Adoption Subsidies and Placement Outcomes for Children in Foster Care

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Abstract

Over 400,000 children in the United States are currently in foster care, many of whom are at risk for long-lasting emotional and health problems. Research suggests that adoption may be one of the more promising options for the placement of these children. The Adoption Assistance and Child Welfare Act of 1980, which provided federal funds for monthly adoption subsidies, was designed to promote adoptions of special-needs children and children in foster care.

Using data from the Adoption and Foster Care Analysis and Reporting Systems for 2000-2006, I consider the effects of these adoption subsidies on the number of adoptions and on time spent in foster care. Because subsidies may be determined endogenously, I employ an identification strategy that exploits state variation in the age at which children are eligible for federal subsidy funds. I find that the number of adoptions increases when children become subsidy eligible, and that most of the increase is from adoptions by foster parents. Conditional on adoption, subsidy eligibility increases the hazard of discharge from foster care. The fact that adoption subsidies are cheaper than the cost of keeping a child in foster care means that removing foster parents' disincentives for adoption could generate substantial cost savings.

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I. Introduction

In 2010, there were over 400,000 children in the United States in foster care.[1] The vast majority of foster children come from disadvantaged backgrounds and are at much greater risk for emotional and health problems than their peers. For example, one-third of these children with reported disability information had some form of clinical disability, such as mental retardation or a physical disability. Additionally, 67.5 percent of children for whom a reason for removal from the home is reported had been abused or neglected, and 26.1 percent had experienced drug or alcohol abuse by a parent. Among children for whom government funding information was available, 49.0 percent were eligible for Medicaid, and Duncan Lindsey (1991) finds that low family income is the single best predictor of a child's placement into foster care.

Social scientists have long considered adoption to be a desirable outcome for many foster children (Triseliotis and Hill 1990, Barth and Berry 1994, Van Ijzendoorn, et al. 2005).[2] Consistent with this view, policies have been introduced at all levels of government to encourage adoption (Hansen 2007a). In 1980, Congress passed the Adoption Assistance and Child Welfare Act (AACWA), which provided federal funds for monthly adoption subsidies designed to

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[1] The AFCARS Report, 2011.

[2] It is important to note that the vast majority of research finding a positive relationship between adoption and later outcomes (including those cited here and elsewhere in the paper) is based on small-sample clinical or survey data. Further, the endogeneity of placement into adoptive homes makes it difficult to establish a causal effect (Triseliotis 2002, Berger et al. 2009). Sacerdote (2007) exploits the random assignment of Korean-American adoptees into adoptive homes and finds that the *type* of adoptive home is an important predictor of outcomes—though these children are likely very different from foster children in the U.S.

promote adoptions of special needs children and children in foster care. From 2000 to 2006, 86.8 percent of children adopted through child welfare services received a subsidy, with the average amount being $571.95 per month.[3] By 2007, the program provided subsidies for 390,900 children at an annual cost to the Federal government of nearly $2 billion, with an additional $1.6 billion spent by states (2008 Green Book).[4] The program was expanded in 2008 to remove income requirements and to provide for kinship care, and the American Reinvestment and Recovery Act of 2008 (ARRA) added an additional $98 million in funding for adoption assistance over 2009 and 2010.[5]

The AACWA has three main goals: to reduce the number of children in foster care and the duration of a child's stay in foster care; to encourage adoption when it is in the child's best interest, and the adoption of special-needs children in particular; and to improve the quality of care and services of children in the child welfare system.[6] This paper will evaluate the success

[3] In comparison, the average monthly amount of TANF payments to families in 2002 was $395.96 (www.ssa.gov). The subsidies generally continue from adoption to the age of 18, so that the average family adopting a toddler would receive over $100,000 in present value during their participation in the program.

[4] The subsidy program is comparable in size to more well-known and more studied programs such as the State Children's Health Insurance Program (SCHIP) and the Supplemental Nutrition Program for Women, Infants, and Children (WIC), which received $3.2 billion and $4.37 billion in federal funds in 2002, respectively (2004 Green Book).

[5] State Adoption Subsidy Profiles, 2006.

[6] These goals are outlined by the National Clearinghouse on Child Abuse and Neglect Information (National Clearinghouse on Child Abuse and Neglect Information, 2006).

of the adoption subsidy program in light of these goals. First, I consider whether eligibility for a subsidy affects the number of children who are adopted. Second, I explore whether certain types of families are more responsive to adoption subsidies, such as older relatives or foster caregivers. This question may be related to the quality of care for adopted children, if (for example) relatives provide better or worse care than other adoptive parents. Third, I consider whether subsidy eligibility reduces time spent in foster care.

Prior research on the adoption subsidy program has generally found that subsidies are correlated with increased adoption rates and reduced time spent in foster care. However, these estimates should not be interpreted as identifying a causal effect. The issue is that subsidy receipt and amounts are determined by the needs and resources of the involved parties, so that estimates based on correlations (Dalberth, Gibbs, and Berkman 2005), conventional OLS estimation (Hansen and Hansen 2006), or OLS with state fixed effects (Hansen 2007a) potentially suffer from omitted variable bias due to unobserved family, child, or case worker characteristics. For example, children who are difficult to place due to behavioral problems may receive higher subsidies and also have longer stays in foster care; this would cause a positive bias in estimates of the effect of subsidies on time to adoption.

To address these issues, I use an identification strategy that accounts for the endogeneity of subsidy receipt. I exploit state-level variation in the minimum age at which children may be designated "special needs" by age, where special needs designation is required for federal subsidy funds. State age minimums range from 0 to 12 years. Moreover, in some states rates of subsidy receipt are very high even for children below the cutoff; these states form a natural control group for whom the age cutoffs should have little effect. Using a differences-in-differences-in-differences approach, in which I compare the effect of eligibility by age for

treatment and control states, I estimate a treatment effect of eligibility on the likelihood of subsidy receipt of five percentage points. The effects are larger for subsamples that are less likely to be eligible for special needs designation for other reasons.

I then investigate whether eligibility for special needs designation by age affects adoption outcomes including the number of adoptions, type of adoptive home, and time spent in foster care. If eligibility is unrelated to unobservable characteristics then any differences in outcomes can be attributed to the increased likelihood of subsidy receipt. This reduced-form approach allows me to provide estimates of the effect of subsidy receipt, and also to estimate the policy-relevant direct effect of age cutoffs on adoption outcomes.

I find that the average number of adoptions over the period in a state/month-of-age cell increases with subsidy eligibility, by 3.72 adoptions (11.3 percent). This increase is driven by adoptions by foster parents. But results from a hazard model show that subsidy eligibility has no effect on the hazard of discharge from foster care for the full sample, suggesting that few children are moved from permanent foster care to adoption by the policies. However, eligibility increases the hazard of discharge from foster care for adopted children—particularly for whites. Thus it seems that the subsidy program is having some success in attaining its goals, though much of the effect is from foster parents who adopt their foster child once he or she is subsidy eligible. While this may mean that the child's care environment does not change with subsidy receipt, child well-being could be improved if there are benefits from a formalized adoptive relationship (see Triseliotis and Hill 1990). But even if there is little effect on the child's quality of care, the findings suggest that a state's choice of age cutoff can have important financial implications, as the monthly costs associated with keeping a child in foster care are higher than the monthly adoption subsidies.

II. Background

A. The Adoption Subsidy Program

The AACWA, signed into law on June 17, 1980, established and funded "a program of federal support to encourage adoptions of children with special needs."[7] The law amends Title IV of the Social Security Act, and requires states to make monthly adoption assistance payments to families that adopt special needs children. The intent of the program was to alleviate the financial burden of adopting a child, and economic theory predicts that the subsidy program should increase the demand for adoption services (Dalberth, Gibbs, and Berkman 2005; Hansen and Hansen 2006). Since 1980, the federal government has broadened the approach to promoting adoptions by providing performance incentives to states and offering tax credits, but the subsidy program remains the largest and most-used policy tool.[8]

In 2007, the subsidy program served 390,900 children per month, with a total cost to the federal government of nearly $2 billion. An additional $1.6 billion was spent by states. These figures represent dramatic increases since the program's inception in 1981, when only 163 children received federal adoption assistance for a total of about $400,000. Inflation-adjusted per-child expenditures exhibit a slight upward trend since the early 1980s. However, the majority of the increase in cost (over 85 percent) has come from increases in the number of children receiving assistance, rather than changes in the amount of assistance received.[9] Figures

[7] Library of Congress, Thomas bill summary (2005).

[8] See Hansen (2007a) for a review of federal programs supporting adoption, through 2001.

[9] The increase in children receiving assistance is in keeping with the dramatic increase in foster care caseloads that occurred over the 1980s and 1990s. Rising rates of female incarceration and

1a and 1b show the dramatic increase in cost and average number of monthly recipients.

