Misplaced at Home? A Partial Observability Approach to Foster Care Placement Decisions

Working Draft

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Abstract

When children are referred to Child Protective Services (CPS) caseworkers must decide whether to remove them from their homes or allow them to remain with their families. Although a large literature examines the consequences of foster care placement, much less is known about children who remain at home despite exhibiting characteristics similar to those of removed children. A central challenge is that both a child's underlying removal risk and whether placement decisions align with that risk are unobserved. This paper develops a partial observability framework to recover latent removal risk and foster care placement decisions using a nationally representative longitudinal sample of children referred to CPS. The model identifies children who are observationally similar to those removed from their homes but who remain with their families, a group I refer to as "misplaced at home." Estimates suggest that a substantial share of investigated children fall into this category. I then examine how latent removal risk and placement status relate to subsequent educational outcomes. I find evidence that a high predicted risk of removal is associated with poorer academic performance. However, children with a high probability of being "misplaced at home" is *not* associated with worse educational outcomes *conditional on predicted risk of removal.*

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1 Introduction

In the United States, Child Protective Services (CPS) plays a critical role in ensuring a safe home environment for children who have been abused or neglected. Experiencing abuse or neglect in childhood is strongly associated with various adverse outcomes. A substantial body of research documents the negative effects of maltreatment on children's physical health, mental health, and educational outcomes. Adults with a history of childhood abuse or neglect are significantly more likely to experience mental health challenges, including higher rates of mood disorders, Post-Traumatic Stress Disorder (PTSD), and personality disorders (Arnow, 2004; Kaplow and Widom, 2007; Widom, 1999; Johnson et al., 1999). Individuals who experienced physical or sexual abuse are more likely to utilize emergency services and seek professional healthcare than those without such experiences (Chartier et al., 2007; Walker et al., 1999). Poor educational outcomes associated with child abuse and neglect include lower test scores and GPA (Coohey et al., 2011; Crozier and Barth, 2005; Eckenrode et al., 1993), increased absenteeism (Leiter, 2007; Leiter and Johnsen, 1997), grade repetition (Kinard, 1999; Leiter and Johnsen, 1997), and behavioral issues (Eckenrode et al., 1993; Kendall-Tackett and Eckenrode, 1996).

When child maltreatment is suspected, reports are made to the Department of Social Services, and the most severe cases are assigned to CPS for further investigation. This investigation can lead to the child's removal from their home and placement into substitute care. Substitute care involves temporary, out-of-home (OOH) living arrangements with a relative (kinship care) or a non-relative (foster care) until permanent arrangements are made. Investigators face the difficult tradeoff between preserving families and child safety when deciding if an OOH placement is warranted. In 2022, over 558,899 children were identified as victims of abuse or neglect, with around 104,747 entering foster care (U.S. Department of Health and Human Services, 2024). Thus, the population of confirmed victims who remained outside foster care was more than four times as large as the population of victims who entered care. Despite its size, this group has received far less attention than children placed in foster care. Although removal from the home may be necessary to protect the child from ongoing harm, it is not without consequences. As a result, child protection policy encourages investigators to exercise caution before recommending OOH placements. This paper shifts attention to the much larger and understudied population of children who remain with their families after CPS involvement. Specifically, I ask: For children who came into contact with CPS due to suspected maltreatment, are they better off staying with their families, even in cases where the home environment is less than ideal?

Out-of-home placements or removals—particularly in foster care—are often deeply disruptive and have been linked to a range of poor developmental and educational outcomes. Several studies have found that children in foster care face significant academic challenges. Compared to their peers, they tend to score lower on standardized tests (Burley and Halpern, 2001), have higher dropout rates (Blome, 1997; Burley and Halpern, 2001), are less likely to pursue a college-preparatory curriculum or earn a GED (Blome, 1997), lower graduation rates (Barrat and Berliner, 2013) and are more likely to repeat grades, require special education, face disciplinary issues at school (Blome,

1997; Burley and Halpern, 2001), and have higher prevalence of depression and anxiety(Turney and Wildeman, 2016). However, much of this research relies on comparisons between foster youth and the general student population, and it remains difficult to disentangle the effects of foster care from the characteristics that led children to enter care in the first place. As a result, the observed disparities may partly reflect pre-existing disadvantages rather than the effects of foster care itself (Stone, 2007).

Research on the long-term effects of foster care placement presents mixed findings. Doyle (2007) studied children in Illinois during the 1990s and found that, at the margin, foster care placement led to worse outcomes—including lower earnings, higher rates of teen motherhood, delinquency, and unemployment. Later work by Doyle Jr. (2008); Doyle (2013) further showed increased use of emergency medical services and higher adult criminal justice involvement among children placed in foster care. Similarly, Roberts (2019) found in South Carolina that foster care roughly doubled the risk of juvenile delinquency over five years post-investigation. On the other hand, more recent studies have documented the potential benefits of removal in specific contexts. Gross and Baron (2022) find that for children at the margin of foster care placement, removal relative to remaining at home after a CPS investigation reduces the risk of subsequent maltreatment and improves school attendance and math achievement. In related work, Gross and Baron (2022) reported a decline in adult criminal behavior following removal. Roberts (2019) also found a 13 percent reduction in grade retention within three years of placement in South Carolina.

Bald, Chyn, and Hastings (2022) find significant positive effects of removal on educational outcomes for girls investigated before age six, with no detectable impacts for boys, indicating heterogeneity in the effects of removal by gender. Sattler, Font, and Panlilio (2025) document heterogeneity by race, finding that early foster care entry is more strongly associated with improved Grade 3 outcomes for Black children (especially reading and sometimes math), while for White children, the main association is reduced chronic absenteeism. Overall, the effects of foster care placement appear to depend on a variety of factors, including the child's age, gender, and the broader context of the removal. Some children—particularly younger ones—may benefit from removal, while others may be more vulnerable to its disruptive consequences. Following Doyle (2007, 2008), a growing literature exploits quasi-random assignment to child protection investigators as an instrument for removal decisions, including Roberts (2019), Gross and Baron (2022), Bald et al. (2022), and Sattler et al. (2025). Since investigator-level identifiers are not available in the data, I adopt a different methodological approach that nonetheless provides complementary evidence on placement decisions and child outcomes. Existing work using caseworker instruments primarily identifies effects for children at the margin of removal. In contrast, my framework allows me to study children who, based on the maltreatment risk they face, are observationally similar to those removed but remain at home with or without supports, including cases that may be non-marginal, such as children who would not be reunified even under a more lenient placement decision. This distinction makes it possible to assess the maltreatment risk faced by children and to evaluate whether children who meet removal criteria would have fared better if left with their families and

supported by the Department of Social Services, an alternative option available to caseworkers.

This paper contributes to the literature by developing an alternative methodology that identifies latent maltreatment risk and the probability of misplacement, allowing for complementary evidence on placement decisions and their eventual consequences. While much of the existing literature relies on variation induced by investigator assignment as an instrument for placement decisions, this paper instead models maltreatment risk based on observed characteristics and recovers the predicted probability that a child is misplaced at home. I then apply this framework to a nationally representative sample of children investigated by CPS to assess the impacts of (i) a child being at high risk of maltreatment and (ii) being "misplaced at home" [1] on subsequent schooling outcomes. In addition, the analysis restricts the sample to children who have been referred to CPS, ensuring that they are meaningfully comparable to one another. This paper identifies observed characteristics that influence placement decisions and underlying maltreatment risk. It also examines the factors contributing to misplacement—cases where children remain at home despite having similar observables to those who are removed. Finally, the study examines how predicted removal risk and the probability of being misplaced at home affect child outcomes, regardless of actual placement.

