Child Protection and Adult Crime: Using Investigator Assignment to Estimate Causal Effects of Foster Care

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This paper uses the randomization of families to child protection investigators to estimate causal effects of foster care on adult crime. The analysis uses a new data set that links criminal justice data to child protection data in Illinois, and I find that investigators affect foster care placement. Children on the margin of placement are found to be two to three times more likely to enter the criminal justice system as adults if they were placed in foster care. One innovation describes the types of children on the margin of placement, a group that is more likely to include African Americans, girls, and young adolescents.

I. Introduction

One of the strongest predictors of criminal activity, and the externalities that result, is family background (Loeber and Stouthamer-Loeber 1986; Widom 1989; Case and Katz 1991; Sampson and Laub 1993; Donohue

Special thanks to Josh Angrist, John Cawley, Mark Duggan, Robert Goerge, Michael Greenstone, Jeff Grogger, Jon Gruber, Steve Levitt, Lucy Mackey-Bilaver, Bruce Meyer, Doug Miller, Robert Moffitt, Phil Oreopoulos, Jim Poterba, Roberto Rigobon, Tom Stoker, and Tavneet Suri for their comments and advice on this research program. I would like to acknowledge the Chapin Hall Center for Children at the University of Chicago for the creation of the Integrated Database on Child and Family Programs in Illinois that was used in this study. All findings, interpretations, and conclusions based on the use of the IDB are solely my responsibility and do not necessarily represent the views of the Chapin Hall Center for Children. I would also like to acknowledge the National Science Foundation for its support under grant SES-0518757.

[*Journal of Political Economy,* 2008, vol. 116, no. 4]

and Levitt 2001; Pezzin 2004; Currie and Tekin 2006).[1] Meanwhile, interventions for youths at risk of criminal behavior have shown some success and provide motivation for child welfare policy (Oreopoulos 2003; Kling, Ludwig, and Katz 2005; Belfield et al. 2006). Perhaps the most far-reaching child welfare intervention is foster care: the temporary placement of abused or neglected children with a substitute family.

Foster care affects the lives of a large number of children who are at high risk for later criminal activity. Each year in the United States, states spend $20 billion on child protection services, including the investigation of over 2 million children. Approximately 800,000 children spend some time in foster care in any given year, and the average length of stay in care is 2 years (Bess et al. 2002; U.S. DHHS 2004, 2006). In terms of criminal justice involvement, nearly 20 percent of the U.S. prison population under the age of 30, and 25 percent of these prisoners with prior convictions, report spending part of their youth in foster care.[2] Jonson-Reid and Barth (2000*a*, 2000*b*) and Doyle (2007) find higher rates of juvenile delinquency among foster children, and Courtney, Terao, and Bost (2004) surveyed children who turned 18 in foster care in the Midwest and found that 67 percent of the boys and 50 percent of the girls had a history of juvenile delinquency.[3]

Little is known whether foster care placement is likely to reduce or exacerbate the propensity for adult criminal behavior. The removal of children from abusive parents may protect children from further abuse and reduce the likelihood of criminal activity as adults. At the same time, the removal of children from their parents is thought to be traumatic and may lead to worse adult outcomes.[4] Previous research has been hampered by limited data and endogeneity concerns (Goerge, Wulczyn, and Fanshel 1994; McDonald et al. 1996; National Research Council and Institute of Medicine 1998; Courtney 2000; Gelles 2000; Jonson-Reid and Barth 2000*b*). For example, negative outcomes for fos-

[1] Criminal activity has received considerable attention from economists following Becker (1968). Recent papers and reviews include Levitt (1997), Freeman (1999), Glaeser and Sacerdote (1999), Jacob and Lefgren (2003), Di Tella and Schargrodsky (2004), Lochner and Moretti (2004), and Lee and McCrary (2005), among others.

[2] Data were taken from the nationally representative Survey of Inmates in Adult State and Federal Correctional Facilities (1997) and author's calculations.

[3] Foster children are also at high risk of other negative life outcomes including low educational attainment and substance abuse problems (Clausen et al. 1998; Courtney and Piliavin 1998; U.S. DHHS 1999; Dworsky and Courtney 2000; Vinnerljung et al. 2006). An estimated 28 percent of the U.S. homeless population has spent time in foster care as a youth (Burt et al. 1999).

[4] There is a large empirical literature on placement instability and its correlation with later life problems (see, e.g., Newton, Litronwnik, and Landsverk 2000; Smith et al. 2001; James, Landsverk, and Slymen 2004; Zinn et al. 2006). The average foster child in the United States is moved from one home to another at least once, with 25 percent experiencing three or more moves. In Illinois during the 1990s (considered below), 45 percent of foster care stays lasting 1 year had at least one such move within the first year.

ter children could be due to abuse or neglect by family members as opposed to the effects of foster care placement itself (Kerman, Wildfire, and Barth 2002). In addition, children placed in foster care are likely those who benefit most from placement, which can lead to a selection bias such that average outcomes may overstate the benefits of placement for marginal cases.

This aim of this paper is to estimate causal effects of foster care placement on adult crime outcomes. The analysis builds on Doyle (2007), which focused largely on adolescent outcomes: juvenile delinquency, teen motherhood, and employment as a young adult. The empirical strategy uses the idea that child protection cases are effectively randomized to investigators. These investigators affect whether a child is placed in foster care or remains at home. By comparing long-term outcomes for these children across investigators, one can estimate causal effects of foster care among marginal cases: cases in which the investigators may disagree about the recommendation for placement. Doyle found that children on the margin of placement had better outcomes when they remained at home.

There are two main extensions in this paper. First, the outcome measure is adult crime—an outcome that has been closely tied to child maltreatment. A new data set that links Illinois State Police data to child abuse investigation data is employed to track arrests and imprisonment up to age 31. This allows an examination into long-term effects of foster care placement. Further, given that children placed in foster care have been found to be more likely to enter the juvenile justice system, the effects of foster care on adult crime can shed light on whether juvenile justice programs deter future crime or lead to later criminality. The second innovation in the paper describes the characteristics of children who were on the margin of foster care placement. This provides evidence on the types of cases in which the main results are most likely to apply.

The results suggest that among children on the margin of placement, children placed in foster care have arrest, conviction, and imprisonment rates as adults that are three times higher than those of children who remained at home. The large size of the estimated effects and their relative lack of precision suggest caution in the interpretation, though large preventative effects of foster care placement on later criminal justice system involvement appear unlikely for these children.

The paper is organized as follows. Section II presents the empirical framework, which incorporates heterogeneous treatment effects. Section III provides background information on child abuse investigations and the investigator assignment process. Section IV describes the data sources and reports summary statistics. Section V presents the results, and Section VI presents conclusions.

