Fostering Children

Cameron Taylor*

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Abstract

Foster families constitute a crucial input into foster care services. In this paper, a household choice model is built to examine why households choose to be foster parents. The model is motivated by the inability of classical altruism models to explain important facts about foster families and children. In the model, children are costly and foster families get value from taking care of foster children through the human capital of the foster child. The model links a household's decision to foster to their own fertility and wage and makes predictions about which households have the highest willingness to foster based on these factors. The model's predictions find strong support in the data through instrumental variable strategies and the model is able to rationalize many of the motivating facts. A simple form of the model is jointly estimated to more directly compare and quantify the mechanisms. Sending the price of biological children to infinity induces four times more foster families while sending the time cost of foster children to 0 induces 50% more families families. The model and data suggest that foster children are not perfect substitutes for biological children. Alternative theories are discussed in the context of the data and empirical results.

1 Introduction

Foster care is an important social service. In the US, hundreds of thousands of children enter the foster care system every year due to substantiated reports of abuse or neglect. Foster children tend to have lower educational attainment, and significantly higher rates of incarceration and homelessness than the general population (Gypen et al., 2017). They represent some of the most disadvantaged children in society.

The foster care market is organized so that children are removed from their birth homes and then placed either in institutional settings or with volunteer families. The driving motivation behind

*Stanford Graduate School of Business. Email contact: cntaylor@stanford.edu. I thank Rebecca Diamond, Joseph Doyle, Liran Einav, Matthew Gentzkow, Guido Imbens, Eddie Lazear, Yucheng Liang, Paul Oyer, Paulo Somaini and Ali Yurukoglu for comments and feedback. A big thank you to Eddie Lazear for his support throughout this project.

placing children with families is that keeping children in family environments can simulate higher quality childcare through “normal childhood experiences” (Welfare and Institutions Code 16000).

While previous work has focused on the effects of different margins of foster care on child welfare outcomes, very little is understood about how or why families choose to be foster parents. This paper studies how families choose to be foster parents through the lens of a simple price theoretic household model.

An understanding of the motivations and incentives of foster families is crucially tied to the welfare outcomes of children, as economists have long emphasized the importance of parental incentives and investment in children on child welfare. It also sheds light on how policymakers can most affect foster family supply and attack the foster care “shortage problem” in which not all children can be placed in the care of families.[1]

The major contribution of this study is how it uses the data and theory to better understand the data generating process underlying which families choose to be foster families. The mechanisms highlighted are formalized by a simple price theoretic model of household fertility that links a family’s value to foster children through foster children’s human capital and a household’s own fertility and wage.

This paper utilizes two datasets. The first dataset is the Adoption and Foster Care Analysis and Reporting System (AFCARS) which provides detailed data on foster children and their placement circumstances. The analysis focuses on California from 2005-2015 to allow the California-specific institutional details to guide the empirical strategies and because California has the largest child welfare system in the country. AFCARS identifies children at a county-year level and provides detailed observations of the children. The second dataset is the American Community Survey (ACS) which provides a rich set of household observables and identifies foster children in households. The ACS allows for an assessment of which families care for foster children at both the household (micro) and county-year level.

In raw cuts of the data, foster children with lower human capital are placed less often. Foster families tend to be of lower socioeconomic status and the household profiles for families most likely to be foster families mirror the profiles of households most likely to have their own children. Moreover, the age of a foster child is the most important explanatory factor for whether a child is placed.

Using these facts, a model is developed in which households choose whether to foster children based on their own fertility decisions for biological children and a trade-off of between investing in children with their own consumption. The model treats families as getting altruistic utility from the human capital of both biological children and foster children, and, importantly, treats these as substitutable sources of altruistic utility. The model also specifies the relationship between human

[1] Some news coverage of this problem can be found here.

capital, foster children, and their age.

The model makes a series of predictions that link a family's decision to be a foster parent to the foster child's age, and the household's wage and fertility. The intuition behind many of these mechanisms is similar to that captured in the classic quantity-quality fertility literature where families trade off investing in children with labor supply and own consumption (Becker and Lewis, 1973). The additional mechanism that kicks in with foster care is that because foster children are negatively selected on human capital this exacerbates these effects for foster children and is amplified by the child's age.

While some of the predictions are intuitive others are more surprising. In particular, the theory suggests that families with higher wages are less willing to care for older children. This is because the time costs of foster children scale with age due to the selection of children into foster care. Similarly, families with more fertility are relatively more willing to care for older children. This is because the human capital opportunity cost from choosing an older foster child over a biological child is decreasing in the number of children.

The predictions of the model are tested in the ACS data. The empirical strategies utilize a mixture of methods and research designs that vary in their credibility to identify causal effects. In particular, the strategies combine instrumental variable methods from the fertility literature (Black et al., 2005) and rich household observables in the ACS micro data on occupation status.

All of the model predictions are verified in the data. To unify the empirical tests, a simple implementation of the theoretical model is estimated jointly, and counterfactuals are run to assess the impact of the different economic mechanisms highlighted in the model. In particular, if the price of biological children became infinite, the model predicts that there would be almost four times as many foster families. If all families wages were set to 0 (or equivalently there were no time costs of caring for children), then the model predicts that there would be about 50% more foster families. Alternative theories, particularly more classic models of altruistic behavior (Becker, 1974; Andreoni, 1990) do not perform as well in explaining the empirical results. However, some sociological theories do appear to have some explanatory power and could be further examined and distinguished from this paper's theory in future work.

This study is related to a small economics literature on foster care. The most closely related papers are Doyle (2007a) and Doyle and Peters (2007) which provide evidence that foster parents respond to financial incentives in a way that is consistent with traditional economic theory. This prediction is one of the predictions of my model and these papers provide complementary evidence for the model and mechanisms of interest. This paper's contribution over these papers is to study the family foster care decision from a different perspective.

Doyle (2007b) shows that there are large but somewhat imprecise negative effects for children entering foster care. He shows that these negative effects are mainly focused on older children.

This paper explores why older children are placed less, an important candidate for worse outcomes for older children in foster care.

Nelson et al. (2007) examine the impacts of family placement versus institutionalization by studying a natural randomization of children into families and institutions. They find large significant gains from children being placed with families. My paper provides evidence on potential economic mechanisms for why these gains occur.

The organization of the rest of this paper is as follows. Section 2 gives background institutional details that help guide the empirical results and also describes the data. Section 3 examines some important facts in the data to motivate the model. Section 4 presents the model and the model predictions. Section 5 tests the predictions of the model, estimates a structural version of the model and discusses alternative theories and explanations. Section 6 concludes.

2 Institutional Details and Data

2.1 Institutional Details

The important institutional details relevant to the analysis are reviewed in this section. These details are specific to California, but the general principles apply to most states in the US to the best of my knowledge.

A child enters foster care when a county-level investigator is made aware of a maltreatment allegation and petitions the court for the child to be removed. In some cases, the investigator may remove the child without court intervention if the situation is deemed an emergency. California investigators use a tool called "structured decision making" and decide whether to remove the child based on three factors: "risk, harm and danger". Foster care officials communicated to me that these decisions are made with regard only to the child's current state and not to the resources available.

Individuals or families that are interested in fostering a child must go through what is now called the resource family approval process (RFA). This process consists of basic background checks, interviews and home visits. Eligible families include caretakers over 18 years old, that are employed with sufficient income (no clear guidelines across). Families are paid small "stipends" for taking care of children and these stipends depend on the child's age and potentially other characteristics such as medical needs. Table A4 in the Appendix lists the basic rates of foster children. State-level rates were primarily defined by the age of the foster child in California between 2005-2015.

When in foster care, children have a few placement options. The first is to be placed with a foster family. This could be a kin family (a family that is related to the foster child) or a non-kin family. By law, kin families get priority and the county must first search for a kin family placement when looking for children. Other placement options are group homes, institutions or independent living arrangements. The general consensus among foster care professionals is that family homes are better than all other placements and this is reflected in the law. California law states that children should be placed in suitable families (families that pass the basic screening of the RFA) over placing them in group homes when available.

> "*If a child is removed from the physical custody of his or her parents, preferential consideration shall be given whenever possible to the placement of the child with the relative as required by Section 7950 of the Family Code. If the child is removed from his or her own family, it is the purpose of this chapter to secure as nearly as possible for the child the custody, care, and discipline equivalent to that which should have been given to the child by his or her parents. It is further the intent of the Legislature to reaffirm its commitment to children who are in out-of-home placement to live in the least restrictive family setting promoting normal childhood experiences that is suited to meet the child's or youth's individual needs, and to live as close to the child's family as possible pursuant to subdivision (c) of Section 16501.1*" (Welfare and Institutions Code 16000).

Given these institutional details, it is assumed that all placement differences between children can be attributed to whether a household exists that is willing to care for that particular child. I assume that households pick their favorite children and counties do not have preferences over which children to place. In particular, the randomness of certain arrivals of children and availabilities/willingness of families seems to be an important factor in determining what children are placed as opposed to any county-level distinct policies or preferences.

2.2 Main Data Sources

The empirical analysis utilizes two main datasets.

2.2.1 AFCARS

The first main dataset utilized in this paper is the Adoption and Foster Care Analysis and Reporting System (AFCARS). This is a national bi-annual survey of the universe of foster children that are under the supervision of foster care agencies that use title IV-E federal funding. Title IV-E funding is the primary source of the stipends and refunds paid to foster families.

AFCARS provides 1 child observation per year, identifies children over multiple years, and identifies counties with over 1000 active cases. I focus on the years 2005-2015.

AFCARS provides rich observables of children in addition to the child and county identifier. These include demographics (e.g. sex, race, age) and medical conditions (e.g. physical disability, mental disability, etc.). This rich set of variables is helpful in the empirical strategies for discerning the effect of child characteristics on their placement and also as useful controls for child placement circumstances. I provide details of how I clean the data in the Appendix.

Some summary statistics about the children in foster care and the largest identified counties in California studied in this paper can be found in Tables A2 and A3. Some important things to note from it are that Los Angeles contains almost half of the foster child observations, foster children are approximately balanced between the sexes, the number of entires has decreased over time, and many foster children are medically disabled.

The main outcome variables of interest studied in the AFCARS dataset are whether a child is placed with a family or not while in foster care. In particular, for child i in foster care in year t, define the variable *Family Placement*$_{it}$ as an indicator for whether child i is placed with a family in the year observed t.[2] The other options available in this sub-sample are group home, institution, supervised independent living and runaway.

