Child Protection and Child Outcomes: Measuring the Effects of Foster Care

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Little is known about the effects of placing children who are abused or neglected into foster care. This paper uses the placement tendency of child protection investigators as an instrumental variable to identify causal effects of foster care on long-term outcomes—including juvenile delinquency, teen motherhood, and employment—among children in Illinois where a rotational assignment process effectively randomizes families to investigators. Large marginal treatment effect estimates suggest caution in the interpretation, but the results suggest that children on the margin of placement tend to have better outcomes when they remain at home, especially older children. (*JEL* H75, I38, J13)

The child welfare system aims to protect children thought to be abused or neglected by their parents. Over two million children are investigated for child abuse and neglect each year in the United States, and roughly half are found to have been abused (US Department of Health and Human Services 2004). Approximately 10 percent of these abused children will be placed in protective custody known as foster care.

Although foster care is meant to be a temporary arrangement, children stay in care for an average of two years, and there are currently over 500,000 children in care (US Department of Health and Human Services 2005). Roughly 60 percent of foster children return home; 15 percent are adopted; and the remainder "age out" of foster care (Fred C. Wulczyn, Kristen Brunner Hislop, and Robert M. Goerge 2000). Three-quarters of these children live with substitute families, one-third of which are headed by relatives of the children. These families are paid a subsidy of approximately \$400 per month per child (Child Welfare League of America 1999), and states spend over \$20 billion each year to administer these child protective services (Roseana Bess et al. 2002).

Further, foster care policy directly targets children who appear to be at high risk of poor life outcomes. Abused children are three times more likely to die in childhood (Eugene E. Sabotta and Robert L. Davis 1992), with 1,400 child deaths each year directly attributed to child abuse (US Department of Health and Human Services 2004). Those placed in foster care are far more likely than other children to commit crimes, drop out of school, join welfare, experience substance abuse problems, or enter the homeless population (June M. Clausen et al. 1998; Mark E. Courtney and Irving Piliavin 1998; US Department of Health and Human Services 1999; Amy Dworsky and Mark E. Courtney 2000; Bo Vinnerljung et al. 2006). In particular, nearly 20 percent of young prison inmates[1] and 28 percent of homeless individuals spent some time in foster care as a youth (Martha Burt et al. 1999). Mark E. Courtney, Sherri Terao, and Noel Bost (2004) surveyed children

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[1] The 1997 Survey of Inmates in Adult State and Federal Correctional Facilities shows that nearly 20 percent of inmates under the age of 30, and 25 percent of these inmates with prior convictions, reported spending time in foster care as a youth (author's calculations).

who will turn 18 in foster care and found that *two-thirds* of the boys and *half* of the girls had a history of delinquency. The group was three times more likely to have mental health needs and four times more likely to have been treated for a sexually transmitted disease compared to the national average.

Despite the large number of children at high risk of poor life outcomes served by child protective services, it is unclear whether removing children from home and placing them in foster care is beneficial or harmful for child development, especially for children at the margin of placement (Goerge, Wulczyn, and David Fanshel 1994; Thomas P. McDonald et al. 1996; National Research Council 1998; Courtney 2000; Richard J. Gelles, 2000; Melissa Jonson-Reid and Richard P. Barth 2000).[2] Child protection agencies trade off two competing goods: family preservation and child protection (Anthony N. Maluccio, Edith Fein, and Inger P. Davis 1994; Barth 1999). Although an abusive family environment is undoubtedly harmful to child development, removing a child from home may be traumatic as well. For example, placement instability in foster care has been highlighted as a potentially serious problem for child development.[3] The average foster child is moved from one home to another at least once, with a quarter experiencing three or more moves.

There are two main limitations to estimating the effects of foster care placements on child outcomes. First, there is a lack of long-term outcome data. Children investigated for abuse or neglect are not tracked over time in a systematic way. Second, endogeneity and selection bias problems can contaminate comparisons: worse outcomes for foster children compared to other children in the same area could be due to abusive family backgrounds, as opposed to any effect of foster care placement (Benjamin Kerman, Judith Wildfire, and Barth 2002). Meanwhile, those children who are removed are likely those who would benefit most from placement, and a comparison of average outcomes may overstate the benefit of removal for marginal cases.

This paper uses a measure of the removal tendency of child protection investigators as an instrumental variable to identify causal effects of foster care placement on child outcomes for school-age children and youth. Cases are distributed to investigators on a rotational basis within geographic field teams to smooth the case load, which effectively randomizes families to investigators. The instrumental variables estimates focus on variation in foster care placement among marginal cases—those cases where investigators may disagree about the recommendation of removal. These are the cases most likely to be affected by policy changes that alter the threshold for placement.

Using a unique dataset that links children in Illinois with a wide range of government programs, it is possible to compare children placed in foster care with other children who were investigated for abuse or neglect in terms of long-term outcomes, including juvenile delinquency, teen motherhood, employment, and earnings. The results, which apply in particular to children receiving welfare benefits and between the ages of 5 and 15 at the time of the initial investigation, point to better outcomes when children on the margin of placement remain at home. While the large size of the estimated effects and their lack of precision suggest caution in the interpretation, the results suggest that significant benefits from foster care placement in terms of these outcomes appear unlikely for children at the margin of foster care.

The paper is organized as follows. Section I presents the empirical framework, which highlights the possibility of heterogeneous treatment effects across children. It also discusses the policy parameters estimated with the instrumental variables strategy. Section II presents background information on the investigator assignment process in Illinois. Section III describes the data and reports summary statistics. Section IV describes the results, including an investigation

[2] Few studies compare children investigated for abuse. See Desmond K. Runyan and Carolyn L. Gould (1985), Elizabeth Elmer (1986), Michael S. Wald, J. M. Carlsmith, and P.H. Leiderman (1998), and Bilha Davidson-Arad, Dorit Englechin-Segal, and Yochanan Wozner (2003) for four small-scale studies. Jonson-Reid and Barth (2000a, b) studied 160,000 children in California using administrative data and found lower delinquency on average for children who remained at home, especially those who received in-home services.

[3] There is a large empirical literature on placement stability, as it is one observable characteristic in administrative data. See Rae Newton, Alan J. Litronwnik, and John A. Landsverk (2000), Dana K. Smith et al. (2001), Sigrid James, Landsverk, and Donald J. Slymen (2004), and Andrew Zinn et al. (2006).

of how the effects vary over different types of children. Section V concludes.

I. Empirical Framework: Heterogeneous Treatment Effects

The decision to remove a child from home is a difficult one, and child welfare services have historically struggled with the sometimes-conflicting goals of family preservation versus child protection. This is evident from the changing emphasis on child protection and family preservation over recent decades, as foster care populations grew from 100,000 to 600,000 in the 1960s, dropped to 200,000 by the end of the 1970s, and rose to over 500,000 by the end of the 1980s. Recently, family preservation initiatives have been increasingly common (McDonald et al. 1996). Although an abusive home environment undoubtedly harms child development, removing children from home and placing them in a potentially unstable foster family relationship may be harmful as well.

The empirical framework considers how the benefit or harm of the decision to remove a child from home can vary across children. Consider a random coefficient model, in the spirit of Anders Björklund and Robert Moffitt (1987) and James J. Heckman and Edward Vytlacil (2005), for an outcome, Y, such as earnings, observable case characteristics X, an indicator for removal from home R, for child i:

$$(1) \qquad Y_i = X_i\beta + \alpha_i R_i + \varepsilon_i;$$

α_i will be positive for children where the placement is associated with higher earnings, but may be negative for children where the disruption of placement is associated with lower earnings.

Rewriting (1) to reflect the standard single coefficient model reveals two error terms:

$$(2) \qquad Y_i = X_i\beta + \bar{\alpha}R_i + R_i(\alpha_i - \bar{\alpha}) + \varepsilon_i.$$

There are two main sources of econometric problems when estimating equation (2). First, R may be correlated with ε. For example, an omitted variable such as poor family environment may lead to an increased likelihood of removal and a decreased earnings capacity. Second, R will be correlated with α_i if agents select treatment based on expected gains—a correlated random coefficient model. Note that for foster care placement, the treatment is not chosen by the child, but by the child protection system. Although the placement decision may not be based on the returns to earnings, α_i, if earnings were indicative of child well-being in general, then such a correlation may exist.[4]

The estimation will use an instrument, Z, which holds the potential to overcome the endogeneity problems and allow the estimate of marginal treatment effects (MTEs) as Z varies (Heckman and Vytlacil 2005). In particular, the instrument describes the propensity for the investigator assigned to the family to have children placed in foster care.[5] Consider two types of investigators, tough and lenient. The difference in outcomes across these investigators could be used to measure local average treatment effects (LATE): the effects for children induced into foster care on the basis of the investigator assignment (Guido W. Imbens and Joshua D. Angrist 1994). Letting $Z = 1$ if the family is assigned to a tough investigator, and $Z = 0$ if assigned to a lenient one, the estimand is

$$(3) \qquad \alpha^{LATE} = \frac{E(Y|Z=1)-E(Y)|Z=0}{P(R=1|Z=1)-P(R=1|Z=0)},$$

which can be estimated with sample means.

The conditions necessary to interpret the result as a local average treatment effect are:

CONDITION 1 (Existence): *Z is a random variable such that:*

(*i*) P(z) $= E(R|Z = z)$ *is a nontrivial function of z*;

(*ii*) *Z is independent of the error term in the outcome equation.*

[4] α may also be correlated with ε, for example if those who benefit most from placement have the highest earnings capacity. This may also affect the interpretation of the parameters estimated.

[5] This approach is similar to that of Jeffrey R. Kling (2006), who studied the effect of prison sentences on employment and earnings. In that study, the tendencies of randomly assigned judges to impose different prison sentences is used as an instrumental variable. In an analogy to criminal proceedings, investigators studied here are similar to detectives who are the key witnesses in each case.

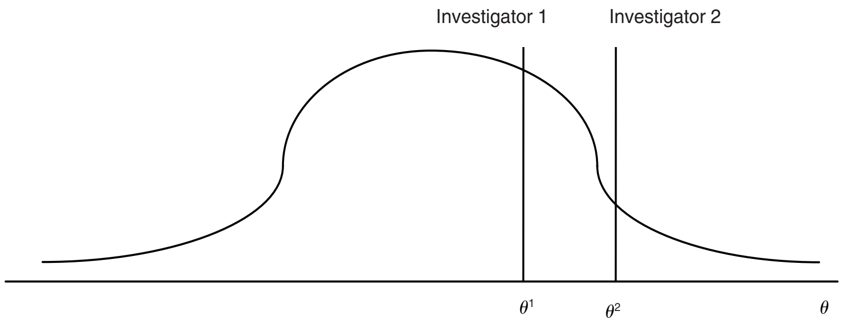


FIGURE 1. ABUSE THRESHOLDS FOR REMOVAL

The first (testable) assumption is that the instrument is associated with foster care placement. The second is an exclusion restriction that Z is not in the outcome equation.[6] In the correlated random coefficient model, the local average treatment effect will incorporate the additional gains associated with selection. This affects the interpretation of the parameter, though the effects are policy relevant: namely, should we encourage the system to act more like strict investigators and push for more child protection, or should we emulate the more lenient investigators and emphasize family preservation?

CONDITION 2 (Monotonicity): *Any child removed by a lenient investigator would also be removed by a strict one, and a child not removed by a strict case manager would not be removed by a lenient one.*

This condition rules out the case where assignment to a case manager described as "lenient" would result in an increased likelihood of placement. To consider the effect of a violation of this assumption, it is necessary to describe the instrument itself.

Consider a simple placement decision model where investigators observe cases along a distribution of abuse levels, θ, as in Figure 1. The two types of investigators are defined by the threshold of abuse required to recommend placement. Each type observes the same abuse levels, as would be true if cases were randomized to investigators, so they can be described by the fraction of children recommended for placement, Z.

The investigator who puts relatively more emphasis on child protection will recommend removal if $\theta > \theta^1$, whereas the investigator who places more emphasis on family preservation will recommend removal for children with $\theta > \theta^2$. For high levels of abuse $(\theta > \theta^2)$, both types of investigators would recommend removal, and the effect of removal on child outcomes cannot be identified. Similarly, in low levels of abuse $(\theta < \theta^1)$, both investigator types would recommend leaving the child at home, and the potential harm to these types of children would also not be identified. Instead, the comparison of outcomes across the investigator types would focus on variation in placement among marginal cases $(\theta^1 < \theta < \theta^2)$. In a policy context, these cases are of interest, as extreme abuse cases are unlikely to be affected in any policy change. In a welfare analysis of child protection as a whole, however, it would be necessary to consider the benefits to children who are removed at higher abuse levels as well.

This can be summarized by a latent index model for child i:

$$R_i^* = -Z_i\gamma + \theta_i; \tag{4}$$

$$R_i = 1 \text{ if } R_i^* > 0. \tag{5}$$

Z_i can be thought to characterize the threshold the investigator assigned to child i must observe before she decides to recommend foster care placement, and γ represents the influence that such a recommendation will actually result in a placement. A child with abuse level θ will be

[6] This assumption may be relaxed to a mean independence.

placed in care if that level is greater than the investigator's threshold for removal multiplied by the effectiveness of that recommendation.

The conditions for identification are:

$$(6)\quad E(Z\theta)=0; E(Z\varepsilon)=0; E(Z(\alpha-\bar{\alpha}))=0; \gamma\neq 0.$$

That is, Z is (mean) independent of θ_i in the selection equation, the error term in equation (1), and the idiosyncratic gains to foster care placement. If investigators are randomized to families, the exclusion restriction would appear to be an accurate description of the role of case managers in the outcome equations. The last condition states that Z must be associated with foster care placement.

The monotonicity assumption is imbedded in the common coefficient γ. This is less straightforward compared to a treatment and control environment, where, for example, the control group may be denied the treatment (Imbens and Angrist 1994). Instead, the model here relies more heavily on the varying ethos in child welfare between family preservation and child protection, coupled with the reliance on practice wisdom, so that investigators are given latitude to reach a removal recommendation (Scottye J. Cash 2001).

Angrist, Imbens, and Donald B. Rubin (1996) described the trade-off involved when the monotonicity assumption is only approximated. First, the bias will decrease with the strength of the relationship between the instrument and foster care placement. Second, in their language, if the effect of foster care placement for "defiers" (for example, those individuals induced to receive the treatment when assigned to the *lenient* investigator) is the same for the "compliers" (those induced to receive the treatment because they are assigned to the strict investigator), then the bias disappears. This may be unlikely when the investigator types are much different from one another, where defiers may represent exceptional cases. In the case of a continuous instrument, however, this would appear to be less of a problem when considering small differences in investigators: that is, measuring MTEs.

An MTE is the limit of the LATE parameter as the difference in the probability of treatment, given the instrument goes to zero. In Figure 1, this would mean comparing outcomes for children across case managers whose thresholds are close together. Letting $P(z)$ equal the $P(R = 1|Z = z)$, the marginal treatment effect is simply the derivative:

$$(7)\qquad \alpha^{\mathrm{MTE}} = \partial E(Y)/\partial P(z).$$

In this setting, the MTE estimates may be of interest in themselves, as they describe whether outcomes improve or become worse as different types of children are induced into foster care based on different values of a particularly policy-relevant instrument: assignment to different types of investigators.[7]

II. Background: Foster Care Placement in Illinois

Reports of abuse or neglect are typically made by physicians, school principals, police, and family members. In Illinois, all reports are made through a statewide hotline that connects to the State Central Register (Illinois Department of Children and Family Services (DCFS) 2003). This allows an intake worker to determine if there were any pending or previous investigations that can aid in the investigation and determine the need for emergency services. The case is then referred to a field team that is closest to the child's residence. A typical team covers one county in Illinois and consists of eight investigators at any given time. These investigators are called "case managers," and they collect the facts to determine whether a child has been abused or neglected.

There are three decisions made by the investigator that can affect foster care placement. First, the investigator may remove the child from home on an emergency basis. Second, the investigator may decide that the case does not have merit. Third, the case manager collects the evidence of the case and presents this evidence, along with a recommendation to a judge in each county's Child Protection Division of the Juvenile Court.

[7] Heckman and Vytlacil (2005) discuss the consequences of a lack of independence between the instrument and the idiosyncratic gains to treatment in an environment of heterogeneous treatment effects. The resulting estimate would include selection bias induced by the placement of children who are most likely to benefit, which may be policy relevant.