Almost half of the funding for the subsidy program comes from state and local funds, but most children are also eligible for federal matching funds under the AACWA. To be eligible for federal funds, the state must first have made reasonable efforts to place the child without assistance, and the child must have been AFDC/TANF- or SSI-eligible prior to removal from their pre-adoptive home. Additionally, the child must be classified as having special needs, where special needs are defined as a condition making it difficult for the child to be placed in an adoptive home. Such conditions include greater age, medical disability, or membership in a sibling group, ethnic group, or minority race. From 2000-2006, 81 percent of children who received a subsidy were eligible for federal funds. Federally-matched payments must be less than the foster care subsidy the family would receive for the child, and terminate when the child reaches the age of 18 (or 21 in the case of mental or physical disability).

To determine subsidy eligibility and amounts, each individual adoptive family negotiates with their state child welfare agency. In making these decisions, states consider the income of the adoptive parents, as well as the needs of the child. Differences in child and adoptive family characteristics, combined with the flexibility that states have when operating their subsidy programs, yield considerable variation in subsidy receipt. From 2000 to 2006, 86.8 percent of children adopted through child welfare services received a subsidy.[10] The average amount was $571.95 per month, with a standard deviation of $418.98; the median was $461.

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reductions in welfare benefits have been cited as primary causes of the increase in caseloads (Swann and Sylvester 2006).

[10] There are 348,848 adoption records for 2000-2006. Subsidy statistics are computed using the subsample for which subsidy information is reported (91 percent of the sample).

The requirement that a child be designated "special needs" in order to receive federal funds is an important feature of the subsidy program. States can choose how they define a special needs child, and in particular, states vary on the age at which a child is designated as being special needs by age. As a result, children of the same age can be designated as having special needs in some states and not in others. Moreover, many states subsidize nearly all children regardless of age, so that the age cutoffs are less meaningful in those states.

B. Related Research

Most prior research on the adoption subsidy program has found that subsidies are correlated with increased adoption rates and reduced time spent in foster care (Sedlak and Broadhurst 1993; Hansen and Hansen 2006; Hansen 2007a). The estimated effects can be large: Hansen (2007a) predicts that an increase of $94 per month in a state's average subsidy would increase the state adoption rate by 130 percent. However, as mentioned in the introduction and discussed in detail below, these estimates likely suffer from omitted variable bias due to unobserved family, child, or case worker characteristics.

One study does use a quasi-experimental strategy to address a related question, which is whether the difference between foster care payments and adoption subsidies affects adoption rates (Argys and Duncan 2008). The authors exploit variation in foster care payments by age and show that large differences decrease adoption rates. Researchers have also used natural experiment or structural approaches to estimate the causal effects of the foster care subsidy program. For example, Doyle (2007) exploits a 1995 policy reform in Illinois that reduced foster care subsidies for relatives, and finds that smaller payments reduce the likelihood that families provide care. To address issues of selection, he uses caseworker assignment as an instrument for entry into foster care. Duncan and Argys (2007) exploit variation in foster care payments by age

and find that higher payments reduce the likelihood that a child is placed in a group home. Finally, Doyle and Peters (2007) model the market for foster care services. They argue that when states set subsidy rates below market clearing rates, changes in the subsidy rate can be used to estimate the supply curve for services (assuming a constant demand curve). The authors find that higher foster care subsidies do increase the supply of foster caregivers.

III. Data

A. Foster Care Data

The AACWA requires all states to report annual data on all children who were in foster care or who were adopted through their child welfare agency to the Children's Bureau of the Administration on Children, Youth and Families. The data are distributed as the Adoption and Foster Care Analysis and Reporting System (AFCARS) by The National Data Archive on Child Abuse and Neglect. I use AFCARS data from 2000 to 2006, and both the Foster Care and Adoption files are used. First, the Foster Care Files contain date of birth, gender, race, and disability information for each child; and age, race, and family structure for birth and foster families. The data contain detailed case histories, including date of removal from the home and reason for removal (such as abuse, neglect, or abandonment); dates for recent placements and for discharge; reason for discharge (including reunification, living with a relative, adoption, emancipation); and sources and amounts for foster care subsidies. Each reporting period (October 1 to September 30) has approximately 800,000 cases, and children who are in care in multiple reporting periods will have records in each period. Therefore, when combining the years to form a pooled cross-section, I identify duplicate observations and keep only the most recent observation (which contains and updates all of the information from the previous

periods).[11] Restricting the sample to children under 18 leaves 2,523,695 cases.

Table 1 contains summary information for the children in this full sample. Twenty percent of children in foster care have a medical condition, and over half have been neglected. Twenty-two percent have suffered physical or sexual abuse. 56.1 percent were receiving a foster care subsidy, with an average monthly payment of $1,239—though this number is skewed by the high subsidies received by children in institutional care.[12] For children in foster or pre-adoptive homes, the average monthly payment is $787. Finally, 67.5 percent would be eligible for special needs by age designation (and therefore for federal funds for this reason) in their state.

Table 1 also shows summary statistics for the subsample of children who are discharged from foster care into adoptive homes. Adopted children are younger than those in the full sample on average, and are more likely to have medical conditions or have been neglected. The average pre-adoptive foster care payment is also lower, at $670.

B. Adoption Data

The Adoption Files include a record for each child with a finalized adoption from foster care. The files contain data on date of birth, gender, race, disability, and special needs

[11] I identify duplicate observations using county, gender, record number (not unique), date of birth, and date of removal from the home. For children who were still in care at the end of the year, I match to a unique record the following year 89.4 percent of the time.

[12] Children are defined as receiving a foster care subsidy if a positive value is recorded for the amount of the monthly foster care payment. Children can receive support from other sources, including AFDC, child support, Medicaid, and Social Security Insurance, and these funds are not always included in the reported monthly foster care amount. The fraction receiving any form of support is 0.897.

designation for each adopted child; and age, race, and family structure for the adoptive parents. The data also identify the pre-adoptive relationship (foster parent, relative, non-relative) and dates for the termination of parental rights and the adoption finalization.[13] I also observe whether the child receives an adoption subsidy, the amount, and whether Title IV-E adoption assistance is claimed. Again, the data for the years 2000-2006 are combined to form a pooled cross-section. There are about 45,000 reported adoptions of children under 18 each year, for 315,855 total cases.

Table 2 describes the characteristics of children who are adopted with and without a subsidy. We see that 87.5 percent of children adopted with a subsidy are designated special needs on the basis of age, race, sibling group, medical condition, or other, compared to only 55.0 percent for those with no subsidy. Those adopted with a subsidy are older and more likely to be black, Hispanic, or to have a medical condition. Adoption outcomes also vary by subsidy receipt—recipients are more likely to be adopted by a foster parent or older relative, and their time from termination of parental rights to adoption is about 53 days longer. [14] All differences between the two groups are statistically significant at the 5 percent level. These differences illustrate the difficulty in interpreting relationships between subsidies and outcomes as causal. We see that children adopted with subsidies are different in observable ways; they are likely to be different in unobservable ways as well. I now turn to a discussion of the empirical strategy

[13] Relatives cannot be classified as foster parents. A non-relative is someone who is neither a relative nor a foster parent prior to adoption.

[14] A child is classified as being adopted by an older relative if the adoptive mother is a relative that is at least 35 years older than the child (most likely a grandmother). The AFCARS data do not separately identify grandparents.

that I will use to address this issue.

IV. The Identification Strategy

The difficulty in establishing a causal relationship between subsidies and adoption outcomes arises because subsidies are potentially correlated with unobserved child, family, and case worker characteristics. Thus, OLS estimates of the effects of subsidies likely suffer from omitted variable bias, though the direction of the bias is unclear.[15] In order to resolve this issue and to identify the effects of the subsidy program, I use an identification strategy that exploits state-level variation in the age at which children are designated special needs on the basis of age. Recall that an important feature of the subsidy program is the requirement that a child be designated as having special needs in order to receive federal funds. States can choose how they define a special needs child, and in particular, states vary on the age at which a child is designated as being special needs by age. As a result, children of the same age can be designated

[15] To see this, consider one of our main questions of interest: whether the availability or amount of a subsidy affects the amount of time a child spends in foster care. Children who are difficult to place for emotional, behavioral, or other unreported reasons might receive higher subsidies and also have longer stays in foster care—resulting in a positive bias in the estimated effect. Alternatively, characteristics of the case worker might negatively bias the estimate, if particularly effective or aggressive case workers award higher subsidies and have lower average times to discharge. Wealthier adoptive families, who receive lower subsidies on average, might also be able to navigate the child welfare system more quickly and therefore have shorter times to discharge, resulting in a positively biased estimate. These are just a few plausible sources of bias in OLS estimation; there are likely others.

as special needs in some states and not in others. To determine whether the subsidy program affects outcomes for children in foster care, I will employ a differences-in-differences-in-differences (DDD) strategy, comparing the effects of age eligibility for children in states with and without a meaningful cutoff. If this eligibility increases the likelihood of subsidy receipt but is unrelated to unobservable characteristics, we can attribute any observed differences in outcomes to differences in subsidy receipt.