The AFCARS data are utilized in the empirical facts and tests to look at placement of foster children by child characteristics. These analyses are conducted so that the unit of observation is a foster child.

2.2.2 ACS

The dataset that is used to gain information about family supply is the American Community Survey 1% sample from 2005-2015 (Ruggles et al., 2019).

Importantly for testing which families are foster families, the ACS identifies foster children in households. The allows for the finest unit of analysis to be a household or family. The characteristics of a"household" refer to the joint characteristics of the primary householder and their spouse or unmarried partner (if one is present). When estimating models and testing at the household level in the ACS, the main outcome variable is an indicator for whether a household i has a foster child in their household called *Foster*$_i$.

The model focuses on household fertility and wage and so the major variables studied in the ACS data are number of biological children and household wage. I measure the number of biological children as the number of biological children that are at most age 18. I get more into how to do this measurement in the empirical strategies. Most of the cleaning of the micro data relates to wage. It is well known that the earnings reports in ACS surveys are inconsistent with minimum wage laws. To deal with this cleaning, all individual wages that are positive but below the Califor-

[2] Note that because the data are not very high-frequency, it is challenging to get at the dynamics of placement with this dataset. I conceptualize my strategy as a noisy measure of overall family placement while in foster care.

nia minimum wage are set to be the minimum wage. Individual wages are also winsorized at the 99% level of wages. Individuals not working receive a wage of 0.

Wage will vary across the head of household and their spouse or partner when present and so a household measure of wage must be constructed. The results are robust to using many different measures of household wage (including minimum wage, maximum wage) and the average wage of the household is the focus in the micro data.

For variables such as race, the race of the head of the household is assumed to be the household race. The ACS only identifies a certain set of counties in California - 3.5% of all families in the data do not have an identified county. County level indicators are important controls in the models to control for the availability of foster children in a particular county. Missing value indicators are added for families that have a missing county, essentially treating unidentified counties as a single aggregate county in California.

Throughout the paper in the ACS data, i is used to refer to a California household, t to refer to a year with $t \in \{2005, \ldots, 2015\}$ and j to refer to a county.

In implementing the empirical strategies in this paper, subsamples of the full ACS data are used. The discussions of these subsamples are deferred to the introduction of the empirical specifications as they are motivated and necessitated by these specifications.

3 Motivating Facts

3.1 Descriptive Statistics: AFCARS

In this section I examine the AFCARS foster child-level data to understand patterns in which types of children are placed with families. Under the assumptions provided by the institutional details, differences in placement of foster children should primarily be attributed to differences in supply. To avoid issues with oversampling selected children, I restrict the analysis to only the characteristics of children entering. The major observables available for this exercise that I focus on are: race, sex, age, medical status and entry reason.

Table 1 provides mean placement with a family by demographic characteristics and disability status. The mean results suggest that black children, boys and children with disabilities tend to be placed less.

Figure 1 shows mean placement by age of the child at entry. Clearly, older children tend to be placed less. This fact will be re-examined later in more detail. Table 2 show mean placement by entry reason for the child. These entry reasons are not mutually exclusive so the Appendix contains a linear model of the entry reasons where each entry reason is treated as a fixed effect to parse out separate effects in an additive model. The results are similar to those in Table 2. By far

Category	Group	Mean Family Placement	Count
Child Race	Black	0.786	79,757
Child Race	Hispanic	0.844	203,050
Child Race	Other	0.831	12,225
Child Race	White	0.834	95,433
Child Sex	Female	0.867	187,176
Child Sex	Male	0.795	203,238
Clinical Disability	Yes	0.852	137,096
Clinical Disability	No	0.904	65,577
Clinical Disability	Not Yet Determined	0.786	153,235

Table 1: Mean Family Placement by Observables

Notes: Mean family placement for all foster children that entered by observables in California between 2005 and 2015. Family placement refers to if the child is in a non-kin family placement, kin family placement or pre-adoptive placement.

the most children that are not placed with families are children with behavioral problems. This is unsurprising because some proportion of these children are juvenile delinquents who are placed in juvenile delinquency facilities by law. However, some of this variation likely still reflects family's willingness to care for these children. Other categories with low amounts of family placement are children that enter because they are addicted to alcohol and because they are disabled.

One useful way to split up these categories is to consider categories that have direct implications for human capital of the child - substance abused child, disabled child, child with behavioral problem - separate from other categories that signify more about the environment of the child including parental qualities or housing. Those categories with direct human capital implications for children including if they were abused, have alcohol abuse problems, or have a disability, tend to have lower placement for the children. The rate of drug abused children placed with families is high because drug abused children include newborns born with drugs in their system and newborns are placed at a much higher rate.

The takeaway from simple cuts of the data suggest that children with lower human capital are placed with families less. This is an important implication for different economic models that could generate fostering behavior. Consider classic models of pure and impure altruism/warm glow (Becker, 1974; Andreoni, 1990). In these models, the public good is overall human capital of children in society. If the human capital production function is concave, then for a fixed investment, investing in a foster child with lower human capital will bring about more returns to society. Unless there is some coordination problem, which seems unlikely given how the system is centralized, this prediction of pure and impure altruism models fails in the data and these models leave many facts unexplained. The implications of these models are now explored further in the ACS data.

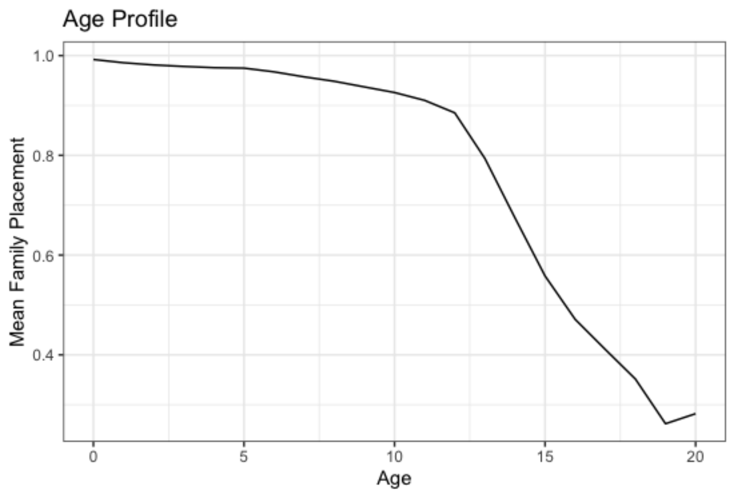

Figure 1: Mean Family Placement by Age

Notes: Mean family placement for all foster children that entered by age of the child in California between 2005 and 2015. Family placement refers to if the child is in a non-kin family placement, kin family placement or pre-adoptive placement.

Category	Group	Mean Family Placement	Count
Physical Abuse	1	0.890	42,220
Sexual Abuse	1	0.867	13,182
Neglect	1	0.935	248,731
Alcohol Abuse Parent	1	0.962	4,746
Drug Abuse Parent	1	0.972	23,674
Alcohol Abuse Child	1	0.357	255
Drug Abuse Child	1	0.912	5,470
Child Disability	1	0.603	730
Child Behavioral Problem	1	0.246	46,474
Parents Died	1	0.885	635
Parents in Jail	1	0.944	7,594
Parents Unable to Cope	1	0.866	111,129
Abandonment	1	0.870	2,137
Child Relinquished	1	0.786	2,124
Housing	1	0.936	12,500

Table 2: Mean Family Placement by Entry Reason

Notes: Mean family placement for all foster children that entered by entry reasons in California between 2005 and 2015. Entry reasons are not mutually exclusive and the mean family placements are for groups of children that have that specified entered reason. Family placement refers to if the child is in a non-kin family placement, kin family placement or pre-adoptive placement.

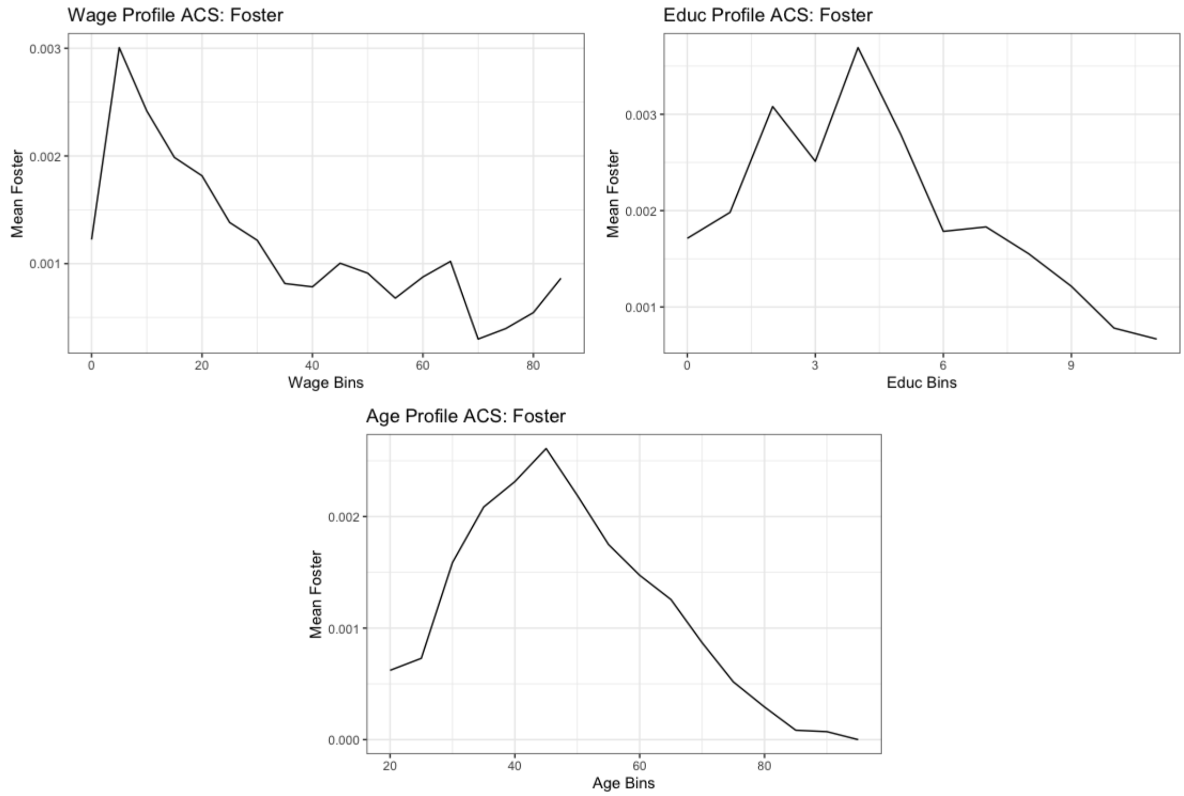

Figure 2: ACS Mean Fostering

Notes: Plots indicate the percent of families in each bucket of observables that have foster children in the ACS in California between 2005-2015. Wages, education and age are measured as an average of the head of household and their partner/spouse. The education and age measures are raw measures in the ACS.

