Adoption Subsidy, Foster Care Payment, and Foster Care Adoption: A Two-stage Least Squares Approach

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Acknowledgement

I am extremely grateful to Professor Allan Collard-Wexler, my faculty advisor, and Professor Alison Hagy, my seminar instructor, who have guided my work through the semesters, provided me with insights that were not readily available, and reminded me of the importance of independent research projects.

Abstract

This paper examines the effect of the change in the magnitude of monthly governmental adoption subsidy on the adoption rate for foster children in foster family structures. In order to account for omitted variable bias attached to the amount of subsidy that a child receives, I construct an instrumental variable that takes advantage of the fact that each state has different policies on: (1) the base age from which a child is eligible for special needs; and (2) the amount of increased adoption subsidy that a child receives, on average, if he or she is eligible for special needs adoption. Using the data from the Adoption and Foster Care Analysis and Reporting System (AFCARS) during the years 2001 to 2012, I find that a dollar increase in the amount of adoption subsidy, holding the amount of foster care payment constant, is expected to increase a foster child's probability of adoption by 0.255%. Although the positive sign of the coefficient is intuitive, and although it is statistically significant at all levels, its magnitude is unrealistically high, suggesting that there may be a problem in the instrument itself or in the accuracy and selection of the data.

I. Introduction

Over the past century, increase in the diversity of cultural interactions and a gradual change in perceptions have allowed more non-traditional households to emerge in the United States. Among them are family units that consist of adoptive parents and their adopted children--the 2010 Census reveals that adopted children constitute approximately 1.5 million, or 2.4 percent, of all children in the United States (Kreider and Lofquist, 2010). The size of the adoption market is considered by some to be over $2 billion dollars (Riben, 2007). Despite the enormous size of the market, however, the literature in economics on the adoption market is surprisingly scarce, perhaps because various policies prohibit it from operating like an archetypal economic market. Legitimate ethical concerns about human trafficking require that the market for adoption disallow the price of adoption from being freely moving to clear the market. Consequently, the structure of the market has induced inefficiency, chiefly the disequilibrium in the foster care adoption market: there is a surplus of children waiting to be adopted in the market for adoption from foster care.

Evidently, a wide practice of adoption is beneficial to improving the welfare of the adopted children, who are expected to enjoy higher-quality care under a well-matched household than under a foster care center. Hansen (2006) suggests that the expense spent on the adoption of a child from foster care has a rate of return of thrice that value, which results from the government's savings from foster care, criminal justice, and special education, among others. Thus, many of the governmental adoption policies have strived to solve one facet from which the problem arises: prospective adoptive parents often must not only endure prohibitively long waiting periods but also bear significant monetary expenses both during and after the process of adopting a child. To partly address the monetary concern, several federal and state-funded adoption assistance programs subsidize prospective adoptive parents. By both lowering the cost associated with adopting a child and increasing the real wealth of the parents, the programs aim to increase the demand for children available for adoption.

Such federal and state-funded subsidy programs for adoption, which started with the Adoption Assistance and Child Welfare Act of 1980, are mainly targeted toward children who are classified as having "special needs" by the criteria set by each state. Though the definitions of children with special needs differ by the state, they generally encompass children with time-invariant (race, disability, and existence of sibling, among ohters) and variant (age) characteristics that make them unlikely to be adopted without financial assistance. Designating such group as the target is supported by many researchers who have concluded that children who are old, non-white, male, and with sibling are less likely than others to be adopted (Bernal et al., 2007 and Baccara et al., 2014). Currently, approximately 84.5% of children adopted from foster care are qualified as having special needs (AFCARS, 2012).

Adoption assistance from the Federal Government is practiced under the Federal Title IV-E Adoption Assistance Program, which provides heightened benefit for the parents who adopt children with special needs (Child Welfare, 2011). Specifically, for those parents, the government provides the maximum amount of tax credit that the program offers, which was $12,970 in 2013, and gives recurring monthly adoption assistance. Further, state-level adoption subsidy is given to parents of those children with special needs who are, for some reason, not qualified for Title IV-E Adoption Assistance

Program. These payments are intended to remedy the relative hardships that children with special needs face in finding a match.

A few papers have previously investigated whether such assistance programs actually increase the number of adoptions (Avery and Mont, 1992, Sedlak and Broadhurst, 1993, Dalberth, 2005, Hanse and Hansen, 2006, and Hansen, 2007). Because the comprehensiveness of the data required for such analysis is available only for adoptions involved with public agencies, almost all of these papers concentrate exclusively on adoption subsidy's effect on foster care adoption. Almost all of those papers find a positive and statistically significant relationship between subsidy receipt and adoption. However, the aforementioned papers do not distinguish between (1) adoption of foster child by the foster parent; and (2) adoption of the child in foster care by a previously unacquainted prospective parent.

In this paper, I attempt to estimate the effect of the change in adoption subsidy on the foster child's probability of adoption by his or her foster parents specifically. Making careful attention to that subgroup only is warranted because, unlike those who adopt previously unacquainted children in foster care, foster parents who adopt their foster children must forgo the foster care payments that the state used to provide before the adoption. In general, AACWA requires that the amount of adoption subsidy given to the parents not be larger than the amount of foster care payments. Thus, the cost of foster parents' adopting their foster children includes a reduction in the monthly subsidy that they receive. In this regard, only considering adoption subsidy would obscure the foster parents' true cost of adoption.

To the best of my knowledge, only one paper (Argys and Duncan, 2012) has performed an estimation that primarily focused on adoption by foster parents. In their paper, Argys and Duncan regress a child's probability of adoption against both the magnitude of adoption subsidy and the difference between adoption subsidy and foster care payment. However, Argys and Duncan's results are likely affected by omitted variable bias, as their results do not control for unobserved child characteristics that may cause the effect of subsidy to be biased. The direction of the bias is not clear: on one hand, among the unobserved child characteristics, factors such as defect in a child's emotional health will be positively correlated with the amount of subsidy that he or she receives and negatively correlated with probability of adoption, causing the result to be biased downwards; on the other hand, Buckles (2013) provides a scenario in which an aggressive case worker solicit higher subsidy of the child and facilitate efficient process of adoption, causing an upward bias of the coefficient.

The contribution of my paper to the literature thus takes the form of refining Argys and Duncan's estimation process by making it robust to the endogeneity problem using a two-stage least squared regression analysis. In the first stage before regressing the rate of adoption against adoption subsidy and foster care payment, I first predict the amount of adoption subsidy by regressing it against a set of variables, one of which is significantly correlated with the adoption subsidy but assumed to be not correlated with the unobserved child characteristics that are causing the endogeneity problem. That variable is the binary variable *treatment group*outcome group* in the differences-in-differences estimator proposed by Buckles (2013). Buckles designates the group of children belonging to states that give much higher amount of subsidy to children with special-needs as the treatment group, and children in those states that do not reward special-needs status as much as the control group. Then, the additional effect for children in the treatment group from being qualified for special needs, relative to the effect for those in the control group, is correlated with the amount of subsidy but uncorrelated with unobserved characteristics that are causing the endogeneity problem. Thus, the term seems to satisfy both the relevance and exclusion conditions necessary for acting as the instrumental variable. After calculating the predicted value of adoption subsidy, then, in the second stage I employ a regression analysis analogous to Argys and Duncan's to capture the effect of the change in adoption subsidy on the probability of adoption of a child, holding foster care payment constant.

I use the Adoption and Foster Care Analysis and Reporting System (henceforth AFCARS) data from 2001 to 2012. The data set is a compilation of individual-level information on (1) all children in foster care; (2) children who were adopted through a public agency, including all adoption of foster children by foster parents; and (3) children who were adopted through a private agency but under the auspices of public agency. Because all public agencies are mandated to report, this biannually published set of data is generally regarded as the most trustworthy source of information on individual-level foster care children, although the accuracy regarding the data's information about each child's amount of adoption subsidy and foster care payment is challenged by the Children's Bureau (AFCARS, 2012). Further, AFCARS data contain information on whether each child is qualified for the special-needs classification as well as on the amount of foster care payment and adoption subsidy that he or she receives (if applicable).