To address these questions, I employ a two-stage empirical strategy along with data from the National Survey of Child and Adolescent Well-Being (NSCAW II). In the first stage, I estimate a partial observability model of Poirier (1980) to recover two key predicted probabilities: the likelihood that a child is at high risk of removal and that a child is mistakenly left at home when out-of-home placement may have been appropriate. In the second stage, I examine how these predicted risks—regardless of actual placements- are associated with short-term academic performance and the prevalence of anxiety and depressive disorders.

This paper finds that nearly 60% of children who are observationally similar to those removed from their homes were likely left in place due to discretionary caseworker decisions. While this estimate should be interpreted with caution, it is consistent with caseworkers applying relatively high removal thresholds and preferring to preserve families where feasible. Misplacement is more common among older children and less likely when caregivers have prior arrests or maltreatment history. There is also suggestive evidence that a higher risk of maltreatment (conditional on the probability of being misplaced at home) leads to worse performance in school, while a higher probability of being misplaced at home (conditional on higher risk of maltreatment) leads to better outcomes.

The remainder of the paper is organized as follows. Section 1 introduces the research question and outlines the contribution. Section 2 provides institutional background on child welfare investigations and placement decisions. Section 3 presents the theoretical model used to estimate risk and misplacement probabilities. Section 4 describes the empirical framework, and Section 5 discusses

[1] I define a child as "misplaced at home" if, based on observed characteristics, the child is observationally similar to others who are removed. Such an outcome may arise because the caseworker made an error, applied a higher removal threshold (as illustrated in the theoretical model), or observed information not captured in the data. In other words, factors unobserved by the econometrician may still be observed by the caseworker. I discuss these mechanisms in greater detail throughout the paper.

the data. Section 6 presents the main findings, and Section 7 concludes.

2 Institutional Background: Child Protective Services

When child maltreatment is suspected, certain individuals are legally required to report their concerns to the Department of Social Services. Typically, mandated reporters include professionals such as educators, healthcare providers, social workers, and law enforcement officers. Reports can also originate from family members, neighbors, or other concerned individuals.

State child welfare agencies screen the referral using available evidence and state-specific legal definitions of maltreatment. Definitions of child maltreatment are largely consistent across states and encompass the most common forms of abuse and neglect (Lee and Weigensberg, 2022). Most states categorize child maltreatment into three primary types: neglect, physical abuse, and sexual abuse. Neglect refers to a caregiver's failure to provide the child with essential needs such as adequate food, clothing, shelter, or medical care. Physical abuse includes any non-accidental physical injury inflicted on a child, while sexual abuse involves direct sexual contact or exploitation.

Based on severity, screened reports are then assigned for CPS investigation. After initiating an investigation, CPS caseworkers collect information through interviews and home assessments. The process generally includes speaking with the person who made the report, interviewing the alleged child victim, and conducting discussions with the child's parents and other household members. Caseworkers also inspect the home environment, gather evidence to support or refute the allegations, and may consult with medical or other relevant professionals when needed. In addition, criminal background checks are conducted on individuals accused of abuse or neglect to assess potential risk to the child.

Following this investigation, CPS workers complete a formal risk assessment and assign a finding. This includes determining whether the child is in immediate danger and deciding what protective measures are necessary to ensure their safety. The outcome of this assessment helps decide whether the case can be closed, requires continued monitoring, or if the child needs to be removed from the home.

Once an investigation is underway, the caseworker faces two primary intervention options: providing in-home services to support family preservation or removing the child from the home. If the caseworker determines that the child cannot be safely left at home, they may initiate emergency protective custody through law enforcement or the family court or formally petition for the child's removal. However, policy emphasizes preserving the family unit whenever safely possible. For instance, the Texas CPS Handbook states, "The caseworker must make reasonable efforts to prevent or eliminate the need to remove the child from the home, including offering Family Preservation Services." Similarly, Arizona's Department of Child Safety guidelines note, "Reasonable efforts to prevent the child's removal are being made by providing safety services as part of a Safety Plan."

These policy guidelines highlight the strong preference for keeping families together when possible. Caseworkers are expected to make every effort to stabilize the home environment before

considering removal. This emphasis on prevention and careful decision-making provides important context for the *no incorrect removal* assumption discussed later in the methodology section.

After the investigation concludes—irrespective of whether removal occurs—the Department of Social Services (DSS) provides ongoing support to the family in alignment with a permanency plan. Services are tailored to the needs of each family member and often involve coordination with Medicaid, schools, and community organizations. These supports may include therapy, behavioral interventions, academic assistance, and other resources. Caregivers may also receive targeted interventions such as parenting programs, substance use treatment, domestic violence services, and home safety support.

Following a removal decision, the next step involves deciding on an appropriate placement for the child. Typical placement options include kinship care, foster care, group homes, residential treatment facilities, etc. Policy guidelines recommend placing the child in the least restrictive, most family-like environment, prioritizing kinship foster homes when available. Foster care is generally preferred over group homes, which are considered more favorable than residential treatment centers or institutional settings.

3 Theoretical Model

To estimate the short-term effects of the risk of maltreatment and the probability of being misplaced at home, I specify a partial observability model. The rationale for using this framework is that we only observe an imperfect and noisy binary outcome —placement status. Yet, the observed outcome reflects multiple latent decisions or states. A partial observability model enables me to decompose the observed outcome into its hidden components. The data only reports if a child was placed out-of-home; however, whether a non-removed child should have been removed is not directly observable. Hence, I decompose the observed placement status into two latent binary components: (1) the child's true underlying placement need contingent upon the risk faced, and (2) the caseworker's decision accuracy.

Risk of Removal

Let $R_i \in \{0, 1\}$ denote the "true" placement status of child i ($1 = \text{OOH}$, $0 =$ remain at home). R_i is unobserved in the data. "True" placement status of a child depends on the latent maltreatment risk factor r_i^*, which is drawn from a continuous normal distribution $F(r^*|z_i)$. Here, z_i captures child i's family-specific attributes such as the permanent caregiver's dependence on drugs or alcohol, history of violence, and demographic characteristics, which may give child i a risk distribution that is different from child j. Formally,

$$r_i^* \sim N(\mu_i(z_i), \sigma_i^2(z_i)). \tag{1}$$

$R_i = 1$ when a child's latent maltreatment risk exceeds a normalized cutoff (set to zero) and child i should be placed in out-of-home (OOH) care. Formally,

$$R_i = \mathbf{1}(r_i^* \geq 0). \tag{2}$$

The probability that a child's true placement status is OOH care, which indicates a high risk of removal, is given by:

$$\Pr(R_i = 1) = \Pr(r_i^* \geq 0) = \Phi\left(\frac{\mu_i}{\sigma_i}\right), \tag{3}$$

where Φ is the standard normal CDF.

Placement Decision

Let $D_i \in \{0, 1\}$ denote the observed placement status, for child i, where $D_i = 1$ indicates that child i was actually placed in OOH care following the investigator's decision. Let $T_i \in \{0, 1\}$ indicate whether the CPS investigator made an *accurate* placement decision for child i, with $T_i = 1$ if the observed decision matches the true placement status ($D_i = R_i$) and $T_i = 0$ otherwise. Assignment error occurs when an investigator either incorrectly (i) places a child in OOH care when it is warranted ($R_i = 1, D_i = 0$), or (ii) places a child in OOH care when it is not ($R_i = 0, D_i = 1$).