3.2 Descriptive Statistics: ACS

Descriptive statistics from the ACS inform which types of models most plausibly generate foster care behavior. Figure 2 provides summary statistics of ACS households by wage, education and age.

The data suggest that families that foster tend to be families with less education and less wages. The age profile follows a relatively standard parabola shape found in the literature on fertility.

Note that these results are starkly different from those found in the previous literature on giving and charity (Chowdhury and Jeon, 2014). One of the fundamental predictions of warm glow is that charitable contributions are a normal good, and so as a household's wage increases, they should be more likely to contribute to the public good. In this case, the patterns in the data suggest that the opposite appears robustly true. In particular, as households become richer they become less likely to contribute to this public good.

There is one potential important factor that could be driving lower wage families to foster more. This is kin foster care - placing children with relatives of their birth family. In California, around

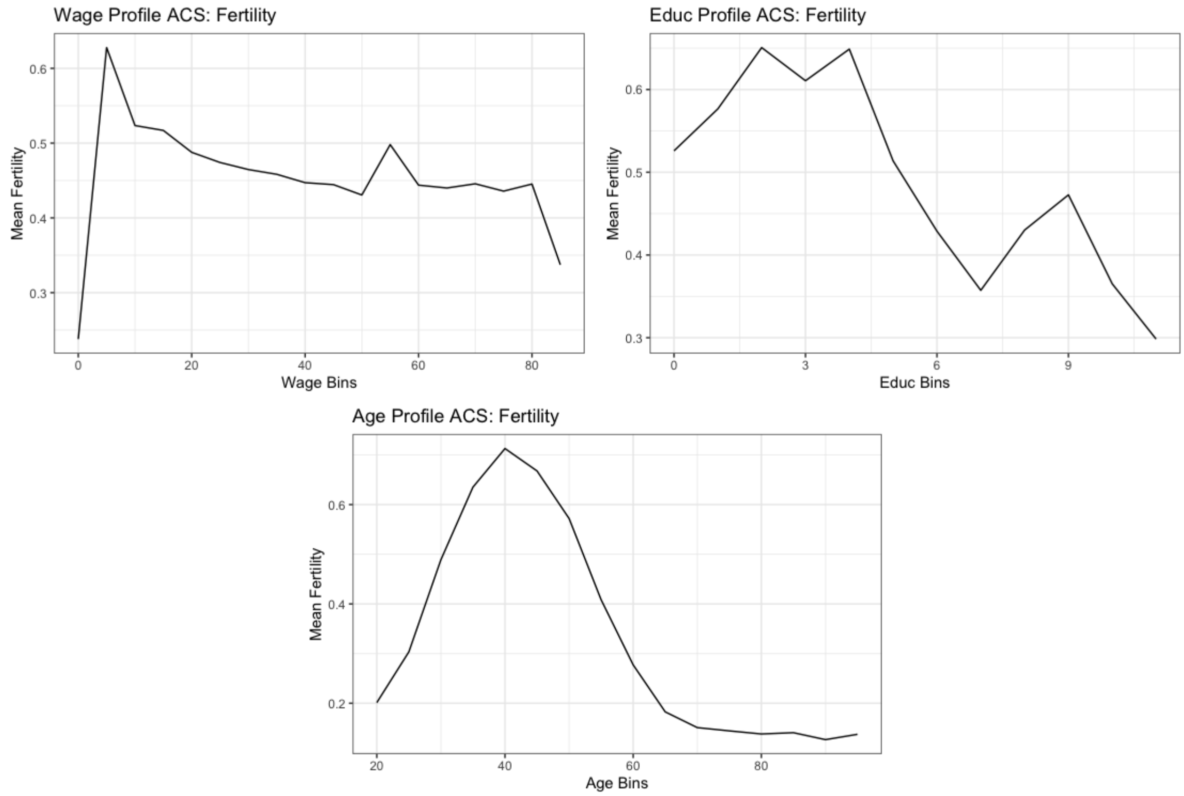

Figure 3: ACS Mean Fertility

Notes: Plots indicate the percent of families in each bucket of observables that have foster children in the ACS in California between 2005-2015. Wages, education and age are measured as an average of the head of household and their partner/spouse. The education and age measures are raw measures in the ACS.

50% of family placements are kin family placements. Since California prioritizes kin foster care, the overall logistic and search cost of foster care is lower for families that are related to a foster children. Since foster children tend to come from low wage households, and wages are likely correlated with families, this could completely drive this relationship.

One way to address whether this relationship is driven mostly by choice set variation instead of supply variation is to look at the shape of the entire wage profile in Figure 2. The median household wage in the full ACS sample is around \$12. If most of the variation in wages driving kin foster families is for households with low wages, the large continued negative wage gradient past median wages would not be expected.

Another way to address this issue is to use race variation. White children are systematically under-represented in the foster care system. Thus, differences in fostering for richer white families likely do not represent kin related variation. Figure A3 in the Appendix plots the wage gradient for white households. The figure shows that even for higher wage white families, families with higher wages tend to foster less. Thus overall, it seems that these wage results are not driven by choice set variation but by supply variation.

Simple cuts of the data suggest that families with lower socioeconomic status and human capital care for foster children. This contradicts other studies' empirical findings on charity and altruism. Thus, classic altruism models continue to appear insufficient to explain the findings.

In an attempt to explore alternative cuts of the data to inform why families care for foster children, consider the economic processes that drive whether a family chooses to have their own biological children. If the factors that determine this process appear related to how families determine whether to foster children, then there might be an important economic relationship connecting these decisions. Figure 3 reproduces the plots in Figure 2 but instead of fostering it looks at the percentage of households that have at least one of their own biological children. The plots look remarkably similar to the fostering plots, suggesting that perhaps these decisions are linked. The model in the next section formalizes this link.

3.3 Comparing Observables in AFCARS

In this section, the child-level observables in AFCARS are more directly compared in linear models to explain the variation in child outcomes taking a more holistic viewpoint of the regression function.

I estimate models of the following form in the AFCARS data:

$$\text{Family Placement}_{it} = X_{it}\beta + \gamma_{j(i,t)} + \delta_t + \epsilon_{it} \tag{1}$$

where X_{it} includes all the observables for child i in year t outlined above. Recall that j is a county. This estimation is performed including all children in the data eligible for placement and also restricting to children only when they enter as with the other AFCARS descriptive statistics. The number of variables for these estimation methods is purposefully reduced in a way that is economically intuitive.

The results of the linear model are in Table 3. They generally reflect the descriptive statistics in the previous sections but highlight more clearly the importance of age as a predictor of family placement. In particular, the difference between a newborn and teenager scales up to over a 25 percentage point difference in placement. The other observables are only able to explain up to about 5 percentage points of the variation in where children are placed. The magnitudes suggest that the differences in family placement between newborns and teenagers is around 25 to 50 percentage points. The percentage of children placed with families is approximately 83% and so the magnitudes are large. Since age is clearly such an important predictor of family placement, one of the goals of the model will be to match this fact in the data.

	Dependent Variable: Placed with a Family
Hispanic	0.017
Other Race	0.023
White	0.014
Male	−0.021
Total Removals	−0.014
No Disability	0.030
Not Yet Diagnosed	0.008
Age	−0.0194
Observations	355,263
R^2	0.434
Adjusted R^2	0.434
County FEs	✓
Year FEs	✓

Table 3: Linear Models for Family Placement

Notes: This table displays coefficient estimates for variables in a linear model based on (1) estimated on the population of California foster children entering between 2005-2015 in AFCARS. Standard errors are omitted since they are not sensible in a population.

4 Model

4.1 Setup

The goal of this section is to create a model that highlights some of the important mechanisms discussed in the previous section and can match those stylized facts. The model will then be used to generate further predictions on the types of families that care for children and make the salient mechanisms more clear.

Instead of standard public good models of altruism, the model states that households have altruistic utility for children that they care for overall. In particular, suppose that households have preferences over three objects. First, they have preferences over the total human capital of biological children that they care for $H_n = h_n n$, where n is the number of biological children and h_n is the human capital per biological child.[3] Households also have preferences over the total human capital of foster children that they care for $H_F = h_F F$ where again h_F is human capital per foster child and F is the total number of foster children. Finally, they also care about their own private consumption c. Their utility over these objects is quasi-linear

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

[3]Following the fertility literature (Becker and Lewis, 1973) for simplicity all children of the same type in a household are assumed to have the same human capital.

where u satisfies $u_1 > 0$, $u_2 > 0$, $u_{11} < 0$ and $u_{22} < 0$. The choice variables for households in the model are F which is restricted to be binary $F \in \{0, 1\}$ for simplicity and the time t_F to invest in foster children.

Note that this utility formulation implies that households are not altruistic in the traditional sense. They do not care about a public good but instead only about the human capital of the children under their care. People undertake "projects" of caring for children and they like to succeed in these projects, where success is defined by how much human capital the child ends up having. Importantly, as will be highlighted later, a families value for taking care of a foster child may depend on the projects they undertake with their own biological children. Moreover, a household values the *overall* human capital of the children they care about, not their *impact* on the human capital of that child.

A household is endowed with an exogenous technology described by (T, p_n, t_n, n, w) which describes their total time budget T, the price of having their own biological children p_n and the time they invest in biological children t_n. It is also assumed to start that n and the household wage w are exogenous. A generalization of the model allowing n to be endogenous is explored in the Appendix.

Foster children have different initial human capital levels $h_{0,F}$ and prices p_F. The age of the foster child is $a \in [0, 1]$ normalized to the unit interval. To match the stylized facts in the previous section, the model should be able to match the stark age gradient seen in the previous section. Prices are allowed to vary with age $p_F(a)$ as they do with the real data (see Table A4).

Human capital for a child of type $j = n, F$ is

$$h_j = \int_0^1 t_j(a)da \tag{3}$$

where $t_j(a)$ is the flow of household investment when the child is age a. Note that it is assumed that all children have the same initial human capital.

