# Fostering Children

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# Introduction

# Introduction

- Foster care is important
    - Over 400,000 children in foster care in US
    - Children removed from birth families due to neglect or abuse
    - Some of the most disadvantaged children in society coming in and out

- Major resource: **foster families**
    - Used to temporarily or permanently care for foster children

# Research Question

- **Research Question**: Which families choose to be foster parents?
- Necessary to understand incentives and motivations of foster parents
- Policy question: What policies most affect supply of foster parents?

# Approach Overview

Three steps

1. Basic facts and institutional details

2. Model of household choice

3. Test predictions, and quantify mechanisms

# Related Literature

1. **Effects of Foster Care**: Doyle (2007b), Bald et al. (2019)

2. **Foster Family Behavior**: Doyle (2007a), Doyle and Peters (2007)

3. **Effects of Families**: Nelson et al. (2007), Sacerdote (2002, 2007), Berrick et al. (1994), Font (2014), Ehrle and Geen (2002)

# Data and Facts

# Data Sources

AFCARS more

- Survey of foster care agencies by Children's Bureau
- Unit of analysis: child-year
- Used to: predict characteristics of children placed with families
- Summary: 500,000 California foster children in 14 California counties, 2005-2015

ACS 1% more

- Unit of analysis: household
- Used to: predict which families choose to be foster parents
- Summary: 150,000 California households, 2005-2015

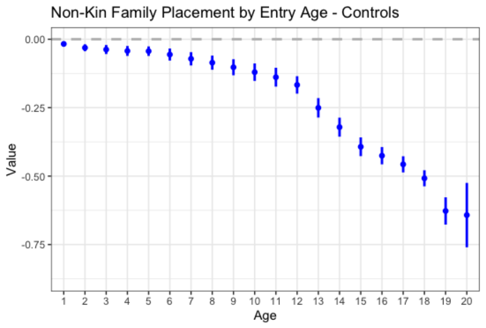
# Child Characteristics and Placement Methods

- **Claim**: Age is an important predictor of whether a child is placed with a family
- Estimate LPM in AFCARS

$$\text{Placed with a Family}_{it} = \beta_a \text{Age}_{it} + X_{it}\beta + \gamma_{j(i,t)} + \delta_t + \epsilon_{it} \quad (1)$$

- $X$ includes all child observables; $j$ is a county; $t$ is a year
- Cluster se's at county level.

# Child Characteristics and Placement Results




**(a)** Age Parameter Estimates

Notes: Plots of $\hat{\beta}_a$ with $a \in [0, 20]$ from (1) with 95% asymptotic confidence intervals. Sample is children who enter and eligible for non-kin family placement.

| Total Variance | 1 |
|---|---|
| Age Variance | 0.1727 |
| Race Variance | 0.0021 |
| Sex Variance | 8e-04 |
| Disabled Variance | 3e-04 |
| $\epsilon$ Variance | 0.7738 |

**(b)** Variance Decomposition

Notes: Variance decomposition from (1) treating age as numerical and leaving out covariance terms. Sample is children who enter and eligible for non-kin family placement.

# Model

# Economic Environment I

- Households have preferences over three objects
  - Total human capital of own biological children $H_n = h_n n$
  - $n$ is number of biological children
  - Total human capital of foster children cared for $H_F = h_F F$
  - Own consumption $c$ (numeraire good)
- Preferences are quasi-linear and $u(\cdot, \cdot)$ measures altruistic utility

$$U(H_n, H_F, c) = u(H_n, H_F) + c \tag{2}$$

# Economic Environment II

- Households have exogenous
  - Time budget $T$
  - Price of biological children $p_n$
  - Time invested in biological children $t_n$
  - Number of biological children $n$
  - Wage $w$
- Foster children have
  - Entry age $a \in [0, 1]$
  - Price $p_F(a)$
- Households choose
  - Whether to foster $F = 0$ or $F = 1$
  - Time invested in foster child $t_F$