Table 3 lists the minimum age at which a child can be designated as having special needs by age in each state, with the age requirement ranging from 0 to 12 years for black children and from 1 to 12 years for white children.[16] Further, the minimum age requirement is more meaningful in some states than others, in large part because rates of subsidy receipt are very high even for children with no particular special needs who are *below* the cutoff in some states. The thirteen states in the column on the right in Table 3 each have subsidy receipt rates above 90 percent for children who are in the two-year window below the age cutoff and who are not designated as special needs by race, medical condition, or sibling group.[17] Many of these children are designated as having special needs for "other" reasons, suggesting that some states are more generous in their use of this designation than others.[18]

[16] In Louisiana, age minimums are lower for boys than for girls; this information has been omitted from Table 3 for simplicity but is taken into account in the estimation.

[17] In Section V, I explore the sensitivity of the results to alternative subsidy rate cutoffs (85 and 95 percent) for defining treatment and control states.

[18] Assignment to treatment and control groups is very similar under alternative definitions of the "less needy" sample. For example, if I instead use the percent of *all* children adopted in the two-year window before eligibility that receive a subsidy, the only change is that Virginia is

In Figure 2, subsidy receipt is plotted as a function of the child's age relative to his or her state cutoff. The sample is all children from states in Table 3. Data are from the Adoption Files and are collapsed to the month level.[19] For states with subsidy rates over 90 percent for below-age children (labeled "control"), we see that nearly 95 percent of children receive a subsidy even before the cutoff, and the rate is constant with no discontinuity at the cutoff point. Meanwhile, for children in the remaining twenty-eight states in Table 3 (the "treatment" states), the average rate is below 80 percent for children below the cutoff, but increases precisely at the point of eligibility before stabilizing at around 87 percent.[20]

Figure 2 shows that children in treated states are more likely to receive subsidies after becoming eligible for the special needs by age designation, while children in control states see no change. I estimate the effect of age eligibility on subsidy receipt among adopted children in a regression framework using the following DDD model:

$$Subsidy_{isa} = \beta_0 + \beta_1 eligible_{isa} * treat_s + \beta_2 eligible_{isa} + X_{isa}\beta_3 + year_{isa}\beta_4 \quad (1)$$

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classified as a control state. If I use the percent of children with no special needs by race (but who may have special needs by sibling group or medical need), Virginia is again a treatment state but Colorado becomes a control state. All results are robust to these changes.

[19] Children with subsidy amounts in excess of $2500 per month, or with more than ten years since termination of parental rights (1.4 percent and 2.6 percent of the sample, respectively) are omitted in this and all subsequent estimation.

[20] Nine states do not have a strict cutoff for special needs by age designation (though children can receive the designation), and are thus omitted from the sample—HI, ID, KY, MA, MN, NC, SD, VT, and WV. In Section V, I discuss results using placebo age cutoffs for these states. New York is also omitted due to incomplete reporting.

$$+ \alpha_a + \delta_s + \tau_s * trend + \varepsilon_{isa}$$

where the subscript *i* denotes the individual child, *s* indexes the state, and *a* indexes the child's age in years.[21] $Subsidy_{isa}$ is a dummy variable indicating subsidy receipt, and $eligible_{isa}$ is a dummy indicating that the child is eligible for special needs by age status in his or her state. $Treat_s$ indicates that the state is in the "treatment" group of states with less than 90 percent subsidy rates for children below the cutoff (states in the left-hand column of Table 3). The matrix X_{isa} includes demographic characteristics of the child (race, gender, and presence of a medical condition), and $year_{isa}$ is a set of dummies indicating the year of adoption. The vectors α_a and δ_s represent age and state fixed effects, respectively.[22] $Trend_a$ is a cubic trend in age (in months), and τ_s gives the state-specific coefficient on the time trend. ε_{isa} is random error. Standard errors are clustered at the state level.

Results from estimating models based on equation (1) are in Table 4, Panel (A). Data are from the Adoption Files for 2000-2006, and the sample includes all adopted children under 18 in either the treated or control states. The parameter of interest is β_1, which gives the differential effect of being eligible for special needs by age designation in treated states relative to control states. The specifications in columns [1] through [4] successively add demographic controls,

[21] The DDD strategy described here is analogous to the more common case with policies varying at the state-*year* level, with age-level variation taking the place of cross-time variation.

[22] The age and state fixed effects account for the main controls for age, state, and treatment status in the DDD model. The fixed effects also account for two of the three two-way interactions; the dummy variable *eligible* accounts for the third (state x age). The triple difference is the interaction of *eligible* and treatment status. 83 percent of the variation in the *eligible x treatment* variable is accounted for by the age and state fixed effects and state-specific trends.

state fixed effects, and the state-specific trends, so that the full specification is in column [4]. In that specification, the estimated treatment effect is 0.0503 (5.7 percent of the mean), and is statistically significant. Meanwhile, eligibility has no effect on subsidy receipt in control states. Looking across specifications, it appears that the state fixed effects and state-specific trends do affect the magnitude of the estimated effect, so all results in the remainder of the paper include them.

Recall that in addition to eligibility due to age, children can also qualify for special needs status due to race, medical conditions, or membership in a sibling group. The next two panels in Table 4 show results for subsamples of the population that are less likely to be eligible for subsidies for these reasons (and are therefore more likely to be affected by the age cutoff). In Panel B, the sample is limited to white children; in Panel C, children who have a medical condition or who appear to be adopted as part of a sibling group are also omitted.[23] In column [4], we see that the effect of becoming eligible for special needs designation due to age increases as the sample becomes less "needy" for other reasons. For white children with no medical conditions and no sibling group, those eligible by age are 11.29 percentage points (13.5 percent) more likely to receive a subsidy. In Panel D, I show results for nonwhites—many of whom would have been eligible for a subsidy even before reaching the age cutoff. For this group, age eligibility does increase the likelihood of subsidy receipt, but the effect is smaller (4.86 percentage points, or a 5.4 percent effect).

In Table 5, I consider two other policy outcomes—the likelihood of receiving federal funding, and the subsidy amount. The specification is the same as in column [4] of Table 4. The

[23] Children were classified as being adopted in a sibling group if they were adopted in the same state on the same day and the birth parents' years of birth and marital status were the same.

results for receipt of federal funds confirm the expected mechanism—children in treated states who are eligible for special needs designation by age are also more likely to receive federal funds, and the effect increases as the sample is restricted. For whites with no medical condition and no sibling group, there is a statistically significant negative effect for children in control states, but the magnitude is small. The effect for nonwhites is smaller than for the other subsamples, and is only significant at the 10 percent level. Subsidy amounts are also greater for eligible children, though the effect is only statistically significant for white children.

The results in Figure 2 and in Table 4 confirm that eligibility for special needs by age status significantly increases subsidy receipt in the treatment states. In the estimation below, I investigate whether the subsidy program has been successful in achieving its goals of increasing the likelihood that a child is adopted, improving quality of care, and reducing time spent in foster care. The approach is reduced-form—I estimate the effects of eligibility for special needs by age designation on placement outcomes. If eligibility is unrelated to unobservable characteristics, we can attribute any observed differences in outcomes to the fact that the eligible children were more likely to receive subsidies. The reduced form estimates also identify the direct effect of being subsidy eligible by age on outcomes, which is an important policy question.

Below I describe the specifics of answering each of these questions, but the general approach is to follow the DDD specification outlined in equation (1). There are two main concerns about using this approach to identify the effects of the subsidy program on adoption outcomes. The first is that states' age cutoffs might be endogenous. In a DDD model with state fixed effects, estimates will be biased if the choice of cutoff is correlated with unobserved state characteristics.[24] States with lower cutoffs might have other more generous policies or more

[24] This is analogous to the usual concern about endogenous policy timing in the more typical

difficulty placing children in adoptive homes, for example. However, Doyle and Peters (2007) find that states do not set market-clearing rates for foster care subsidies, which are closely related to adoption subsidies because of an AACWA requirement that adoption subsidies not exceed foster care subsidies. Also, no state changed its minimum age requirement between 2000 and 2006, which further suggests that policies are not highly responsive to supply and demand for child welfare services. In correspondence with state child welfare agencies, the prevailing sentiment was that the age minimums had been set long ago, and there was both variation in and uncertainty about the process used to set them.[25] In regressions not reported here, I find no relationship between states' minimum age requirements and the number of children in foster care (per 1,000 births).

The second concern is that the control states are not a good comparison group for the treatment states. In Appendix Table 9, I show means for the treatment and control groups. The mean and median cutoff ages are very similar in the two groups. Subsidy amounts for those receiving adoption subsidies are higher in the control states, due to their greater likelihood of being designated with medical need. Importantly, the identification assumption requires not that the treatment and control states be identical, but that the effect of crossing the age threshold

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DDD setup with state-time policy variation.