Whether a decision is accurate depends not only on the underlying maltreatment risk but also on the assigned investigators' propensity to recommend removal, which may vary across investigators due to their own beliefs and actions. In particular, T_i depends on how much value (q_i) a caseworker places on keeping the child home, i.e., the caseworker's threshold for removal based on the signal the caseworker receives about the child's maltreatment risk based on observed socioeconomic and demographic characteristics, denoted r_i, and makes a placement decision accordingly. Then, the correct decision rule is:

$$T_i = \mathbf{1}(r_i \geq q_i \geq 0) = \mathbf{1}(r_i - q_i \geq 0). \tag{4}$$

where r_i is the observed risk by case-worker and q_i captures the caseworker's threshold for removal. In this study, I assume there are no false positives (NFP): investigators prioritize caution by avoiding unnecessary removals. That is, if a child is placed in out-of-home care ($D_i = 1$), then removal was warranted ($R_i = 1$) and the investigator made the correct decision ($T_i = 1$). In other words, the NFP assumption means that if $r_i - q_i \geq 0$, then $r^* \geq 0$. But $r^* \geq 0$ does not imply that $r_i - q_i \geq 0$ thus $T_i = 0$ when $R_i = 1$ can happen. Under this assumption, assignment error occurs only when a child who should have been removed is left in the home due to the investigator's discretion.

Let $H_i = 1$ identify children who are misplaced at home,

$$H_i = \mathbf{1}(R_i = 1, T_i = 0). \tag{5}$$

By parameterizing $r_i^* = z_i\theta + \eta_i$ and $r_i - q_i = m_i\lambda + v_i$, where x_i is a set of socioeconomic and demographic controls, m_i is a subset of caregiver and child characteristics z_i observed and used by the caseworker to make a placement decision, the probability that a child is misplaced at home is

given by:

$$\begin{aligned} Pr(H_i = 1 \mid X_i) &= Pr(R_i = 1, T_i = 0 \mid X_i) \\ &= Pr(r_i^* \geq 0, r_i - q_i < 0 \mid X_i) \\ &= Pr(z_i\gamma + \eta_i \geq 0,\ m_i\lambda + v_i \leq 0 \mid X_i). \end{aligned} \tag{6}$$

where $z_i, m_i \in X$ is the set of covariates.

4 Empirical Framework

Because both R_i and H_i are unobserved, I build on the works of Poirier (1980) and Nguimkeu et al. (2019) and estimate them using a partial observability model. Under the assumption of no false positives, the observed placement status is given by $D_i = R_i \times T_i$, which is used to derive the maximum likelihood function. The bivariate probit model used here allows for covariates that correlate with both R_i and T_i, and identification relies on the probability of actual OOH placement:

$$\Pr(D_i = 1 \mid X_i) = \Pr(R_i = 1, T_i = 1 \mid X_i) = \Pr(r_i^* \geq 0,\ r_i - q_i \geq 0 \mid X_i). \tag{7}$$

This model is often used to deal with one-sided measurement error, especially in survey data where certain outcomes are underreported. It's based on a bivariate probit framework that estimates two correlated binary outcomes, using maximum likelihood estimation. In Poirier (1980)'s original example, a hiring decision is observed only if both the employer makes an offer and the candidate accepts it. A more recent application by Nguimkeu et al. (2019) looks at survey responses, like food stamp participation. For someone to report they are receiving food stamps, two things have to happen: they should actually receive them, and they have to choose to report it. Having variables that are related to both, one can use the model to estimate the true rate of participation, even for people who do not report it.

I take this approach and apply it to a new setting, where the main concern is children who should have been placed in out-of-home care but weren't. For children who are actually removed from the home, we observe $R = T = 1$, and the parameters in equation (6) are estimated accordingly. The probability of misplacement, $H = 1$, is then identified based on children who are observationally similar in terms of their z_i characteristics but were not removed. In this framework, a "misplacement" is defined as a case where a child shares observable characteristics with those who were removed, yet remains at home. It is important to interpret this notion of "misplacement" with caution, as caseworkers may have access to additional information beyond what is captured in m_i when making placement decisions. Consequently, access to data with a more comprehensive set of attributes in m_i would help the model better approximate the information available to caseworkers and provide more dependable assessments of potential misplacement.

Assumptions

Since $D_i = 1$ implies $T_i = R_i = 1$, the distribution of D_i is given by:

$$\Pr(D_i = 1) = \Pr(R_i = 1, T_i = 1) = \Phi_2(z_i\gamma, m_i\lambda; \rho) \tag{8}$$

$$\begin{aligned} \Pr(D_i = 0) &= \Pr(R_i = 1, T_i = 0) + \Pr(R_i = 0, T_i = 1) \\ &= 1 - \Phi_2(z_i\gamma, m_i\lambda; \rho) \end{aligned} \tag{9}$$

where ρ is the correlation between error terms η_i and v_i, and their variances are normalized to one [2] . $\Phi_2(z_i\gamma, m_i\lambda; \rho)$ denotes the standard bivariate normal cumulative distribution function. The log-likelihood function is then:

$$\mathcal{L}(\gamma, \lambda, \rho) = \sum_{i=1}^{n} D_i \log\left[\Phi_2(z_i\gamma, m_i\lambda; \rho)\right] + (1 - D_i) \log\left[1 - \Phi_2(z_i\gamma, m_i\lambda; \rho)\right]. \tag{10}$$

To avoid local non-identification of the parameters in Equation (10), as discussed in Poirier (1980), we require the following restrictions on the covariates z_i and m_i:

Restriction 1: At least one variable in z_i must be excluded from m_i, or vice versa. This is necessary to separately identify the latent processes for R_i and T_i.

Restriction 2: At least one continuous covariate must be included in both z_i and m_i, although it does not need to be unique to either equation.

The following assumptions are required to ensure the model is correctly specified:

Assumption 1: η_i and v_i are independent of all variables in x_i, z_i, and m_i.

Assumption 2: The matrix $E(x_i x_i')$ is non-singular.

Assumption 3: The error terms η_i and v_i are assumed to be independent for $i \neq j$ and identically distributed as bivariate normal with mean zero, unit variances, and correlation ρ.

Assumption 4: $D_i = 1$ implies $R_i = 1$ $T_i = 1$ equivalently $\Pr(R_i = 0, T_i = 1) = 0$. This assumption rules out false-positive placement decisions: any child observed in out-of-home care must have both warranted removal ($R_i = 1$) and be subject to a correct placement decision by the investigator ($T_i = 1$).

Assumptions 1 and 2 are standard. Assumption 3, or independence across observations, is not required for identification, but it is required for computational feasibility, as estimating the likelihood allowing for correlated observations involves high-dimensional integration. Assumption 4 follows from the structure of the partial observability model.

[2] The constant-variance assumption applies to the error term η_i, not to the latent risk $R_i^* = z_i'\gamma + \eta_i$; variation in $z_i'\gamma$ may cause the variance of R_i^* to differ across observations without implying heteroskedasticity of the error term.