# Human Capital

- Human capital of any child is determined as a flow of rate of household time investment:

$$h_j = \int_0^1 t_j(a)da, \; j = n, F$$

- Foster children are abused/neglected: assume flow while abused/neglected is normalized to 0
- Household invests $t_F$ into foster child gives human capital

$$h_F(a) = (1 - a)t_F$$

# Value of Foster Care

Budget constraint:

$$c = w(T - t_n n - t_F F) - p_n n - p_F(a)F \tag{3}$$

Value of foster care:

$$V_F(a, n, w) := \max_{t_F} u(h_n n, t_F(1 - a)) + w(T - t_n n - t_F) - p_n n - p_F(a) \tag{4}$$

Value of not fostering:

$$V_0(a, n, w) := u(h_n n, 0) + w(T - t_n n) - p_n n \tag{5}$$

Net value/willingness to pay for foster care:

$$V(a, n, w) := V_F(a, n, w) - V_0(a, n, w) \tag{6}$$

# Assumptions and Model Results

Assumptions

1. $u_{12} < 0$
2. $u_2(x, y) < -u_{22}(x, y)y, \ \forall x, y$

Under 1 and 2:

$$\frac{\partial V}{\partial w} < 0, \frac{\partial V}{\partial n} < 0, \frac{\partial V}{\partial a} < 0$$
$$\frac{\partial V}{\partial a \partial n} > 0, \frac{\partial V}{\partial a \partial w} < 0$$

Provides 5 predictions. Proofs and Intuition

# Empirical Tests

# Empirical Setup and Endogeneity

- Model has no heterogeneous or unobserved tastes
- Unobserved taste parameter for household $i$ $\xi_i$

$$V_F = u(h_{n,i}n_i, h_F, \xi_i) + w_i(T - t_{n,i}n_i - t_F) - p_{n,i}n_i - p_F$$

- $\xi_i =$ "taste for children" correlated with housing decisions $n_i$ and $w_i$ then OVB
- Goal: isolate causal effects / real comparative statics from this type of endogeneity

# Testing Fertility Predictions Setup

- Exogenous shocks: shock to $n$ - **birth of twins** and shock to $p_n$ - **same-sex couple status**
- Estimate in ACS

$$\text{Foster Child in HH}_i = \beta_1 \text{Num Child}_i + X_{it}\beta_2 + \epsilon_{it} \tag{7}$$
$$\text{Num Child}_i = \alpha_1 Z_i + X_{it}\alpha_2 + \nu_{it}$$

- $X_{it}$ includes household age, race, county-year (market) fixed effects, $Z_i$ is whether first birth is twins, couple is same-sex
- Estimate with 2SLS and cluster se's at market level Sample details

# Fertility Predictions Results

| | OLS (Twins) | OLS (Same-Sex) | Twins IV | Same-Sex IV |
|---|---|---|---|---|
| Num Child | $-0.314^{*}$ | $-0.409^{***}$ | $-2.884^{**}$ | $-4.469^{***}$ |
| | (0.161) | (0.134) | (1.301) | (1.368) |
| First Stage F-stat | - | - | 823 | 1,996 |
| Observations | 131,544 | 169,501 | 131,544 | 169,501 |
| Mean($y$) | 2.281 | 2.165 | 2.281 | 2.165 |
| SD(Num Child) | 1.00 | 1.23 | 1.00 | 1.23 |

Robustness

Notes: All regressions include demographic controls for a second-order polynomial in the age of the household and race of the head of the household. They also include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

# Wage Predictions Setup

- Endogeneity: less altruistic sort into higher wage jobs
- Strategy: Allow for altruism differences between occupations but not within occupations
- Estimate LPM in ACS

$$\text{Foster Child in HH}_i = \beta_1 \text{HH Wage}_i + X_{it}\beta_2 + \epsilon_{it} \tag{8}$$

- $X_{it}$ includes **maximum earner occupation**, household age, race, county-year (market) fixed effects Occupations
- Estimate with OLS and cluster se's at market level

