Fostering Children

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Abstract

The motivations of families that decide to care for foster children are examined by linking family and child characteristics through an extension of the neoclassical model of fertility. The model assumes that families get altruistic utility from foster children that is substitutable with altruistic utility from biological children. Importantly, this creates incentives for families to invest in the human capital foster children. However, families also care about their own consumption. The model makes predictions with respect to a family's willingness to foster based on the number of biological children of the family, wage of the family, and age of the child. The predictions are tested in the data and find strong support. Alternative theories are assessed. These results suggest that foster families value foster children similarly to biological children, creating incentives for foster families to invest in children, but that families also take their own consumption and time use when providing these services. The model provides a lens through which to interpret the welfare effects of family placement on foster children.

1 Introduction

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

The foster care market is organized so that children are removed from their birth homes and then placed either in institutional settings or with other families. The driving motivation behind placing children with families is that keeping children in family environments can simulate higher

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quality childcare through "normal childhood experiences" (Welfare and Institutions Code 16000). However, the quality of these family environments is endogenous to the selection of families that choose to foster and adopt these children.

While previous work has focused on the effects of different margins of foster care on child welfare outcomes, very little is understood about how or why families choose to be foster parents. This paper studies how families choose to be foster parents through the lens of a simple price theoretic household model. The basic question it addresses is: why do families choose to become foster families? An understanding of this motivation is crucially tied to the welfare outcomes of children, as economists have long emphasized the importance of parental incentives and investment in children on child welfare. It also sheds light on how policymakers can tackle the foster care "shortage problem" in which not all children can be placed in the care of families.[1]

The major contribution of this study is how it formalizes and tests key mechanisms driving families to choose to be foster parents using economic theory and various identification strategies. The mechanisms highlighted are formalized by a simple price theoretic model of household fertility. The model makes a clear link between a family's incentives and a foster child's human capital by comparing it to the economics fertility literature on altruism (Becker, 1991). It also allows for an exploration of other ways in which foster child characteristics may impact foster family supply.

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

To better understand the importance of placement with families in my sample, basic correlations of family placement with later child outcomes such as education, homelessness and incarceration are examined. The correlations are consistent with those found in the literature (Sacerdote, 2002, 2007; Nelson et al., 2007) and suggest large positive effects for children placed with families. The rest of the paper is devoted to understanding the mechanisms underlying these effects.

The AFCARS data is used to describe what child characteristics are the most important for determining whether a child is placed in foster care or not. The motivation for the exercise is to try to utilize differences in foster family supply across child characteristics to learn more about important factors driving foster family supply. The exercise reveals that foster child age is by some

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

simple metrics the most important observable characteristic for determining foster family supply. The strong negative relationship between family supply and age is consistent across counties, although counties are heterogeneous in how they are able to place children by age, particularly older children.

Using these facts, a model is developed in which households choose whether to foster children based on their own fertility decisions for biological children and a trade-off of between investing in children with their own consumption. The model treats families as getting altruistic utility from the human capital of both biological children and foster children, and, most importantly, treats these as substitutable sources of altruistic utility. The model also specifies the relationship between human capital, foster children, and their age. Older children enter the foster care system with lower human capital because human capital investments are treated as a flow investment and the government has an imperfect monitoring system. This impacts both how families value them from an altruistic standpoint and a time cost standpoint.

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

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

The predictions of the model are tested utilizing the AFCARS and ACS data. The empirical strategies utilize a mixture of methods and research designs that vary in their credibility to identify causal effects. In particular, the strategies combine instrumental variable methods from the fertility literature (Black et al., 2005), rich household observables in the ACS micro data, and panel data methods at the county-year level. The strength in the empirical approach is in building a body of credible and robust empirical evidence across many dimensions of the data.

The empirical results tell a story that is strongly consistent with the model and provide evidence for the major theoretical mechanisms highlighted by the theory. Alternative theories do not perform as well in explaining the empirical results. However, some sociological theories do appear to have some explanatory power and could be further examined and distinguished from this paper's theory in future work.

The model and data paint a picture of foster families who care for foster children like biological children, but are sensitive to child and family-specific costs. Importantly, the altruistic links between a child's human capital and a family's decision to foster provide evidence that foster families behave in a way that is consistent with their utility depending on foster children's human capital. This provides evidence for a key mechanism through which the positive effects of family placement over institutional placement work (Nelson et al., 2007). However, foster families also account for children's different time costs and sunk human capital when making these decisions. Thus, while altruism aligns foster family and social incentives, altruism combined with the consumption-related incentives are likely to create differential placement and welfare effects for children of different initial human capital and time requirements. This is consistent with the important age patterns in family placement and negative outcomes for older foster children found in the data (Doyle, 2007b).

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

There are many papers that estimate welfare effects of foster care or different types of foster care placement on foster children. While my paper does not credibly estimate causal effects on welfare, it does provide evidence for mechanisms through which families influence the welfare of foster children.

Doyle (2007b) shows that there are large but somewhat imprecise negative effects for children entering foster care. He shows that these negative effects are mainly focused on older children. This paper further explores why this negative age gradient exists with respect to these outcomes from the side of foster families.

Nelson et al. (2007) examine the impacts of family placement versus institutionalization by studying a natural randomization of children into families and institutions. They find large significant gains from children being placed with families. My paper provides evidence on economic mechanisms for how these gains are realized through the alignment of family incentives with a child's human capital.

Font (2014) examine welfare outcomes for children placed with kin families and non-kin families, and finds that children placed with non-kin families generally have better outcomes, although the results are mixed. This paper nuances the understanding between kin and non-kin placements by providing evidence that non-kin families are motivated by altruism. These altruistic effects can help rationalize why kin and non-kin outcomes are consistently different, as one of the major worries for placing children with non-kin families is a lack of incentive to invest in them appropriately (Ehrle and Geen, 2002).

The organization of the rest of this paper is as follows. Section 2 describes the institutional details of foster care and data used for the empirical tests. In Section 3 the relationship between family placement and child welfare outcomes is examined. Section 4 examines the importance of foster child age in determining family placement. Section 5 develops the model and lays out its predictions. Section 6 is devoted to testing the implications and predictions of the model, and summarizing the body of evidence presented. Section 7 concludes.

2 Institutional Details and Data

2.1 Institutional Details

Because foster care is not commonly known to economists, a few important details are provided. These details are specific to California, but the general principles apply to most states in the US to the best of my knowledge.

A child enters foster care when a county-level investigator is made aware of a maltreatment allegation and petitions the court for the child to be removed. In some cases, the investigator may remove the child without court intervention if the situation is deemed an emergency. California investigators use a tool called "structured decision making" and decide whether to remove the child based on three factors: "risk, harm and danger".

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

When in foster care, children have a few placement options. The first is to be placed with a foster family. This could be a kin family (a family that is related to the foster child) or a non-kin family. By law, kin families get priority and the county must first search for a kin family placement when looking for children. Other placement options are group homes, institutions or independent living arrangements.

An important institutional detail is that counties are required, by law, to place children in suitable families (families that pass the basic screening of the RFA) over placing them in group homes when available. California legislation going back to 2005 states:

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

Given these institutional details, it is assumed that all placement differences between children can be attributed to child and household characteristics. To aid in this interpretation, the main analysis is conducted away from the set of children that are the most subject to county-specific placement policies: children that enter with behavioral problems, some of which are juvenile delinquents and have special placement requirements in detention facilities.

In general, in talking with foster care professionals and studying foster care institutional details, the matching process appears to be quite myopic, and social workers essentially "look for beds". Thus, the placement of a child is almost entirely on the burden of an available family. Families are also able to reject placements with children before or after placement occurs. Most placement decisions occur through county social workers, but there are also private institutions that certify families and attempt to place children as well.

Another important feature of matching mentioned in the introduction, and evidenced in the quote above, is that counties attempt to place children within their county due to the priority of reunifying children with their birth family. See Table A1 for the placement tendencies of the counties I analyze in my data. Almost all counties place more than half of their children within the same county, and many place more than 75% in their county. This allows for an interpretation of each county as a separate "market" which is useful for the empirical strategies. Since some children are placed outside of their county, this introduces measurement error in the county level household variables and so only works to make the effects more difficult to detect.

2.2 Main Data Sources

The empirical analysis utilizes two main data sets.

2.2.1 AFCARS

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

AFCARS provides 1 child observation per year, identifies children over multiple years, and identifies counties with over 1000 active cases. I focus on the years 2005-2015[2] and the balanced-sub panel of 14 counties in California that are identified in every one of these years. All observations of children outside of the year range of 2005-2015 and that did not enter into one of these 14 counties in California are dropped.

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

In cleaning the 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.[3]

Finally, to make the empirical analysis as close to the model as possible, the tests focus on children that are eligible for placement with foster families that are not their own relatives (non-kin placements). Thus all children placed in a kin placement are removed from the empirical analysis. As motivated by the institutional details, this is an appropriate way to measure non-kin supply because kin placements are always prioritized by California law. Approximately 1/2 of all family placements in the data are non-kin.[4] The reason for this is that the added incentives and benefits of caring for a related child may include important social networking or family-specific effects that are not captured in the model. However, many of the results examined are robust to including kin placements and having the sample be all foster children, which shows the external

[2]While AFCARS has data back to 2000, the ACS only has county-level identifiers starting in 2005.

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

[4]About 20% of non-kin foster care placements are pre-adoptive homes where the family intends to adopt the child. This differs significantly by age, with about 25% being pre-adoptive for children less than 10 and 10% being pre-adoptive for children over 10 years old.

validity of the major theoretical mechanisms.

Some basic descriptive facts about the children in foster care and the counties studied 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. A child is defined as disabled if the child has any of the following conditions: mental retardation, visual or hearing disability, physical disability, emotionally disturbed or other diagnosed medical condition.

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 at time t, define the variable *Family Placement* as an indicator for whether child i is placed with a pre-adoptive home or a non-kin foster family in the year observed t.[5] The other options available in this sub-sample are group home, institution, supervised independent living and runaway.

The AFCARS data are utilized in the empirical facts and tests to look at placement of foster children by child characteristics. These analyses are conducted so that the unit of observation of is a foster child, but the variation used to identify the parameters comes from county-year level changes in supply variables.

2.2.2 ACS

The dataset that is used to gain information about family supply is the American Community Survey 1% sample from 2005-2015 (Ruggles et al., 2019). From 2005 onward this data identifies the county that individuals live in and so can be combined with the AFCARS data to look at interactions between child characteristics and family characteristics. Importantly, it identifies all the counties that AFCARS identifies over this time period so that there are no county selection problems on the side of the ACS.

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

The model focuses on household fertility and wage and so the major variables studied in the ACS data are number of biological children and household wage. Most of the cleaning of the micro data relates to wage. It is well known that the earnings reports in ACS surveys are inconsistent with

[5]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.

minimum wage laws. To deal with this cleaning, all individual wages that are positive but below the California minimum wage are set to be the minimum wage. Individual wages are also winsorized at the 99% level of wages. Individuals not working receive a wage of 0.