[25] I contacted the State Subsidy Contact Person given on the website of the North American Council for Adoptable Children (State Adoption Subsidy Profiles, 2006), using both e-mail and telephone calls. A response was received from 22 of the 38 states contacted. When asked who set the age minimum, responses included the child welfare division director, the Department of Children and Families, social services officers, adoption program managers, state legislators, combinations of these, and others.

would have been the same in treatment and control states in the absence of a binding cutoff. While I have no reason to think that this would not be the case, the strategy outlined by equation (1) can further help address concerns about the estimation strategy. The inclusion of state fixed effects accounts for age-invariant unobserved state characteristics, and the state-specific cubic age trends allow for differences across states in age profiles in the dependent variable. I also include year-of-age dummies in all specifications to allow for any secular relationship between certain ages and the dependent variable. Finally, I explore the robustness of the results to alternative definitions of the treatment and control states below.

V. Effects of Subsidy Eligibility on Placement Outcomes

A. Number of Adoptions

First, I investigate how eligibility for a subsidy affects the number of children that are adopted. For this analysis, the data are collapsed to cells by state and age-in-months. Figure 3 shows how the average number of adoptions in a cell is related to the child's age relative to the cutoff, in treatment and control states.[26] For control states, the number of adoptions is generally declining with age, but there is no discontinuity at the cutoff. In treatment states, however, there is an increase in adoptions at the cutoff before a gradual decline with age. While the figure is

[26] In states in which the age cutoff varies by race, some cells cannot cleanly be assigned as treatment or control; these states are therefore omitted from the figure (7 percent of cells). These cells are included in the regression analysis below, where the eligibility measure is the fraction eligible in the cell.

suggestive, the data are noisy and there appear to be important trends in adoptions by age.[27] I therefore turn to regression analysis, which allows for the inclusion of state-specific time trends.

The specification is:

$$nadopt_{ms} = \beta_0 + \beta_1 eligible_{ms}*treat_s + \beta_2 eligible_{ms} + \alpha_a + \delta_s + \tau_s*trend + \varepsilon_{ms} \quad (2)$$

The notation is as in equation (1), although the data are collapsed to cells by state and age-in-months. The dependent variable is the number of adoptions of children of age-month *m* in state *s;* the mean of this variable is 32.87 adoptions. As the dependent variable is a count variable, the equation is estimated using a Poisson model.[28] The parameter β_2 identifies the semielasticity of the number of adoptions in the age-in-moths cell to changes in the fraction eligible for the control states. Since eligibility has no effect on the likelihood of subsidy receipt in these states, β_2 should be close to zero. The coefficient β_1 identifies the differential effect of subsidy eligibility in a treatment state. Data are from the Adoption Files, and results are shown for the full sample and for the subsamples.

Results are in Table 6. I report average marginal effects from the Poisson model, which should be interpreted as changes in the number of adoptions in the cell. In the first column, we

[27] Figure 3 shows that there are differences in levels and trends between the treatment and control groups; importantly, the results are robust to omitting the control group and estimating a simple differences-in-differences model.

[28] The negative binomial model was considered in lieu of the Poisson because the data are overdispersed—the null hypothesis that the data fit a Poisson distribution is rejected at the 1 percent level. However, the negative binomial model fails to converge in some cases. The cost of using the Poisson when the data are overdispersed is a loss of precision (Cameron and Trivedi 2005).

see that eligibility for special needs by age status has a practically meaningful and statistically significant effect on the number of adoptions in the age-month cell. Eligible age-month cells have 3.7 additional adoptions, an 11.3 percent increase relative to the mean. The effect is also positive for the subsamples, though not statistically significant for nonwhites. Recall that eligibility increases the likelihood of receiving a subsidy by 5.03 percentage points, suggesting that increasing the subsidy rate for a cell by 10 percentage points would increase the number of adoptions by 22.5 percent. There is no effect of eligibility on the number of adoptions in the control states.[29]

Importantly, the increase in adoptions observed upon eligibility could reflect an actual increase in the number of children ever adopted, or simply a shift in the timing of adoptions. Below, I present evidence on time spent in foster care that suggests that subsidy eligibility moves few children from permanent foster care to adoption, and discuss the implications of changes in timing for children and for policy.

B. Number of Adoptions and Type of Adoptive Home

Next, I see whether the number of adoptions changes for certain types of adoptive families, or certain types of children. The former can shed light on how the adoption subsidy program affects quality of care, and also identifies the type of adoptive family that is most

[29] One might wonder whether the effect of eligibility varies by age. I do find that the increase in the number of adoptions associated with eligibility is greater in states with a low cutoff (below age seven). However, the effect of eligibility on subsidy receipt is also greater in these states. The implied effect of a ten percentage-point increase in the subsidy rate on the percent increase in adoptions is actually similar in low- and high-cutoff states (31.66 percent vs. 29.7 percent), though the effect is statistically insignificant for the latter.

responsive to the policy, which may have important financial implications. The latter question can address whether the AACWA is successful in its goal of improving outcomes for special needs children in particular.[30] The specification is the same as in equation (2), but the dependent variable is the number of adoptions (a) by older relatives, (b) by foster parents, (c) by non-relatives, (d) of children with a medical condition, or (e) of children who are nonwhite.

The average marginal effects from separate Poisson regressions are in Table 7. Because Illinois requires all adoptive parents to become foster parents first there is no variation in the type of adoptive parent; therefore the state is omitted from these regressions. The first column of Table 7 shows the effect of eligibility on the total number of adoptions for the sample omitting Illinois—the estimate is close to that for the full sample above at 3.14. In the next three columns, we see that 77 percent (2.43/3.14) of the increase in adoptions comes from foster parents.[31] Adoptions by foster parents increase 14.6 percent relative to the mean. Coefficients for the other types of adoptive parents are positive (there is no evidence that subsidies *deter* adoptions for these groups), but are not statistically different from zero. Thus, it appears that the child that is adopted upon becoming age-eligible is likely to be adopted by a foster parent. This is consistent with Argys and Duncan's (2008) finding that foster parents are more likely to adopt when the difference between foster care and adoption subsidies is smaller. However, if the availability of subsidies primarily increases adoptions by foster parents (or changes their timing), most children will see no change in their caregiver as a result of the policy. The implications of

[30] Here, "special needs" refers to conditions that may make it difficult for a child to find a permanent home (consistent with the AACWA goals), and not to official designation as special needs.

[31] Adoptions by younger relatives and step-parents are an omitted category.

this finding for child well-being and child welfare costs are discussed below.

The last two columns of Table 7 show the treatment effect of the subsidy program on adoptions to children who may have special needs. The estimated effect on the number of adoptions of children with medical conditions who are nonwhite is positive but statistically insignificant. For all but one of the models in Table 7, there is again no evidence of an effect of eligibility on adoptions in the control states.

C. Length of Stay in Foster Care

Finally, to determine whether the AACWA has achieved its goal of reducing time spent in foster care, I estimate a hazard model that shows how the subsidy program affects a child's probability of discharge from care. The hazard model is an appealing choice because it allows me to include children with incomplete spells—children who may be the most important for policy makers since they are in perpetual foster care. The hazard model also allows for time dependence (the fact that the likelihood of discharge may depend on time already spent in care).

I use a specification that allows the main covariate (whether the child is subsidy eligible by age in his or her state) to vary over time. In the hazard model, each observation is a spell in foster care, measured in days from last removal from the home to the date of discharge, or to the date of most recent report for children still in care. Children who were emancipated or who ran away or died during foster care (1.6 percent of cases) are omitted, leaving 2,008,059 children. Figure 4 shows Kaplan-Meier survival estimates, which indicate the fraction of children still in care by length of spell.

I estimate a parametric hazard model in a Weibull form, where the hazard rate for person i in period t is defined as $\lambda(it) = \rho \exp(x_{it}\beta)t^{\rho-1}$.[32] The hazard is increasing in duration if ρ is

[32] The Weibull form was chosen based on the shape of the Kaplan-Meier survival estimates, and

greater than one. Data are from the Foster Care Files, which include children still in care. The specification for the set of covariates included in x is similar to that in equation (1), although the age dummies are treated as a time-varying characteristic in the model.[33] The specification for the covariates in the hazard is:

$$x_{isa} = \beta_0 + \beta_1 \, eligible_{isa} * treat_s + \beta_2 \, eligible_{isa} + X_{isa} \, \beta_3 + year_{isa} \, \beta_4 + \alpha_a + \delta_s + \tau_s * trend \quad (3)$$

where variables and subscripts are defined as above. Results are shown for all foster children and by discharge reason, for the white and nonwhite samples.