II. Empirical Framework

The decision to remove a child from home is a difficult one. Placement in foster care may protect children from parental abuse, but the separation of children from their parents may be traumatic as well. To estimate effects of foster care on the likelihood of criminal behavior later in life, the empirical framework follows Doyle (2007) and allows for treatment effect heterogeneity using a random coefficient model (Bjorklund and Moffitt 1987). Let Y represent an outcome such as an indicator for an adult arrest, X represent observable case characteristics, and R indicate whether the child was removed from home. For child i, then, the model can be written as

$$Y_i = X_i\beta + \alpha_i R_i + \varepsilon_i. \tag{1}$$

The treatment effect, α_i, will be positive for children when the removal increases the likelihood of an arrest as an adult and will be negative for children who benefit from the protection against parental abuse or neglect in a way that decreases the likelihood of arrest later in life.

A child is placed in foster care ($R = 1$) following a child protection investigation. Placement will be affected by observable characteristics, X, unobserved characteristics, θ, and the influence of the investigator when she makes a placement recommendation. Let Z be a measure of the foster care placement tendency of the investigator assigned to child i. A simple model of removal can then be written as

$$R_i = 1(Z_i\gamma + X_i\delta + \theta_i > 0). \tag{2}$$

Consider two types of investigators described as strict and lenient. Strict investigators are defined as having a high placement rate, $Z = z_H$, and lenient ones are defined as having a low placement rate, $Z = z_L$. The difference in outcomes across these investigators could then be used to measure a local average treatment effect (LATE) (Imbens and Angrist 1994). This is the average treatment effect for "compliers," children induced into foster care on the basis of the investigator assignment. When $P(z) = P(R = 1|Z = z)$, the parameter can be calculated using sample means according to

$$\alpha^{\mathrm{LATE}}(P(z_H),\ P(z_L)) = \frac{E(Y|P(Z) = P(z_H)) - E(Y|P(Z) = P(z_L))}{P(z_H) - P(z_L)}. \tag{3}$$

The identifying assumptions that justify interpreting (3) as a local average treatment effect are the independence of Z with ε, α, and θ: an exclusion restriction that is likely to be met if the investigators were randomly assigned. In addition, $\gamma \neq 0$: the instrument is associated with foster care placement. Implicit in the common coefficient γ is a monotonicity assumption: any child removed by a lenient investigator would also be removed by a strict one, and a child not removed by a strict investigator would not be removed by a lenient one. For example, this condition rules out cases in which assignment to an investigator described as "lenient" would result in an increased likelihood of placement. While it is not possible to identify compliers in the data, it is possible to describe their observable characteristics (Abadie 2003). These characteristics highlight the types of cases in which the results are most relevant.

This paper uses a continuous instrument rather than a binary one, and it is possible to estimate marginal treatment effects (MTE): the average treatment effect for children on the margin of foster care placement—a margin that varies with the instrument. This is the limit of the LATE as the difference in the propensity of placement goes to zero, or analogous to (3), it is the derivative[5]

$$\alpha^{\mathrm{MTE}}(P(z)) = \frac{\partial E(Y|P(z))}{\partial P(z)}. \tag{4}$$

In this setting, the MTE estimates describe whether outcomes for children on the margin of foster care improve or become worse as we move from more lenient to more strict investigators. In the estimation of MTEs, the likelihood that the monotonicity condition holds for any level of the instrument decreases. However, the bias from the failure of the monotonicity assumption disappears when the treatment effect is common across compliers and "defiers" (those induced into foster care on the basis of the assignment to an investigator who is slightly less strict) (Imbens and Angrist 1994; Angrist, Imbens, and Rubin 1996). Given the similarity of the cases at the margin among investigators with nearly identical placement tendencies, this assumption appears reasonable. For comparisons of the MTEs across investigators with large differences in recommendation thresholds, violations of the monotonicity condition become more salient.

III. Background

Children suspected of being abused or neglected are reported to the Illinois Department of Children and Family Services (DCFS) by physi-

[5] Doyle (2007) describes this application in greater detail, drawing on discussions in Heckman and Vytlacil (2005) and Moffitt (forthcoming). Using a potential outcomes framework and letting a superscript of Y equal one if the child were placed in foster care, and zero otherwise, one can write the parameters as

$$\alpha^{\mathrm{LATE}} = E(Y^1 - Y^0 | -z_H\gamma < \theta \leq -z_L\gamma),$$

$$\alpha^{\mathrm{MTE}} = E(Y^1 - Y^0 | \theta = -z\gamma).$$

cians, educators, police, and family members. The cases are then referred to a DCFS field team. A typical team covers one county in Illinois and consists of eight investigators at any given time. The investigator reviews the allegations in the report and interviews the family and the reporter of the abuse or neglect.

These investigators, called "case managers," can affect foster care placement in three ways. First, the case manager may decide that the case is unsubstantiated, in which case the investigation is unlikely to proceed any further. Second, in emergency situations, the investigator may arrange to have a child removed from home immediately. Third, most foster care placements follow a court hearing by a child protection judge. The investigator presents evidence of the abuse or neglect to this judge. The investigator can affect the outcome of this hearing by the quality of the investigation conducted and the persuasiveness of the recommendation.[6]

Most families accused of abuse or neglect are effectively randomized to case managers who investigate the cases. The assignment process is referred to as "the rotation." For example, if there were eight members on a team, there would be a list of investigators and each new case would be assigned to the next investigator on the list. This has the advantage of smoothing the caseload and ensuring that any one investigator is not consistently assigned time-intensive cases. The process appears to be self-enforced, since case managers note that they abide by it to avoid managing too many cases (according to conversations with case managers). The key exceptions are the following: (1) if a family is investigated on more than one occasion, an effort is made to reassign the original case manager to investigate the subsequent allegations; (2) some field teams assign case managers to particular neighborhoods; (3) if the family speaks only Spanish, an effort is made to assign a Spanish-speaking case manager; and (4) cases involving sexual abuse are assigned to specially trained case managers. The analysis will take these exceptions into account, as described below.

The main results will compare child outcomes across investigators, and differences are interpreted as effects of foster care placement. These investigators have little contact with the family before or after the investigation.[7] Their main role is to gather evidence for the foster care placement hearing. As a result, differences in outcomes across investi-

[6] This approach is similar to that of 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 are used to construct an instrumental variable. In an analogy to criminal proceedings, investigators studied here are similar to detectives who are the key witnesses in each case.

[7] Foster care stays are supervised by a separate set of case managers. More detail on the potential impacts that investigators may have on families is discussed in the working paper version of this paper.

gators should stem largely from differences in the likelihood of foster care placement.