Most foster care placements are made through the court system.

At this point, it may be useful to discuss why case managers might arrive at different recommendations. If the removal decision were always clear, there should be no variation across case managers with randomly assigned families. There is a literature on case manager variation in recommendations, which provides some support for the identification strategy employed here. In particular, case managers are thought to rely more heavily on "practice wisdom" than administrative rules when making placement referrals (Cash 2001).[8] In addition, the standard for foster care placement does vary over time and with the amount of resources available to child protective services, such as federal funding and monthly subsidies paid to foster parents (Julian Simon 1975; Claudia Campbell and Susan Whitelaw Downs 1987; Patricia Chamberlain, Sandra Moreland, and Kathleen Reid 1992; Rebecca Hegar and Maria Scannapieco 1995; Doyle and H. Elizabeth Peters 2007). It appears that the threshold for placement is not constant across time or across investigators.

Rotational Assignment of Case Managers.— In general, families are assigned to case managers on a rotational basis in an effort to smooth the case load. The assignment process is referred to as "the rotation," and it appears to be self-enforced: case managers note that they abide by it to avoid managing too many cases.[9]

One limitation in using the case manager assignment as a randomization device is that exceptions are made, and the main analysis will focus on cases that are most likely to enter the rotational assignment process. First, if a family is investigated more than once, an effort is made to reassign the same case manager to investigate the most recent allegation. The exogenous variation in case manager assignment stems from the initial investigation. To rely only on this type of variation, the case manager assigned to the family's first investigation will be considered.[10]

Second, some field teams assign case managers to particular neighborhoods. For example, one team divides its county into east and west, with half of the case managers assigned to each subteam. If particular types of case managers are assigned to neighborhoods more likely to have child abuse or neglect, then a comparison across case managers would capture differences in these neighborhoods as well. The analysis here will focus on subteams defined as the interaction between the child's ZIP code of residence and the field team assigned.

Third, if the family speaks only Spanish, an effort is made to assign a Spanish-speaking case manager. Like the neighborhood consideration, if some case managers specialize in Spanish-speaking cases, then differences across case managers would incorporate differences in Spanish-speaking versus English-speaking cases as well. For this reason, the subteams will be defined separately for Hispanic cases.

Last, cases involving sexual abuse and drug-exposed children are assigned to case managers specially trained to investigate these cases, given the greater need for training and closer cooperation with police. These allegations, which make up 13 percent of all first investigations, will not be considered, as they are less likely to enter the rotational assignment.

In essence, the results will consider the effect of assignment to different types of case managers, categorized by their rate of foster care placement, on long-term child outcomes. One question that arises is whether these investigators affect families in ways other than through foster care placement. These investigators do not supervise the case once a child enters foster care. Foster care stays are overseen by a separate division within IL DCFS that works with private child welfare agencies to recruit and supervise foster families. One potential area where they may have an impact is the recruitment of relatives to care for foster children, as the investigators often interview family members.

[8] For example, P.J. Nasuti and Peter J. Pecora (1993) found that case managers using the Utah Risk Assessment Scales reviewing fictional cases had inter-rater reliability ranging from 57 percent to 81 percent. Peter Rossi, John Schuerman, and Stephen Budde (1996) found similar differences in case manager assessments of fictional cases.

[9] From conversations with case managers.

[10] Some cases report the initial reporter as the Department of Children and Family Services, the agency that runs the Division of Child Protection. These referrals are likely the result of previous cases, so they are not treated as the first investigation for the family.

An IL DCFS rule requires a relative to be sought first, however, regardless of the case manager assigned to investigate the case. An examination of any relationship between the investigator type and observable case characteristics, including placement type, will be explored in detail below. It appears that the role of the investigator is concentrated on determining whether a child has been abused or neglected—evidence that will be used to make the foster care placement decision. As a result, the differences in outcomes across investigators should largely stem from differences in the likelihood of foster care placement.[11]

III. Data and Descriptive Statistics

A unique dataset that combines a wide array of administrative agencies in Illinois is used to carry out the analysis. These data are collected by the Chapin Hall Center for Children, a research institute located at the University of Chicago, and linked using personal identifiers together to create the Illinois Integrated Database (Goerge, John Van Voorhis, and Bong Joo Lee 1994).

The core of the data comes from the Illinois Department of Children and Family Services. The Child Abuse and Neglect Tracking System (CANTS) provides details of the investigation, including the initial reporter of abuse, the allegations, the field team assigned to the case, and the case manager assigned to investigate. CANTS data include the child's age, sex, race, and address. The alleged perpetrators are also included in the tracking system. To consider the effect of removal from home, the analysis focuses on the 81 percent of cases where the alleged perpetrator is a natural parent, stepparent, or cohabitating adult.

Meanwhile, the Child and Youth Centered Information System tracks children in foster care, and the two systems have been linked to determine whether the child was ever removed from home. The two information systems reflect the fact that once a child is placed in foster care a separate agency supervises the case.

In terms of longer-term outcomes, the prevalence of delinquency found in previous work suggests that this is an important one to consider. For children in Cook County, which includes the city of Chicago, the investigation data are linked with the Delinquency File of the Juvenile Court of Cook County. These data track children who enter the juvenile courts, and all entries between July 1, 1990, and December 31, 2000, are available. An appearance before the juvenile court system usually entails three juvenile arrests (or an arrest for a serious charge). This implies that a court appearance identifies a child who has had a number of episodes with police and serves as a measure of delinquency.

Second, the database includes Medicaid Paid Claims data. These data contain payment records for medical services funded by the Illinois Department of Public Aid from January 1, 1990, through June 30, 2001. The variables include demographic measures used in the linkage and service dates, along with diagnosis and procedure codes. Births to girls 19 years of age and younger have been identified using these diagnosis and procedure codes.

The Medicaid data do appear informative of health care use. For example, all foster children are supposed to have a medical checkup within 90 days of entering foster care, and entry into foster care is associated with a 40 percentage point increase in the likelihood of a medical checkup within one year of the abuse report. This also suggests an immediate benefit of foster care entry in terms of preventive health care.[12]

Third, the Illinois Department of Employment Security's unemployment insurance program provides employment and earnings data for 2002 and the first two quarters of 2003. According to the Department, businesses that employ one or more individuals within any 20-week period in a calendar year are required to report employee

[11] Family preservation services, such as counseling and vouchers for maid services, became increasingly common in the late 1990s. These programs are generally administered by separate case managers, as the investigators are focused on child protection investigations.

[12] This result is the 2SLS estimate of the effect of foster care entry on medical checkups similar to those presented below for longer-term outcomes. The estimated coefficient on foster care placement is 0.41 with a standard error of 0.09. The mean rate of wellness visits within one year of the abuse report for all Medicaid-enrolled children is 64 percent.

wages on a quarterly basis.[13] The state estimates that approximately 95 percent of all paid jobs in Illinois are contained in this database. In addition to the missing data, for a small segment of the population it is difficult to unduplicate individuals or link them across quarters because of the relatively few linkage variables: only name and social security number. Robert Kornfeld and Howard Bloom (1999) found similar results using unemployment insurance wage report and self-report data, though earnings of individuals with a prior arrest record were somewhat different. Employment measures were similar, however. Given that former foster children are overrepresented in prison surveys, such a concern should be kept in mind. Differences in employment appear to be less sensitive to the measurement problems, however.

A. *Sample Construction*

The outcome data are considered more reliable beginning in 1990, so all first investigations of parental abuse or neglect from between July 1, 1990, and June 30, 2001, are considered. The foster care placement measure is observable through June 30, 2003. Each outcome covers slightly different time periods, and the Data Appendix reports the time period for each data source. As noted in Section II, sexual abuse cases (which represent 8 percent of cases) and drug exposure cases (representing another 5 percent of cases) are excluded because these children are less likely to enter the rotational assignment.[14]

There are two main restrictions of the data. First, every foster child is statutorily eligible for Medicaid. Once in Medicaid, the personal identifiers available to match children with outcomes, including social security number, improve. It may be possible, then, to find foster children more likely to be matched to the employment data, say, simply due to the greater availability of the identifiers. To compare children with the same identifiers and prevent this type of bias, the analysis here will focus on all children receiving Medicaid prior to the abuse/neglect report. This represents 42 percent of all first-time abuse reports. Although this restriction will affect the interpretation of the results, it considers an important group, especially for foster care. Of the children placed in foster care in Illinois, 82 percent had received Medicaid prior to the abuse report.[15]

The second major restriction is on the age of children, to ensure that children are old enough at the end of the sample period to be at risk for the outcomes considered here (a young child cannot have a teen birth, for example). All children who are at least 15 at the end of the sample period for the delinquency and teen motherhood samples, and at least 18 for the employment sample, will be considered. All children who were investigated when they were 16 or older in the delinquency and teen motherhood samples, and all children who were first investigated when they were 17 or older in the employment sample, were excluded, which results in an uncensored foster care placement measure.[16] The analysis will focus, then, on school-age children roughly between the ages of 5 and 15 at the time of the abuse investigation. The results here should therefore be regarded as the effects of foster care placement for older children.

The delinquency outcome necessarily relates to children in Cook County, while the teen motherhood outcome relates to girls. Another 1 percent of the observations had missing child characteristics or had too few case manager investigations to calculate the instrument defined below. Finally, in a few cases, the child was delinquent prior to the abuse report, and these cases are excluded from the delinquency analysis.[17] These restrictions result in 15,039

[13] Some nonprofits and local government entities are exempt.

[14] Results were similar when sexual abuse cases were included. Drug exposure largely relates to infants, who are excluded from the outcome comparisons due to age restrictions described below.

[15] This is especially important for the teen motherhood and employment outcomes, which require a social security number for the match. Interestingly, the instrumental variables point estimates for the delinquency results are similar when non-Medicaid children are included in the analysis, as the instrumental variable is unrelated to Medicaid receipt.

[16] Placement is often quite different for children older than 15, who often enter an Independent Living program.

[17] We exclude 670 prior delinquency cases. Employment is not subject to this concern, given the restriction that investigated children be at least 18 in 2002. The teen motherhood outcome should be regarded not as a pregnancy outcome but rather the decision to bear a child prior to the

children in the delinquency sample, 20,091 girls in the teen motherhood sample, and 30,415 children in the employment sample.

Further, for the few cases where the delinquency or teen birth occurred between the time of the investigation and the placement, the wait for removal may have contributed to the outcome. It is important not to associate these delinquencies or births with foster care placement. In the outcome comparisons, the indicator for removal is set to zero for these cases.

B. *Summary Statistics*

To better understand the types of allegations, reporters, and other child characteristics, Table 1 reports summary statistics for the delinquency sample—those children considered for juvenile delinquency using data from Cook County. The most common reporter of abuse is the family itself (29 percent). These reports can stem from domestic violence reports or from a concerned grandparent, for example. School personnel (13 percent), police (13 percent), and physicians (12 percent) are known as mandated reporters—they are required by law to report suspected abuse or neglect.

The average age of all first-investigated children in Illinois is 6.5, with half of the children under the age of 5, yet the children considered here are 11 years old on average. This is due to the restriction that these children are at least 15 years old in 2000.

In terms of race and ethnicity, 76 percent of the sample is African American and 12 percent is Hispanic, compared to 26 percent and 20 percent, respectively, for school-age children in Cook County as a whole in 2000. Meanwhile, 47 percent of the investigated children are boys.

Another characteristic observed is the allegation. Roughly half of the allegations are for abuse, and the other half for neglect. The most common report of neglect is a lack of supervision. This occurs when a child is found unsupervised or when a parent abandons a child, which may partly be due to child behavior problems. Environmental neglect is claimed in 15 percent of the allegations, when the child's living conditions are hazardous. Physical abuse is the primary allegation 17 percent of the time, and is usually described as bruises, cuts, or broken bones. Meanwhile, nearly one-quarter of the allegations are "substantial risk of harm," which describes children deemed to be in imminent danger. Together, the characteristics in Table 1 describe the types of cases seen by child protective services and will be used as controls in the analysis below, including indicators for each year of age at the time of the investigation.

The teen motherhood and employment samples are statewide, with 47 percent of the children coming from Cook County. Reports are less likely to come from family members (22 percent versus 29 percent in Cook County); children are less likely to be African American (49 percent versus 76 percent); and they are more likely to be white (42 percent versus 11 percent). Meanwhile, the allegation is more likely to be substantial risk of harm (32 percent versus 24 percent) and less likely to be lack of supervision (30 percent versus 37 percent). Full summary statistics are located in a supplementary appendix available on the *AER* Web site (http://www.e-aer.org/data/dec07/20050982_app.pdf).

Compared to the statewide foster care population, the observable characteristics for all investigated children are similar to the employment sample, with the biggest difference being the average age (5.9 versus 12.4). There were more physician reports among the population of first-investigated children (17 percent versus 10 percent), reflecting physician interventions for infants, and fewer school reports (9 percent versus 14 percent). The population is more likely to be white (48 percent versus 42 percent) and less likely to be African American (41 percent versus 49 percent), largely due to the restriction that the children previously received Medicaid. In terms of allegations, physical abuse reports were less common among the full population (12 percent versus 20 percent), with much of the difference coming from the 8 percent of sexual abuse cases and 5 percent of drug-exposed children who were excluded because they were less likely to enter the rotational assignment as described in Section II. Rates of the other major allegation categories were similar in the full population. Last, the full population included 43 percent from Cook County versus 47 percent in the employment sample.

age of 18 (abortions are not available in Medicaid). Point estimates were virtually identical when 597 cases where the woman gave birth less than nine months after the initial abuse report were excluded.

Table 1—Summary Statistics: Delinquency Sample

Variable		*Mean*	*Standard deviation*	*Maximum*	*Minimum*
	Foster care placement	0.27	0.44	0	1
Initial reporter	Physician	0.12	0.33	0	1
	School	0.13	0.33	0	1
	Police	0.13	0.34	0	1
	Family	0.29	0.46	0	1
	Neighbor	0.06	0.23	0	1
	Other government	0.09	0.29	0	1
	Anonymous	0.15	0.35	0	1
	Other reporter	0.03	0.16	0	1
Age at report	Age	11.3	2.5	5	15
Sex	Boy	0.47	0.50	0	1
Race	White	0.11	0.31	0	1
	African American	0.76	0.43	0	1
	Hispanic	0.12	0.32	0	1
	Other race/ethnicity	0.01	0.10	0	1
Allegation	Physical abuse	0.17	0.38	0	1
	Substantial risk of harm	0.24	0.43	0	1
	Other abuse	0.02	0.15	0	1
	Lack of supervision	0.37	0.48	0	1
	Environmental neglect	0.15	0.36	0	1
	Other neglect	0.04	0.20	0	1
Location	Cook County	1.00	0.00	1	1
Outcome	Delinquency	0.17	0.38	0	1
	Observations	15,039			

To place the results in context with foster care in the United States, note that the average length of stay is two years compared to an average length of stay of four years in the state of Illinois.[18] In addition, the average age of foster children currently in care is ten, with 30 percent under the age of five (US Department of Health and Human Services 2004). Illinois also relies more heavily on kinship foster care, with half of all initial placements going to a relative, compared to 23 percent for all foster children currently in family foster care. Last, the sample studied here is disproportionately African American compared to the US foster care population (49 percent versus 35 percent), with similar rates for whites, and fewer Hispanics (7 percent versus 17 percent). One advantage of considering Illinois is that it includes a large city as well as smaller cities to compare the results.

In summary, the results here consider a large urban state and school-age children who were receiving public aid prior to the investigation. These restrictions should be kept in mind when interpreting the results.

IV. Estimation

A. *Investigator Assignment*

Given the rotational assignment process within geographic teams, the instrument will be calculated for each case manager–team group, where the team is defined by the case team × ZIP code × Hispanic × report year cells. The main analysis is done at the child level, so the

[18] Under court order to reduce lengths of stay, the state made efforts to reduce this time in foster care beginning in 1997.

instrument is defined for each child i assigned to case manager c in investigation subteam j as:

$$(8) \quad Z_{icj} = d_{icj}\,(1/(n_c - n_{cj})) \sum_{k=-j} n_{ck}\,(\bar{R}^{ck} - \bar{R}^{k}),$$

where d_{icj} is an indicator that the case manager c and subteam j correspond to the ones assigned to child i; n_c is the total number of children investigated by case manager c; n_{cj} is the number of children investigated by case manager c in investigation team j; $\bar{R}^{ck}$ is the fraction of children investigated by case manager c in subteam k who are eventually removed from home; and $\bar{R}^{k}$ is the fraction of investigated children in subteam k who are eventually removed from home.

