Why Do Families Foster Children? A Beckerian Approach

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Abstract

Less than half of the hundreds of thousands of abused and neglected children in foster care are able to find a foster family to take care of them while the rest are placed in restrictive group home settings. This paper proposes that households choose to foster children following a Becker-style model in which households maximize the human capital of the children they care for and can receive human capital flows from both foster children and biological children. The demand for foster children and the age of foster children depends on the number of biological children and the household wage. I test the main predictions of the model using twins as an instrument and a rich set of household observable characteristics. A parameterized version of the model suggests that the substitutability of foster children and biological children is a stronger lever affecting fostering than foster care subsidies, and the wage of a household is almost as important as the subsidy in determining fostering.

Keywords: foster care, model, fertility, wages

JEL codes: J13, D13

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1 Introduction

Hundreds of thousands of children enter the US foster care system every year due to substantiated reports of abuse or neglect (Children's Bureau, 2016). Foster children tend to have lower educational attainment, and significantly higher rates of incarceration and homelessness than the general population and represent some of the most disadvantaged children in society (Gypen et al., 2017). To ensure that children have good experiences in foster care, the state recruits volunteer families in an effort to provide high quality childcare and encourage "normal childhood experiences" (Welfare and Institutions Code 16000). However, over half of foster children are placed in group homes or institutions due to a lack of available families. This phenomenon is often referred to as the foster care family "shortage".[1][2] Previous research has suggested that institutional settings are detrimental to children's outcomes later in life (Nelson et al., 2007). It is important to understand why households select into being foster families to help the state recruit more households and ease the shortage. However, there has been little work done examining behavioral data to understand why households decide to foster children as policymakers and social workers continue to look for effective recruiting solutions.[3]

This paper argues that fostering can be explained by a Beckerian model where households trade off working, caring for biological children, and caring for foster children. The model posits that biological children and foster children both provide human capital utility flows to parents and are thus substitutes. It also argues that there are distinct attributes that distinguish foster children and biological children. The paper tests the model predictions applying instrumental variable and selection on observable methods to data from the American Community Survey (ACS) and the Adoption and Foster Care Analysis and Reporting System (AFCARS). The paper also estimates the parameters of a stylized version of the model using the ACS data to quantify the importance of the novel mechanisms.

This paper conjectures that characteristics that have been important for explaining fertility choices in the economics literature (Becker, 1960) may play an important role in explaining why families choose to foster. To the best of my knowledge, economic models of foster care have only analyzed how the foster care subsidy affects a family's choice to foster. This paper focuses on household preferences over the human capital of foster children and the costs related to caring for foster children. The model incorporates these ideas by focusing on two characteristics. First it focuses on the number of biological children of a household, an alternate source of human capital flow. Second it focuses on the the wage, which affects the cost of caring for foster children and biological children. It also addresses the wrinkle that families can choose to foster children of different starting ages incorporating this explicitly as a choice variable. Age is an important determinant of whether a child is placed with a foster family or remains in an institution. The model assumes that abused and neglected children have lower human capital stocks, and so older foster children will have relatively lower human capital stocks to begin with then their younger counterparts.[4]

[1] Author's calculations using AFCARS data from 2010 to 2015.

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

[3] Exceptions include, among others, Berrick et al. (1994), Baum and Crase (2001), Rhodes et al. (2006), Duncan and Argys (2007), Doyle (2007a), Doyle and Peters (2007).

[4] The model in this paper differs in some aspects from other quality-quantity models. The model treats fertility for biological children as exogenous and assumes that investments into children come through time invested by households. Some other quality-

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 model predicts that under certain assumptions older foster children will be demanded less by households, households with a higher wage will demand less foster children, households with (exogenously) more biological children[5] will demand less foster children, households with a higher wage will prefer younger foster children over older foster children, and households with (exogenously) more biological children will prefer older foster children over younger foster children.

I test the model predictions using ACS and AFCARS data. The first empirical result of this paper is that older children are fostered by households much less than younger children. These results are consistent with literature on age patterns of children more likely to go into group homes (Ryan et al., 2008). One contribution of this paper is that it provides an economic interpretation of this pattern through the lens of child human capital and time costs. The second empirical result shows that a plausibly exogenous shock to the number of biological children decreases demand for foster children consistent with the model mechanism in which biological and foster children are substitutes. I establish this result using a twins instrument to exploit plausibly exogenous shocks to the stock of biological children following Angrist and Evans (1998) and Black et al. (2005). The third empirical result shows that households with higher wages are less likely to care for foster children, even after partialling out a rich set of explanatory variables including a household's occupation, racial make-up and age. The fourth empirical result applies the twins instrument and shows that households with more exogenous biological children that also foster children tend to foster older children. The fifth and final reduced form result applies the same selection on observables strategy to identify the relationship between household wage and the age of foster children in a household and finds that higher wage households tend to foster younger children.

To quantify the two main mechanisms at play presented in the model, and compare to the traditional policy lever of price subsidies, I estimate a simple parametric version of the model. I find that a reduction in biological children increases the percentage of households that foster children more than a similar percentage increase in the subsidy.[6] The estimated model parameters also suggest that biological children and foster children are substitutes, there are negative wage effects with the number of foster children, and households have upward sloping supply curves in response to foster care subsidies. To get these results, I run the following counterfactuals within the estimated model. I compare how a 50% reduction in the number of biological children, a 50% reduction in the time required to care for foster children, and a 50% increase in the foster care subsidy contribute to the percent of households in the data that foster children.

While the results in this paper are robust, there are some important limitations to this study that stem from how the foster care problem is approached. Perhaps the most important one is that the model does not distinguish between kin and non-kin families. One idea for how to differentiate between kin and non-kin

quantity models discuss how levers such as formal education can generate quality investments which while not requiring more time investment (Doepke et al., 2022).

[5]The model focuses on exogenous shifts in the wage since the empirical analysis uses a plausibly exogenous shifter of biological children, twins, to identify the relationship between biological children and foster children in household's utility functions. Section 2.4 also examines a simplified version of the model in the case in which the number of biological children is endogenously and jointly determined with foster care.

[6]While outside the scope of this paper, there may be other important spillovers with raising subsidies that change the quality distribution of foster homes.

foster care is to add the assumption that kin families have differing weights on the values of the child's human capital. Since kin families are related to the child and the child's family, one hypothesis that could be tested is that kin families give a higher weight to the foster child's human capital. Unfortunately, the ACS data does not identify kin and non-kin families, making it hard to distinguish kin and non-kin specific mechanisms. Future research could address this limitation and distinguish motivations for kin and non-kin families, especially if these families contribute differently to improving foster children's outcomes (Berrick et al., 1994).

This paper contributes to the literature in both social work and economics that aims to understand why households decide to be foster families. Related papers examine how financial incentives affect decisions by households within foster care such as adoption (Hansen and Hansen, 2006; Hansen, 2007; Buckles, 2013; Argys and Duncan, 2013). The most closely related papers are Duncan and Argys (2007), Doyle (2007a) and Doyle and Peters (2007) which provide evidence that foster parents increase their supply in response to financial incentives. This mechanism is also incorporated in the model below: if the subsidy for caring for foster children increases, households are more willing to be foster parents, and thus there is a lower reliance on group homes in foster care. This paper's model builds on these models by adding and testing 4 other predictions about what makes households more or less likely to be foster parents to enrich the literature's understanding of how certain household characteristics affect their probability of fostering children overall and of fostering children of different ages.[7]

The model in this paper is also related to models in recent papers that take a Beckerian approach to study questions related to parenting styles (Doepke and Zilibotti, 2017), the career costs of children (Adda et al., 2017), and the incidence of child neglect (Seiglie, 2004). The last paper is particularly relevant as many foster children come from homes of abuse and neglect. This paper contributes a Beckerian approach to studying fostering decisions that affect hundreds of thousands of neglected and abused children in the US every year.

The organization of the rest of this paper is as follows. Section 2 presents the model. Section 3 describes the data used for all empirical work in the paper. Section 4 presents the methods and results from testing the predictions of the model. Section 5 discusses evidence on the model from the literature. Section 6 parameterizes a version of the model in Section 2, estimates that model, and runs counterfactual simulations. Section 7 concludes.

2 Model

2.1 Setup

The model consists of households and a pool of foster children looking for homes. Households make lifetime fostering decisions over how many foster children to have, F, and the age of the foster children they care for, a.[8] Each child has an age between 0 and 18 which is normalized to be in $[0, 1]$. I assume that after any

[7] The reasons that households may foster for reasons other than financial incentives has been pointed out by Baum and Crase (2001) using interviews of foster parents. This paper is one of the few to the best of my knowledge to use behavioral data as opposed to survey data. Outside of providing a new lens into fostering, behavioral data may suffer less from selection problems.

[8] I assume for parsimony of the model that families cannot care for foster children of different ages at the same time.

child turns 18, a household caring for that child no longer pays any costs for that child. Thus, a family that cares for a child of age a will pay dollar and time costs for $(1-a)$ of the time they would for a biological child.[9]

The model follows the Beckerian tradition in assuming that households have preferences over the human capital of children they care for and their own consumption. Households have preferences over the (final) 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.[10] Households also have preferences over the (final) 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 which is the numeraire good. Their utility over these objects is assumed to be separable in utility over human capital flows from children and consumption

$$U(H_n, H_F, c) = u^K(H_n, H_F) + c \tag{1}$$

where u^K is the utility from "Kids" and satisfies $u_1^K > 0$, $u_2^K > 0$, $u_{11}^K \leq 0$ and $u_{22}^K \leq 0$. A child's human capital depends on the household's investment into them: t_F for foster children, and t_n for biological children. A central hypothesis of the model tested in the data is that $u_{12}^K < 0$: households care about gaining utility from the human capital of children they care for, which can either be biological children or foster children.[11]

A household is endowed with an exogenous technology described by (T, p_n, t_n, w) which describes their total time budget T, the price of investing in their own biological children p_n, the (exogenous) time required to raise a biological child t_n, and their wage w. I treat n and t_n as exogenous and fixed for most of the exposition of this paper, as it makes the key comparative statics simpler to derive. This limitation is explored more in Subsection 2.4 below.