IV. Data

This paper uses a unique data set that links adult crime outcomes to child abuse investigation data. The crime outcomes are captured from the Computerized Criminal History System (CCHS) of the Illinois State Police, an administrative database of all arrests in the state. The system also relates these arrests to the associated charges, offenses, court dispositions, and sentences. The main identifiers to link children to adults are the social security number, name, and date of birth; these identifiers are available for 2000–2005.

One issue with the state police data is that the reports, especially linkages between the arrest and court systems, are known to be of higher quality outside of Cook County, which includes Chicago. Cook County has a large number of administrative units and a history of sporadically providing data to the CCHS (according to conversations with researchers at the Illinois Criminal Justice Information Authority). In addition, across the five years of data, social security numbers were available for approximately 80 percent of those arrested outside of Cook County and for only 65 percent of those arrested within Cook County. For these reasons, the results below focus on children who were living outside of Cook at the time of the abuse investigation, although results for Cook County children will be discussed as well.

Detailed abuse investigation and foster care placement data are available from the Illinois DCFS. For data quality reasons, all first investigations of parental abuse or neglect between July 1, 1990, and June 30, 2003, are used in the analysis. One limitation of these data is that they include names in only 25 percent of the cases and no social security numbers. These data have been linked to the Illinois Longitudinal Public Assistance Database, which includes a rich set of personal identifiers, including name, date of birth, and social security number. This linkage between the DCFS and Public Assistance data was carried out by the Chapin Hall Center for Children using family names, dates of birth, and addresses (Goerge, Van Voorhis, and Lee 1994).

There are two main restrictions of the data:[8] (1) To compare children with social security numbers, the analysis considers children in the Public Assistance Database prior to the abuse/neglect report. This group represents over 80 percent of foster children in Illinois. (2) All children who were at least 18 in 2005 are included, since younger children are

[8] More detailed information on the sample construction and potential limitations are available in the working paper version of the paper and in online App. A.

TABLE 1
Summary Statistics

Variable	Mean	Standard Deviation
Foster care placement	.16	.36
Race:		
White	.71	.46
African American	.25	.43
Hispanic	.03	.18
Initial reporter:		
Physician	.07	.25
School	.17	.38
Police	.21	.41
Family	.18	.38
Neighbor	.07	.25
Other government	.14	.35
Anonymous	.12	.33
Other reporter	.03	.17
Age at report	11.0	3.1
Sex: boy	.50	.50
Allegation:		
Lack of supervision	.26	.44
Environmental neglect	.11	.31
Other neglect	.06	.24
Substantial risk of harm	.35	.48
Physical abuse	.20	.40
Other abuse	.02	.16
Observations	23,254	

Note.—The statistics pertain to children investigated outside of Cook County between July 1, 1990, and June 30, 2003, and who were at least 18 years old in 2005.

not at risk for an adult arrest. This results in a sample of children between the ages of 4 and 16 at the time of the initial child protection report: children who would be between the ages of 18 and 31 in 2005. Thus, the results focus on older, poorer children than the population of children who are investigated for abuse or neglect. In addition, sexual abuse cases (8 percent of the total) are excluded, since these cases do not enter into the rotational assignment of investigators.

The analysis sample includes over 23,000 children. To better understand the types of allegations, reporters, and child characteristics in the child protection system, table 1 reports summary statistics: 16 percent of the children investigated were eventually placed in foster care (approximately 10 percent of investigated children are placed in foster care in the United States as a whole, and the higher placement rate here largely reflects the restriction of the sample to children who received Public Assistance at some point prior to the abuse report); 71 percent of the investigated children are white, compared to 87 percent of the population aged 5–14 in 2000 in Illinois outside of Cook County (figure from the U.S. Census of Population); the reporters of the abuse or neglect are typically school officials, police, and family members; and

43 percent of the cases are categorized as neglect as opposed to abuse. The observable characteristics for all investigated children in Illinois are similar, with the exception that the analysis sample is older.[9] Together, the characteristics in table 1 are used as controls in the analysis below, including individual indicators for each age.

V. Estimation

A. *Investigator Assignment*

In order to describe the results in terms of marginal treatment effects, it is useful to characterize investigators according to their placement rates. Given the rotational assignment process within geographic teams subject to the exceptions listed in Section III, this measure is calculated for subteam cells defined by the field team, the zip code of the child's residence, a Hispanic indicator, and the report year. The main analysis is conducted at the child level, and the instrument is the case manager placement differential, which is defined for each child i assigned to case manager c in investigation subteam j as

$$Z_{icj} = d_{icj} \cdot \frac{1}{n_c - n_{cj}} \sum_{k=-j} n_{ck}(\bar{R}^{ck} - \bar{R}^{k}), \tag{5}$$

where d_{icj} is an indicator that child i was initially assigned to case manager c in subteam j, 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 were eventually removed from home, and $\bar{R}^{k}$ is the fraction of removals for subteam k.

Algebraically, this case manager placement differential is analogous to an investigator fixed effect in a model of removal with subteam fixed effects. The difference is that it is calculated for all subteams not including the family's subteam, as in a jackknife instrumental variables estimator (JIVE).[10] Results from a model estimated by limited information maximum likelihood (LIML) that uses case manager fixed ef-

[9] A more detailed description is available in the working paper version. Cook County cases are more likely to be African American (76 percent), more likely to be reported by family members (27 percent), and less likely to be physical abuse.

[10] JIVE has been found to be more robust to situations with many instruments—a potential concern here given that the number of investigators increases with the number of cases (Stock, Wright, and Yogo 2002; Hahn and Hausman 2003). The calculation is restricted to case managers with at least 10 investigations; 733 case managers are considered outside of Cook County, with a weighted average of 74 investigations per case manager. The total number of observations used in the calculation differs slightly from the analysis sample since subteams with only one case manager are excluded from the calculation. These cases are still assigned a case manager placement differential, however, since this measure is calculated using data from all cells other than the family's own cell.

TABLE 2
Child Characteristics and Case Manager Assignment
Dependent Variable: Case Manager Placement Differential

Variable	Coefficient	p-Value
Race (other race excluded):		
White	.000	.999
African American	−.002	.782
Hispanic	.007	.528
Initial reporter (other reporter excluded):		
Physician	−.001	.846
School	.000	.988
Police	.002	.739
Family	.001	.759
Neighbor	.004	.513
Other government	−.000	.965
Anonymous	−.003	.482
Age at report (youngest ages excluded):		
Age 6	.003	.565
Age 7	.010	.011*
Age 8	.001	.870
Age 9	.000	.969
Age 10	.002	.542
Age 11	−.000	.960
Age 12	.001	.806
Age 13	.001	.720
Age 14	.004	.433
Age 15	.005	.285
Age 16	.002	.596
Sex: boy	−.001	.518
Allegation (other neglect excluded):		
Lack of supervision	−.006	.084
Environmental neglect	−.004	.226
Substantial risk	−.000	.915
Physical abuse	−.000	.905
Other abuse	−.001	.867
Mean of dependent variable	−.004	
Standard deviation of dependent variable	.091	
Number of investigators	733	
Observations	23,254	

Note.—Data are for school-aged children outside of Cook County. p-values calculated using standard errors are clustered at the case manager level. All models include year indicators.
* Significant at 5 percent.

fects as instruments and subteam fixed effects as controls are reported as well. An advantage of the global JIVE measure in (5) is that the results can be illustrated in the figures below.

