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

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- This paper: how can we make productive use of all this credible evidence?
  - Setting: welfare reform experiments and their impacts on children.
- Frisch (1933) had the answer: “use a model”.

A traditional approach to aggregation

Traditional meta-analysis:

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- α *typically not* a policy parameter of interest (Heckman 1992, Heckman & Vytlacil 2005)
- example: welfare experiment populations are highly selected and treatments are complicated bundles.

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Structural meta-analysis:

- Target parameters are policy invariant primitives (preferences, technology, etc)
- Differences in design and setting useful for identification and well articulated inside model
- Outcomes can be calculated for full range of counterfactuals

  Todd & Wolpin (2005), Attanasio, Meghir & Santiago (2011), Duflo, Hanna & Ryan (2012), Rodriguez (2018)

Application: Welfare Reform

- Obtained micro data from three RCT evaluations of welfare-to-work programs by MDRC
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- The model can:
  - Forecast counterfactual policy environments
  - Forecast same policy when rest of environment changes (labor markets, taxes, etc)
  - Forecast same policy on general population (experiment popn highly selected)

Model

- Environment:
  - Agent is single mother, endowed with $L = 112$ hours per week.
  - Type k, site l, treatment arm j, time t
  - Investment period is $T = 17 \times 4$ quarters.

- Choices:
  - Participate in food stamps/welfare, $S \in \{0,1\}$, $A \in \{0,1\}$
  - Work, $H \in \{0,1\}$
  - If $H = 1$, choose formal care ($F = 1$) or informal care ($F = 0$)
  - Invest in child (I) or consume privately (C)

$$\text{Value today} = \text{Payoff today} + \beta \times \text{Value tomorrow}$$

Value today		Payoff today		Value tomorrow
child skills		work		child skills
welfare status		welfare		welfare status
welfare remaining		childcare	$\mapsto$	welfare remaining
job offer		investment		job offer
		child skills		

show me math

Value today	$=$	Payoff today	$+$	$\beta \times$ Value tomorrow
child skills welfare status welfare remaining job offer		work welfare childcare investment child skills	$\mapsto$	child skills welfare status welfare remaining job offer

show me math

Preferences:

$$u_k(C, d, A_{t-1}, \theta; \mathcal{R}) = \log(C) + \alpha_{\theta,k}\log(\theta) - \alpha_{H,k}H + \alpha_{F,k}F - \mathcal{R}A\alpha_R(1-H) - \alpha_P(1-A_{t-1})A + \epsilon_d$$

ϵ_d is nested logit, variances $(\sigma_P, \sigma_H, \sigma_F)$, k indexes latent type.

Value today	=	Payoff today	+	$\beta \times$ Value tomorrow
child skills welfare status welfare remaining job offer		work welfare childcare investment child skills	$\mapsto$	child skills welfare status welfare remaining job offer

show me math

Technology:

$$\theta_{t+1} = I_t^{\delta_{I,t}} \theta_t^{\delta_\theta}, \qquad \kappa = H + F$$

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

Value today	=	Payoff today	+	$\beta \times$ Value tomorrow
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show me math

Earnings:

$$\log(W_{klt}) = \mu_k + \beta_{W,1}\text{Unemp}_{lt} + \beta_{W,2}\text{Age} + \eta_t$$

where η_t follows a job ladder process with separation rate δ_k, and job offer rates $\lambda_{0,k}, \lambda_{1,k}$.

Work requirements can improve job-finding: $\lambda^{\mathcal{R}}_{0,k} > \lambda_{0,k}$.