Table 8 shows the results from the hazard model, for all foster children and by discharge reason. For the full sample, I find no effect of eligibility on time spent in foster care. But conditional on adoption, the hazard coefficient is positive, though marginally significant (p = 0.119). For whites, the effect is statistically significant, and the point estimate indicates that subsidy eligibility increases the hazard of discharge by about 7.8 percent. Given that eligibility increases the likelihood of subsidy receipt by 0.0503, a ten percentage point increase in the subsidy rate would increase the hazard of discharge for white adopted children by 14.02 percent. Subsidies have no effect on discharge hazards for white children who are reunified or placed with a relative or guardian. For nonwhite children, there is little effect of eligibility on discharge hazards for children who are adopted or discharged to a relative or guardian, but I do find a surprising decrease in the hazard for reunified children. For all results in Table 8, subsidy

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because it allowed the use of time-varying covariates. Results using a Cox proportional hazard model have the same sign and are similar in magnitude, though not statistically significant.

[33] To allow age to vary over time, individual spells in foster care are split into shorter spells defined by age in years. Therefore the age dummies in this case control for age during the spell, rather than age at discharge as in all other specifications.

eligibility has no effect in control states.

One caveat is that if subsidy eligibility actually does induce adoptions that otherwise would not have taken place, the increase in the discharge hazard for adoptees could be a result of composition effects (for example, if "marginal" adoptees are discharged more quickly than the average adopted child). However, the fact that I find no effect of eligibility on the discharge hazard for the full sample suggests that subsidy eligibility does not have a large impact on the total number of adoptions. The finding that subsidy eligibility increases the discharge hazard for adopted children is therefore likely driven by an acceleration of adoptions upon eligibility. This may or may not translate to less time in foster care (see the discussion below)—an important outcome given that researchers often find that long stays in foster care are associated with poor outcomes. Relative to children in long term foster care, adopted children have lower placement disruption rates, are more attached to their caregivers, are more able to form healthy adult relationships, and experience fewer emotional difficulties later in life (Barth and Berry 1994, Triseliotis and Hill 1990, Triseliotis 2002). Permanent placements have been shown to be more successful when placement occurs at an earlier age (Lahti 1982).

D. Specification checks

In results not shown here, I have explored the sensitivity of the above results to specification and choice of control group.[34] First, I have reproduced all results using a simple difference-in-differences model for the treatment states. All results are robust to this change, suggesting that they do not depend on the control group estimates. I have also assigned placebo cutoff ages to the nine states without a strict age cutoff, drawn from the distribution of cutoff ages in the remaining states (with replacement). Difference-in-differences results for these states

[34] All results are available upon request.

find no effect of the placebo cutoffs on subsidy receipt. In the preferred specification for the full sample, the point estimate for the effect of the cutoffs on receipt is -0.0001 (standard error = 0.0078). Further, I find no effects of the placebo laws on the number of adoptions or on the discharge hazard.

I also investigated the robustness of the results to alternative specifications of the state-specific age trends. While I chose the cubic trend because very young children are likely different from older children who are different from teenagers, I find similar effects of eligibility on subsidy receipt with both a quadratic and quartic trend. The effects of eligibility on the number of adoptions and on hazard rates are also robust to this choice, though in a few cases results become marginally significant with the quadratic specification.[35] Finally, I consider defining the treatment and control states using a cutoff of both 95 and 85 percent for rates of subsidy receipt for less-needy children (as opposed to the 90 percent cutoff used in the above results). When using the 85 percent cutoff, Louisiana, New Hampshire, Utah, and Wyoming are reclassified as control states. This change has little effect on estimates of the effect of eligibility on subsidy receipt or on the number of adoptions. The effect of eligibility on the hazard of discharge to an adoptive home for whites does become statistically insignificant ($p = 0.137$). When using the 95 percent cutoff, Alaska, California, Montana, Nevada, and Oklahoma are reclassified as treatment states. In this case, the estimated effect of eligibility on subsidy rates is smaller in magnitude, and statistically insignificant for whites. This suggests that under this definition, a large portion of the "treatment" group does not actually receive treatment. As a result, I no longer find effects of eligibility on adoption outcomes in many cases.

[35] Also, the hazard model is computationally demanding when quartic trends are used, so in some cases results could not be obtained.

VI. Discussion

At first glance, the results in Table 6 seem to suggest that the AACWA has had some success in achieving its goal of increasing the number of adoptions of children in foster care. However, I find that eligibility has no effect on the hazard of discharge from foster care for the full sample, but increases the hazard for adopted children. This suggests that the subsidy program may have little effect on the total number of adoptions, but does affect the timing of adoptions. Potential adoptive families may wait until the child is subsidy eligible to adopt, which could actually increase the time the child spends in foster care. The effect of the subsidy program on the total time children spend in care is ambiguous.

Further, the increase in adoptions upon eligibility is driven by adoptions by foster parents. This means that for many children, the care environment may change very little—they still have the same caregiver. As a result, it is difficult to say what has happened to the quality of care for these children. Because adoption subsidies can be no greater than foster care subsidies, the switch from the latter to the former may mean that there are fewer resources in the home once the child is adopted. In the AFCARS data, the average foster care payment for children who were eventually adopted was $670 per month, compared to the average adoption subsidy of $572. One recent estimate of the effect of an increase in permanent income on child well-being suggests that the effects of a $1,200 increase in annual income are likely to be small (Violato et al. 2011), and Sacerdote (2007) finds that adoptive family income had little effect on the education outcomes of a sample of Korean-American adoptees. On the other hand, some research suggests that children may benefit from the act of formalizing the relationship through adoption, as adoption provides stability. Triseliotis and Hill (1990) report that foster children who were adopted by their long-term foster parents experienced increased security, permanence,

and a greater sense of belonging after the adoption was finalized (see also Hansen (2007b)).

But even if there is little effect on child well-being, there are important financial implications if eligibility rules change the timing of adoptions by foster parents. The results in Table 7 indicate that some foster parents are unwilling to adopt when doing so would mean foregoing $670 per month on average, but are willing when (smaller but still large) adoption subsidies are available. Since foster care payments are $100 higher on average per month, child welfare agencies could reduce costs by making adoption subsidies available to these foster parents, lessening the incentive to wait for eligibility to adopt. As a back-of-the-envelope calculation, a state with the maximum cutoff age of 12 would have seen an additional 292 children adopted by their foster parent between 2000 and 2006 if they instead had a cutoff of 2 (2.4294 x 120 months of age)—or 42 adoptions per year. Assuming that these adopted children had a median age of seven, the state would save $5,321 in present discounted value subsidy costs per child over the child's life.[36] Thus, the state would have eliminated $1,553,732 in present discounted value from the child welfare budget by allowing these parents to receive adoption subsidies. This number is likely an underestimate, as it does not account for the indirect costs associated with foster care placements (Barth 1997, Barth, et al. 2006). According to a report prepared for the Department of Health and Human Services, "some of the undocumented costs are the worker's time in assessing, arranging, and monitoring the placement; developing foster homes; and court services" (Westat et al., 2002). In New Jersey in 2000, 73 percent of average per-child costs for children in the care of a foster parent were for subsidy payments; these

[36] That is, a child adopted at seven instead of twelve would have sixty months (5 years x 12) of payments that are $100 lower per month. $5,321 is the present discounted value of the savings, using a discount rate of 5 percent.

additional costs make up the remainder.[37] If our example state had a similar cost structure, allowing these parents to receive adoption subsidies would have reduced costs by over $2.1 million.[38] For comparison, the average state spending on foster care and adoption payments in state fiscal year 2006 was $68.8 million (DeVooght et al., 2008).

VII. Conclusion

Since the introduction of the AACWA in 1980, federal and state spending on adoption subsidies has increased dramatically, due largely to the rise in the number of eligible children. As a policy matter, it is important to know whether this large government program is having any impact on children in child welfare services. In this paper, I evaluate the success of the adoption subsidy program in light of its goals, and consider the impact of subsidy eligibility on the number of adoptions (in total and by characteristics of the child and adoptive family) and on time spent in foster care.

I use a differences-in-differences-in-differences framework that exploits variation in states' definition of special needs by age and in states' rates of subsidy receipt to identify the effect of adoption subsidies on these outcomes. In the preferred specification, being eligible for

[37] According to the Westat et al. report (2002), the average annual cost of a foster care placement in New Jersey in 2000 was $8,139. In the AFCARS Foster Care data, the average monthly foster care payment for children in foster homes in New Jersey was $494, or $5,928 annually.

[38] Hansen (2007b) performs a cost-benefit analysis, in which she includes estimates of the benefits of adoption from previous epidemiological and clinical research. She estimates that each additional dollar spent on the adoption of a child from foster care produces about three dollars in benefits.

special needs designation increases rates of subsidy receipt by 5.03 percentage points. Reduced form estimates of the effect of subsidy eligibility on the number of adoptions in a state/age-in-months cell show that eligibility is associated with an 11 percent increase in the number of adoptions in the cell. This increase in adoptions is driven by adoptions to foster parents. But results from a hazard model of discharge from foster care show no effect of eligibility on the hazard of discharge for the full sample, suggesting that few children are moved from permanent foster care to adoption by the policy. However, the hazard of discharge is increased for adopted children, indicating that adoptions are finalized more quickly when the child is subsidy eligible.