If the rotational assignment effectively randomized cases to investigators, observable characteristics of the case should be unrelated to the instrument. Table 2 presents the results of a model in which the dependent variable is the case manager placement differential, Z_{icj}, and the standard errors are clustered at the case manager level to reflect dependence across children assigned to the same investigator. The table shows that there is variation in placement rates across case managers:

the instrument has a mean of zero and a standard deviation of 9 percent. Little relation between the case manager differential and the observable case characteristics is found, however. It does not appear that "tough cases" are assigned to particular investigators.[11]

B. *Foster Care Placement and Crime Outcomes*

Figure 1 provides a first look at the results. The horizontal axis is the case manager placement differential, which has a mean of zero and ranges from -0.25 to 0.25. The three lines report local linear regressions of (1) the removal indicator, (2) a predicted removal indicator using the X characteristics in table 1, and (3) the arrest indicator, all regressed against the case manager placement differential evaluated at each percentile of the differential.[12]

Predicted placement appears unrelated to the case manager placement differential, as in the results from table 2. Second, the placement differential is positively related to actual foster care placement. An increase in the differential from the 10th percentile to the 90th percentile, representing an increase from -0.10 to 0.11, is associated with an increase in foster care placement from 0.14 to 0.21, for an implied first-stage estimate of 0.33: an increase in the placement differential by 10 percentage points is associated with an increase in the placement rate by 3.3 percentage points, or 21 percent of the mean placement rate.

Given the implied first-stage coefficients of close to one-third, the local linear regression estimates for the arrest indicator are reported using the second vertical axis with a scale that is one-third of the placement rate axis to show the type of changes in outcomes that are associated with an increase in the placement probability from zero to one. One feature is that the arrest rates are fairly high despite the potential for measurement error due to imperfect linkage between the systems. Of the investigated children outside of Cook County, 26 percent were found arrested in Illinois between 2000 and 2005. As noted above, the sample is restricted to investigated children who were at least 18 in 2005; some of these children were at risk of arrest for shorter time periods

[11] Further tests suggest that the case manager placement differential is not associated with characteristics of foster children, including the type of placement and the length of stay. The lack of a relationship with length of stay suggests that potential mistakes by particularly strict investigators are not ameliorated by the foster care system in the form of shorter stays.

[12] The results are shown using pilot bandwidths that were chosen by minimizing the sum of squared errors between the local linear estimator and a fourth-degree polynomial model. For the foster care placement regression, the bandwidth is 0.034. This bandwidth was used for the predicted probability of placement as well. For the arrest regression, the bandwidth is 0.056. Results are robust to bandwidths down to 0.01, with larger fluctuations below 0.02, although the results are similar to those shown in fig. 1 when the smaller bandwidths are used.

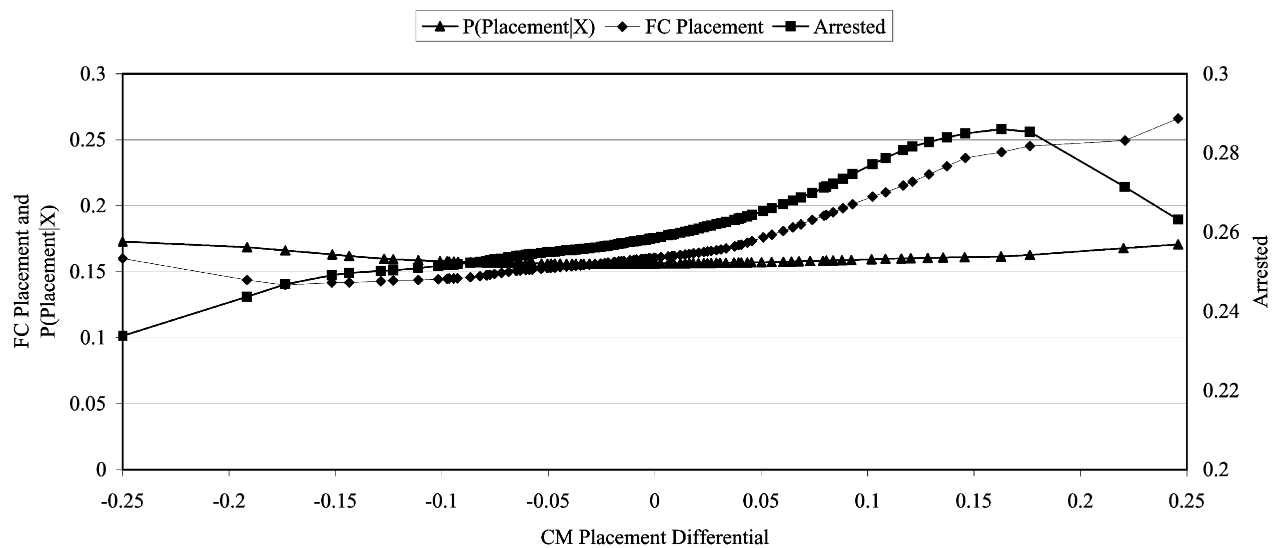

Fig. 1.—Foster care placement (actual and predicted) and arrest indicator vs. case manager placement differential. Local linear estimates, evaluated at each percentile of the case manager placement differential. Pilot bandwidth chosen by cross-validation is 0.034 for the actual and predicted placement rates. For the arrest rate the bandwidth is 0.056.

than others. When children who were 25 in 2005 are considered—children at risk of an adult arrest for the full time period—the 5-year arrest rate is 40 percent for boys and 27 percent for girls.

Figure 1 shows that the arrest rate relationship with the case manager placement differential is remarkably similar in shape to the foster care placement relationship. For the change from the 10th percentile to the 90th percentile discussed above, the arrest rate increases from 0.25 to 0.28.

Foster Care Placement

The first-stage relationship between the child's foster care placement status and the case manager placement differential was estimated with and without controls for child i assigned to an investigator c in subteam j in year t according to the following model:

$$R_{icj} = \phi_0 + \phi_1 Z_{icj} + \phi_2 X_i + \sum_k \delta_k 1(t_i = k) + \omega_{icj}, \tag{6}$$

where δ represents a vector of year effects for the date of child i's initial investigation. This equation was estimated by ordinary least squares (OLS), although results are similar with a probit model.[13]

Table 3 shows the results. The estimated coefficient on the case manager placement differential is 0.23. The estimate is unaffected by the introduction of controls, as suggested by table 2. In contrast, the control variables are associated with foster care placement. For example, physician, police, and other government reports are strongly associated with increases in the likelihood of foster care placement compared to school reports; African American children are also much more likely to be placed.