Child Outcomes

From the first-stage bivariate probit model, I can estimate the predicted probability of child i being at high risk of removal and being placed in OOH care ($\hat{R}_i$) and the probability that child i is "incorrectly" left in the home ($\hat{H}_i$). Although these probabilities are interesting in their own right, I also incorporate them into a model for child outcomes.

$$y_i = \beta x_i + \alpha_1 \hat{R}_i + \alpha_2 \hat{H}_i + \varepsilon_i \tag{11}$$

In the above specification, primary outcomes of interest y_i include short-term grade repetition, academic performance, and prevalence of anxiety disorder among children. The error term ε_i in equation (11) is assumed to be independent of all covariates in x_i, z_i, and m_i. The coefficient α_1 captures the direct effect of being at high risk of removal conditional on being misplaced at home and $\hat{S}$ and x, while α_2 captures the effect of being misplaced at home conditional on being misplaced at home and $\hat{R}$ and x. A negative α_2 suggests that the investigator's misplacement at home can potentially be harmful for the child, and $\alpha_2 > 0$ implies that family preservation may still benefit the child despite elevated risk.

5 Data

I use restricted-access data from the National Survey of Childhood and Adolescent Wellbeing II (NSCAW II). NSCAW II is a nationally representative longitudinal study of children in the child welfare system. Developed by the U.S. Department of Health and Human Services (DHHS) in consultation with experts in child development and child welfare, NSCAW was designed to inform federal, state, and local policy by tracking children's experiences and well-being over time.

NSCAW collects detailed information on children's physical health, mental health, academic outcomes, social functioning, and behavioral development. It is the first national child welfare study to include direct input from children and caregivers. The data allows researchers to link child outcomes with family characteristics, child welfare experiences, and broader community factors. However, NSCAW does not contain identifiers that allow researchers to observe or link outcomes to individual caseworkers, therefore making a caseworker instrument design infeasible for this paper.

The NSCAW II cohort consists of 5,872 children, from birth to 17.5 years old, sampled from child welfare investigations closed between February 2008 and May 2009. Baseline interviews were conducted from April 2008 to December 2009, with an 18-month follow-up conducted between October 2009 and January 2011. Data collection for the third wave took place between June 2011 and December 2012. The NSCAW II cohort, which included children aged roughly 2 months to 17.5 years at baseline, ranged in age from 34 months to 20 years by Wave 3.

In this study, the sample is restricted to 3131 children who were living at home in Wave 1. By Wave 2, 2838 of these kids were still at home, and 293 kids were placed in out-of-home (OOH)

care. OOH care is defined as removal from permanent caregivers (biological or adoptive parents) to placements such as kinship care, foster homes, or group homes. To construct z_i, I use scores for total physical assault, neglect, and psychological aggression; caregiver characteristics such as alcohol and drug dependency, arrest history, and experiences of domestic violence; and child-level variables including sex, age, age squared, and an indicator for being older than five. Many of the variables included in this study have been shown in the literature to be associated with child maltreatment and the substantiation of maltreatment by CPS. Parental substance misuse is a strong predictor of child maltreatment and is associated with increased CPS reports, substantiations, and child removals (Dubowitz et al., 2011; Wulczyn, 2009). Caseworkers who identify substance use are more likely to substantiate maltreatment allegations and recommend out-of-home placements (Font and Maguire-Jack, 2015; Freisthler et al., 2017). In a systematic review of the literature, Austin (2016) found a strong link between previous parental involvement with the criminal justice system and incidents of child maltreatment. McGuigan and Pratt (2001) also found that domestic violence is significantly related to different types of child abuse.

I use the Total Physical Assault, Neglect, and Psychological Aggression scores, measured from the 8-point Parent–Child Conflict Tactics Scales (CTSPC), because they capture the extent of maltreatment a permanent caregiver may direct toward a child. The underlying assumption behind these measures is that many forms of maltreatment are framed by parents as discipline and may also be interpreted by children as discipline. These behaviors are reported by children in response to questions such as "Did a parent or other caregiver hit you in the past week or month?" and "How many times did this occur?", which document both the incidence and frequency of violence.

The CTSPC is grounded in conflict theory, which views conflict as a normal and inevitable part of human relationships but distinguishes this from using physical or psychological aggression as a strategy to manage conflict. To capture the frequency and severity of such acts, the CTSPC employs an eight-point Likert-type scale (1 time, 2 times, 3–5 times, 6–10 times, 11–20 times, more than 20 times, not in the past 12 months, never) as outlined by Straus et al. (1998). One can refer to Appendix Three of the NSCAW II survey documentation for further details on how these scores are calculated. Caregiver alcohol dependency is identified by an AUDIT (Alcohol Use Disorders Identification Test) score greater than 5, while drug dependency is indicated by a DAST-20 (Drug Abuse Screening Test) score exceeding 3. The AUDIT is a 10-item WHO screening tool designed to detect hazardous and harmful alcohol use, and DAST is a brief, 20-item yes/no screening instrument designed to identify individuals who may be misusing psychoactive drugs to provide a quantitative index of the severity of alcohol and drug-related problems.

The vector m_i includes child characteristics such as sex, race, age, and age squared; indicators for whether the caregiver has more than three arrests, a prior history of maltreatment, or ongoing domestic violence; caregiver's total number of arrests and its square; indicator for caregiver's drug and alcohol dependency; and an indicator for whether the child is older than five, household poverty level.

The exclusion restrictions are based on differences in the information available to researchers

and caseworkers. The risk equation or vector z_i includes survey-specific scores for physical assault, neglect, and psychological aggression. These scores were constructed exclusively for research purposes and were not part of the information available to caseworkers. They provide detailed measures of harmful behavior in the home and therefore help identify the child's underlying need for removal. Their quadratic terms allow the relationship between these behaviors and risk to be nonlinear. Because caseworkers could not observe these scores, they are excluded from the decision equation.

Vector z_i also includes caregiver-reported measures of ever having been arrested and domestic violence in the household as well as household poverty level. These measures provide information about underlying household instability and exposure to violence that may not have been known to the caseworker. The decision equation, or vector m_i, instead includes caseworker-reported variables such as the number of documented arrests and active domestic violence, which are more visible and immediately relevant to the placement decision. Any arrest history may indicate underlying instability, while repeated documented arrests may cause the caseworker to view that instability as more persistent or severe. Similarly, domestic violence in the household captures the child's underlying exposure, whereas active domestic violence is an immediate signal on which the caseworker can act.

Child race enters the vector m_i but not the risk equation. Conditional on the controls for caregiver behavior, maltreatment, substance dependence, domestic violence, poverty, and child characteristics, race itself is not an intrinsic source of danger within the home. It is, however, immediately observable and may influence how caseworkers perceive otherwise similar circumstances or apply the removal threshold. The race coefficients therefore capture racial differences in placement assessments conditional on modeled risk, rather than an intrinsic effect of race on child safety.

Outcomes of interest include grade repetition, academic performance, and the prevalence of anxiety disorders among children. Grade repetition and diagnoses of depression or anxiety are binary indicators provided by caregivers. Children aged at least eight years at the time of the Wave 3 interview self-report the remaining outcomes. Academic performance is assessed across four subjects: language studies, social sciences, science, and mathematics, and categorized as Failing, Below Average, Average, or Above Average.