Wage will vary across the head of household and their spouse or partner when present and so a household measure of wage must be constructed. A few different measures of wage are examined including the average wage among the head of household and their spouse/partner, the maximum wage among this group, the minimum wage, and the wage of the female head of household, partner or spouse if one exists. The results are robust to using any of these measures of wage and the average wage of the household is the focus in the micro data.

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

When aggregating the ACS data up to the county-year level and combining it with the AFCARS data, county-year level means of household variables are used. To improve the precision of the county-level data, only *eligible households* are used in this aggregation: households that are not institutions (certain types of group quarters in the ACS) with a head of household that is at least 21.[6] Households with a zero measured wage in the data are dropped when taking county aggregates since the county level measure of wages is log wages.

A rich set of demographic county level controls from the data can be extracted to improve the empirical strategies, including racial breakdowns of eligible individuals by county-year, the marriage rate, and the median household age. These are all used as controls in the main specifications as these demographics could reflect cultural or other economic factors not captured by the model but also predictive of child outcomes. Summary statistics of the ACS sample are presented in Tables A4 and A5.

Throughout the paper, i is used to refer to a household in the ACS micro data and a child in the AFCARS data, t to refer to a year with $t \in \{2005, \dots, 2015\}$ and j to refer to a county where $j \in \{\text{Alameda}, \dots, \text{Tulare}\}$.

3 Child Welfare and Family Placement

The goal of this section is to replicate some of the relationships found in previous research between family placement and welfare outcomes of foster children in my data. Previous research has found that better families cause better outcomes for children (Sacerdote, 2002, 2007), and that family environments cause better outcomes as opposed to institutional environments (Nelson et al., 2007).

[6] While the technical requirement is 18, many counties state that they don't consider adults under 21.

The main dataset used for this exercise is the the National Youth in Transition Database (NYTD). The NYTD surveys foster children when they are ages 17,19 and 21. The NYTD and AFCARS share common child identifiers which allow for linkage. The NYTD survey measures important outcomes for foster youth including employment, homelessness and incarceration. Outcomes of age 21 children are examined to maximize the likelihood that they are at-risk for these outcomes. Around 600 total children without missing outcomes are linked between the NYTD and AFCARS data in California. Note that the sample is non-representative for the general population. First, the age distribution is very different from all foster care entries, skewing towards older children. Second, these are children that were in foster care at age 17, and so they are a highly selected sample from the foster care population. However since previous studies focus on placement effects of younger children (Nelson et al., 2007), this is a useful comparison.

To test for the link between family placement and welfare outcomes, I regress an indicator for the relevant welfare outcome on the percent of time a child is in a family placement in the AFCARS data. The outcome measures used are: does the child have employment (full or part time), does the child have at least a high school degree or GED, was the child homeless in the past two years, and was the child incarcerated in the past two years.[7] Figure 1 provides coefficient estimates and confidence intervals on the family placement variable for these regressions. The means of the outcome variables are 60% for employment, 85% for education higher than high school, 25% for homelessness, and 11% for incarceration.

Figure 1 shows that family placement is associated with extremely large positive improvements in outcomes, ranging in magnitude from 15 to 20 percentage point changes, and 20 to over 100 percent of the mean variable. The estimates mirror the strong relationships found in the literature.

The major threat to identification is that children that are placed with families are highly selected and would probably do better regardless of family placement. While there is not an apparent direct strategy for dealing with this in the data, these regressions also include controls for the child's sex and race, two factors that help to control for effects of general demographics of foster children on their outcomes.

The goal of this section was to present evidence consistent with previous evidence that family placement is strongly related to child welfare improvements. The large magnitudes from the regressions combined with the evidence from the previous literature provide significant evidence of positive impacts of family placements.

[7] For incarceration children that ever entered for behavioral reasons are left out to avoid including juvenile delinquents.

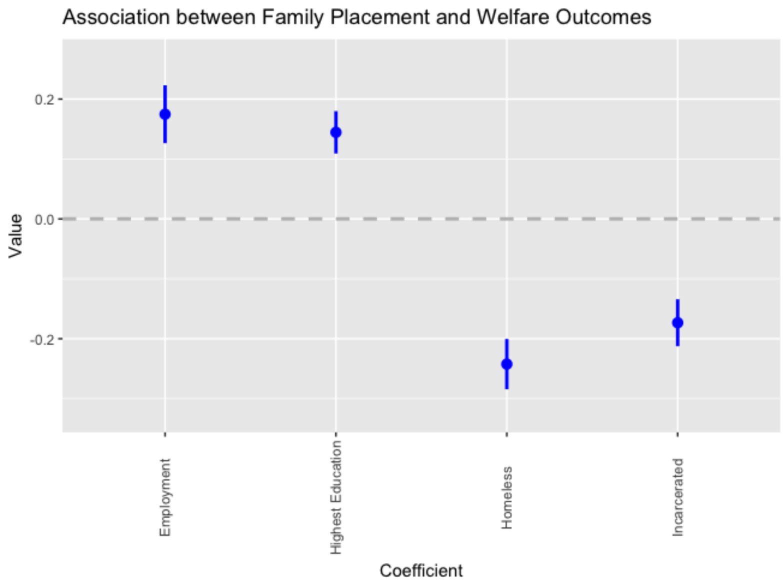

Figure 1: Welfare Outcomes and Family Placement
Notes: Regression coefficients with 95% asymptotic confidence intervals are plotted for a regression of (welfare measure) on the percentage of observations that a child is with a family. The number of observations in each regression is respectively: 666 (employment), 684 (highest education), 672 (homeless), 557 (incarceration). As noted in the footnote, I drop potential juvenile delinquents from the incarceration calculation.

4 Which children are placed with families?

4.1 Age Gradients

What child characteristics determine whether a child is placed with a family? The answer to this question is a useful input to understanding why families provide foster care.

In the AFCARS data, models of the following form are estimated:

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

where X_{it} includes the sex, race and medical disability status of child i in year t. Recall that j is a county. This estimation is performed including all children in the data eligible for placement and also restricting to children only when they enter. The entry-only estimation gives us a sense of how much of placement by age is driven by selection into age by unobservables (children that are older are unobservably less likely to be placed for other reasonns). The number of variables for these estimation methods is purposefully reduced in a way that is economically intuitive. The implications of age in the full-dimensionality of the data are explored below.

The $\{\hat{\beta}_a\}$ and their asymptotic confidence intervals for both models are plotted in Figure 2. Both the direction and magnitudes of these results is quite striking. All show clear negative pat-

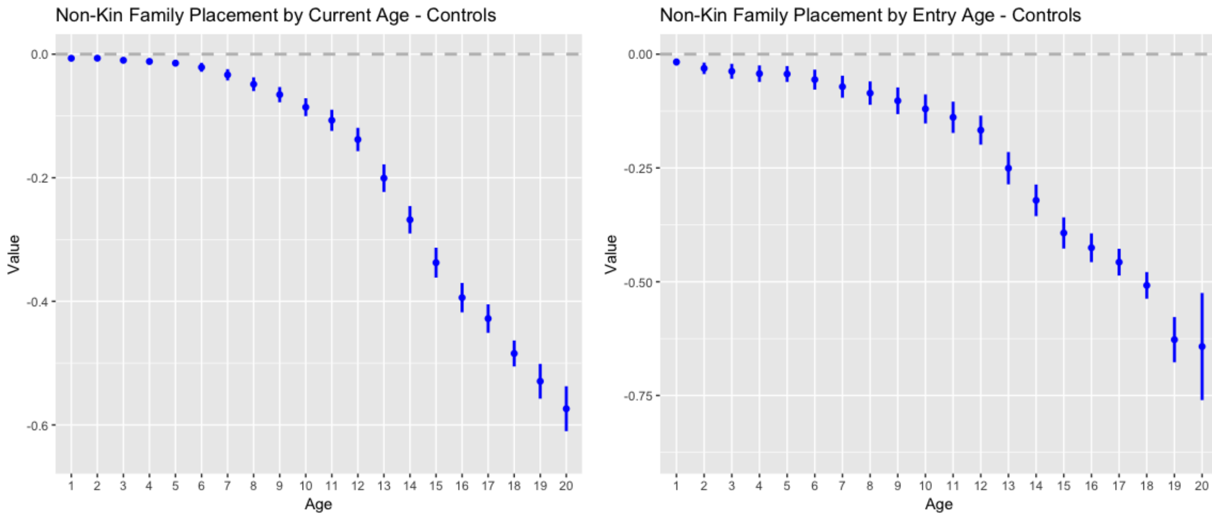

Figure 2: Age Facts

Notes: This plot displays $\hat{\beta}_a$ along with asymptotic 95% confidence intervals for $a \in \{1, \ldots, 20\}$ from (1).

terns with respect to wage and almost perfect monotonicity. The magnitudes suggest that the differences in family placement between newborns and teenagers is around 30 to 60 percentage points. The percentage of children placed with non-kin families is approximately 80-85% and so these relationships are large.

To put these magnitudes in perspective consider the magnitudes of placement differences by other sources considered in the literature. Two other intuitive sources of placement differences are race and sex. Previous research (Baccara et al., 2014) has found evidence for significant preference differences over these characteristics for adoptive families. Both race and sex are included as variables in (1). The coefficients on these variables suggest effects on the order of 2 to 5 percentage points, which is dwarfed by the gradient displayed in Figure 2.

Since the set of child factors is large and the exercise performed here is purely descriptive, it is also informative to use some basic machine learning methods to optimize predictive properties of the model. To do this, linear additive models are estimated using ridge regression and the LASSO. I estimate additive linear models utilizing the ridge and lasso penalties and OLS predicting child placement with a non-kin family with all child observables that are determined before entry in AFCARS. For simplicity age is treated as a numerical variable in these models. The variables are grouped into year, county, demographic, medical and entry factors.

The ridge regression and LASSO routine use 10-fold cross validation to choose the penalty parameter (Hastie et al., 2009). The $|\hat{\beta}_j \times \text{SD}(x_j)|$ from the model are plotted in Figure A5 in the Appendix where x_j is one of the independent variables in the linear model. This object provides a simple and easy to compute metric to measure the explanatory power of a variable j. The figure shows that the ridge, LASSO and OLS regression results are extremely similar with the LASSO and OLS coefficients almost identical, and that age clearly dominates in the explanatory measure, having an explanatory measure of over 3 times the next variable (whether a child is emotionally disturbed).

4.2 Age Gradients Across Counties

The age gradients in Figure 2 are striking. A natural question is whether they persist when looking across counties. This is important because counties are heterogeneous in their populations of social workers, institutions, families, and children. If counties have particularly different patterns for age, this age pattern might reflect an institutional detail or composition differences in counties independent of any fundamental economic relationship between age and foster family supply. If counties have almost identical patterns for age, then this would mean that age is a fundamental shifter but is invariant to the supply heterogeneity across California counties.

The smoothed placement probabilities of children by age across all the counties identified in the AFCARS data are plotted in Figure 3 using a loess smoother with a bandwidth of 0.75. The fitted placement probabilities all slope downward suggesting a common negative relationship between age and placement. Importantly, the variance in placement across counties increases in age - almost all children between ages 0 and 5 are placed with families in every county. Thus, counties have different abilities to care for children of different ages, particularly older children. If at least some of the differences between counties in placement can be interpreted as coming from household decisions to care for children it seems that supply conditions are heterogeneous for older children. This provides a clear benefit for studying age variation to better understand the supply decisions of foster families.