The case manager removal differential is analogous to a case manager fixed effect in a model predicting removal with subteam fixed effects: the propensity of a case manager's investigation to result in foster care placement relative to the types of cases seen by this case manager's subteams. It is calculated for all subteams other than the family's subteam, so that each family's removal decisions do not enter into their calculation. It is not conditional on child characteristics to allow a direct examination of whether the rotational assignment of cases results in case manager placement tendencies that are unrelated to the characteristics of a given child's case. In contrast, a model with controls may mask the possibility that case managers are assigned to particular types of cases.

Heckman (1981) and William H. Greene (2001) discuss the ability of small sample sizes per group to allow for meaningful estimates of fixed effects, with a rule of thumb of eight observations per group. The calculation is restricted to case managers with at least ten investigations. In the delinquency sample there are 409 case managers considered, with an average of 38 investigations per case manager used in constructing the measure.[19] In the teen motherhood and employment samples, the figures are 705 and 28, and 815 and 37.[20]

The measure is constructed on subteam cells where there is more than one case manager. Children investigated in a subteam cell with only one case manager will still have a nonmissing instrument, however, as it is calculated for all other subteam cells. There are 1,465 subteams used in the calculation in the delinquency sample, with an average of 7 observations per cell, 1,961 in the teen motherhood sample and 3,824 in the employment sample, both with an average of 5 children per cell. The calculation is weighted by the number of children in the subteam to extract the signal from cells with the least noise. Further, the results were similar when the report-year interactions were not used in the cell construction to increase the number of children per cell.

The instrument is calculated for the case manager originally assigned to the case. The foster care placement indicator is equal to one if the child is ever removed from home, and this may occur during a subsequent investigation with a different case manager. Case managing is well known to be a difficult occupation, with 20 percent of case managers who began in 1990 no longer working five years later. For 1991 case manager entrants, 37 percent were no longer working five years later. These two cohorts of case managers had median tenures of ten years and eight years, respectively. As a result, the relationship between the assigned case manager and ultimate foster care placement is unlikely to be one to one, and the strength of this first-stage relationship will be described below.

The resulting instruments reveal some variation in placement rates across case managers. The instrument has a mean of zero and a standard deviation of 9 percent in the delinquency sample, 10 percent in the teen motherhood sample, and 7 percent in the employment sample.

The rules and regulations described in Section II imply that families are effectively randomized to investigators within the rotational assignment pool. If this were the case, then child

[19] The total number of observations used in the calculation differs slightly from the analysis sample, as subteams with only one case manager are excluded from the calculation. These cases are still assigned a case manager removal differential, however, as this measure is for all cells other than for a given family. The calculation in the delinquency sample also included the 670 prior delinquency cases excluded in the main results.

[20] Note that if the number of investigators grows with the sample size, these fixed effects would suffer as weak instruments (Jinyong Hahn and Jerry A. Hausman 2003; James Stock, James Wright, and Motohiro Yogo 2002). The strength of the instrument is considered below.

TABLE 2—CHILD CHARACTERISTICS AND CASE MANAGER ASSIGNMENT: DELINQUENCY SAMPLE

Dependent variable: Case manager removal differential Variable		Coefficient	t	p-value
Initial reporter	Physician	−0.006	−0.81	0.416
(Other reporter excluded)	School	−0.005	−0.74	0.457
	Police	−0.008	−1.11	0.269
	Family	−0.003	−0.52	0.605
	Neighbor	−0.005	−0.73	0.464
	Other government	−0.007	−0.96	0.339
	Anonymous	−0.007	−1.07	0.287
Age at report	Age 6	0.005	0.41	0.679
(Youngest age excluded)	Age 7	0.012	1.07	0.284
	Age 8	0.009	0.90	0.367
	Age 9	0.015	1.42	0.156
	Age 10	0.008	0.72	0.470
	Age 11	0.009	0.94	0.346
	Age 12	0.010	0.99	0.324
	Age 13	0.013	1.26	0.207
	Age 14	0.009	0.91	0.366
	Age 15	0.009	0.89	0.373
Sex	Boy	−0.002	−1.20	0.232
Race/ethnicity	White	−0.014	−1.32	0.186
(Other race excluded)	African American	−0.015	−1.22	0.224
	Hispanic	−0.012	−0.88	0.377
Allegation	Physical abuse	−0.002	−0.43	0.668
(Other neglect excluded)	Substantial risk of harm	−0.006	−0.94	0.348
	Other abuse	0.003	0.43	0.670
	Lack of supervision	−0.005	−0.98	0.325
	Environmental neglect	−0.007	−1.29	0.199
	Mean of dependent variable	0.0001		
	Standard deviation	0.0921		
	F-statistic of joint significance	0.84		
	p-value	0.75		
	Number of case managers	409		
	Observations	15,039		

Note: t-statistics and F-statistic are calculated using standard errors clustered by case manager.

characteristics should be similar across investigators and therefore should not predict the case manager's removal differential. To test this hypothesis, the instrument can be regressed on the child characteristics. For child i investigated during month m of year t, the following model is estimated using ordinary least squares:

$$Z_{icj} = \pi_0 + \pi_1 X_{icj} + \delta_{t(i)} + \eta_{m(i)} + \mu_{icj}, \tag{9}$$

where X is a vector of child characteristics, and δ and η represent vectors of indicators for the year and month of child i's investigation. The standard errors are clustered at the case manager level to reflect the dependence across cases assigned to the same investigator.

Table 2 reports the results for the delinquency sample. The observable child characteristics do not appear related to the case manager's removal

TABLE 3—CHILD CHARACTERISTICS AND CASE MANAGER ASSIGNMENT

Dependent variable: Case manager removal differential

Sample:	Delinquency (1)	Teen motherhood (2)	Employment (3)
F-statistic of joint significance	0.84	1.07	0.96
p-value	0.75	0.34	0.54
Mean of dependent variable	0.0001	−0.0007	−0.0007
Standard deviation of dependent variable	0.0921	0.1035	0.0729
Number of case managers	409	705	815
Observations	15,039	20,091	30,415

Notes: All models include full controls (individual year, month, and age indicators). F-statistics are calculated using standard errors clustered by case manager.

differential. For example, children with a report from the police are found to have only a 0.3 percentage point decrease in the case manager removal differential compared to school reports, despite the fact that police reports are associated with an increased likelihood of placement. Another example is the following: African American children are more likely to be placed compared to white children, yet case managers assigned to African American families have a 0.1 percentage point lower removal differential compared to white cases.

One summary of the relationship between the child characteristics and the case manager removal rate is an F-test for joint significance. For the models predicting the removal differential, a lack of joint significance for these characteristics is not rejected: in the delinquency sample, the F-statistic is 0.84 with a p-value of 0.75; in the teen motherhood sample, it is 1.07 and 0.34; and in the employment sample, the F-statistic is 0.96 with a p-value of 0.54, as shown in Table 3.[21]

Another test to see whether case managers with high removal frequencies are assigned tougher cases is to examine the length of stay once in foster care. More abusive families can be expected to cause longer stays away from them. If strict case managers are assigned to these families, then length of stay should be correlated with the removal differential. In these samples, children typically stay in care for four years for the state-wide samples and five years for the Cook County sample. A higher case manager removal differential is not related to the length of stay, however.[22]

To further explore the type of care received, the placement type can be compared as well. Although case managers do not supervise foster children once placed in care, case managers do investigate the family and may be aware of a relative who is willing to provide foster care, as described in Section II. Nevertheless, an initial placement with relatives is not related to the case manager removal differential. Of the children placed in foster care, roughly half are initially placed with relatives, but a 10 percentage point increase in the case manager removal differential is associated with only a 0.2 percentage point increase in relative placement for the delinquency and teen motherhood samples, and a 0.2 percentage point decrease in the employment sample. This is not surprising, given the administrative rule that relatives are sought first for any child placed in foster care. Still, the lack of a relationship between the investigator and the

[21] An F-test for the child characteristics only (excluding the year and month indicators) results in F-statistics (p-value) of 0.83 (0.71), 1.15 (0.28), and 0.93 (0.57) for the delinquency, teen motherhood, and employment samples.

[22] A 10 percentage point increase in the case manager removal differential is associated with a 0.1 year reduction in care in the delinquency sample, a 0.02 year reduction in the teen motherhood sample, and a 0.01 year reduction in the employment sample, none of which is statistically significant. Results are reported in the Web appendix.

placement type is suggestive that the investigator has little impact on the type of care received once in foster care.

Finally, if case managers with higher removal frequencies place particular types of children who just so happen to be more frequently observed, this would be a violation of the monotonicity condition. If this were the case, then observable characteristics, such as allegations or reporters, may be more prevalent for case managers with higher removal differentials, *conditional on foster care placement*. When the case manager removal differential is regressed on child characteristics for children placed in foster care, however, child characteristics are again unrelated to the case manager removal differential in each of the three samples.[23]

B. *Case Manager Assignment and Foster Care Placement*

Children assigned to case managers with high removal differentials may be more likely to be placed in foster care as well. To test this first-stage relationship, the estimating equation for child i assigned to an investigator c in subteam j during month m in year t is

$$R_{icj} = \phi_0 + \phi_1 Z_{icj} + \phi_2 X_{icj} + \delta_{t(i)} + \eta_{m(i)} + \omega_{icj}. \quad (10)$$

This equation is estimated using a probit model, with standard errors clustered at the case manager level, though results are nearly identical with a linear probability model.

Table 4 reports the results for the delinquency sample and shows that the case manager removal differential is positively associated with foster care placement. The estimated marginal effect of 0.3 implies that an increase in the removal differential from one standard deviation below the mean to one standard deviation above—representing an approximately 20 percentage point increase—would be associated with a 6 percentage point increase in the likelihood of removal, or 22 percent of the mean removal rate.

The probability of removal does not increase one for one with the case manager removal rate. This is likely due to a type of measurement error that attenuates the effect toward zero. First, the case manager of the initial investigation is used to characterize the case manager type, though this may not represent the case manager in subsequent investigations given the investigator turnover described above. Second, the case manager is the lead investigator in the case, whereas a judge has the final say on foster care stays. Nevertheless, the removal rate is associated with placements, with a Chi-squared statistic of 28, well above the rule of thumb of 10 for weak instruments (James Stock, James Wright, and Motohiro Yogo 2002).

The addition of controls to the model does not change the estimates very much, as expected, given that the control variables appear unrelated to the case manager removal differential. In contrast, these variables are associated with foster care placement. For example, police and physician reports are strongly associated with increases in the likelihood of foster care placement, compared to school reports, and African American children are also more likely to be placed. Those suspected of being physically abused and of "other abuse" (which represents the most serious allegations, such as burns) are less likely to be placed. This may be due to a higher reporting rate for such incidents, many of which may not be due to child abuse. Also, "lack of supervision," which often implies a missing mother and may describe problem behavior on the part of the child as well, is more likely to result in a placement, compared to environmental neglect, which represents hazardous living conditions that may be more easily remedied. Similar results are seen in the teen motherhood and employment samples that are statewide, though smaller differences in the allegation types are found. Meanwhile, Cook County cases are more likely to result in placement (with a coefficient of 0.06 and 0.08 in the two statewide samples, and a standard error of 0.01 in each).[24]

[23] The F-statistic of joint significance is 0.85, 1.05, and 1.05 for the delinquency, teen motherhood, and employment samples, with p-values of 0.75, 0.39, and 0.39. Results are reported in the Web appendix.

[24] Full results are in the Web appendix.

TABLE 4—CASE MANAGER ASSIGNMENT AND FOSTER CARE PLACEMENT: JUVENILE DELINQUENCY SAMPLE

Dependent variable: Case manager removal differential

	Model:	Probit			Probit		
		Coefficient	S.E.	*p*-value	Coefficient	S.E.	*p*-value
Key explanatory variables	Case manager removal differential	0.30	0.07	0.00	0.27	0.05	0.00
Initial reporter (Other reporter excluded)	Physician				0.10	0.03	0.00
	School				−0.02	0.03	0.43
	Police				0.14	0.03	0.00
	Family				0.05	0.03	0.06
	Neighbor				0.02	0.03	0.53
	Other government				0.07	0.03	0.03
	Anonymous				−0.06	0.03	0.02
Age at report (Youngest age excluded)	Age 6				0.05	0.05	0.21
	Age 7				0.05	0.04	0.18
	Age 8				0.02	0.04	0.66
	Age 9				0.03	0.04	0.44
	Age 10				0.03	0.04	0.42
	Age 11				0.02	0.04	0.55
	Age 12				0.00	0.04	0.97
	Age 13				−0.02	0.04	0.63
	Age 14				−0.04	0.04	0.32
	Age 15				−0.07	0.03	0.08
Sex	Boy				−0.01	0.01	0.14
Race/ethnicity (Other race excluded)	White				0.00	0.05	0.95
	African American				0.11	0.04	0.02
	Hispanic				−0.03	0.05	0.50
Allegation (Other neglect excluded)	Physical abuse				−0.07	0.02	0.00
	Substantial risk of harm				0.00	0.02	0.88
	Other abuse				−0.09	0.02	0.00
	Lack of supervision				0.00	0.02	0.89
	Environmental neglect				−0.08	0.02	0.00
	Chi-squared (1) stat.	17.9			27.8		
	Mean of dep. var.	0.27					
	Observations	15,039					

Note: Marginal effects and standard errors clustered at the case manager level are reported.

Table 5 reports the first-stage results for all three samples. The placement rate is lower outside Cook County, with the statewide placement rate in the employment sample of 23 percent. The marginal effect of the removal differential on placement ranges from 0.2 to 0.33. Chi-squared statistics of the significance of the instrument in predicting placement range from 28 to 55 in the models with controls. For all three samples, then, it appears that the removal differential does have some explanatory power and does not suffer as a weak instrument.

To explore the source of this first-stage relationship across case managers, Figure 2 presents local linear regressions of an indicator for foster care placement on the case manager removal differential for each of the three samples. Each point represents the local linear regression

Table 5—Case Manager Assignment as a Predictor of Removal

Dependent variable: Foster care placement	Delinquency sample		Teen motherhood sample		Employment sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Case manager removal differential	0.301	0.274	0.231	0.204	0.327	0.288
	(0.071)	(0.052)	(0.050)	(0.035)	(0.060)	(0.039)
Mean of dependent variable	0.27		0.21		0.23	
Chi-squared (1) statistic	17.9	27.8	21.5	34.2	29.3	55.0
Observations	15,039		20,091		30,415	
Full controls	No	Yes	No	Yes	No	Yes

Note: Results of probit models, with marginal effects and standard errors clustered at the case manager level, are reported.

estimate evaluated at a percentile of the case manager removal differential, and the estimates use a bandwidth of 0.05.[25]

The figures show how much variation in placement can be attributed to the instrument. The top line reports the results for the delinquency sample, and an increase from the tenth percentile to the ninetieth percentile in the removal differential (from –0.10 to 0.11) is associated with an increase in the placement rate from 0.25 to 0.31. This implies a first-stage slope estimate of 0.29. The middle line is for the employment sample, and the rise in placement is evident for case manager removal differentials that are greater than zero when the placement rate increases from 21.6 percent to 29 percent. The bottom line is for the teen motherhood sample, and the increase in placement is seen in the interquartile range of the instrument where the placement rate increases from 18 percent to 23 percent.

The first-stage results graphed in Figure 2 show a fairly monotonic increase in foster care placement with the case manager removal differential, especially within the interquartile range of the instrument. This provides modest support for the monotonicity condition, though that assumption applies to each individual rather than the averages reported in Figure 2.

Case Manager Characteristics.—Some information is known about the case manager as well, including sex, race, experience, educational attainment (highest degree), and Spanish-speaking ability. The most stable relationship in these data is that male case managers are slightly less likely to be associated with foster care placement. These case manager characteristics are much less predictive compared to the case manager removal differential, however. It appears that differences in removal rates are more idiosyncratic than systematic when it comes to case manager characteristics.