Foster children also have human capital levels and prices.The price of a foster child is the fixed cost of caring for that child over the from age a to age 1. A crucial difference when modeling the price of a foster child versus a biological child is that households that care for foster children are paid a subsidy.[12] I will write the price of fostering a child as $p_F = \bar{p}_F - s_F$, where s_F is the foster care subsidy.

A key choice that households make if fostering is the age of the foster child. As stated above, the age of the foster child is $a \in [0, 1]$ normalized to the unit interval. The model assumes a foster child's age affects the price, the time cost, and the initial human capital of the child. Prices are allowed to vary with age due

[9] This is to keep the model parsimonious but foster children and biological children likely do require some time investments post age 18. For the model, it is only really important that the amount of time post age 18 is similar for both types of children.

[10] 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.

[11] This utility formulation implies that households do not treat fostering children as contributing to a public good, but instead as incorporating 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. I discuss more below the difference in implications for a competing model in which households aim to maximize their impact on a foster child's human capital.

[12] Table A4 in the Appendix lists the monthly subsidy rates of foster children for California between 2005-2015.

to the subsidy $p_F(a) = \bar{p}_F - s_F(a)$ as they do with real subsidies in California (see Table A4). The time required to care for a foster child is also affected by the age, and I model the total time spent on caring for a foster child as $t_F + \bar{t}(a)$. The term $\bar{t}(a)$ is meant to reflect that older children may require more time to care for due to more behavioral problems (Heflinger et al., 2000; Turney and Wildeman, 2016).[13]

Human capital for a child of type $j = n, F$ at the end of their childhood ($a = 1$) is

$$h_j = \int_0^1 t_j(a)da \tag{2}$$

where $t_j(a)$ is the flow of household investment when the child is age a. I assume that all children have the same initial human capital. I assume that a child that is in an abusive or neglected home receives $t_n(a) = 0$.[14] This is a normalization relative to the eventual time investment that they will receive while in foster care and is not strictly required.

These assumptions imply that for a family investing t_F time in a foster child of age a for the age of the child from a to 1, the resulting human capital of the foster child is

$$h_F(a) = (1-a)t_F. \tag{3}$$

Equation (3) 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 - households have less control over their final human capital. This is because of the fact that older children have less time to be impacted.

If households spend all their time investing in children or working then their budget constraint can be written as

$$c = w(T - t_n n - (1-a)(t_F + \bar{t}(a))) - p_n n - (1-a)(\bar{p}_F - s_F(a))F \tag{4}$$

For simplicity consider a household making a discrete choice between $F = 1$ and $F = 0$. Then together (1), (3) and (4) imply that the value of providing foster care for a child of age a for a household with technology (T, p_n, t_n, n, w) is

$$V_F(a,n,w) := \max_{t_F \geq 0} u^K(h_n n, t_F(1-a)) + w(T - t_n n - (1-a)(t_F + \bar{t}(a))) - p_n n - (1-a)(\bar{p}_F - s_F(a))F \tag{5}$$

and the value of not fostering is

$$V_0(a,n,w) := u^K(h_n n, 0) + w(T - t_n n) - p_n n \tag{6}$$

[13]Outside of evidence from the literature: 1.45% of children under age 10 have behavioral problems as part of their reason for entry into foster care compared to 28.6% of children over age 10 in the data sample examined in this paper. These behavioral problems likely affect the time and effort required to care for the child.

[14]To microfound the age of foster children consider the following setup: some families have $t_n = 0$ 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.

Together (5) and (6) can be used to define the net value of foster care for caring for a child of age a for a household with characteristics (n, w):

$$V(a, n, w) := V_F(a, n, w) - V_0(a, n, w) \tag{7}$$

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

2.2 Results

The model contributes the following predictions to how household characteristics affect fostering behavior and choices over the age of foster children.

A well-known empirical fact is that older children are placed with foster families less often. The model implies that under certain conditions households may demand less older children due to their time costs if the subsidy is not sufficient to offset these costs

Proposition 1. Suppose that $\bar{t}'(a)$ is large enough and $s_F'(a)$ is small enough:

$$(1-a)w\bar{t}'(a) > w(t_F + \bar{t}(a)) + \bar{p}_F - s_F(a) + (1-a)s_F'(a) \tag{8}$$

Then $\frac{\partial V}{\partial a} < 0$

Proof. Using the envelope theorem,

$$\begin{aligned}\frac{\partial V}{\partial a} &= -u_2^K(h_n n, t_F(1-a))t_F + w(t_F + \bar{t}(a)) - w(1-a)\bar{t}'(a) + (\bar{p}_F - s_F(a)) + (1-a)s_F'(a) \\ &= -u_2^K(h_n n, t_F(1-a))t_F + [w(t_F + \bar{t}(a)) + \bar{p}_F - s_F(a) + (1-a)s_F'(a) - (1-a)w\bar{t}'(a)]\end{aligned}$$

and the condition (8) implies the result since $-u_2^K t_F < 0$. $\square$

Condition (8) shows there are two forces affecting demand for older foster children. The first is that older children receive higher subsidies, and also have less costs associated with them because households care for them for less time. The second is that the behavioral problems of older foster children are more costly on a time flow consistency basis. If this second force dominates, it can drive lower demand for older children.

I now examine a parametric example to illuminate (8) using model primitives. Suppose that $u^K(t_n n, t_F(1-a)) = \log(t_n n + \alpha t_F(1-a))$ and $t_n = 1$. Then the optimal choice of t_F when fostering is given by

$$t_F = \frac{\alpha - wn}{\alpha w(1-a)}$$

and so we can write

$$V_F(n, a, w) - V_0(n, a, w) = \log(\alpha/w) - \frac{\alpha - wn}{\alpha} - w\bar{t}(a)(1-a) + s_F(a)(1-a)$$

and in this case (8) becomes

$$w\frac{\partial}{\partial a}(\bar{t}(a)(1-a)) > \frac{\partial}{\partial a}(s_F(a)(1-a)).$$

The model rationalizes less demand for older children with fixed time costs that rise more steeply than the subsidy.

The model connects traditional Beckerian fertility decisions with fostering decisions through the household's utility over human capital of biological and foster children. It implies that households have a smaller net value for fostering when they have more biological children.

Proposition 2. Suppose that $u_{12}^K < 0$, then $\frac{\partial V}{\partial n} < 0$

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

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

since $t_F > 0$ and $u_{12}^K < 0$. □

The incorporation of the human capital of foster children into the utility function u^K and the condition $u_{12}^K < 0$ provides a structural connection to traditional Beckerian fertility models and links the focal choice variable (biological children) with foster care. I explore the implications of keeping n exogenous in Section 2.4 below.

As in other Beckerian models in which wages impact how household's make childcare decisions over biological children, the same applies to foster children. As in many Beckerian models where households with higher wages demand less biological children, households with higher wages demand less foster children.

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

Proof. Applying the envelope theorem and differentiating V with respect to w yields

$$\frac{\partial V}{\partial w} = -(t_F + \bar{t}(a))(1-a) < 0$$

since $t_F + \bar{t}(a) > 0$. □

This wage comparative static is directly due to 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 $t_F + \bar{t}(a)$. I explore the limitations of this quasi-linearity assumption Subsection 2.4 below. [15]

[15] All types of children are normal goods in this model, so while this prediction focuses on wage rate changes, the model also implies that increases in unearned income should increase the demand for child consumption more broadly. The model does not make an explicit prediction on how unearned income affects the composition of biological children and foster children and is not tested because the empirical analysis is not well set up for testing how exogenous increases in unearned income affect fostering. However, Section 2.5 discusses single vs. two parent households and suggests that two parent households increased childcare consumption is mainly due to increases in biological children, not foster children. Comparing single and two parent households is one way to test for an increase in unearned income since the time and resource budget constraint is expanded (holding fixed other characteristics) with two parents instead of one.

What types of families are most likely to be willing to care for older foster children? This question is important due to the major lack of households available to care for older children. The model provides some insights into this question: it connects a households biological child stock and wages with the value of older foster children. First, 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. Suppose that $u_{12}^K < 0$, then $\frac{\partial^2 V}{\partial a \partial n} > 0$

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

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

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

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

and so the sign of this expression depends on the sign of the second term $t_F'(a)(1-a)-t_F(a)$ since $u_{12}^K < 0$.

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

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

and implicitly differentiating this expression with respect to a yields

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

Since $u_{22}^K < 0$, $(1-a) \in (0,1)$ and $u_2^K > 0$, 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 families receiving decreasing marginal utility from the human capital of any type of child. Families with a high number of own children already have a high utility flow of human capital from children and so the human capital utility flow lost from caring for an older child compared to a younger child is substantially lower.

The model also gives conditions under which households with a higher wage will prefer younger foster children.

Proposition 5. Suppose that $u_{12}^K < 0$ and $\bar{t}'(a)$ is large enough so that

$$-t_F'(a)(1-a) + t_F - \bar{t}'(a)(1-a) + \bar{t}(a) < 0 \tag{9}$$

then $\frac{\partial^2 V}{\partial a \partial w} < 0$

Proof. First the envelope theorem gives us that:

$$\frac{\partial V}{\partial w} = -(t_F + \bar{t}(a))(1-a)$$

and so

$$\frac{\partial^2 V}{\partial w \partial a} = t_F - (1-a)t'_F(a) + \bar{t}(a) - \bar{t}'(a)(1-a).$$

The condition (9) then directly implies the result. $\square$

If the fixed time cost of caring for older children is high enough, then high wage families will be deterred from caring for them. This pushes against the fact that the endogenous cost of caring for older children are reduced since time costs are normalized by $(1-a)$ for older children. If these fixed time costs are large enough, older children will be demanded less by high wage families.