The two-stage least squares regression suggests that $1 increase in the amount of adoption subsidy, holding the amount of foster care payment constant, is associated with a 0.255% increase in a foster child's probability of adoption. The coefficient is significant at all levels and has an expected sign, but its implausibly high magnitude suggests that there may be a problem either in the assumptions made about the instrument itself or in the data-selecting method.

In section II, I further expound on the existing economics literature on the topic of adoption subsidy. Specifically, I take careful attention to the work of Argys and Duncan (2012), from which I borrow the variables used for the first-stage of my two-stage least squares regression analysis, and Buckles (2013), from which I borrow the specification for my first- and second-stage regression. In section III, I describe the theoretical framework that informs my estimation process. In section IV, I detail the AFCARS data set that I used, including its strengths, weaknesses, and the available and unavailable information about the foster care children that can be gathered from the data. In section V, I present my two-stage least squares estimation process. I end my paper with a concluding remark and suggestions for further avenues of research in Section VI.

II. Literature Review

Despite widespread practice of adoption and its importance in influencing the welfare of adopted individuals, there is a relative dearth of economics literature concerned with the topic. However, with an increasing availability of large collections of data on adoption, there has been a recent surge in the interest in adoption, especially on the adoption assistance program.

Although the Adoption Assistance and Child Welfare Act of 1980 (P.L. 96-272) marked the inception of state and governmental subsidy for adoption, a lack of proper data prevented economists from effectively investigating the effect of subsidy on adoption before 1995, when the Adoption and Foster Care Analysis and Reporting System (AFCARS) stabilized to the form it is today. Some works before 1995 do exist, however (Avery and Mont, 1992 and Sedlak and Broadhurst, 1993). For example, Avery and Mont (1992), who independently collected data from foster care centers in New York, find that adoption is positively correlated with probability of adoption of a child with mental disability. Though the scope of the data for the study may limit the representativeness of its result, it is nevertheless consistent with later papers that used national data.

Since then, many papers on the effect of adoption subsidy, such as Dalberth, 2005, Hanse and Hansen, 2006, Hansen, 2007, and Argys and Duncan, 2012, have employed AFCARS data to perform a cross-section multivariate regression on a child's probability of adoption and similarly found that eligibility for adoption subsidy is positively correlated with prospective adoptive parents' propensity to adopt a child. Hansen and Hansen (2006), for instance, use 1996 AFCARS report and find that states with more generous policies on adoption subsidy have significantly higher number of adoptions per 100,000 people. They further deem that the adoption subsidy policy is the most powerful predictor of the number of adoptions from foster care among those variables that are under the direct control of policymakers.

However, to the best of my knowledge, the only paper that considers a child's foster care payments on top of adoption subsidy as the primary focus is Argys and

Duncan (2012), who acknowledge that the difference between foster care payment and adoption subsidy may be the primary determinant in a foster care parents' decision to adopt the child whom they are currently taking care of. Indeed, Argys and Duncan regress a child's probability of adoption against both the difference (adoption subsidy subtracted by foster care payment) and the magnitude of the adoption subsidy receipt itself and find that both coefficients are positive and significant. In particular, they find that, holding foster care payment constant, increasing the adoption subsidy by $100 is correlated with a 4.6 percentage point increase in the rate of adoption for boys and a 5.9 percentage point increase for girls. Increasing *both* the foster care payment and adoption subsidy by $100 is still positively correlated with the rate of adoption for both sexes, with a 3.7 percentage point increase for boys and 6.2 percentage point increase for girls.

As mentioned previously, Argys and Duncan (2012)'s paper uses an estimation process that likely suffers from omitted variable bias that may skew the effect of adoption subsidy. Specifically, there may be unobserved characteristics of a child (or a factor related to the child) that may be positively or negatively correlated with the eligibility of adoption subsidy and positively or negatively correlated with his or her probability of adoption. To address this problem, I use a two-stage least squares estimation process, identifying an instrument not correlated with the unobserved characteristics in order to obtain the predicted values of adoption subsidy.

The instrument that I use is the variable in the differences-in-differences estimation proposed by Buckles (2013) that captures the differential effect on the treatment group over time relative to the control group. Her diff-in-diff estimation takes advantage of two aspects of the subsidy program: (1) each state has different qualifications for the minimum age that a child must be in order to be qualified as having "special needs" by the criterion of age alone; and (2) the rate of increase in the amount of subsidy that a child receives from being eligible for special needs classification differs among children in different states. To the extent that the variation in the minimum age requirements, which range from 0 to 12 years old, does not reflect an environment unique to each state, it imbues a randomness to the data that separates the effect of age on the probability of adoption from the effect of eligibility of special needs on the probability. Buckles classifies children who reside in states that provide a large increase in the amount of subsidy from being eligible for special needs as part of the treatment group, whereas children of those states whose eligibility does not significantly affect the amount of subsidy are part of the control group. The time component of the diff-in-diff estimation is related to the child's special needs status: children belong to the outcome group when they become eligible for special needs due to their age. The result of Buckles' diff-in-diff estimation of the effect of eligibility of subsidy on the number of adoptions shows that the eligibility of subsidy causes an 11 percent increase in the number of adoptions in the cell. A direct comparison between Buckles' and Hansen and Hansen's results cannot be made because Buckles looks at the effect of a child's being eligible for subsidy, whereas Hansen looks at that of the magnitude of the subsidy receipt. In my paper, I repurpose the term that captures the differential effect of the treatment group over time in Buckles' diff-in-diff estimation to use it instead as the instrument for my two-stage least squares estimation.

Finally, many other papers focus on different aspects of adoption. Some estimate the demand for and supply of adoption (Bernal et al., 2007 and Baccara et al., 2014), while others have estimated the value of adoption (Barth, 1997 and Hansen, 2006). Although they do not have a direct bearing on the topic of my paper, they do help shed light on prospective adoptive parents' bias in terms of race, gender, and age that may partially explain the surplus of children available for adoption in the adoption market. Moreover, some papers also reveal prospective adoptive parents' monetary concerns of adopting a child. For example, in identifying the determinants of demand for adoption, Bernal et al. (2007) find that a prospective adoptive parent's demand for adoption is not significantly affected by the parent's income, whereas other factors such as marital status, religious affiliation, and sterility are significantly correlated with adoption. Such finding indicates that the income effect created by adoption subsidy may not significantly increase a prospective parent's propensity to adopt, contrary to the conclusions reached by other subsidy-specific papers. Evidently, this paper by itself is inadequate for investigating adoption subsidy, since it does not take into account the substitution effect that prospective adoptive parents may face from the increase in adoption subsidy (relative to the amount of foster care payment).

Papers on the value of adoption are also helpful in that they can put my result in a monetary perspective. Hansen (2006), for example, evaluates the net present value of adoption using clinical and epidemiological evidence. She finds out that the net present value of adoption is $375,000 for early adoption (speedy adoption of a child of age 3), $302,000 for late adoption (speedy adoption of a child of age 8), and $281,000 for delayed adoption (adoption of a child put into foster at age 3 but is not adopted until age 8). If Hansen's estimated NPV is close to the actual value, then an 11% increase in the number of adoptions from foster care resulted by adoption subsidy, as estimated by

Beckles (2013), may indicate that the benefit of adoption subsidy indeed outweighs its cost and thus that the magnitude of subsidy receipt should be increased.

III. Theoretical Framework

In this section, I first explain the general economic background that motivates the use of adoption subsidies for children with special needs. To do so, I model the market for special needs children and the market for children without special needs separately to illustrate the disequilibrium that the adoption subsidy aims to address as well as the intended effect of the subsidy. Finally, I look at the demand-side framework specifically. In particular, I discuss the prospective adoptive parent's decision framework in choosing whether to adopt their foster children with respect to both the magnitude of the adoption subsidy and that of the foster care payment. In the end, I show that the economic theories predict that (1) increasing adoption subsidy while holding the amount of foster care payment constant; or (2) both increasing adoption subsidy and foster care payment by the same amount will increase a child's probability of adoption if adoption is a normal good.