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show me math

Resource constraint:

$$C + g_\kappa I + p_{F,klj} F \leq Y_{ljt}(S, A, H \times W_{klt}) + y_k$$

Identification of Production

Model yields outcome equation:

$$\log(\theta_t) = \mu_k + \sum_{s=0}^{t} \delta_\theta^{t-s} \left(\delta_I \log(\text{net income}_s) + \tilde{g}_1 \times \text{Mom Working}_s \right.$$
$$\left. + \tilde{g}_2 \times \text{Formal Care Used}_s\right) + \delta_\theta^t \log(\theta_0) + \xi_t$$

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Which implies two sets of moment conditions:

1. Use assignment to treatment conditional on location.
2. Use all variation conditional on a flexible function of type and η_0.

other parameters

Estimation

Strategy:

- Use SIPP to pin down distribution of latent variables in representative population.
- Estimate initial distribution of latent variables directly.
- Stage 1: Estimate prices, transitions, preferences, via maximum likelihood.
  more details
- Stage 2: Bayesian estimation of production parameters using pseudo-likelihood implied by each of two moment conditions.

Estimation - Data

	CTJF	CTJF	FTP	FTP	MFIP	MFIP	MFIP	SIPP
Arm	0	1	0	1	0	1	2	0
Less than Highschool	0.401	0.428	0.437	0.476	0.346	0.353	0.368	0.273
Highschool	0.495	0.481	0.533	0.502	0.443	0.453	0.456	0.351
Some College	0.093	0.078	0.025	0.02	0.211	0.194	0.176	0.299
College	0.012	0.012	0.004	0.002	0	0	0	0.078
AFDC Participation	0.51	0.498	0.39	0.354	0.464	0.571	0.643	0.253
Foodstamps Participation	0.606	0.614	0.552	0.546	0.488	0.115	0.14	0.337
Mother's age	26.691	26.767	27.039	26.752	26.268	26.462	26.683	28.2
Number of Children	1.807	1.809	1.99	1.96	1.688	1.724	1.817	1.754
Employed	0.497	0.556	0.446	0.479	0.486	0.539	0.485	0.639
Earnings	534.185	551.806	337.862	376.537	538.512	560.03	461.347	1550.693
Person-Quarter Observations	35939	37255	28035	27972	52614	47214	31482	11197
Individuals	1956	2025	1335	1332	2923	2623	1749	953

Preference Estimates

Type	Type-Specific Parameters					
	α_H	α_A	α_S	α_F	α_θ	y
$k = 1$	-0.63	-0.34	-0.66	0.18	0.32	229.71
	(0.12)	(0.03)	(0.07)	(0.22)	(0.00)	(38.63)
$k = 2$	-1.01	-0.46	0.21	0.85	0.28	627.79
	(0.15)	(0.03)	(0.02)	(0.28)	(0.00)	(69.32)
$k = 3$	-0.97	-1.14	0.95	1.17	0.23	1105.14
	(0.15)	(0.08)	(0.08)	(0.34)	(0.00)	(122.96)
$k = 4$	0.10	-1.04	1.05	-0.99	0.18	147.67
	(0.19)	(0.08)	(0.09)	(0.12)	(0.00)	(22.71)
$k = 5$	-1.07	-1.82	1.73	0.20	0.17	1979.23
	(0.20)	(0.16)	(0.16)	(0.16)	(0.00)	(308.73)
	Global Parameters					
	β	σ_3	σ_2	σ_1	α_R	α_P
	0.34	1.16	0.56	0.34	0.04	1.63
	(0.05)	(0.24)	(0.04)	(0.03)	(0.02)	(0.15)