These findings indicate that adoptive parents—in particular foster parents who plan to adopt—do respond to the financial incentives of the adoption subsidy program. Lowering eligibility requirements would help the program achieve its goals of promoting adoption and reducing time spent in foster care. The fact that adoption subsidy eligibility rules affect the timing of permanent adoptions by foster parents also has important financial implications—removing the disincentive for foster parents to adopt could generate savings from reduced subsidies and other costs of keeping a child in foster care.

However, it is important to keep in mind that the goal is not simply to promote adoption, but to do so when it is in the child's best interest. The extent to which the program has improved the well-being of these at-risk children depends critically on one's assumptions about the effects of various placements. Much of the research cited in this paper finds that adoption is a desirable outcome for foster children (particularly when compared with long-term stays in foster care). But as Triseliotis (2002) and Berger (2009) point out, the ability of previous researchers to identify a causal effect has been limited by small sample sizes, a lack of data on long-term outcomes for adopted children, and concerns over the endogeneity of placements. Thus, future

research that resolves these issues would shed light on how the subsidy program has affected child well-being.

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Figure 1a: Title IV-E Adoption Assistance, 1981-2007, Average Number of Recipients per Month (Thousands)

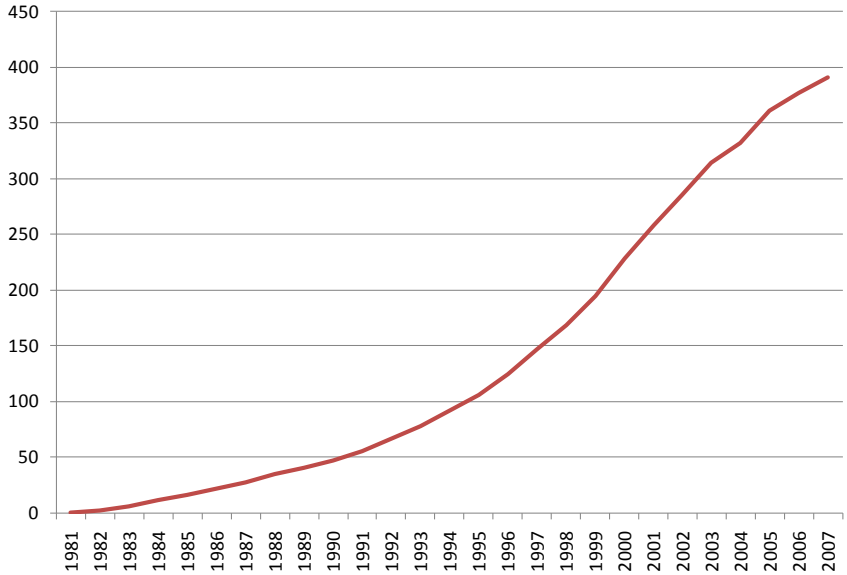
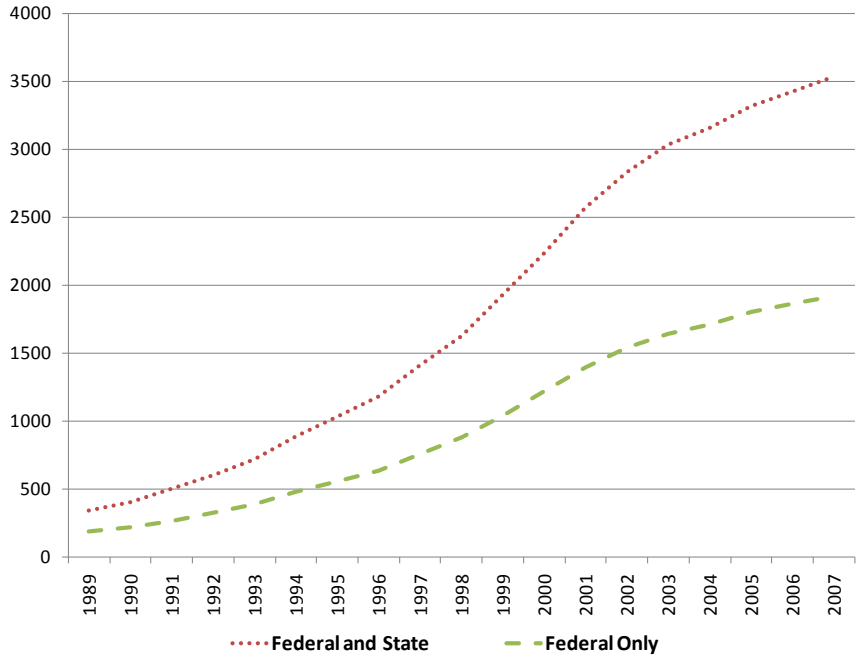
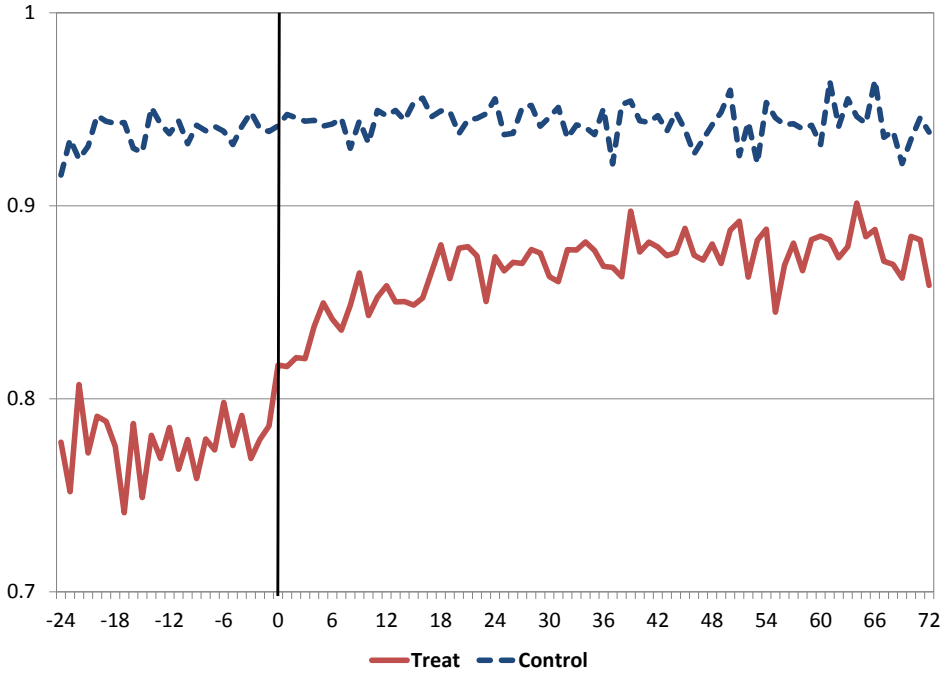


Figure 1b: Title IV-E Adoption Assistance, Annual Expenditures, 1989-2007 (2007 Dollars in Millions)



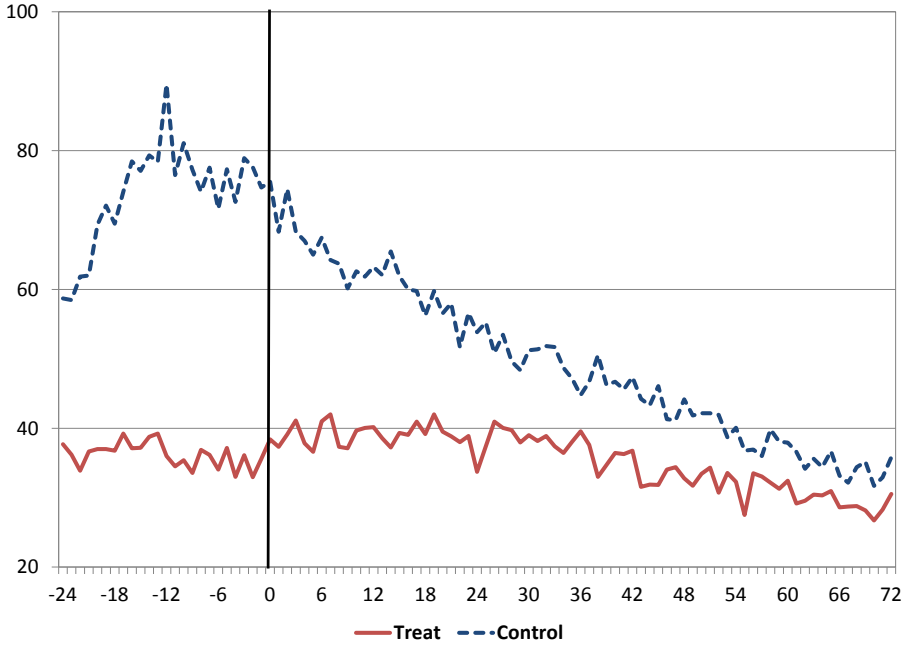
Source: U.S. House of Representatives, Committee on Ways and Means, Green Book, 1994, 2008.