It is assumed for simplicity that while a child is in an abusive or neglected home they receive $t_n(a) = 0$.[4] This is a normalization relative to the eventual time investment that they will receive while in foster care and is not strictly required.[5]

These assumptions imply that for a family investing t_F time in a foster child of age a, the

[4] To microfound the age of foster children consider the following setup: some families have $t_F = 0$ and the government has an imperfect monitoring technology that detects abuse and neglect at a certain rate. This imperfect monitoring technology will create an age distribution over children entering foster care.

[5] It is only important in the model that this time investment is lower than the one they receive in foster care in equilibrium, otherwise being removed from foster care was not optimal in the first place.

resulting human capital of the foster child is

$$h_F(a) = (1-a)t_F. \tag{4}$$

This gives two implications of the impacts of age. First, for the same fixed investment by a household, older children will have less overall human capital. This is because they are children with a larger "gap" in human capital than their more early removed foster care counterparts. Second, the marginal productivity of investment into a foster children is decreasing in their age. This is because of the fact that older children have less time to be impacted.

Assuming households spend all their time investing in children or working, the budget constraint for a household is

$$c = w(T - t_n n - t_F F) - p_n n - p_F(a)F. \tag{5}$$

Then together (2), (4) and (5) imply that the value of providing foster care for a child of age a for a household with certain technology (T, p_n, t_n, n, w) is

$$V_F(a,n,w) := \max_{t_F \geq 0} u(h_n n, t_F(1-a)) + w(T - t_n n - t_F) - p_n n - p_F(a) \tag{6}$$

and the value of not fostering is

$$V_0(a,n,w) := u(h_n n, 0) + w(T - t_n n) - p_n n \tag{7}$$

Together (6) and (7) allow us to define the net value or willingness to pay for foster care

$$V(a,n,w) := V_F(a,n,w) - V_0(a,n,w) \tag{8}$$

The object $V(a,n,w)$ will give predictions on how household level observables should change a household's willingness to foster.

4.2 Assumptions

To derive the man theoretical results, some additional assumptions are needed.

$$\begin{gathered} u_{12} < 0 \\ u_2(x,y) < -u_{22}(x,y)y, \ \forall x,y \\ |p'_F(a)| \text{ is small enough} \end{gathered} \tag{9}$$

The first condition in (9) states that households treat utility from human capital of biological children and foster children as substitutes. The marginal gain to a household from a child's human capital is decreasing in the total amount of child human capital under their care.

The second condition in (9) is more technical and guarantees that households will invest more time into children that enter with lower initial human capital. This condition technically states that households' utility functions are concave enough over foster children's human capital. A class of suitable univariate utility functions that satisfy the univariate analogue of the second condition of (9), $f'(x) < -f''(x)x$, are functions $f(x;\alpha) = -x^{-\alpha}$ where $\alpha > 0$. These functions are "more concave" than log utility and functions in the class x^α for $\alpha \in (0,1)$.

The last condition simply guarantees that the price paid for age is not increasing fast enough to offset the costs of taking care of older foster children to match the empirical patterns in the data.

Before moving onto the formal results, it is worth describing the key economic mechanisms in the model. First note that families generally trade-off the enjoyment of having children and investing in their well-being, and private consumption. This is common in economic models of fertility (Becker, 1960). This trade-off comes through two sources. First it appears in the fixed prices of having children, including the biological costs of the mother bearing the child, the costs of medical visits related to the pregnancy, and the cost of things like food and clothes for the children. Second it appears in the time invested by households. Importantly though, this time investment has an implicit cost of time, making time investments more costly for richer households. Thus, the model implies a wage gradient with respect to both own fertility and fostering, both patterns that show up in the previous facts.

The most innovative part of the model is that families value human capital of their own children and foster children, and these human capital sources are substitutable. This makes it so that families with their own biological children value foster children differently.

4.3 Results

The model makes five predictions with respect to the household and foster child level observables. They are listed in order below and discussed.

First, the model implies that families have a smaller net value for older children.

Proposition 1. $\frac{\partial V}{\partial a} < 0$

Proof. Using the envelope theorem, $\frac{\partial V_F}{\partial a} = -u_2(h_n n, t_F(1-a))t_F - p'_F(a) < 0$ since p'_F is small enough. □

This prediction matches the stylized facts generated before and comes from the model's assumption that older children have a lower initial stock of human capital when they enter the foster market. In general, if we let h_0 be a parameter in the model that indicates initial human capital, the same type of comparative static would hold. Households value children with lower human capital less because they like human capital.

Second, the model implies that families have a smaller net value for fostering when they have more children.

Proposition 2. $\frac{\partial V}{\partial n} < 0$

Proof. Applying the envelope theorem and differentiating V_0 with respect to n yields

$$\frac{\partial V}{\partial n} = u_1(h_n n, t_F(1-a)) - u_1(h_n n, 0) < 0$$

since $t_F > 0$ and $u_{12} < 0$. □

This comes directly from the fact that the human capital of biological children and foster children are substitutes in the household's utility function.

The model also implies that families have a smaller net value for fostering when they have a higher wage.

Proposition 3. $\frac{\partial V}{\partial w} < 0$

Proof. Subtracting V_F and V_0 and applying the envelope theorem gives

$$\frac{\partial V}{\partial w} = -t_F < 0$$

since $t_F > 0$. □

This wage comparative static is direct because of the quasi-linearity assumptions on utility which remove income effects of children and causes families with higher wages to see children as more costly because of the time costs t_F. If income effects were allowed then it is possible that this comparative static runs the other way. However, these income effects would allow and in fact necessitate that the comparative static of wage and own fertility is also positive, contradicting what is commonly observed in data that households with higher wages have significantly less children.

The model also implies how n and w interact with a child's age and initial human capital. These predictions are quite specific to the model and so provide a particularly robust form of testing the theory.

For these cross predictions, the model predicts that families with more children n have a less steep age gradient, meaning that families with more children are relatively more willing to care for older children than younger children than families with less children.

Proposition 4. $\frac{\partial^2 V}{\partial a \partial n} > 0$

Proof. First the envelope theorem and the proof above gives us that:

$$\frac{\partial V}{\partial n} = u_1(h_n n, t_F(1-a)) - u_1(h_n n, 0)$$

Now differentiating with respect to a and noting that $t_F^*(a)$ is a function of a due to the envelope theorem gives us that

$$\frac{\partial^2 V}{\partial a \partial n} = u_{12}(h_n, t_F(1-a))\Big(t_F'(a)(1-a) - t_F(a)\Big)$$

and so the sign of this expression depends on the sign of the second term $t_F'(a)(1-a) - t_F(a)$.

The sign of this expression can be found from the inner maximization problem the household solves when picking t_F for a child. The first order condition for that problem is given by

$$u_2(h_n n, t_F(1-a))(1-a) = w$$

and implicitly differentiating this expression with respect to a yields

$$u_{22}(h_n n, t_F(1-a))(1-a)(t_F'(a)(1-a) - t_F(a)) - u_2(h_n n, t_F(1-a)) = 0$$

Since $u_{22} < 0$, $(1-a) \in (0,1)$ and $u_2 > 0$, it must be that the inner expression $(t_F'(a)(1-a) - t_F(a))$ is negative.

Thus the cross partial is a negative term multiplied by a negative term which yields a positive term. □

This comparative static comes from the fact that families get decreasing marginal returns from human capital from both types of children. The trade-off for older and younger children in the model is initial human capital. Because families with a high number of own children already have a high utility flow of human capital from children, the human capital cost of caring for an older or a younger child is substantially lower. Households that have no children really care about the human capital since they are still at a very high curvature part of their utility function.

Finally, the model predicts that families with higher wages w have a steeper age gradient.

Proposition 5. $\frac{\partial^2 V}{\partial a \partial w} < 0$

Proof. First the envelope theorem and the proof above gives us that:

$$\frac{\partial V}{\partial w} = -t_F$$

and so the cross partial is simply $-t'_F(a)$.

Now suppose that the assumption on the second line of (9) holds. Then the cross partial of the objective function in (6) with respect to a and t_F (the choice variable) is

$$-u_{22}(h_n n, t_F(1-a))t_F(1-a) - u_2(h_n n, t_F(1-a))$$

and setting $x = h_n n$ and $y = t_F(1-a)$, (9) tells us that

$$-u_{22}(h_n n, t_F(1-a))t_F(1-a) - u_2(h_n n, t_F(1-a)) < 0$$

Then by Topkis' Theorem since this cross partial is strictly negative and $\{t_F : t_F \geq 0\}$ is a lattice, it must be that $t'_F(a) > 0$. $\square$

This is clearly where the second assumption in (9) is required. Importantly this assumption implies that $t'_F(a) > 0$ so that households invest more in older children and children with lower human capital. Economically, investing in older children has a lower marginal productivity of investment which pushes towards households investing less in older children, but also has a higher initial gain since older children have lower human capital initially. If instead only the initial human capital was varied and not the marginal productivity of investment, the marginal return to investment would always be higher and thus households would always invest more in low human capital children and the second assumption in (9) is unnecessary.

4.4 Comparison to Alternative Models

In traditional models of altruism discussed in the empirical facts section, preferences would take the form $u(H) + c$ or $u(H, h_i) + c$ where H is the human capital of all children in society. Mathematically, this model is also equivalent to a version of the "impact model" where families care about their overall impact on children. This is because families that aim to maximize their impact on a child will also maximize the overall stock of human capital of children in society.

The model presented here is starkly different from these traditional models. Households are not altruistic in that they do not care for the public good. Their only incentive comes from the fact that they enjoy caring for children, and particularly enjoy higher human capital children.

More alternative models and theories are discussed after the main empirical results are presented.

4.5 Adding Tastes to the Model

The model so far has not included any heterogeneity or tastes. In reality and in the data, there is likely some unobserved taste parameter ξ_i for household i such that their utility of fostering is

$$u_i(H_n, H_F) + c = u(H_n, H_F, \xi_i) + c$$

and so if ξ_i is correlated with household level decisions on the observables n_i and w_i, models that do not account for these unobserved tastes will yield inconsistent parameter estimates. Thus, the goal of my empirical strategies when assessing the predictions is to find exogenous variation in the household level observables to allow for consistent parameter estimates.

5 Empirical Results

To test the model predictions the AFCARS and the ACS data are combined with other auxiliary datasets. First, some of the other preliminary implications and assumptions of the model are examined. Then the main empirical tests are conducted on the propositions derived above along with the more informal prediction related to the price of biological children.