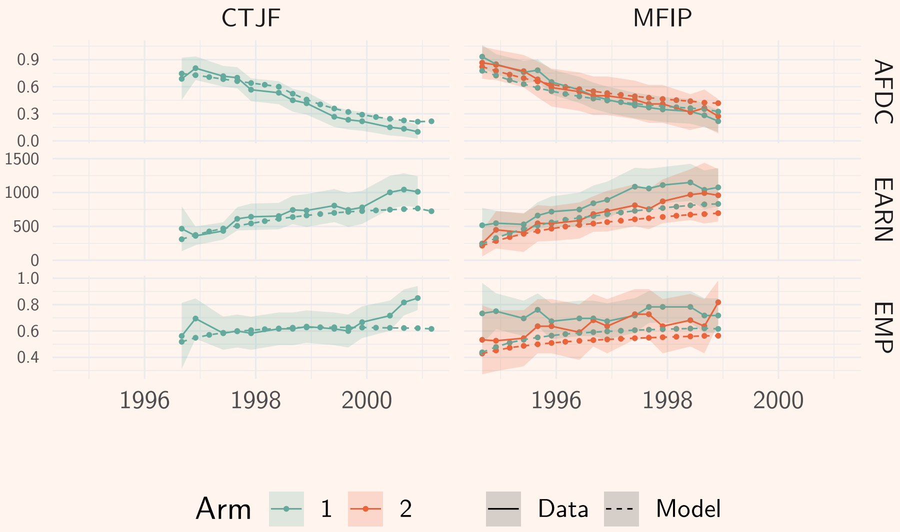
Wage Process

Type	Type-Specific Parameters		
	λ_0	λ_1	δ
$k = 1$	0.15	0.53	0.11
	(0.00)	(0.03)	(0.00)
$k = 2$	0.19	0.74	0.10
	(0.01)	(0.04)	(0.00)
$k = 3$	0.16	0.48	0.27
	(0.00)	(0.03)	(0.01)
$k = 4$	0.06	0.66	0.02
	(0.00)	(0.03)	(0.00)
$k = 5$	0.08	0.24	0.05
	(0.00)	(0.02)	(0.00)
	Global Parameters		
	μ_o	σ_o	λ_R
	-0.43	0.88	0.42
	(0.02)	(0.02)	(0.04)

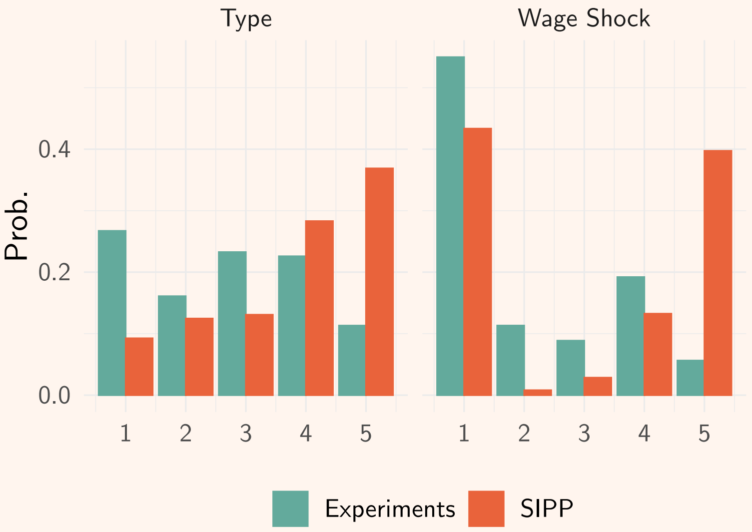
Model Fit


CTJF Applicant
CTJF Recipient
FTP Applicant
FTP Recipient
MFIP New Applicant
MFIP Re-applicant
MFIP Recipient
SIPP Rep. sample
AFDC
EARN
EMP
0.0
0.3
0.6
0.9
0
500
1000
1500
1992
1994
1996
1998
2000
Arm
0
1
2
Data
Model