Figure 2: Fraction Receiving a Monthly Subsidy Relative to State Cutoff



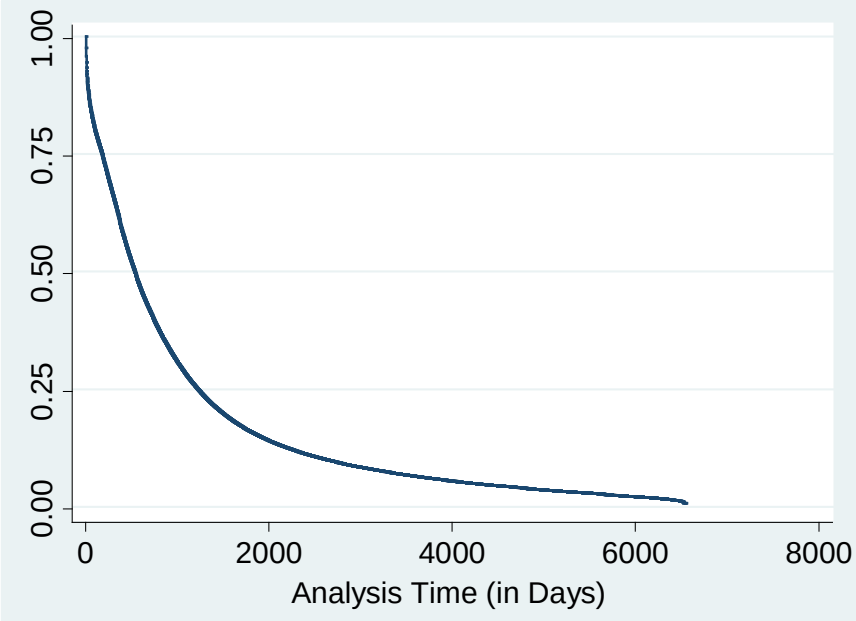
Source: Adoption Files, 2000-2006. The horizontal axis is age in months, relative to state cutoff; observations are at the month level. Treatment states have a rate of subsidy receipt below 90 percent for children in the two-year window below the state's minimum age cutoff. See Table 3 for classification of treatment and control states. Children over 18 or with more than 10 years since termination of parental rights are excluded.

Figure 3: Number of Adoptions Relative to State Cutoff



Source: Adoption Files, 2000-2006. The horizontal axis is age in months, relative to state cutoff; observations are at the month level. Treatment states have a rate of subsidy receipt below 90 percent for children in the two-year window below the state's minimum age cutoff. See Table 3 for classification of treatment and control states. In states in which the age cutoff varies by race, some cells cannot cleanly be assigned as treatment or control; these states are omitted from the figure (7 percent of cells). Children over 18 or with more than 10 years since termination of parental rights are excluded.

Figure 4: Kaplan-Meier Survival Estimate: Discharge from Foster Care



Source: AFCARS Foster Care Files, 2000-2006. Each observation is a spell in foster care; time to discharge is defined as the number of days between the latest removal from the home and the date of discharge. The sample is restricted to children under 18 with fewer than 10 years since termination of parental rights. Children in states with incomplete reporting or that do not have a strict cutoff for special needs designation by age are omitted, as are children who were emancipated, transferred, or who ran away or died while in foster care. There are 2,008,059 observations in the figure.

Table 1: Characteristics of Children in Foster Care, AFCARS 2000-2006

	Full Sample		Discharge Reason: Adoption	
Independent Variable	Mean	Std. Dev.	Mean	Std. Dev.
Age	9.11	5.53	6.78	4.23
Male	0.5157	0.4998	0.5053	0.5000
Medical Condition	0.1988	0.3991	0.2814	0.4497
Black	0.3255	0.4686	0.3648	0.4814
Hispanic	0.1629	0.3693	0.1597	0.3663
Removed for Abuse	0.2171	0.4123	0.1936	0.3951
Removed for Neglect	0.5164	0.4997	0.6278	0.4834
Receiving Foster Care Subsidy	0.5614	0.4962	0.5945	0.4910
Amount of Foster Care Payment	$1,239.13	$1,530.17	$670.28	$568.65
Eligible for Special Needs Status by Age	0.6750	0.4684	0.5923	0.4914
Observations	2,524,861		339,443	

Source: AFCARS Foster Care Files, 2000-2006. The full sample is restricted to children under 18.

Table 2: Characteristics of Adopted Children, by Subsidy Receipt, AFCARS 2000-2006

	Without Subsidy		With Subsidy	
Independent Variable	Mean	Std. Dev.	Mean	Std. Dev.
Monthly Subsidy Amount	-	-	$571.95	$418.98
Qualifies for Special Needs Status by Age	0.4294	0.4950	0.5653	0.4957
Designated Special Needs	0.5497	0.4975	0.8752	0.3305
Age at Adoption	5.68	4.26	6.82	4.17
Age Parental Rights Terminated	5.29	3.91	6.32	3.92
Male	0.4976	0.5000	0.5037	0.5000
Medical Condition	0.2197	0.4140	0.2871	0.4524
Black	0.3208	0.4668	0.3797	0.4853
Hispanic	0.1408	0.3478	0.1638	0.3701
Time to Finalization, in Days	417.98	411.28	470.59	437.55
Adopted By:				
Foster Parent	0.5526	0.4972	0.6053	0.4888
Older Relative	0.1285	0.3346	0.1776	0.3822
Non-Relative	0.2095	0.4070	0.1520	0.3590
Observations	41,667		274,188	

Source: AFCARS Adoption Files, 2000-2006. The full sample is restricted to children under 18 who were adopted from the public welfare agency. An older relative is defined as a relative who is at least 35 years older than the child. Step-parents and other relatives are an omitted category. All differences in means between the two samples are statistically significant at the 5 percent level.

Table 3: State Cutoffs for Special Needs Designation by Age

Pre-Cutoff Subsidy Rate <= 90% (Treatment)						Pre-Cutoff Subsidy Rate > 90% (Control)		
State	Minimum Age for Special Needs Designation	Pre-Cutoff Subsidy Rate for Less Needy Children	State	Minimum Age for Special Needs Designation	Pre-Cutoff Subsidy Rate for Less Needy Children	State	Minimum Age for Special Needs Designation	Pre-Cutoff Subsidy Rate for Less Needy Children
AL	2/8	42.4	MI	3	52.9	AK	8	94.6
AZ	6	75.2	MS	6	46.8	CA	3	91.0
AS	2/9	65.2	NE	8	84.2	ME	5	98.1
CO	7	73.5	NH	6	7.8	MD	6	96.3
CT	2/8	55.6	NJ	2/10	10.1	MO	5	99.2
DE	8	29.4	NM	5	10.7	MT	6	90.6
DC	2	45.0	PA	5	78.2	NV	6	94.7
FL	8	59.4	SC	6/10	83.3	ND	7	95.5
GA	1/8	4.8	TN	5/9	52.8	OH	6	95.5
IL	1	56.0	TX	2/6	73.7	OK	8	92.7
IN	2	18.1	UT	5	85.2	OR	8	95.8
IA	2/8	68.1	VA	6	78.5	RI	12	97.9
KS	12	74.1	WA	6	82.7	WI	10	100.0
LA	0/12	89.3	WY	6	87.5			

Age minimums are from the North American Council on Adoptable Children. For states in which the minimum age varies by race, ages are given as nonwhites/whites. Ten states are omitted due to incomplete reporting or because they do not have a strict age cutoff. Treatment states have a rate of subsidy receipt below 90 percent for children in the two-year window below the state's minimum age cutoff with no special needs by race, sibling group, or medical condition.

Table 4: Effect of Eligibility for Special Needs by Age Designation on Subsidy Receipt

	[1]	[2]	[3]	[4]
Panel A: Full Sample				
Eligible * Treat	0.1435**	0.1353**	0.1120**	0.0503**
	(0.0300)	(0.0301)	(0.0229)	(0.0132)
Eligible	-0.0353*	-0.0280	-0.0390**	0.0003
	(0.0201)	(0.0212)	(0.0144)	(0.0067)
Fraction Receiving Subsidy	0.8661	0.8776	0.8776	0.8776
Observations	272,611	258,849	258,849	258,849
Panel B: Whites				
Eligible * Treat	0.1497**	0.1436**	0.1272**	0.0488**
	(0.0355)	(0.0343)	(0.0241)	(0.0160)
Eligible	-0.0421*	-0.0335	-0.0516**	-0.0089
	(0.0246)	(0.0282)	(0.0170)	(0.0087)
Fraction Receiving Subsidy	0.8512	0.8619	0.8619	0.8619
Observations	149,966	141,834	141,834	141,834
Panel C: White, No Med, No Siblings				
Eligible * Treat	0.2203**	0.2166**	0.2114**	0.1129**
	(0.0521)	(0.0490)	(0.0379)	(0.0256)
Eligible	-0.0281	-0.0449	-0.0658**	-0.0052
	(0.0356)	(0.0355)	(0.0208)	(0.0124)
Fraction Receiving Subsidy	0.8167	0.8335	0.8335	0.8335
Observations	64,535	60,067	60,067	60,067
Panel D: Nonwhites				
Eligible * Treat	0.1183**	0.1260**	0.0964**	0.0486**
	(0.0358)	(0.0359)	(0.0328)	(0.0186)
Eligible	-0.0321*	-0.0196	-0.0254**	0.0106
	(0.0169)	(0.0153)	(0.0105)	(0.0073)
Fraction Receiving Subsidy	0.8873	0.8992	0.8992	0.8992
Observations	111,623	106,592	106,592	106,592
Demographic Controls		X	X	X
State Fixed Effects			X	X
State-Specific Trends				X

**, * denote significance at the 5 percent and 10 percent levels. Source: AFCARS Adoption Files, 2000-2006. Each column is a separate OLS regression; all regressions include age dummies and year fixed effects. Demographic controls include indicators for sex, race, and the presence of a medical condition. State-specific trends are cubic. See Table 3 for definition of treatment group. Standard errors are clustered at the state level and are in parentheses.