5.1 Preliminary Evidence on Wage and Fertility

The model suggests that, absent strong income effects, families with higher wages will have less children in general, irrespective of foster care decisions. While this relationship has been shown at more macro levels across countries and even within the US (Becker, 1960; Jones and Tertilt, 2006), it is useful to examine these relationships using the micro level ACS sample in this paper.

Consider the following empirical model of fertility:

$$\text{Num Child}_i = \beta_w \text{Wage}_i + X_i\beta + \epsilon_i \tag{10}$$

where i is a household in the ACS and X_i includes the race of the household, the age of the household, and a county-year fixed effect. Num Child measures the number of biological children in the household under the age of 18. The specific analysis sample are explained more in the section implementing the fertility predictions. The hypothesis of the theory is that $\beta_w < 0$.

The results are displayed in Table 4. In both samples, wage is negatively related to the number of children and is statistically significant at a level much smaller than 1%. This provides robust evidence of the negative correlation between wage and fertility in the micro data.

To assess the relative magnitudes of wage versus cultural factors that are captured by race,

	Dependent Variable: Number of Children	
	Twins Sample	Same-Sex Sample
	(1)	(2)
Wage	-0.013^{***}	-0.013^{***}
	(0.0003)	(0.0003)
Black Family	0.385^{***}	0.329^{***}
	(0.015)	(0.018)
Hispanic Family	0.659^{***}	0.627^{***}
	(0.020)	(0.018)
Other Race Family	0.051^{***}	0.066^{***}
	(0.007)	(0.008)
Age Polynomial	✓	✓
Market Fixed Effects	✓	✓
Observations	226,775	169,501
Adjusted R^2	0.252	0.222

Table 4: Fertility and Wages

Notes: All regressions are estimated with OLS with a dependent variable of the number of children at most 18 years old in the household. The wage variable is the average wage among the head of household and their spouse or partner. The same-sex sample refers to the sample of households with a head of household and a partner or spouse. If one of these individuals is a female they must be at most 35 and the average age of these individuals must be at most 45. The twins sample includes only households of females that are at most 35. 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. Standard errors are robust clustered for market-level correlated errors. *p<0.1; **p<0.05; ***p<0.01

consider the estimated impact of moving from a 10th percentile to 90th percentile average wage on number of children in the data. The difference between these is approximately \$33 in the samples in both columns. This leads to an impact of the number of children of about 0.432 highly comparable to the effects of the cultural factors that are captured by a family being Black or Hispanic relative to White.

5.2 Testing the Main Model Predictions

The model's main empirical content is the predictions it makes related to age and other child factors through Propositions 1 through 5. The motivating facts already showed that older children and children with lower human capital are placed with families less. The goal of this section is to test Propositions 2 through 5 using the ACS data.

Importantly, the strategy pursued splits these predictions up separately, attempting to isolate for each prediction some analogous natural experiment in the data with respect to the independent variable of interest. This is done for transparency and to avoid the potential bad control problem

(Angrist and Pischke, 2008) in which attempting to derive multiple causal effects in one regression is challenging. In a later section a simple empirical version of the model is estimated structurally to allow for the main mechanisms to be examined simultaneously in the data.

5.2.1 Testing Proposition 2

Proposition 2 states that families with more children are less likely to be foster parents because they have a lower marginal utility for foster care. Importantly, the model makes this prediction when altruism for children is substitutable between foster children and biological children. To examine this prediction I utilize two instrumental variables strategies. The first strategy has been popularized by the quantity-quality literature (Black et al., 2005) - using the presence of twins as a plausibly exogenous shock to n. The second strategy utilizes same-sex couples as a plausibly exogenous shifter of p_n which should induce more consumption of foster child human capital when human capital sources are substittutes.[6]

The main dependent variable of interest in this analysis is the indicator for whether a household has a foster child *Foster*$_i = \mathbf{1}\{\text{household } i \text{ has a foster child}\}$. The independent variable of interest in the analysis is Num Child$_i$, the number of biological children of the head of the household in a household. The twins instrument is an indicator for if the first child born to a family is a multiple birth. The same-sex instrument is an indicator for if the head of household and their partner or spouse are the same recorded sex. I do not use ACS designated same-sex married couples since the legalization of same-sex marriage in California happened in the middle of my sample.

Note that the twins instrument restricts to households in which the family has at least one child. The same-sex instrument is complementary to this instrument in that it allows me to look at households that also have no children. However, the same-sex instrument only allows me to look over households that have a head of household and a partner or spouse, so single person households are omitted.

I further restrict the sample to reduce measurement problems with the number of children in the household. I follow Angrist and Evans (1998) by restricting the ages of households that I consider. It is crucial for the strategy that the number of children is appropriately measured. Since the model makes predictions over the overall human capital of children that a household presides over, older households where children have moved out will be measured as having less children than they should. Thus, following Angrist and Evans (1998) I restrict the samples to have females between the ages of 21 and 35 and measure children by household children under the age of 18. For the same-sex sample, I look at households where the average age of the couple is in between 21 and 45, and if a female is present it must follow the 21 to 35 rule. It is important to allow men in

[6]While there is not a specific prediction related to the effect of p_n in the setup of the model it is not hard to change the model to allow n to be endogenous as well and then get this comparative static with respect to p_n.

couples to have an age older than 35. The cutoff 45 is chosen since 95% of couples with a female between the age of 21 and 35 have an average household age less than 45.

The basic empirical strategy used on these two samples can be summarized by

$$\begin{aligned} \text{Foster}_i &= \beta_1 \text{Num Child}_i + X_{it}\beta_2 + \epsilon_{it} \\ \text{Num Child}_i &= \alpha_1 Z_i + X_{it}\alpha_2 + \nu_{it} \end{aligned} \tag{11}$$

where I am interested in the parameter β_1 in (11) and Z_i is one of the two instruments mentioned. The theory hypothesizes that $\beta_1 < 0$.

The control vector X includes county-year fixed effects, the midpoint of age between the head of household and their unmarried partner or spouse, and the race of the head of the household. Time subscripts are included because there is a year attached to each household as well. County-year fixed effects are important when using the ACS micro data because the composition and number of foster children entering the system in any county-year could impact a families decision to foster. When the model has these fixed effects, the parameter estimates are identified by looking at the variation among families within each county-year cell identified in the data, netting out these county-year children supply-side characteristics.

The identifying assumption for each instrument is that it affects the number of children that families have but is uncorrelated with ϵ_{it}. The appeal of twins is that it is, in principle, a biological shock that should be uncorrelated with economic factors and decision-making. Angrist and Evans (1998) show that this twins measure is correlated with observables in the ACS data, particularly education and age. This remains true in the ACS sample used in this study. Correlation with observables could signify correlation with unobservables that could leave the IV estimates inconsistent.

In the case of same-sex couples, the appeal of the instrument is that if conditional on observables households have the same tastes for children and foster care, the only difference between same-sex and non same-sex couples is the technology of child production where it is much more costly for same-sex couples to produce children. This instrument suffers from the problem that a couple being same-sex is highly correlated with many other observables that predict whether a family fosters. If there are unobservables of same-sex couples that also affect their propensity to foster that are not included in the model, then the estimates will be biased.

The results from implementing the IV estimator (11) are in Table 5. The first two columns (1)-(2) show OLS regressions with a rich set of demographic and market level controls. These specifications indicate a weak but relatively precise negative relationship between own fertility and fostering in the data.

Columns (3) and (4) of Table 5 implement the main IV estimators. The F-statistics in the first-

	Dependent Variable: Foster Child in Household			
	OLS (Twins)	OLS (Same-Sex)	Twins IV	Same-Sex IV
	(1)	(2)	(3)	(4)
Num Child	-0.314^{*}	-0.409^{***}	-2.884^{**}	-4.469^{***}
	(0.161)	(0.134)	(1.301)	(1.368)
Demographics	✓	✓	✓	✓
Market Fixed Effects	✓	✓	✓	✓
First Stage F-stat	-	-	823	1,996
Observations	131,544	169,501	131,544	169,501
Mean($y \times 1000$)	2.281	2.165	2.281	2.165
SD(Num Child)	1.00	1.23	1.00	1.23

Table 5: Fertility Predictions for Proposition 2

Notes: All means and parameter estimates in the table are multiplied by 1000 for readability. 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. Standard errors are robust clustered for market-level correlated errors. *p<0.1; **p<0.05; ***p<0.01

stage are very large - each close to 1000 easily passing the benchmark rule-of-thumb of 10 (Stock et al., 2002) suggesting that the instruments are strong shifters of fertility.

The magnitudes of the IV estimates indicate that a 1 standard deviation increase in the number of children decreases the chance of being a foster parent by over 100% of the mean rate, a substantial economic quantity. The parameter estimates from the preferred IV specification are also almost 10 times the magnitude of estimates from the OLS results. The larger IV results can be rationalized in the context of the model by considering ξ_i - families that have more children might also have higher idiosyncratic tastes for caring for children, both factors pushing against the negative relationship in the theory and understating this relationship in the basic correlations.

As well it is useful to compare treatment effect heterogeneity among the two IVs.The same-sex IV generates a much larger effect of own fertility on fostering. This is expected by the theory: since the same-sex instrument can identify effects of moving from no children to some children and the twins instrument can only identify effects of moving from 1 child to multiple children, concave utility would imply that moving from 0 to 1 child would have a much stronger effect on the value of fostering than moving from 1 to 2 children.

What are threats to the conclusions from these results? First consider the twins instrument. A major worry regarding using twins as an instrument is that since 2000 or so, around 30% of all twins born in the US have been due to fertility treatments instead of natural conception (Kulkarni et al., 2013). Thus the selection of families into fertility treatments is captured in a large way by the twins instrument. In particular, in my data, having twins is correlated with having a higher education, wage and age. Those households choosing to receive fertility treatments likely reflect some of this correlation.

To reduce this worry and try to net out the selection into twins, the regressions are re-run including family wage and education as controls. While family wage may be seen as a "bad control" (Angrist and Pischke, 2008) since the presence of twins may impact a families wage (Angrist and Evans, 1998) the hope is that wage is a proxy for earlier wages that were determined at the time of twins to differentiate between fertility treatments. Thus the empirical strategy's validity on using this control strategy to isolate the "good variation" in the IV from natural conception. The results are almost identical (estimate = -2.55, se = 1.23) Similarly, the regressions are run on lower wage families that are less likely to be able to afford IVF. The parameter estimates are even stronger and statistically significant (estimate = -5.57, se=0.6) for these families.