Validation: Holdout Sample



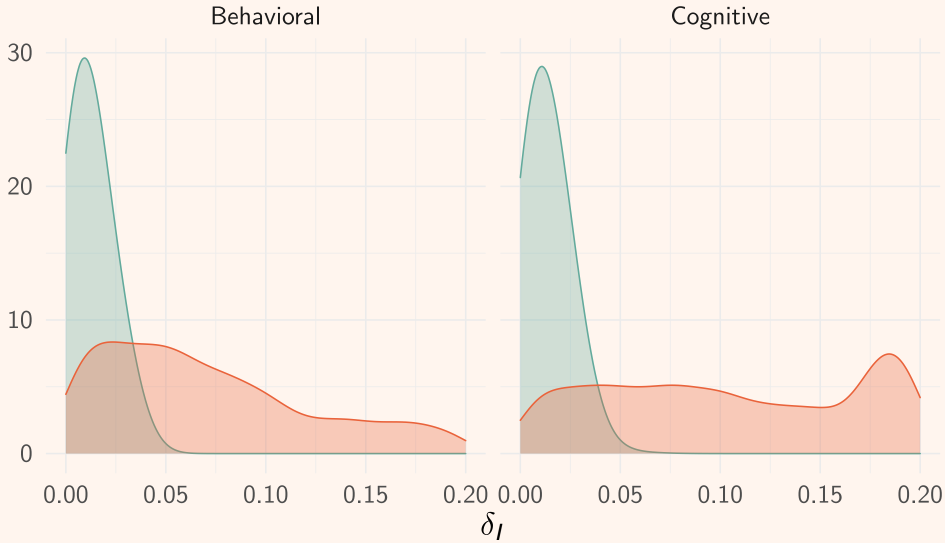
Evidence of Strong Selection in Experiments



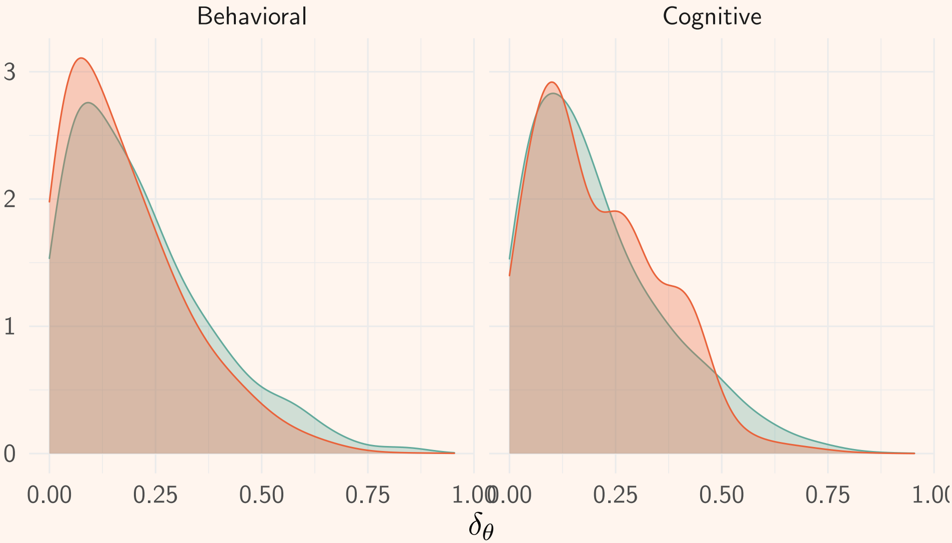
Factor Loadings

Measure	λ_B^m	λ_B^m	σ_m^2
BPI-Externalizing	-3.70	-	5.86
	(0.14)		(1.23)
BPI-Internalizing	-2.32	-	7.55
	(0.08)		(0.91)
Positive Behavior Scale	6.49	-	63.34
	(0.23)		(23.84)
School Engagement	0.16	0.96	2.03
	(0.14)	(0.14)	(0.10)
Ever Repeat Grade	0.79	-0.80	0.04
	(0.25)	(0.25)	(0.00)
Ever Suspended	-0.05	-0.05	0.08
	(0.02)	(0.02)	(0.00)
School Achievement - Parent	-	0.51	0.72
		(0.03)	(0.02)
School Achievement - Teacher	-	0.42	1.29
		(0.06)	(0.09)