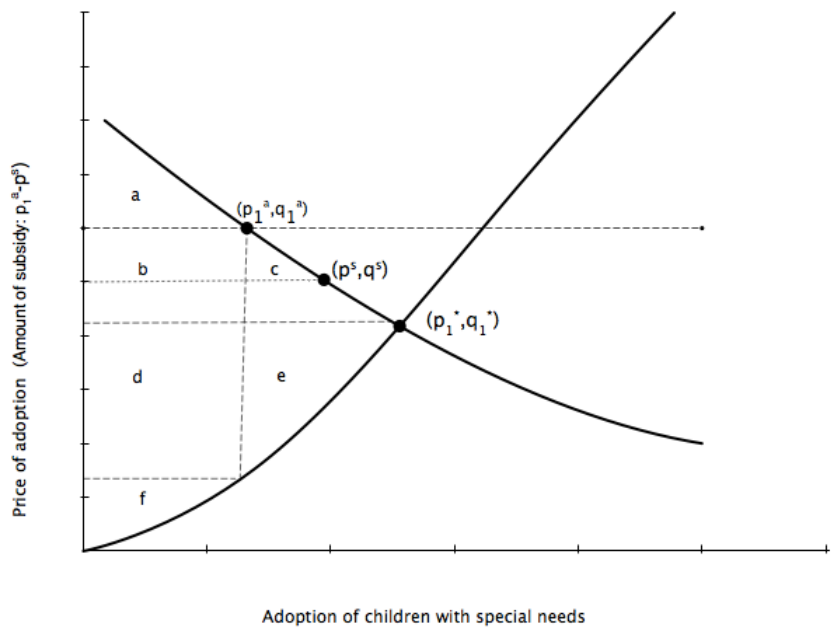
At its most rudimentary, an economic analysis of adoption treats the practice of adoption as an instance of transaction within an adoption market. In this market, the demand consists of the prospective adoptive parents, and the supply can be said to consist of either the birth mothers of the children or the agencies themselves that facilitate the adoption.

As early as 1978, economists Landes and Posner (1978) recommended an abolishment of such policies and a practice of attaching monetary price to parental rights in order to promote equilibrium in the market. In the same vein, recently Blackstone et al.

(2008) suggested a market segmentation approach based on the child characteristics that lead to price differentiation among the different segments. Evidently, attaching price to the parental rights of children available for adoption will be impossible (and likely undesirable). However, the government nonetheless differentiates price among children with different characteristics by providing different amount of subsidy receipts among different groups. Subsidizing children with special needs effectively makes the cost of adopting children who are non-white, old, and have siblings smaller than adopting their counterparts. Further, the upfront cost of adopting children through public agency (through which most special needs children are adopted) is significantly smaller than that of adopting children through private agency due to lower facilitation and consultation fee. Thus, the cost of adopting children with special needs is lower than that of adopting their counterpart.

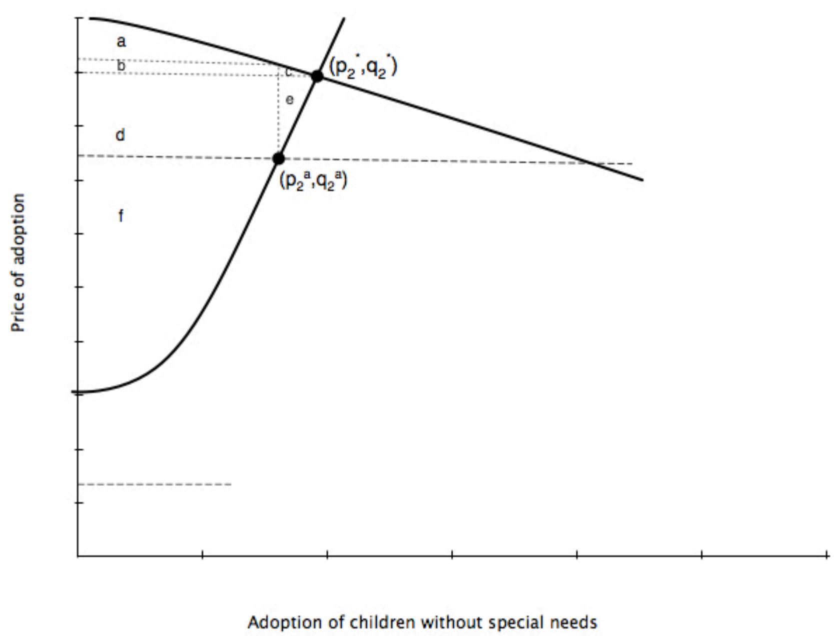
A rough sketch of the adoption market that takes account for these aforementioned points is illustrated in Figure 1 and 2. Figure 1 illustrates the market for children with special needs, and Figure 2 illustrates the market for children without special needs. The aggregate demand for children without special needs is higher than that for those with special needs. The market clearing point for each graph, (p_1^*, q_1^*) and (p_2^*, q_2^*) respectively, represents the desirable point at which there is no child that is available for adoption. Because monetary price cannot be attached to adoption, however, the actual points become (p_1^a, q_1^a) and (p_2^a, q_2^a), in which p_2^a is higher than p_1^a because the cost of adoption is higher if done through a private agency rather than through a public agency. In this case, the dead weight loss will range from (c+e) to (b+c+d+e) for both markets, in which (d+e) in the market for children without special needs includes the increased waiting time that the prospective adoptive parent must bear.

Figure 1: Adoption Market for Children with Special Needs and the Effect of Adoption Subsidy



p_1^* is the market-clearing price; p_1^a is the actual price before adoption subsidy; and p^s is the price after subsidy. Thus, the amount of subsidy is p^s subtracted by p_1^a.

Figure 2: Adoption Market for Children Without Special Needs



p_2^* is the market-clearing price, and p_2^a is the actual price.

With the inclusion of adoption assistance for children with special needs, the price of adoption for special needs children falls, and the resulting point becomes (p^s, q^s) in the Figure 1. p^s is still higher than p_1^* because a look at the current adoption market clearly indicates that the amount of adoption subsidy given to children with special needs is not enough to clear the market. Even with the subsidy, there were 101,666 children from foster care available for adoption in 2012 fiscal year (AFCARS Report, 2012). On the other hand, there is a consensus that the private agency market is experiencing a shortage of children available for adoption, as the number of children available for adoption demanded by the prospective adoptive parents exceeds the number supplied (Bernal et al.. 2007). Thus, a higher degree of price differentiation through a greater subsidy toward children with special needs is required for the price to fall to p_1^* and for the market to clear.

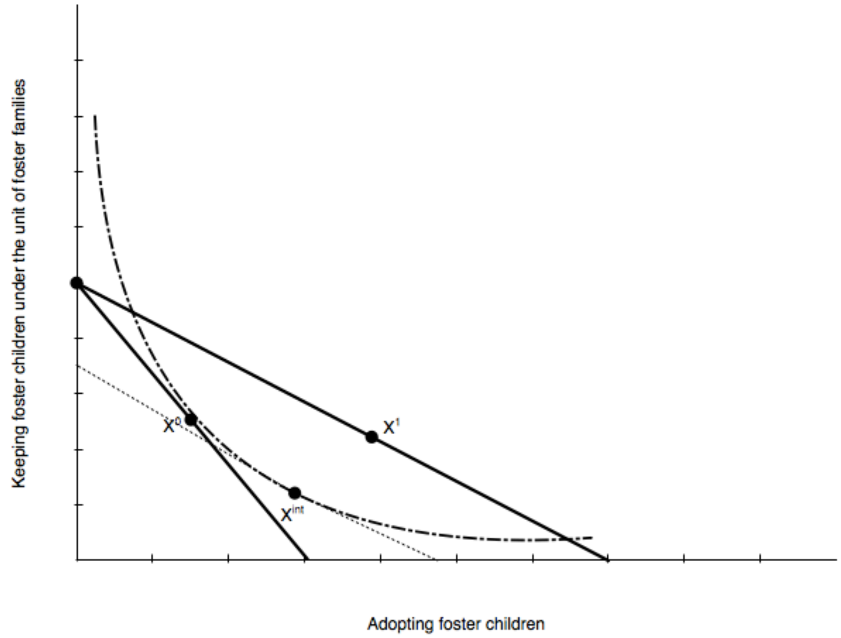
Though the graphs above give a rough sense of the adoption markets for children with special needs and without special needs when the two markets are viewed separately, the main shortcoming of these illustrations is that they do not account for the interactions between the two markets that are expected to arise. For example, if the monthly adoption subsidy is given to adoptive parents of children with special needs, then, intuitively, the demand should fall for children available for adoption not qualified for special needs. However, such interactions between the two markets are not illustrated in the graphs presented above.