# Wage Predictions Results

| | Univariate OLS | OLS | OLS |
|---|---|---|---|
| HH Wage | $-0.052^{***}$ | $-0.039^{***}$ | $-0.022^{***}$ |
| | (0.008) | (0.008) | (0.008) |
| Occupation FEs | No | No | Yes |
| Observations | 169,501 | 169,501 | 169,501 |
| $R^2$ | 0.002 | 0.0047 | 0.0083 |
| Mean($y$) | | 2.165 | |
| SD(HH Wage) | | 14.3 | |

Notes: All regressions include demographic controls for a second-order polynomial in the age of the household and race of the head of the household. They also include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. $^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01

# Age-Based Predictions

- Within ACS foster families: test for differing age gradients by household observables
- Estimate

$$\text{Median Age of Foster Child}_i = \beta_1 \text{HH Characteristic}_i + X_{it}\beta_2 + \epsilon_{it} \tag{9}$$

- Include standard market and demographic controls
- Estimate LPM and cluster se's at market level

# Age-Based Predictions Results

| | OLS | Twins IV | OLS | OLS w/ Occ FEs |
|---|---|---|---|---|
| Num Child | 0.834** | 4.821*** | | |
| | (0.356) | (1.231) | | |
| HH Wage | | | −0.095** | −0.157** |
| | | | (0.037) | (0.075) |
| Observations | 300 | 300 | 367 | 367 |
| Mean($y$) | 9.2 | 9.2 | 8.4 | 8.4 |
| SD($X$) | 1.07 | 1.07 | 11.4 | 11.4 |

Notes: All regressions include demographic controls for a second-order polynomial in the age of the household and race of the head of the household. They also include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. *p<0.1; **p<0.05; ***p<0.01

AFCARS Age Predictions

# Structural Estimation

# Empirical Model Setup

- Ignore human capital, age and treat time investment exogenous. $F = 1$ if and only if

$$u(n, F) - u(n, 0) - wt_F - p_F \geq 0 \tag{10}$$

- Let

$$u(n, F) = \log(n + 1) + \log(F + 1) + \alpha \log(2 + n + F)$$

  where $\alpha$ is a substitution parameter

- Let $p_F = \$500$ be the monthly base rate and $t_F = 4 * 40/2 = 80$ for 40 hours per week divided over HH

# Empirical Model Estimation

- Binary choice. Set value of not fostering to 0. Choose to foster $y_i = 1$ if $y_i^* \geq 0$ where

$$y_i^* = \beta_0 + X_{D,i}\beta + \alpha \log\left(\frac{2+n_i}{1+n_i}\right) + \psi(p^F - w_i \cdot t_F) + \epsilon_i \quad (11)$$

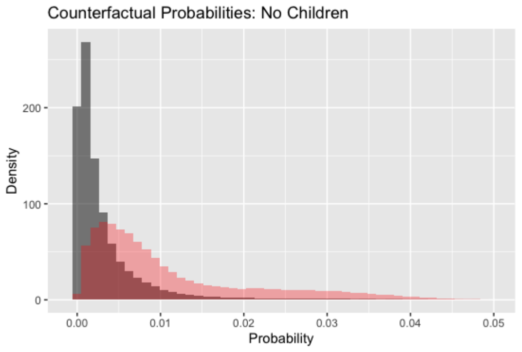
  where $\epsilon_i \sim N(0,1)$, $X_{D,i}$ is vector of demographics and $\psi$ is a consumption parameter
- Estimate IV Probit with Newey two step method Details
- Instruments: same-sex and within-occupation wage First Stage
- Demographics, foster care prices, time of care exogenous

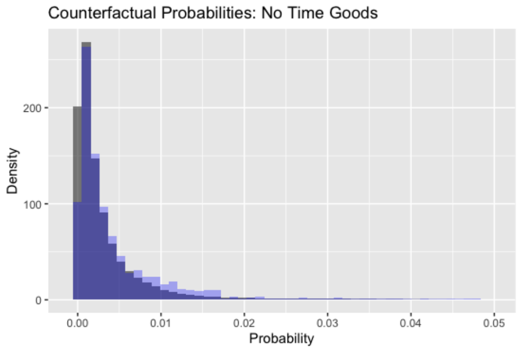
# Empirical Model Parameter Estimates

| | Parameter Estimate | S.E. |
|---|---|---|
| $\alpha$ | 2.0669 | 0.4149 |
| $\psi$ | 8.3784e-05 | 2.4815e-05 |

- Expected sign and statistically significant
- Run two counterfactuals
    - Suppose all families had no children $n_i = 0, \forall i$: what would distribution of foster probabilities be?
    - Suppose foster children had no time cost $t_F = 0$: what would distribution of foster probabilities be?