4.3 Summary of Facts and Next Steps

The facts suggest that placement mostly differs by age of the foster child. If family placement welfare effects are relatively invariant to age, this suggests important expected treatment effects of foster care by child age. Moreover, differences in age profiles across counties suggest heterogeneity across counties in family placement for older children. The rest of this paper focuses on the questions: how do these facts about age inform how we think about the households supply decision?

5 Model

The primary goal of the model is to illuminate what factors drive households to foster children and also make older children less cared for. The model will produce predictions and relationships that

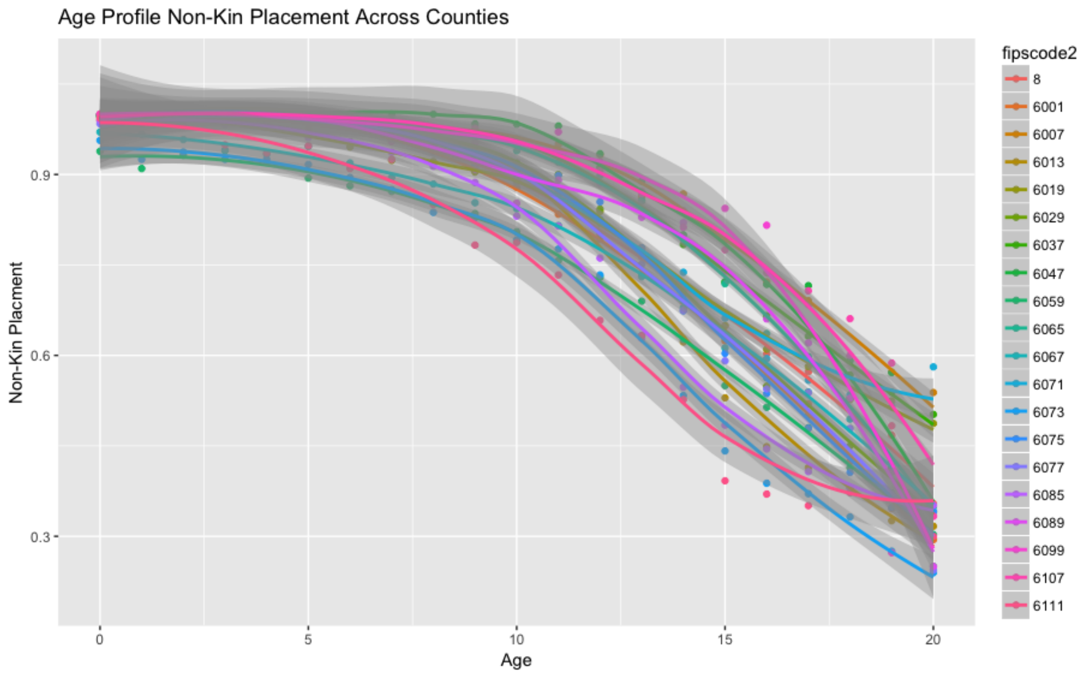

Figure 3: Placement by Age Between Counties
Notes: This plot shows loess smoother age profiles of non-kin placement across the identified California counties in my sample from 2005 to 2015. Fipscode corresponds to the official fipscode of the county. Fipscode 8 corresponds to non identified counties.

can be tested in the data.

5.1 Model Setup

The model highlights a few important economic objects that are feasible to measure in the data. The model derives from the classic models of quality and quantity in the fertility literature (Becker and Lewis, 1973) while adding a foster care margin.

5.1.1 Household Utility and Objects

Suppose that households have joint utility $U(\cdot)$ over two goods: children and own consumption c. Their utility over children is measured by their altruism. In the standard models of fertility (Becker, 1991) households get utility from biological children that they produce. The nuance of adding foster children is that there is an alternate source of children available to households now. Thus, there are essentially three goods that households have preferences over: biological children, foster children, and own consumption. It is assumed that preferences are additively separable in altruism towards children u and own consumption v so that utility takes the form $U = u + v$, common in this literature (Becker, 1992)

Households total value for children is based on the value for own biological children n and foster children F according to

$$u(n, F) \tag{2}$$

where u satisfies the following properties: $u_1, u_2 > 0$ and $u_{11}, u_{22}, u_{12} < 0$. The conditions on the first and second partial derivatives are standard utility assumptions. The assumption that $u_{12} < 0$ is meant to capture the fact that the altruism flow utility households get from biological children and foster children are substitutable - the extra utility a household receives from a child is diminishing in the number of children they have, regardless of whether they are a biological or foster child. The assumption that altruism for children is diminishing in the number of children is a standard assumption in the economics fertility literature (Becker, 1992).

While foster care is tightly linked to different forms of altruism in the child welfare literature this utility formulation anchors foster care altruism through the utility function and conceptualizes it as coming from the same source as altruism towards biological children. This is important when human capital is built into the model later in that $u_{12} < 0$ anchors incentives to invest in foster children similarly to incentives to invest in biological children.

For simplicity the household's decision to foster is assumed to be a binary decision $F \in \{0, 1\}$ and n is treated as exogenously given. In the Appendix the model is extended to allow for n to be chosen endogenously and show that most of the major predictions hold.

Consistent with the classic quantity-quality models children are costly both with a fixed cost and a time cost. Assume that children have some fixed quality and that each child has both a fixed price p and a fixed time-intensive cost t. Let these be p_n and p_F, and t_n and t_F for biological children and foster children respectively. As is standard in these models, assume that households spend equal time investing in all biological children and equal time investing in all foster children.

Each household is assumed to have a total time budget T and a wage w. Any time that the household does not spend on childcare they spend working. Letting the consumption good be the numeraire good, the budget constraint for the household is then

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

Putting these factors together along with the additive separability assumption yields that utility is

$$U = u(n, F) + v(w(T - t_n n - t_F F) - p_n n - p_F F) \tag{4}$$

This utility object (4) captures the main economic intuition and insights of this paper. Households are altruistic towards children and so enjoy caring for them, but children are costly both through a fixed cost and the opportunity cost of labor. This cost for families is scaled by their wage, an intuition captured by the quantity-quality fertility literature and a key point in determining the negative relationship between income and fertility.

5.1.2 Human Capital and Age

Children's entry into foster care and the impact of a foster child's age on human capital is assumed to be driven by human capital, Human capital will affect a household's altruistic utility and the time cost of a child.

Instead of considering a single household now consider a population of households where each household lives in a community (county) C that has a local county government. Suppose that each household has a t_n associated with it which induces a distribution of t_n in any county C. Any child's human capital, h, depends on the time invested by the household, and so the distribution of t_n induces a distribution of child human capital h. Suppose for simplicity that the human capital function is $h(t) = t$.

The community government aims to maximize the total human capital in the community and has the ability to provide t_g (expected) time investment for children at unlimited capacity. Thus, for any child in a household that has $t_n < t_g$, the government intervenes and removes that child from their families and places them in foster care.

Suppose further that childhood consists of the unit interval with a child's age $a \in [0, 1]$. Treat the time investment and human capital function as a flow instead of a stock, as in the dynamic human capital literature (Cunha and Heckman, 2007). Also, assume that the government has an imperfect monitoring technology, so that they discover $t_n < t_g$ potentially only after some time in the child's life has past a. This generates an age distribution of children entering foster care.

Following the literature on human capital and altruism for children, suppose that families get altruistic utility from a child in a way that is proportional to the human capital of their child. Let the human capital be h_n and h_F for biological and foster children respectively. Then utility now takes the form

$$u(h_n n, h_F F). \tag{5}$$

Thus, utility for a child is now weighted by the human capital of that child.

Because human capital and time investments are a flow, a child's overall human capital when removed at age a will be a convex combination of the time investment they received before and the new time investment. This implies that the overall human capital of a child that had flow investment $t_n < t_g$ and that enters foster care at age a and is placed with a family or in an institution that invests t_F is

$$h(a) = at_n + (1 - a)t_F. \tag{6}$$

Consider how this impacts a family's valuation for a child. Since foster children will have a lower human capital for the same time investment, they will contribute less to a family's altruistic utility. In particular consider a family that invests $t'_n > t_g$ in biological children and, conditional on caring for a foster child, invests $t_F \in [t_g, t'_n]$. In this setup, the foster child's human capital who originally comes from a family with investment t_n, conditional on being placed with this new family, is

$$at_n + (1-a)t_F$$

whereas the biological child has human capital

$$t'_n > at_n + (1-a)t_F$$

and so it is clear that a foster child's human capital is less than a biological child's human capital and is decreasing in their age of removal a so that $h_n > h_F$ and $h'_F(a) < 0$ when placed with a family.

Note that this argument does not allow families to choose t_F. Without further assumptions on behavior, it is possible that t_F is so large that $h_F > h_n$. However, is not hard to show that if we endogenize t_F and t'_n that $h_F > h_n$ will always be true because the marginal return to time investment on a biological child is always higher than on a foster child when $a > 0$.

For example, consider the following problem where families choose the (total) human capital of foster children $h_F F = t_F F$ and biological children $h_n n = t_n n$ by choosing these time investments and suppose that a foster child's entering human capital is 0 for simplicity:

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

The first order condition and MRS equation for determining optimal investment simply consists of equating the marginal utilities since the price of time investment is the same:

$$u_1(t_n n, (1-a)t_F F) = (1-a)u_2(t_n n, (1-a)t_F F)$$

Assuming that $u_1 = u_2$, if $t_n n \leq (1-a)t_F F$ then this equation cannot hold since $a > 0$. Thus $h_n n > h_F(a)F$ must be true when $a > 0$.

Continuing to assume that $u_1 = u_2$ and adding the assumption that $u_{11} = u_{22}$ yields that the marginal altruistic utility of the first biological child versus the first foster child when a household has no children is

$$u_1 h_n > u_1 h_F.$$

Thus human capital differences translate into marginal utility differences in biological children and foster children. This occurs in this model with symmetric preferences over biological and foster children; it only relies on the foster care selection rule and a family preference dependence on human capital of the child. These assumptions of symmetry are continued to be made throughout the paper, although they are not strictly necessary for the proofs and predictions and can be relaxed appropriately.[8]

The relationship between age and human capital also allows for an analysis of how t_F depends on a. Suppose that human capital affects the time required to monitor and properly care for a child, and that children with lower human capital require more time. Suppose that this relationship is given by $\tau(h)$ with $\tau'(h) < 0$. Then, if all foster children were adopted and families treated caring for a child as one period, then $t_F(a) = \tau(h(a))(1-a)$ and so $t'_F(a) = \tau'(h(a))h'(a)(1-a) - \tau(h(a))$. If τ' and h' are large enough then $t'_F > 0$. There are two other forces that push towards $t'_F > 0$. One is that not all children will be adopted and many will be reunified with their families eventually and so the total time of care is really not $1-a$.[9] The other force is that households likely can and want to smooth their time investment and consumption, and so this pushes towards younger children having smaller time costs. Thus, while $t'_F > 0$ is not strictly implied by the assumptions of the model, there are natural additional assumptions that imply it, and it is assumed since it will be consistent with the data and the empirical tests.