The probability of removal does not increase one-for-one with the case manager placement differential, likely because of measurement error that attenuates the effect toward zero. In particular, the case manager of the initial investigation is used to characterize the case manager type, although this may not represent the case manager in subsequent investigations given significant investigator turnover. Second, the case manager is the lead investigator in the case, whereas a judge makes the final decision on most foster care placements. Nevertheless, the removal rate is associated with placements.[14]

[13] Probit models and other robustness checks are in the working paper version of this paper, as well as in online App. table B3.

[14] As described above, Stock et al. (2002) discuss how JIVE and LIML are more robust to weak instruments in the case of many instruments. The F-statistic on the case manager placement differential—when the instruments are combined into one propensity score—is over 40, whereas the individual investigator indicator (in a model with subteam fixed effects) is 1.7.

TABLE 3
CASE MANAGER ASSIGNMENT AND FOSTER CARE PLACEMENT
Dependent Variable: Foster Care Placement

	Coefficient (1)	Standard Error (2)	Coefficient (3)	Standard Error (4)
Case manager placement differential	.229	.036**	.233	.035**
Race:				
White			−.002	.029
African American			.093	.029**
Hispanic			−.030	.031
Initial reporter:				
Physician			.043	.018*
School			.025	.015
Police			.073	.016**
Family			.016	.015
Neighbor			−.013	.016
Other government			.084	.016**
Anonymous			.002	.016
Age at report:				
Age 6			−.027	.018
Age 7			.001	.016
Age 8			.008	.017
Age 9			.014	.017
Age 10			.016	.017
Age 11			.016	.017
Age 12			.020	.017
Age 13			.020	.018
Age 14			.016	.017
Age 15			−.007	.018
Age 16			−.017	.018
Sex: boy			−.016	.005**
Allegation:				
Physical abuse			−.172	.015**
Substantial risk			−.180	.015**
Other abuse			−.162	.019**
Lack of supervision			−.152	.015**
Environmental neglect			−.188	.016**
Mean of dependent variable	.16			
Observations	23,254			

NOTE.—Models are estimated by OLS. Data are for school-aged children outside of Cook County. Standard errors are clustered at the case manager level. All models include year indicators.
* Significant at 5 percent.
** Significant at 1 percent.

Crime Outcomes

To compare crime outcomes, Y, empirical models for child i investigated by case manager c in subteam j during year t are of the form

$$Y_{icj} = \alpha_0 + \alpha_1 R_{icj} + \alpha_2 X_i + \sum_k \delta_k 1(t_i = k) + \varepsilon_{icj}. \tag{7}$$

This model is estimated separately for each outcome by OLS and two-

TABLE 4
Foster Care Placement and Crime Outcomes: 2000–2005

	Model					
	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)	LIML (5)	LIML (6)
	A. Dependent Variable: Arrested					
Foster care placement	.075	.060	.388	.391	.226	.217
	(.008)**	(.008)**	(.189)*	(.182)*	(.113)*	(.111)*
Mean of dependent variable	.260					
Full controls	No	Yes	No	Yes	No	Yes
Observations	23,254	23,254	23,254	23,254	22,691	22,632
	B. Dependent Variable: Sentence of Guilty/Withheld					
Foster care placement	.045	.039	.403	.405	.236	.241
	(.007)**	(.007)**	(.160)*	(.154)**	(.092)**	(.092)**
Mean of dependent variable	.151					
Full controls	No	Yes	No	Yes	No	Yes
Observations	23,254	23,254	23,254	23,254	22,691	22,632
	C. Dependent Variable: Sentenced to Prison					
Foster care placement	.035	.031	.219	.225	.176	.176
	(.005)**	(.005)**	(.104)*	(.102)*	(.070)*	(.070)**
Mean of dependent variable	.066					
Full controls	No	Yes	No	Yes	No	Yes
Observations	23,254	23,254	23,254	23,254	22,691	22,632

Note.—Data are for children investigated for abuse or neglect outside of Cook County. Standard errors are clustered at the case manager level. All models include year indicators. Columns 1 and 2 report estimates from models estimated by OLS. Columns 3 and 4 report estimates from models estimated by 2SLS, with the case manager removal differential as the excluded instrument. Columns 5 and 6 report estimates from models estimated by LIML, with individual investigator indicators as the excluded instruments and subteam by year fixed effects. The LIML models use a sample limited to investigators with at least five investigations in the analysis sample.
* Significant at 5 percent.
** Significant at 1 percent.

stage least squares (2SLS), with the case manager placement differential, Z_{icj}, used as an instrument for the indicator for removal, R_{icj}.

Similarly, the following model is estimated by LIML:

$$Y_{icj} = \alpha_0 + \alpha_1 R_{icj} + \alpha_2 X_i + \sum_k \omega_k 1(T_i = k) + \varepsilon_{icj}, \tag{8}$$

where T_i is a subteam indicator to estimate the model within the pool of investigators who could have been assigned to a child, and case manager indicators are used as excluded instruments. The LIML estimates are restricted to the sample of investigators with at least five investigations in the analysis sample.

Table 4 reports the crime outcome results. As discussed above, the mean arrest rate in the sample is 26 percent. In terms of the OLS results, children who were placed in foster care have higher crime outcomes, with arrest rates 6–7.5 percentage points higher. The conviction rate in this sample is 15 percent, and those who enter foster care have conviction rates that are 4 percentage points higher.[15] Likewise, the imprisonment rates are higher as well: 3 percentage points higher compared to a mean of 7 percent.

When the models are estimated using instrumental variables, foster care placement is associated with large increases in crime outcomes, as implied by figure 1. In terms of arrests, with 2SLS the coefficient on removal is 0.39 and with LIML it is 0.22. The estimates are similar with the addition of controls to the models. For guilty verdicts, the instrumental variable results again show larger effects of placement, with a coefficient of 0.2–0.4. Large increases in imprisonment are found as well, with coefficients close to 0.2. These estimates are statistically significantly different from zero, although the standard errors are large, and the 2SLS and LIML estimates are not statistically significantly different from the OLS estimates or each other.

The results suggest that foster care placement results in arrest propensities that are two to three times higher compared to investigated children who remained with their parents.[16] Such large differences are possible with juvenile arrest rates of 50–67 percent for children who age out of foster care. The large coefficients and standard errors suggest caution in the interpretation, however. In comparison, Doyle (2007) used the instrumental variable strategy employed here to measure the effects of foster care placement on juvenile delinquency in Cook County. Point estimates suggested a delinquency rate that was three times higher for children placed in foster care than for investigated children who remained at home.[17] It appears that such an increase in delinquency is not associated with deterrence from the adult criminal justice system for this set of children.

