# A Structural Meta-Analysis of Welfare-to-Work Experiments and Their Impacts on Children

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## Introduction

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- Suppose: have treatment effects from a number of differently designed experiments.
- Want: a method to aggregate this information for policy and prediction
  - Experiments are costly, would like cheaper alternative to evaluate counterfactual policies
  - Design future experiments more effectively
- This paper: estimates a structural model using experimental outcomes, exploiting differences in design to identify key parameters.
  - Application: welfare reform experiments in the United States

# A Simple Description of Methodology

- Let  $\mathbf{Y}_k$  be vector of statistics from experiment or study k (k = 1, ..., K)
- Let  $\gamma$  index a class of models that predicts population values:

$$n_k^{1/2}(\mathbf{Y}_k - \mathbf{m}_k(\gamma)) \rightarrow_d \mathcal{N}(0, \Omega_k)$$

-  $\gamma$  can be estimated by minimum distance:

$$\hat{\gamma} = \arg\min(\mathbf{Y} - \mathbf{m}(\gamma))'\mathbf{W}(\mathbf{Y} - \mathbf{m}(\gamma))$$

- This is a way to aggregate information from experiments/studies.

# A Simple Description of Methodology

$$n_k^{1/2}(\mathbf{Y}_k - \mathbf{m}_k(\gamma)) \rightarrow_d \mathcal{N}(0, \Omega_k)$$

#### Traditional meta-analysis:

- $\mathbf{Y}_k$  are mean impacts,  $\mathbf{m}_k$  is linear model
- Single parameter of interest: Average Treatment Effect  $(\alpha)$
- Population framework:  $\alpha_k \sim F(\alpha)$ , differences across experiments is nuisance variation
- $\hat{\alpha}$  is a weighted average, or can be estimated with Bayesian methods (Rubin 1981, Meager 2019)
- $\alpha$  may not be policy parameter of interest (Heckman 1992)

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#### Structural meta-analysis:

- $\gamma$  now define policy invariant primitives (preferences, technology, etc)
- Differences in design and setting useful for identification
- Outcomes articulated for full range of counterfactuals
   Todd & Wolpin (2005), Attanasio, Meghir & Santiago (2011), Duflo, Hanna & Ryan (2012), Rodriguez (2018)
- Can apply same frequentist or Bayesian methods

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  - Compile averages from publicly available reports more info

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- Four crucial design choices:
  - Benefit formulae (generosity and work incentives)
  - Time limits on participation
  - Work requirements
  - Child care subsidies
- Exploit variation in these choices to identify key parameters

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  - Compile averages from publicly available reports more info
- Four crucial design choices:
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- Exploit variation in these choices to identify key parameters
- Highlighted counterfactuals of interest:
  - \$1,000 unconditional transfer to households
  - A policy reform with only work requirements
  - Key outcome: impact on academic and behavioral outcomes of children

#### Results from highlighted counterfactuals:

- 1,000 transfer  $\rightarrow 2-3\%$  s.d. increase in academic and behavioral outcomes
  - About one third of prominent estimates: Duncan, Morris & Rodrigues (2011), Dahl
     & Lochner (2012)
  - \* Akee, Copeland, Costello & Simeonova (2018)

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- No significant impact of work requirements
- No evidence of negative impact of non-maternal care.
  - Bernal (2008), Agostinelli & Sorrenti (2018), Mullins (2019)

## Model

Goal: write model with clear mapping to average treatment effects.

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- Environment:
  - Agent is single mother, endowed with L=112 hours per week.
  - Site k, treatment arm j, time t
  - Investment period is T=17 years.
- Choices:
  - Participate in welfare,  $A \in \{0, 1\}$
  - Work,  $H \in \{0, 1\}$
  - If H=1, choose formal care (F=1) or informal care (F=0)
  - Divide hours at home into housework q, and time with child,  $\tau$ .
  - Spend *x* in money investments on child, *C* on private consumption.