To illustrate (9) I continue with the parametric example above where $u^K(t_n n, t_F(1-a)) = \log(t_n n + \alpha t_F(1-a))$ and $t_n = 1$. Recall that

$$V_F(n,a,w) - V_0(n,a,w) = \log(\alpha/w) - \frac{\alpha - wn}{\alpha} - w\bar{t}(a)(1-a) + s_F(a)(1-a).$$

Then taking the cross-partial with respect to age and wage yields

$$-\frac{\partial}{\partial a}(\bar{t}(a)(1-a))$$

and so if the fixed time costs of caring are larger for older children, i.e. $\frac{\partial}{\partial a}(\bar{t}(a)(1-a)) > 0$, this will drive higher wage families to demand less older children since their opportunity cost of time is higher.

Finally, the model is able to recover a result from the literature: higher subsidies imply more demand for fostering.

Proposition 6. $\frac{\partial V}{\partial s_F} > 0$

Proof. $\frac{\partial V}{\partial s_F} = (1-a) > 0$ $\square$

2.3 Comparison to Alternative Models

The model makes a specific assumption about household preferences over children's human capital. The child's *final* human capital state is the only state variable the household cares about. An alternative way to set up this model would be to model preferences over foster child human capital as $u^K(H_S)$ where H_S is the human capital of all foster children in society. This alternative assumption implies that families care about their overall impact on foster children and may imply that demand more foster children with lower initial human capital. Some of the empirical facts on the types of children that are placed with families seem at odds with this assumption (Ryan et al., 2008).

2.4 Endogenous Fertility Choices

Two of the main limitations of the model in its current form are first, that biological children are treated as exogenous as opposed to modeled jointly endogenously with fostering, and, second, that the model currently does not capture some aspects of the quantity-quality model. This section addresses those limitations.

To address endogeneity of choices of fostering and biological children, I examine a simplified version of the model in which households only choose the amount of biological children and foster children. Suppose that households solve

$$\max_{n,F,c} \delta^K \log(n + \alpha F(1-a)) + \log(c) \tag{10}$$

$$\text{s.t. } wT \geq (1-a)\bar{t}_F(a)F + (1-a)p_F(a)F + p_n n + \bar{t}_n n + c \tag{11}$$

This model shares the same key features as the previous model except that now it emphasizes joint endogenous choices over n and F as opposed to t_F while fostering.

The solution to this model, because of the perfect substitutability between biological and foster children inside the log terms, is to have $F^* > 0$ if and only if

$$\frac{1}{\alpha}(\bar{p}_F - s_F(a) + w\bar{t}_F(a)) \leq p_n + w\bar{t}_n \tag{12}$$

Equation (12) shows that similar tradeoffs occur as in the model in Section 2.1. Fostering is more likely if the subsidy is higher. If foster children are more time consuming than biological children $\bar{t}_F > \bar{t}_n$ then fostering is less likely in higher wage households. Equation (12) also shows that higher wage households prefer lower age foster children if $\bar{t}'_F(a) > 0$.

One of the drawbacks of the models analyzed so far are that they do not contain the prediction that fertility (or fostering) decreases in wage. The model simplifies to compare $F = 1$ to $F = 0$ and shows that higher wage households gain less utility from $F = 1$, but this is not because of the classic quality-quantity tradeoffs; it is because children are assumed to require only costly time investments that scale with the wage.

I now present a version of the model that follows Doepke et al. (2022) and allows for two different types of costs. Suppose now that households make costly investments e_F and e_n into foster children and biological children which is transformed into a child's human capital according to e^γ where $\gamma \in (0, 1)$. Households now solve

$$\max_{n,F,e_n,e_F,c} \delta^K \log(n e_n^\gamma + \alpha F(1-a)e_F^\gamma) + \log(c) \tag{13}$$

$$\text{s.t. } wT \geq (1-a)\bar{t}_F(a)F + (1-a)p_F(a)e_F F + p_n e_n n + \bar{t}_n n + c \tag{14}$$

where investments into quality are now part of the cost $p_F(a)$ and p_n.

The optimal investment into quality of foster children in this model is given by

$$e_F^* = \frac{\gamma}{1-\gamma}\frac{w\bar{t}_F(a)}{p_F(a)} \tag{15}$$

This version of the model recovers the wage effect of quantity-quality models: higher wage families opt for higher "quality" children and less quantity of children. However, it is more difficult to generate predictions for other model characteristics in this setup, and some results may actually differ from the model in Section 2.1. In particular, because in this version of the model the cost of investing in children is not related to a household's wage, and time costs are fixed, this model can generate different predictions than the main model in this paper.[16]

2.5 Alternative Characteristics that Explain Fostering: One vs. Two-Parent Households and Unearned Income Effects

One household characteristic that has not been explored as a primary driver of fostering behavior is the number of parents in the household. The model can accommodate this possibility by allowing for the total budget constraint of the household to be increased when adding a two-parent household. Since utility from children's human capital is a normal good in this model, two-parent households should demand more utility flows form children's human capital than one-parent household. In the model's current form, it is unclear whether two parent households will increase their child human capital flow through biological children, foster children, or both. Empirically, using one of the samples described in Section 3.2 (the "Young Mothers" sample) and controlling for demographics, young mothers in a married couple have 0.424 more biological and foster children than single mothers (s.e. = 0.0062), and 0.424 more biological children than single mothers (s.e. = 0.0062). This correlation suggests most of the effect of one vs. two parent households manifests in determining biological child demand instead of foster child demand.

2.6 Alternative Explanations for Lower Placement of Older Foster Children: Adoption

Adoption is an important outcome of foster care with over 10% of foster children in the sample used in this paper being adopted by their foster parents. Adoption may determine household's preferences over foster child age. If families prefer to be able to adopt their foster children, there are two important considerations with respect to adoption that may make older children less attractive. First, they are more likely to have their parental rights terminated than younger children (Radel and Madden, 2021). Second, their consent may be required to be adopted (Considering Adoption, 2022a). If families get a utility boost from adopting a foster child these factors may make older children less attractive. However, there are practical factors that make adopting older children easier and may drive a higher rate of parental rights termination. Higher parental rights termination may be due to the fact that parental rights termination is endogenous and a function of the latent demand for younger and older children. More younger children may have parental rights terminated because they have a higher chance at the preferred "outside option" of adoption. Another practical factor that pushes against ease of adoption of younger children is that at any given time, a much higher percentage of younger children are placed in foster families than older children (see Figure 1). As Considering Adoption

[16]Doepke et al. (2022) allow for time costs of investing in a child's quality along with costs independent of time. The added lever of choosing fostering and foster quality (along with the number of biological children and the quality of biological children) further complicates the analysis. One unresolved puzzle in this paper is how to better reconcile differences between the model and empirical patterns presented in this paper and other classic quantity-quality models.

(2022b) says: “For example, if [you] are interested only in adopting a newborn, you will likely find that it is hard to adopt a foster child that meets your preferences. Although it’s sometimes possible to adopt a baby or an infant from foster care, the average foster child is about 8 years old. This means that hopeful parents whose goal is to raise a child from infancy could be in for a long wait.” It seems unlikely that preferences over adoption are a primary driver of lower rates of placement for older children.

3 Data

The paper now moves to two empirical exercises related to the model in Section 2.1. First, I test the model’s predictions using regression analysis. Second, I quantify the importance of the different model mechanisms by parameterizing a simplified version of the model and running counterfactuals.

This section introduces the data used in the empirical analysis. The empirical analysis utilizes two main datasets described in the following subsections.

3.1 AFCARS

This paper uses the Adoption and Foster Care Analysis and Reporting System (AFCARS) to analyze placement patterns for foster children and to measure subsidy rates. AFCARS is a national bi-annual survey of the universe of children that are under the supervision of foster care agencies in the USA 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 placements for children entering in California in the years 2005-2015. There are three reasons to focus on California. The first is the availability of foster care subsidy data for the state (see Table A3) and confidence in the quality of the AFCARS data for California. The second is that subsidies do not change much over this time period. The third is that California is confirmed to have foster care subsidy rates that primarily vary by age. This was confirmed by my discussion with Santa Clara County foster care officials. There are two reasons to focus on foster care placements between 2005 and 2015. First, the ACS only has geographic identifiers at a level more granular than the state level starting in 2005.[17]. Second, the year 2015 is one of the latest years for which reliable Adoption and Foster Care Analysis and Reporting System (AFCARS) data is currently available .[18] The AFCARS sample used in this paper has 355,263 total child-entries.

AFCARS provides observables of children in addition to the child and county identifier. These include demographics (e.g. sex, race, age) and reasons for entry (e.g. neglect, disability). This set of observable characteristics 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 more details of how I clean the data in the Appendix Section A.2.

Some summary statistics about the children in foster care and the largest identified counties in California

[17] See https://usa.ipums.org/usa/acs.shtml

[18] The NCANDS organization that hosts the AFCARS data usually recommends using data from at least a few years back because corrections are made over a few year time time.

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.[19] The other options available in this sub-sample are group home, institution, supervised independent living and runaway.

3.2 ACS

This paper uses the American Community Survey 1% sample from 2005-2015 (Ruggles et al., 2019) to measure household fostering and household characteristics.