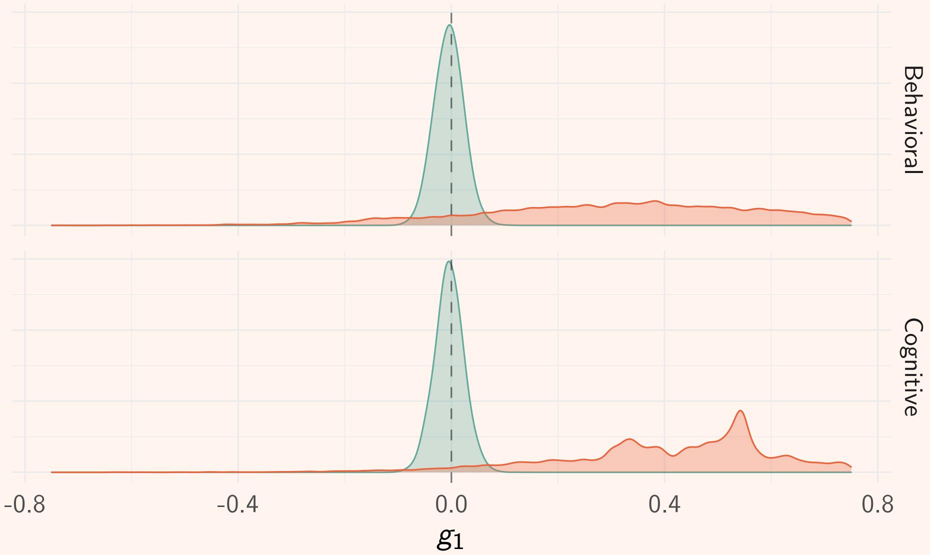
Estimates of the return to resources (δ_I)



Effects show rapid decay



IV doesn't tell us much about effects of care



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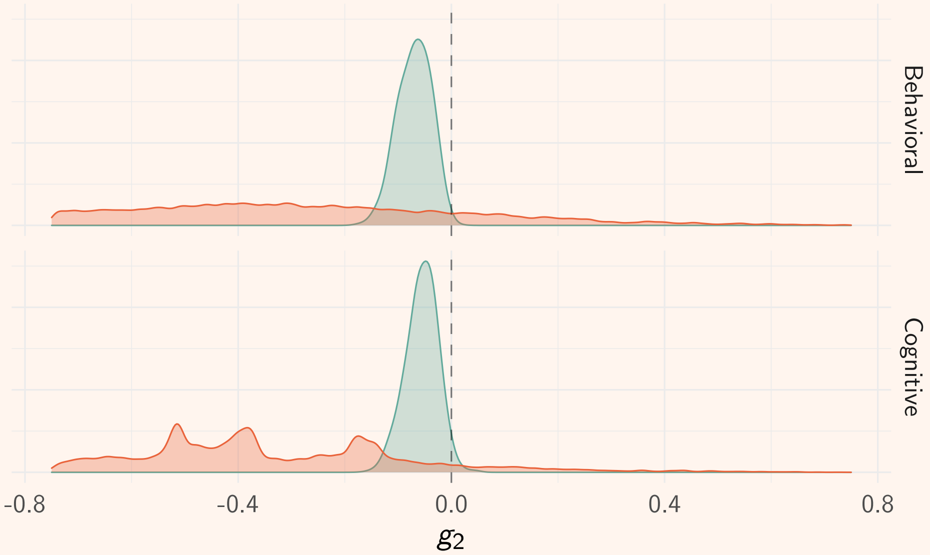
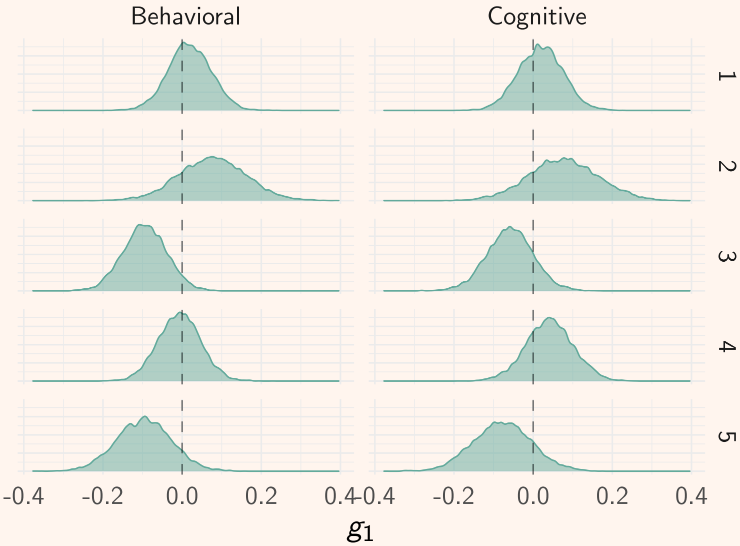