C. *Foster Care Placement and Child Outcomes*

The empirical models will consider outcomes, Y, for child i assigned to case manager c in subteam j during month m in year t of the form

$$Y_{icj} = \alpha_0 + \alpha_1 R_{icj} + \alpha_2 X_{icj} + \delta_{t(i)} + \eta_{m(i)} + \nu_{icj}, \tag{11}$$

where the case manager removal differential, Z_{icj}, will be used as an instrument for the indicator for removal, R_{icj}. The outcomes will be estimated separately, given the different samples used. In particular, the delinquency and teen motherhood outcomes are binary and will be estimated using probit and IV probit maximum likelihood models, while the employment and earnings outcomes will be estimated using OLS and 2SLS.

[25] When the percentiles were calculated, case manager removal differentials of zero occupied three percentiles in the juvenile delinquency sample, four percentiles in the teen motherhood sample, and three percentiles in the employment sample, resulting in 98, 97, and 98 estimates for the three samples. The shape of the first-stage relationship is similar for a wide range of bandwidths from 0.01 to 0.1, though a bandwidth of 0.1 reveals larger fluctuations.

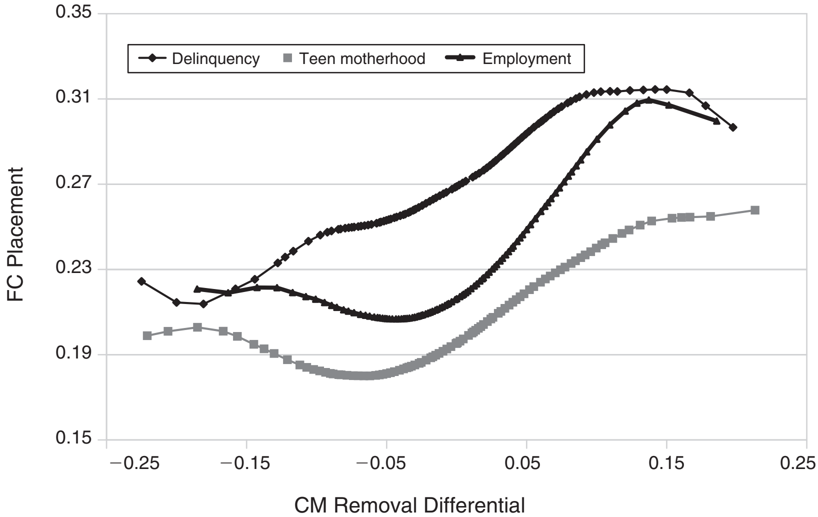


FIGURE 2. FC PLACEMENT VERSUS CASE MANAGER REMOVAL DIFFERENTIAL

Notes: Local linear regressions for the three samples. Bandwidth = 0.05.

Juvenile Delinquency.—Juvenile delinquency is a common occurrence for this group. Of the 15,039 children considered here, 17 percent are found to come before the Juvenile Court of Cook County. Table 6 reports the results, where the probit models reveal little difference between those placed in foster care and those not placed in care.

Delinquency differences are found to be greater when estimated with an IV probit model, with a marginal effect estimate of 0.26 and a standard error of 0.14 in a model with no controls. When controls are included, the marginal effect estimate increases to 0.35 with a standard error of 0.14, largely due to the control for the sex of the child. The controls also reveal that boys, older children at the time of the initial investigation, and children investigated in the early 1990s were more prone to delinquency.

These IV point estimates are quite large. If 10 percent of these marginal cases were placed in foster care, then a 30 percentage point difference would imply that foster children have a delinquency rate three times that of children who were not placed in foster care.[26]

The larger IV results suggest that the estimated causal effects of foster care on delinquency are worse than the conditional means comparison would imply, although differences between the IV and non-IV results are not statistically significant. A key difference between the two sets of results is that the IV calculation estimates the effects for marginal cases—those induced into foster care due to the case manager assignment. The usual omitted variables bias in the means comparison—that foster children come from worse families and would have worse outcomes regardless of placement—may be outweighed by a selection bias: children with higher expected benefits from foster care placement, such as severely abused children, are more likely to be placed. As a result, the means comparison may understate any negative effect from placement for marginal cases.

In any event, the large coefficients and standard errors suggest some caution in the interpretation. The results do suggest that large benefits to foster care placement are unlikely for children on the margin, at least in terms of juvenile delinquency.

Teen Motherhood.—For girls, teen pregnancy is often cited as a correlate to such other problems as poverty, less educational attainment, and welfare dependency. As with delinquency,

[26] The calculation uses the weighted average 0.9*0.14 + 0.1*(0.14+0.30) = 0.17, the mean delinquency rate for the sample.

Table 6—Foster Care Placement and Juvenile Delinquency

Dependent variable: Juvenile delinquency

	Model:	Probit				IV Probit			
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
	FC placement	0.01	0.01	0.00	0.01	0.26	0.14	0.35	0.14
Initial reporter	Physician			0.00	0.02			−0.02	0.02
(Other reporter excluded)	School			0.00	0.02			0.00	0.02
	Police			0.02	0.02			−0.01	0.03
	Family			0.00	0.02			−0.01	0.02
	Neighbor			0.01	0.03			0.00	0.03
	Other government			0.03	0.02			0.01	0.02
	Anonymous			0.01	0.02			0.03	0.02
Age at report	Age 5			—	—			—	—
(Youngest age excluded)	Age 6			0.06	0.05			0.04	0.05
	Age 7			0.10	0.05			0.08	0.05
	Age 8			0.13	0.05			0.12	0.05
	Age 9			0.13	0.05			0.12	0.05
	Age 10			0.17	0.06			0.15	0.05
	Age 11			0.19	0.06			0.18	0.05
	Age 12			0.22	0.06			0.21	0.05
	Age 13			0.23	0.06			0.23	0.06
	Age 14			0.23	0.06			0.23	0.06
	Age 15			0.12	0.05			0.14	0.05
Sex	Boy			0.19	0.01			0.19	0.01
Race/ethnicity	White			−0.07	0.03			−0.07	0.03
(Other race excluded)	African American			−0.02	0.04			−0.05	0.04
	Hispanic			−0.07	0.03			−0.07	0.03
Allegation	Physical abuse			−0.01	0.02			0.01	0.02
(Other neglect excluded)	Substantial risk of harm			−0.03	0.01			−0.03	0.02
	Other abuse			−0.02	0.02			0.01	0.03
	Lack of supervision			−0.02	0.02			−0.03	0.02
	Environmental neglect			−0.02	0.02			0.00	0.02
	Mean of dep. var.	0.17							
	Observations	15,039							

Note: Marginal effects and standard errors clustered at the case manager level are reported.

teen motherhood is common, with 35 percent of the sample having a teen birth.

Table 7 reports the results, and children who entered foster care are found to have a 9 to 10 percentage point higher teen birth rate. The control variables reveal that older children at the time of the investigation, African American children, and children investigated in the early 1990s had higher teen birth rates. Meanwhile, children investigated in Cook County had slightly lower teen birth rates.[27]

When the case manager removal differential is used as an instrument for removal in an IV Probit model, girls who were removed from

[27] Results with all covariates are available in the Web appendix.

Table 7—Foster Care Placement and Teen Motherhood

Dependent variable	Teen pregnancy			
Model	Probit (1)	Probit (2)	IV Probit (3)	IV Probit (4)
Foster care placement	0.106 (0.009)	0.090 (0.010)	0.171 (0.158)	0.291 (0.171)
Mean of dependent variable	0.35			
Full controls	No	Yes	No	Yes
Observations	20,091			

Note: Marginal effects and standard errors clustered at the case manager level are reported.

Table 8—Foster Care Placement and Employment & Earnings

Dependent variable	Fraction of quarters working in 2002				Average quarterly earnings in 2002			
Model	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)	OLS (5)	OLS (6)	2SLS (7)	2SLS (7)
Foster care placement	−0.023 (0.006)	0.002 (0.006)	−0.110 (0.120)	−0.154 (0.113)	−82.8 (29.5)	−50.4 (30.6)	−851 (597)	−1,296 (626)
Mean of dep. var.	0.320				1,044			
Full controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	30,415							

Notes: Standard errors clustered at the case manager level are reported. Average quarterly earnings include those with zero earnings.

home are found to have even higher teen birth rates, similar to the delinquency results. The estimated marginal effect is 0.17, with a standard error of 0.16. With the inclusion of controls, especially age controls, the estimate increases to 0.29, with a standard error of 0.17—a difference that is marginally statistically significant at the 10 percent level. Again, the estimates are large (representing a teen birth rate of foster children twice that for those who remained at home), with large standard errors as well.

Employment and Earnings.—Employment and earnings are also of interest as measures of stability and long-term success for these children. The data are available on a quarterly basis, and the employment measure is the fraction of quarters that the individual was employed in 2002. The earnings measure is the average quarterly earnings, including those who had zero earnings. The age restriction results in investigated children who were between the ages of 18 and 28 in 2002. Given the large dropout rate in this group—over 60 percent for Chicago schools—most of the investigated children should be in the labor force by the age of 18. Nevertheless, this group has low employment and earnings levels, with the average individual found employed 32 percent of the time earning $1,044 in an average quarter (including zero earnings).

Table 8 reports the results for employment and earnings. The OLS results suggest almost no difference between investigated children who were placed in foster care and those who remained at home. Employment differences are also small across children described by the control variables, with younger children at the time of the investigation, boys, African Americans, and residents of Cook County slightly less likely to be found working. Similar results are found for quarterly earnings, with the exception of slightly higher wages in Cook County.[28]

[28] Results with all covariates are available in the Web appendix.

When foster care placement is instrumented, however, the children who were removed are associated with an 11 percentage point reduction in the fraction of quarters worked, and earnings of less than $850. When controls are introduced, these estimates increase to –0.15 and –$1,296, largely due to the controls for year of investigation and age at investigation. This reflects the relative imprecision of the estimates, with standard errors of 0.11 and $626, respectively. Only the earnings outcome is statistically significant at the 5 percent level. These results are consistent with the delinquency and teen motherhood results that children on the margin of placement appear to have better longer-term outcomes when they remain at home.

Marginal Treatment Effects.—One way to explore the source of the IV results is by estimating marginal treatment effects, as described in Section I. Given the lack of precision in the main results, however, these results should be regarded with some caution.

As the propensity to be placed in foster care increases with the case manager placement differential, the delinquency and teen motherhood rates also rise and the employment measures tend to fall (figures are provided in the Web appendix). The first derivative of each of these relationships with respect to the probability of placement represents the marginal treatment effect function. The shape of this function compares the treatment effects as they vary across children who are removed at different rates, depending on the investigator who was assigned to the case. For example, among low removal rate investigators, the marginal child will likely have worse unobserved abuse levels before being placed in foster care by such "lenient" investigators than children on the margin among high removal rate investigators.

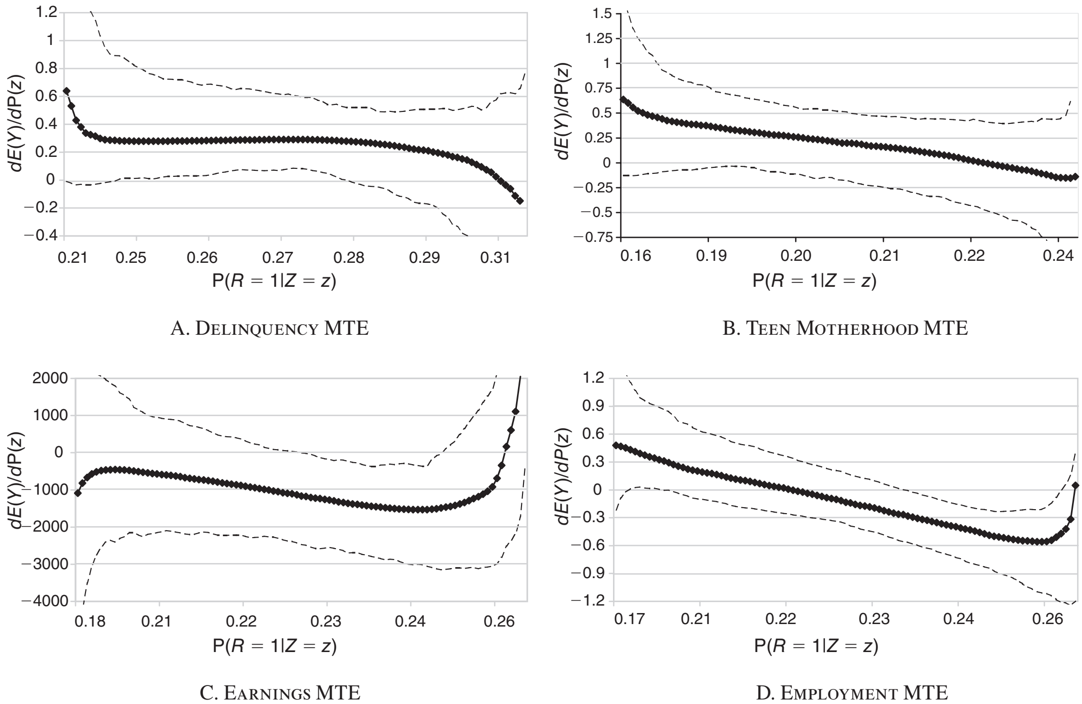
To calculate the MTE function, the predicted probability of placement was estimated using a probit model. The case manager removal differential was the only explanatory variable in the model to capture the variation in placement solely due to the instrument. The relationship between each of the outcome variables and the predicted probability of placement was then estimated using a local quadratic estimator and a bandwidth of 0.037.[29] The estimates of the first derivative of this relationship were evaluated at each percentile of the predicted probability of placement and reported in Figure 3.[30]

The first feature is that the predicted probabilities range from 0.16 to 0.45 in the delinquency sample, and 0.1 to 0.35 in the teen motherhood and employment samples. With the lack of full support for the probability of placement on the unit interval, especially at the extremes, estimating parameters such as the average treatment effect will not be possible. Rather, the marginal treatment effects are considered to trace out how outcomes vary across children who are induced into foster care, as the probability of treatment varies with the instrument. These parameters are necessarily dependent on the instrument considered, though an advantage of the instrument considered here is that it exploits variation that is naturally within the bounds of likely policy changes.

The relationship between delinquency and the probability of placement induced by case manager assignment is fairly linear. Figure 3A shows that this results in an MTE function that is roughly flat at 0.27, with a decline in the top quartile of the predicted propensity of

[29] The local quadratic estimator was chosen as the first derivative of the relationship is sought and local quadratic estimators are thought to have better properties (Jianqing Fan and Irene Gijbels 1996). In practical terms, the results are nearly identical when a local linear regression was estimated instead. The pilot bandwidth was chosen by minimizing the sum of squared errors between the local quadratic estimator and a fourth-degree polynomial model. For the delinquency, teen motherhood, and employment and earnings samples, the resulting pilot bandwidths were 0.070, 0.037, 0.047, and 0.075. Larger bandwidths lead to more linear relationships (and flatter MTE estimates). To explore variations from linearity, the minimum bandwidth from these models was chosen: 0.037. Results are robust to bandwidths down to 0.020, with larger fluctuations in the MTE function at $h = 0.010$.

[30] The local quadratic estimates are reported in the Web appendix, while the derivative is reported in Figure 3. The derivative comes directly from the local quadratic coefficients. In practice, considering the ratio of discrete differences between percentiles in the outcome and the predicted probability of placement yielded the same results. Confidence levels of 5 to 95 percent were calculated using a bootstrap procedure clustered at the case manager level. The propensity score was reestimated in each of the 250 resamplings to capture the variation in the point estimates caused by estimating this variable.



A. Delinquency MTE

B. Teen Motherhood MTE

C. Earnings MTE

D. Employment MTE

Figure 3

Notes: Figures report the results of a local quadratic estimator evaluated at each percentile of P(z). Confidence intervals of 5 to 95 percent reported, calculated using a bootstrap with 250 replications, clustered at the case manager level. Bandwidth = 0.037.

removal. This decline at the upper levels of this propensity suggests that children on the margin of placement among the highest removal rate case managers (children who are likely to have *less* severe unobserved abuse levels) appear to avoid the negative effects of foster care placement. Note that these abuse level comparisons do not include the most severe abuse levels when all case managers would agree to the placement referral.

