REMOVING CHILDREN FROM HOME: A MULTILEVEL ANALYSIS OF PREDICTORS FOR PLACEMENT IN FOSTER CARE

by

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DEDICATION

This is dedicated to children and families everywhere; to single mothers and fathers struggling to get by and under stress, to children in need of a loving family to take good care of them. To those social workers who care passionately about improving the lives of the children they serve. And, most importantly, to my family: my kind and supportive husband, Adam, and my wonderful little boy, Cason, who brings immeasurable joy to my life and all those who know him.

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LIST OF ABBREVIATIONS AND SYMBOLS

Adoption and Foster Care Analysis and Reporting System ..... AFCARS
alpha ..... α
beta ..... β
Child Abuse Prevention and Treatment Act ..... CAPTA
Confidence Interval CI
Child Protective Services ..... CPS
eta ..... η
Fourth National Incidence Study of Child Abuse and Neglect NIS-4
Full maximum likelihood ..... ML
Generalized Linear Mixed Modeling ..... GLMM
Hierarchical Linear Modeling ..... HLM
mu ..... μ
National Child Abuse and Neglect Data System ..... NCANDS
National Data Archive on Child Abuse and Neglect ..... NDACAN
National Survey of Child and Adolescent Well-Being ..... NSCAW
Odds Ratios ..... OR
Restricted maximum likelihood ..... REML
Standard deviation ..... *SD*
Standard error ..... SE

ABSTRACT

REMOVING CHILDREN FROM HOME: A MULTILEVEL ANALYSIS OF PREDICTORS FOR PLACEMENT IN FOSTER CARE

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The foster care system is intended as a temporary safety net to protect children and youth at risk of harm. Difficult decisions are made every day to place victims of child abuse or neglect in foster care. The focus of this study is to identify what characteristics, at either the individual or state level, increase the likelihood of placement and assess changes over time in factors that impact likelihood of placement. Secondary data from the National Child Abuse and Neglect Data System are used in a multilevel logistic regression model. Results show that infants, neglect, and prior victimizations all increase the likelihood of foster care placement. Foster care placement has decreased over time, despite tremendous variation between states. This thesis contributes to the existing literature in the field on indicators of increased likelihood of foster care placement, as well as provides a pedagogical example of how multilevel models can address important structural issues within the social sciences.

CHAPTER ONE: STATEMENT OF PROBLEM

Infants and children are among the most vulnerable in our society, and when families are not functioning well and children are at risk of harm in their own homes, there is a need for an intervention. But as the social world is dynamic, so too are notions such as 'risk,' 'harm,' and what sorts of interventions are most appropriate. Therefore, measuring and quantifying changes and identifying indicators related to social policies and practice is a constantly evolving process to better capture the social structures and forces at play. This paper will explore indicators of placement in foster care within the United States, and consider structural factors that may influence the likelihood of this happening. Understanding that child welfare policy and practice is not static, several years (2007 through 2010) are examined to determine whether there has been meaningful change in the impact of these indicators, given the changes observed in other aggregate statistics at the national level. To provide a broader historical context for these recent trends, this chapter begins by providing a brief and selective history of child welfare within the United States.

A Brief History of Child Welfare

A review of the history of perspectives on child welfare in the United States reveals a constantly shifting theoretical framework, punctuated by a series of legislative acts of reform. Prior to the mid 19th century, orphans and children in poverty were often

placed alongside adults in almshouses, without differential treatment for their needs. Beginning with the Progressive era, we saw the emergence of children's rights. In the early 19th century, orphanages and institutional care became the primary mechanism to protect and care for children. As the move toward children's rights gained momentum, there was eventually a shift from orphanages and institutional care to family based care. The first private agency to place children in family settings was the New York Children's Aid Society (NYCAS), created in the 1880's to address juvenile delinquency and take care of abandoned children. This group began the practice of "orphan trains" to move inner-city children out west to serve as farmhands and other laborers in exchange for room and board.