5.1.3 Putting the Model Together

The previous sections present a model of how families value foster children and how foster child age influences these values. Putting together the different relationships, the impact of age on utility for a family that fosters is

$$u(h_n n, h_F(a)F) + v(w(T - t_n n - t_F(a)F) - p_n n - p_F(a)F) \tag{7}$$

The dependence of p_F on a is allowed as counties can and do set prices that depend on child age: see Table 1. Note that $p'_F(a) \geq 0$. Holding fixed $p_F(a)$, and taking a derivative with respect to a the utility from foster children F is decreasing in age because $h'_F(a) < 0$ and $t'_F(a) > 0$.[10] Thus the model is able to informally replicate the negative age patterns we see in the data if $p'_F(a)$ is not increasing fast enough.[11] It is worth breaking down the intuition for how age affects family supply that comes from (7).

The first mechanism that affects utility through age a is the human capital factor, $h_F(a)$. Fami-

[8] I see this as a strength of the model as it seems empirically more difficult to justify that families "care less" for foster or adopted children.

[9] Approximately 30% of children in non-kin family placements at any time will be reunified with their families. This only varies by a few percentage points across ages.

[10] If we endogenize the t_F selection, this result still holds due to the envelope theorem.

[11] In the frictionless version of the model with $p'_F(a) = 0$, there would be a discontinuous drop at some threshold age - all children over this age would not be placed with families. This is not strikingly inconsistent with Figure 3.

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 1: California Basic Foster Care Rates

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

lies will value older children less because they have sunk human capital investments that are lower due to the selection rule of foster care. Due to this, foster families are unable to make a substantial impact on the child's overall human capital and benefit altruistically in that way. If children placed for adoption or foster care were from a set of families that invest a higher amount of human capital than average, the model predicts that these children would be more highly valued than biological children through these altruism flows.

The second mechanism is that due to lower relative human capital, older children require more time input to take care of $t_F(a)$. Families value children that require less time to take care of because of the opportunity cost of their time, their wage w, which contributes to the rest of their consumption.

Finally we can express the family supply decision in terms of (7). A family is willing to supply their labor for a foster child $F = 1$ if and only if their overall utility from $F = 1$ is larger than when $F = 0$, or when

$$u(h_n n, h_F(a)) + v(w(T - t_n n - t_F(a)) - p_n n - p_F(a)) - u(h_n n, 0) - v(w(T - t_n n) - p_n n) \geq 0. \quad (8)$$

Equation (8) will provide the source of the predictions that give the theory empirical content. These predictions will guide the rest of the paper.

The only additional assumptions that are made before moving onto the formal predictions and theoretical results are the following:

$$
\begin{aligned}
v(x) &= x \\
u_{11} &< u_{12}
\end{aligned} \tag{9}
$$

(9) specifies that households have quasi-linear utility in consumption and that the substitutability term is not larger than the cross-partial. Quasi-linear utility specifications are a hallmark of a long theoretical literature in market design and auction theory and make the theoretical analysis more transparent and tractable. The second assumption in (9) is a standard assumption to ensure that the first-order conditions are sufficient in the case that n is chosen endogenously. It will be satisfied in any instance where utility has the form

$$u(n, F) = m(h_n n) + m(h_F F) + m(h_n n + h_F F)$$

where m is strictly increasing and concave.

Using (9) the supply condition can be simplified to

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

Before moving onto the predictions, it is worth discussing some aspects of the model.

5.2 Model Discussion

The most difficult assumption to swallow related to the household's decision in the model is that n is treated as exogenous here. In any serious theoretical treatment that closely links fertility decisions to the decision to foster, it seems crucial to treat n as endogenous. The trade-off with a model that treats n endogenously is that many extra technical assumptions on utility and prices are required to produce the predictions and mechanisms of interest. These assumptions and their proofs obscure the main economic intuition that underlies the results. I show in the Appendix that most of the predictions go through when treating n as endogenous and then making appropriate assumptions on u.[12]

While the quasi-linear assumption is useful for simplifying the proofs and the exposition of the model, exact quasi-linear utility in consumption is not necessary. It could be relaxed to $v(x) = x^\sigma/\sigma$ for some σ close enough to 1 and the results would go through.

Finally, the model deviates from much of the current literature in empirical modeling in not

[12] I do not explore the cross-partial results with respect to age when treating n as endogenous as these require technical assumptions on third derivatives of u in the most general setups.

including tastes in utility. In standard demand models a heterogeneous taste factor is often added. In this case, it would be natural to assume that households or families have different tastes for foster care.

Tastes are not explicitly included in the model to save on notation and highlight the key economic mechanisms at play. A natural extension of the model to include tastes would include a taste parameter ξ that enters into utility so that altruistic value from fostering for family i is

$$u(h_n n_i, h_F(a), \xi_i).$$

This also provides a clear reason for the need of credible identification strategies: it is possible that ξ_i and n_i or ξ_i and w_i (or both) are correlated. When this is the case, the correlation between whether a family is a foster family and their fertility n_i or wage w_i may not capture the true counterfactual of shifting families fertility or earning potential because of the selection on unobservable tastes. For this reason, the empirical strategies attempt to find ways to reduce the endogeneity caused by ξ_i and the observable economic fundamentals that are examined. How these strategies relate to ξ_i and correct for such endogeneity is discussed more when the tests are developed. However, in developing the predictions, ξ_i is left out for simplicity of the derivations and presentations. Leaving out tastes make the mechanisms the centerpiece of the paper. Indeed, a model with just tastes has essentially no empirical content when taken to the data (Stigler and Becker, 1977).

5.3 Model Predictions

The model gives five formal predictions that illuminate the incentives of families to care for foster children. The intuition for each of these propositions is provided. Another informal prediction of the model will also be discussed that is made formal in the Appendix.

Proposition 1. Families with more children n are less likely to be foster parents - they have a lower marginal utility for foster care.

Proof. Consider the partial derivative of (10) with respect to n. This is the marginal utility of a foster child with respect to changing the number of children n exogenously. This expression is equal to

$$u_1(h_n n, h_F(a)) - u_1(h_n n, 0) < 0$$

since $h_F(a) > 0$ and $u_{12} < 0$. Thus, we have that the overall marginal utility of fostering is decreasing in n. □

The intuition for this result comes from the structure of utility. The assumption that $u_{12} <$

0 implies that biological children and foster children as imperfect substitutes in production of altruistic utility. When families choose to have more children n, the marginal utility from an additional child, foster or otherwise, is lowered because the household already gets utility from biological children.

Another sensible prediction that is in the same vein as Proposition 1 would be that, because n and F enter into the utility function in a way that resembles substitutes, if we were to treat n as endogenous, then the cross-price derivative between the price of children p_n and foster children F would be positive. Because the theory is not written to treat n as endogenous this is not provided as a formal result of the model. However, the Appendix shows that treating n as endogenous in the model and with quasi-linear utility this result holds. The key assumption is again that $u_{12} < 0$.

The next result concerns the wage of the household and their desire to be foster parents.

Proposition 2. Families with higher wages w are less likely to be foster parents.

Proof. Consider the partial derivative of (10) with respect to w, the marginal utility of a foster child with respect to changing the household wage w exogenously. This is simply

$$-t_F(a) < 0$$

and thus the marginal utility is negative in wage. □

This result relies on the fact that households that choose to be foster parents must surrender some of their working time to care for children. The intuition for this result is a variant of the intuition provided for the wage-fertility relationship that is closely studied in economics (Becker, 1992) - because children are time-intensive goods in the model, high wage households will have less children. This logic extends to foster children.

However, something more subtle that is not captured in this simplified model is the fact that if $t_F > t_n$, so that foster children are more time-intensive due to their lower human capital, the wage effect of foster children is more significant than the wage effect of biological children. It is shown in the Appendix that when treating n as endogenous, if higher wages induce families to have less children, demand for foster children declines faster in wages than demand for biological children is always larger this is true in the Appendix. Thus this negative wage effect for foster children is robust and not just a feature of replacing the biological child label with the foster child label in the model.

The model also allows for the analysis of how a child's age impacts family's propensities to foster. First the effects of own fertility on age are examined

Proposition 3. Families with more children n are more willing to care for older children i.e. a closer to 1.

Proof. Consider the cross-partial of the left-hand side of (10) with respect to n and a. Taking the derivative of the equation in the proof of Proposition 1 with respect to a yields

$$u_{12}(h_n n, h_F(a))h'_F(a) > 0$$

since $u_{12} < 0$ and $h'_F(a) < 0$. □

The intuition for this result is that as n gets larger, due to the concavity of u and substitutability between biological and foster children, the loss in human capital when moving from a biological child to a foster child is lessened. Families with more children are less sensitive to age differences between foster children through $h_F(a)$ since they are already at such a concave part of their altruistic utility.

The model also implies a specific relationship between the wage of family's and the age of foster children.

Proposition 4. Families with a higher wage w are less willing to care for older children.

Proof. Consider the cross-partial of the left-hand side of (10) with respect to w and a. This is simply

$$-t'_F(a) < 0$$

since $t'_F(a) > 0$ has been argued. □

The intuition for this result is similar to the result on wage. Wage is a measure of the price of time and foster children are costly in terms of time. The theory as written states that $t'_F(a) > 0$ so that older children are more time intensive, thus having a differentially even higher price for high wage families.

A final prediction to point out that is quite easy to see from (10) and holds in almost all consumer choice models such as this is that households will care for foster children more when p_F decreases.

Proposition 5. Holding fixed a, when p_F decreases, families are more willing to care for foster children.

Proof. The derivative of (10) with respect to price is -1 due to the quasi-linearity assumption. □

In this model p_F encompasses the expenditures by families on children net of the subsidies they receive from the government for their services. Thus, it is possible that $p_F \leq 0$, though most studies have argued that $p_F \geq 0$ (DeVooght et al., 2013).

6 Empirical Tests and Results

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

6.1 Preliminary Evidence

In this section evidence on the assumptions and preliminary implications of the model are examined. Most of these are related to how foster care is generated.

First, the rule generating the removal of children by households can be assessed. There is a large literature that looks at the risk factors associated with foster care. Doyle and Peters (2007) discuss how some of these major factors include single parenthood and drug abuse. Single parenthood can be seen as a decreased time budget of the household T, leading to lower equilibrium human capital investments in children. Drug abuse can be seen as time-intensive consumption or correlated with low human capital that causes households to substitute away from quality human capital investment t_n in children.

These implications can also be investigated directly in the AFCARS and ACS data. To examine the impacts of human capital on entry, one can relate the median education of an adult in a county and the entry rate of foster children, defined as the total number of foster children entering between 2005-2015 divided by the population. While the model does not make it clear that parental or household human capital impacts the human capital of the child, models of parental investment often have a dependence of investment efficiency on parental human capital (Cunha and Heckman, 2007). Thus, if human capital drives entry into foster care we would expect a negative relationship between household human capital and entry into foster care.[13]

The mean rate of entry for counties with a median education of some college is almost half the rate of entry for counties with a median of completing high school. This effect is statistically significant when put in a regression framework at the 95% level.