The results for teen motherhood show more curvature in the relationship between the outcome and the predicted placement variation. This results in a downward-sloping MTE function, as shown in Figure 3B. This again suggests that among children on the margin, foster care placement tends to have a smaller negative effect for those with higher removal rates. While it appears that there are heterogeneous effects across the instrument values, the standard errors are too wide to statistically reject a slope of zero.

The employment measures are more mixed. The earnings MTE fluctuates around –\$1,000 with a downward slope in the interquartile range of predicted placement and an increase in the top quartile. The employment MTE shows a downward slope throughout, with point estimates below zero only in the top half of the predicted removal propensities, suggesting that worse employment differences are found for children on the margin of placement among high removal rate case managers.

These MTE results suggest that the delinquency result is fairly robust over different margins of foster care placement; that the negative teen motherhood results are found largely among children assigned to low removal rate case managers—children who likely have relatively greater abuse levels; and that negative employment results are found for those assigned to the high removal rate case managers—a margin focused on those with relatively lower abuse levels. Again, all these comparisons are among children on the margin of placement, albeit along different margins as defined by the instrument.

Differences across Child Types.—The marginal treatment effect results suggest that there may be heterogeneous effects of foster care placement across different types of children. To investigate this further, Table 9 reports the results of the IV estimation broken into subgroups defined by key childhood characteristics. As in the MTE comparison, these results aim to describe the types of children that drive the main results.

The table reports the Chi-squared statistics in the delinquency and teen motherhood samples, and the *F*-statistics in the employment samples, which test whether the relationship between the instrument and foster care placement is different from zero. These tend to be greater than 20, even in the smaller samples.

The first comparison is between abuse and neglect allegations, and the results are mixed. The placement rate is found to be higher in neglect cases, and the jump in delinquency is most noticeable in the neglect cases as well. Meanwhile, the jump in teen motherhood is found in abuse cases, and the sign flips to negative for neglect cases (again with large and standard errors). The first-stage relationship is not as strong in the neglect sample for the teen motherhood outcome, however, with a Chi-squared statistic of 12. The employment results are similar across allegation types, though lower quarterly earnings among foster care entrants appear more concentrated in the abuse cases.

One important caveat, when interpreting the main results, is that these children are between 5 and 15 years of age when they are investigated to allow for an examination of longer-term outcomes, but half of children investigated are under the age of 5. One way to begin to investigate the role of age is to consider children who were investigated when they were under the age of ten with those who are ten years of age and older. The removal rates are higher for the younger children, as this is an indicator for ever having been removed as a child, and they were at risk of removal for longer periods of time. The bulk of the data reside in the above-ten category, and the results are similar to the main results for this group.[31] The point estimates are smaller for the under-ten group in terms of delinquency; a negative sign is found for the teen motherhood sample (which also had a weaker first stage with a Chi-squared statistic of 8.5); and a somewhat smaller effect is found for quarterly earnings. Meanwhile, the point estimate for the fraction of quarters employed suggests that children under the age of ten have worse outcomes relative to the older group.

For race, the bulk of the data is among nonwhites and the results are similar when whites are excluded from the estimation. The point estimate of the effect of placement on delinquency is greater for girls. Delinquency is much less common among girls as a group, and the interaction between the juvenile delinquency and foster care systems may lead to a relatively larger increase for girls than for boys. The employment effects are similar across boys and girls, though the point estimate for fraction of quarters worked suggests a larger drop for boys.

Across areas, the more urban Cook County has larger increases in teen motherhood and larger declines in employment outcomes compared to the rest of the state.

A final subgroup comparison breaks the sample into two groups based on the propensity of placement estimated using the child characteristics in Table 1, along with three-digit ZIP code indicators to capture neighborhood characteristics.[32] Note that this analysis differs from the MTE results which considered children with

[31] Recall that the sample is limited to children who are at least 15 years old by the end of the sample period: 2000 in the delinquency sample. A five-year-old, for example, would have to be investigated in 1990 to enter the analysis sample, while children who were ten years old at the time of the investigation may be observed from 1990 through 1995.

[32] A propensity score matching exercise was also conducted which largely mimicked the OLS results. In particular, the probability of foster care placement was estimated using the full controls in Table 1 along with three-digit ZIP code indicators. The data were then broken into deciles based upon these predicted probabilities. The delinquency comparisons show small differences across the two groups, with a tendency to have slightly lower delinquency for foster children at lower probability of removal deciles. Teen motherhood comparisons are similar to the OLS results of teen birth rates for foster children 10 percentage points higher, beginning with the third decile. Smaller differences are found for the lowest two deciles, though the observable characteristics are not balanced for these deciles. The employment differences are small across the deciles. Wages are slightly lower for foster children, similar to the OLS results, though larger reductions are found in the third and ninth deciles. Full results are in the Web appendix.

TABLE 9—INSTRUMENTAL VARIABLE RESULTS, BY CHILD CHARACTERISTICS

	Allegation		Age group		Race	Sex		Predicted P(placed|X)	
	Abuse (1)	Neglect (2)	Age < 10 (3)	Age 10+ (4)	Nonwhite (5)	Girl (6)	Boy (7)	< Median (8)	≥ Median (9)
Panel A: Dependent variable: Delinquency									
Foster care placement	0.192	0.421	0.078	0.452	0.352	0.473	0.268	0.701	0.165
	(0.226)	(0.167)**	(0.202)	(0.152)***	(0.133)***	(0.176)***	(0.207)	(0.120)***	(0.145)
Mean of dependent variable	0.161	0.179	0.152	0.177	0.177	0.082	0.270	0.157	0.185
Mean of placement	0.237	0.297	0.403	0.226	0.282	0.270	0.273	0.136	0.406
Chi-squared (1) statistic	15.36	16.37	10.53	23.18	28.46	18.59	17.94	10.28	18.63
Observations	6,566	8,473	3,821	11,218	13,412	7,920	7,119	7,508	7,508

	Allegation		Age group		Race	Location	Predicted P(placed|X)	
	Abuse (1)	Neglect (2)	Age < 10 (3)	Age 10+ (4)	Nonwhite (5)	Cook County (7)	< Median (8)	≥ Median (9)
Panel B: Dependent variable: Teen motherhood								
Foster care placement	0.495	−0.172	−0.123	0.449	0.399	0.354	0.460	0.241
	(0.143)***	(0.249)	(0.217)	(0.152)***	(0.137)***	(0.168)**	(0.360)	(0.163)
Mean of dependent variable	0.343	0.360	0.226	0.404	0.395	0.373	0.314	0.391
Mean of placement	0.175	0.239	0.287	0.171	0.254	0.263	0.091	0.321
Chi-squared (1) statistic	26.18	11.74	8.41	30.99	35.06	26.34	10.37	28.34
Observations	10,477	9,614	5,957	14,134	11,753	9,507	9,961	9,961

	Allegation		Age group		Race	Sex	Location	Predicted P(placed|X)	
	Abuse (1)	Neglect (2)	Age < 10 (3)	Age 10+ (4)	Nonwhite (5)	Boy (6)	Cook County (7)	< Median (8)	≥ Median (9)
Panel C: Dependent variable: Fraction of quarters working									
Foster care placement	−0.150	−0.143	−0.308	−0.110	−0.128	−0.221	−0.424	0.003	−0.228
	(0.146)	(0.166)	(0.205)	(0.132)	(0.128)	(0.159)	(0.192)**	(0.274)	(0.130)*
Mean of dependent variable	0.344	0.295	0.291	0.325	0.273	0.280	0.275	0.346	0.296
Mean of placement	0.196	0.258	0.321	0.209	0.271	0.229	0.283	0.110	0.343
F statistic	32.82	21.01	16.90	44.47	31.56	27.86	20.33	19.54	34.87
Observations	15,533	14,882	4,739	25,676	17,536	14,469	14,210	15,100	15,099

	Allegation		Age group		Race	Sex	Location	Predicted P(placed|X)	
	Abuse (1)	Neglect (2)	Age < 10 (3)	Age 10+ (4)	Nonwhite (5)	Boy (6)	Cook County (7)	< Median (8)	≥ Median (9)
Panel D: Dependent variable: quarterly earnings									
Foster care placement	−1,684	−731	−898	−1,438	−1,293	−1,481	−2,160	−1,699	−1226
	(749)**	(974)	(946)	(784)*	(701)*	(962)	(1,029)**	(1,563)	(670)*
Mean of dependent variable	1,125	960	752	1,098	892	986	978	1,080	1014
Mean of placement	0.196	0.258	0.321	0.209	0.271	0.229	0.283	0.110	0.343
F statistic	32.82	21.01	16.90	44.47	31.56	27.86	20.33	19.54	34.87
Observations	15,533	14,882	4,739	25,676	17,536	14,469	14,210	15,100	15,099

Notes: Panels A and B are estimated with an IV probit model with full controls. Panels C and D are estimated with a 2SLS model with full controls. Marginal effects and standard errors clustered at the case manager level are reported. Chi-squared (1) and *F*-statistics test the first-stage relationship between the instrument and foster care placement. Columns 8 and 9 used a predicted probability of removal from a probit model with full controls and indicators for the three-digit ZIP code of residence. Standard errors clustered at the case manager level are reported.

* Significant at 10 percent level.
** Significant at 5 percent level.
*** Significant at 1 percent level.

similar observable characteristics among those at the margin of placement, while this exercise compares the effects of placement across children who have different observable characteristics. The estimated propensities range from 2 percent to 63 percent in the delinquency sample, 1 percent to 57 percent in the teen motherhood sample, and 2 percent to 63 percent in the employment sample.

For delinquency and teen motherhood, the negative effects of placement are concentrated among those who are less likely to be placed. This is consistent with larger IV results representing worse results for children at the margin compared to the average foster child. As with the previous results, however, the estimates are imprecisely estimated. Again, the employment results are mixed, with the negative effects of placement on the fraction of quarters working found solely for those with a larger propensity to be placed in foster care, though the point estimates for earnings are larger for those with lower propensities to be placed in care. Similar results are found when broken into quartiles as well (reported in the Web appendix).

Specification Checks.—Table 10 reports the results of some specification checks. The first set of checks uses 2SLS, as opposed to the maximum likelihood IV probit in the main results. The point estimates, as well as the standard errors, are slightly smaller. That said, the results are roughly similar to those presented earlier with large IV estimates. For delinquency, the point estimate is 0.28; for teen motherhood, the estimate is 0.27. The employment results are replicated from Table 8 for comparison.

Panel B introduces ZIP code fixed effects to control for the type of neighborhood that may influence the outcomes. The estimates are similar, as expected, given that the instrument is calculated within ZIP code areas.

To compare the results presented here with the larger literature on the local average treatment effect with a binary instrument, an indicator that the case manager removal differential is greater than zero was used instead of the differential itself. A coarse measure of removal tendencies may more accurately categorize those case managers with a high versus a low threshold for recommending foster care placement. The results in Table 10 show similar, though somewhat larger, point estimates.[33]

The results were also robust to alternative specifications for the instrument, including the use of a prior removal rate that described the frequency of foster care placements for case managers calculated on all investigations prior a given family's case. Last, the results were robust to IV probit estimation that used a two-step method: residuals were obtained from a first-stage linear regression of placement on the instrument and controls, and a polynomial in these residuals was added to a probit model of the outcome on a foster care placement indicator and controls. When a quartic in the first-stage residual was included, for example, the marginal effect of removal on delinquency was 0.340 (s.e. = 0.172), and for teen motherhood the effect was 0.343 (s.e. = 0.181).[34]

Limitations.—One of the main limitations of the approaches above is that the outcome data are available only for children who remain in Illinois. For example, if families who are investigated leave the state, they will not be removed, and they will not be found in the outcome data. This may partly explain the increases in juvenile delinquency and teen motherhood, though this explanation would generally not be consistent with the decline in employment. Further, when the analysis is restricted to children who were found in the public aid data through age ten, similar point estimates are found (though the standard errors increase with the smaller sample sizes).

Another limitation is that the empirical strategy does not lend itself to an analysis of the effect of length of stay in foster care on outcomes. Rather, the difference across placement status is considered. When models are considered for children who were either not removed or were in foster care for more than one year, the results are similar. This is partly due to the

[33] When the delinquency and teen motherhood LATE models were estimated with 2SLS, the coefficients were 0.27 (s.e. = 0.11) and 0.37 (s.e. = 0.20), respectively.

[34] Another set of tests used the instrument fully interacted with the child characteristics in the first stage instead of just the level. The resulting F-statistic was lower, however, as variation in these interactions may require too much from the data. The 2SLS estimates are similar, however, with slightly lower point estimates.

TABLE 10—MODEL SPECIFICATION CHECKS

Model	Dependent variable	Delinquency (1)	(2)	Teen motherhood (3)	(4)	Employment (5)	(6)	Quarterly earnings (7)	(8)
A. 2SLS	Foster care placement	0.226	0.282	0.169	0.269	−0.110	−0.154	−851	−1,296
		(0.122)*	(0.117)**	(0.151)	(0.162)*	(0.120)	(0.113)	(597)	(626)**
B. 2SLS w/ ZIP fixed effects	Foster care placement	0.261	0.314	0.194	0.270	−0.115	−0.156	−980	−1,374
		(0.120)**	(0.119)***	(0.132)*	(0.144)*	(0.096)	(0.106)	(549)*	(603)**
C. LATE (binary instrument)	Foster care placement	0.205	0.322	0.255	0.391	−0.119	−0.157	−1,193	−1,803
		(0.102)**	(0.133)**	(0.146)*	(0.181)**	(0.136)	(0.138)	(671)*	(814)**
	Full controls	No	Yes	No	Yes	No	Yes	No	Yes
	Mean of dep. var.	0.17		0.36		0.32		1,044	
	Observations	15,039		20,091		30,415		30,415	

Notes: Standard errors reported are clustered at the case manager level. Columns 5 and 6: employment measure is the fraction of quarters worked in 2002.
Panel C: An indicator that the CM removal differential is greater than zero is the intrumental variable. Marginal effects from IV probit models are reported for delinquency and teen motherhood.
*** Significant at, or below, 1 percent.
** Significant at, or below, 5 percent.
* Significant at, or below, 10 percent.

fact that most children in the datasets that focus on older children are in care for more than a year.

A third limitation is that the benefit of foster care placement in terms of child safety is addressed only through its impact on the outcomes studied here. Using the Medicaid data, reports of broken bones are found to increase with placement, though such a result could reflect more cautious foster parents or case workers being more likely to take the child to the hospital. Although the outcomes studied here represent a wider range of outcomes than previously studied, there are likely unobserved benefits and costs to be considered in future research.

V. Conclusions

With the child welfare system affecting so many children who appear to be at high risk of poor life outcomes, it would be useful to know whether abused children benefit from being removed from their families. The analysis here uses the effective randomization of abuse investigators, who differ somewhat in their tendency to have children placed in foster care, to estimate causal effects of placement on longer-term outcomes. Children assigned to investigators with higher removal rates are more likely to be placed in foster care themselves, and they are found to have higher delinquency rates, along with some evidence of higher teen birth rates and lower earnings.

The point estimates are large and relatively imprecisely estimated, with only the delinquency and earnings results statistically significantly different from zero and none statistically different from the conditional mean comparison, which suggests some caution in the interpretation. Nevertheless, the estimates suggest that large gains from foster care placement are unlikely for this group of children at the margin of placement, at least for the outcomes studied here.

When interpreting the results, three main caveats should be kept in mind. First, the sample consists of school-age welfare recipients investigated in Illinois. In addition, the negative effects in terms of delinquency and teen motherhood are found in the 10–15 age group where most of the data reside. Future work will consider younger

Data Appendix

Source	*Time frame*	*Key variables*	*Age restriction*
Child abuse and neglect tracking system, Illinois Department of Children and Family Services	July 1 1990– June 30, 2001	Investigation data	Infant—age 16 at time of the report
Child and youth centered information system, Illinois Department of Children and Family Services	July 1 1990– June 30, 2003	Removal	Infant—age 16 at time of the report
Online data entry and display system, Illinois Department of Employment Security	January 1, 2002– June 30, 2003	Employment and earnings	Child at least 18 in 2003
Medicaid management information system, Illinois Department of Public Aid	July 1, 1990– June 30, 2001	Teen births	Girls at least 15 in 2001
Delinquency file, Juvenile Court of Cook County, Illinois	July 1, 1990– December 31, 2000	Juvenile delinquency	Child at least 15 in 2000

children as they become at risk for these adolescent and young-adult outcomes. In addition, Illinois is a large urban state where placement of children with family members is more popular than the nation as a whole.