Care effects are heterogeneous



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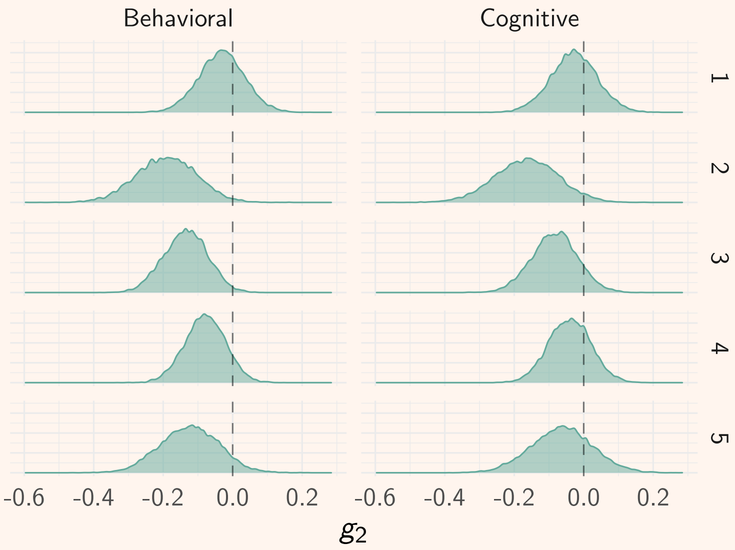

Decomposition Exercise

- What components of the treatment were responsible for the treatment effects?
- What would outcomes look like if we used only one reform instead of an ensemble?
- What would the impacts on children be?