The ACS identifies foster children in households and this paper focuses on the unit of analysis to be household, consistent with the model in Section 2. To the best of my knowledge this paper is one of the first to analyze foster children in the ACS. 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 key independent variables studied in the ACS data are the number of biological children in a household and the household wage. I measure the wage of a working adult in a household by dividing the annual earnings income by the number of weeks worked and the usual hours worked per week. This provides a measure of the exogenous hourly wage for a household member. I divide each adults total income from wages by their usual hours worked per week and the number of weeks worked to get each adults wage. When a range of weeks is reported in the ACS I take the midpoint. Wages are not observed for non-workers in the ACS. As discussed in Bollinger and Hirsch (2013), missing wages for non-workers present an important challenge and can lead to biased estimates in wage regressions. For the main results in the text, I predict the wage of households in which any adult (head of household, spouse or partner) has no work reported using an OLS method following methods similar to other work that deals with missing wages (Heckman and LaFontaine, 2006; Bredemeier and Juessen, 2013). In addition to this prediction procedure, I further assess the robustness of the results of how wage is measured for non-workers in two ways. The first way follows a suggestion of Bollinger and Hirsch (2013) which is also implemented by Heckman and LaFontaine (2006). I restrict the sample to households where there is at least one adult with a non-missing wage and analyze the wage results for that subset of households and take the household wage to be the non-missing wage. Table A9 contains these results. Finally, I also look at robustness of the results to how we handle non-worker wages by examining results imputing wages of non-working adults to 0 before taking household averages. These results can be found in Tables A5-A8. The results are qualitatively robust to how missing wages are

[19] 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.

handled.

The main wage rate I focus on in this paper is the average wage of the head of household, their spouse (if one exists) and their unmarried partner (if one exists). While the average wage of the household is an important aggregate measure of the earning potential of a household,[20] different wages may have different implications for a family's demand for foster children. In particular, one important wrinkle in the literature has been that wage rates for women and men in couples may have different implications for fertility choices (Hotz et al. (1997); Schultz (1997); Doepke et al. (2022)). For this reason the empirical analysis also explores how the wage rates of women in a household differentially predict demand for foster children.[21] The wage rates of women in a household are measured as the average wage of any female heads of households, spouses and unmarried partners. Non-working females pose a potential problem here (as discussed in the previous paragraph). I deal with non-working females by predicting their wages using an OLS regression while also assessing robustness to alternative ways of dealing with non-working females. The wage rates of men are measured analogously as the average wage of any male heads of households, spouses, and unmarried partners.[22]

To ensure accurate measurement of biological children in a household I measure the number of biological children in a household as the number of biological children recorded in the ACS that are under 18 years old and focus the analysis on two subsamples. The first subsample consists of households that are not group quarters (institutions) that have a female head of household, female spouse or female unmarried partner present that is between the ages of 21 and 35. The second is a subset of the first, which further refines the sample to households having at least 1 child in the household where the oldest child in the household is at most 18 years of age. The restriction to households with mothers between the ages of 21 and 35 is to ensure that, in the sample, the number of biological children in the household (under age 18) can be measured accurately. Females that are more than 35 years old may have children that are more than 18 years old and have left the household if the adult female had a child around the age of 17. This logic and procedure follows Angrist and Evans (1998). For simplicity throughout the rest of the paper I call the first subsample the "Young Mothers" sample and the second subsample the "Twins" sample. There are 226,775 households in the "Young Mothers" sample and 131,544 households in the "Twins" sample.

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

[20] Note that in the Beckerian framework and a certain version of the theory model above, with two parents, the parent with the higher exogenous wage may specialize in the labor market and the parent with the lower exogenous wage may specialize in household production e.g. raising children. In this case, the minimum wage in the household may be the more informative wage rate. Section 4.3.2 reports briefly on an analysis that uses the minimum wage instead of the average.

[21] As with the above we impute wages with an OLS method when wages of females are missing. We also look at the robustness of the results to leaving out women without any wage information (e.g. focusing the analysis only on working women). See Table A9 for results.

[22] Note that less than 0.5% of households in the ACS that I pull from have more than 1 female head of household, and less than 0.75% of households in the ACS that I pull from have more than 1 male head of households, so in practice these averages are mainly averages of a single number. All samples analyzed have females and in households without any males as heads/partners/spouses I take their wage rate to be 0.

county, essentially treating unidentified counties as a single aggregate county in California.

Table A1 in the Appendix provides sample means for the Young Mothers and Twins subsamples broken out by families with and without foster children. 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.

4 Reduced Form Tests of the Predictions of the Model

4.1 Age of Foster Child and Placement with Foster Family

This section analyzes the relationship between a foster child's age and their placement in a foster family. Proposition 1 shows that older children may be placed in families less if their time costs are too high or their initial human capital stocks are too low. I estimate linear probability models of the form

$$\text{Placement with Family at entry}_{it} = \sum_{k=1}^{20} \beta_k \mathbf{1}\{\text{Age}_{it} \text{ at entry} = k\} + X_{it}\gamma + \epsilon_{it} \tag{16}$$

across all children i entering foster care in year t in California between 2005-2015 where $\beta_0 = 0$ is normalized to 0. Placement with family is an indicator that takes the value 1 if the child is placed in a kin foster family, non-kin foster family or pre-adoptive home. Because children show up in the data for multiple years in foster care, to avoid issues with overcounting children that remain in foster care for a long time, I focus only on entering children so that every observation is a unique child-entry pair.[23] The β_k coefficients then tell us how the age of a child predicts their placement. In some specifications I include other entry reason controls, demographic controls, county and fiscal year fixed effects in X_{it}. Proposition 1 predicts that β_k should be decreasing in k. For this method to recover appropriate estimates of β_k parameters, it must be that the age that a child enters is orthogonal to the error term ϵ_{it} in the equation conditional on the set of controls X_{it}. I compare β_k estimates with and without a set of demographic and entry reason controls.

Figure 1 provides estimates of β_k along with asymptotic 95% confidence intervals. Each β_k represents the percentage point probability difference in placement with a family, holding other observables fixed. Two model specifications are included, one that includes no controls (univariate) and one that includes a set of entry controls including county and year fixed effects, 17 indicators for circumstances of a child's entry (for example: total previous removals, child had a behavioral problem, child had a drug abuse problem, etc.), race and sex.

The estimates from the univariate model show a strong negative estimated relationships between a child's age at entry and their probability of placement in foster care. There is a monotonically decreasing trend in the coefficient estimates as k gets larger except for at $k = 20$. 20 year old entries into foster care represent less than 0.1% of all child entries observed. All coefficient estimates are statistically significant at the 1%

[23] Considering the placement of a single foster children over time may conflate the impact of age on placement outcomes with the discovery of an econometrically unobservable feature of children that makes them less likely to be placed in families. If there is a point in time in which foster children are realized to be incompatible with foster families, and the child remains in foster care, there will be a mechanical relationship between age and placement outside of a family. Focusing on entries eliminates this mechanical force in estimating how age affects placement.

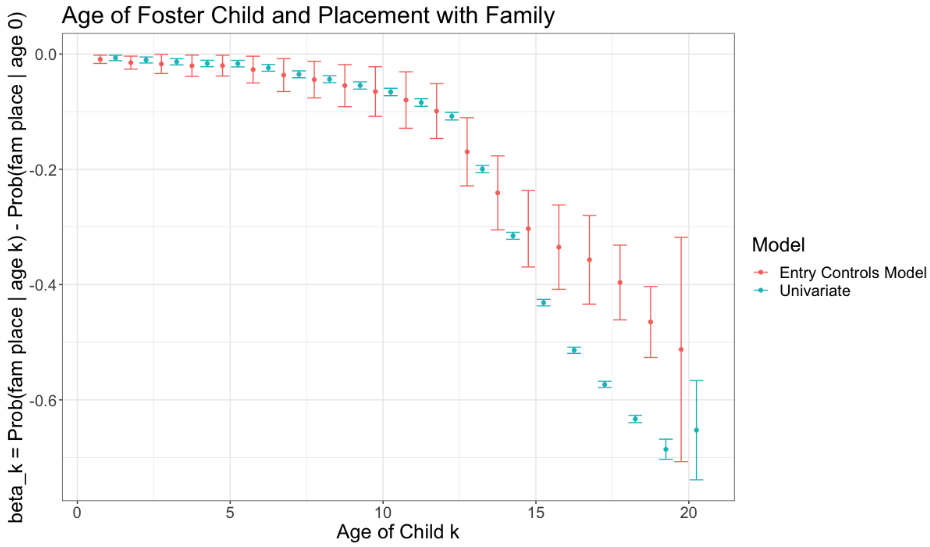

Figure 1: Age of a Foster Child and their Probability of Placement with a Family

Notes: This figure displays estimates of coefficients on indicators for ages 1, 2, ..., 20 in two OLS regressions using an outcome variable of an indicator for placement with a non-kin family, kin family or pre-adoptive home. The sample for both of these regressions is all foster child entries into foster care between 2005-2015 in California, resulting in 355,263 total child-entries. The "Univariate" regression includes only age variables while the "Entry Controls Model" includes the age variable along with controls for demographics, entry reasons, county fixed effects, and fiscal year fixed effects. The demographics and entry reason controls include race, sex, total removals from birth family into foster care, disability status, entry due to physical abuse, entry due to sexual abuse, entry due to neglect, entry due to alcohol abusing parent, entry due to drug abusing parent, entry due to alcohol abusing child, entry due to drug abusing child, entry due to child disability, entry due to child behavioral problem, entry due to parents dying, entry due to parents in jail, entry due to an inability to cope, entry due to abandonment, entry due to relinquishment and entry due to housing problems. Other controls include county of entry fixed effects and fiscal year fixed effects. The entry controls model that includes county fixed effects uses clustered standard errors for the confidence intervals clustered at the county-level.

level. The univariate model predicts that 13 year old foster children are about 19.9 percentage points less likely to be placed with a family than a newborn foster child. The mean placement rate in this sample is 0.834.

The estimates change when other entry controls are added. For example, this model predicts that 13 year old foster children are about 16.9 percentage points less likely to be placed with a family than a newborn foster child. The differences between the entry control and univariate model estimates are amplified at larger ages. For example, $\hat{\beta}_{15}$ implies a placement difference of 51.4 percentage points for 15 year olds in the univariate model while the model with a richer set of controls implies a difference of 33.5 percentage points. The monotonic trend in the coefficients is still present when adding these controls. The standard errors are quite a bit larger but the coefficient estimates are still statistically significant from 0 at the 5% level.