Value today

child skills welfare remaining Payoff today
work
welfare
childcare
investment
child skills

Payoff today  $+ \beta \times Value tomorrow$ 

 $\mapsto \begin{array}{c} \text{child skills} \\ \text{welfare remaining} \end{array}$ 

show me math

show me math

#### Preferences:

$$u_k(C, d, \theta; \mathcal{R}) = \alpha_C \log(C) + \alpha_\theta \log(\theta) - \alpha_{H,k} H + \alpha_{F,k} F - \mathcal{R} A[\alpha_{R,k} (1-H) + \alpha_{R2,k} H] + \epsilon_d$$
  
 $\epsilon_d$  is nested logit, variances  $(1, \sigma_H, \sigma_F)$ .

show me math

#### Resource constraint:

$$C + x + p_{F,kj}F + w_q(\tau + 30H) \le Y_{kjt}(A, H) + w_qL$$

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## Technology:

$$\theta_{t+1} = I_t^{\delta_{I,t}} \theta_t^{\delta_{\theta}}, \qquad I_t = \mathcal{I}_t(\tau, x, \kappa), \ \kappa = H + F$$

- Let  $g_{\kappa,t}I_t$  be solution to cost-minimization problem,  $\kappa \in \{0,1,2\}$
- Marschak (1953): sufficient to estimate prices  $(g_{0,t},g_{1,t},g_{2,t})$

**Parameter** 

Preferences

Coefficient on consumption ( $\alpha_C$ )

What it determines show me math

Response of participation to program generosity

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Var of work util. shocks  $(\sigma_H)$ 

What it determines show me math

Response of participation to program generosity Response of work to financial incentives

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Response of participation to program generosity

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Effect of work requirements

What it determines show me math

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Technology

Log-relative price of investment  $(\hat{g}_1, \hat{g}_2)$ 

What it determines show me math

Response of participation to program generosity Response of work to financial incentives

Response of child care use to price changes Effect of work requirements

Effect on child outcomes of non-maternal care

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Cobb-Douglas share on investment  $(\delta_I)$ 

What it determines show me math

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Cobb-Douglas share on skills ( $\delta_{\theta}$ )

What it determines show me math

Response of participation to program generosity

Response of work to financial incentives Response of child care use to price changes

Effect of work requirements

Effect on child outcomes of non-maternal care Effect on child outcomes of increase in income

Persistence of effects on child outcomes

- Identification follows from understanding of these key relationships
  - Example: Wage elasticity of LFP  $(\sigma_H)$  identified by experimental variation in work incentives, time variation in wages.

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  - Example: Wage elasticity of LFP  $(\sigma_H)$  identified by experimental variation in work incentives, time variation in wages.
- Analytical solution provides transparent identification analysis (see paper)
- Analogy: rank condition in linear IV (separate variation in treatment components)
- Site-specific parameters identified by control group means

### Estimation - Data

- Public reports means of LFP, participation, rates of paid child care use & OOP child care costs, across treatment groups,  $\mathbf{X}_k$  for site k.
- Standard deviations  $\hat{\mathbf{s}}_k$  imputed or inferred from effect sizes

$$rac{X_{k,i} - \mathbf{m}_{k,i}(\gamma)}{\hat{s}_{k,i}} \sim \mathcal{N}(0,1)$$

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$$rac{X_{k,i} - \mathbf{m}_{k,i}(\gamma)}{\hat{\mathbf{s}}_{k,i}} \sim \mathcal{N}(0,1)$$

- Vector of treatment effects for academic outcomes  $(M_{A,k})$ 
  - Parental rating of school achievement, grade repetition, Woodcock-Johnson
- Vector of treatment effects for behavioral outcomes  $(M_{B,k})$ 
  - Behavioral problems index, positive behaviors, suspension
- Measurement of treatment effect at site *k*, treatment *j*:

$$\Delta \overline{M}_{Z,k,j,l} = \lambda_{Z,j} \Delta \mathbb{E}[\log(\theta)|k,j] + \zeta_{Z,k,j,l}, \ Z \in \{A,B\}$$

## Estimation - Procedure

- Have global  $(\gamma_G)$ , and site specific  $(\gamma_k)$  parameters
- Follow meta-analysis literature (Rubin 1981, Meager 2019) and estimate Bayesian hierarchical model:

$$p(\gamma|X,M) \propto \prod_{k=1}^{K} \phi(X_k, M_k|s_{M,k}, s_{X,k}, \gamma_G, \gamma_k) p(\gamma_k|\gamma_H) p(\gamma_H, \gamma_G)$$

#### Where:

- Use loose priors
- $\phi(\cdot|s,\gamma)$  is normal density with mean implied by model solution given  $\gamma$  and standard deviation s.