Now I turn the scope specifically to the demand for adoption of foster children with special needs by their foster parents, which is the topic of my research. Figure 1 suggests that being eligible for the adoption subsidy for foster parents would increase the quantity of children adopted from q_1^a to q^s. My research's aim is analogous to estimating the magnitude of the difference between the two points when the demanders are the foster parents[1]. Economic theory informs that this would be determined by the relationship between foster care payment and adoption subsidy.

Figure 3 illustrates the community indifference curve and the collective budget constraint that arise if we treat the group of foster parents as a whole entity. The horizontal axis is the number of children who are adopted, while the vertical axis is the number of children who are still under the units of foster families. Suppose that, before the change in the amount of subsidy, the cost of adopting a child was p_x^0 and the cost of keeping him or her as a foster child was p_y^0, and that the parents opted to choose bundle x^0.

Figure 3: Income and substitution effect following adoption subsidy

[1] In fact, my research looks at the effect of the change in the quantity of adoption subsidy,



X^0 is the initial bundle chosen before the introduction of adoption subsidy, and X^1 is the bundle chosen with adoption subsidy. Movement from X^0 to X^{int} is a pure substitution effect, whereas that from X^{int} to X^1 is a pure income effect. This graph illustrates an example case, in which the practice of adoption is a normal good and adoption is relatively substitutable with keeping the foster child under the unit of foster family.

When the amount of adoption subsidies increases while foster care payment stays the same, the new cost of adoption, p_x^1, is lower than p_x^0, and so the monetary constraint rotates outwards with respect to the vertical intercept. The bundle that will be chosen after the increase in subsidy depends on both the income effect and the substitution effect. The degree of substitutability between adopting a child and keeping him or her as a foster child is unclear. On the one hand, adopting a child entails a massive responsibility on the parents, both legally and psychologically. In this regard, the substitutability between the two options may be small. On the other hand, the practical difference between raising a foster child and raising an adopted child may be not significant in most instances. In that perspective, the degree of substitutability may be big since foster parents who have the intention to adopt their foster children may nevertheless hold off the actual process of adoption if raising a foster child is cheaper than raising an adopted child. Illustrated in Figure 3 is an example of a final bundle x^1, when adoption of a foster child is a normal good and the degree of substitutability between adopting a child and keeping him or her as a foster child is relatively high.

In the end, in my estimation process, looking at how an increase in adoption subsidy affects the probability of adoption while holding foster care payment constant will reveal the magnitude of change from x^0 to x^1. Similarly, looking at how increases in both adoption subsidy and foster care payment by an equal amount affect the probability of adoption will reveal the income effect of adoption[2]. Economic theory detailed above suggests that increasing adoption subsidy holding constant foster care payment should increase the probability that a child is adopted, given that adoption is not a giffen good; and that increasing adoption subsidy should also increase the probability, given that adoption is not an inferior good.

IV. Data

This paper uses data published by The Adoption and Foster Care Analysis and Reporting System (AFCARS) from 2001 to 2012 regarding children in foster care and adoptions of children from the foster care system. The AFCARS collects individual-level reports on all children in foster care, children adopted with title IV-E agency facilitation, and children adopted through private agencies but under the auspices of public child welfare agency. Children in foster care during at least some time of the reporting period

[2] However, increasing the absolute amount of foster care payment and adoption subsidy by the same amount will not be a pure income effect, because pure income effect requires that the *ratio* between the two goods stay the same.

are recorded in the Foster Care File, while those adopted from foster care or any other types of public agency are recorded in the Adoption File. Thus, for example, a child who was adopted in 2008 from foster care would be recorded in both the 2008 Foster Care File and 2008 Adoption File. The states are also encouraged, but not mandated, to report information on adoptions by private agencies not under contract with public child welfare agency. Any state and tribal title IV-E (foster care) agency is currently required to submit its data to avoid a penalty. It has been published annually from 1995 up to this date, but it is generally regarded that AFCARS data are the most reliable from 1998, when the penalty has started to be imposed to the agencies that did not report to the system. For the 2013 fiscal year, the total number of adoptions held with public agency involvement was 52,039 and that of children waiting for adoption 101,666 after any missing data were removed (AFCARS, 2012).

The report published by the system includes demographic information on the adopted children and those waiting to be adopted, such as their age, race, sex, and disability (if any), and it records their months in foster care, the state in which they reside, and relationship with their adoptive parents (if applicable). It also contains basic information on the foster and adoptive parents as well as the birth mothers, such as their age, race, marital status, and family structure. For adopted children, the data set contains information on the date at which the adoption was finalized and when the parental rights were terminated. Most importantly, it contains, among others, individual-level information on the amount of foster care payment that foster parent(s) in a foster family unit receives; whether an adopted child is qualified for having special needs; and the amount of monthly subsidy that the child receives, if applicable. Thus, the AFCARS data set provides a useful set of variables for my research topic.

The AFCARS data are usually deemed as superior to all other sources of data because they deal with the whole population of foster care centers and because foster care centers are obligated to report to the system. Consequently, the data set is reasonably safe from self-selection bias. The regularity with which the report is published is also a significant advantage over other reports. However, other sources of data exist. Bernal et al. (2007), for example, looked at the National Survey of Family Growth (NSFG) when analyzing the prospective adoptive parents' determinants of demand for adoption. The NSFG, conducted by the National Center for Health Statistics, is compiled by surveying between 7,600 and 11,000 nationally representative, randomly selected women. Compared with the AFACRS data set, the NSFG contains more specific details on prospective adoptive female parents, such as their marital information, reproductive health, and familial history, and thus is particularly useful for investigating the determinants of demand for adoption. However, the NSFG has been conducted only in 1973, 1976, 1982, 1988, 1995, and 2002. Moreover, it is not appropriate for my research primarily because the number of observations for foster parents is too small. Bernal et al. also employed the Survey of Income and Program Participation (SIPP) conducted by the US Census Bureau, which is a more representative survey than NSFG in that it provides information on all types of people rather than just female. Moreover, it shows whether a parent's child is a biological child, a foster child, or an adopted child and is fairly done at a regular interval, having 13 panel data from 1984 to 2004. However, it is not used in my research because it does not contain information on the foster care children who have not yet been adopted, including their special needs status, nor does it indicate whether parents of foster child or the adopted child are receiving foster care payment or adoption subsidy, respectively.

The AFCARS lacks some information that may be of use for my topic of research. First, it contains only basic demographic information on the foster care and adoptive parents. The parents' levels of income, for example, are not recorded in the report. Because the level of income of the adoptive parents influences the amount of subsidy for adoption to a degree, the omission of such information may pose a problem. Moreover, the AFCARS data do not display the cost of finalizing the adoption for each adopted child. Though the cost of adopting children from foster care, including the cost of consultation and facilitation, are suspected to be generally low and relatively uniform across the families, available data for the cost would have served as a useful control variable.

An important concern to note is that the codebook for the Foster Care Files states that "the Children's Bureau has serious concerns about [the] accuracy [of the magnitude for foster care payments] for many states." Indeed, the variables that record the magnitude of adoption subsidies or foster care payments of the observations, if any, contain many values that seem unreasonable. For instance, the 99th percentile of the adoption subsidies is \$2018 per month, and the 99th percentile of foster care payments is \$5250, both of which raise serious reservations. Still, these are the only individual-level records of the magnitudes of the two forms of subsidy. In order to evaluate the impact that such unreasonable errors may cause, I include regression results obtained when observations whose adoption subsidies or foster care payments fall within the highest 1%, 5%, and 10% percentile are excluded from the estimation.