Table 5: Effect of Eligibility for Special Needs by Age Designation on Federal Funding and Subsidy Amount

	Sample			
	All	White	White, No Med, No Siblings	Nonwhite
Dependent Variable =1 if Received				
Eligible * Treat	0.0598**	0.0765**	0.1620**	0.0361*
	(0.0171)	(0.0179)	(0.0341)	(0.0206)
Eligible	-0.0081	-0.0200	-0.0322*	0.0022
	(0.0088)	(0.0126)	(0.0173)	(0.0137)
Fraction Receiving Federal Funds	0.7181	0.6764	0.6535	0.7750
Dependent Variable is Subsidy Amount ($)				
Eligible * Treat	16.55	22.52*	55.37**	7.87
	(10.88)	(13.13)	(18.03)	(9.41)
Eligible	-4.41	-10.23	-16.07	0.36
	(8.36)	(11.20)	(12.06)	(6.94)
Mean Subsdiy Amount	489.64	479.13	459.59	500.79
	258,849	141,821	60,067	106,592

**, * denote significance at the 5 percent and 10 percent levels. Source: AFCARS Adoption Files, 2000-2006. Each column is a separate OLS regression that includes include age dummies, state and year fixed effects, state-specific cubic trends, and demographic controls (indicators for sex, race, and the presence of a medical condition). See Table 3 for definition of treatment group. Standard errors are clustered at the state level and are in parentheses.

Table 6: Effect of Subsidy Eligibility on Number of Adoptions in a Month

	Sample			
	All	White	White, No Med, No Siblings	Nonwhite
Eligible * Treat	3.7180**	1.8278**	1.2229**	0.6847
	(1.6224)	(0.7673)	(0.5630)	(0.5627)
Eligible	-0.9642	-0.4907	0.0135	-0.1184
	(1.2501)	(0.7071)	(0.4175)	(0.3468)
Average Number Adoptions	32.87	18.25	7.92	6.16
[Standard Deviation]	[57.69]	[34.29]	[19.51]	13.81
Median Number Adoptions	15	9	3	2

**, * denote significance at the 5 percent and 10 percent levels. Source: AFCARS Adoption Files, 2000-2006. Data are collapsed to cells defined by state and child's age at adoption in months. Values are average marginal effects from Poisson regression models, where the dependent variable is the number of adoptions in the cell. Regressions include state fixed effects, state-specific cubic age trends, and dummies for age in years. Subsidy See Table 3 for definition of treatment group. Standard errors are clustered at the state level and are in parentheses.

Table 7: Effect of Subsidy Eligibility on Number of Adoptions in a Month, by Characteristics of Adoptive Family and Child

	Total # Adopted	# Adopted by:			# With Medical Condition	# Nonwhite
		Older Relative	Foster Parent	Non-Relative		
Eligible * Treat	3.1443**	0.2576	2.4294**	0.4626	0.9696	1.4165
	(1.3958)	(0.2811)	(0.9724)	(0.4243)	(0.8588)	(0.9341)
Eligible	-0.8242	-0.1875	-0.6240	-0.0754	-0.7619*	-0.1165
	(0.9972)	(0.2379)	(0.5263)	(0.2617)	(0.4469)	(0.5573)
Dependent Variable Mean	31.17	5.99	16.60	6.12	8.56	11.55
[Standard Deviation]	[56.62]	[18.01]	[30.88]	[9.40]	[14.06]	[20.65]
Dependent Variable Median	15	1	8	3	4	5

**, * denote significance at the 5 percent and 10 percent levels. Source: AFCARS Adoption Files, 2000-2006. Data are collapsed to cells defined by state and child's age at adoption in months. Values are average marginal effects from Poisson regression models, where the dependent variable is the number of adoptions in the cell with the indicated characteristic. An older relative is defined as a relative who is at least 35 years older than the child. Step-parents and other relatives are an omitted category. Regressions include state fixed effects, state-specific cubic age trends, and dummies for age in years. Illinois is omitted because of a state policy that requires all adoptive parents to become foster parents before finalization. See Table 3 for definition of treatment group. Standard errors are clustered at the state level and are in parentheses.

Table 8: Hazard Model Estimates of the Effect of Subsidy Eligibility on Probability of Discharge from Foster Care

Independent Variable	All	Discharged to: Adoptive Home	Reunified with Parents	Relative/ Guardianship
Panel A: Full Sample				
Eligible * Treat	0.0411	0.0784	-0.0251	0.0362
	(0.0391)	(0.0502)	(0.0328)	(0.0441)
Eligible	-0.0248	-0.0112	0.0073	-0.0164
	(0.0241)	(0.0303)	(0.0152)	(0.0391)
Mean Days in Foster Care	595.60	1,203.27	322.59	479.28
[Standard Deviation]	[766.52]	[759.34]	[456.74]	[630.60]
Observations	1,913,488	270,736	797,694	223,463
Panel B: White				
Eligible * Treat	0.0228	0.0705**	-0.0119	0.0348
	(0.0268)	(0.0339)	(0.0276)	(0.0320)
Eligible	-0.0389	-0.0167	-0.0069	-0.0149
	(0.0241)	(0.0240)	(0.0163)	(0.0310)
Mean Days in Foster Care	504.14	1,068.15	291.54	400.91
[Standard Deviation]	[627.73]	[642.37]	[385.23]	[502.79]
Observations	1,081,484	147,222	480,785	123,373
Panel C: Nonwhites				
Eligible * Treat	-0.0297	0.0435	-0.1031**	0.0121
	(0.0489)	(0.0658)	(0.0297)	(0.0663)
Eligible	-0.0069	-0.0092	0.0176	-0.0027
	(0.0241)	(0.0528)	(0.0165)	(0.0556)
Mean Days in Foster Care	726.50	1,394.97	374.59	593.24
[Standard Deviation]	[918.46]	[865.03]	[554.16]	[732.29]
Observations	811,688	120,290	308,546	98,352

** denotes significance at the 5 percent level. Source: AFCARS Foster Care Files, 2000-2006. Results are coefficients from a hazard model with a Weibull distribution. Time to discharge is the number of days between the latest removal from the home and the date of discharge. Each column is a separate regression that includes age dummies, year dummies, state and year fixed effects, and demographic controls (indicators for sex, race, and the presence of a medical condition). See Table 3 for definition of treatment group. Standard errors are clustered at the state level and are in parentheses.

Appendix Table 9: Summary Statistics for Treatment and Control Samples

	Treated	Control
Median Cutoff Age	6	5
Mean Cutoff Age	5.54	5.18
Foster Care Data:		
Age	8.96	8.97
Male	0.5136	0.5167
Medical Condition	0.1734	0.2518
Black	0.3571	0.2935
Hispanic	0.1269	0.2390
Removed for Abuse	0.2326	0.2130
Removed for Neglect	0.5148	0.5214
Receiving Foster Care Subsidy	0.5287	0.5055
Subsidy Amount	$1,167.36	$1,219.43
Eligible for Special Needs by Age	0.6731	0.6909
Observations	1,281,632	838,221
Adoption Data:		
Receiving Adoption Subsidy	0.8200	0.9359
Subsidy Amount	$521.33	$652.89
Designated Special Needs by Age	0.2667	0.2461
Days to Adoption	459.71	465.21
Adopted by Older Relative	0.1196	0.2673
Adopted by Foster Parent	0.6168	0.5439
Observations	176,534	114,658

Source: AFCARS Adoption and Foster Care Files, 2000-2006. The full sample is restricted to children under 18 who were adopted from the public welfare agency, with fewer than 10 years since termination of parental rights. An older relative is defined as a relative who is at least 35 years older than the child. See Table 3 for classification of treatment and control states. With the exception of age, all differences in means between treatment and control groups are statistically significant at the 1 percent level.