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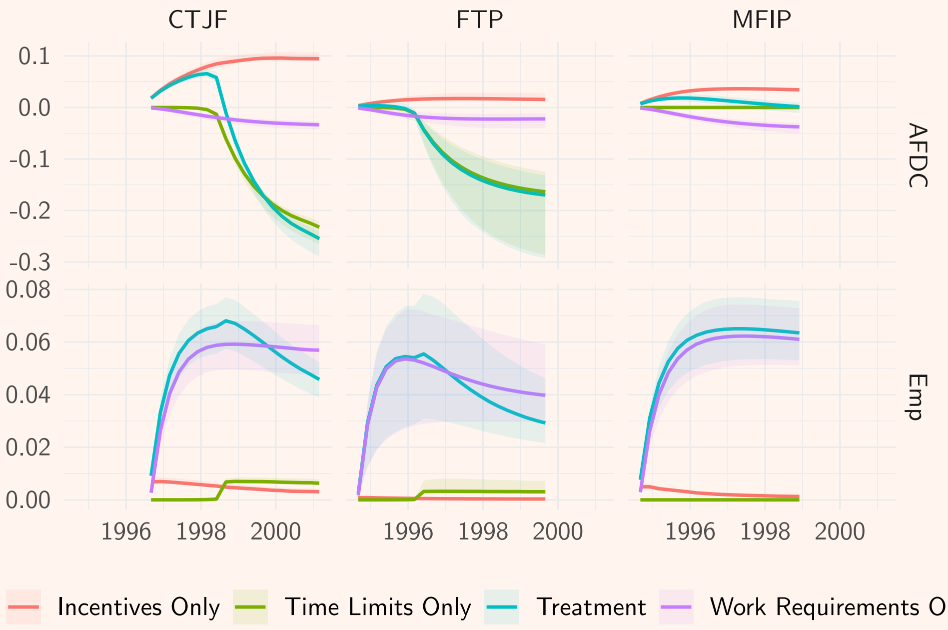
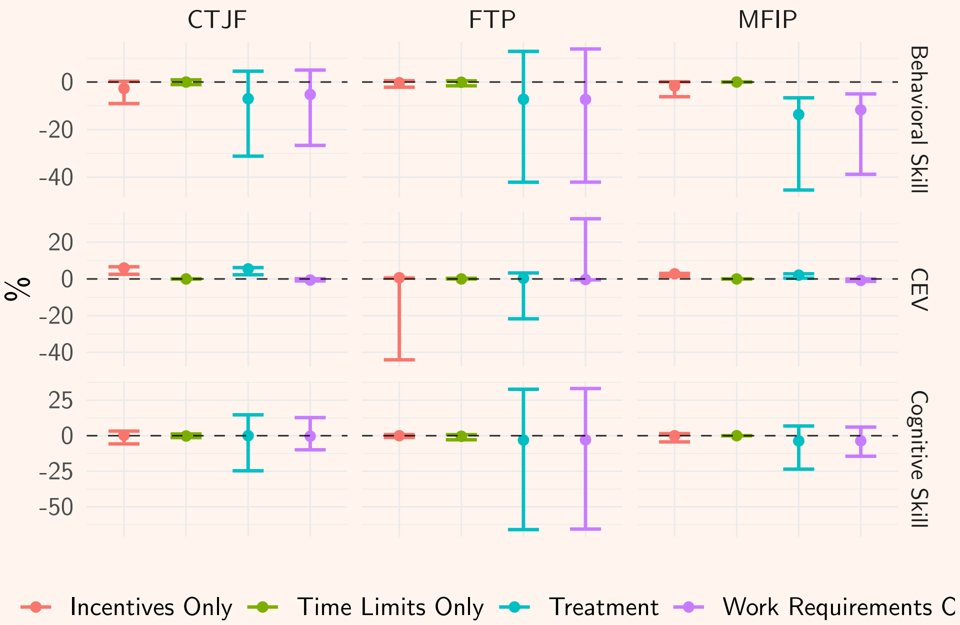
- We can explore this using the model by introducing each piece in isolation.



CTJF
FTP
MFIP
AFDC
Emp
0.1
0.0
-0.1
-0.2
-0.3
0.08
0.06
0.04
0.02
0.00
1996
1998
2000
Incentives Only
Time Limits Only
Treatment
Work Requirements Or



CTJF
FTP
MFIP
Behavioral Skill
CEV
Cognitive Skill
%
0
-20
-40
20
0
-20
-40
25
0
-25
-50
Incentives Only
Time Limits Only
Treatment
Work Requirements C

No Negative Impacts on Skills in Experiment Population

	FTP			
	Treatment	Incentives Only	Work Requirements Only	Time Limits Only
Behavioral Skill	-7.27	-0.29	-7.33	-0.10
	[-18.95, 16.09]	[-1.74, 0.30]	[-18.99, 16.19]	[-0.99, 0.88]
Cognitive Skill	-3.05	0.01	-2.91	-0.38
	[-14.19, 15.37]	[-0.51, 1.33]	[-14.10, 15.58]	[-1.56, 0.50]
CEV	0.37	0.67	-0.32	-0.00
	[-18.98, 5.06]	[-31.05, 0.50]	[-0.72, 21.99]	[-0.01, 0.13]
	CTJF			
	Treatment	Incentives Only	Work Requirements Only	Time Limits Only
Behavioral Skill	-7.02	-2.72	-5.26	-0.00
	[-22.80, 1.96]	[-7.08, 0.15]	[-18.04, 2.31]	[-0.84, 0.74]
Cognitive Skill	0.02	0.28	-0.37	-0.20
	[-9.62, 10.33]	[-3.61, 3.74]	[-9.33, 8.54]	[-1.14, 0.70]
CEV	5.49	5.97	-0.59	-0.00
	[3.16, 6.25]	[3.46, 6.36]	[-1.44, 0.44]	[-0.02, -0.00]