# Empirical Model Counterfactuals




- No Children counterfactual: $4\times$ increase in foster families
- No Time Goods counterfactual: 50% increase in foster families

# Conclusion

# Conclusion

- Strong evidence that foster families take into account the economic mechanisms highlighted by the model
- Foster kids are a substitute for biological children, and time costs also play an important role
- Older children are tougher to place
- Too much subsidy compression?

# Questions? Thank You!

# Appendix

# Foster Care Shortage

HUFFPOST

NEWS POLITICS ENTERTAINMENT COMMUNITY LIFE PERSONAL VIDEO SHOPPING HIGHLINE

**Dr. John DeGarmo, Contributor**
Leading Expert in Parenting and Foster Care

## The Foster Care Crisis: The Shortage Of Foster Parents In America

05/01/2017 08:54 am ET | **Updated** May 01, 2017

## States Are Struggling to Meet Foster Care Needs. New Federal Rules Could Help.

Amid an opioid crisis that has increased the need for foster care, states are struggling to find enough foster families to take in kids. A shortage of affordable housing in many places is making the problem even worse.

BY STATELINE | DECEMBER 6, 2018 AT 10:30 AM

*By Teresa Wiltz*



Back to Intro

# AFCARS Sample

- Substantive restrictions: California foster children NOT in kin placement
- Non-kin and kin placements: kin placements are preferred by law (California Welfare and Institutions Code 16000) so suitable measure of non-kin placement
- Why non-kin placements: Remove variation related to availability of relative
    - Results mostly go through including kin placements
- Overall sample: Children not in kin placement in identified counties in California between 2005-2015 (14 total counties)

Back

# ACS Sample

- Has standard set of observables over which model will make predictions
    - Wage: average wage of head of household and partner/spouse
    - Number of Children: number of biological children of head of household
- Sample: Younger households in California from 2005-2015 to avoid mis-measurement of fertility (Angrist and Evans 1998)
- Answer questions related to: which families have foster children?
- 0.2% of households have foster children.

Back

# County Level Characteristics

| County | Child Obs | Obs Entry | Obs Exit | Avg Entry Age | % White | % Male | % Disabled |
|---|---|---|---|---|---|---|---|
| Alameda | 19518 | 6187 | 7077 | 8.30 | 0.18 | 0.46 | 0.49 |
| Contra Costa | 12688 | 3940 | 4453 | 6.96 | 0.29 | 0.48 | 0.17 |
| Fresno | 20511 | 7351 | 7008 | 6.39 | 0.17 | 0.50 | 0.26 |
| Kern | 22508 | 8848 | 9461 | 4.70 | 0.32 | 0.51 | 0.17 |
| Los Angeles | 177647 | 55335 | 58293 | 7.09 | 0.11 | 0.48 | 0.49 |
| Orange | 20726 | 5892 | 6936 | 7.32 | 0.29 | 0.48 | 0.43 |
| Riverside | 51974 | 21089 | 21584 | 6.65 | 0.28 | 0.50 | 0.33 |
| Sacramento | 38375 | 14224 | 15647 | 6.45 | 0.32 | 0.50 | 0.36 |
| San Bernardino | 39612 | 13568 | 13875 | 6.55 | 0.29 | 0.49 | 0.51 |
| San Diego | 41507 | 13866 | 15419 | 5.96 | 0.26 | 0.50 | 0.18 |
| San Francisco | 11222 | 2736 | 3458 | 7.78 | 0.14 | 0.48 | 0.35 |
| San Joaquin | 14444 | 4351 | 4343 | 5.54 | 0.25 | 0.51 | 0.25 |
| Santa Clara | 16854 | 6333 | 7295 | 7.98 | 0.19 | 0.47 | 0.36 |
| Tulare | 10523 | 3849 | 3961 | 5.96 | 0.25 | 0.51 | 0.37 |
| Total | 498109 | 167569 | 178810 | 6.71 | 0.21 | 0.49 | 0.38 |