	Dependent variable:			
	Number of Biological Children			
	(1)	(2)	(3)	(4)
Wage	-0.00093^{***}	-0.0126^{***}	-0.0105^{***}	-0.0119^{***}
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Demographic Controls	-	✓	-	✓
County-Year Effects	✓	✓	✓	✓
Sample	Young Mothers	Young Mothers	Twins	Twins
Sample Mean Dep Var	1.17	1.17	1.98	1.98
Observations	226,775	226,775	131,544	131,544
R^2	0.067	0.247	0.040	0.124

Table 1: 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 on two ACS subsamples described in Section 3.2. The wage variable is the average wage among all heads of households, spouses of the head of the household, and partners of the head of the household. For households in which any of the head of household, spouse or partner has no working history, we impute their wage average wage using a linear regression with a polynomial in average age in the household, indicators for race of the head of household, and average years of education in the household. More details can be found in Appendix A.5 and results that impute wages of non-working adults to be 0 can be found in Table A5. Regressions with demographic controls include controls for race (black, hispanic, white, other) and a second-degree polynomial in age. All regressions indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust clustered at the county-year level and computed using a block bootstrap to account for sampling variation in the predictions of wages for non-workers using 100 bootstrap replications. *p<0.1; **p<0.05; ***p<0.01

4.2 Evidence on Wages and Fertility

The model implies that there is a negative relationship between wage rates and fostering children. Extensions of the main model that allow for endogenous biological children in Section 2.4 also imply that there should be a negative relationship between wage rates and biological children. I now test this prediction in the data. While the relationship between wages and biological child fertility has been examined extensively at more macro levels across countries and within the US (Becker, 1960; Jones and Tertilt, 2006), I provide new estimates in the ACS sample defined for this paper.

Consider the following empirical model of fertility:

$$\text{Num Child}_i = \beta_w \text{Wage}_i + X_i \beta + \epsilon_i \tag{17}$$

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 hypothesis of the theory is that $\beta_w < 0$.

The results are displayed in Table 1. In both the Young Mothers and Twins samples, wage is negatively related to the number of children and is statistically significant at a level much smaller than 1%. As discussed in Section 3.2, missing wages for non-workers can lead to biased estimates here, so I implement alternative specifications of the wages in these results to test robustness in Section A.4.

4.3 Testing the Main Model Predictions

The goal of this section is to test Propositions 2 through 5 using the ACS data. I isolate for each prediction an analogous natural experiment in the data with respect to the independent variable of interest. One reason to do this is to avoid the 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 parametric version of the model is estimated to allow for the main mechanisms to be examined simultaneously in the data.

4.3.1 Testing the Relationship Between Biological Children and Foster Children (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 the human capital of foster children. Importantly, the model makes this prediction when flows from the human capital of children is substitutable between foster children and biological children. To examine this prediction I utilize an instrumental variables strategy that 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 main dependent variable of interest in this analysis is an indicator for whether a household has a foster child $\text{Foster}_i = \mathbf{1}\{\text{household } i \text{ has a foster child}\}$. 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. Note that the twins instrument restricts to households in which the family has at least one child.

It is crucial for this 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 the samples used in this analysis follow Angrist and Evans (1998) and restrict the female head of household, spouse or partner to be between the ages of 21 and 35 and measure the number of biological children as the number of children in the household under the age of 18. See Section 3.2 for more discussion.

The empirical strategy can be summarized in the following equations

$$\begin{aligned} \text{Foster}_i &= \beta_1 \text{Num Child}_i + X_{it}\beta_2 + \epsilon_{it} \qquad (18) \\ \text{Num Child}_i &= \alpha_1 \text{Twins}_i + X_{it}\alpha_2 + \nu_{it} \end{aligned}$$

where I am interested in the parameter β_1 in (18) and Twins_i is an indicator for a birth with twins. 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.

	Dependent variable:
	Twins Indicator
Age	0.001
	(0.001)
Age^2	-0.00001
	(0.00001)
Black family	-0.001
	(0.001)
Hispanic family	-0.003^{***}
	(0.001)
Other family	-0.003^{***}
	(0.001)
Years of education	0.001^{***}
	(0.0001)
County-year Effects	✓
Mean dep var	0.0101
Observations	131,544
R^2	0.004

Table 2: Correlation Between Twins and Demographics

Notes: This table shows the results from a regression of the twins indicator variable on a set of demographic variables for households in the Twin Sample in the ACS described in Section 3.2. Regressions include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust clustered at the county-year level. *p<0.1; **p<0.05; ***p<0.01

The main identifying assumption for the twins 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. I test whether this is true in the sample used in this paper, too. Table 2 shows the results from an OLS regression of the twins binary instrument on age, age squared, indicators for the race of the family, and the median years of education of the heads of household and their spouse. Table 2 shows that hispanic and families of other race types (ex: Asian) predict a lower probability of having twins compare to a white family. It also shows that families with higher average education have a higher probability of having twins. These patterns could reflect the use of IVF or similar methods that are more likely to lead to twins (Kulkarni et al., 2013) and could signify that the instrument is correlated with unobservables which may also correlate with providing foster care. I address the omitted variable bias due to IVF by controlling for wage and education below, and compare results with and without these controls.

The results from implementing the IV estimator (18) are in Table 3. The first three columns (1)-(3) show OLS regressions including a varying amount of demographic and socioeconomic controls. As more controls are added, these OLS regressions show a stronger negative relationship between the number of biological children and whether a household selects into being a foster family. The stepwise inclusion of different types of controls generate substantial variation in the coefficient.

	Dependent Variable: Foster Child in Household Indicator					
	OLS	OLS	OLS	Twins IV	Twins IV	Twins IV
	(1)	(2)	(3)	(4)	(5)	(6)
Number Biological Children	-0.0131	-0.314^{*}	-0.524^{***}	-2.904^{**}	-2.884^{**}	-2.547^{**}
	(0.142)	(0.161)	(0.179)	(1.331)	(1.299)	(1.225)
Education and wage controls			✓			✓
Demographic controls		✓	✓		✓	✓
County-Year Fixed Effects	✓	✓	✓	✓	✓	✓
First Stage F-stat	-	-	-	739	826	928
Observations	131,544	131,544	131,544	131,544	131,544	131,544
Mean($y \times 1000$)	2.281	2.281	2.281	2.281	2.281	2.281
SD(Num Child)	0.99	0.99	0.99	0.99	0.99	0.99

Table 3: Fertility Predictions for Proposition 2

Notes: This table shows OLS and IV regression results for the outcome variable of whether a foster child is in the household. These models are estimated on the Twins sample described in more detail in Section 3.2. All means and parameter estimates in the table are multiplied by 1000 for readability. Demographic controls include a second-order polynomial in the age of the household and race of the head of the household. All regressions include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust-clustered at the county-year level. *p<0.1; **p<0.05; ***p<0.01

Columns (4)-(6) of Table 3 implement the main IV estimator with the same varying amount of demographic and socioeconomic controls. The F-statistics in the first-stage are very large - each larger than 500 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 in columns (4)-(6) of Table 3 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 in column (5) are also almost 10 times the magnitude of estimates from the corresponding OLS results in column (2). One rationalization of this large difference may be selection bias in the OLS results. In particular, families that have more children might also have more idiosyncratic tastes for caring for children overall - their utility functions may weight u^K more highly than own consumption - and so this could weaken any negative relationship between biological and foster children.

What are threats to the validity of these results? One 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). The twins instrument thus likely captures some amount of selection into fertility treatments. In particular, Table 2 showed that the correlations in the data are consistent with this story.

To reduce this worry and try to net out the selection into twins, column (6) includes wage and education controls. These represent some of the most important potential omitted variables if we are worried about IVF, since higher wage and educated families are more likely to be able to afford and utilize IVF. The IV coefficient estimate in column (6) decreases in absolute value but remains statistically indistinguishable from the other IV coefficients in columns (4) and (5). Thus, when controlling for major factors that should explain a household's selection into IVF, the relationship between biological children and fostering remains statistically significant, economically large and consistent with the model prediction.

4.3.2 Testing Whether High Wage Families Foster Less (Proposition 3)

Proposition 3 states that families with higher wages w are less likely to be foster parents. The empirical strategy to identify the relationship between wages and fostering consists of using a selection on observables assumption in the following model

$$\text{Foster}_i = \beta_1 \text{Wage}_i + X_{it}\beta_2 + \epsilon_{it}. \tag{19}$$

The theory predicts that $\beta_1 < 0$. X is a vector of the same controls used in (18). I focus on the average wage of the household as the main wage measure in (19).[24] The main threat to identification in this set-up is that households that are more altruistic in general, and thus more likely to dedicate their time to fostering a child, may take on a lower wage to satisfy their altruistic desires. To mitigate this factor, detailed ACS occupation codes of the maximum household earner in the household are added as controls.[25] This empirical strategy utilizes the leftover wage variation within occupations to identify the wage effect. In other words, altruism and child tastes are allowed to vary at the occupation level for households, but cannot vary systematically with wages within an occupation. One assumption that makes this strategy valid is that the within-occupation wage variation in the ACS data is due to general luck or skills in the occupation orthogonal to child and altruistic tastes. I run OLS models on both the Young Mothers and Twins samples.

The results from estimation are given in Table 4. Columns (1)-(3) estimate (19) in the Young Mothers sample and columns (4)-(6) estimate (19) in the Twins sample. Column (1) and column (4) regress the fostering indicator on the household wage variable controlling only for the county-year that the household is located in in the data. Household wages are negatively correlated with being foster parents in the data. Columns (2) and (5) add demographic controls to these specifications. This negative correlation remains precise and increases slightly in magnitude when including demographic controls. Finally columns (3) and (6) include the occupation indicators as controls. There is a large dip in the magnitude of the coefficients from column (2) to column (3) and from column (5) to column (6). The resulting relationships remain negative and statistically significant at the 1% level. To interpret these wage coefficients, a one standard deviation increase in the wage has an impact on being a foster parent of approximately 14% of the mean. The partial correlation is consistent with the predictions of the model. As discussed in Section 3.2, missing wages for non-workers can lead to biased estimates here, so I implement alternative specifications of the wages in these results to test robustness in Section A.4.