In 1889, the American Pediatric Society was formed to focus on children's medical needs. Several seminal works were published over the next couple of decades highlighting the long term detrimental impacts that child poverty has on society, such as Hunter's 1904 publication *Poverty*. Leaders such as Jane Addams were pivotal in the move toward providing better care for struggling women and children, with the Hull House in Chicago, IL and she also made great strides in the establishment of child labor laws. In 1912, the Children's Bureau was established by President Taft, which still holds primary responsibility for administering child welfare programs in the country. It began with the mission to investigate and report statistics on infant mortality, birth rates, orphanages, juvenile courts, etc., and has evolved to its current mission to "provide for the safety, permanency, and well-being of children through leadership, support for

necessary services, and productive partnerships with States, Tribes and communities." (US Dept of HHS, ACYF, Children's Bureau, 2012).

In the 1960's a heightened awareness of child abuse emerged, and in 1974, Congress passed the Child Abuse Prevention and Treatment Act (CAPTA) which provided federal funding for state child protective services and has been amended and reauthorized over the years, as recently as 2003.

The safety and well-being of our nation's children is often inextricably tied to social problems such as poverty, homelessness, substance abuse and mental health issues either by adolescents or by parents. These problems tend to converge and produce struggling families in need of assistance. How to best address those needs has been an ongoing debate. Foster care is intended to provide children with a safe and temporary home to children and youth whose families are unable to care for them. Although some children stay in the system too long and eventually 'age out' of foster care, the majority of children entering the foster care system are reunified with their families as soon as possible or some other permanent arrangement is found (adoption, guardianship, permanent home with a relative).

Numbers of Children in Foster Care

Efforts to report national statistics on the numbers of children in foster care began in 1982 with the Voluntary Cooperative Information System (VCIS), but not all states participated in this effort. In 1995, legislation passed requiring states to report data to a new system, the Adoption and Foster Care Analysis and Reporting System (AFCARS), and the quality and completeness of the data began to improve.

The reported numbers of children in foster care began to climb from 280,000 in care on the last day of 1986, and more than doubled in numbers to a peak of 567,000 in care on the last day of 1999. The increase may be partially attributable to improved reporting, but almost all states increased their numbers of children in care during this time period. After the peak, a decline began, and the number of children in care on the last day of the year has decreased to 401,000 in 2011 (US Dept of HHS, ACYF, Children's Bureau, 2012). To place this within the context of the US child population, the rates of children in foster care per 1,000 children in the population exhibited a similar trend, initially rising to a peak in 1999 at 7.9 per 1,000; then declining continuously to 5.5 per 1,000 in 2010[1].

[1] Rates were calculated by dividing the numbers of children reported as in foster care on the last day of each Federal Fiscal Year (as provided in reports online by the US Dep. of HHS, ACYF, Children's Bureau, 2012), by the total number of children (<18 years old) in the U.S. population for each year as reported in population estimates by the U.S. Census Bureau, 2012.