Among the data in AFCARS Foster Care File and Adoption File from 2001 to 2012, I keep only the latest observation for a child so that there are no repetitive observations. I assume that two observations belong to the same child if both their AFCARS ID (not unique but same across a child's observations in a span of years) and date of birth are the same. If a child who was previously in foster care was adopted by his or her foster parent(s), then his or her record will be recorded in the Foster Care File and Adoption File during the last year. In this case, I only keep the observation recorded in the Adoption File to eliminate repetitive data.

The observations dropped also include observations for children in states whose guidelines on the age-specific cut-offs regarding the eligibility for special needs are not clear, eliminating data for children in ten states[3]. Data on children who are placed outside of their home states are also excluded due to uncertainty on the particular state policy to which they are subjected. Further measures are taken to rid any observations with a characteristic that is either impossible or unreasonable, e.g. impossible dates of birth and negative amount of monthly subsidy, or lack crucial information in one or more of the variables included in the regression. Because the research only pertains to children whose placement was foster care, data for children who were placed in other institutional settings, such as group home or supervised independent living, are dropped. Finally, in the Adoption Files, I only keep observations for children whose previous relationship with their adoptive parents was that of foster care children and foster care parents, in line

[3] They are AK, HI, ID, KY, MA, MN, NC, SD, VT, and WV.

with this paper's goal. In the end, a total of 1,777,058 observations are included in the estimation process.

Now I present descriptive statistics for some of the important variables in the AFCARS data. Table 1 summarizes the demographic characteristics of the observations in my data set. Among children adopted under the auspices of public agency involvement, the average age of adoption was 6 years, quite lower than the average of all data. Also noticeable is that a higher percentage of black children and a lower percentage of white children were in the foster care than were actually adopted, corroborating the racial bias found by Baccara et al. (2014). The gender bias, however, is not immediately prevalent, as the percentage of male observations adopted is higher than in the total data set. Transracial adoption is fairly common, constituting 25% of the total instances of adoption. Finally, among all adoptions carried out that involve foster care center, 55% were carried out by foster parents of their foster children.

Table 1—Descriptive Statistics for the 2001-2012 AFACRS combined data set

Children Involved with Foster Care		
Variable	Adopted	All
Age (years)	6.01[1] (4.30[2])	7.71 (5.58)
Less than 1 year (%)	1.20	4.81
1 year (%)	10.29	8.36
2 years (%)	13.97	9.09
3 or more years (%)	74.54	77.73
Sex		
Male (%)	50.94	49.69
Female (%)	49.06	50.31
Race[3]		
Black (%)	27.52	27.85
Hispanic (of any race) (%)	16.39	16.31
White (%)	42.39	41.54
Asian (%)	0.41	0.44
American Indian or Alaskan Native (%)	1.47	1.52
Pacific Islander (%)	0.07	0.09
Unable to Determine (%)	7.80	5.61
Transracial adoption (%)	25.16	-
Relationship prior to adoption		
Foster parent (%)	54.97	-
Step parent (%)	0.12	

Other-relative (%)	25.88	
Non-relative (%)	20.72	-
Observations	52,039	1,777,058

Source: Adapted from the 2012 AFCARS Foster Care Data, 2012 AFCARS Adoption Data, and 2012 AFCARS Report (2013)
[1]Values are means, except for observations.
[2]Values are standard deviations.
[3]Following the designations used by AFCARS Report, a child is recorded as being a particular race only if he or she is not of Hispanic origin.

Table 2 lists the descriptive statistics on special needs eligibility and adoption subsidy pertaining to children who are adopted. Of the children adopted from foster care during 2001-2012 fiscal years, 85.2% were classified as having special needs, and 89.7% received monthly adoption subsidy. Of children who were classified as having special needs, 93.3% received monthly adoption subsidy, much higher than the 69.0% for children who were not eligible for special needs classification. The average amount of subsidy received was \$674.2 per month with a standard deviation of \$2,475.62. The high standard deviation suggests that the data may contain many outliers. Indeed, the 99th percentile goes up to \$975, and the highest recorded observation is \$53,500, an amount that is almost certainly an error. A similar problem with even a bigger magnitude arises regarding the amount of foster care payments for children in foster care: the 90th percentile sits at an extremely high \$1,500, and the 99th percentile is at \$14,180. To account for these patently erroneous numbers, I run multiple regressions in the estimation process excluding varying levels of outliers—1, 5, and 10th percentiles—to see if doing so affect the result.

The median amount of monthly subsidy that children with special needs received was \$450, higher than the \$360 for the median of children without special needs. The median amount of foster care payment is \$167, lower than the \$360 for the median of adoption subsidy.

Table 2— Descriptive Statistics for the 2001-2012 AFACRS combined data set, continued
Children Involved with Foster Care in 2012 Fiscal Year

Variable	Value
Among adopted children	
Eligible for special needs (%)	85.21[1]
Receive monthly adoption subsidy (%)	89.73
Among those with special needs (%)	93.34
Among those without special needs (%)	69.04
Amount of monthly adoption subsidy ($)	444 (2252.92[2])
Among those with special needs ($)	674.17 (2,475.62)
1^{th} percentile ($)	0
10^{th} percentile ($)	225
50^{th} percentile ($)	450
90^{th} percentile ($)	674
99^{th} percentile ($)	975
Among those without special needs ($)	378.22 (615.35)
1^{th} percentile ($)	0
10^{th} percentile ($)	0
50^{th} percentile ($)	360
90^{th} percentile ($)	756
99^{th} percentile ($)	2,281
Observations	271,781
Among foster children in foster care	
Receive monthly foster care payment (%)	54.32
Amount of monthly foster care payment ($)	980.43 (5,021.93)
1^{th} percentile ($)	0
10^{th} percentile ($)	0
50^{th} percentile ($)	167
90^{th} percentile ($)	1,500
99^{th} percentile ($)	14,180
Observations	1,487,463

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files
[1]Values are means, except for observations and percentiles.
[2] Values are standard deviations.

V. Estimation Process

I use a two-stage least squares regression to find the effect of the change in adoption subsidy on the probability of adoption given the amount of foster care payment. I go through the two levels in detail.

A. First stage

As mentioned in the literature review section, each state independently determines the criteria by which the children available for adoption in their states are classified as having special needs. The minimum age requirement in each state is described in Table 3 below. It can be seen that the range in the requirements among the states is quite large. Louisiana has the lowest minimum age requirement for non-Caucasian children at 0, and Rhode Island for all children and Louisiana for Caucasians has the highest requirement at 12. In particular, there exists a variation in the minimum age requirement among the states at which a child can be classified as having special needs by the criterion of age alone. After contacting North American Council for Adoptable Children, Buckles tentatively concluded that the differences in the guidelines do not reflect any state-specific characteristics. Thus, the variation allows for a separation the effect of age on the probability of adoption from the effect of eligibility of special needs.

Included in Table 3 are the average subsidy rates that children in a particular state receive when their age does not qualify for special needs designation, relative to what they receives when they do qualify for the designation. For example, for children in Alaska, children who do not qualify for special needs designation receive 42.4% of the amount that those who do qualify receive. Of the 40 states and D.C. in the table, 27 states have high monetary reward for children who qualify for special needs. In particular, in those states, children without special needs, on average, receive less than 90% of children who do qualify for special needs. These 27 states are designated to be in the treatment group, while the other 13 states are put in the control group.

Table 3—Minimum age requirement for being classified as having special needs[1]

Ratio of Non-special Needs Subsidy Rate to Special Needs Subsidy Rate < 90% (Treatment)						Ratio > 90% (Control)		
ST	Age-cutoff for Special Needs	Ratio	ST	Age-cutoff for Special Needs	Ratio	ST	Age-cutoff for Special Needs	Ratio
AL	2/8	42.4	MI	3	52.9	AK	8	94.6
AZ	6	75.2	MS	6	46.8	CA	3	991.0
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	NO	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			

Source: Buckles (2013).

[1] For cells that contain two different years, the first one is for non-Caucasians, and the second one is for Caucasians. Ten states--AK, HI, ID, KY, MA, MN, NC, SD, VT, and WV--did not have a clear minimum age requirement and were thus omitted from the estimation.