Back

# County Level ACS Characteristics

| County | % White | % Black | % Hispanic | Family Age | % Married | Avg Log Wage | 90% Log Wage | Num Child |
|---|---|---|---|---|---|---|---|---|
| Alameda | 0.46 | 0.1 | 0.1 | 49.27 | 0.64 | 2.9 | 3.78 | 1.53 |
| Contra Costa | 0.6 | 0.07 | 0.1 | 51.55 | 0.7 | 2.93 | 3.84 | 1.62 |
| Fresno | 0.48 | 0.04 | 0.35 | 49.82 | 0.66 | 2.48 | 3.37 | 1.79 |
| Kern | 0.54 | 0.04 | 0.32 | 48.91 | 0.68 | 2.49 | 3.38 | 1.78 |
| Los Angeles | 0.39 | 0.07 | 0.27 | 49.27 | 0.62 | 2.66 | 3.62 | 1.61 |
| Orange | 0.58 | 0.01 | 0.17 | 50.18 | 0.7 | 2.83 | 3.73 | 1.65 |
| Riverside | 0.57 | 0.05 | 0.26 | 51.64 | 0.67 | 2.59 | 3.46 | 1.72 |
| Sacramento | 0.61 | 0.07 | 0.11 | 50 | 0.62 | 2.69 | 3.51 | 1.63 |
| San Bernardino | 0.46 | 0.07 | 0.32 | 49.09 | 0.68 | 2.58 | 3.43 | 1.68 |
| San Diego | 0.61 | 0.04 | 0.19 | 49.73 | 0.66 | 2.74 | 3.61 | 1.57 |
| San Francisco | 0.53 | 0.05 | 0.05 | 47.91 | 0.49 | 3.01 | 3.95 | 1.38 |
| San Joaquin | 0.51 | 0.06 | 0.24 | 50.05 | 0.67 | 2.57 | 3.41 | 1.71 |
| Santa Clara | 0.47 | 0.02 | 0.13 | 48.55 | 0.71 | 3.03 | 3.94 | 1.58 |
| Tulare | 0.49 | 0.01 | 0.43 | 49.55 | 0.7 | 2.35 | 3.23 | 1.9 |
| Total | 0.52 | 0.05 | 0.22 | 49.68 | 0.66 | 2.7 | 3.59 | 1.65 |

Back

# Sample Details

- Start with: households with females between ages (21, 35) and take only children who are less than 18 (over 99% of females younger than 35 have
- This is identical selection to Angrist and Evans (1998); reason is that children older than 18 likely to move out (college)
- For the twins results - must restrict only to households with at least one child
- For same-sex results: look at households where average age is in (21, 45) and if a female is present, they must follow the rule above. Older age useful because many households with around 35 have spouse or partner older than 35 (95% less than 45) Back to Fertility Predictions

# Proofs and Intuition

All results come from applying **envelope theorem** on $V(a, n, w)$

$$\frac{\partial V}{\partial w} = -t_F^*$$
$$\frac{\partial V}{\partial n} = u_1(h_n n, t_F^*(1-a)) - u_1(h_n n, 0)$$
$$\frac{\partial V}{\partial a} = -u_2(h_n n, t_F^*(1-a))t_F^* - p_F'(a)$$

To get sign of cross partials: need sign of $\frac{\partial t_F^*}{\partial a}$.