Second, the results consider a group on the margin of placement. While this speaks directly to the policy question of whether we should place greater emphasis on family preservation or child protection, it does not attempt to measure the benefit of placement for children in such danger that all investigators would agree the child should be placed.

Last, the outcomes studied here may relate to child well-being as an adolescent, though they may not reflect the potential prevention of serious child abuse in extreme cases. To the extent that the children on the margin of placement are less likely to suffer from the most serious abuse, this may be less of a concern. Still, child welfare agencies may be willing to trade off higher delinquency, teen motherhood, and unemployment rates for slightly lower levels of serious abuse.

REFERENCES

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. 1996. “Identification of Causal Effects Using Instrumental Variables.” *Journal of the American Statistical Association*, 91(434): 444–55.

Barth, Richard P. 1999. “After Safety, What Is the Goal of Child Welfare Services: Permanency, Family Continuity or Social Benefit?” *International Journal of Social Welfare*, 8(4): 244–52.

Bess, Roseana, Cynthia Andrews Scarcella, Amy Jantz, Victoria Russell, and Rob Geen. 2002. “The Cost of Protecting Vulnerable Children III: What Factors Affect States’ Fiscal Decisions.” In *Assessing the New Federalism Occasional Paper No. 61,* 1–38. Washington, DC: Urban Institute.

Björklund, Anders, and Robert Moffitt. 1987. “The Estimation of Wage Gains and Welfare Gains in Self-Selection.” *Review of Economics and Statistics*, 69(1): 42–49.

Burt, Martha, Laudan Y. Aron, Toby Douglas, Jesse Valente, Edgar Lee, and Britta Iwen. 1999. *Homelessness: Programs and the People They Serve: Findings of the National Survey of Homeless Assistance Providers and Clients*. Washington, DC: Urban Institute.

Campbell, Claudia, and Susan Whitelaw Downs. 1987. “The Impact of Economic Incentives on Foster Parents.” *Social Service Review*, 61(4): 509–609.

Cash, Scottye J. 2001. “Risk Assessment in Child Welfare: The Art and Science.” *Children and Youth Services Review*, 23(11): 811–30.

Chamberlain, Patricia, Sandra Moreland, and Kathleen Reid. 1992. “Enhanced Services and Stipends for Foster Parents: Effects on

Retention Rates and Outcomes for Children." *Child Welfare*, 71(5): 387–404.

Child Welfare League of America. 1999. *State Child Welfare Agency Survey*. Washington, DC: CWLA.

Clausen, June M., John Landsverk, William Ganger, David Chadwick, and Alan Litrownik. 1998. "Mental Health Problems of Children in Foster Care." *Journal of Child and Family Studies*, 7(3): 283–96.

Courtney, Mark E. 2000. "Research Needed to Improve the Prospects for Children in Out-of-Home Placement." *Children and Youth Services Review*, 22(9–10): 743–61.

Courtney, Mark E., and Irving Piliavin. 1998. *Foster Youths Transitions to Adulthood: Outcomes 12 to 18 months after Leaving Out-of-Home Care*. Madison, WI: University of Wisconsin-Madison.

Courtney, Mark E., Sherri Terao, and Noel Bost. 2004. *Midwest Evaluation of the Adult Functioning of Former Foster Youth: Conditions of Youth Preparing to Leave State Care*. Chicago: Chapin Hall Center for Children at the University of Chicago.

Davidson-Arad, Bilha, Dorit Englechin-Segal, and Yochanan Wozner. 2003. "Short-Term Follow-Up of Children at Risk: Comparison of the Quality of Life of Children Removed from Home and Children Remaining at Home." *Child Abuse & Neglect*, 27(7): 733–50.

Doyle, Joseph, and H. Elizabeth Peters. 2007. "The Market for Foster Care: An Empirical Study of the Impact of Foster Care Subsidies." http://www.mit.edu/~jjdoyle.

Dworsky, Amy, and Mark E. Courtney. 2000. "Self-Sufficiency of Former Foster Youth in Wisconsin: Analysis of Unemployment Insurance Wage Data and Public Assistance Data." Report for US Department of Health and Human Services. http://aspe.hhs.gov/hsp/fosteryouthWI00.

Elmer, Elizabeth. 1986. "Outcome of Residential Treatment for Abused and High-Risk Infants." *Child Abuse and Neglect*, 10(3): 351–60.

Fan, Jianqing, and Irene Gijbels. 1996. *Local Polynomial Modeling and Its Applications (Monographs on Statistics and Applied Probability Number 66)*. London: Chapman and Hall.

Gelles, Richard J. 2000. "How Evaluation Research Can Help Reform and Improve the Child Welfare System." *Journal of Aggression, Maltreatment, and Trauma*, 4(1): 7–28.

Goerge, Robert M., John Van Voorhis, and Bong Joo Lee. 1994. "Illinois's Longitudinal and Relational Child and Family Research Database." *Social Science Computer Review*, 12(3): 351–65.

Goerge, Robert M., Fred C. Wulczyn, and David Fanshel. 1994. "A Foster Care Research Agenda for the 90s." *Child Welfare*, 73(5): 525–49.

Greene, William H. 2001. "Estimating Econometric Models with Fixed Effects." http://econpapers.repec.org/paper/fthnystfi/01-10.htm.

Hahn, Jinyong, and Jerry Hausman. 2003. "Weak Instruments: Diagnosis and Cures in Empirical Econometrics." *American Economic Review*, 93(2): 118–25.

Heckman, James J. 1981. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time–Discrete Data Stochastic Process." In *Structural Analysis of Discrete Data with Econometric Applications*, ed. Charles Manski and Daniel McFadden, 114–78. Cambridge, MA: MIT Press.

Heckman, James J., and Edward Vytlacil. 2005. "Structural Equations, Treatment Effects, and Econometric Policy Evaluation." *Econometrica*, 73(3): 669–738.

Hegar, Rebecca, and Maria Scannapieco. 1995. "From Family Duty to Family Policy: The Evolution of Kinship Care." *Child Welfare*, 74(1): 201–15.

Illinois Department of Children and Family Services. 2003. *Manual for Mandated Reporters*. Chicago: Illinois Department of Children and Family Services.

Imbens, Guido W., and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica*, 62(2): 467–75.

James, Sigrid, John Landsverk, and Donald J. Slymen. 2004. "Placement Movement in Out-of-Home Care: Patterns and Predictors." *Children and Youth Services Review*, 26(2): 185–206.

Jonson-Reid, Melissa, and Richard P. Barth. 2000a. "From Maltreatment Report to Juvenile Incarceration: The Role of Child Welfare Services." *Child Abuse & Neglect*, 24(4): 505–20.

Jonson-Reid, Melissa, and Richard P. Barth. 2000b. "From Placement to Prison: The Path to

Adolescent Incarceration from Child Welfare Supervised Foster or Group Care." *Children and Youth Services Review*, 22(7): 493–516.

Kerman, Benjamin, Judith Wildfire, and Richard P. Barth. 2002. "Outcomes for Young Adults Who Experienced Foster Care." *Children and Youth Services Review*, 24(5): 319–44.

Kling, Jeffrey R. 2006. "Incarceration Length, Employment, and Earnings." *American Economic Review*, 96(3): 863–76.

Kornfeld, Robert, and Howard S. Bloom. 1999. "Measuring Program Impacts on Earnings and Employment: Do Unemployment Insurance Wage Reports from Employers Agree with Surveys of Individuals?" *Journal of Labor Economics*, 17(1): 168–97.

Maluccio, Anthony N., Edith Fein, and Inger P. Davis. 1994. "Family Reunification: Research Findings, Issues, and Directions." *Child Welfare*, 73(5): 489–504.

McDonald, Thomas P., Reva I. Allen, Alex Westerfelt, and Irving Piliavin. 1996. *Assessing the Long-Term Effects of Foster Care: A Research Synthesis*. Washington, DC: CWLA.

National Research Council and Institute of Medicine. 1998. *Violence in Families*. Washington, DC: National Academy Press.

Nasuti, J. P., and Peter J. Pecora. 1993. "Risk Assessment Scales in Child Protection: A Test of the Internal Consistency and Interrater Reliability of One Statewide System." *Social Work Research and Abstracts*, 29(2): 28–33.

Newton, Rae, Alan J. Litronwnik, and John A. Landsverk. 2000. "Children and Youth in Foster Care: Disentangling the Relationship Between Problem Behaviors and Number of Placements." *Child Abuse & Neglect*, 24(10): 1363–74.

Rossi, Peter, John Schuerman, and Stephen Budde. 1996. *Understanding Child Maltreatment Decisions and Those Who Make Them*. Chicago: Chapin Hall Center for Children.

Runyan, Desmond K., and Carolyn L. Gould. 1985. "Foster Care for Child Maltreatment: Impact on Delinquent Behavior." *Pediatrics*, 75(3): 562–68.

Sabotta, Eugene E., and Robert L. Davis. 1992. "Fatality after Report to a Child Abuse Registry in Washington State, 1973-1986." *Child Abuse and Neglect*, 16(5): 627–35.

Simon, Julian. 1975. "The Effect of Foster-Care Payment Levels on the Number of Foster Children Given Homes." *Social Service Review*, 49(3): 405–11.

Smith, Dana K., Elizabeth Stormshak, Patricia Chamberlain, and Rachel Bridges Whaley. 2001. "Placement Disruption in Treatment Foster Care." *Journal of Emotional and Behavioral Disorders*, 9(3): 200–05.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo. 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments." *Journal of Business and Economic Statistics*, 20(4): 518–29.

US Department of Health and Human Services, Administration on Children, Youth and Families. 1999. *Title IV-E Independent Living Programs: A Decade in Review*. Washington, DC: US Government Printing Office.

US Department of Health and Human Services, Administration on Children, Youth and Families. 2004. *Child Maltreatment 2002*. Washington, DC: US Government Printing Office.

US Department of Health and Human Services, Administration on Children, Youth and Families. 2005. *The AFCARS Report: Preliminary FY 2003 Estimates as of April 2005*. Washington, DC: US Government Printing Office.

Vinnerljung, Bo, Knut Sundell, Cecilia Andree Lofholm, and Eva Humlesjo. 2006. "Former Stockholm Child Protection Cases as Young Adults: Do Outcomes Differ Between Those that Received Services and Those that Did Not?" *Children and Youth Services Review*, 28(1): 59–77.

Wald, Michael S., J. M. Carlsmith, and P. H. Leiderman. 1988. *Protecting Abused and Neglected Children*. Stanford, CA: Stanford University Press.

Wulczyn, Fred H., Kristen Brunner Hislop, and Robert M. Goerge. 2000. "Foster Care Dynamics 1983–1998." Chicago: Chapin Hall Center for Children.

Zinn, Andrew, Jan DeCoursey, Robert M. Goerge, and Mark E. Courtney. 2006. "A Study of Placement Stability in Illinois." Chicago: Chapin Hall Center for Children.

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1. Mical Raz, Vivek Sankaran. 2019. Opposing Family Separation Policies for the Welfare of Children. *American Journal of Public Health* **109**:11, 1529-1530. [Crossref]
2. Bridget Colacchio Wesley, Julia Pryce, Gina M. Samuels. 2019. Meaning and Essence of Child Well-Being According to Child Welfare Professionals. *Child and Adolescent Social Work Journal* **140**. . [Crossref]
3. Mikkel Sølvsten. 2019. Robust estimation with many instruments. *Journal of Econometrics* . [Crossref]
4. Signe Hald Andersen. 2019. The effect of aftercare on human capital acquisition among foster care alumni. *Children and Youth Services Review* **103**, 28-41. [Crossref]
5. Randi Hjalmarsson, Matthew J Lindquist. 2019. The Causal Effect of Military Conscription on Crime*. *The Economic Journal* **129**:622, 2522-2562. [Crossref]
6. Manudeep Bhuller, Gordon Dahl, Katrine Loken, Magne Mogstad. 2019. Incarceration, Recidivism and Employment. *Journal of Political Economy* . [Crossref]
7. Troy Quast, Melissa A. Bright, Chris Delcher. 2019. The relationship between foster care entries and high-dose opioid prescribing in California. *Addictive Behaviors* **93**, 52-58. [Crossref]
8. Franziska Brunner, Elisabeth Stück, Dahlnym Yoon, Martin Rettenberger, Peer Briken. 2019. Heimaufenthalt in der Kindheit und Rückfallrisiko für Sexualdelinquenz im Erwachsenenalter: Mediieren potenziell traumatisierende Kindheitserfahrungen den Zusammenhang?. *Forensische Psychiatrie, Psychologie, Kriminologie* **13**:2, 178-187. [Crossref]
9. Qi Wu, Susan M. Snyder. 2019. Factors Associated with the Decision-Making Process in Kinship Diversion. *Journal of Family Social Work* **22**:2, 161-186. [Crossref]
10. Mohajer Abbass Hameed. 2019. The tripartite tragedy: Alcohol and other drugs, intimate partner violence and child abuse. *Children Australia* **44**:01, 32-41. [Crossref]
11. Elizabeth Carpenter-Song. 2019. "The Kids Were My Drive": Shattered Families, Moral Striving, and the Loss of Parental Selves in the Wake of Homelessness. *Ethos* **47**:1, 54-72. [Crossref]
12. Anders Hjern, Bo Vinnerljung, Lars Brännström. 2019. Outcomes in adulthood of adoption after long-term foster care: A sibling study. *Developmental Child Welfare* **1**:1, 61-75. [Crossref]
13. Martin Bergström, Marianne Cederblad, Kickan Håkansson, Ann Kristine Jonsson, Christian Munthe, Bo Vinnerljung, Ingegerd Wirtberg, Pernilla Östlund, Knut Sundell. 2019. Interventions in Foster Family Care: A Systematic Review. *Research on Social Work Practice* **26**, 104973151983210. [Crossref]
14. Sarah A. Font, Maria Cancian, Lawrence M. Berger. 2019. Prevalence and Risk Factors for Early Motherhood Among Low-Income, Maltreated, and Foster Youth. *Demography* **56**:1, 261-284. [Crossref]
15. David Dean, John Pepper, Robert Schmidt, Steven Stern. 2019. The effects of youth transition programs on labor market outcomes of youth with disabilities. *Economics of Education Review* **68**, 68-88. [Crossref]
16. SHAI BERNSTEIN, EMANUELE COLONNELLI, BENJAMIN IVERSON. 2019. Asset Allocation in Bankruptcy. *The Journal of Finance* **74**:1, 5-53. [Crossref]
17. Bhaven Sampat, Heidi L. Williams. 2019. How Do Patents Affect Follow-On Innovation? Evidence from the Human Genome. *American Economic Review* **109**:1, 203-236. [Abstract] [View PDF article] [PDF with links]
18. Jacob Nielsen Arendt, Mette Verner. Long-Term Effects of a Social Intervention for Vulnerable Youth: A Register-Based Study 221-236. [Crossref]