To assess some potential omitted variables bias problems with the same-sex instrument I use the CPS volunteer supplement to allow for controlling for general propensity to volunteer time and general altruistic tastes. When a regression is run on fostering with the two independent variables being same-sex couple status and the volunteer status of the couple (which measures what proportion of the couple volunteer) the coefficient on same-sex couple is almost identical to when volunteer is not included (parameter estimates = (5.05, 5.03), ses = (1.04, 1.04)) making it unlikely that differences in altruism are driving the differences we see in fostering by same-sex couples.

5.2.2 Testing Proposition 3

Proposition 3 states that families with higher wages w are less likely to be foster parents. The same dependent variable is used as in the previous section with a focus on a new independent variable. The empirical strategy consists of estimating the following model

$$\text{Foster}_i = \beta_1 \text{Wage}_i + X_{it}\beta_2 + \epsilon_{it}. \tag{12}$$

Here β_1 is the parameter of interest and the theory predicts that $\beta_1 < 0$. X is a vector of the same controls used for the number of children. The main threat to identification in this set-up is that households that are more altruistic in general may take on a lower wage to satisfy their altruistic desires. To mitigate this factor in the regression detailed ACS occupation codes of the maximum household earner in the household are added as controlled.[7] Then the empirical strategy utilizes the leftover wage variation within occupations to identify the wage effect. In other words,

[7]There are over 500 observed occupations in my ACS sample. Some examples in the ACS include: Chief executives and legislators, agents and business managers of artistss, human resource managers, mechanical engineers, social workers.

	Dependent Variable: Foster Child in Household		
	Univariate OLS	OLS	OLS
	(1)	(2)	(3)
HH Wage	-0.052^{***}	-0.039^{***}	-0.022^{***}
	(0.008)	(0.008)	(0.008)
Occupation Fixed Effects			✓
Demographics		✓	✓
Market Fixed Effects		✓	✓
Observations	169,501	169,501	169,501
R^2	0.002	0.0047	0.0083
Mean(y)		2.165	
SD(HH Wage)		14.3	

Table 6: Wage Predictions for Proposition 3

Notes: All means and parameter estimates in the table are multiplied by 1000 for readability. Columns (2)-(3) 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. Standard errors are robust clustered for market-level correlated errors. *p<0.1; **p<0.05; ***p<0.01

altruism and child tastes are allowed to vary at the occupation level for households, but cannot vary systematically with wages within an occupation. This within-occupation wage variation is likely due to general luck or skills in the occupation orthogonal to child and altruistic tastes.

Wage is measured in the ACS at the household level by looking at the overall wage income of the household and dividing by the usual hours worked and weeks worked in the last year to back out the hourly wage. The results are robust to many other measures of wage, including wage of the female household, the head of household/spouse/partner with the smallest wage, etc. The main estimation sample is the same sample used in the same-sex instrumental variables analysis in the previous section.

The results from estimation are given in Table 6. Column (1) provides the raw correlation in the data. Household wages are negatively correlated with being foster parents in the data. This negative correlation remains precise but drops in magnitude when including controls. The somewhat large drop in point estimate for the effect of wage when including occupation controls is consistent with the altruistic story that motivates the empirical strategy - some of that wage variation did seem to be induced by differential altruism. However, it also is consistent with potential selection on unobservables.

Nonetheless the wage impacts still remain strong in Column (3). In this model and sample, a one standard deviation increase in the wage has an impact on being a foster parent of approximately 20% of the mean. Thus the correlation points to an important economic relationship consistent with the theory.

An important issue that not addressed so far discussed in the motivating facts is that the cost of receiving a foster child may be correlated with wage. In particular, if human capital is correlated with wage and across families, then families with a lower wage may have more opportunities to be foster parents because they are more likely to have related children enter foster care. Because kin care is especially popular in black communities (Berrick et al., 1994) and foster care children are disproportionately black, the wage effects are examined only with white families who have above median wages, trying to isolate this pure wage variation from the likelihood of having a related child enter foster care. The results continue to show statistically precise negative effects of wage (estimate = -0.026, se = 0.0126) suggesting that these relationships are not primarily driven by availability of kin foster children.

5.2.3 Testing Proposition 4 and 5

Propositions 4 and 5 make predictions about the age gradients across families with different observables. I test these predictions by estimating the likelihood of a family caring for a child of a specific age by the household level observables. The predictions suggest that (1) households with more children should be more likely to care for older children within the set of foster families and (2) households with higher wages should be less likely to care for older children within the set of foster families.

Specifically, I estimate models of the form

$$\text{Median Age of Foster Child}_i = \beta_1 \text{HH Characteristic}_i + X_{it}\beta_2 + \epsilon_{it} \tag{13}$$

in the ACS. To make the tests more robust and utilize the identification strategies developed for the previous predictions, both the twins instrument and the occupation fixed effect strategies are used in addition to looking at the basic correlations in (13).

The results are contained in Table 7. The signs of all the predictions follow the theory. Families with more children are more likely to care for older children. This is true in both the simple linear models in column (1) and in using the twins instrument in column (2). The twins instrument suggests that the number of children in a household is an important determinant of the age of foster children in their household in the sense that a one standard deviation change in the number of children (approximately one child) makes the predicted age of child the household cares for increase by about 5 years. The wage regressions with occupation fixed effects suggest that a one standard deviation change in the wage leads to a predicted median age of the foster child of about 1 year.

These predictions can also be tested at the county-year level in the AFCARS data by aggregating the household level data to the county-year level. The details of these tests are contained in the

	Dependent Variable: Median Age of Foster Child			
	OLS	Twins IV	OLS	OLS w/ Occupation FEs
	(1)	(2)	(3)	(4)
Num Child	0.834^{**}	4.821^{***}		
	(0.356)	(1.231)		
HH Wage			-0.095^{**}	-0.157^{**}
			(0.037)	(0.075)
Demographics	✓	✓	✓	✓
Market Fixed Effects	✓	✓	✓	✓
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

Table 7: Age Gradient Predictions

Notes: All columns 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. Standard errors are robust clustered for market-level correlated errors. *p<0.1; **p<0.05; ***p<0.01

Appendix. The results of those exercises are aligned with the results here.

5.2.4 Auxillary Evidence on the Model

Another unexamined but obvious implication of the model presented is that if the price of a foster child p_F decreases, this will increase the willingness of families to care for those children. This prediction has been tested directly by Doyle (2007a) who uses an event-study analysis and a discrete change in payments to kin foster families to estimate elasticities of providing care with respect to foster payments. The evidence suggests that kin families respond to prices in ways consistent with the model and the general story of this paper. Similarly Doyle and Peters (2007) use variation in state-level foster care subsidies to identify the foster care supply curve. As in Doyle (2007a), they find evidence for an upward sloping supply curve.

5.3 Quantifying the Effects in a Structural Model

While the previous tests can successfully identify certain comparative statics, they are not particularly easy to compare and interpret as behavioral parameters. To improve interpretation I parameterize a simple version of the theoretical model, estimate behavioral parameters, and then run simple counterfactuals to illuminate and compare the mechanisms more clearly.

Consider a simplified version of the model in which all biological children and foster children fixed human capital values and the utility over having n biological children and a foster child

$(F = 1)$ is $u(n, F)$ and so the decision to foster for household i is based on

$$u_i(n_i, F) - u_i(n_i, 0) - w_i \cdot t_{F,i} - p_{F,i} \geq 0. \tag{14}$$

Assume that $p_{F,i} = p_F = \$500$ the monthly subsidy rate and $t_{F,i} = t_F = \frac{4(40)}{2}$ the number of hours a household must spend caring for a foster child per month where there are 4 weeks in a month, 40 hours of care per week, divided by households with two adults.

The functional form assumptions are that first

$$U_i(n_i, F, c) = u_i(n_i, F) + \psi c \tag{15}$$

and that the form of altruistic utility is

$$u_i(n_i, F) = F \cdot (\beta_0 + X_{D,i}\beta_D) + \log(n_i + 1) + \log(F + 1) + \alpha \log(1 + n_i + F) \tag{16}$$

where β_0 and β_D measure constant and demographic based utility flows ($X_{D,i}$ is a vector of demographics for the household) and α measures the substitutability between biological children and foster children. Foster children and biological children are substitutes in the empirical model if and only if $\alpha > 0$.

Adding in consumption, the net value from fostering is

$$y_i^* = \beta_0 + X_{D,i}\beta + \alpha \log\left(\frac{2 + n_i}{1 + n_i}\right) + \psi(p^F - w_i \cdot t_F) + \epsilon_i \tag{17}$$

where $\epsilon_i \sim N(0, 1)$. Thus the two main structural parameters of interest are α and ψ.

Note that as discussed before, it is likely that n_i and w_i are endogenous. Thus the identification strategies before are used to strengthen the credibility of the empirical model by using an IV probit. The instrument for the term involving n_i is the same-sex instrument while the instrument for the consumption term is the within-occupation wage residual. The model is estimated using the Newey two-step method (Newey, 1987). Household demographics, foster care prices and the time of care for foster children are treated as exogenous across households. The first stage is in Table A6 in the Appendix. The first stage suggests that the same-sex instrument captures most of the variation in fertility term while the wage instrument captures most of the variation in the wage and consumption term, as desired by the conceptual empirical strategy.

The parameter estimates for the main structural parameters α and ψ are shown in Table 8. They are of the expected sign and statistically significant.

It is more useful to assess the economic mechanisms through two counterfactuals. The first counterfactual sends the price of biological children to infinity for all households and set $n_i =$

	Parameter Estimate	S.E.
α	2.0669	0.4149
ψ	8.3784e-05	2.4815e-05

Table 8: Structural Parameter Estimates

Notes: Structural parameter estimates derived from estimating (17) on the same-sex couple sample in the ACS using an indicator for whether a couple is same-sex as in instrument and the within-occupation wage residual as an instrument.