Table 4 - Descriptive Statistics for age cut-offs on special needs eligibility

Variable	Overall	Foster Care File	Adoption File
Adopted children in special needs (%)	-	-	0.8521
Age alone sufficient for special needs (%)	0.6036	0.6153	0.5432

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files

As can be seen in Table 4, among the observations recorded, roughly 60% of them are eligible for special needs on the basis of age only, as specified according to the states in which the children reside. Though not included in the table, among those eligible based on their age, 89% of them are actually qualified for special needs; among children whose ages are not sufficient for the designation, 79% are qualified for special needs, perhaps based on other reasons. Conversely, among children actually designated as being in special needs, 58% are eligible for special needs on the basis of age only, as opposed to the 38% if they are not designated as being in special needs. Finally, among children who have been already adopted, 54% are eligible for special needs based on their age, while among children who are still in foster care, 62% are eligible for special needs based on the age cut-off. The big discrepancy is probably due to the fact that children who are younger are more likely to be adopted than their older counterpart.

With these classifications, I predict the adoption subsidy using the following regression model:

$$\widehat{subsidy}_{isa} = \beta_0 + \beta_1 treatment_s{*}eligible_{isa} + \beta_2 eligible_{isa} + \beta_3 X_{isa} + y_a + \gamma_s + \varepsilon_{isa}$$

for each child i in state s at age a, where $Subsidy_{isa}$ is the amount of adoption subsidy, β_0 is the constant, $treatment_s$ equals one if the child lives in a treatment state, $eligible_{isa}$ equals one if the child becomes eligible for special needs by his or her age according to the guideline of the state that he or she resides in, X_{isa} is a vector that includes observable child characteristics such as sex, race, disability status, and reason for removal from birth parents, y_a are age dummy variables, γ_s are state fixed effects, and ε_{isa} is the error term. Note that the state fixed effects encompass the binary variable for the treatment group that would otherwise have been needed.

Buckles (2013) uses the set of variables on the right hand side to perform the diff-in-diff-in-diff estimation, but I use them for the first stage of my two-stage least squares estimation. The instrument variable for adoption subsidy that makes it possible to perform the two-stage least squares regression is $treatment_s{*}eligible_{isa}$. For it to act as an instrumental variable, two conditions must be satisfied: (1) the relevance condition, i.e. the variable is significantly correlated with the variable for the amount of adoption subsidy; and (2) the exclusion condition, i.e. it is uncorrelated with the probability of adoption other than through its correlation with the amount of adoption subsidy; that is, the variable is not correlated with unobserved child characteristics.

I can directly test the relevance condition by running the regression and seeing if β_1 is statistically significant. I assume that the exogenous condition also holds because unobserved child characteristics correlated with both adoption subsidy and the probability of adoption should be controlled for by the variable $eligible_{isa}$. For example, consider that a child has a psychological health problem included in the error term that is positively correlated with his or her eligibility for special needs designation and negatively correlated with probability of adoption**.** In that case, the effect will be controlled for in the term $eligible_{isa}$ and thus will not factor into the term $treatment_s*eligible_{isa}$. The results, however, suggest that this assumption may not be true.

B. Second stage

In the second stage, now I regress the probability of adoption against the predicted amount of foster care payment, child characteristics, and the predicted amount of subsidy that a child receives, obtained from the first stage, among others.

Note that only the children who are in foster care at the reporting period receive foster care payments and that, conversely, only those adopted receive adoption subsidies. Thus, the data in the Foster Care File do not include information on the adoption subsidy that the children in foster care would have received had they been adopted. Likewise, data in the Adoption File do not include the foster care payment that the children would have received had they been in the care of a foster family. Thus, since I want to regress the probability of adoption against those two variables, there needs to be a proxy for both.

The proxy for adoption subsidy arises naturally from the two-stage least squares process, because the first-stage regression will generate predicted adoption subsidies for not only adopted children but also foster children. On the other hand, the proxy for foster care payment is not evident. In this paper, I construct a proxy for foster care payment through a combination of child, state, and time characteristics that are shared by observations in both the Foster Care File and Adoption File. By doing so, I am able to predict the foster care payments for children who are adopted. The regression that was run in constructing the proxy has an R-squared value of 21.4% when observations containing the highest 1% of payments are excluded. Previous papers in the literature have each approached this problem in a different manner. For example, Argys and Duncan have handled this problem by collecting information on state-level monthly foster care rate policies from other sources altogether, including the Child Welfare League of America, state publications, and the North American Council on Adaptible Children (2012). As a result, the variable regarding the foster care rate for a child in their paper had the granularity of each state-age-year level but not the individual level, since such would be the extent of differentiation that a state policy would allow. Instead, the variable used in this paper is individual-level, with the trade-off being that the estimation may suffer from a proxy that has little explaining power regarding the variation in the amount of foster care payments.

I use the equation:

$$Pr(adopt_{isa}=1) = \beta_0 + \beta_1(\widehat{FosterCare}_{isa} - \widehat{subsidy}_{isa}) \\ + \beta_2\widehat{subsidy}_{isa} + \beta_3 eligible_{isa} + \beta_4 X_{isa} + y_a + \gamma_s + \varepsilon_{isa}$$

for each child i in state s at age a, where $adopt_{isa}$ is a binary variable that equals one if the child is adopted, β_0 is the constant, $\widehat{FosterCare}_{isa}$ is the predicted amount of foster care payment that the child receives, $\widehat{subsidy}_{isa}$ is the predicted magnitude of adoption subsidy, $eligible_{isa}$ carried over from the first stage for control, X_{isa} is a vector that includes observable child characteristics such as sex, race, disability status, and reason for removal from birth parents, y_a are age dummy variables, γ_s are state fixed effects, and ε_{isa} is the error term. The coefficients of interest are β_1 and β_2. The marginal effect for β_1 will be the effect on the probability of adoption of an increase in both the foster care payment and adoption subsidy by equal amount, and the marginal effect for β_2 will be the effect on the probability of adoption of an increase in the adoption subsidy, holding foster care payment constant.

VI. Results

I. First stage

In the first stage, I regress the amount of monthly subsidies that children in the Adoption File receive against the following: a dummy variable that equals one if a child is eligible for special needs on the basis of his or her age; an interactive dummy variable that equals one if a child is both qualified for age-based special needs and resides in a state that belongs to a treatment group; child characteristics, including their age, sex, and disability, if any; and state and time effects. Heteroskedasticity-robust standard errors are used.

The result of this regression is shown in Panel A of Table 5. When observations above the 99th percentile, 95th percentile, or 90th percentile are excluded from the regression (column (2), (3), and (4), respectively), the coefficient for the interaction variable--the instrument for this two-stage regression--is positive and significant at all levels. The dummy variables for *eligible* are also positive and significant at all levels for the three columns. For example, when the highest 1% observations are excluded, children who are qualified for special needs due to their age, among others, are expected to receive $11.99 more than if they were ineligible, holding other factors constant. Children who, on top of being qualified, reside in the treatment group are expected to receive an additional $10.89 than otherwise. Overall, the significant and positive coefficients are consistent with the speculation that children who are eligible for subsidy by the basis of their age and reside in a treatment group are likely to receive a higher magnitude of monthly adoption subsidy than children who do not belong to one or both of those criteria. As an increasingly larger number of outliers is excluded from the regression, the value of the coefficient for the interaction variable becomes bigger, while that for the variable *eligible* decreases, and both variables stay significant.

