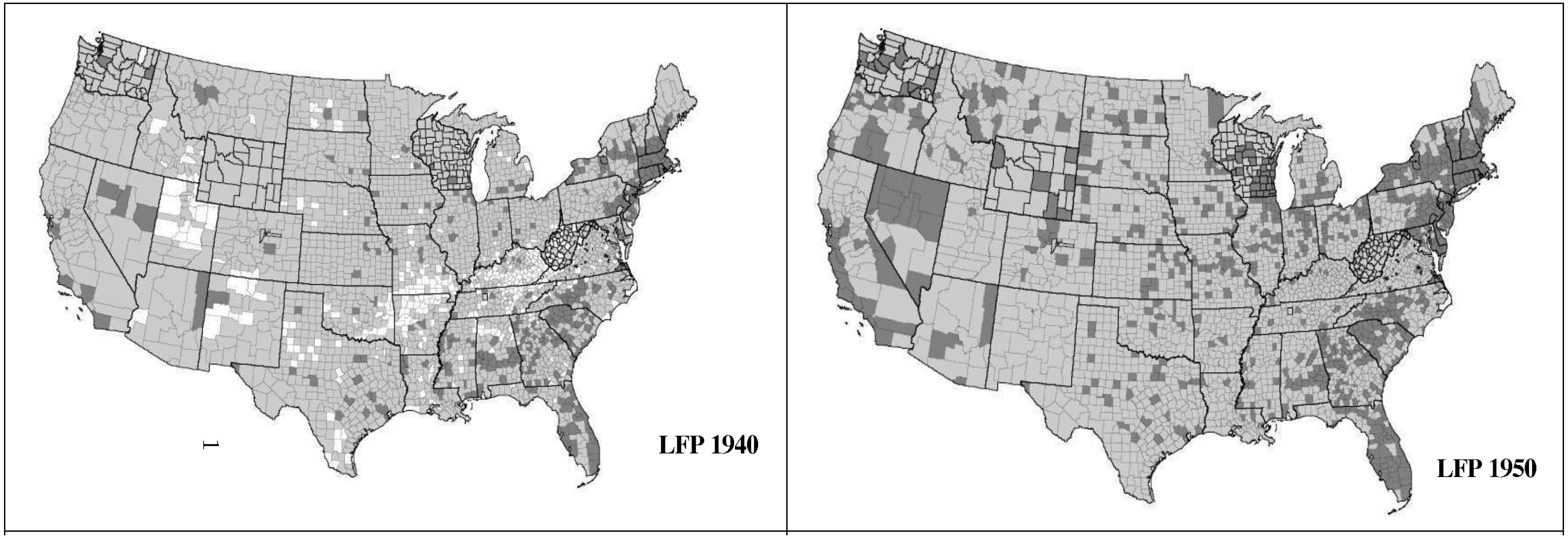
- High initial uncertainty makes $h_{i,t}$ low. High-intensity participation rises later, in the 1970's and 80's.
- More high-wage work raises the average wage at the end of the century.

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%.