[24] The analogous regression to that in Column (3) of Table 4 using the wage of the minimum wage head of household / spouse / partner leads to a coefficient of -0.03102 (s.e. = 0.0092) when multiplied by 1000. Note that this results uses the procedure that imputes non-working adults in a household to have wage 0. Female wages are examined in the next subsection.

[25] 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 artists, human resource managers, mechanical engineers, social workers.

	Dependent Variable: Foster Child in Household Indicator					
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Household Wage	-0.022^{***}	-0.037^{***}	-0.020^{***}	-0.049^{***}	-0.061^{***}	-0.043^{***}
	(0.006)	(0.006)	(0.007)	(0.010)	(0.010)	(0.011)
Occupation Fixed Effects			✓			✓
Demographics		✓	✓		✓	✓
County-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations		226,775			131,544	
R^2	0.0034	0.0040	0.0067	0.0043	0.0048	0.0087
Sample		Young Mothers			Twins	
Mean(y)		1.834			2.281	
SD(HH Wage)		12.56			12.21	

Table 4: Wage Predictions for Proposition 3

Notes: This table gives OLS regressions of the foster child indicator variable on the household average wage with varying sets of controls across two ACS subsamples described in Section 3.2. The household average wage is taken as the average wage across the head of household, spouses and partners in the household. For households in which any of the head of household, spouse or partner has no working history, we impute their wage average wage using a linear regression with a polynomial in average age in the household, indicators for race of the head of household, and average years of education in the household. More details can be found in Appendix A.5 and results that impute wages of non-working adults to be 0 can be found in Table A6. All means and parameter estimates in the table are multiplied by 1000 for readability. Columns (2)-(3) and (5)-(6) include demographic controls for a second-order polynomial in the age of the household and race of the head of the household. Occupation fixed effects in columns (3) and (6) give an indicator for one of the 530 listed occupation of the head of household or spouse in the ACS (the one with the largest wage is picked). All regressions include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust clustered at the county-year level and computed using a block bootstrap to account for sampling variation in the predictions of wages for non-workers using 100 bootstrap replications. *p<0.1; **p<0.05; ***p<0.01

4.3.3 Extending the Wage Tests to Allow for Mother's Wage Rates to Differ

Economic fertility models predict that the wage rates of mothers can have different effects on fertility than fathers' wage rates. I test whether this generalizes to the case of demand for foster children. Table 5 shows results from regressing the foster indicator on the average wage of females and the average wage of males that are either heads of households, spouses or unmarried partners. I focus on the Young Mothers sample and restrict the sample further to married couples.[26] Columns (2) and (4) further add occupation indicators. Female wages shift demand for foster children more than male wages. Columns (1) and (3) show an approximate 2/3 increase in the coefficient. Moreover, column (2) remains statistically significant for female wages while column (4) suggests that male wages are not important for affecting foster care demand when controlling for occupation. As discussed in Section 3.2, missing wages for non-workers can lead to biased estimates here, so I implement alternative specifications of the wages in these results to test robustness in Section A.4.

[26]For simplicity I assume that the male wage is 2*average household wage - average female wage.

	Dependent Variable: Foster Child in Household Indicator			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Female Wage	−0.030***	−0.018**		
	(0.006)	(0.008)		
Male Wage			−0.018**	−0.010
			(0.008)	(0.008)
Occupation Fixed Effects		✓		✓
Demographics	✓	✓	✓	✓
County-Year Fixed Effects	✓	✓	✓	✓
Observations	132,156	132,156	132,156	132,156
R^2	0.005	0.01	0.005	0.009

Table 5: Mother's Wage Rate and Foster Care

Notes: This table provides OLS regression coefficients of results for regressing the foster child indicator on different measures of household wages for married couples in the Young Mothers sample described in Section 3.2. Columns (1) and (2) regress the foster child indicator variable on female wage where female wage is measured as the wage of average wage of all female heads of households, spouses or partners in a household along with demographic controls and county-year fixed effects. Females that are not working have wages imputed following A.5 and Table A7 shows results that impute wages of non-working females to be 0. Column (2) further includes occupation fixed effects for the females. If more than one occupation is present, it takes the most common occupation code. Columns (3) and (4) regress the foster child indicator variable on female wage where female wage is measured as the wage of average wage of all male heads of households, spouses or partners in a household along with demographic controls and county-year fixed effects. Column (4) further includes occupation fixed effects for the max earner in the household. Heads of household, spouses, and partners with a wage of 0 are grouped into the same occupation code. Standard errors are robust clustered at the county-year level and computed using a block bootstrap to account for sampling variation in the predictions of wages for non-workers using 100 bootstrap replications. *p<0.1; **p<0.05; ***p<0.01

4.3.4 Testing How Biological Children and Wages Affect Foster Child Age (Propositions 4 and 5)

Propositions 4 and 5 make predictions about the relationship between a household's demand for older foster children and their wage and number of biological children. These predictions can provide insights into which households might be most willing to care for older foster children. The predictions are that (1) households with more children should be more likely to care for older children when fostering and (2) if older children are time consuming enough, households with higher wages should be less likely to care for older children when fostering.

I estimate models of the form

$$\text{Median Age of Foster Child}_i = \beta_1 \text{Household Characteristic}_i + X_{it}\beta_2 + \epsilon_{it} \tag{20}$$

in the ACS. I utilize the identification strategies developed for the previous predictions of Propositions 2 and 3 in addition to looking at the partial correlations in (20).

The results are contained in Table 6. 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

	Dependent Variable: Median Age of Foster Child			
	OLS	Twins IV	OLS	OLS w/ Occupation FEs
	(1)	(2)	(3)	(4)
Number Biological Children	0.834^{**}	4.821^{***}		
	(0.356)	(1.231)		
Household Wage			-0.096^{***}	-0.070
			(0.032)	(0.078)
Demographics	✓	✓	✓	✓
County-Year Effects	✓	✓	✓	✓
Subsample	Twins	Twins	Young Mothers	Young Mothers
Observations	300	300	416	416
Mean(y)	9.2	9.2	8.3	8.3
SD(X)	1.07	1.07	9.4	9.4

Table 6: Age Gradient Predictions

Notes: This table provides OLS and IV regression results where the outcome is the median age of the foster child that a household cares for, and these models are estimated across the Twins and Young Mothers sample, where these samples are further restricted to households that have a foster child in them. The outcome variable is the median age of all the foster children that a household cares for. Column (1) is an OLS regression of the median age of foster children on the number of biological children in the house under age 18. Column (2) instruments the number of biological children with the twins dummy. Column (3) is an OLS regression of the median age of foster children on the average wage of the household. See Section A.5 for how wages of nonworking adults are handled and Table A8 for results that impute wages of nonworking adults to be 0. Column (4) adds occupation fixed effects for the max earner in the household to the specification in Column (3). 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 at the county-year level. In columns (3) and (4) the standard errors are computed using a block bootstrap to account for sampling variation in the predictions of wages for non-workers using 100 bootstrap replications. *p<0.1; **p<0.05; ***p<0.01

of children in a household is an important determinant of the age of foster children in their household: a one standard deviation change in the number of children (approximately one child) makes the predicted median age of child the household cares for increase by about 5 years. Column (3) looks at the correlation between foster child age and wages without occupation fixed effects in the Young Mothers sample, and column (4) adds occupation fixed effects. Adding occupation fixed effects makes the standard error much larger and leads to statistical insignificance in the relationship, but both columns (3) and (4) suggest a negative relationship between foster child age and wage as predicted by the theory.[27] As discussed in Section 3.2, missing wages for non-workers can lead to biased estimates here, so I implement alternative specifications of the wages in these results to test robustness in Section A.4.

[27] 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 Appendix in Table A10. The results of those exercises are aligned with the results here.

5 Evidence from the Literature on the Effect of the Subsidy on Fostering

Proposition 6 states that an increase in subsidy should induce more fostering behavior from households. I now discuss existing evidence in the literature on this prediction.

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 expand their supply in response to an increase in the subsidies paid to them.[28] 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 from national foster care data in the US.

Another set of related papers are Argys and Duncan (2013) and Buckles (2013) who find that the number of adoptions increases with adoption subsidies, suggesting that households respond positively to financial incentives to adopt foster children from foster care.[29][30]

6 Quantifying the Effects in a Stylized Model

The tests in Section 4 are designed to identify parameters that correspond to comparative statics in the model. In this section I parameterize a simple version of the model, estimate behavioral parameters, and then run simple counterfactuals to compare the novel mechanisms proposed in this paper. The empirical model makes an explicit effort to compare the traditional policy lever of subsidies for foster children with the new mechanisms explored in this paper.

6.1 Structural Model Setup

Consider a simplified version of the model in Section 2.1 in which all biological children and foster children have fixed human capital values and the binary decision of household i to foster a child $F_i = 1$ is based on the following equation

$$U_i(F_i = 1|n_i, t_{F,i}, p_{F,i}) - U_i(F_i = 0|n_i, t_{F,i}, p_{F,i}) \geq 0 \tag{21}$$

where U_i is household i's utility, n_i is their stock of biological children, $t_{F,i}$ is the time required to care for a foster child for household i and $p_{F,i}$ is the fixed cost of caring for a foster child for household i. Assume that $p_{F,i} = -s_{F,c(i),\tau(i)}$ the average monthly subsidy rate in household i's county of residence $c(i)$ in the year of the ACS survey $\tau(i)$,[31] and $t_{F,i} = \frac{4(40)}{2}$ the number of hours a household must spend caring for a foster

[28] More precisely, Doyle (2007a) finds an elasticity of approximately 0.5.

[29] Argys and Duncan (2013) also find that adoption subsidies make adoption more attractive than long-term foster care.