19. Laura Perrone, Kristin Bernard, Mary Dozier. Adoption and Foster Placement . [Crossref]
20. Marina Haddock Potter, Sarah A. Font. 2019. Parenting influences on adolescent sexual risk-taking: Differences by child welfare placement status. *Children and Youth Services Review* **96**, 134-144. [Crossref]
21. Ing-Haw Cheng, Felipe Severino, Richard Townsend. 2019. Do Consumers Strike Bad Deals with Debt Collectors? Evidence from Out-of-Court Settlements. *SSRN Electronic Journal* . [Crossref]
22. Troy Quast. 2018. State-level variation in the relationship between child removals and opioid prescriptions. *Child Abuse & Neglect* **86**, 306-313. [Crossref]
23. Miyoung Yoon, Anna E. Bender, Jiho Park. 2018. The association between out-of-home placement and offending behavior among maltreated youth: A systematic review. *Children and Youth Services Review* **95**, 263-281. [Crossref]
24. David Arnold, Will Dobbie, Crystal S Yang. 2018. Racial Bias in Bail Decisions*. *The Quarterly Journal of Economics* **133**:4, 1885-1932. [Crossref]
25. Jason Rodriguez, Naomi Glenn-Levin Rodriguez, Kendralin Freeman. 2018. Student evaluations of teaching: phrenology in the 21 st century?. *Race Ethnicity and Education* **82**, 1-19. [Crossref]
26. Stefan Sjöström, Adam Öhman. 2018. What if an Investigative Journalist Calls? Media Relations in Social Work. *The British Journal of Social Work* **48**:7, 2077-2095. [Crossref]
27. Kath McFarlane. 2018. Care-criminalisation: The involvement of children in out-of-home care in the New South Wales criminal justice system. *Australian & New Zealand Journal of Criminology* **51**:3, 412-433. [Crossref]
28. Joseph J. Doyle, Anna Aizer. 2018. Economics of Child Protection: Maltreatment, Foster Care, and Intimate Partner Violence. *Annual Review of Economics* **10**:1, 87-108. [Crossref]
29. Magne Mogstad, Alexander Torgovitsky. 2018. Identification and Extrapolation of Causal Effects with Instrumental Variables. *Annual Review of Economics* **10**:1, 577-613. [Crossref]
30. Matthew Knepper. 2018. When the Shadow Is the Substance: Judge Gender and the Outcomes of Workplace Sex Discrimination Cases. *Journal of Labor Economics* **36**:3, 623-664. [Crossref]
31. Adi Mana, A. Rosa Naveh. 2018. Facilitating a Therapeutic Environment. *The Family Journal* **26**:3, 293-299. [Crossref]
32. Patrick Gaulé. 2018. Patents and the Success of Venture-Capital Backed Startups: Using Examiner Assignment to Estimate Causal Effects. *The Journal of Industrial Economics* **66**:2, 350-376. [Crossref]
33. Kathleen S. Kenny. 2018. Mental Health Harm to Mothers When a Child Is Taken by Child Protective Services: Health Equity Considerations. *The Canadian Journal of Psychiatry* **63**:5, 304-307. [Crossref]
34. Georges Abi Tayeh, Toufic Naba, Ogarite Habib, Elie Attieh, Fersan Mansour, Assaad Kesrouani, Samer Maalouf. 2018. Tubal ligation and early menopause: a case-control study. *Obstetrics & Gynecology International Journal* **9**:2. . [Crossref]
35. Christina Felfe, Rafael Lalive. 2018. Does early child care affect children's development?. *Journal of Public Economics* **159**, 33-53. [Crossref]
36. Will Dobbie, Jacob Goldin, Crystal S. Yang. 2018. The Effects of Pre-Trial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges. *American Economic Review* **108**:2, 201-240. [Abstract] [View PDF article] [PDF with links]
37. Emily Keddell. 2018. The vulnerable child in neoliberal contexts: the construction of children in the Aotearoa New Zealand child protection reforms. *Childhood* **25**:1, 93-108. [Crossref]

38. Kelcey L. Hall, Jill D. Stinson, Michele R. Moser. 2018. Impact of Childhood Adversity and Out-of-Home Placement for Male Adolescents Who Have Engaged in Sexually Abusive Behavior. *Child Maltreatment* **23**:1, 63-73. [Crossref]
39. Rebecca Orsi, Samantha M. Brown, Kelly E. Knight, Audrey M. Shillington. 2018. Remaining home: Well-being outcomes and co-occurring parental substance use following a maltreatment investigation in middle childhood. *Children and Youth Services Review* **84**, 118-124. [Crossref]
40. Troy Quast, Eric A. Storch, Svetlana Yampolskaya. 2018. Opioid Prescription Rates And Child Removals: Evidence From Florida. *Health Affairs* **37**:1, 134-139. [Crossref]
41. Nicholas Lovett, Yuhan Xue. 2018. Family First or the Kindness of Strangers? Foster Care Placements and Adult Outcomes. *SSRN Electronic Journal* . [Crossref]
42. Manudeep Bhuller, Gordon B. Dahl, Katrine Vellesen LLken, Magne Mogstad. 2018. Incarceration, Recidivism, and Employment. *SSRN Electronic Journal* . [Crossref]
43. Manudeep Bhuller, Gordon B. Dahl, Katrine Vellesen Løken, Magne Mogstad. 2018. Incarceration Spillovers in Criminal and Family Networks. *SSRN Electronic Journal* . [Crossref]
44. Jason Adams, Ken Chow, David Rose. 2018. Assessing Active Labour-Market Programs: How Effective Is Ontario Works?. *SSRN Electronic Journal* . [Crossref]
45. Shanna N. Felix, Laura E. Agnich, April Schueths. 2017. An evaluation of a Court Appointed Special Advocates (CASA) program in the rural south. *Children and Youth Services Review* **83**, 48-56. [Crossref]
46. Will Dobbie, Paul Goldsmith-Pinkham, Crystal S. Yang. 2017. Consumer Bankruptcy and Financial Health. *The Review of Economics and Statistics* **99**:5, 853-869. [Crossref]
47. Karen M. Kolivoski, Jeffrey J. Shook, Kevin H. Kim, Sara Goodkind. 2017. Placement type matters: Placement experiences in relation to justice system involvement among child welfare-involved youth and young adults. *Journal of Human Behavior in the Social Environment* **27**:8, 847-864. [Crossref]
48. Robbin Pott. 2017. Delivering social work services in collaboration with the legal representation for individual clients: An effective, ethical and economical approach to supporting families in child abuse and neglect legal proceedings. *Child Abuse & Neglect* **73**, 24-29. [Crossref]
49. Henri Fraisse. 2017. Households Debt Restructuring: The Re-default Effects of a Debt Suspension. *The Journal of Law, Economics, and Organization* **33**:4, 686-717. [Crossref]
50. April L. Murphy, Whitney Harper, Austin Griffiths, Christopher Joffrion. 2017. Family Reunification: A Systematic Review of Interventions Designed to Address Co-Occurring Issues of Child Maltreatment and Substance Use. *Journal of Public Child Welfare* **11**:4-5, 413-432. [Crossref]
51. Cora Bartelink, Leontien de Kwaadsteniet, Ingrid J. ten Berge, Cilia L. M. Witteman. 2017. Is It Safe? Reliability and Validity of Structured Versus Unstructured Child Safety Judgments. *Child & Youth Care Forum* **46**:5, 745-768. [Crossref]
52. Antti Kääriälä, Heikki Hiilamo. 2017. Children in out-of-home care as young adults: A systematic review of outcomes in the Nordic countries. *Children and Youth Services Review* **79**, 107-114. [Crossref]
53. Bryn King, Melissa Van Wert. 2017. Predictors of Early Childbirth Among Female Adolescents in Foster Care. *Journal of Adolescent Health* **61**:2, 226-232. [Crossref]
54. Dana DeHart, Cheri Shapiro. 2017. Integrated Administrative Data & Criminal Justice Research. *American Journal of Criminal Justice* **42**:2, 255-274. [Crossref]
55. Nicholas E. Kahn, Josh Gupta-Kagan, Mary Eschelbach Hansen. 2017. The Standard of Proof in the Substantiation of Child Abuse and Neglect. *Journal of Empirical Legal Studies* **14**:2, 333-369. [Crossref]
56. Iryna Hayduk. 2017. The Effect of Kinship Placement Laws on Foster Children's Well-Being. *The B.E. Journal of Economic Analysis & Policy* **17**:1. . [Crossref]

57. Lars Brännström, Hilma Forsman, Bo Vinnerljung, Ylva B. Almquist. 2017. The truly disadvantaged? Midlife outcome dynamics of individuals with experiences of out-of-home care. *Child Abuse & Neglect* **67**, 408-418. [Crossref]

58. Nicholas E. Kahn, Mary Eschelbach Hansen. 2017. Measuring racial disparities in foster care placement: A case study of Texas. *Children and Youth Services Review* **76**, 213-226. [Crossref]

59. Bryn King. 2017. First Births to Maltreated Adolescent Girls: Differences Associated With Spending Time in Foster Care. *Child Maltreatment* **22**:2, 145-157. [Crossref]

60. Craig J. Forsyth. 2017. The Sociologist as Story Teller: The Broken Foster Care System Used as Mitigation at Criminal Trial. *American Journal of Criminal Justice* **42**:1, 134-147. [Crossref]

61. Kristin Turney, Christopher Wildeman. 2017. Adverse childhood experiences among children placed in and adopted from foster care: Evidence from a nationally representative survey. *Child Abuse & Neglect* **64**, 117-129. [Crossref]

62. Christine A. Marsh, Jenny Browne, Jan Taylor, Deborah Davis. 2017. A researcher's journey: Exploring a sensitive topic with vulnerable women. *Women and Birth* **30**:1, 63-69. [Crossref]

63. Maria Cancian, Steven T. Cook, Mai Seki, Lynn Wimer. 2017. Making parents pay: The unintended consequences of charging parents for foster care. *Children and Youth Services Review* **72**, 100-110. [Crossref]

64. Aron Shlonsky, Robyn Mildon. Assessment and Decision Making to Improve Outcomes in Child Protection 111-129. [Crossref]

65. Daniel Tartakovsky. 2017. Gender Differences in Reactions to Setbacks: Evidence from High School Debate Competitions. *SSRN Electronic Journal* . [Crossref]

66. Felipe Goncalves, Steven Mello. 2017. Does the Punishment Fit the Crime? Speeding Fines and Recidivism. *SSRN Electronic Journal* . [Crossref]

67. Catherine A. LaBrenz, Rowena Fong. 2016. Outcomes of family centered meetings for families referred to Child Protective Services. *Children and Youth Services Review* **71**, 93-102. [Crossref]

68. Raymie H. Wayne, Brenda D. Smith. 2016. Threats to Perceptions of Fairness in the Termination of Parental Rights. *Juvenile and Family Court Journal* **67**:4, 27-41. [Crossref]

69. Frank Sloan, Lindsey Eldred, Sabrina McCutchan, Alyssa Platt. 2016. Deterring Rearrests for Drinking and Driving. *Southern Economic Journal* **83**:2, 416-436. [Crossref]

70. Sarah Font. 2016. A defense of "soft coercion" in the child welfare system and targeted programs—A response to Pelton (2016). *Child Abuse & Neglect* **59**, 122-124. [Crossref]

71. J.J. Cutuli, Robert M. Goerge, Claudia Coulton, Maryanne Schretzman, David Crampton, Benjamin J. Charvat, Nina Lalich, JessicaA. Raithel, Cristobal Gacitua, Eun Lye Lee. 2016. From foster care to juvenile justice: Exploring characteristics of youth in three cities. *Children and Youth Services Review* **67**, 84-94. [Crossref]

72. Thomas Cornelissen, Christian Dustmann, Anna Raute, Uta Schönberg. 2016. From LATE to MTE: Alternative methods for the evaluation of policy interventions. *Labour Economics* **41**, 47-60. [Crossref]

73. Peter Fallesen. 2016. Downward spiral: The impact of out-of-home placement on paternal welfare dependency. *Children and Youth Services Review* **66**, 45-55. [Crossref]

74. Hui Huang, Joseph P. Ryan, Michelle-Ann Rhoden. 2016. Foster care, geographic neighborhood change, and the risk of delinquency. *Children and Youth Services Review* **65**, 32-41. [Crossref]

75. Arpit Gupta, Christopher Hansman, Ethan Frenchman. 2016. The Heavy Costs of High Bail: Evidence from Judge Randomization. *The Journal of Legal Studies* **45**:2, 471-505. [Crossref]

76. Sara Wakefield, Kathleen Powell. 2016. Distinguishing Petty Offenders from Serious Criminals in the Estimation of Family Life Effects. *The ANNALS of the American Academy of Political and Social Science* **665**:1, 195-212. [Crossref]
77. Karen Zilberstein. 2016. Parenting in Families of Low Socioeconomic Status: A Review with Implications for Child Welfare Practice. *Family Court Review* **54**:2, 221-231. [Crossref]
78. Joseph P. Ryan, Brian E. Perron, Hui Huang. 2016. Child Welfare and the Transition to Adulthood: Investigating Placement Status and Subsequent Arrests. *Journal of Youth and Adolescence* **45**:1, 172-182. [Crossref]
79. D. Figlio, K. Karbownik, K.G. Salvanes. Education Research and Administrative Data 75-138. [Crossref]
80. Arpit Gupta, Christopher Hansman, Ethan Frenchman. 2016. The Heavy Costs of High Bail: Evidence from Judge Randomization. *SSRN Electronic Journal* . [Crossref]
81. Olivier De Groote, Koen Declercq. 2016. Tracking and Specialization of High Schools: Does School Choice Matter?. *SSRN Electronic Journal* . [Crossref]
82. Lars H. Andersen, Christopher Wildeman. 2015. Measuring the Effect of Probation and Parole Officers on Labor Market Outcomes and Recidivism. *Journal of Quantitative Criminology* **31**:4, 629-652. [Crossref]
83. Michael Nycyk, John Rigsby-Jones, Margaret Redsell. 2015. The Value of External Support Services when Children Transition into Foster Care: An Example of a Volunteering Project. *Children Australia* **40**:4, 367-371. [Crossref]
84. J. Christopher Graham, Alan J. Dettlaff, Donald J. Baumann, John D. Fluke. 2015. The Decision Making Ecology of placing a child into foster care: A structural equation model. *Child Abuse & Neglect* **49**, 12-23. [Crossref]
85. Sarah A. Font, Kathryn Maguire-Jack. 2015. Reprint of "Decision-making in child protective services: Influences at multiple levels of the social ecology". *Child Abuse & Neglect* **49**, 50-62. [Crossref]
86. Sei-Young Lee, Margarita Villagrana. 2015. Differences in risk and protective factors between crossover and non-crossover youth in juvenile justice. *Children and Youth Services Review* **58**, 18-27. [Crossref]
87. Jesse Russell, Stephanie Macgill. 2015. Demographics, policy, and foster care rates; A Predictive Analytics Approach. *Children and Youth Services Review* **58**, 118-126. [Crossref]
88. Signe Hald Andersen, Peter Fallesen. 2015. Family matters? The effect of kinship care on foster care disruption rates. *Child Abuse & Neglect* **48**, 68-79. [Crossref]
89. Sarah A. Font, Kathryn Maguire-Jack. 2015. Decision-making in child protective services: Influences at multiple levels of the social ecology. *Child Abuse & Neglect* **47**, 70-82. [Crossref]
90. Peter W. Choate. 2015. Termination of Parental Rights: A Commentary on Ben-David. *Journal of Family Social Work* **18**:4, 243-252. [Crossref]
91. Diana J. English, Richard Thompson, Catherine Roller White. 2015. Predicting risk of entry into foster care from early childhood experiences: A survival analysis using LONGSCAN data. *Child Abuse & Neglect* **45**, 57-67. [Crossref]
92. David Dean, John Pepper, Robert Schmidt, Steven Stern. 2015. THE EFFECTS OF VOCATIONAL REHABILITATION FOR PEOPLE WITH COGNITIVE IMPAIRMENTS. *International Economic Review* **56**:2, 399-426. [Crossref]
93. Wladimir Zanoni, Gabriel Weinberger. 2015. Effects of Childcare Subsidies on Employment and Earnings of Low-Income Mothers. *The B.E. Journal of Economic Analysis & Policy* **15**:2, 589-619. [Crossref]