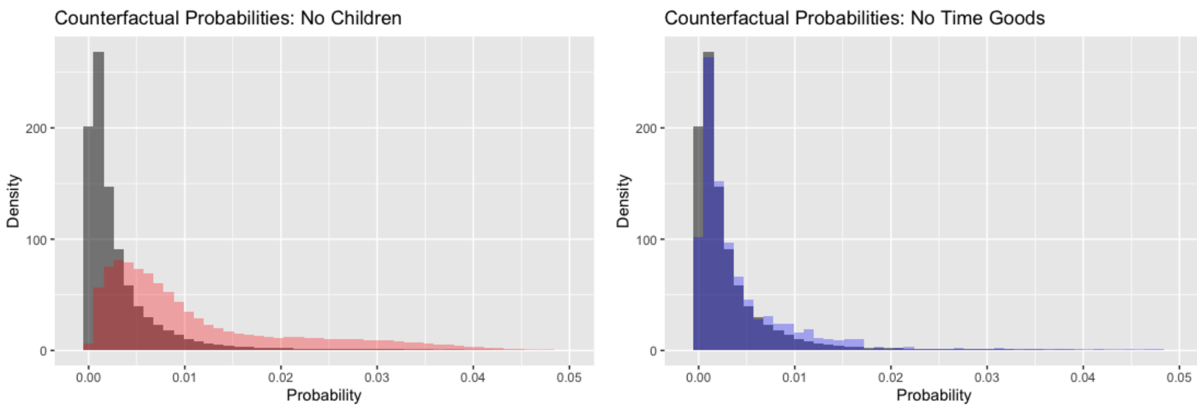

Figure 4: Counterfactuals

Notes: Counterfactuals run from estimating foster probabilities from (17). The grey bars indicate model estimated probabilities in the model. The red bars in the left panel indicate predicted probabilities from simulating the model with $n_i = 0$ for all households. The blue bars in the right panel indicate predicted probabilities from simulating the model with $t_F = 0$.

0. This counterfactual assesses the degree to which foster children and biological children are substitutes and also examines how the valuing of the human capital of children affects foster care decisions.[8]

The second counterfactual sets the time required to care for foster children t_F to 0, thus creating no differential prices by wages for households. This counterfactual assesses the degree to which the wage gradient and time price of foster children deters families from caring for them.

The results of the counterfactuals are contained in Figure 4 in the form of counterfactual probability prediction histograms. In both cases there is a probability mass shift towards the right. The shift is far more stark for the no child counterfactual than for the no time goods counterfactual. Thus, equating the number of biological children to 0 in all households induces a much larger fostering change than equating all household wages to 0. In particular, the no child counterfactual induces approximately four times as many foster families as in the baseline in the data. The no time goods counterfactual induces approximately 50% more foster families as in the baseline in the data.

[8]Note that, importantly, this is a partial equilibrium counterfactual since sending the price of biological children to infinity would also change the supply side as no foster children would eventually enter the foster care system.

One particularly useful exercise is to assess what α would be required so that the fostering probability decisions of households approximately match the own biological fertility decisions of households $n_i^* = \mathbf{1}\{n_i > 0\}$ predicted by the model when $p_n \to \infty$. This addresses in some sense how far away biological children and foster children are from being perfect substitutes. The approximate value of α needed is about $\alpha \approx 6$, three times the value of α estimated in the data. Thus, the model suggests that there remains some strong disutility of foster children over biological children. This is unlikely to be auxiliary costs since households are paid to care for foster children and do not have to bear the fertility costs, and so likely comes from the differential human capital of foster children relative to biological children in the model or other unmodeled costs.

5.4 Summary of the Tests and Alternative Theories

The predictions of the model find strong support in the data, and other natural implications of the theory find support as well. While some of these predictions could be generated by an alternative explanation, the value of this set of findings combined with the theory is that it is difficult to generate these predictions and results with alternative models.

For example, the wage effects are easy to generate with many models. Wages could be correlated with the general altruism of families and so only serve as a proxy for their altruism. However, the wage and age interaction effect seems more difficult to fit into this theory. Why would families be less altruistic to younger or older children? There is no clear basis for this. A similar story could be told for the fertility effects - it is challenging to generate the fertility and age interactions without appealing to human capital.

The fact that so many of the predictions are verified in the data and that some of these predictions are particularly specific to the model of interest provides strong support for the economic mechanisms it highlights in a unified way as being important. To further strengthen the connection between the theory and the data, I examine two competing explanations and their implications for the empirical results in this paper are examined.

5.4.1 Pure and Impure Altruism

As discussed, the basic cuts of the data are not consistent with classical models of altruism, pure and impure. It is useful to re-evaluate these theories after the empirical results and a more in-depth look at the model proposed in this paper.

Recall that in classical altruism models, there is some public good that households contribute to. This theory treats society as playing a public goods game and analyzes an equilibrium of public good contributions by households. To fit this theory into foster care, consider the caring for low human capital children as contributing to the public good of the overall stock of human capital in society.

One of the major implications of impure altruism is that if income is redistributed to more altruistic households, total contribution to the public good will increase. For the wage effects found in this paper to be consistent with the theory it must be that the wage effects only reflect wage and income increases for less altruistic families at the expense of more altruistic families. This is challenging to examine in the data as both the reallocation of wages over the time period in the data and the joint distribution of altruism and wages is hard to identify. Thus, while the wage predictions in the data are not strictly rejected, the challenge of implementing a feasible empirical test makes it much less valid as a falsifiable theory in this case.

A more basic implication of the warm glow theory is that charity is likely a normal good and so higher incomes should induce more caring for foster children. The empirical results in Table 6 directly contradict this claim.

Finally, the warm glow theory has no real way to incorporate own fertility and biological children into how households make decisions of whether to be foster parents, and match some of the foster and fertility facts analyzed in this paper.

5.4.2 Psychological and Sociological Theories of Adoption and Foster Care

The vast majority of the psychology and sociology literature around adoption and foster care studies the psychological implications for foster children, not the selection of families who perform these services. However, Zamostny et al. (2003) provides an overview of the literature on adoption and does mention some theories and evidence related to the decision to adopt and foster. I examine two specific ideas coming out of that literature. One prominent theory is that the psychological effect of loss from infertility induces families to seek children to adopt (Kirk, 1964).

The idea of loss as infertility can be explicitly incorporated into my model as the price of own children. Those families that experience infertility have a higher price of having own biological children due to the realization that they are unable to conceive. The substitutability in the utility function causes them to seek foster children instead. Thus, this theory of loss and infertility appears complementary to the theory presented here, and indeed consistent with one aspect of the data.

Another theory from sociology is that the choice between adoption and having biological children is based on a conceptualization of appropriate family structures. Thus, families with more flexible views of suitable families are more likely to adopt or foster children. In particular marginalized communities have been found to have these more flexible viewpoints (Wegar, 2000).

The ideas related to family structure are consistent with the empirical fact that same-sex couples are substantially more likely to foster children Under the view of this theory, this positive correlation completely reflects that same-sex couples are marginalized and this is what contributes to their more open view of the world. The wage effects in Table 6 could even be consistent with this theory if households with lower wages have more open views of families due to similar types of marginalization, even when controlling for a rich set of demographics.

What the family concept model does not provide is a way to better understand how an exogenous increase in the number of biological children decreases the propensity to foster as shown in the IV estimates of Table 5. There is no clear relationship between having an extra child and the conceptualization of family structure - adding a foster child to a larger family or smaller family does not have a clear difference in how open families are.

Similarly, the interaction between number of children and age of the child does not have a clear basis in this family conception theory. Families with more biological children might reflect more or less openness to unusual family structures, depending on social norms about family sizes.

Overall, the family openness theory does a good job explaining some of the empirical results but is not able to capture some of the subtleties in the data and provide a rigorous foundation for their roots. It is not too surprising that the family structure theory does seem consistent with many of the empirical results - the theory tightly links the decision to be a foster parent to the decision to be a biological parent in a way that is similar but less structured than the model in this paper does. The emphasis on human capital and systematic analysis with respect to utility is the major innovation and contribution of the theory over these ideas.

6 Conclusion

This paper studies why families provide foster care to children. The facts do not appear consistent with canonical altruism models and so I develop a fertility-based model that treats foster children and biological children as substitutes. The model makes clear predictions that are then tested in the data using various identification strategies. The predictions find strong evidence in the data. The predictions relating the interactions between child age and fertility and wages are probably most specific to the model and thus provide the most robust test of the theory. The fertility effects in a simple structural model seem to be the strongest of the effects examined. Alternative theories are discussed and examined for their performance in explaining the empirical results and how they relate to this paper's model.

One natural extra question is whether the large age and human capital gradients in child placement constitute a social inefficiency. If subsidies were raised to allow for market clearing, would social welfare improve? The answer to this question is not obvious if family treatment effects are different for children with different human capital and different ages.

What are the implications of the results in this paper for the welfare of foster children? The results in this paper suggest that foster children and biological children are substitutes, and that families with lower wages have a lower opportunity cost of caring for children. The wage effects seem to have a more unambiguous direction: families with lower wages tend to have lower human capital then this might suggest that foster children are placed with less capable families. The families could still make children better off than their next best alternative, but there exist other families who are potentially deterred because of consumption effects. However, the fertility effects in this paper suggest that a stronger mechanism is that certain families have higher prices or different technologies for producing biological children. The correlation between this technology and human capital is unclear, but might suggest that the effects of families could be quite positive.

While the decision to care for abused and neglected children does not seem a natural candidate for a rational choice framework, this paper shows that it provides a useful way to understand this important social behavior and the frame the welfare implications of that behavior.

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Appendix

Data and Institutional Details

AFCARS Cleaning Details

In cleaning the AFCARS data, all children that do not have a most recent observation in 2015 and are never flagged as entering the system are dropped from the analysis. The county of a child is defined to be the county of entry not the county of current placement, though the results are not sensitive to this decision. The reasoning for this is to facilitate an interpretation of the results as the county directly responsible for the well-being of the child. Other standard cleaning procedures are performed which include dropping children older than age 20 as California law only states that it provides foster care service for children up to age 21, and assigning a single race or sex for children with more than one observed race or sex over the years observed.[9]

County	Percent in County
Alameda	0.57
Contra Costa	0.73
Fresno	0.87
Kern	0.91
Los Angeles	0.83
Orange	0.75
Riverside	0.81
Sacramento	0.8
San Bernardino	0.77
San Diego	0.88
San Francisco	0.42
San Joaquin	0.81
Santa Clara	0.73
Tulare	0.83

Table A1: Inter County Placements

Notes: Average percent of children placed in county between 2005 and 2015. Includes all types of placements. Data source: California Child Welfare Indicators.

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

Table A2: Child Characteristics by County

Notes: Summary statistics by county for all children in the county-year samples of AFCARS.