Assumption 2 guarantees this is positive in the $t_F$ FOC: households caring for older children attempt to "catch up", not "give up". Back to Model Results

# Fertility Predictions Robustness

- Is this just consumption-based effects?
  - Split by wage: stronger for lower wage families (est=-5.574, s.e. = 0.603)
- Regressing foster on same-sex has similar effects (est=4.06, s.e.=1.23) - this gives a particular mechanism for this effect
  - Direct regression of foster on same-sex tests $p_n$ prediction; using same-sex IV tests $p_n$ effect by focusing it only through $n$ consumption
- Twins IV has IVF worry: effects stronger and more precise for lower wage (less susceptible to IVF treatment)
- Same sex IV robust to adding community service participation from CPS volunteer supplement Back to Results

# ACS Occupations

- In sample: over 500 occupations for maximum earner
- Examples in ACS
    - 0010=Chief executives and legislators
    - 0050=Agents and business managers of artists
    - 0620=Human Resource managers
    - 0840=Financial analysts
    - 1460=Mechanical Engineers
    - 2010=Social Workers

Back to Wage Setup

# Age-Based Predictions Setup (AFCARS)

- Use AFCARS and estimate models of form

$$\begin{aligned}\text{Placed with Family}_{it} = &\beta_1 \text{County HH Attribute}_{j(i,t),t} \times \text{Old}_{it} \\ &+ X_{it}\beta_2 + \epsilon_{it}\end{aligned} \tag{12}$$

  where Old is an indicator if a child is above median age of 10
- $X_{it}$ includes rich child characteristics and county-level racial composition, age of households and year effects
- Estimate with OLS, cluster standard errors at county level

# Age-Based Predictions Results (AFCARS)

| | OLS | OLS | OLS | OLS | OLS |
|---|---|---|---|---|---|
| Old × Num Child | 0.302*** | 0.042 | | | 0.026 |
| | (0.103) | (0.174) | | | (0.113) |
| Old × Avg Wage | | | −0.017*** | −0.025*** | −0.027*** |
| | | | (0.003) | (0.008) | (0.008) |
| Old | −0.831*** | −1.198** | −0.069 | −0.260 | −0.188 |
| | (0.191) | (0.482) | (0.048) | (0.357) | (0.326) |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | No | Yes | No | Yes | Yes |
| Observations | 498,109 | 498,109 | 498,109 | 498,109 | 498,109 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | | |

Back to ACS Agre predictions

# Assessing Other Theories

- Warm Glow (Andreoni, 1990): households like contributing to public good
  - Some consistency with age effects if human capital sunk
  - Takes no stand on fertility effects which are very strong here

- Psychology and Sociology (Wegar, 2000): Foster families more likely to be families with more flexible interpretation of family
  - Consistent with same-sex couples and potentially even wage results
  - But does not explain fertility and interaction effects

$$
\begin{aligned}
Foster_{it} &= \beta_0 + X_{D,i}\beta_D + \alpha \log\left(\frac{2+n_i}{1+n_i}\right) + \psi(p^F - w_i t_F) + \epsilon_i \\
\log\left(\frac{2+n_i}{1+n_i}\right) &= \alpha_{10} + X_{D,i}\alpha_{1D} + \alpha_{11} Same\ Sex_i + \alpha_{12} Wage\ Res_i + \nu_{1i} \\
p^F - w_i t_F &= \alpha_{20} + X_{D,i}\alpha_{2D} + \alpha_{21} Same\ Sex_i + \alpha_{22} Wage\ Res_i + \nu_{2i} \\
(u_i, \nu_i) &\sim N(0, \Sigma)
\end{aligned}
$$

- Use Newey (1987) min chi-squared estimator
    - Regress endogenous on exogenous; run probit regression on endogenous, exogenous, fitted residuals; scale coefficients

Back to Empirical Model

# IV Probit First Stage

| | Child U | Cons U |
|---|---|---|
| | (1) | (2) |
| Same Sex | 0.1897*** | −127.545*** |
| (t stat) | (65.583) | (-11.6) |
| Within Occupation Wage | 0.00043*** | −67.968*** |
| (t stat) | (12.49) | (-514.52) |
| Observations | 169,501 | 169,501 |
| KP F Stat | 2824 | 88969 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

Back to Empirical Model