The estimated causal effects of foster care on crime outcomes are larger than the conditional means comparison in columns 1 and 2 would imply. A key difference between the two sets of results is that the in-

[15] The measure is "found guilty" or "withheld judgment," which is often used as a probationary measure. Results are similar when the outcome is simply a guilty verdict. The mean of the guilty-only outcome is 11 percent, and the reduced-form coefficient is 0.075 (standard error 0.031) with a 2SLS estimate of 0.33 (standard error 0.14).

[16] To evaluate a 22-percentage-point difference, consider the following example. If the placement rate at the margin were 10 percent and the 5-year arrest propensity were 26 percent, then the arrest rate for those not placed in foster care would be 24 percent and the rate for those placed in foster care would be 46 percent, to arrive at the weighted average $0.1(0.46) + 0.9(0.24) = 0.26$. The 2SLS estimate of a 39-percentage-point difference would imply an analogous comparison of 61 percent vs. 22 percent.

[17] This implies that some of these investigated children may have already been in prison during 2000–2005, although the point estimates are nearly identical when the subset of children who were less than 18 in 2000 were considered to avoid left censoring in the adult arrest indicator.

strumental variable estimates apply to marginal cases—those induced into foster care as a result of the case manager assignment. The usual omitted variables bias in the means comparison—that foster children come from abusive families and would have worse outcomes regardless of foster care placement—may be outweighed by a selection bias: children with higher expected benefits from foster care placement are more likely to be placed. For example, severely abused children may benefit greatly from foster care placement in terms of later criminal propensities, whereas marginal cases may be particularly harmed by placement relative to remaining at home.

C. *Effects across Different Types of Cases*

Given that some children may benefit from placement and others may be harmed, it would be useful to characterize the observable characteristics of children most likely to benefit from (or least likely to be harmed by) foster care placement. With the approach in this paper, it is possible to characterize the types of children most likely to be induced into foster care as a result of the investigator assignment—individuals who are "compliers" in the local average treatment effect context (Abadie 2003). In the case of a binary instrument, the relative likelihood that a complier is a boy, for example, is the ratio of the first-stage coefficient on the case manager placement differential when the model is estimated using data on boys only relative to the first-stage coefficient when all the data are used to estimate it.[18] It is also possible to estimate the instrumental variable results within subgroups to consider marginal cases within case types.

Panel A of table 5 shows the first-stage estimates for subgroups of interest, as well as the ratio of the main coefficient of interest relative to the overall first-stage coefficient. Given the variability in the data, none of these differences are statistically significantly different from one, but they suggest that some groups are more likely to be compliers. Most striking is that the first stage is stronger for African American youths,

[18] For binary Z as in Sec. II and R_T representing the potential removal indicator for a given type of investigator ($T = H$ or L), the probability that a complier is a boy ($X = 1$) relative to the probability that a child in the population is a boy is given by

$$\frac{P(X=1 \mid R_H=1,\ R_L=0)}{P(X=1)} = \frac{P(R_H=1,\ R_L=0 \mid X=1)}{P(R_H=1,\ R_L=0)}$$

$$= \frac{E(R \mid Z=Z_H,\ X=1) - E(D \mid Z=Z_L,\ X=1)}{E(R \mid Z=Z_H) - E(D \mid Z=Z_L)}.$$

I thank Josh Angrist for this derivation. The first-stage comparisons in table 5 are nearly identical when a binary instrument is considered—defined as the case manager placement differential being greater or less than zero.

TABLE 5

RESULTS ACROSS CHILD CHARACTERISTICS

	Subgroup							
	Sex		Allegation/ Reporter		Race		Location (Matched by Name and Date of Birth)	
	Boy (1)	Girl (2)	Abuse (3)	Neglect (4)	White (5)	African American (6)	Non-Cook (7)	Cook (8)
	A. Dependent Variable: Placed in Foster Care							
Case manager placement differential	.211	.302	.276	.24	.213	.367	.256	.295
	(.052)**	(.047)**	(.047)**	(.058)**	(.040)**	(.081)**	(.040)**	(.058)
Relative to overall first stage	.92	1.32	1.21	1.05	.93	1.60	1.12	1.29
	B. Dependent Variable: Arrested, 2000–2005							
Foster care placement:								
OLS	.062	.060	.051	.070	.059	.057	.079	.061
	(.012)**	(.011)**	(.012)**	(.013)**	(.011)**	(.010)**	(.009)	(.008)
2SLS	.221	.509	.385	.389	.541	.591	.235	.201
	(.298)	(.187)**	(.203)	(.297)	(.263)*	(.249)*	(.210)	(.111)
Mean of dependent variable	.305	.215	.261	.259	.249	.248	.344	.403
Observations	11,673	11,581	13,149	10,105	16,402	17,459	23,899	22,357

NOTE.—Panel A reports the first-stage coefficients for each subgroup and the relative first stage to the overall first-stage coefficient reported in table 3, with the exception of cols. 7 and 8, which report the first-stage coefficient in each set of counties relative to the first stage from a pooled sample of all counties. The OLS and 2SLS cells report coefficients on foster care placement, with the second set instrumented by the case manager placement differential. Standard errors clustered at the case manager level are reported. In cols. 7 and 8, the match using name and date of birth allows the use of individuals with missing social security numbers, resulting in larger sample sizes.

* Significant at 5 percent.

** Significant at 1 percent.

with a first-stage coefficient that is 60 percent higher than the overall first stage. Girls are more likely to be affected by the instrument as well (32 percent higher). Compliers are 21 percent more likely to have suffered from abuse as opposed to neglect compared to the full sample. In particular, children with allegations of "other abuse"—allegations that tend to be serious such as burns—are present in 2.5 percent of the cases and have a first stage that is more than two times higher than the overall first stage. These allegations may be more routinely referred to child protective services, despite the possibility that they are due to accidents. Similarly, reports from physicians are more likely to be affected by the instrument (42 percent higher than the overall first stage).

Police reports were also more likely to be affected by the instrument (42 percent higher) especially compared to school reports (24 percent lower). In terms of age, young adolescents, between the ages of 11 and 13, are more likely to be affected by the instrument, with first-stage coefficients approximately 45 percent higher than the overall first stage.