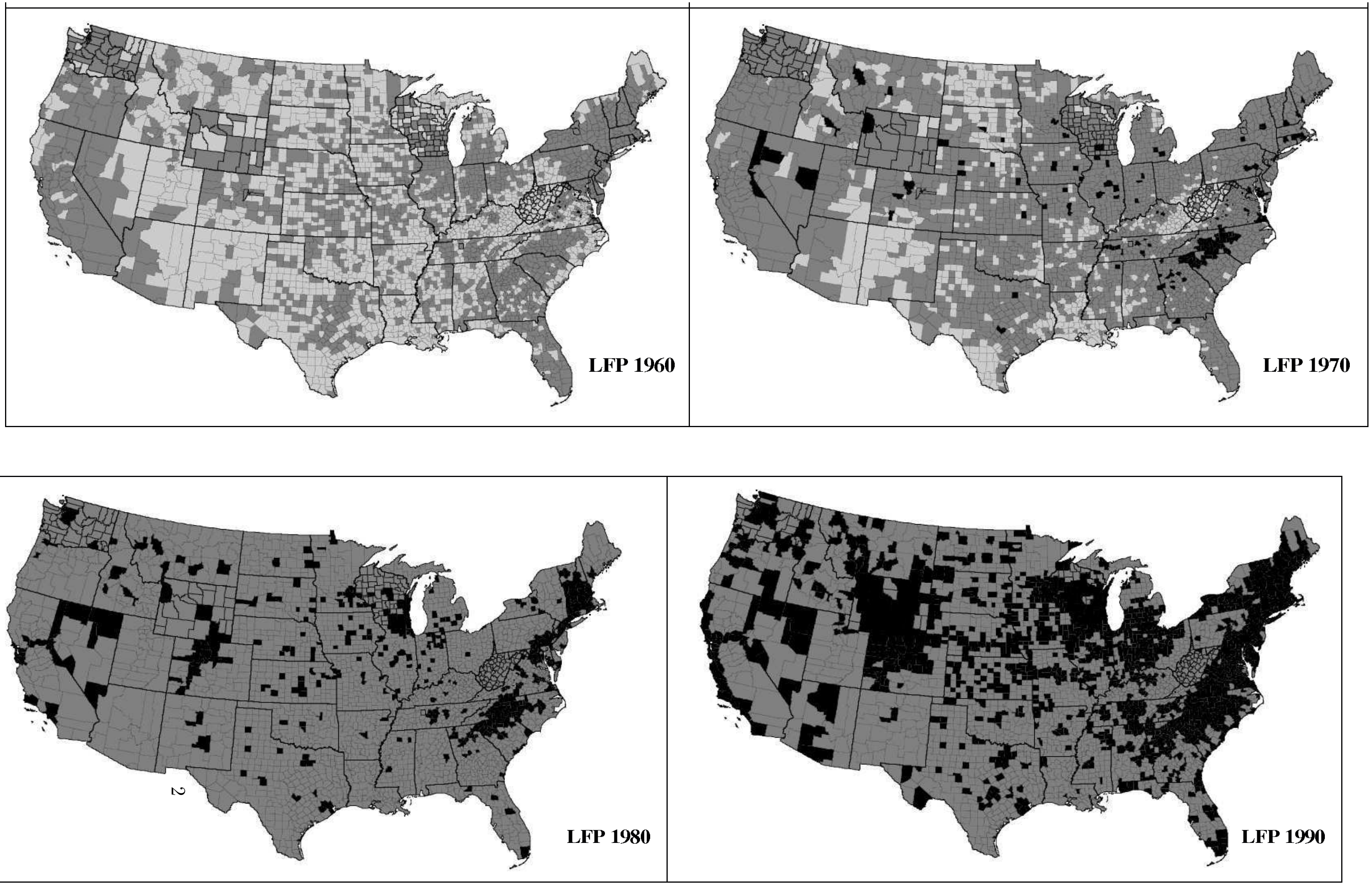
The Smoking Gun: Geographic Diffusion

- 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.



Legend:

0% $\leq$ LFP $\leq$ 8%	☐ (white)
8% $<$ LFP $\leq$ 20%	■ (light grey)
20% $<$ LFP $\leq$ 40%	■ (dark grey)
LFP $>$ 40%	■ (black)


LFP 1960
LFP 1970
LFP 1980
LFP 1990

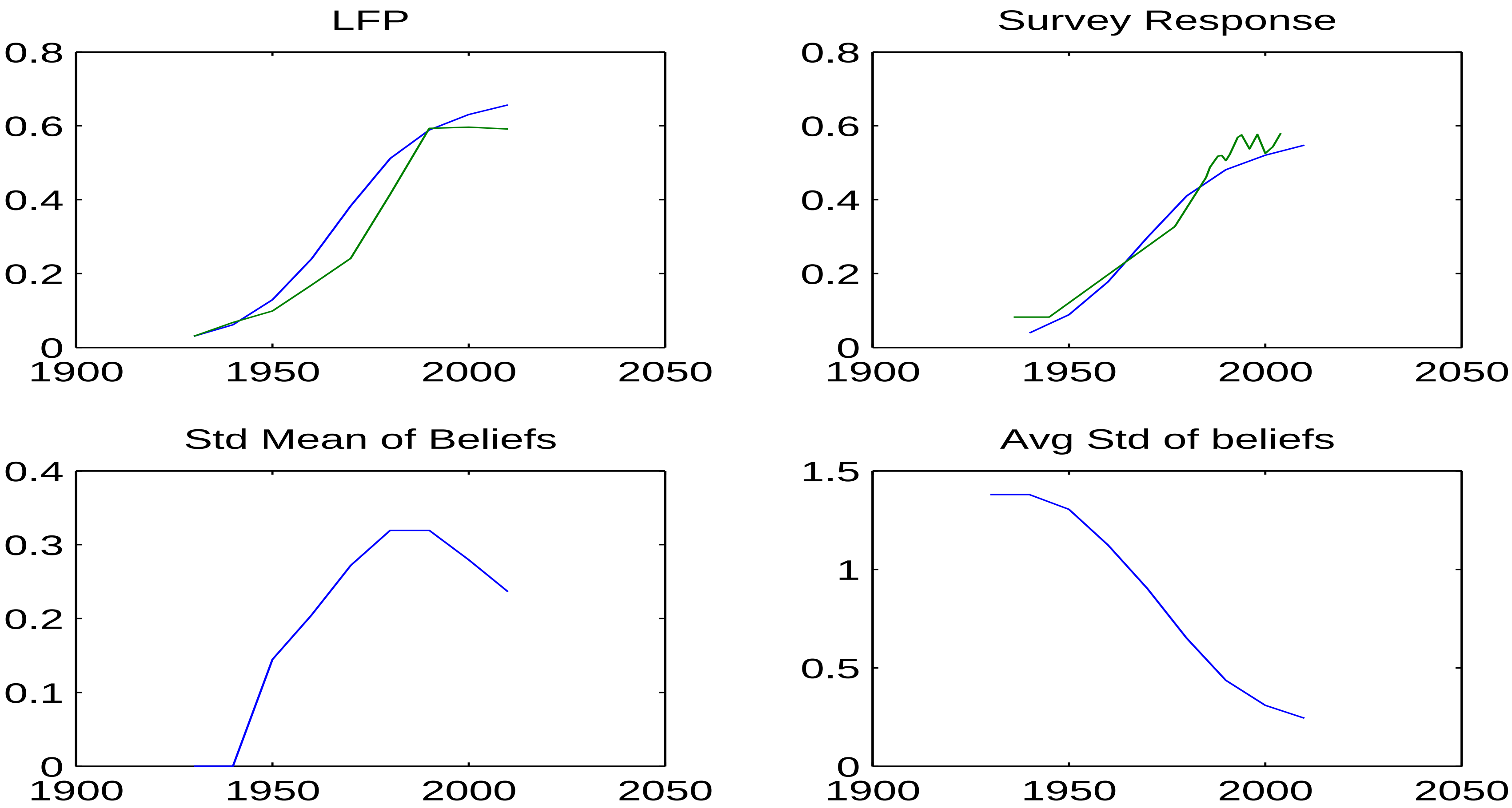
Conclusion: What we add to existing theories