Year	Child Obs	Obs Entry	Obs Exit	Avg Entry Age	% White	% Male	% Disabled
2005	54978	17391	18721	6.76	0.25	0.48	0.39
2006	52924	17544	18724	6.86	0.23	0.48	0.43
2007	52247	17567	19178	6.90	0.23	0.49	0.43
2008	49756	16037	19249	6.98	0.21	0.48	0.40
2009	46721	15557	18168	6.83	0.19	0.50	0.38
2010	42910	14221	16821	6.61	0.21	0.49	0.42
2011	39189	13373	13943	6.66	0.21	0.49	0.38
2012	38371	13192	12971	6.64	0.21	0.49	0.38
2013	39197	14065	12994	6.57	0.19	0.50	0.41
2014	40420	14509	13432	6.50	0.19	0.49	0.36
2015	41396	14113	14609	6.39	0.20	0.50	0.21
Total	498109	167569	178810	6.71	0.21	0.49	0.38

Table A3: Child Characteristics by Year

Notes: Summary statistics by year for all children in the county-year samples of AFCARS.

Figure A3: ACS White Wage Mean Fostering

Notes: Plots indicate the percent of families in each bucket of observables that have foster children in the ACS in California between 2005-2015. Wages are measured as an average of the head of household and their partner/spouse.

Theory Appendix

Consider the model but instead treat n and F as real numbers and treat n as a choice variable. Suppose that $t_F > 0$ and $t_n > 0$ are fixed for simplicity. Then the first order condition is given by

$$\begin{aligned} u_1(t_n n, t_F(1-a)F)t_n &= wt_n + p_n \\ u_2(t_n n, t_F(1-a)F)t_F(1-a) &= wt_F + p_F(a) \end{aligned} \tag{18}$$

Some additional assumptions are useful: $t_F > t_n$ so that more time is invested in foster children and $t_F(1-a) < t_n$ so that their human capital is still less. These can be justified by similar concavity assumptions used in the main text of the paper.

Lemma 1. Under quasi-linear utility, standard Inada conditions, and the assumption that $u_{11} = u_{22} < u_{12}$, the first order condition characterizes the optimum of the household's problem.

Proof. I check the second order conditions. For maximizing a function $f(x, y)$ the necessary condition for a maximum is $f_{11}f_{22} - f_{12}^2 > 0$ and $f_{11} < 0$. In this case the maximization problem is

$$\max_{n\geq 0, F\geq 0} u(t_n n, t_F(1-a)F) + w(T - t_n n - t_F F) - p_n n - p_F F$$

and here $f_{11} = u_{11}(t_n n, t_F(1-a)F)t_n^2 < 0$ and

$$f_{11}f_{22} - f_{12}^2 = u_{11}(t_n n, t_F(1-a)F)^2 t_n^2 t_F^2 (1-a)^2 - u_{12}(t_n n, t_F(1-a)F)^2 t_n^2 t_F^2 (1-a)^2 < 0$$

due to the assumptions on $u_{11} = u_{22}$ and $-u_{12} < -u_{11}$. Thus this we have a local maximum.

[9] The modal race or sex is taken for these. If there are equal numbers, the first observation is taken for these.

Year	Age 0-4	Age 5-8	Age 9-11	Age 12-14	Age 15-21
2005	414	450	479	533	580
2006	398.36	433	460.9	512.86	558.09
2007	390.94	424.94	452.32	503.31	547.69
2008	371.24	403.52	429.52	477.94	520.09
2009	339.51	368.63	392.3	436.9	475.13
2010	335.65	364.44	387.84	431.93	469.73
2011	323.5	351.25	373.8	416.3	452.73
2012	545.86	591.07	621.77	650.77	681.48
2013	551.87	597.23	628.31	657.71	688.79
2014	554.18	599.6	630.98	660.72	692.1
2015	566.9	613.05	645.18	675.67	707.81

Table A4: California Basic Foster Care Rates

Notes: Basic monthly rates (stipends) for foster care in California in 2005 dollars.

The Inada conditions ensure that this local maximum is global and that there is no corner solution. Thus the first order conditions completely characterize the solution. □

Proposition 6. If $\frac{\partial n^*}{\partial w} < 0$ then $\frac{\partial F^*}{\partial w} < 0$.

Proof. Consider the FOC under the quasi-linear assumption. We can simplify it to

$$\begin{aligned} u_1(t_n n, t_F(1-a)F)t_n &= wt_n + p_n \\ u_2(t_n n, t_F(1-a)F)t_F(1-a) &= wt_F + p_F(a) \end{aligned} \tag{19}$$

Shorten the notation to $u_1 := u_1(t_n n, t_F(1-a)F)$, $u_2 := u_2(t_n n, t_F(1-a)F)$ and the same for higher order derivatives. Then implicitly differentiating the simplified first order conditions (19) with respect to w yields

$$\begin{aligned} (u_{11}t_n\frac{\partial n^*}{\partial w} + u_{12}t_F(1-a)\frac{\partial F^*}{\partial w})t_n &= t_n \\ (u_{12}t_n\frac{\partial n^*}{\partial w} + u_{22}t_F(1-a)\frac{\partial F^*}{\partial w})t_F(1-a) &= t_F \end{aligned}$$

Solving this system for the partial derivatives yields

$$\begin{aligned} \frac{\partial n^*}{\partial w} &= \frac{u_{22}(t_F(1-a))^2 t_n - t_F u_{12} t_n t_F(1-a)}{(t_F(1-a))^2 t_n^2(u_{11}u_{22} - u_{12}^2)} \\ \frac{\partial F^*}{\partial w} &= \frac{u_{11}t_n^2 t_F - t_n u_{12} t_n t_F(1-a)}{(t_F(1-a))^2 t_n^2(u_{11}u_{22} - u_{12}^2)} \end{aligned}$$

Now note that

$$\begin{aligned}\frac{\partial n^*}{\partial w} - \frac{\partial F^*}{\partial w} &= \frac{u_{22}(t_F(1-a))^2 t_n - u_{11}t_n^2 t_F + t_n u_{12} t_n t_F(1-a) - t_F u_{12} t_n t_F(1-a)}{(t_F(1-a))^2 t_n^2(u_{11}u_{22} - u_{12}^2)} \\ &= \frac{u_{11}((t_F(1-a))^2 t_n - t_n^2 t_F) + u_{12} t_n t_F(1-a)(t_n - t_F)}{(t_F(1-a))^2 t_n^2(u_{11}u_{22} - u_{12}^2)}\end{aligned}$$

where I use the symmetry of utility. Now note that the denominator is positive since $u_{11}u_{22} > u_{12}^2$ is required for the first order condition to characterize a maximum. Then since $u_{11} < 0$ and $u_{12} < 0$, and $t_F > t_n > t_F(1-a)$ and is not hard to see that the whole expression is positive. Thus, if $\frac{\partial n^*}{\partial w} > \frac{\partial F^*}{\partial w}$ and the conclusion follows. □

Proposition 7. $\frac{\partial F^*}{\partial p_n} > 0$.

Proof. Consider implicitly differentiating (19) with respect to p_n. This yields

$$\begin{aligned}h_n(u_{11}t_n\frac{\partial n^*}{\partial p_n} + u_{12}t_F(1-a)\frac{\partial F^*}{\partial p_n}) = 1 \\ h_F(u_{12}t_n\frac{\partial n^*}{\partial p_n} + u_{22}t_F(1-a)\frac{\partial F^*}{\partial p_n}) = 0\end{aligned}$$

Simplifying these and solving for $\frac{\partial F^*}{\partial p_n}$ yields

$$\frac{\partial F^*}{\partial p_n} = \frac{-u_{12}}{t_n t_F(1-a)(u_{22}u_{11} - u_{12}^2)}$$

and since $u_{12} < 0$ this is positive as required. □

Proposition 8. $\frac{\partial F^*}{\partial p_F} < 0$.

Proof. Consider implicitly differentiating (19) with respect to p_F. This yields

$$\begin{aligned}h_n(u_{11}t_n\frac{\partial n^*}{\partial p_F} + u_{12}t_F(1-a)\frac{\partial F^*}{\partial p_F}) = 0 \\ h_F(u_{12}t_n\frac{\partial n^*}{\partial p_F} + u_{22}t_F(1-a)\frac{\partial F^*}{\partial p_F}) = 1\end{aligned}$$

and so simplifying this and solving for $\frac{\partial F^*}{\partial p_F}$ yields

$$\frac{\partial F^*}{\partial p_F} = \frac{u_{11}}{(t_F(1-a))^2(u_{22}u_{11} - u_{12}^2)}$$

and since $u_{11} < 0$ this is negative as required. $\square$

Proposition 9. Suppose that there is an exogenous increase in n, then demand for foster children is reduced.

Proof. Considering (19) and letting n_0 be an exogenously endowed set of biological children, we can write this as

$$u_1(t_n(n+n_0), t_F(1-a)F)t_n = wt_n + p_n$$
$$u_2(t_n(n+n_0), t_F(1-a)F)t_F(1-a) = wt_F + p_F(a)$$

Note that we need to add some curvature to the consumption function to get the result of interest. Instead of changing the consumption value function a trick we can use is to suppose that the price of additional children n is decreasing in n_0: $p_n = p_n(n_0)$ where $p_n' < 0$. Then implicitly differentiating with respect to n_0 we get that we can write the system as

$$t_n^2 u_{11}\frac{\partial n^*}{\partial n_0} + t_n t_F(1-a)u_{12}\frac{\partial F^*}{\partial n_0} = p_n'(n_0)$$
$$t_n t_F(1-a)u_{12}\frac{\partial n^*}{\partial n_0} + (t_F(1-a))^2 u_{22}\frac{\partial F^*}{\partial n_0} = 0$$

and then rearranging and solving for $\frac{\partial F^*}{\partial n_0}$ yields

$$\frac{\partial F^*}{\partial n_0} = \frac{-u_{12}p_n'(n_0)}{t_n t_F(1-a)(u_{11}u_{22} - u_{12}^2)}$$

and since $u_{12}, p_n' < 0$ we have that this is negative as required. $\square$

Empirical Results

	Dependent Variable: Foster Child Placed with a Family				
	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

Table A5: Age Predictions in the AFCARS Data

Notes: Models estimated on all children eligible for non-kin placement in foster in California between 2005-2015 in the AFCARS data. The Old independent variable is an indicator for if a child is older than age 10, the median age of a foster child. The set of demographic controls consists of racial composition of county and average age of households in the county. Standard errors are clustered at the county-level. *p<0.1; **p<0.05; ***p<0.01

Dependent Variable:	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

Table A6: IV Probit First Stage

Notes: This provides the first stage regressions for the IV probit model as linear models. Child U corresponds to the log term in (17) and Cons U corresponds to the price minus wage term in (17). KP F stats are Kleibergen and Paap (2006) F statistics.