A particularly striking feature of child entries in foster care in California is the spike in entries of newborns in Figure A5. This is due to the screening of newborn infants who have drugs in their system. The removal of these children is consistent with the model if a child's drug exposure predicts whether the household will be low human capital investors.

One of the assumptions of the model is that children with less human capital require more time

[13]This becomes more complicated when thinking about a distribution of human capital since the government might be using a relative or absolute rule. The model as stated has the government using an absolute rule based on t_g, but it is not hard to imagine that t_g also varies with county level human capital.

to care for. One piece of evidence related to this is provided by Kalenkoski et al. (2005) who show that the time spent on childcare is positively correlated with whether a household has a disabled child conditional on a rich set of observables about the household. If disabled children have lower overall human capital, this fact is consistent with the model. Older children in the AFCARS data are statistically significantly more likely to have a disability upon entry (p-value less than 0.01).

Finally, the model stresses the importance of wage in explaining fertility patterns. In particular, the model suggests that, absent strong income effects, families with higher wages will have less children in general, irrespective of foster care decisions. While this relationship has been shown at more macro levels across countries and even within the US (Becker, 1960; Jones and Tertilt, 2006), it is useful to examine these relationships using the micro level ACS data to assess the household level predictions.

Consider the following empirical model of fertility:

$$\text{Num Child}_i = \beta_w \text{Wage}_i + X_i \beta + \epsilon_i \tag{11}$$

where i is a household in the ACS and X_i is 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 19. To flexibly and robustly allow for age to affect the model, (11) is estimated in two ways. The first specification includes a quadratic polynomial in age and looks over all households. The second specification restrict to households with an age between 25 and 35 and does not include a race control. A specification is also estimated with just wage on this set of families between 25 and 35. All specifications only focus on married households for simplicity. The hypothesis of the theory is that $\beta_w < 0$.

The results are displayed in Table 2. In all specifications wage is negatively related to the number of children and is statistically significant at a level much smaller than 1%. This provides robust evidence of the negative correlation between wage and fertility in the micro data. Moreover, the R^2 of the model in (2) where only wage is included is 0.06, which appears to be quite high for a model that only includes a numerical variable of wage and a linear relationship between wage and number of children.

To assess the relative magnitudes of wage versus cultural factors that are captured by race, consider the estimated impact of moving from a 10th percentile to 90th percentile average wage on number of children in the data. The difference between these is approximately \$33 in the samples in columns (2) and (3). This leads to an impact of the number of children of about 0.43, highly comparable to the effects of the cultural factors that are captured by a family being Black or Hispanic relative to White.

	Dependent variable:		
	Number of Children		
	All Married Households	Married Households Age 25-35	
	(1)	(2)	(3)
Wage	-0.002^{***}	-0.022^{***}	-0.013^{***}
	(0.0002)	(0.0001)	(0.0004)
Black Family	0.064^{***}		0.345^{***}
	(0.010)		(0.028)
Hispanic Family	0.367^{***}		0.562^{***}
	(0.008)		(0.020)
Other Race Family	0.055^{***}		0.001
	(0.007)		(0.011)
Age Quadratic Polynomial	Yes	No	No
County-Year FEs	Yes	No	Yes
Observations	2,461,538	377,534	377,534
R^2	0.311	0.058	0.130
Adjusted R^2	0.311	0.058	0.129

Table 2: Fertility and Wages

Notes: Estimates from (11). Samples are either all married households (1) or all married households with an average household age of the partners between 25 and 35. Number of Children measures the number of biological children of the head of household that are age 18 or younger. Standard errors in columns (1) and (3) are clustered at the County-Year level and include County-Year fixed effects. *p<0.1; **p<0.05; ***p<0.01

6.2 Testing the Main Model Predictions

The model's main empirical content is the predictions it makes related to age and other child factors through Propositions 1 through 5. The goal of this section is to test Propositions 1 through 4 in the most convincing way possible in my data. The order of the tests follow the order of the predictions. I also discuss some of the more informal predictions of the model and evidence for Proposition 5.

6.2.1 Testing Proposition 1

Proposition 1 states that families with more children are less likely to be foster parents because they have a lower marginal utility for foster care. Importantly, the model makes this prediction when altruism for children is substitutable between foster children and biological children. To examine this prediction I utilize 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.

Since the ACS micro data identifies foster children, this strategy can be used at the household level in the ACS. The main dependent variable of interest is $\text{Foster}_i = \mathbf{1}\{\text{household } i \text{ has a foster child}\}$. The number of children of the head of the household that are 21 or younger, Num Child_i, is the main independent variable of interest.[14] The instrument Twins_i is calculated by identifying all second births of children of the head of household that have the same birth quarter and the same age as the first birth in the household. The analysis for this exercise focuses on married households as the household theories most readily apply to them (Angrist and Evans, 1998).

The basic empirical strategy can be summarized by

$$\begin{aligned} \text{Foster}_i &= \beta_1 \text{Num Child}_i + X_{it}\beta_2 + \epsilon_{it} \\ \text{Num Child}_i &= \alpha_1 \text{Twins}_i + X_{it}\alpha_2 + \nu_{it} \end{aligned} \tag{12}$$

where I am interested in the parameter β_1 in (12). 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 demand side characteristics.

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

A major worry regarding using twins as an instrument is that since 2000 or so, around 30% of all twins born in the US have been due to fertility treatments instead of natural conception (Kulkarni et al., 2013). Thus the selection of families into fertility treatments is captured in a large way by the twins instrument. In particular, in my data, having twins is correlated with having a higher education, wage and age. Those households choosing to receive fertility treatments likely reflect some of this correlation. To reduce this worry and try to net out the selection into twins, the regressions also include family wage and education as controls. While family wage may be seen as a "bad control" (Angrist and Pischke, 2008) since the presence of twins may impact a families wage

[14] The age restriction is done so that the propsective ages of foster children and biological children are similar.

(Angrist and Evans, 1998) the hope is that wage is a proxy for earlier wages that were determined at the time of twins to differentiate between fertility treatments. Thus the empirical strategy's validity on using this control strategy to isolate the "good variation" in the IV from natural conception.[15]

The results from implementing the IV estimator (12) are in Table 3. The first column shows a bivariate regression of the foster care indicator on the total number of children in the household. These results suggest a marginally significant negative correlation in the most basic cut of the data between the number of children and those fostering children.

The second column adds controls for the age of the household, the race of the household and county-year fixed effects. The correlation is now more substantially negative and statistically significant - consistent with the model.

Investigating which of the controls strengthens the relationship is informative in the context of the model. Adding household age is enough to strengthen the relationship between fostering and the number of children. Age of the household can be seen as a measure for the price of own children p_n due to fertility problems growing with age. Moreover, families with higher ages will also tend to have more children because they can accumulate a larger stock of children over time. Thus, without controlling for age, the basic correlation suggests that the data conflates some of the price and consumption effects.

Columns (3) and (4) of Table 3 implement the main IV estimator that uses twins as the exogenous shifter. The F-statistics in the first-stage are very large - well over 1000 easily passing the benchmark rule-of-thumb of 10 (Stock et al., 2002). Columns (3) and (4) differ in their use of controls. Both show statistically significant negative relationships between the number of children and the likelihood of being a foster parent. If we believe the exclusion restriction then this provides causal evidence for the prediction of Proposition 1.

The magnitudes of the IV estimates indicate that a 1 standard deviation increase in the number of children (approximately 1 child in the sub-sample of estimation) decreases the chance of being a foster parent by around 65% of the mean rate, a substantial economic quantity. The parameter estimates from the preferred IV specification are also about 5 times the magnitude of estimates from the OLS results. The larger IV results can be rationalized in the context of the model if heterogeneous tastes are added to u - families that have more children might also have lower wages and higher idiosyncratic tastes for caring for children, both factors pushing against the negative relationship in the theory and understating this relationship in the basic correlations.

[15] Another challenge in the implementation of this strategy in the micro data is that kin and non-kin foster children are not identified. There could be reasons to believe that the marginal altruistic utility for kin vs non-kin foster children differs. In particular, if kin children are "closer" to biological children, they may have a higher marginal utility simply due to altruistic weighting. In the model, if this is true, then the marginal utility of foster care is higher for kin foster children, and so this should decrease the impact of n on the willingness to be a foster parent, biasing the estimate positive. In California, using the AFCARS data, I calculate that a little less than half of foster children placed with families are kin placements.

	Dependent variable:			
	Foster Family			
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Number of Children	-0.075^{*}	-0.332^{***}	-2.257^{***}	-1.708^{***}
	(0.031)	(0.100)	(0.308)	(0.532)
Family Age		0.151		0.519^{***}
		(0.125)		(0.179)
Family Age^2		-0.001		-0.006^{**}
		(0.002)		(0.002)
Black Family		5.488^{***}		5.724^{***}
		(1.259)		(1.255)
Hispanic Family		2.178^{***}		2.746^{***}
		(0.349)		(0.432)
Other Race Family		-0.678^{***}		-0.677^{***}
		(0.232)		(0.231)
Education and Wage Controls	No	No	No	Yes
Observations	1,492,654	1,492,654	1,492,654	1,492,654
Adjusted R^2	0.00000	0.003	-0.002	0.002
Mean$(y) \times 1000$		2.85		

Table 3: Child Predictions

Notes: All coefficients and standard errors are multiplied by 1000. The dependent variable is an indicator for whether a household in the ACS has a foster child present. Number of children measures own biological children of the head of the household under the age of 22. The instrument is twins, which is constructed by looking at families with 2nd children born in the same birth quarter and year as their 1st child. Standard errors in columns (2) and (4) are clustered at the County-Year level and include County-Year fixed effects. *p<0.1; **p<0.05; ***p<0.01

It is important to note that this IV strategy is only able to identify the parameter estimate for the impact of more children on families with at least one child, since the IV is undefined for families with no children. Under the assumption that $u_{11} < 0$ and $u_{12} < 0$, the marginal utility of foster care for moving from no children to 1 child decreases more than subsequent children. Thus, if we believe that treatment-effect heterogeneity is small enough for this IV in that it provides an externally valid parameter estimate, the theory suggests that the parameter estimate would be even larger for the effect of moving from no biological children to at least one biological child.

There are other ways to estimate the effect of interest that are closer to what the literature has pursued. In particular following Angrist and Evans (1998) I utilize an alternate specification with an indicator for the household having at least 2 children. While the coefficient estimate differs mechanically the the magnitude of the effects are almost identical.