Table 5 - First-stage Least Squares Regression Results

Panel A

	Amount of Monthly Adoption Subsidy			
Variables	Absolute, Outliers Included	Absolute, 99th Excluded	Absolute, 95th Excluded	Absolute, 90th Excluded
Eligible*treatment	24.88[1]	10.89	23.05	36.26
	(24.90[2])	(2.83)***[3]	(2.13)***	(1.93)***
Eligible	-0.39	11.99	6.72	5.64
	(26.80)	(2.59)***	(1.85)***	(1.63)***
Control Variables				
Child Characteristics	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
F-statistic	436.72	1,038.23	1,160.98	1,038.86
R-squared	0.139	0.294	0.283	0.277
Observations	246,651	244,191	234,667	222,875

Panel B		
	Amount of Monthly Adoption Subsidy (absolute, excluding the highest 1th percentile)	
Variables	White	Non-white
Eligible*treatment	18.22	0.10
	(4.02)***	(4.11)
Eligible	17.32	7.54
	(3.78)***	(3.63)**
Control Variables		
Child Characteristics	Yes	Yes
Time	Yes	Yes
State	Yes	Yes
Age	Yes	Yes
F-statistic	546.18	5337.54
R-squared	0.316	0.278
Observations	115,096	129,095

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files
[1]Values are means, except for observations.
[2]Values are standard errors.
[3]One, two, and three stars indicate that the coefficients are significant at the 10%, 5%, and 1% levels, respectively. If there is no star attached, the coefficient is not significant at any of the three levels.

As one way to check the sensitivity of this first-stage regression result, I emulate Buckles' approach of running the regression with a subsample of children whose race is white and another with those whose races are not white (2013). Because children whose races are not white are more likely to be in special needs even when they are not eligible on the basis of their ages, the effect of their being eligible for special needs on the basis of age only should be smaller than the overall sample. Similarly, for children whose race is white, the effect of their being eligible for special needs by their age should be higher than the overall sample. Indeed, as can be seen in Panel B of Table 5, the results follow this intuition. The coefficient of *eligible*treatment* Children whose race is white is $18.22, higher than the average of $10.89; on the other hand, the coefficient of the variable for children whose races are not white is not significantly different from zero.

The values obtained when using the logarithm of the amount of monthly subsidies rather than their absolute values are recorded in the appendix of the paper. Unlike the results obtained when using the absolute values, the resulting coefficients for *eligible*treatment* are negative. For example, when excluding observations whose monthly amounts of subsidies are higher than 99th percentile, the regression indicates that children who, on top of being qualified, reside in the treatment group are expected to receive a 5% decrease in the monthly amount. Still, the sign of the coefficient for the variable *eligible* remains positive, as the results indicate that children who are qualified for special needs due to their age, among others, and who do not reside in the treatment group are expected to receive around 3% more than if they were ineligible, holding other factors constant. The magnitudes of the coefficients experience almost no variation regardless of the levels of outliers excluded from the regression. Unfortunately, it is unclear why the sign of the instrument changes when we use the logged value instead of the absolute value. These coefficients are comparable to the ones obtained by Buckles, whose results were $16.55 and -$4.41 for the variables *eligible*treatment* and *eligible*, respectively (2013).

Now I carry out the second stage regression using the values of the first column. The results for second-stage regression using the values of other columns are included in the appendix.

II. Second stage

In the second stage, I regress a dummy variable that equals 1 if the child is currently adopted against the following: the predicted amounts of adoption subsidies for children in both Foster Care File and Adoption File, obtained from the first stage; the predicted amounts of monthly foster care payments for children in those two files, obtained from a proxy that combines a number of variables about child characteristics; child characteristics, including their age, sex, race, and the types of disability, if any; and state and year dummies. As in the first-stage regression, robust standard errors are recorded. Because I use the linear probability model, the predicted probability of adoption can lie below zero or above one. The coefficients for the resulting regression are shown in Table 6.

Table 6 - Second-stage Least Squares Regression Results

Variables	Adopted by Foster Family Absolute, 99th Excluded	Absolute, 95th Excluded	Absolute, 90th Excluded	Excluding Monetary Variables
Change in only adoption subsidy by \$100[1]	0.255[2] (0.011)[3]***[4]	0.252 (0.01)***	0.255 (0.011)***	-
Change in both payments by \$100	-0.342 (0.012)***	-0.334 (0.0125)***	-0.327 (0.013)***	-
Eligible	-0.032 (0.002)***	-0.033 (0.002)***	-0.032 (0.005) ***	-0.057 (0.001)***
Female	-0.116 (0.004)***	-0.114 (0.004)***	-0.113 (0.005) ***	0.000 (0.001)
White	0.318 (0.010)***	0.311 (.010)***	0.311 (0.010) ***	0.048 (0.001)***
Asian	0.066 (0.003)***	0.061 (0.003)***	0.062 (0.003) ***	0.022 (0.003)***
Black	0.431 (0.014)***	0.421 (0.014)***	0.418 (0.015) ***	0.045 (0.001)***
Pacific Islander	0.044 (0.005)	0.040 (0.005)***	0.041 (0.005) ***	0.010 (0.005)**
American Indian or Alaskan Native	0.027 (0.003)***	0. 332 (0.013)***	0.332 (0.013) ***	0.007 (0.002)***
Hispanic Origin	0.056 (0.002)***	0.056 (0.002)***	0.056 (0.002) ***	-0.005 (0.001)***
Mentally Retarded	0.688 (0.025***	0.461 (0.025)***	0.653 (0.025) ***	0.019 (0.002)***
Visual or Olfactory Disability	0.4780 (0.018)***	0.461 (0.018)***	0.452 (0.019) ***	-0.030 (0.002)***
Physical Disability	-1.502 (0.062)***	-1.492 (0.063)***	-1.489 (0.065)***	0.102 (0.003)***
Emotionally Disturbed	0.385 (0.011)***	0.382 (0.011)***	0.375 (0.012)***	0.055 (0.001)***
Other Disablity	0.239 (0.005)***	0.235 (0.005)***	0.232 (0.005)***	0.116 (0.001)***

Control Variables				
Age	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
F-statistic	2,235.92	2,137.77	2,023.36	2,145.99
R-squared (%)	0.126	0.125	0.124	0.100
Observations	1,683,988	1,615,836	1,530,590	1,701,206

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files

[1]The coefficient for *difference* indicates the effect of a $100 increase in the amount of adoption subsidy, holding foster care payment constant; and that for *both payments* indicates the effect of $100 increase in both the amount of adoption subsidy and foster care payment.

[2]Values are means, except for observations.

[3]Values are standard errors.

[4]One, two, and three stars indicate that the coefficients are significant at the 10%, 5%, and 1% levels, respectively. If there is no star attached, the coefficient is not significant at any of those three levels.

The value of the coefficient for *difference* when the highest 1th percentile is excluded (column 1) indicates that a $1 increase in the amount of adoption subsidy, holding the amount of foster care payment constant, is expected to increase a child's probability of adoption by 0.255%. The median amount of monthly subsidy is $360; thus, to put into context, a 10% increase in the current average monthly subsidy, while the amount of foster care payment remains constant, is expected to be associated with a 9.18% increase in a child's probability of adoption, which is more than half the average adoption rate in this data (16.21%). Intuitively, the sign of the coefficient is expected, but its magnitude is too high to be reasonable.

The value of the coefficient for the variable *both payments* indicates that a $1 increase in both the amount of foster care payment and adoption subsidy is associated with a 0.342% decrease in adoption, holding others constant. At its face value, the negative sign would indicate that the process of adopting a foster care child is an inferior good; however, there is no identifiable reason why foster care parents will be less likely to adopt their foster care children if they are better off financially. Moreover, as was with the coefficient *difference*, the magnitude is implausible. When the regression is run while the coefficient for *both payments* is assumed to be zero (recorded in Table 8 of the appendix), the coefficient for *difference* stays almost identical. Finally, a $1 increase in the amount of foster care payment, holding adoption subsidy constant, is associated with a 0.597% decrease in a child's probability of adoption. Barring the magnitude, it seems reasonable to speculate that the negative sign arises because the increased opportunity cost of adopting a foster child makes parents more reluctant to carry out the adoption.

The coefficients for the control variables seriously call into question the validity of the results obtained. For example, the results indicate that a child's probability of adoption from foster care family is 11% higher if the child is male than his female counterpart. Likewise, the probability of adoption is shown to be higher for a child whose race is black than his or her counterpart of white race, and that having any form of diagnosable disability that is not physical is expected to be associated with an increase in that child's probability of adoption. Overall, most of the values of the coefficients for these control variables do not align with previous papers that dealt with the determinants of demand for adoption (Baccara et al., 2014).