## Review: Important Parameters

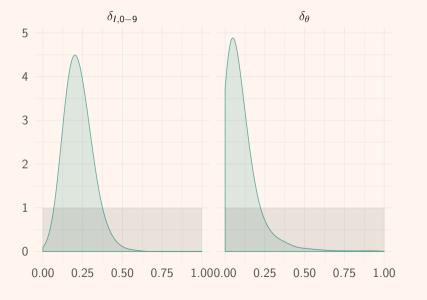
#### Child outcomes:

$$\mathbb{E}_{kjt}\log(\theta_{t+1}) = \frac{\delta_{l,t}}{\log(Y_{kjt}(H,A) + w_q(L-30H))} - \frac{\hat{\mathbf{g}}_{\kappa,t}}{\log(Y_{kjt}\log(\theta_t))} + \frac{\delta_{\theta}}{\log(\theta_t)}$$

#### Important parameters are:

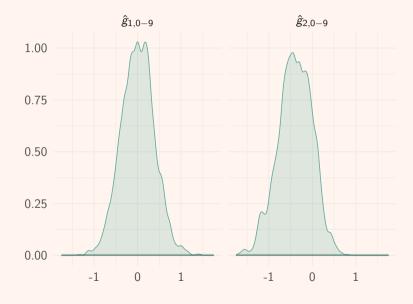
- $\delta_I$ : important of resources in household
- $\delta_{\theta}$ : persistence of impacts
- $(\hat{g}_{1,t},\hat{g}_{2,t})$ : log-relative investment prices under different care arrangements

# Estimates - effect of aggregate investment (with persistence)



- -1% increase in resources  $\rightarrow 0.22\%$  increase in skills.
- Note very low persistence.
- Caveat: this parameter hard to identify with these data.

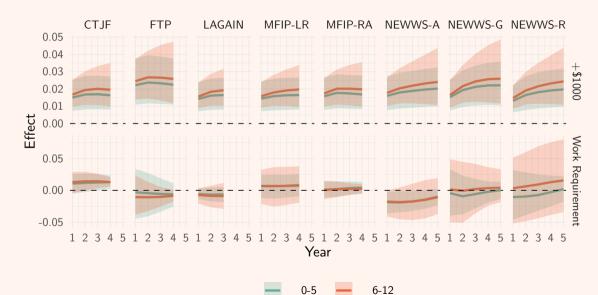
## Estimates - relative investment prices



- $\hat{g}$  < 0 implies form of care more effective than time at home.
- Only mild evidence that paid care better than unpaid.
- Paid care not good proxy for formality?



### Child impacts for two counterfactuals



## Summarizing Findings

#### We just saw:

- An extra \$1000/year leads to  $\approx$  2-3% of s.d. increase in academic and behavioral outcomes.
- Smaller than some non-experimental benchmarks in literature.
- No evidence of persistence.
- No evidence for negative impact of nonmaternal care.

## Summarizing Findings

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- An extra 1000/year leads to  $\approx 2-3\%$  of s.d. increase in academic and behavioral outcomes.
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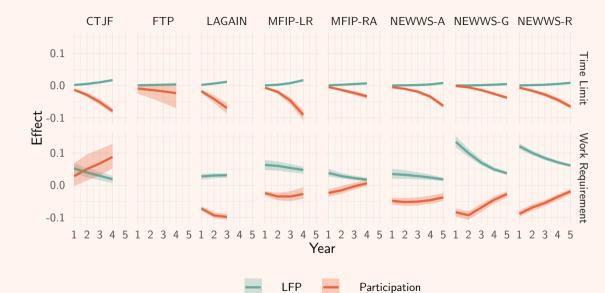
#### Some other counterfactuals of interest:

- Time limits vs work requirements see it
- Useful labor supply elasticities and price elasticities of care use see it
- Estimates of discounting see it

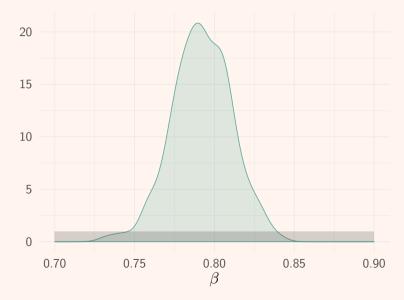
#### Conclusion

- Current method is useful way to use public data...
- Important extension: disaggregated data for individual heterogeneity
- Auxiliary data from public panel (SIPP,PSID,NLSY,CPS)
  - Potentially deal more explicitly with sample selection issues
  - External validity
  - Long-run outcomes
- General agenda for structural work