6.2.2 Testing the Relationship with Price of Own Children using Same-Sex Couples

One of the informal predictions of the model was that an increase in p_n should increase demand for foster children under the assumption that foster children and biological children are substitutable in producing altruistic utility $u_{12} < 0$.[16] To test this in the data I examine the probability of being a foster family for same-sex couples. The idea behind this empirical test is that same-sex couples face a larger cost of having biological children because they require a mediator to have biological children. If same-sex couples have the same preferences and prices as other households conditional on observables, then same-sex status only measures a shift in p_n and so a positive correlation between same-sex would confirm the prediction of interest. One appeal of using same-sex status as an identifier is the possibility that families and households cannot select into being same-sex households as opposed to heterosexual households due to biologically endowed sexual preferences. This makes the measure of same-sex a more plausibly exogenous shifter of prices than other prices shifters that could conflate other important geographic and cultural factors,

The formal empirical test consists of regressing the Foster indicator on an indicator for a couple being same-sex. Same-sex couples are identified in the data by looking at whether the sex of the head of household and their spouse or unmarried partner match. This is an improvement over methods that utilize identified married same-sex couples in the ACS because many same-sex couples that live together but are not married during this period should still count as forming a household. This definition leaves single households with only a head of household undefined, so they are dropped from the analysis. The OLS model is augmented with the same set of controls used in (12) and Table 3.[17]

The results in Table 4 confirm that same-sex households are substantially more likely to be foster parents, and even more so with a rich set of controls. The parameter estimates suggest that a same-sex household has a 0.5 percentage point higher chance of being a foster parent than a non same-sex household, well over 100% of the mean proportion of foster parents in the sample. Thus there appear to be substantial substitution effects in the data when interpreted through the lens of the model.

One obvious threat to the empirical strategy is that same sex couples may differ in their general altruism levels or tastes, which could affect their $u(\cdot)$ within the model or in a more general sense, their propensity to foster, independent of the price of biological children. Previous studies have found evidence for differences in altruism by gender (Andreoni and Vesterlund, 2001) which could

[16] See the Appendix for a formal derivation treating n as endogenous.

[17] Since picking out married couples selects away many of the same-sex households for this test, I do not restrict to married couples as I do in the previous analysis.

	Dependent variable:	
	Foster Family	
	(1)	(2)
Same Sex Couple	5.296***	5.592***
	(0.303)	(1.360)
Family Age		0.312***
		(0.033)
Family Age^2		−0.003***
		(0.0003)
Black Family		6.207***
		(0.797)
Hispanic Family		2.527***
		(0.300)
Other Race Family		−0.428**
		(0.198)
Controls	No	Yes
Observations	2,713,362	2,713,362
R^2	0.0001	0.003
Adjusted R^2	0.0001	0.003
Mean$(y) \times 1000$	3.08	

Table 4: Same-Sex Regressions

Notes: All coefficients and standard errors are multiplied by 1000. The dependent variable is an indicator for whether a household in the ACS has a foster child present. Same sex couple is defied as the head of household and either their spouse or unmarried partner being the same sex. Standard errors in column (2) are clustered at the County-Year level. *p<0.1; **p<0.05; ***p<0.01

naturally suggest altruism differences by sexual preferences or couple status.

To examine this hypothesis I use the volunteer supplement to the CPS from 2005-2015. This allows me to measure volunteering status of households. Volunteering status is measured as the mean number of heads of households, spouses or unmarried partners who state that they volunteer at all. A univariate regression of the volunteer measure on same sex couples (looking again only over households with a spouse or unmarried partner present) yields a positive coefficient of about 0.0275 with a standard error of 0.0145 and a p-value of 0.057. Thus, this correlation is not significant at the 5% level and with a magnitude of only 2.75 percentage points compared to a mean of 29.2, it seems unlikely that the large parameter estimates above could be completely driven by differential altruism or tastes. The results suggest that it is credible to attribute some or even most of the effects of same-sex status on fostering to these price differences, providing further evidence for the substitutability patterns emphasized by the model. Importantly $u_{12} < 0$ drives these results in the model.

6.2.3 Testing Proposition 2

Proposition 2 states that families with higher wages w are less likely to be foster parents. The empirical test of this proposition utilizes the ACS micro data in a similar way to the test of Proposition 1 although the identification strategy is admittedly less credible.

My empirical strategy consists of estimating the following model

$$\text{Foster}_i = \beta_1 \text{Wage}_i + X_{it}\beta_2 + \epsilon_{it}. \tag{13}$$

Here β_1 is the parameter of interest and the theory predicts that $\beta_1 < 0$. X is a vector of the same controls used for the number of children. The main threat to identification in this set-up is that households that are more altruistic in general may take on a lower wage to satisfy their altruistic desires. To mitigate this factor in the regression detailed occupation codes of the minimum household earner in the household are added as controlled. Then the empirical strategy utilizes the leftover wage variation within occupations to identify the wage effect. If selection into industries is a good proxy for altruistic preferences that translate into labor decisions, then the leftover wage variation used to identify the parameters should be uncorrelated with household altruism. However, if tastes for children drive certain people to focus less on their careers or pursue lower wages in a way not captured by this regression control identification strategy, this selection effect could make the estimates inconsistent.

Wage is measured in the ACS at the household level by looking at the overall wage income of the household and dividing by the usual hours worked and weeks worked in the last year to back out the hourly wage. The results are robust to many other measures of wage, including wage of the female household, the head of household/spouse/partner with the smallest wage, etc.

The results from estimation are given in Table 5. Column (1) provides the raw correlation in the data. Household wages are negatively correlated with being foster parents in the data. This negative correlation remains precise but drops in magnitude when including controls. The somewhat large drop in point estimate for the effect of wage when including occupation controls is consistent with the altruistic story that motivates the empirical strategy - some of that wage variation did seem to be induced by differential altruism. However, it also is consistent with potential selection on unobservables.

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

An important issue that not addressed so far is that the cost of receiving a foster child may be correlated with wage. In particular, if human capital is correlated with wage and across families,

	Dependent variable:		
	Foster Family		
	(1)	(2)	(3)
Household Wage	-0.050^{***}	-0.046^{***}	-0.037^{***}
	(0.002)	(0.005)	(0.005)
Family Age		0.381^{***}	0.361^{***}
		(0.035)	(0.035)
Family Age^2		-0.004^{***}	-0.004^{***}
		(0.0003)	(0.0003)
Black Family		6.533^{***}	6.294^{***}
		(0.884)	(0.880)
Hispanic Family		1.856^{***}	1.622^{***}
		(0.291)	(0.278)
Other Race Family		-0.685^{***}	-0.717^{***}
		(0.186)	(0.191)
Occupation Indicator	No	No	Yes
Observations	2,450,070	2,450,070	2,450,070
Adjusted R^2	0.0002	0.003	0.004
Mean$(y) \times 1000$		3.08	

Table 5: Wage Predictions: Micro Data

Notes: All coefficients and standard errors are multiplied by 1000. The dependent variable is an indicator for whether a household in the ACS has a foster child present. Wage is computed in the ACS as the average household wage by taking the mean wage-income and dividing by the usual hours worked per week and the number of weeks worked in the last year (rounded). Standard errors in columns (2) ad (3) are clustered at the County-Year level and include county-year fixed effects. *p<0.1; **p<0.05; ***p<0.01

then families with a lower wage may have more opportunities to be foster parents because they are more likely to have related children enter foster care. Because kin care is especially popular in black communities (Berrick et al., 1994) and foster care children are disproportionately black, the wage effects are examined only with white families who have above median wages, trying to isolate this pure wage variation from the likelihood of having a related child enter foster care. The coefficient estimate (-0.023) is smaller but remains statistically significantly negative (s.e. = 0.008).

Unlike the fertility prediction, there is no clear empirical strategy in the micro data that can more plausibly isolate the causal effect except for controlling for the important economic factors guided by the model as done here. One idea is to use a Bartik style instrument with the county-level variation. However, this turns out to be quite uninformative using my data because I can only identify 14 counties in the single state of California and the Bartik strategy is consistent in the number of counties and does not perform well in the face of spatial correlation (Goldsmith-Pinkham et al., 2018).

6.2.4 Testing Proposition 3

Proposition 3 states that families with more children n are more willing to care for older children. While the micro data does contain the ages of the foster children that are placed with families, the families that do end up caring for children comprises a selected sample of families. To avoid any sample selection bias, the county-year variation in the merged AFCARS and (aggregated) ACS data are used to form these empirical tests.[18]

The empirical strategy consists of utilizing county-year level variation in fertility to see its relationship to the impact of family placement on older children. In particular, the empirical specification is of the following form:

$$\text{Placed with a Family}_{it} = \beta_1 \text{Num Child}_{j(i,t),t} \times \text{Age}_{it} + X_{it}\beta_2 + \epsilon_{it} \tag{14}$$

where i now indexes a foster child in the AFCARS dataset, the dependent variable is an indicator for whether the child is placed with a family, $j(i,t)$ is the county of child i at time t, Num Child measures the average number of children in households in the county, and age is treated as a numerical variable for children. The theory implies that $\beta_1 > 0$ since the age gradient in more fertile counties should be lower. Recall that the intuition is that the human capital opportunity cost of foster children decreases significantly as fertility increases.

X_{it} includes Num Child and Age, and also includes a vector of controls that include a rich set of demographic controls at the county and child level. The controls are also interacted with child age to more credibly isolate this differential age effect as coming from the number of children. The county level controls include the racial composition and the median family age and the marriage rate and in some specifications utilize time fixed effects. When time fixed effects are included in the interaction, the identifying variation nets out a common California fertility time trend, making the variation more plausibly exogenous.[19] Standard errors are clustered at the county level in all specifications.

Table 6 contains the results of estimation of (14). In all specifications there is a positive and statistically significant interaction term, consistent with the theoretical predictions. The magnitude of the interaction term is on the order of a few percentage points for every child. To interpret,

[18] The correlations between the number of children and the age of foster children in the micro data are positive though statistically weak.

[19] When I utilize county-level fixed effects I do not get any statistically significant results among any of the interacted variables. I interpret this as a lack of power in my empirical strategy due to the large geographic regions of counties, the small number of total counties and the short time span.

	Dependent variable:			
	Placed with a Family			
	(1)	(2)	(3)	(4)
Age	-0.061^{***}	-0.075^{***}	-0.039	-0.106^{***}
	(0.011)	(0.014)	(0.028)	(0.023)
Num Child	-0.110^{**}	-0.047	0.058	0.089
	(0.043)	(0.077)	(0.040)	(0.071)
Age $\times$ Num Child	0.019^{***}	0.026^{***}	0.022^{**}	0.027^{**}
	(0.006)	(0.007)	(0.011)	(0.012)
Age $\times$ Per White			-0.001	-0.021
			(0.014)	(0.013)
Age $\times$ Per Black			0.052	0.015
			(0.041)	(0.038)
Age $\times$ Per Hispanic			0.032^{**}	0.020
			(0.014)	(0.013)
Age $\times$ Median Family Age			-0.00001	0.002^{***}
			(0.0004)	(0.0005)
Age $\times$ Marriage Rate			-0.055^{***}	-0.061^{***}
			(0.019)	(0.018)
Year Fixed Effects	No	Yes	No	Yes
Child Demographic Controls	Yes	Yes	Yes	Yes
Observations	498,109	498,109	498,109	498,109
Adjusted R^2	0.210	0.216	0.227	0.233

Table 6: Fertility and Age of Foster Children

Notes: Parameter estimates from estimating equation (14). When Year fixed effects are included, I include them interacted with child age as well. Standard errors are clustered at the county level in all specifications. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

consider the median foster child age in this sample of 10 years old. A 1 SD change in the number of children across county-year variation in specification (3) yields a placement probability difference of about 2.8 percentage points. For 15 year olds, this climbs up to 4.3 percentage points.