Summary statistics (weighted and unweighted) of all variables are included in Tables A1-A4. The weighted sample OOH placement rate is about 8% for a sample of 3131 kids. A comparison of the weighted summary statistics in Table 1 between in-home and OOH children reveals that OOH children are associated with caregivers who exhibit higher rates of arrests and substance dependency, and they experience slightly elevated levels of neglect, maltreatment, and exposure to domestic violence.

Table 1: Summary Stats Weighted - By OOH Status

	In-Home					OOH				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Total Aggression Score	0.55	1.18	0	12	2838	0.48	1.46	0	10	293
Neglect Score	0.16	0.52	0	5	2838	0.18	0.50	0	3	293
Psychological Aggression Score	1.24	1.73	0	12	2838	1.16	1.59	0	9	293
CG Drug Dependency	0.06	0.24	0	1	2838	0.14	0.35	0	1	293
CG Alcohol Dependency	0.07	0.25	0	1	2838	0.10	0.30	0	1	293
CG arrest >3	0.05	0.23	0	1	2838	0.12	0.33	0	1	293
CG ever arrested	0.33	0.47	0	1	2838	0.51	0.50	0	1	293
Child Race	3.38	0.93	1	4	2838	3.50	0.90	1	4	293
Child Sex	0.49	0.50	0	1	2838	0.48	0.50	0	1	293
Child Age	6.96	4.61	0	16	2838	9.17	6.49	0	17	293
% Poverty Level	2.26	1.01	1	4	2838	2.36	0.97	1	4	293
CG no. of arrests	0.78	1.61	0	10	2838	1.41	2.12	0	10	293
History of Maltreatment	0.50	0.50	0	1	2838	0.54	0.50	0	1	293
History of Domestic Violence	0.23	0.42	0	1	2838	0.24	0.43	0	1	293
Active Domestic Violence	0.10	0.30	0	1	2838	0.12	0.32	0	1	293

6 Results

Stage 1 Results: Misplacements and Marginal Effects

The results of the bivariate probit regression are presented in Table A3. In Table 1, I have the average predicted probabilities $\hat{R}_i$, $\hat{H}_i$, and $\widehat{CM}_i$ from the bivariate probit regression from the sample of 3131 kids, irrespective of their actual placement status. I define $\widehat{CM}_i = \hat{H}_i/\hat{R}_i$, which captures the probability of misplacement conditional on being at risk of removal. The first column, first row shows that approximately 70% of children in the sample are predicted to be at high risk of removal. In other words, based on observable characteristics, these children are similar to those who have actually been placed in OOH care. Notably, the mean predicted risk of removal varies substantially across most demographic categories. Black children are 6 percentage points more likely to be at high risk of removal and 8 percentage points more likely to be misplaced at home than white children. This finding differs from existing evidence that Black children are more likely than White children to be referred for maltreatment, substantiated as victims, and to enter foster care before age five (Putnam-Hornstein et al., 2013). However, it aligns with their additional finding that, after adjusting for socioeconomic risk factors, Black children have a lower risk of referral, substantiation, and foster care entry than their socioeconomically similar White counterparts. I also find that, while male kids are 8 percentage points more likely to be at high risk of removal, they are also more likely to be misplaced at home. Children from relatively better-off households are less likely to be identified as high risk. This pattern is intuitive given that neglect—the most common form of maltreatment—is strongly associated with poverty (see Bullinger et al. (2021) for a survey of literature). Children in more economically stable households are less likely to experience neglect or financial instability that may compromise their well-being.

Table 2: Average Predicted Probability

	High Risk of Removal (R)	Misplaced at home (H)	OOH Placement (D)	Conditional Misplacement (H/R)
Full Sample	0.70	0.62	0.08	0.81
Child Gender				
Female	0.67	0.59	0.08	0.79
Male	0.74	0.67	0.08	0.82
Child Race				
American Indian	0.63	0.57	0.07	0.80
Other	0.65	0.63	0.02	0.90
Black	0.76	0.69	0.07	0.85
White	0.70	0.61	0.09	0.78
HH Poverty Level				
$< 50\%$	0.71	0.65	0.07	0.83
$50\% - < 100\%$	0.73	0.65	0.07	0.83
$100\% - 200\%$	0.70	0.60	0.09	0.77
$> 200\%$	0.64	0.57	0.07	0.78

The second column, first row tells us that approximately 62% of the sample is predicted to be placed at home when they likely"should" have been placed in out-of-home (OOH) care. That is, the average joint probability of $R = 1$ and $T = 0$ is 0.62. Furthermore, 81% of children identified as high risk for removal are conditionally misplaced at home, representing approximately 56% of the overall sample. These are substantial proportions. This implies that most children in the dataset share similar observable characteristics, making children who remained at home appear similar to those who were removed. While this suggests a potentially high misplacement rate, it is important to interpret these findings cautiously. First, the sample consists of children who were investigated by Child Protective Services (CPS), a population that is already at substantially elevated risk of maltreatment compared with children in the general population. Second, these patterns are consistent with the possibility that caseworkers apply a relatively high threshold for removal decisions, i.e., $q^* >> 0$. In the model, this corresponds to situations in which the risk perceived by caseworkers is lower than the child's underlying latent risk at home, such that $r^* > 0$ while $r < 0$, leading to placement decisions that may be classified as misplacements within the framework of the model. However, it is also important to acknowledge that caseworkers may have access to additional, unobserved information not fully captured in the data that influences their removal decisions. Nonetheless, given the constraints of the available data, this approach provides a novel and informative perspective that differs significantly from previous analyses. Interestingly, the gap between the share of children predicted to be at high risk of removal and those likely to be misplaced is about 8%, which closely corresponds to the weighted average of the OOH placement rate observed in the sample. Next, I examine the factors associated with a child's likelihood of being misplaced at home. As shown in Table 3, children older than five are 96 percentage points more likely to be misplaced at home compared to those under five. One possible explanation is that caseworkers often take into account a child's ability for self-protection when making placement decisions (Child Welfare Information Gateway, 2021b,a). Additionally, older children are generally more challenging to place in foster care than younger children or infants, due

to the more complex needs that often accompany adolescence, including behavioral challenges and prior exposure to trauma. Both Sattler et al. (2018) and Oosterman et al. (2007) find that older age at placement significantly increases the risk of placement breakdown, with adolescents being over seven times more likely than younger children to initiate disruptions, contributing to frequent moves and delayed permanency. A similar pattern emerges for being at high risk of removal: age is negatively associated with the probability of being at high risk of removal. However, I also find that each additional year of age is associated with a 10-percentage-point decrease in the likelihood of being misplaced at home. Taken together with the large effect for the "older than five" indicator, this suggests a jump in the marginal effect at age five, after which the likelihood of misplacement as well as being at high risk of removal declines with age.