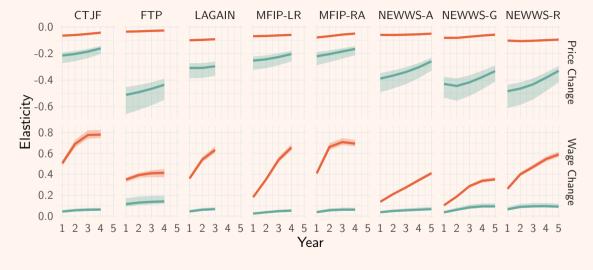


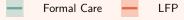
# Estimates - Discounting Go back



- Time limits precisely identify  $\beta$
- Some evidence that welfare participants exhibit time inconsistency (Chan 2017)

## Estimates - Price and Wage Elasticities Go back





#### Model - Full

Dynamic program:

$$V_{kjt}(\theta_t, \omega_t) = \mathbb{E} \max_{l_t, d_t} \{ u_k(C_t, d, \theta_t; \mathcal{R}_{kj}) + \epsilon_d + \beta V_{kjt+1}(\theta_{t+1}, \omega_{t+1}) \}$$

Subject to:

$$U(C, d, \theta) = \alpha_C \log(C) + \alpha_\theta \log(\theta) - \alpha_{H,k}H - \alpha_{A,k}A + \alpha_{F,k}F + \epsilon_d$$
$$\theta_{t+1} = I_t^{\delta_{I,t}}\theta_t^{\delta_\theta}, \qquad I_t = \mathcal{I}_t(\tau, x, H, F)$$
$$C + x + p_{F,kj}F + w_q(\tau + 30H) \le Y_{kjt}(A, H) + w_qL$$

too much math!!!

# Model - Specifying Technology

- Work with dual:

$$e(I, H, F) = \min_{\tau, x} w_q \tau + x$$
 s.t.  $\mathcal{I}_t(\tau, x, H, F) \ge I$ 

- Linear expenditure function:

$$e(I, H, F) = g_{\kappa, t}I_t, \qquad \kappa = H + F \in \{0, 1, 2\}$$

- Marschak (1953): sufficient to estimate prices  $(g_{0,t}, g_{1,t}, g_{2,t})$ , subject to policy invariance.
- Note interpretation of prices

# Model - Budgets (Control Group Example)

$$\begin{aligned} Y_{k0t}(A,H) &= E_{kt}H + A \cdot [\mathsf{AFDC}_{kt}(E_{kt}H) + \mathsf{SNAP}_t(E_tH)] \\ \mathsf{AFDC}_{kt}(E) &= \max\{B_k(n,y) - (1 - 0.33) \max\{E - 120, 0\}, 0\} \end{aligned}$$

- $B_k(n, y)$  is benefit standard for family size n in year y
- Fixed earnings disregard of \$120/month
- Variable earnings disregard of 33% of monthly earnings
- Treatments will modify these parameters, affecting incentives.

### Model - Work Requirements and Time Limits

- Let  $\mathcal{R}_{kj}$  indicate whether a work requirement applies:

$$u_k(C, d, \theta; \mathcal{R}) = \alpha_C \log(C) + \alpha_\theta \log(\theta) - \alpha_{H,k} H + \alpha_{F,k} F - \mathcal{R} A[\alpha_{R,k} (1 - H) + \alpha_{R2,k} H] + \epsilon_d$$

- Let  $\Omega$  be the number of periods of welfare use permitted. For control groups,  $\Omega=\infty.$
- Let  $\omega$  track the number of periods remaining:

$$\omega_{t+1} = \omega_t - A_t$$

- When  $\omega=$  0, eligible for food stamps only.

### Model - Child Care Subsidies



- No explicit change in subsidy formula.
- Administrative expansion
- Estimate to get price,  $p_{F,kj}$ , of formal care.