To understand the magnitudes of these estimates better consider the standard deviation of placement for 10 year olds and 15 year olds in the sample. This are respectively approximately 0.3 and 0.48, suggesting that the child differences can explain a little less than 10% of the variation in placement for 10 year olds and 15 year olds across counties.

While these magnitudes are not extremely large, their non-triviality and consistency across specifications provie evidence of a real economic relationship predicted by the model through Proposition 3.

6.2.5 Testing Proposition 4

The final major proposition that I test in the data is Proposition 4 which states that families with a higher wage should be less willing to care for older children. Recall that this is driven by the lower human capital of entering older children, which translates into higher time costs. As with testing Proposition 3, county-level variation is utilized to avoid the sample selection problems in the micro data.

The empirical strategy mirrors the strategy used in the previous section where instead of using number of children at the county-year level wages are examined. Wages are measured in the main specifications through the average log household wage, though the result is robust to other percentiles of the wage distribution. As in the previous empirical strategy, the results with time fixed effects are considered to be the most plausible estimates of the true effect since they net out common trends in wages across these California counties over the time period, only measuring deviations across counties from these common trends.

Note that the estimate of the wage effect through this method may be potentially biased because of the fact that county-level wages also impact the selection of children that enter into foster care. The natural implication for wages on the the overall selection of foster children that higher wages should lead to more human capital investment and thus foster children with higher human capital. This should make fostering a child more desirable at the county level. The implications are less clear for the differential effects by age without the model. Using the logic of the model in which human capital investments are a flow, older children should benefit the most from higher wages. Thus, this bias works against this method finding a negative wage gradient.

Table 7 contains the results from estimation. As predicted the interaction between child age and the average log wage is negative in all but 1 of the specifications and is quite stable. The lack of precision in specification (3) seems to come from the fact that year fixed effects are not included in the interaction, which means the highly correlated time variation among all the interacted variables causes the power to be very weak. In column (4) when netting out these time trends we recover estimates that are even stronger than those of columns (1) and (2).

The magnitudes from column (4) suggest that a 1 SD change in average log wage impacts the placement of a 10 year old versus a newborn by 4.3 percentage points and for a 15 year old by 6.4 percentage points. Using the same magnitude checks as in the previous section these represent just over 10% of the variation in placement for 10 year olds and 15 year olds across counties, substantially large economic quantities.

Similar to the evidence presented in the previous section on the relationship between the number of children the magnitudes and consistency of the cross estimates suggests the evidence of the relationship as implied by the theory.

	Dependent variable:			
	Placed with a Family			
	(1)	(2)	(3)	(4)
Age	0.035***	0.039***	0.049	0.011
	(0.011)	(0.013)	(0.057)	(0.054)
Avg Log Wage	0.025	0.040	0.064	0.095
	(0.049)	(0.047)	(0.088)	(0.109)
Age × Avg Log Wage	−0.024***	−0.025***	−0.013	−0.030**
	(0.004)	(0.004)	(0.014)	(0.015)
Age × Per White			0.002	−0.041**
			(0.020)	(0.018)
Age × Per Black			0.051	−0.035
			(0.051)	(0.043)
Age × Per Hispanic			0.026	−0.021
			(0.033)	(0.032)
Age × Median Family Age			−0.001	0.002***
			(0.0005)	(0.001)
Age × Marriage Rate			−0.027	−0.023*
			(0.020)	(0.012)
Year Fixed Effects	No	Yes	No	Yes
Child Demographic Controls	Yes	Yes	Yes	Yes
Observations	498,109	498,109	498,109	498,109
Adjusted R^2	0.217	0.221	0.226	0.232

Table 7: Wage and Age of Foster Children

Notes: Parameter estimates from estimating equation (14) where I replace Num Child with Avg Log Wage. When Year fixed effects are included, I include them interacted with child age as well. Standard errors are clustered at the county level in all specifications. *p<0.1; **p<0.05; ***p<0.01

6.2.6 Evidence for Proposition 5

Another implication of the model presented is that if the price of a foster child decreases, this will increase the willingness of families to care for those children. This prediction has been tested directly by Doyle (2007a) who uses an event-study analysis and a discrete change in payments to kin foster families to estimate elasticities of providing care with respect to foster payments. The evidence suggests that kin families respond to prices in ways consistent with the model and the general story of this paper.

Similarly Doyle and Peters (2007) use variation in state-level foster care subsidies to identify the foster care supply curve. As in Doyle (2007a), they find evidence for an upward sloping supply curve.

6.3 Summary of the Tests and Alternative Theories

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

For example, the wage effects are easy to generate with many models. Wages could be correlated with the general altruism of families and so only serve as a proxy for their altruism. While the empirical strategy does attempt to reduce the bias induced from such an effect, this worry still remains. However, while the general wage direction is not too specific to the model, the wage and age interaction effect seems more difficult to fit into this theory. Why would families be less altruistic to younger or older children? There is no clear basis for this. A similar story could be told for the fertility effects - it is challenging to generate the fertility and age interactions without appealing to human capital and substitutable altruism.

The fact that so many of the predictions are verified in the data, and that some of these predictions are particularly specific to the model of interest provides strong support for the economic mechanisms it highlights in a unified way as being important. These economic mechanisms shed light on the motivations of foster families, and provide strong suggestive evidence that foster families can positively influence children's welfare, but respond to time and price costs as in the standard fertility literature.

To further strengthen the connection between the theory and the data, some competing explanations are discussed and their implications for the empirical results in this paper are examined.

6.3.1 Warm Glow Theory

An important economic theory that specifies how households participate in altruistic activities is warm glow (Andreoni, 1990). This theory treats society as playing a public goods game and analyzes an equilibrium of public good contributions by households. To fit this theory into foster care, consider the caring for low human capital children as contributing to the public good of the overall stock of human capital in society.

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

A more basic implication of the warm glow theory is that charity is likely a normal good and so higher incomes should induce more caring for foster children. The empirical results in Table 5 directly contradict this claim.

The warm glow theory must also make a stand on how the age of a foster child contributes to the public good. Investment in older children should contribute less to the public good if their human capital is sunk. Without any sense of human capital or understanding how investments in older children differ from younger children in the social utility function, this seems challenging to generate. However, augmenting the warm glow theory with human capital would produce this prediction.

Finally, the warm glow theory has no real way to incorporate own fertility into how households choose decisions of whether to be foster parents.

Overall, it seems challenging to generate the patterns in the data using the warm glow theory, especially without augmenting the model with human capital.

6.3.2 County Matching Procedures

Because foster care is a matching market, it could be that the patterns in the data presented in this paper represent differences in institutional market designs and technology between counties.

In particular, consider the proposed relationship between wages and placement. If wages proxy for county-level income which impacts county-level matching technology, then this could influence overall family placement. Since the wage specifications use micro ACS data and include county-year fixed effects, the empirical strategy essentially holds county technology fixed. Thus, technology does not seem able to explain these margins.

County technology also has a difficult time explaining the county-level correlations. Why would a county with better technology be particularly good or worse at placing children of different ages? There does not seem to be a good theoretical basis for such a result and yet Figure 3 shows substantial heterogeneity in age placement, particularly for older children.

It is important to note, however, that this discussion and the empirical results do not imply that technological differences are important drivers of family placement between counties. Indeed, it seems likely that technology differences between placement systems could make a large difference. The important conclusion for this paper is that these technological differences are not able to generate the empirical results focused on in this paper.

6.3.3 Psychological and Sociological Theories of Adoption and Foster Care

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

Most of the work done on the psychology of adoption and foster care comes from clinical research and emphasizes the role of loss and sociological views of family structures - experiencing infertility, etc. One prominent theory is that the psychological effect of loss from infertility induces families to seek children to adopt (Kirk, 1964).

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

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

The ideas related to family structure are consistent with the correlations presented in Table 4 that examined the propensity of same-sex couples to foster children. Under the view of this theory, this positive correlation completely reflects that same-sex couples are marginalized and this is what contributes to their more open view of the world. The wage effects in Table 5 could even be consistent with this theory if households with lower wages have more open views of families due to similar types of marginalization, even when controlling for a rich set of demographics.

What the family concept model does not provide is a way to better understand how an exogenous increase in the number of biological children decreases the propensity to foster as shown in the IV estimates of Table 3. There is no clear relationship between having an extra child and the conceptualization of family structure - adding a foster child to a larger family or smaller family does not have a clear difference in how open families are.

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

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

7 Conclusion

This paper has studied why families provide foster care to children. Motivating family placement as tightly linked to welfare outcomes, the age of the child is an important descriptive predictor of whether a child is placed with a family or not. A model is developed of how households decide to foster children where they value foster children through altruism like they do biological children but must sacrifice own consumption for them.

The model makes clear predictions that are then tested in the data using various identification strategies. The predictions find strong evidence in the data. The predictions relating the interactions between child age and fertility and wages are probably most specific to the model and thus provide the most robust test of the theory. Alternative theories are discussed and examined for their performance in explaining the empirical results and how they relate to this paper's model. Out of the alternative theories discussed, a theory of families being willing to provide foster care based on a conceptualization of appropriate family structure seems the most able to explain the other facts, though the model presented does a better job in these specific circumstances. An investigation into the nuanced differences between such a theory and my own model could prove useful for distinguishing more effectively between these theories and deriving the welfare implications of such a distinction.

The results in this paper have important welfare implications. The empirical tests provide evidence that families behave in a way that is consistent with them gaining altruistic utility from foster children in similar ways to biological children. This evidence suggests that it is more likely that family-based foster care provides significant welfare improvements to children from a human capital investment standpoint - families will select into being foster parents because they get altruism from children's human capital and then invest appropriately, aligning social incentives. Moreover, if these families have higher human capital than the birth families of these children, there would appear to large gains from placing children with families.

However, the evidence and the model point out that families consider their own consumption needs and opportunity costs when deciding whether to foster as well, consistent with the previous literature (Doyle, 2007a; Doyle and Peters, 2007). This paints a picture of foster families that are altruistic and helpful but practical - they are motivated by altruism and willing to invest in children, but are also conscious of their own consumption. This data suggest that this is major feature driving the striking age gradient.

The results also speak to a much larger scholarly debate which argues that children being cared for by biological parents is crucial for their well-being (Hamilton et al., 2007). In the setting of foster care, the model and the empirical tests suggest that families choose to care for non-biological children in a way that treats them substitutable with children. While the quantitative magnitudes for altruism and investment outcomes are difficult to compute with the current data, this paper provides strong evidence that we cannot outright reject that the mechanisms that we think guide families to invest a lot in their biological children also guide families to invest in non-biological children.

As noted in the introduction, these findings also nuance the literature on kin and non-kin placement in foster care (Font, 2014; Berrick et al., 1994) Some of the major worries of non-kin placement is the worry about motivations for caring for children. Kin placements seem to provide a natural placement option to maximize potential altruism. The non-kin placement analysis provides evidence that altruism motivates families looking for non-kin placements, mitigating such a worry. This altruism combined with differences in human capital could in fact be an explanation for some of the negative effects of kin placement relative to non-kin placement.