Changing the Population of Interest

- What would the effects of these policies be on the general population, not just on applicants?
- What would the effect on child outcomes be?
- We can use the model to explore this, applying these policies to the SIPP sample.

Negative Impacts on Skills in Broader Population

Table: Treatment Effects

	FTP	CTJF	MFIP
Behavioral Skill	-10.00	-12.10	-12.25
	[-36.32, -3.09]	[-44.14, -3.94]	[-43.65, -4.52]
Cognitive Skill	-2.84	-4.03	-3.65
	[-12.38, 5.16]	[-14.97, 5.94]	[-14.20, 5.82]
CEV	1.19	2.80	2.03
	[0.83, 1.53]	[2.36, 3.19]	[1.60, 2.42]

Conclusion

- In some contexts, the effects of many experiments or quasi-random policy interventions are well understood through standard economic models
- Other potential examples: job training, microfinance, minimum wages.
- This is one context in which the model appears to work quite well.
- Researchers must still make decisions about what variation they are willing to use.
- Model uncovers rich treatment effect heterogeneity with implications for broad effect of policies

- Type selection for each site l:

$$P[k|l, X_m] \propto \exp(X_{m,l}\beta_{l,k})$$

where X_m includes number of kids, age of youngest kid, education, and application status.

- Then estimate $P(\eta|k, \text{App status})$ nonparametrically.

- Impose that η is drawn from stationary distribution in SIPP.

go back

Key Model Parameters

Parameter	What it determines show me math
Preferences	
Var of participation util. shocks (σ_P)	Response of participation to program generosity

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Technology	
Log-relative price of investment ($\hat{g}_1, \hat{g}_2$)	Effect on child outcomes of non-maternal care
Cobb-Douglas share on investment (δ_I)	Effect on child outcomes of increase in income
Cobb-Douglas share on skills (δ_θ)	Persistence of effects on child outcomes

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- Preference parameters then identified by parametric restrictions of nested logit.
- With choice probabilities and finite dependence, identification guaranteed by conditional moments of random assignment only.

back

Model - Full

Dynamic program:

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

Subject to:

$$U(C, d, \theta) = \alpha_C \log(C) + \alpha_\theta \log(\theta) - \alpha_{H,k} H - \alpha_{A,k} A + \alpha_{F,k} F + \epsilon_d$$

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

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

too much math!!!

Model - Specifying Technology

- Work with dual:

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

- 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)

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

- $B_k(n, y)$ 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:

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

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

- Let ω track the number of periods remaining:

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

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

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.

go back

Identification of Production Parameters

Let Δ denote the difference operator between treatment j and control outcomes:

$$\mathbb{E}\Delta\log(\theta_{t+1}) = \delta_{I,t}\Big(\sum_{D}\Delta P_{kjt,D}\big[\log(Y_{k0t}(H,A) + w_q(L - 30H)) - \hat{g}_{\kappa,t}\big]$$

$$P_{kjt,D}\Delta\log(Y_{kt}(H,A))\Big) + \delta_\theta\mathbb{E}\Delta\log(\theta_t)$$

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

too much math!!!

Identification of Preferences I

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

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

And under time limits:

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

Parameters identified by levels and treatment responses.

Identification of Preferences II

Fixing the choice of A, formal care use:

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

Work:

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

Parameters identified by levels and treatment responses.