# MDRC's Welfare to Work Experiments

- 5 experiments, welfare recipients randomly assigned:
  - Family Transition Program, Minnesota Family Investment Program, National Evaluation of Welfare-to-work Strategies, Jobs First, LA Greater Avenues for Independence
  - 1991-1999
- Data compiled from publicly available reports

Bloom, Kemple, Morris, Scrivener, Verma, and Hendra (2000), Bloom, Scrivener, Michalopoulos, Morris, Hendra, Adams-Ciardullo, Walter (2002), Freedman, Knab, Gennetian, and Navarro (2000), Gennetian and Miller (2000), Hamilton, Freedman, Gennetian, Michalopoulos, Walter, Adams-Ciardullo, and Gassman-Pines (2001), Miller, Knox, Gennetian, Dodoo, Hunter, and Redcross (2000)

### Other things to know

Some other things you should know about these experiments:

- Treatment randomly assigned to applicants (both new and those for re-certification)
- Slightly more complicated for NEWWS and LA-GAIN (part of assignment to existing JOBS program).
- No significant impacts on hours, wages, fertility. Minimal impact on marital status.



#### Identification of Production Parameters

Let  $\Delta$  denote the difference operator between treatment j and control outcomes:

$$\mathbb{E}\Delta\log(\theta_{t+1}) = \frac{\delta_{l,t}\left(\sum_{D}\Delta P_{kjt,D}\left[\log(Y_{k0t}(H,A) + w_q(L-30H)) - \hat{\mathbf{g}}_{\kappa,t}\right]\right)}{P_{kjt,D}\Delta\log(Y_{kt}(H,A)) + \delta_{\theta}\mathbb{E}\Delta\log(\theta_t)}$$

where  $\hat{g}_{\kappa,t} = \log(g_{\kappa,t}/g_{0,t})$  is the relative log-price under formal and informal care.

### Identification of Preferences I

Let  $\rho_{kit}(\omega) = P[A = 1|k, j, t, \omega]$ . When no time limit applies:

$$\log\left(\frac{\rho_{kjt}(\infty))}{1-\rho_{kjt}(\infty))}\right) = \frac{\alpha_{C,t}}{\log\left(\frac{Y_{kjt}(0,1)+w_qL}{w_qL}\right) - \frac{\sigma_H}{\log\left(\frac{1-P_{H,t}(1)}{1-P_{H,t}(0)}\right) - \frac{R_{kj}\alpha_{R,k} - \alpha_{H,k}}{\alpha_{H,k}}\right)}$$

And under time limits:

$$\log\left(\frac{\rho_{kjt}(\omega)}{1-\rho_{kjt}(\omega)}\right) - \log\left(\frac{\rho_{kjt}(\infty)}{1-\rho_{kjt}(\infty)}\right) = \frac{\beta}{\left[\log\left(\frac{\rho_{kjt+1}(\omega)}{1-\rho_{kjt+1}(\omega-1)}\right) - \log\left(\frac{\rho_{kjt+1}(\infty)}{1-\rho_{kjt+1}(\infty)}\right)\right]}$$

Parameters identified by <u>levels</u> and <u>treatment responses</u>.

#### Identification of Preferences II

Fixing the choice of A, formal care use:

$$\log\left(\frac{P_{F,kjt}(A)}{1 - P_{F,kjt}(A)}\right) = \sigma_F^{-1} \left[\alpha_{C,t} \log\left(\frac{Y_{kjt}(1,A) + w_q(L - 30) - p_{F,k}}{Y_{kjt}(1,A) + w_q(L - 30)}\right) + \frac{\alpha_{F,k}}{1 - \alpha_{F,k}} - \alpha_{C,t} + \alpha_{$$

Work:

$$\log \left( \frac{P_{H,kjt}(A)}{1 - P_{H,kjt}(A)} \right) = \sigma_H^{-1} \left[ \alpha_{C,t} \log \left( \frac{Y_{kjt}(1,A) + w_q(L - 30) - p_{F,k}}{Y_{kjt}(0,A) + w_qL} \right) - \alpha_{H,k} + A \mathcal{R}_{kj} (\alpha_{R,k} - \alpha_{R2,k}) + \alpha_{F,k} - \Gamma_t (\hat{g}_{2,t} - \hat{g}_{1,t}) - \sigma_F \log(P_{F,kjt}(A)) \right]$$

Parameters identified by <u>levels</u> and <u>treatment responses</u>.