Table 3: Marginal Effects On Being Misplaced at Home

	(1)
Total Aggression Score	-0.02
	(0.050)
Neglect Score	0.02
	(0.034)
Psychological Aggression Score	0.03*
	(0.013)
Child age >5	0.96*
	(0.507)
CG Drug Dependency	0.05
	(0.046)
CG Alcohol Dependency	-0.01
	(0.034)
CG ever arrested	0.00
	(0.022)
Child Age	-0.10***
	(0.006)
History of Maltreatment	-0.06*
	(0.034)
History of Domestic Violence	0.03
	(0.029)
HH poverty level $< 50\%$	-0.06*
	(0.037)
HH poverty level $100\% - 200\%$	-0.02
	(0.034)
HH poverty level $> 200\%$	-0.04
	(0.044)
CG arrest >3	-0.01
	(0.034)
CG no. of arrests	-0.02**
	(0.007)
Observations	3131

Heteroscedastic robust standard errors in parentheses
Average marginal effects : $\frac{d \Pr(H=1)}{dz}$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I find that a prior history of maltreatment by the caregiver reduces the likelihood of a child being misplaced at home by approximately 6 percentage points, while each additional caregiver arrest is associated with a 2 percentage point decrease in this likelihood. These findings suggest that caseworkers may be less confident in a child's safety when the permanent caregiver has a history of maltreatment or criminal involvement. Children in households with income below 50% of the poverty threshold have a 6 percentage point lower predicted probability of being misplaced at home than children in the reference income group. I also find no significant association between caregiver substance use or alcohol dependency and a child's likelihood of being misplaced at home.

Table 4: Marginal Effects On Being at High Risk of Removal

	(1)
Total Aggression Score	-0.04
	(0.078)
Neglect Score	0.02
	(0.049)
Psychological Aggression Score	0.04**
	(0.018)
Child age > 5	1.38*
	(0.726)
CG Drug Dependency	0.12**
	(0.056)
CG Alcohol Dependency	-0.02
	(0.035)
CG ever arrested	0.01
	(0.032)
Child Age	-0.09***
	(0.006)
History of Maltreatment	-0.05
	(0.035)
History of Domestic Violence	0.05
	(0.040)
HH poverty level < 50%	-0.07
	(0.042)
HH poverty level 100% − 200%	-0.01
	(0.037)
HH poverty level > 200%	-0.03
	(0.046)
Observations	3131

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
CG refers to individuals primarily responsible for the child's well-being at home (e.g., biological, adoptive, or foster parents, grandparents)

However, as shown in Table 4, caregiver drug dependency is associated with a 12 percentage point increase in the child's predicted probability of being at high risk of removal. I also find that,

a one-point increase in the Psychological Aggression Score is associated with a 4 percentage point increase in the predicted probability of being at high risk of removal.

Stage 2 Results: Child Outcomes

The predicted probabilities of high risk of removal ($\hat{R}$) and misplacement at home ($\hat{H}$) are used as key regressors in models of child outcomes. Table 5 reports results from ordered probit models for academic performance in Math, Social Science, Language, and Science, each measured in four categories: "Failing," "Below Average," "Average," and "Above Average." Controlling for child age and gender, I find that a 100 percentage point increase in a child's predicted risk of removal is associated with a 31 percentage point higher probability of failing in Science. The corresponding negative marginal effect for the "Above Average" category suggests that exposure to a high-risk home environment significantly reduces the likelihood of above-average performance in Science. The marginal effects are similar in magnitude across specifications with and without controls.

Table 5: Marginal Effects on Subject Specific Performance

	No Controls				With Controls			
	Mathematics	Social Sciences	Language	Sciences	Mathematics	Social Sciences	Language	Sciences
$R = 1$								
Failing	-0.142	0.103	0.140	0.350***	-0.130	0.0432	0.157	0.306**
	(0.157)	(0.093)	(0.095)	(0.128)	(0.161)	(0.097)	(0.101)	(0.138)
Below Avg	-0.201	0.164	0.269	0.355**	-0.182	0.0692	0.302*	0.304*
	(0.204)	(0.148)	(0.166)	(0.157)	(0.207)	(0.158)	(0.173)	(0.169)
Average	-0.0804	0.244	0.410*	0.461**	-0.0731	0.103	0.460*	0.398*
	(0.083)	(0.229)	(0.241)	(0.220)	(0.083)	(0.237)	(0.252)	(0.224)
Above Avg	0.424	-0.511	-0.819*	-1.166***	0.385	-0.215	-0.919*	-1.008**
	(0.431)	(0.459)	(0.468)	(0.447)	(0.441)	(0.490)	(0.485)	(0.492)
$H = 1$								
Failing	0.134	-0.117	-0.176*	-0.364***	0.108	0.0531	-0.221*	-0.234
	(0.164)	(0.097)	(0.106)	(0.134)	(0.191)	(0.121)	(0.131)	(0.176)
Below Avg	0.188	-0.184	-0.336*	-0.369**	0.151	0.0850	-0.425**	-0.232
	(0.214)	(0.155)	(0.176)	(0.169)	(0.251)	(0.188)	(0.217)	(0.208)
Average	0.0754	-0.275	-0.514**	-0.478**	0.0608	0.127	-0.648**	-0.304
	(0.087)	(0.240)	(0.247)	(0.233)	(0.099)	(0.279)	(0.305)	(0.266)
Above Avg	-0.397	0.576	1.026**	1.210**	-0.320	-0.265	1.294**	0.770
	(0.454)	(0.478)	(0.479)	(0.476)	(0.535)	(0.586)	(0.588)	(0.632)
Observations	469	454	464	459	469	454	464	459

Robust standard errors in parentheses.

With Controls: controlling for child age and sex.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, I find no significant association between a child's predicted risk of removal and academic performance in Mathematics and Social Science. Table 5 also suggests that remaining at home despite a predicted need for removal is associated with better academic outcomes in some subjects. In the specification without controls, predicted misplacement at home is associated with a lower probability of failing in Language and Sciences. After controlling for child characteristics,

the association remains marginally significant for Language but becomes statistically insignificant for Sciences.

Since there is no apparent reason a child's performance in some subjects should differ systematically from their performance in others, I restructure the data by stacking performance across the four subjects into a panel format. As a result, each child contributes four observations—one for each subject—which ensures a consistent sample size that was not possible when analyzing the subjects separately. Using the restructured data, I estimate equation 11 with and without controls.

Table 6: Average Marginal Effects on Academic Performance

	(1) Without Controls	(2) With Controls
R=1		
Failing	0.126**	0.106*
	(0.057)	(0.061)
Below Avg	0.177**	0.149*
	(0.084)	(0.090)
Average	0.188**	0.158
	(0.093)	(0.098)
Above Avg	-0.491**	-0.414*
	(0.228)	(0.245)
H=1		
Failing	-0.147**	-0.0864
	(0.060)	(0.076)
Below Avg	-0.206**	-0.121
	(0.089)	(0.112)
Average	-0.220**	-0.129
	(0.098)	(0.119)
Above Avg	0.572**	0.337
	(0.239)	(0.304)
Observations	1846	1846

Robust standard errors in parentheses

Controls include Child age, age squared, child sex

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 shows that higher predicted removal risk is associated with poorer academic performance. After controlling for child age, age squared, and sex, a 10 percentage point increase in predicted removal risk is associated with a 1.06 percentage point increase in the probability of failing, a 1.49 percentage point increase in the probability of below-average performance, and a 4.14 percentage point decrease in the probability of above-average performance. These associations are statistically

[2]Robust standard errors are used in place of bootstrapped standard errors in Tables 5, 6, and 7 because bootstrapping within the partial observability framework led to convergence issues.

significant at the 10% level. The marginal effects for removal risk remain similar in magnitude across specifications, although their statistical significance weakens with controls. In contrast, predicted misplacement at home is associated with better academic performance in the specification without controls, but these estimates shrink and become statistically insignificant after controls are included. Thus, the results provide suggestive evidence linking higher predicted removal risk to poorer academic outcomes, but no clear evidence of an association between misplacement at home and academic performance after accounting for these child characteristics. These results should be viewed as suggestive evidence of effects rather than definitive conclusions, as the relatively large standard errors call for cautious interpretation. Table 7 reports the marginal effects of predicted removal risk and misplacement at home on grade repetition and anxiety disorder. The estimates are not stable across specifications with and without controls. Although the associations are statistically significant without controls, they weaken and become statistically insignificant after controlling for child characteristics. These results therefore provide neither clear nor consistent suggestive evidence linking predicted removal risk or misplacement at home to either outcome.