Panel B of table 5 reports results for the arrest outcome across subgroups to test whether marginal cases within these categories have different effects of foster care placement. A larger jump in arrests is found for girls, despite similar OLS results. Cases categorized as abuse or neglect had similar results, as did cases that varied by race. In addition to the results in table 5, similar results were found for children under the age of 10 at the time of the first investigation compared to those who were at least 10 years old.[19]

The main results focused on children outside of Cook County for data quality reasons, although in principle the instrumental variable estimators should overcome biases related to data imperfections. When matches were made by the name and date of birth (where names were first transformed using SOUNDEX software so that similar names have the same linkage variable), the results are similar across the two geographic areas. In particular, 34 percent of children outside of Cook County and 40 percent of children within Cook County are matched to the arrest database using these less precise identifiers. Table 5 shows that the 2SLS estimate in terms of arrests is 0.20 (standard error 0.11) for children from Cook County; the estimate for children from outside of Cook is 0.23 with a standard error of 0.21.[20]

[19] Results were also similar for children under and over the age of 10 and for children who had relatively high and low predicted probabilities of placement. These results are available in online App. table B2.

[20] Another set of comparisons considered the class of the offense: drug, property, violent, and other. Similar results were found for these categories with the exception of drug offenses. These offenses were not related to foster care placement when estimated by OLS (coefficient 0.004, stantard error 0.005), nor using 2SLS (coefficient 0.026, standard error 0.087), compared to the 7.5 percent drug arrest rate over this time period. These results are available in the working paper version as well as online App. table B1.

D. *Marginal Treatment Effects*

To further explore the source of the instrumental variable results, it is possible to estimate marginal treatment effects as described in Section II. First, the predicted probability of placement was estimated using a probit model. The case manager placement differential was the only explanatory variable in the model to capture the variation in placement solely due to the instrument.

Next, the relationship between the outcome indicators and this predicted probability was estimated using a local quadratic estimator.[21] Figure 2*A* reports the results. First, the instrument achieves variation in the probability of placement from 0.11 to 0.23. Further, as suggested by figure 1, the arrest rate increases with the placement propensity. An increase from the 10th percentile of predicted placement to the 90th percentile (an increase from 0.13 to 0.19) is associated with an increase in the arrest rate from 0.25 to 0.27, for an estimated local average treatment effect of 0.33.

The derivative of this relationship provides the marginal treatment effect estimates. Figure 2*B* shows the results, along with 5–95 percent confidence intervals.[22] The 2SLS estimate of 0.4 is in the heart of the data. In addition, the MTE function for arrests is above zero: increases in the likelihood of placement are associated with increases in arrests among both lenient and strict investigators. An upward slope in the point estimates suggests that children on the margin of placement among the high-removal investigators have the largest increases in arrest rates. These are likely children with unobservable characteristics that make them the least likely to be placed in foster care, since the margin for relatively strict investigators should entail relatively less abuse or neglect compared to investigators who leave more children at home.[23]

[21] The local quadratic estimator was chosen because the first derivative of the relationship is sought and local quadratic estimators are thought to have better properties than local linear methods (Fan and Gijbels 1996). In practical terms, the results are nearly identical when a local linear regression was estimated instead. The pilot bandwidth is 0.031, chosen by minimizing the sum of squared errors between the local quadratic estimator and a fourth-degree polynomial model. Results are robust to bandwidths from 0.01 to 0.1. For example, at a bandwidth of 0.01, the arrest rate increases for the first 30 percentiles of predicted placement, is flat for the next 30 percentiles at 0.26, and increases for the remaining percentiles up to a maximum of 0.29 at the 97th percentile.

[22] Confidence intervals 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.

[23] Figures for the other outcomes are in the working paper version and in online App. fig. B1.

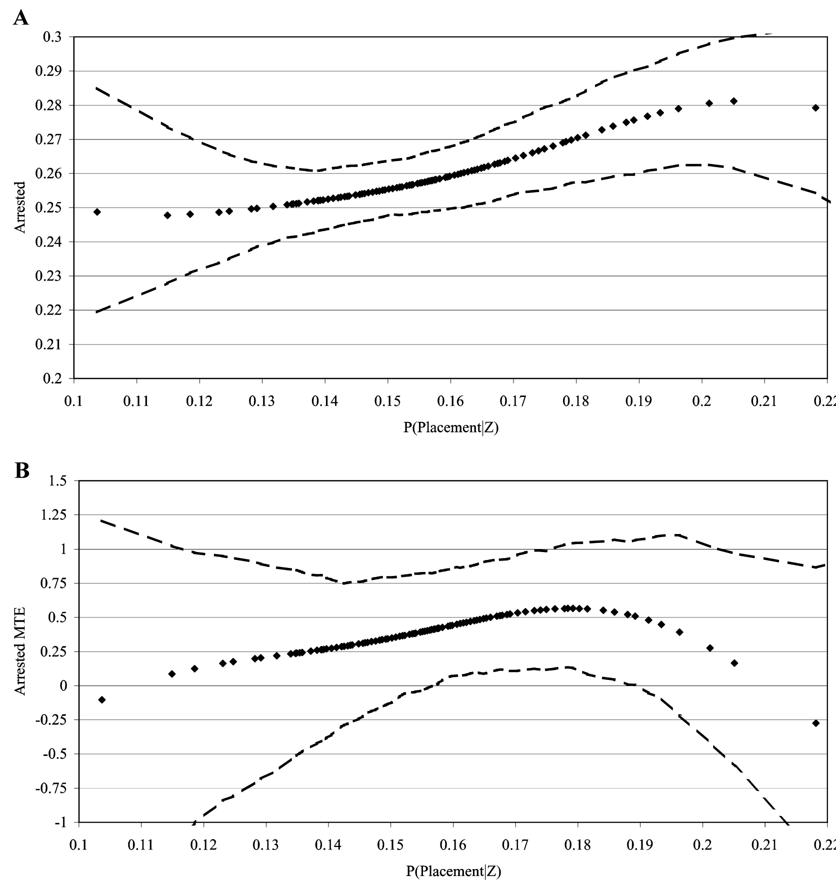

FIG. 2.—*A*, Arrested vs. $P(\text{Placement}\,|\,Z)$. *B*, Arrested marginal treatment effects. Local quadratic and associated derivative estimates, evaluated at each percentile of $P(\text{Placement}\,|\,Z)$: the predicted placement from a probit model that includes only the case manager placement differential. Dashed lines report 5–95 percent bootstrapped confidence intervals. Pilot bandwidth chosen by cross-validation is 0.031.

VI. Conclusion

Foster care placement is a far-reaching intervention in the lives of children who are at high risk of arrests and incarceration as adults. The analysis here uses the effective randomization of families to child protection investigators to estimate causal effects of foster care placement on crime outcomes. The results suggest that children placed in care have two to three times higher arrest, conviction, and imprisonment rates than children who remained at home. The point estimates are large and relatively imprecisely estimated, however, which suggests some caution in the interpretation. Nevertheless, it appears that children at the margin of placement have better outcomes when they remain at home.