94. Jesse Russell. 2015. Child Welfare Finance and Foster Care Outcomes. *Journal of Public Child Welfare* **9**:2, 134-152. [Crossref]
95. Will Dobbie, Jae Song. 2015. Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection. *American Economic Review* **105**:3, 1272-1311. [Abstract] [View PDF article] [PDF with links]
96. Alberto Galasso, Mark Schankerman. 2015. Patents and Cumulative Innovation: Causal Evidence from the Courts *. *The Quarterly Journal of Economics* **130**:1, 317-369. [Crossref]
97. Patrick Gaule. 2015. Patents and the Success of Venture-Capital Backed Startups: Using Examiner Assignment to Estimate Causal Effects. *SSRN Electronic Journal* . [Crossref]
98. Hannah Laqueur, Ryan Copus. 2015. Machines Learning Justice: The Case for Judgmental Bootstrapping of Legal Decisions. *SSRN Electronic Journal* . [Crossref]
99. Alberto Galasso, Mark A. Schankerman. 2015. Patent Rights and Innovation by Small and Large Firms. *SSRN Electronic Journal* . [Crossref]
100. Matthew J. Lindquist, Torsten Santavirta. 2014. Does placing children in foster care increase their adult criminality?. *Labour Economics* **31**, 72-83. [Crossref]
101. Peter Fallesen. 2014. Identifying divergent foster care careers for Danish children. *Child Abuse & Neglect* **38**:11, 1860-1871. [Crossref]
102. Kevin R. White, Qi Wu. 2014. Application of the life course perspective in child welfare research. *Children and Youth Services Review* **46**, 146-154. [Crossref]
103. Gordon B. Dahl, Andreas Ravndal Kostøl, Magne Mogstad. 2014. Family Welfare Cultures *. *The Quarterly Journal of Economics* **129**:4, 1711-1752. [Crossref]
104. Peter Fallesen, Natalia Emanuel, Christopher Wildeman. 2014. Cumulative Risks of Foster Care Placement for Danish Children. *PLoS ONE* **9**:10, e109207. [Crossref]
105. Elizabeth Joanne Gifford, Lindsey Morgan Eldred, Allison Vernerey, Frank Allen Sloan. 2014. How does family drug treatment court participation affect child welfare outcomes?. *Child Abuse & Neglect* **38**:10, 1659-1670. [Crossref]
106. Timo Harrikari. 2014. Social disorganization and the profile of child welfare: Explaining child welfare activity by the community-level factors. *Child Abuse & Neglect* **38**:10, 1671-1682. [Crossref]
107. Stephanie Macgill, Alicia Summers. 2014. Assessing The Relationship Between The Quality Of Juvenile Dependency Hearings And Foster Care Placements. *Family Court Review* **52**:4, 678-685. [Crossref]
108. Hui Huang, Joseph P. Ryan. 2014. The location of placement and juvenile delinquency: Do neighborhoods matter in child welfare?. *Children and Youth Services Review* **44**, 33-45. [Crossref]
109. Søren Dalsgaard, Helena Skyt Nielsen, Marianne Simonsen. 2014. Consequences of ADHD medication use for children's outcomes. *Journal of Health Economics* **37**, 137-151. [Crossref]
110. S. H. Andersen, C. Wildeman. 2014. The Effect of Paternal Incarceration on Children's Risk of Foster Care Placement. *Social Forces* **93**:1, 269-298. [Crossref]
111. Christopher Wildeman, Jane Waldfogel. 2014. Somebody's Children or Nobody's Children? How the Sociological Perspective Could Enliven Research on Foster Care. *Annual Review of Sociology* **40**:1, 599-618. [Crossref]
112. Christopher Wildeman, Kristin Turney. 2014. Positive, Negative, or Null? The Effects of Maternal Incarceration on Children's Behavioral Problems. *Demography* **51**:3, 1041-1068. [Crossref]
113. Frank Ainsworth, Patricia Hansen. 2014. Family Foster Care: Can it Survive the Evidence?. *Children Australia* **39**:2, 87-92. [Crossref]

114. A. Aizer. 2014. Rising Inequality and Intergenerational Mobility: The Role of Public Investments in Human Capital. *CESifo Economic Studies* **60**:2, 280-311. [Crossref]
115. Eric French, Jae Song. 2014. The Effect of Disability Insurance Receipt on Labor Supply. *American Economic Journal: Economic Policy* **6**:2, 291-337. [Abstract] [View PDF article] [PDF with links]
116. Christopher Wildeman, Natalia Emanuel. 2014. Cumulative Risks of Foster Care Placement by Age 18 for U.S. Children, 2000–2011. *PLoS ONE* **9**:3, e92785. [Crossref]
117. Nina Santavirta, Torsten Santavirta. 2014. CHILD PROTECTION AND ADULT DEPRESSION: EVALUATING THE LONG-TERM CONSEQUENCES OF EVACUATING CHILDREN TO FOSTER CARE DURING WORLD WAR II. *Health Economics* **23**:3, 253-267. [Crossref]
118. Sarah A. Font. 2014. Kinship and Nonrelative Foster Care: The Effect of Placement Type on Child Well-Being. *Child Development* **44**, n/a-n/a. [Crossref]
119. Scott Brave, Thomas Walstrum. 2014. Estimating Marginal Treatment Effects using Parametric and Semiparametric Methods. *The Stata Journal: Promoting communications on statistics and Stata* **14**:1, 191-217. [Crossref]
120. William P. Warburton, Rebecca N. Warburton, Arthur Sweetman, Clyde Hertzman. 2014. The Impact of Placing Adolescent Males into Foster Care on Education, Income Assistance, and Convictions. *Canadian Journal of Economics/Revue canadienne d'économique* **47**:1, 35-69. [Crossref]
121. Anna Aizer, Joseph J. Doyle. Economics of Child Well-Being: Measuring Effects of Child Welfare Interventions 1563-1602. [Crossref]
122. Alan J. Dettlaff. The Evolving Understanding of Disproportionality and Disparities in Child Welfare 149-168. [Crossref]
123. Bryn King, Emily Putnam-Hornstein, Julie A. Cederbaum, Barbara Needell. 2014. A cross-sectional examination of birth rates among adolescent girls in foster care. *Children and Youth Services Review* **36**, 179-186. [Crossref]
124. Peter Fallesen. 2013. Time well spent: The duration of foster care and early adult labor market, educational, and health outcomes. *Journal of Adolescence* **36**:6, 1003-1011. [Crossref]
125. Mimi Abramovitz, Jochen Albrecht. 2013. The Community Loss Index: A New Social Indicator. *Social Service Review* **87**:4, 677-724. [Crossref]
126. Innessa Colaiacovo. 2013. Not Just the Facts: Adjudicator Bias and Decisions of the Immigration and Refugee Board of Canada (2006–2011). *Journal on Migration and Human Security* **1**:4, 122-147. [Crossref]
127. Tessa Bell, Elisa Romano, Robert J. Flynn. 2013. Multilevel correlates of behavioral resilience among children in child welfare. *Child Abuse & Neglect* **37**:11, 1007-1020. [Crossref]
128. Mary I. Armstrong, Jayme R. Swanke, Anne Strozier, Svetlana Yampolskaya, Patty J. Sharrock. 2013. Recent changes in the child welfare system: One state's experience. *Children and Youth Services Review* **35**:10, 1712-1718. [Crossref]
129. Nicole Maestas,, Kathleen J. Mullen,, Alexander Strand. 2013. Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt. *American Economic Review* **103**:5, 1797-1829. [Abstract] [View PDF article] [PDF with links]
130. Joseph J. Doyle. 2013. Causal effects of foster care: An instrumental-variables approach. *Children and Youth Services Review* **35**:7, 1143-1151. [Crossref]
131. Sara Goodkind, Jeffrey J. Shook, Kevin H. Kim, Ryan T. Pohlig, David J. Herring. 2013. From Child Welfare to Juvenile Justice. *Youth Violence and Juvenile Justice* **11**:3, 249-272. [Crossref]
132. Alberto Galasso, Mark Schankerman, Carlos J. Serrano. 2013. Trading and enforcing patent rights. *The RAND Journal of Economics* **44**:2, 275-312. [Crossref]

133. Sarah Font, Kathryn Maguire-Jack. 2013. Academic engagement and performance: Estimating the impact of out-of-home care for maltreated children. *Children and Youth Services Review* **35**:5, 856-864. [Crossref]

134. Alexander Gelber, Adam Isen. 2013. Children's schooling and parents' behavior: Evidence from the Head Start Impact Study. *Journal of Public Economics* **101**, 25-38. [Crossref]

135. Joshua P. Mersky, Colleen Janczewski. 2013. Adult well-being of foster care alumni: Comparisons to other child welfare recipients and a non-child welfare sample in a high-risk, urban setting. *Children and Youth Services Review* **35**:3, 367-376. [Crossref]

136. Jesse Russell, Alicia Summers. 2013. An Overview of the Courts Catalyzing Change Preliminary Protective Hearing Benchcard Study. *Juvenile and Family Court Journal* **64**:2, 1-16. [Crossref]

137. Frank A. Sloan, Alyssa C. Platt, Lindsey M. Chepke, Claire E. Blevins. 2013. Deterring domestic violence: Do criminal sanctions reduce repeat offenses?. *Journal of Risk and Uncertainty* **46**:1, 51-80. [Crossref]

138. Marni D. Brownell, Douglas P. Jutte. 2013. Administrative data linkage as a tool for child maltreatment research. *Child Abuse & Neglect* **37**:2-3, 120-124. [Crossref]

139. Gregory N. Price. 2013. Hurricane Katrina as an Experiment in Housing Mobility and Neighborhood Effects: Were the Relocated Poor Black Evacuees Better-Off?. *The Review of Black Political Economy* **40**:2, 121-143. [Crossref]

140. SCOTT CUNNINGHAM, KEITH FINLAY. 2013. PARENTAL SUBSTANCE USE AND FOSTER CARE: EVIDENCE FROM TWO METHAMPHETAMINE SUPPLY SHOCKS. *Economic Inquiry* **51**:1, 764-782. [Crossref]

141. Alicia Summers, Corey Shdaimah. 2013. Improving Juvenile Dependency Case Timeliness Through Use of the One Family, One Judge Model. *Juvenile and Family Court Journal* **64**:1, 23-34. [Crossref]

142. Frank A. Sloan, Alyssa Platt, Lindsey M Chepke, Claire Blevins. 2013. Deterring Domestic Violence: Do Criminal Sanctions Reduce Repeat Offenses?. *SSRN Electronic Journal* . [Crossref]

143. Alberto Galasso, Mark A. Schankerman. 2013. Patents and Cumulative Innovation: Causal Evidence from the Courts. *SSRN Electronic Journal* . [Crossref]

144. Michael Malcolm. 2012. Can buy me love: the effect of child welfare expenditures on maltreatment outcomes. *Applied Economics* **44**:28, 3725-3736. [Crossref]

145. GULCIN GUMUS, JUNGMIN LEE. 2012. ALTERNATIVE PATHS TO PARENTHOOD: IVF OR CHILD ADOPTION?. *Economic Inquiry* **50**:3, 802-820. [Crossref]

146. Hilary L. Surratt, Steven P. Kurtz. 2012. Foster Care History and HIV Infection among Drug-Using African American Female Sex Workers. *AIDS and Behavior* **16**:4, 982-989. [Crossref]

147. Joseph P. Ryan. 2012. Substitute Care in Child Welfare and the Risk of Arrest. *Child Maltreatment* **17**:2, 164-171. [Crossref]

148. Frank Ainsworth, Patricia Hansen. 2012. Doing Harm While Doing Good: The Child Protection Paradox. *Child & Youth Services* **33**:2, 146-157. [Crossref]

149. Hui Huang, Joseph P. Ryan, Denise Herz. 2012. The journey of dually-involved youth: The description and prediction of rereporting and recidivism. *Children and Youth Services Review* **34**:1, 254-260. [Crossref]

150. Nicole Maestas, Kathleen J. Mullen, Alexander Strand. 2012. Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt. *SSRN Electronic Journal* . [Crossref]

151. Lil Tonmyr, Gabriela Williams, Susan M. Jack, Harriet L. MacMillan. 2011. Infant Placement in Canadian Child Maltreatment-Related Investigations. *International Journal of Mental Health and Addiction* **9**:5, 441-459. [Crossref]

152. Bo Vinnerljung, Anders Hjern. 2011. Cognitive, educational and self-support outcomes of long-term foster care versus adoption. A Swedish national cohort study. *Children and Youth Services Review* **33**:10, 1902-1910. [Crossref]
153. Richard Bavier. 2011. Children residing with no parent present. *Children and Youth Services Review* **33**:10, 1891-1901. [Crossref]
154. Eun Koh, Mark F. Testa. 2011. Children discharged from kin and non-kin foster homes: Do the risks of foster care re-entry differ?. *Children and Youth Services Review* **33**:9, 1497-1505. [Crossref]
155. E. Christopher Lloyd, Richard P. Barth. 2011. Developmental outcomes after five years for foster children returned home, remaining in care, or adopted. *Children and Youth Services Review* **33**:8, 1383-1391. [Crossref]
156. Judy Havlicek. 2011. Lives in motion: A review of former foster youth in the context of their experiences in the child welfare system. *Children and Youth Services Review* **33**:7, 1090-1100. [Crossref]
157. Angela R. Ausbrooks, David M. Gwin, J. Karen Brown. 2011. Legislative Advocacy for and by Youth Transitioning From Foster Care: A Practice/Education Collaboration. *Journal of Public Child Welfare* **5**:2-3, 234-250. [Crossref]
158. Sharon Bessell. 2011. Participation in decision-making in out-of-home care in Australia: What do young people say?. *Children and Youth Services Review* **33**:4, 496-501. [Crossref]
159. Atsushi Inoue, Barbara Rossi. 2011. Testing for weak identification in possibly nonlinear models. *Journal of Econometrics* **161**:2, 246-261. [Crossref]
160. Eva Tideman, Bo Vinnerljung, Kristin Hintze, Anna Aldenius Isaksson. 2011. Improving Foster Children's School Achievements: Promising Results from a Swedish Intensive Study. *Adoption & Fostering* **35**:1, 44-56. [Crossref]
161. Mette Ejrnæs, Morten Ejrnæs, Signe Frederiksen. 2011. Risk Factors of Entry in Out-of-Home Care: An Empirical Study of Danish Birth Cohorts, 1981–2003. *Child Indicators Research* **4**:1, 21-44. [Crossref]
162. Eric French, Christopher Taber. Identification of Models of the Labor Market 537-617. [Crossref]
163. Nicole Maestas, Kathleen J. Mullen, Alexander Strand. 2011. Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt. *SSRN Electronic Journal* . [Crossref]
164. Alberto Galasso, Mark A. Schankerman, Carlos J. Serrano. 2011. Trading and Enforcing Patent Rights. *SSRN Electronic Journal* . [Crossref]
165. James A. Rosenthal, Susy Villegas. 2010. Living situation and placement change and children's behavior. *Children and Youth Services Review* **32**:12, 1648-1655. [Crossref]
166. Joshua P. Mersky, James Topitzes. 2010. Comparing early adult outcomes of maltreated and non-maltreated children: A prospective longitudinal investigation. *Children and Youth Services Review* **32**:8, 1086-1096. [Crossref]
167. Maureen Norton-Hawk. 2010. Exporting Gender Injustice: The Impact of the U.S. War on Drugs on Ecuadorian Women. *Critical Criminology* **18**:2, 133-146. [Crossref]
168. Jeremy Thornton, Lisa Cave. 2010. THE EFFECTS OF ORGANIZATIONAL FORM IN THE MIXED MARKET FOR FOSTER CARE. *Annals of Public and Cooperative Economics* **81**:2, 211-245. [Crossref]
169. Jeanne Flavin, Lynn M. Paltrow. 2010. Punishing Pregnant Drug-Using Women: Defying Law, Medicine, and Common Sense. *Journal of Addictive Diseases* **29**:2, 231-244. [Crossref]
170. Eric French, Christopher R. Taber. 2010. Identification of Models of the Labor Market. *SSRN Electronic Journal* . [Crossref]

171. Barbara Rossi, Atsushi Inoue. 2010. Testing for Weak Identification in Possibly Nonlinear Models. *SSRN Electronic Journal* . [Crossref]

172. Leslie J. Harris. 2010. Challenging the Overuse of Foster Care and Disrupting the Path to Delinquency and Prison. *SSRN Electronic Journal* . [Crossref]

173. Lawrence M. Berger, Sarah K. Bruch, Elizabeth I. Johnson, Sigrid James, David Rubin. 2009. Estimating the "Impact" of Out-of-Home Placement on Child Well-Being: Approaching the Problem of Selection Bias. *Child Development* **80**:6, 1856-1876. [Crossref]

174. Richard P. Barth. 2009. An alternative response to "The best interests of the child thesis: some thoughts from Australia". *International Journal of Social Welfare* **18**:4, 440-442. [Crossref]

175. Dorothy A Scott. 2009. The landscape of child maltreatment. *The Lancet* **373**:9658, 101-102. [Crossref]

176. David Autor, Susan N. Houseman. 2009. Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from 'Work First'. *SSRN Electronic Journal* . [Crossref]

177. Melissa O'Donnell, Dorothy Scott, Fiona Stanley. 2008. Child abuse and neglect - is it time for a public health approach?. *Australian and New Zealand Journal of Public Health* **32**:4, 325-330. [Crossref]

178. Scott Cunningham, Greg Rafert. 2008. Parental Methamphetamine Use and Foster Care: Is the Growth in Foster Care Admissions Explained by the Growth in Meth Use?. *SSRN Electronic Journal* . [Crossref]