Table 7: Average Marginal Effects on Grade Repetition & Anxiety Disorder

	No Control		With Control	
	Grade Repetition	Anxiety Disorder	Grade Repetition	Anxiety Disorder
$R = 1$	-0.225**	-0.239***	-0.100	-0.001
	(0.102)	(0.082)	(0.112)	(0.118)
$H = 1$	0.222**	0.219***	0.067	-0.047
	(0.100)	(0.079)	(0.121)	(0.141)
Child Age	No	No	Yes	Yes
Child Sex	No	No	Yes	Yes
Observations	1990	1990	1990	1990

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The findings suggest that leaving these children in the home does not seem to harm them with respect to the short-term outcomes examined. However, these results should be viewed with caution. The sample is relatively small, and the available covariates provide only a limited characterization of children's and families' circumstances. The outcomes analyzed here were measured only 12 to 18 months after the intervention, which may be too short a window to capture the full effects of early adversity or intervention decisions. The absence of large or precisely estimated effects over this period does not rule out stronger effects on outcomes later in life or on alternative measures of academic achievement, such as standardized test scores. Furthermore, the model does not account for the duration or severity of neglect or abuse a child may have experienced at home. For children placed in out-of-home care, the length and frequency of placement are likely important factors shaping outcomes, but due to limited data availability, the current model does not consider them. Similarly, for children who remained at home, the model does not account for the provision or type

of services the family may have received. These services—such as parenting support, mental health care, or substance use treatment—could play a key role in whether family preservation is ultimately helpful.

7 Conclusion

This paper examines an important but underexplored question in child welfare: what happens when children who would likely benefit from placement in OOH care are instead left at home? This question is particularly important because much of the existing literature focuses on whether foster care is harmful, yet it is difficult to disentangle the effects of out-of-home placement from the underlying effects of maltreatment and neglect that result in such placements. By asking the reverse question—whether preserving kids at home is itself harmful—and comparing observationally similar children who are placed in OOH care with those who are not, this paper provides an informative insight into how these effects can be separated. Using a nationally representative dataset and a partial observability framework, I identify children at high risk of removal and estimate the likelihood of being misplaced at home due to caseworker discretion. I assess the consequences of potential misplacement and family preservation efforts by combining these predictions with short-term outcomes.

The results suggest that a significant share of children—nearly 62% are likely to have remained at home despite being observationally similar to those who were removed. This pattern points toward caseworkers operating with a relatively high threshold for removal and a preference for preserving family unity when possible. At the same time, such decisions may also reflect discretionary judgment or the use of information not directly observed in the data. Misplacement is more likely among older children, who are typically harder to place in foster care, and less likely when caregivers have a known history of maltreatment or arrests. These patterns are consistent with how risk is perceived and managed in frontline decision-making.

Regarding outcomes, a higher risk of removal is associated with lower performance in science, pointing to the adverse academic effects of exposure to "neglectful" home environments. However, no significant evidence is found of a relationship between predicted misplacement and academic or behavioral outcomes in the short run. This is not entirely surprising, as the consequences of maltreatment and suboptimal placement decisions may take longer to manifest in observable academic or behavioral measures. At the same time, this pattern highlights important opportunities for future research. The current framework does not capture the duration or intensity of maltreatment and does not incorporate information on the type and quality of in-home services provided following an investigation, along with other determinants of child mental health. Access to richer data over longer time horizons would allow for a more comprehensive assessment of how family environments and service provision interact to shape child outcomes.

Taken together, the findings suggest that while caseworkers often favor keeping children at home when possible, this approach may carry meaningful risks, particularly in situations where the home

environment remains unsafe or adequate support systems are not in place.

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Appendix

Table A1: Summary Stats Unweighted

	Mean	SD	Min	Max	N
Total Aggression Score	0.38	0.87	0	12	3131
Neglect Score	0.15	0.51	0	5	3131
Psychological Aggression Score	0.98	1.61	0	12	3131
CG Drug Dependency	0.15	0.35	0	1	3131
CG Alcohol Dependency	0.08	0.26	0	1	3131
CG arrest >3	0.08	0.27	0	1	3131
CG ever arrested	0.38	0.49	0	1	3131
Child Race	3.35	0.92	1	4	3131
Child Sex	0.48	0.50	0	1	3131
Child Age	5.28	5.10	0	17	3131
% Poverty Level	2.20	1.01	1	4	3131
CG no. of arrests	0.97	1.84	0	10	3131
History of Maltreatment	0.47	0.50	0	1	3131
History of Domestic Violence	0.27	0.44	0	1	3131
Active Domestic Violence	0.15	0.36	0	1	3131
OOH Placement	0.09	0.29	0	1	3131

Table A2: Summary Stats Unweighted - By OOH Status

	In-Home					OOH				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Total Aggression Score	0.38	0.87	0	12	2838	0.31	0.93	0	10	293
Neglect Score	0.15	0.52	0	5	2838	0.17	0.48	0	3	293
Psychological Aggression Score	1.00	1.62	0	12	2838	0.85	1.42	0	9	293
CG Drug Dependency	0.13	0.34	0	1	2838	0.26	0.44	0	1	293
CG Alcohol Dependency	0.07	0.26	0	1	2838	0.13	0.33	0	1	293
CG arrest>3	0.07	0.25	0	1	2838	0.15	0.35	0	1	293
CG ever arrested	0.37	0.48	0	1	2838	0.49	0.50	0	1	293
Child Race	3.35	0.92	1	4	2838	3.34	0.92	1	4	293
Child Sex	0.48	0.50	0	1	2838	0.52	0.50	0	1	293
Child Age	5.20	4.92	0	16	2838	6.12	6.50	0	17	293
% Poverty Level	2.21	1.01	1	4	2838	2.16	1.01	1	4	293
CG no. of arrests	0.91	1.75	0	10	2838	1.58	2.52	0	10	293
History of Maltreatment	0.46	0.50	0	1	2838	0.54	0.50	0	1	293
History of Domestic Violence	0.26	0.44	0	1	2838	0.29	0.46	0	1	293
Active Domestic Violence	0.16	0.36	0	1	2838	0.14	0.35	0	1	293

Table A3: Summary Stats Weighted

	Mean	SD	Min	Max	N
Total Aggression Score	0.54	1.20	0	12	3131
Neglect Score	0.17	0.52	0	5	3131
Psychological Aggression Score	1.23	1.72	0	12	3131
CG Drug Dependency	0.07	0.25	0	1	3131
CG Alcohol Dependency	0.07	0.25	0	1	3131
CG arrest >3	0.06	0.24	0	1	3131
CG ever arrested	0.35	0.48	0	1	3131
Child Race	3.39	0.93	1	4	3131
Child Sex	0.49	0.50	0	1	3131
Child Age	7.12	4.82	0	17	3131
% Poverty Level	2.27	1.00	1	4	3131
CG no. of arrests	0.83	1.66	0	10	3131
History of Maltreatment	0.50	0.50	0	1	3131
History of Domestic Violence	0.23	0.42	0	1	3131
Active Domestic Violence	0.10	0.30	0	1	3131
OOH Placement	0.08	0.26	0	1	3131