The data focused on school-aged children investigated in Illinois during the 1990s. Further, the analysis does not attempt to measure the benefits of placement for children in such danger that all investigators would agree that the child should be placed in care. The results are generally robust across groups, but some children appear more likely to be on the margin of placement—cases in which the main results apply. These include children who were young adolescents at the time of the investigation, victims of abuse (as opposed to neglect), girls, and African Americans.

References

Abadie, Alberto. 2003. "Semiparametric Instrumental Variable Estimation of Treatment Response Models." *J. Econometrics* 113 (2): 231–63.

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. 1996. "Identification of Causal Effects Using Instrumental Variables." *J. American Statis. Assoc.* 91 (434): 444–55.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *J.P.E.* 76 (March/April): 169–217.

Belfield, Clive R., Milagros Nores, Steve Barnett, and Lawrence Schweinhart. 2006. "The High/Scope Perry Preschool Program: Cost-Benefit Analysis Using Data from the Age-40 Followup." *J. Human Resources* 41 (1): 162–90

Bess, Roseana, Cynthia Andrews, Amy Jantz, Victoria Russell, and Rob Green. 2002. *The Cost of Protecting Vulnerable Children III: What Factors Affect States' Fiscal Decisions.* Assessing the New Federalism Occasional Paper no. 61. Washington, DC: Urban Inst.

Bjorklund, Anders, and Robert Moffitt. 1987. "The Estimation of Wage Gains and Welfare Gains in Self-Selection Models." *Rev. Econ. and Statis.* 69 (February): 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 Inst.

Case, Anne, and Lawrence F. Katz. 1991. "The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths." Working Paper no. 3705, NBER, Cambridge, MA.

Clausen, June M., John A. Landsverk, William Ganger, David Chadwick, and Alan J. Litrownik. 1998. "Mental Health Problems of Children in Foster Care." *J. 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 Rev.* 22 (9–10): 743–61.

Courtney, Mark E., and Irving Piliavin. 1998. *Foster Youth Transitions to Adulthood: Outcomes 12 to 18 Months after Leaving Out-of-Home Care.* Madison: Univ. Wisconsin–Madison, School Soc. Work.

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: Univ. Chicago, Chapin Hall Center for Children.

Currie, Janet, and Erdal Tekin. 2006. "Does Child Abuse Cause Crime?" Working Paper no. 12171 (April), NBER, Cambridge, MA.

Di Tella, Rafael, and Ernesto Schargrodsky. 2004. "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack." *A.E.R.* 94 (March): 115–33.

Donohue, John J., and Steven D. Levitt. 2001. "The Impact of Legalized Abortion on Crime." *Q.J.E.* 116 (May): 379–420.

Doyle, Joseph. 2007. "Child Protection and Child Outcomes: Measuring the Effects of Foster Care." *A.E.R.* 97 (December): 1583–1610.

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.* Washington, DC: U.S. Dept. Health and Human Services.

Fan, Jianqing, and Irene Gijbels. 1996. *Local Polynomial Modeling and Its Applications.* Monographs on Statistics and Applied Probability, no. 66. New York: Chapman & Hall.

Freeman, Richard. 1999. "The Economics of Crime." In *The Handbook of Labor Economics*, vol. 3C, edited by David Card and Orley Ashenfelter. New York: North-Holland.

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

Glaeser, Edward L., and Bruce Sacerdote. 1999. "Why Is There More Crime in Cities?" *J.P.E.* 107, no. 6, pt. 2 (December): S225–S258.

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

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

Hahn, Jinyong, and Jerry Hausman. 2003. "Weak Instruments: Diagnosis and Cures in Empirical Econometrics." *A.E.R. Papers and Proc.* 93 (May): 118–25.

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

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

Jacob, Brian, and Lars Lefgren. 2003. "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration and Juvenile Crime." *A.E.R.* 93 (5): 1560–77.

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

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

———. 2000*b*. "From Placement to Prison: The Path to Adolescent Incarceration from Child Welfare Supervised Foster or Group Care." *Children and Youth Services Rev.* 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 Rev.* 24 (5): 319–44.

Kling, Jeffrey R. 2006. "Incarceration Length, Employment and Earnings." *A.E.R.* 96 (June): 863–76

Kling, Jeffrey R., Jens Ludwig, and Lawrence F. Katz. 2005. "Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment." *Q.J.E.* 120 (1): 87–130.

Lee, David S., and Justin McCrary. 2005. "Crime, Punishment, and Myopia." Working Paper no. 11491 (July), NBER, Cambridge, MA.

Levitt, Steven D. 1997. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *A.E.R.* 87 (3): 270–90.

Lochner, Lance, and Enrico Moretti. 2004. "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self Reports." *A.E.R.* 94 (1): 155–89.

Loeber, Rolf, and Magda Stouthamer-Loeber. 1986. "Family Factors as Correlates and Predictors of Juvenile Conduct Problems and Delinquency." In *Crime and Justice: An Annual Review of Research*, vol. 7, edited by Michael Tonry and Norval Morris. Chicago: Univ. Chicago Press.

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: Child Welfare League of America Press.

Moffitt, Robert. Forthcoming. "Estimating Marginal Treatment Effects in Heterogeneous Populations." *Annales d'Economie et de Statistique*, special issue on Econometrics of Evaluation.

National Research Council and Institute of Medicine. 1998. *Violence in Families.* Edited by Rosemary Chalk and Patricia A. King. Washington, DC: Nat. Acad. Press.

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 and Neglect* 24 (10): 1363–74.

Oreopoulos, Philip. 2003. "The Long-Run Consequences of Living in a Poor Neighborhood." *Q.J.E.* 118 (4): 1533–75.

Pezzin, Liliana E. 2004. "Effects of Family Background on Crime Participation and Criminal Earnings: An Empirical Analysis of Siblings." *Estudios Economicos* 34 (3): 487–514.

Sampson, Robert J., and John H. Laub. 1993. *Crime in the Making: Pathways and Turning Points through Life.* Cambridge, MA: Harvard Univ. Press.

Smith, Dana K., Elizabeth Stormshak, Patricia Chamberlain, and Rachel Bridges Whaley. 2001. "Placement Disruption in Treatment Foster Care." *J. Emotional and Behavioral Disorders* 9 (3): 200–205.

Stock, James, James Wright, and Motohiro Yogo. 2002. "A Survey of Weak Instruments and Weak Identification in GMM." *J. Bus. and Econ. Statis.* 20 (4): 518–29.

U.S. DHHS (U.S. 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: U.S. Government Printing Office.

———. 2004. *Child Maltreatment 2002.* Washington, DC: U.S. Government Printing Office.

———. 2006. *The AFCARS Report.* Washington, DC: U.S. 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 Rev.* 28 (1): 59–77.

Widom, C. S. 1989. "The Cycle of Violence." *Science* 244 (4901): 160–66.

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