The results remain very similar when observations whose foster care payments or adoption subsidies lie in the highest 5^{th} or 10^{th} percentile are excluded from the first- and second-stage regressions. This similarity stands in contrast to the noticeable difference of the coefficient for *eligible*treatment* during the first-stage regression. A dollar increase in the adoption subsidy, holding constant foster care payment, is associated with a 0.252% and 0.255% in the probability of adoption for column 2 and column 3, respectively, while a dollar increase in both the amount of foster care payment and adoption subsidy is expected to decrease the probability of adoption by 0.333% and 0.327%, respectively, holding others constant.

VI. Discussion and Conclusion

Taken at their face values, the results of this paper's regressions indicate that a positive change in adoption subsidy, holding foster care payment constant, has an enormously positive effect on the adoption rate of children in foster family structure, thus suggesting that policies that increase the amount of adoption subsidy could effectively encourage more adoptions. However, our intuition and economics models tell us that these results are unrealistic. The result obtained for *difference* of 25.5% is roughly six times bigger than Argys and Duncan's results, which suggested that a hundred dollar increase in the monthly adoption subsidy for a child is associated with a 4.6% increase in the probability of adoption if the child is a boy and 5.9% if the child is a girl (2012). For *both payments*, Argys and Duncan retrieve values of 3.7% for boys and 6.2% for girls and hugely differ from this paper's values in terms of both the sign and the magnitude of the coefficients. Furthermore, Argys and Duncan's results include negative signs for *black*, *Hispanic*, and *disabled*, conforming to the racial and health-related biases mentioned in various works in the literature.

Table 7 –Result for Regression in which Eligible*Treatment is directly inserted

Variables	Adopted by Foster Family
Eligible*Treatment	0.028[1] (0.001[2])***[3]
Eligible	-0.002 (0.001)
Female	0.002 (0.001)***
White	0.057 (0.001)***
Asian	0.024 (0.003)***
Black	0.044 (0.001)***
Pacific Islander	0.431 (0.014)***
American Indian or Alaskan Native	0.012 (0.002)***
Hispanic Origin	-0.000 (0.001)
Mentally Retarded	0.018 (0.002)***
Visual or Olfactory Disability	-0.019 (0.002)***
Physical Disability	0.103 (0.003)***
Emotionally Disturbed	0.079 (0.001)***
Other Disability	0.110 (001)***
Control Variables	
Age	Yes
Time Effects	Yes
Fixed Effects	Yes
F-statistic	2,283.33
R-squared (%)	12.69
Observations	1,701,206

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files

[1]Values are means, except for observations.

[2]Values are standard errors.

[3]One, two, and three stars indicate that the coefficients are significant at the 10%, 5%, and 1% levels, respectively. If there is no star attached, the coefficient is not significant at any of those three levels.

There are several clues suggesting possible reasons behind the failure of this paper's attempt to find meaningful results. Consider Table 7: When *eligible*treatment* is directly inserted into the second-stage regression in place of *difference* and *both payments*, the value of its coefficient turns out to be 2.78% (for the 99th percentile regression). Combined with the fact that the variable's coefficient during the first-stage regression was $10.89, it seems that this instrument itself suggests that a $10 increase in payment is associated with a roughly 2.8% increase in the probability of adoption, or a 28% increase for a $100 increase in adoption subsidy, consistent with this paper's second-stage regression result. Thus, it is likely that the term *eligible*treatment* may be correlated with unobserved variables in addition to payments that are also associated with the child's probability of adoption, and the age-state groups belonging to the *eligible*treatment* may be different from others in ways that are correlated with the child's probability of adoption. In other words, the variable may not pass as an instrument because it fails the exogeneity condition for consistent estimation. If this is the case, a different instrument must be found to account for the endogeneity of the instrument on adoption subsidy.

Another possibility is that, as the Children's Bureau has suggested, the validity of the reported data for individual-level foster care payments and monthly adoption subsidies is wildly lacking in terms of accuracy. Indeed, there exist outliers for both adoption subsidies and foster care payments that are impossible in reality, and even those data points that may not seem dubious in isolation can still be erroneous. To confirm this suspicion, further investigation on the data-collecting method for these two variables must be taken, and Adoption and Foster Care Analysis and Reporting System must provide a more precise and robust guideline upon which foster cares can report these data.

Another weakness of this paper's approach is that proxy for foster care payments has to be constructed with a very limited set of variables, because the variables that can be included must appear both on the Adoption File and the Foster Car File. Consequently, the R-squared value of this proxy hovers above 21%. Moreover, this paper assumes that the amounts of foster care payments that foster children receive are not susceptible to endogenity problem similar to adoption subsidies, a simplification that may be dubious.

Finally, the inherent nature of using individual-level reported amount of payments may be causing an endogenity problem, as self-selection bias will occur. In order to avoid doing so, an approach similar to Argys and Duncan's must be taken, which uses the guidelines that states provide in terms of their policies regarding the payments instead of the actual reported payments.

Estimating the effect of magnitude of adoption subsidy on adoption rate is an important question that could provide a method through which the government can encourage the practice of adoption. However, this paper's results are suspect, and the aforementioned reasons must be accounted for if the effect of adoption subsidy is to be correctly estimated. As a further avenue of investigation, I hope to seek another set of instruments for the amount of adoption subsidy and foster care payment that children receive that could account for bias coming from omitted variables correlated with those two types of payments.

Appendix

Table 8 - Second-stage Least Squares Regression Results When Income Effect is Assumed to be Zero

Variables	Adopted by Foster Family Absolute, 99th Excluded	Absolute, 95th Excluded	Absolute, 90th Excluded	Excluding Monetary Variables
Change in adoption subsidy only by \$100[1]	0.255[2] (0.011)[3]***[4]	0.252 (0.011)***	0.255 (0.011)***	-
Change in both payments by \$100	-	-	-	-
Eligible	-0.032 (0.002)***	-0.033 (0.002)***	-0.032 (0.002) ***	-0.057 (0.001)***
Female	-0.021 (0.001)***	-0.020 (0.004)***	-0.020 (0.001) ***	0.000 (0.001)
White	0.164 (0.164)***	0.163 (.005)***	0.166 (0.005) ***	0.048 (0.001)***
Asian	0.033 (0.003)***	0.033 (0.003)***	0.035 (0.003) ***	0.022 (0.003)***
Black	0.175 (0.006)***	0.174 (0.006)***	0.175 (0.006) ***	0.045 (0.001)***
Pacific Islander	0.030 (0.005)	0.029 (0.005)***	0.031 (0.005) ***	0.010 (0.005)**
American Indian or Alaskan Native	0.136 (0.006)***	0.134 (0.006)***	0.138 (0.006) ***	0.007 (0.002)***
Hispanic Origin	0.024 (0.001)***	0.025 (0.001)***	0.025 (0.001) ***	-0.005 (0.001)***
Mentally Retarded	0.075 (0.003)***	0.067 (0.004)***	0.067 (0.004) ***	0.019 (0.002)***
Visual or Olfactory Disability	0.029 (0.003)***	0.025 (0.003)***	0.025 (0.003) ***	-0.030 (0.002)***
Physical Disability	-0.815 (0.040)***	-0.816 (0.040)***	-0.827 (0.041)***	0.102 (0.003)***
Emotionally Disturbed	0.105 (0.002)***	0.108 (0.002)***	0.107 (0.002)***	0.055 (0.001)***
Other Disability	0.081 (0.002)***	0.081 (0.002)***	0.081 (0.002)***	0.116 (0.001)***

Control Variables				
Age	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
F-statistic	2,236.05	2,137.76	2,023.36	2,145.99
R-squared (%)	0.126	0.125	0.124	0.100
Observations	1,684,041	1,615,836	1,530,590	1,701,206

Source: 2001 - 2012 AFCARS Foster Care Files and Adoption Files

[1]The coefficient for *difference* indicates the effect of a $100 increase in the amount of adoption subsidy, holding foster care payment constant; and that for *both payments* indicates the effect of $100 increase in both the amount of adoption subsidy and foster care payment.

[2]Values are means, except for observations.

[3]Values are standard errors.

[4]One, two, and three stars indicate that the coefficients are significant at the 10%, 5%, and 1% levels, respectively. If there is no star attached, the coefficient is not significant at any of those three levels.

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