Table A4: Summary Stats Weighted - By OOH Status

	In-Home					OOH				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Total Aggression Score	0.55	1.18	0	12	2838	0.48	1.46	0	10	293
Neglect Score	0.16	0.52	0	5	2838	0.18	0.50	0	3	293
Psychological Aggression Score	1.24	1.73	0	12	2838	1.16	1.59	0	9	293
CG Drug Dependency	0.06	0.24	0	1	2838	0.14	0.35	0	1	293
CG Alcohol Dependency	0.07	0.25	0	1	2838	0.10	0.30	0	1	293
CG arrest >3	0.05	0.23	0	1	2838	0.12	0.33	0	1	293
CG ever arrested	0.33	0.47	0	1	2838	0.51	0.50	0	1	293
Child Race	3.38	0.93	1	4	2838	3.50	0.90	1	4	293
Child Sex	0.49	0.50	0	1	2838	0.48	0.50	0	1	293
Child Age	6.96	4.61	0	16	2838	9.17	6.49	0	17	293
% Poverty Level	2.26	1.01	1	4	2838	2.36	0.97	1	4	293
CG no. of arrests	0.78	1.61	0	10	2838	1.41	2.12	0	10	293
History of Maltreatment	0.50	0.50	0	1	2838	0.54	0.50	0	1	293
History of Domestic Violence	0.23	0.42	0	1	2838	0.24	0.43	0	1	293
Active Domestic Violence	0.10	0.30	0	1	2838	0.12	0.32	0	1	293

Table A5: Bivariate Probit Regression: Stage 1

Total Assault Score	-0.72
	(1.029)
Assault Score Squared	0.46
	(0.546)
Neglect Score	0.28
	(0.546)
Neglect Score Squared	-0.15
	(0.176)
Psychological Aggression Score	0.58*
	(0.238)
Psychological Agg. Score Squared	-0.09*
	(0.034)
Child age > 5	13.27
	(10.096)
CG Drug Dependency	1.15*
	(0.560)
CG Alcohol Dependency	-0.19
	(0.347)
CG Ever Arrested	0.06
	(0.305)
Child Sex	0.36
	(0.265)
Child Age	-4.38
	(2.483)
Age Squared	0.17*
	(0.083)
History of Maltreatment	-0.45
	(0.298)
History of Domestic Violence	0.45
	(0.422)
$< 50\%$	-0.66
	(0.424)
$100\% - 200\%$	-0.07
	(0.337)
$> 200\%$	-0.28
	(0.466)
Constant	13.95
	(8.714)
Child Sex	-0.21
	(0.148)
Child Age	-0.26*
	(0.103)
Age Squared	0.03***
	(0.004)
CG Drug Dependency	0.32
	(0.192)
CG Alcohol Dependency	-0.04
	(0.242)
CG Arrest > 3	0.08
	(0.398)
Asian/Hawaiian/Pacific Is	-0.49
	(0.383)
Black	0.34
	(0.255)
White	0.50
	(0.260)
$< 50\%$	0.23
	(0.185)
$100\% - 200\%$	0.21
	(0.196)
$> 200\%$	0.23
	(0.244)
No. of Arrests	0.27**
	(0.098)
Arrests Squared	-0.03*
	(0.010)
History of Maltreatment	0.38
	(0.199)
Active Domestic Violence	-0.07
	(0.262)
Child age > 5	-0.22
	(0.428)
Constant	-2.00***
	(0.349)
athrho	0.04
	(0.294)
Observations	3131

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table A6: Marginal Effects

	(1) Mathematics	(2) Social Sciences	(3) Language	(4) Sciences
A=1				
Failing	-0.155	0.0429	0.154	0.296**
	(0.166)	(0.098)	(0.101)	(0.138)
Below Avg	-0.219	0.0687	0.296*	0.296*
	(0.212)	(0.158)	(0.174)	(0.168)
Average	-0.0873	0.102	0.451*	0.385*
	(0.087)	(0.237)	(0.256)	(0.223)
Above Avg	0.461	-0.214	-0.902*	-0.977**
	(0.451)	(0.492)	(0.492)	(0.492)
U=1				
Failing	0.163	0.0537	-0.215	-0.213
	(0.200)	(0.121)	(0.131)	(0.175)
Below Avg	0.230	0.0859	-0.412*	-0.213
	(0.256)	(0.188)	(0.216)	(0.204)
Average	0.0921	0.128	-0.629**	-0.278
	(0.104)	(0.279)	(0.313)	(0.261)
Above Avg	-0.486	-0.268	1.256**	0.705
	(0.545)	(0.586)	(0.599)	(0.625)
Observations	469	454	464	459

Robust errors in parentheses

Controls include- Child age, age sqaured

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Marginal Effects

	(1) Mathematics	(2) Social Sciences	(3) Language	(4) Sciences
A=1				
Failing	-0.122	0.0412	0.142	0.294**
	(0.159)	(0.102)	(0.094)	(0.138)
Below Avg	-0.174	0.0655	0.269	0.289*
	(0.209)	(0.164)	(0.167)	(0.166)
Average	-0.0690	0.0977	0.410*	0.381*
	(0.082)	(0.246)	(0.244)	(0.219)
Above Avg	0.365	-0.204	-0.821*	-0.964**
	(0.441)	(0.510)	(0.471)	(0.487)
U=1				
Failing	0.0580	0.0457	-0.185	-0.221
	(0.183)	(0.129)	(0.121)	(0.176)
Below Avg	0.0824	0.0727	-0.349*	-0.217
	(0.252)	(0.200)	(0.206)	(0.204)
Average	0.0328	0.108	-0.533*	-0.287
	(0.099)	(0.297)	(0.296)	(0.262)
Above Avg	-0.173	-0.227	1.067*	0.726
	(0.532)	(0.625)	(0.577)	(0.625)
Observations	469	454	464	459

Robust standard errors in parentheses

Controls include- Child age, age squared, child sex, poverty level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Marginal Effects

	(1) Mathematics	(2) Social Sciences	(3) Language	(4) Sciences
A				
Failing	-0.179	0.00862	0.118	0.188
	(0.174)	(0.105)	(0.091)	(0.144)
Below Avg	-0.256	0.0137	0.228	0.188
	(0.224)	(0.167)	(0.166)	(0.165)
Average	-0.101	0.0202	0.345	0.244
	(0.089)	(0.247)	(0.257)	(0.217)
Above Avg	0.536	-0.0425	-0.691	-0.621
	(0.469)	(0.518)	(0.490)	(0.512)
U10				
Failing	0.120	0.0815	-0.163	-0.109
	(0.199)	(0.136)	(0.117)	(0.187)
Below Avg	0.172	0.129	-0.315	-0.109
	(0.267)	(0.207)	(0.205)	(0.203)
Average	0.0680	0.191	-0.476	-0.141
	(0.104)	(0.302)	(0.313)	(0.262)
Above Avg	-0.360	-0.402	0.954	0.359
	(0.562)	(0.640)	(0.601)	(0.649)
Observations	469	454	464	459

Robust standard errors in parentheses

Controls include- Child age, age squared, child sex, poverty level, child race

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$