[30] While the decision to adopt from foster care is not directly modeled in this paper, one possible way to incorporate the decision of whether to adopt a child from foster care in the model here is to attach a higher weight of utility to the human capital of the child you are fostering and commit to caring for that children for a longer amount of time, since an adopted child will be a larger part of that family's life.

[31] AFCARS is known to have some issues with measuring subsidy rates. Based on institutional knowledge of the maximum rates for children of around \$1,500 I only consider monthly subsidies in this calculation that max out at \$1,500. Also I lump all counties that are not identified in AFCARS into a single county. The subsidies range between \$318 to \$938 in my sample.

child per month where there are 4 weeks in a month, 40 hours of care per week, divided by households with two adults. Note that this model abstracts from child age for simplicity.

I assume that utility takes the structure

$$U_i(F_i|n_i, t_{F,i}, p_{F,i}) = u_i(F|n_i) + \psi s_{F,c(i),\tau(i)} - \eta t_F w_i + \epsilon_i \cdot 1\{F_i = 1\} \tag{22}$$

where utility is quasi-linear in consumption and households either care for children or work and ϵ_i is a random taste shock for caring for foster children. I assume that the form of utility from biological and foster children's human capital is given by

$$u_i(F|n_i) = F \cdot (\beta_0 + X_{D,i}\beta_D) + \log(n_i + 1) + \log(F + 1) + \alpha \log(1 + n_i + F) \tag{23}$$

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 county and year fixed effects) and α measures the substitutability between biological children and foster children. Foster children and biological children are substitutes if and only if $\alpha > 0$.

Equations (21), (22) and (23) imply the net value from fostering is

$$u_i^* = \beta_0 + X_{D,i}\beta + \alpha \log\left(\frac{2 + n_i}{1 + n_i}\right) + \psi s_{F,c(i),\tau(i)} - \eta t_F w_i + \epsilon_i \tag{24}$$

where ϵ_i is some unobserved taste shock. The three main structural parameters to be estimated are α, ψ and η.

6.2 Identifying the Parameters of the Structural Model

As discussed in the reduced form methods above, it is likely that the observed values of n_i and w_i are correlated with ϵ_i. I identify α and η by utilizing instruments for both n_i and for w_i. The instrument for the $\log\left(\frac{2+n_i}{1+n_i}\right)$ term is the twins instrument while the instrument for the w_i term is the within-occupation wage residual.

The model adds a new variable to the analysis: the subsidy s. It is likely that the subsidy s is also correlated with unobservables of the quality of foster children in a county. For identifying ψ, I include county and year fixed effects in $X_{D,i}$ so that ψ is identified off of subsidy changes that net out average county-level subsidies, and a common time trend between all counties. I also compare the estimate of ψ to those in the literature to further gain confidence in the resulting estimate.

I estimate the model parameters by fitting a linear probability model of an indicator for selecting into foster care on the terms in (24) with instruments for both endogenous terms. Household demographics are treated as exogenous across households. The first stage is in Table A11 in the Appendix. The first stage suggests that the twins instrument captures most of the variation in fertility term while the wage instrument captures most of the variation in the wage and consumption term.

	Parameter Estimate	S.E.
α	0.02686**	0.01302
ψ	2.92e-07	1.87e-07
η	5.21e-07***	1.43e-07

Table 7: Structural Parameter Estimates

Notes: Structural parameter estimates derived from estimating (24) on the twins sample in the ACS using an indicator for a household has twins as in instrument and the within-occupation wage residual as an instrument. These estimates include county and year fixed effects. Standard errors are clustered at the joint county-year level.

	Baseline	Counterfactual 1: Reduce n_i by 1 (50%)	Counterfactual 2: Reduce τ_f by 50%	Counterfactual 3: Increase s_F by \$300 (50%)
Percent of households that select into fostering children	0.00228	0.00671	0.00263	0.00316
Number households considered	131,544	131,544	131,544	131,544

Table 8: Counterfactuals

Notes: Counterfactuals run from estimating foster probabilities from (24). Baseline corresponds to what is observed in the ACS data.

6.3 Structural Model Parameter Estimates and Counterfactuals

The parameter estimates for α, ψ and η are shown in Table 7. The positive estimate of α suggests that foster children and biological children are substitutes, as predicted by the human capital mechanism of the model. The positive estimate of ψ suggests households choose to foster more when subsidies are higher. The positive estimate of η suggests that households with higher wages prefer to foster children less, consistent with the interpretation of time costs being higher for these households in the model. The parameters on wage and fertility are statistically significant. The parameter on subsidy is marginally statistically significant ($p = 0.11$).

I run two counterfactuals to compare the economic forces presented in the model. The first counterfactual sends the price of biological children to a high enough price that each household reduces their equilibrium biological child count n_i by 1 child. This is an approximate 50% decrease in biological children in the twins sample where this counterfactual is introduced (the mean number of biological children is 1.98). This counterfactual assesses the degree to which foster children and biological children are substitutes and how valuing the human capital of children affects foster care decisions.[32]

The second counterfactual reduces the time required to care for foster children t_F by 50%, reducing the wage-based cost of fostering 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 third counterfactual increases subsidies by \$300, about 50% of the subsidy value on average. This counterfactual provides a comparison of the other counterfactuals to a traditional policy lever in which households desire to be foster families due to the increased income.

[32]Note that, importantly, this is a partial equilibrium counterfactual since changing the price of biological children would also change the supply side of children that would eventually enter the foster care system.

The results of the counterfactuals are contained in Table 8. Table 8 shows the percentage of households that foster children in each counterfactual. Reducing each households number of biological children by 1 predicts that 0.671% of all households will be foster families, an almost three times increase in the base rate of fostering. Cutting the time cost of caring for a foster child by half predicts that 0.263% of all households will be foster families due to the increase in non-child-based consumption that occurs. Finally increasing the subsidy by 50% or $300 leads to 0.316% of households being foster families.

The price response counterfactual implies an elasticity of approximately 0.77.[33] Doyle (2007a) finds a similar elasticity of 0.5 for kin care in Illinois. Using the 0.5 elasticity number leads to a 25% increase in supply of families so that now 0.285% of households foster. The qualitative comparison to the traditional policy lever remains similar when using this estimate from the literature.

The results suggest that the child-specific human capital mechanism is stronger than both the own-consumption mechanism coming from the time of caring for children and the income mechanism coming from the subsidy. These results provide evidence that the novel mechanism proposed by the model in this paper is an important determinant of fostering behavior. These results could help with informing policy levers to recruit foster families by providing a new lens through which to interpret how families choose to be foster families.

7 Conclusion

This paper proposes that households make decisions to select into foster care based on a model where they consider utility from the human capital of the children they care for and their own consumption. The model makes clear predictions that are then tested in the data using various identification strategies. There is evidence of the models main predictions in the data. A simple structural model suggests that the fertility and human capital mechanisms in the model are important for determining which families choose to foster children.

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 can provide a unifying and novel way to understand this important social behavior. The new mechanisms analyzed in this paper provide new ways to think about recruiting foster families to deal with the foster family shortage.

Conflict of interest: The author declares no competing interests.

[33] Calculation: approximate $(0.003157445 - 0.002280606)/0.002280606 = 38.44\%$ increase in supply from a 50% increase in price gives an elasticity of 0.77.

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	Young Mothers Sample		Twins Sample	
	Foster Child Present in Household	Foster Child Not Present in Household	Foster Child Present in Household	Foster Child Not Present in Household
Average Wage	$13.40	$18.40	$12.30	$16.80
Average Female Wage	$9.70	$15.30	$8.50	$12.60
Average Number Biological Children under 18	1.47	1.16	2.03	1.98
Average Education	6.16	7.56	5.90	6.84
Average Age	32.7	30.7	32.8	31.7
Percent Married	0.623	0.583	0.66	0.716
Percent Hispanic	0.543	0.369	0.567	0.478
Percent Black	0.0793	0.0497	0.09	0.0544
Number Observations	416	226,359	300	131,244

Table A1: ACS Subsample Means

Notes: This table gives means for demographic variables for households in the two main subsamples conditional on having a foster child present in the household and conditional on not having a foster child present in the household. Wage is the average wage of any head of household, spouse or partner. Female wage is the average wage of any female head of household, spouse, or partner. Education is measured using the IPUMS standard: 0 = no school, 1 = up to grade 4, 2 = up to grade 8, 3 = grade 9, 4 = grade 10, 5 = grade 11, 6 = grade 12, 7= 1 year of college, 8 = 2 years of college, 9 = 3 years of college, 10 = 4 years of college, 11 = 5 or more years of college. The education variable is measured as the median among all heads of households, spouses and partners in the household at the household level. Age is the average age of all heads of households, spouses and partners. Race is measured as the race of the head of household.

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A Online Appendix

A.1 Additional Data Summary Tables

A.2 Additional Data Details

A.2.1 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.[34]

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.

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

A.3 Theory Appendix

A.3.1 Model Extension: Kin and Non-Kin Foster Families

The model presented does not include a distinction between kin and non-kin foster families. Kin families are those that are related to the foster child (i.e. uncle, aunt, grandparent) while non-kin families are not related to the foster child. There is a large literature studying the difference in these families (Berrick et al., 1994). How does this distinction change how we should think about the theoretical model?

One way that kin families may differ from non-kin families is in how they weight the human capital of the foster child in their utility. There are two reasons to believe that this weight should be stronger. First, it is possible that kin families may attach a stronger weight to a family member than a non-family member, similar to how parents likely attach a stronger weight to their own children than to other children. Alternatively, they may attach a stronger weight to related children because they are more likely to interact with that child's biological parents over time, and those biological parents may attach a strong weight to the utility of their own child.

I model this possibility by letting there be two utility functions U_k and U_{nk} where

$$\begin{aligned} U_k &= u(H_n, \theta H_F) + c \\ U_{nk} &= u(H_n, H_F) + c \end{aligned}$$

where $\theta > 1$.