Finally, the emphasis on child age in the model and the related empirical results suggest that the mechanism through which older children receive less placement and worse outcomes in Doyle (2007b) is through the foregone human capital from late detection of low investment. This suggests that the gains to a more aggressive screening of younger children for maltreatment and abuse instead of "waiting for evidence" could be more economically efficient in producing improved child welfare outcomes, though ethically problematic.

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

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Appendix

Data and Institutional Details

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

Table A1: Inter County Placements

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

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

Table A2: Child Characteristics by County

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

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

Table A3: Child Characteristics by Year

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

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

Table A4: Household Characteristics by County

Notes: Summary statistics by county for the households used in the county-year level analysis of the ACS.

	% White	% Black	% Hispanic	Family Age	% Married	Avg Log Wage	90% Log Wage	Num Child
2005	0.57	0.05	0.19	48	0.67	2.72	3.57	1.75
2006	0.55	0.05	0.2	48.07	0.67	2.7	3.57	1.74
2007	0.54	0.05	0.21	48.5	0.67	2.74	3.6	1.75
2008	0.54	0.05	0.21	48.93	0.66	2.73	3.59	1.63
2009	0.53	0.05	0.22	49.21	0.66	2.73	3.61	1.64
2010	0.51	0.05	0.22	49.43	0.65	2.7	3.59	1.64
2011	0.51	0.05	0.23	50.57	0.64	2.66	3.57	1.61
2012	0.5	0.05	0.23	50.61	0.65	2.66	3.57	1.63
2013	0.5	0.05	0.23	50.57	0.65	2.67	3.6	1.6
2014	0.49	0.05	0.24	51.14	0.65	2.7	3.59	1.61
2015	0.49	0.05	0.23	51.43	0.65	2.72	3.62	1.59
Total	0.52	0.05	0.22	49.68	0.66	2.7	3.59	1.65

Table A5: Household Characteristics by Year

Notes: Summary statistics by year for the households used in the county-year level analysis of the ACS.

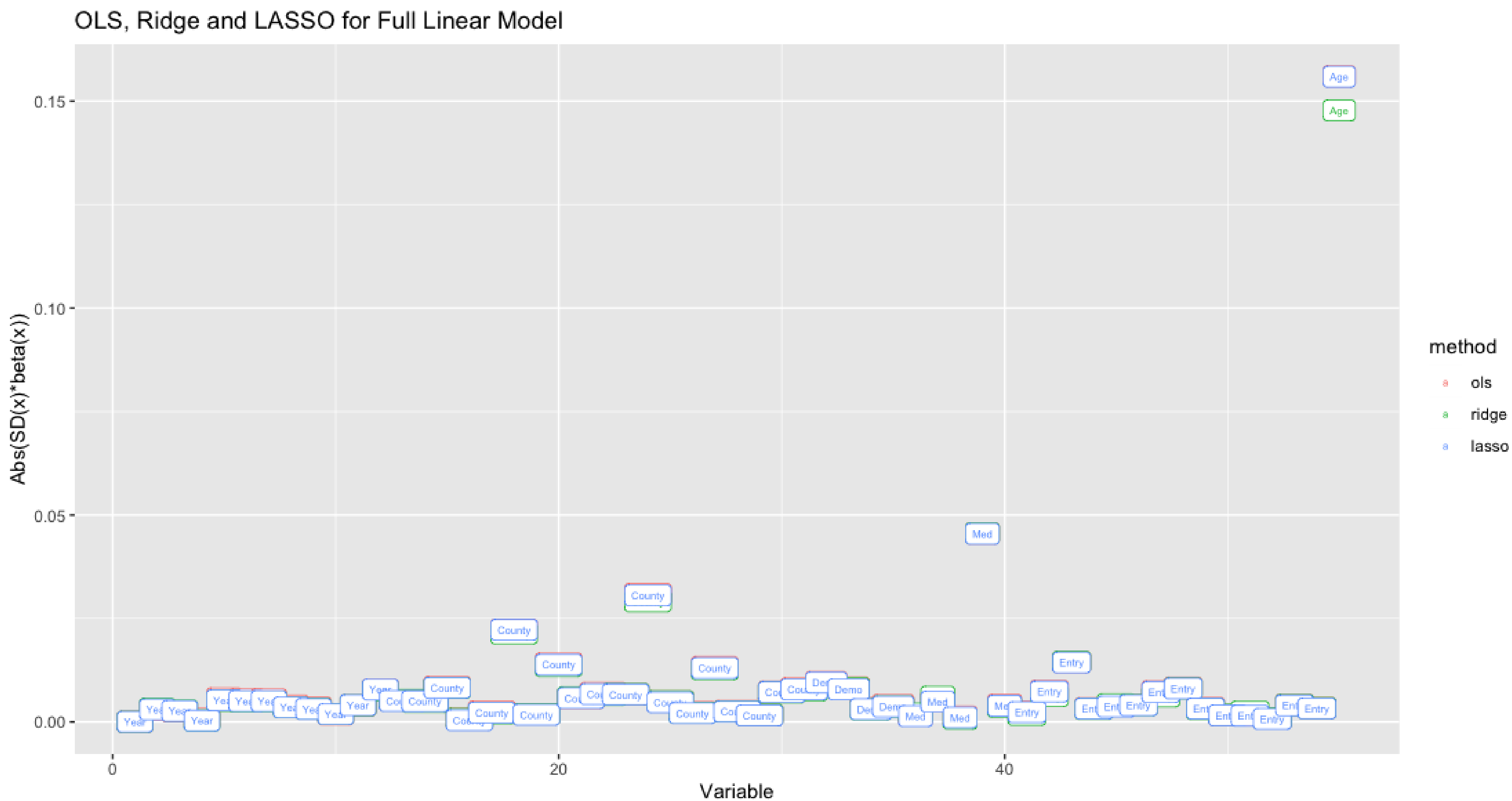

Figure A5: Predictive Factors for Child Placement: Ridge and OLS

Notes: Each observation in the plot is $|\hat{\beta}_j \times \mathrm{SD}(x_j)|$ where j runs over all child observables determined before placement in the AFCARS data. The OLS and LASSO coefficients are almost identical.

Theory Appendix

Consider the model but instead treat n and F as real numbers and treat n as a choice variable. Then the first order condition is given by

$$\begin{aligned} u_1(h_n n, h_F(a)F)h_n &= v'(w(T - t_n n - t_F(a)F) - p_n n - p_F(a)F)(wt_n + p_n) \\ u_2(h_n n, h_F(a)F)h_F(a) &= v'(w(T - t_n n - t_F(a)F) - p_n n - p_F(a)F)(wt_F(a) + p_F(a)) \end{aligned} \tag{15}$$

Lemma 1. Under quasi-linear utility and the appropriate assumptions on utility, the first order condition characterizes the optimum of the household's problem.

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

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

and here $f_{11} = u_{11}(h_n n, h_F F)h_n^2 < 0$ and

$$f_{11}f_{22} - f_{12}^2 = u_{11}(h_n n, h_F F)^2 h_n^2 h_F^2 - u_{12}(h_n n, h_F F)^2 h_n^2 h_F^2 < 0$$

due to the assumptions on $u_{11} = u_{22}$ and $u_{12} > u_{11}$. Thus this we have a local maximum. The Inada conditions ensure that this local maximum is global and that there is no corner solution. Thus the first order conditions completely characterize the solution. □

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

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

$$\begin{aligned} u_1(h_n n, h_F(a)F)h_n &= wt_n + p_n \\ u_2(h_n n, h_F(a)F)h_F(a) &= wt_F(a) + p_F(a) \end{aligned} \tag{16}$$

Shorten the notation to $u_1 := u_1(h_n n, h_F(a)F)$, $u_2 := u_2(h_n n, h_F(a)F)$ and the same for higher order derivatives. Then implicitly differentiating the simplified first order conditions (16) with respect to w yields

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

Figure A5: Age of Entry Distribution
Notes: This is the age distribution of children in the main analysis sample from AFCARS for the years 2005-2015 - i.e. children eligible for placement with non-kin. A point in the histogram is the age of a child at entry.

Solving this system for the partial derivatives yields

$$\frac{\partial n^*}{\partial w} = \frac{u_{22}h_F^2 t_n - t_F u_{12} h_n h_F}{h_F^2 h_n^2 (u_{11}u_{22} - u_{12}^2)}$$
$$\frac{\partial F^*}{\partial w} = \frac{u_{11}h_n^2 t_F - t_n u_{12} h_n h_F}{h_F^2 h_n^2 (u_{11}u_{22} - u_{12}^2)}$$

Now note that

$$\frac{\partial n^*}{\partial w} - \frac{\partial F^*}{\partial w} = \frac{u_{22}h_F^2 t_n - u_{11}h_n^2 t_F + t_n u_{12} h_n h_F - t_F u_{12} h_n h_F}{h_F^2 h_n^2 (u_{11}u_{22} - u_{12}^2)}$$
$$= \frac{u_{11}(h_F^2 t_n - h_n^2 t_F) + u_{12} h_n h_F (t_n - t_F)}{h_F^2 h_n^2 (u_{11}u_{22} - u_{12}^2)}$$

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

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

Proof. Consider implicitly differentiating (16) with respect to p_n. This yields

$$h_n(u_{11}h_n\frac{\partial n^*}{\partial p_n} + u_{12}h_F\frac{\partial F^*}{\partial p_n}) = 1$$
$$h_F(u_{12}h_n\frac{\partial n^*}{\partial p_n} + u_{22}h_F\frac{\partial F^*}{\partial p_n}) = 0$$

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

$$\frac{\partial F^*}{\partial p_n} = \frac{-u_{12}}{h_n h_F(u_{22}u_{11} - u_{12}^2)}$$

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

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

Proof. Consider implicitly differentiating (16) with respect to p_F. This yields

$$h_n(u_{11}h_n\frac{\partial n^*}{\partial p_F} + u_{12}h_F\frac{\partial F^*}{\partial p_F}) = 0$$
$$h_F(u_{12}h_n\frac{\partial n^*}{\partial p_F} + u_{22}h_F\frac{\partial F^*}{\partial p_F}) = 1$$

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

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

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

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

Proof. Considering (16) and letting n_0 be an exogenously endowed set of biological children, we can write this as

$$u_1(h_n(n + n_0), h_F(a)F)h_n = wt_n + p_n$$
$$u_2(h_n(n + n_0), h_F(a)F)h_F(a) = wt_F(a) + p_F(a)$$

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

$$\begin{aligned} h_n^2 u_{11} \frac{\partial n^*}{\partial n_0} + h_n h_F u_{12} \frac{\partial F^*}{\partial n_0} &= p_n'(n_0) \\ h_n h_F u_{12} \frac{\partial n^*}{\partial n_0} + h_F^2 u_{22} \frac{\partial F^*}{\partial n_0} &= 0 \end{aligned}$$

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

$$\frac{\partial F^*}{\partial n_0} = \frac{-u_{12} p_n'(n_0)}{h_n h_F (u_{11} u_{22} - u_{12}^2)}$$

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