- 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.

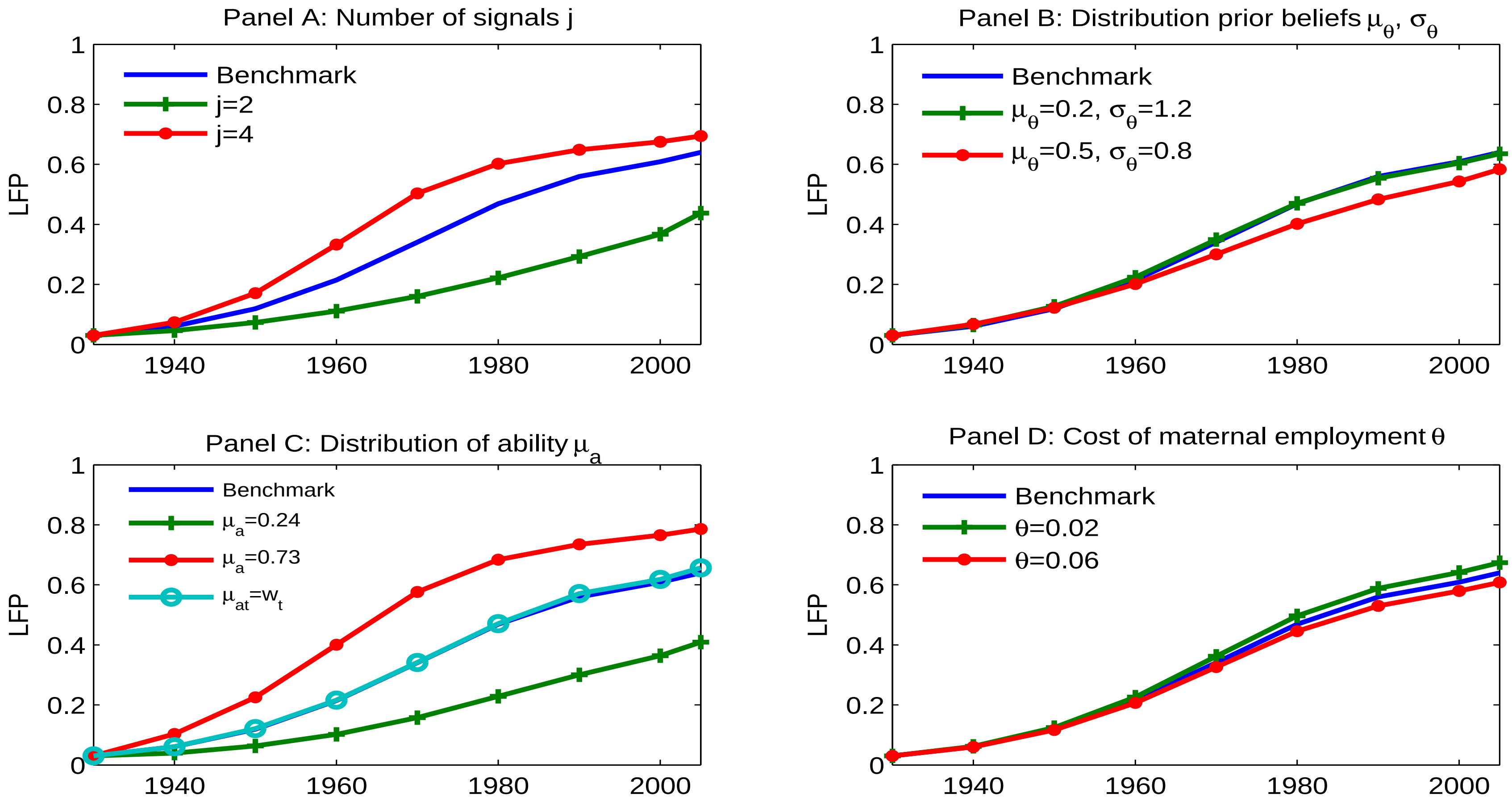
Learning from decisions of others

- 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



Sensitivity analysis



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.