Let V_k and V_{nk} represent the corresponding values of fostering for kin and non-kin families corresponding to (7). Given these assumptions, I now study the how biological children and wages affect a family's propensity to foster if they are a kin or non-kin foster family.

- $\frac{\partial V_k}{\partial n} < \frac{\partial V_{nk}}{\partial n} < 0$. Kin foster families are more responsive to their own biological children in making fostering decisions than non-kin foster families.
- $\frac{\partial V_k}{\partial w} = \frac{\partial V_{nk}}{\partial w} < 0$. Kin and non-kin foster families are equally responsive to wage changes in fostering decisions.

A.3.2 Model Extension: Age of Biological Children

Suppose that households also consider the age of their biological children when making decisions in the model in Section 2.1. I assume in the model that the final human capital of a biological child remains the same regardless of the age at which fostering is considered. As with foster children in the model, older biological children have lower overall costs because households have to care for them less. So we can write the value of fostering as

$$V_F(a, n, w) := \max_{t_F \geq 0} u^K(h_n n, t_F(1-a)) + w(T-(1-a)t_n n-(1-a)(t_F+\bar{t}(a)))-(1-a)p_n n-(1-a)(\bar{p}_F - s_F(a))F \tag{25}$$

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.

and the value of not fostering is

$$V_0(a,n,w) := u^K(h_n n, 0) + w(T-(1-a)t_n n) - (1-a)p_n n \tag{26}$$

These modifications will cancel out when we compute the net value of fostering $V_F - V_0$ and so biological child age does not change the main conclusions.

A.4 Empirical Results Appendix

A.5 Wage Imputation Procedure

This section outlines the wage imputation procedure used for adults in a household with a missing wage. Let $NW_i \in \{0,1\}$ be an indicator for whether household i has any adult that is not working. For all households with $NW_i = 0$ I estimate the following model

$$\begin{aligned}\text{Average HH Wage}_i = \beta_0 + \beta_1 \cdot \text{Average HH Age}_i + \beta_2 \cdot \text{Average HH Age}_i^2 + \beta_3 \cdot \text{Head of Household Black}_i \\ +\beta_4 \cdot \text{Head of Household Hispanic}_i + \beta_5 \cdot \text{Head of Household Other Race}_i + \beta_6 \cdot \text{Average HH Education} + \epsilon_i, \\ NW_i = 0\end{aligned}$$

I estimate the model on both the Young Mothers and Twins sample. The R-squared of this model on each respective sample is 0.276 and 0.328.

To impute female wages I estimate a similar model. Let $NW_i^F \in \{0,1\}$ be an indicator for whether a household has any female adult (head of household, spouse, or partner) that is not working. Then I estimate

$$\begin{aligned}\text{Female Wage}_i = \beta_0 + \beta_1 \cdot \text{Female Age}_i + \beta_2 \cdot \text{Female Years of Education} + \epsilon_i, \\ NW_i^F = 0\end{aligned}$$

	Dependent variable:			
	Number of Biological Children			
	(1)	(2)	(3)	(4)
Wage	-0.0127^{***}	-0.0129^{***}	-0.0105^{***}	-0.0106^{***}
	(0.0004)	(0.0003)	(0.0002)	(0.0003)
Demographic Controls	-	✓	-	✓
County-Year Effects	✓	✓	✓	✓
Sample	Young Mothers	Young Mothers	Twins	Twins
Sample Mean Dep Var	1.17	1.17	1.98	1.98
Observations	226,775	226,775	131,544	131,544
R^2	0.034	0.253	0.029	0.127

Table A5: Fertility and Wages, Impute Missing Wages with 0

Notes: All regressions are estimated with OLS with a dependent variable of the number of children at most 18 years old in the household on two ACS subsamples described in Section 3.2. The wage variable is the average wage among all heads of households, spouses of the head of the household, and partners of the head of the household. I impute adults not working to have wages of 0. Regressions with demographic controls include controls for race (black, hispanic, white, other) and a second-degree polynomial in age. All regressions indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust clustered at the county-year level. *p<0.1; **p<0.05; ***p<0.01

I estimate this on the subset of the Young Mothers sample that is married. The R-squared of this model on this sample is 0.199.

When I compute standard errors of the OLS regression estimates in the Tables that use this imputation procedure above I take bootstrap replication samples that re-estimate the imputation model and the OLS regression estimates to account for the statistical uncertainty introduced in the imputation step. I use 100 bootstrap replications and take their standard deviation to compute these standard errors.

	Dependent Variable: Foster Child in Household Indicator					
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Household Wage	-0.030^{***}	-0.037^{***}	-0.022^{***}	-0.043^{***}	-0.048^{***}	-0.032^{***}
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Occupation Fixed Effects			✓			✓
Demographics		✓	✓		✓	✓
County-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations		226,775			131,544	
R^2	0.0034	0.0040	0.0067	0.0043	0.0048	0.0087
Sample		Young Mothers			Twins	
Mean(y)		1.834			2.281	
SD(HH Wage)		14.38			13.95	

Table A6: Wage Predictions for Proposition 3, Impute Missing Wages with 0

Notes: This table gives OLS regressions of the foster child indicator variable on the household average wage with varying sets of controls across two ACS subsamples described in Section 3.2. The household average wage is taken as the average wage across the head of household, spouses and partners in the household. I impute adults not working to have wages of 0. All means and parameter estimates in the table are multiplied by 1000 for readability. Columns (2)-(3) and (5)-(6) include demographic controls for a second-order polynomial in the age of the household and race of the head of the household. Occupation fixed effects in columns (3) and (6) give an indicator for one of the 530 listed occupation of the head of household or spouse in the ACS (the one with the largest wage is picked). All regressions include indicators for every county-year. Unidentified counties are collectively identified as a single unidentified county. Standard errors are robust clustered at the county-year level. *p<0.1; **p<0.05; ***p<0.01

	Dependent Variable: Foster Child in Household Indicator			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Female Wage	-0.025^{***}	-0.018^{***}		
	(0.005)	(0.007)		
Male Wage			-0.015^{**}	-0.006
			(0.006)	(0.006)
Occupation Fixed Effects		✓		✓
Demographics	✓	✓	✓	✓
County-Year Fixed Effects	✓	✓	✓	✓
Observations	132,156	132,156	132,156	132,156
R^2	0.005	0.01	0.005	0.009

Table A7: Mother's Wage Rate and Foster Care, No Wage Imputation

Notes: This table provides OLS regression coefficients of results for regressing the foster child indicator on different measures of household wages for married couples in the Young Mothers sample described in Section 3.2. Columns (1) and (2) regress the foster child indicator variable on female wage where female wage is measured as the wage of average wage of all female heads of households, spouses or partners in a household along with demographic controls and county-year fixed effects. I impute adults not working to have wages of 0. Column (2) further includes occupation fixed effects for the females. If more than one occupation is present, it takes the most common occupation code. Columns (3) and (4) regress the foster child indicator variable on female wage where female wage is measured as the wage of average wage of all male heads of households, spouses or partners in a household along with demographic controls and county-year fixed effects. Column (4) further includes occupation fixed effects for the max earner in the household. Heads of household, spouses, and partners with a wage of 0 are grouped into the same occupation code. Standard errors are robust clustered at the county-year level. *p<0.1; **p<0.05; ***p<0.01

	Dependent Variable: Median Age of Foster Child			
	OLS	Twins IV	OLS	OLS w/ Occupation FEs
	(1)	(2)	(3)	(4)
Number Biological Children	0.834**	4.821***		
	(0.356)	(1.231)		
Household Wage			−0.069***	−0.102**
			(0.026)	(0.037)
Demographics	✓	✓	✓	✓
County-Year Effects	✓	✓	✓	✓
Subsample	Twins	Twins	Young Mothers	Young Mothers
Observations	300	300	416	416
Mean(y)	9.2	9.2	8.3	8.3
SD(X)	1.07	1.07	11.0	11.0

Table A8: Age Gradient Predictions, Impute Missing Wages with 0

Notes: This table provides OLS and IV regression results where the outcome is the median age of the foster child that a household cares for, and these models are estimated across the Twins and Young Mothers sample, where these samples are further restricted to households that have a foster child in them. The outcome variable is the median age of all the foster children that a household cares for. Column (1) is an OLS regression of the median age of foster children on the number of biological children in the house under age 18. Column (2) instruments the number of biological children with the twins dummy. Column (3) is an OLS regression of the median age of foster children on the average wage of the household (see Section 3.2 for more details on how wage is calculated); I impute adults not working to have wages of 0. Column (4) adds occupation fixed effects for the max earner in the household to the specification in Column (3). 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 at the county-year level. *p<0.1; **p<0.05; ***p<0.01

	Corresponding Table:Column				
	Table 4:(3)	Table 4:(6)	Table 5:(2)	Table 5:(4)	Table 6:(4)
Coefficient (s.e.) on Wage of maximum earner in household	-0.0096 (0.0048)	-0.017 (0.007)	-0.018 (0.008)	-0.0045 (0.007)	-0.077 (0.031)
Numbers of observations	209,238	120,390	126,274	126,274	375

Table A9: Main Wage Results Dropping Non-Workers

Notes: This Table shows the coefficient on the wage regressions for a select set of results in the Tables in the main text. In each regression the specification is the same except that we use the maximum wage of the head of household, spouse, or partner, and further limit the sample to include only households where that maximum wage is above 0 (e.g. the maximum earner has a valid income and thus a valid wage measure).

	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 A10: 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)
Twins	−0.052***	−79.22***
(t stat)	(-51.622)	(-4.019)
Within Occupation Wage	3.624e-04***	−66.73***
(t stat)	(19.505)	(-174.38)
Observations	131,544	131,544
F Stat	2664	30408

Table A11: Structural Model First Stage

Notes: This provides the first stage regressions for the structural model as linear models. Child U corresponds to the log term in (24) and Cons U corresponds to the price minus wage term in (24). The sample used is the twins subsample. See other tables and the main text for descriptions of this sample.