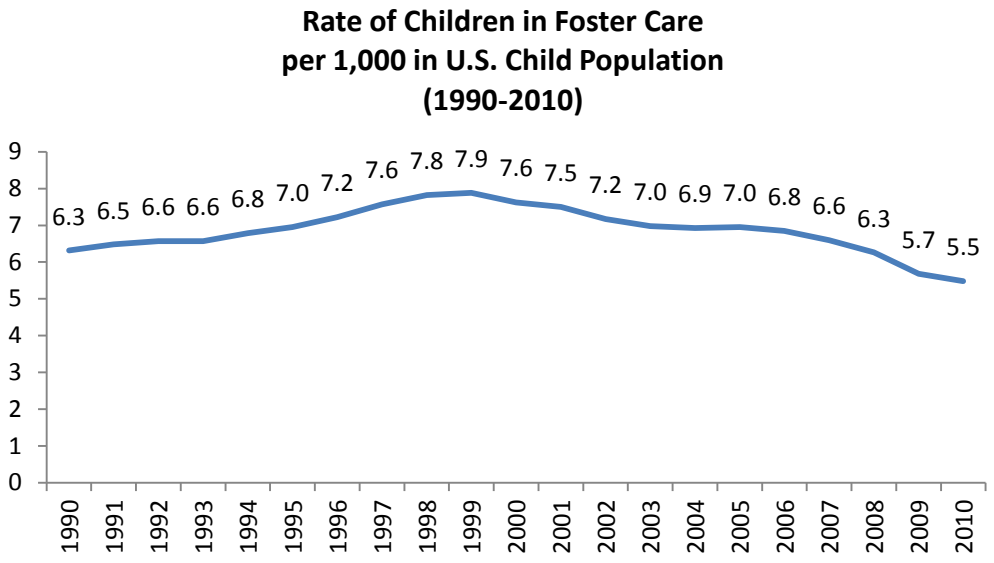

Figure 1. The Rate of Children in Foster Care (on September 30th each year) per 1,000 Children in U.S. Child Population, 1990-2010

Recent legislation and policy reform have pushed states to reduce the numbers of children in foster care. The Fostering Connections to Success and Increasing Adoptions Act of 2008 (H.R. 6893/P.L. 110-351) facilitates significant changes in funding and policy to help reduce the numbers of children in foster care, provides training to the workforce, and provides financial incentives and assistance to States to increase their numbers of adoptions from foster care. In accordance with this agenda, Casey Family Services (among other child advocacy groups) have promoted a campaign to safely reduce the number of children and youth in foster care by 50% by 2020. They target the states with the largest caseloads as the greatest candidates to show a percent reduction in caseload size. These initiatives both reflect and reinforce a shifting trend in child welfare

practice to move away from using foster care as the answer to keeping children safe, but to find ways to keep children safely in their homes whenever possible.

Research Problem

Nationally, the number of children referred to Child Protective Services has remained relatively stable over the past five years, holding somewhat constant around 3.3 million referrals involving approximately 6 million children per year. Reports of child abuse and neglect sometimes lead to removal from home and placement in foster care, for the safety of the child. But despite the relatively stable referral rates, the numbers of children in foster care have declined by 25 percent over the last decade, with the sharpest declines in just the past several years. This trend is particularly surprising given the rise in rates of children in poverty and the economic recession that the country has suffered over the past several years, as studies have shown correlations between poverty and child maltreatment. Despite the initial paradox this appears to present, a review of the literature reveals there are many factors to which we may attribute the decrease of children in foster care. Collectively, the field of child welfare hails the reduction as a very positive trend, as the foster care experience is known to have deleterious effects on child well-being (Dolan, Casanueva, Smith and Ringeisen, 2011). But the trend also raises concerns about whether children are truly safer in their own homes than in the past, because if victims of child abuse and neglect remain at home, it gives rise to concerns for their safety and well-being. Recent research indicates they are as safe, or safer, than in the past, touting new practices to improve preventive services and alternatives to foster care (Casey Family Programs, 2011). This is heartening, but some of the indicators used by

the field to measure child safety are confounded by changes in practice, policy and definitions that may challenge the comparability of the measures across time.

The story does not end once a child is placed in foster care. There may still be risk of harm; there may be new problems such as placement instability and the possibility of never establishing a permanent and supportive family. How long children stay in care and whether or not they leave foster care to a permanent home are very important phenomena to track. But this thesis focuses specifically on those children who have been found to be victims of child abuse and neglect, and whether the decision is made to place them in foster care or leave them in their homes. It examines state variation and trends over time in these practices to see how the likelihood of foster care placement may be different depending on the state.

This paper will explore potential predictors for foster care entry and whether or not they may have changed over time. A claim that has been made by experts in the field is that children who are placed in foster care now exhibit more challenging circumstances than they did in the past, thereby changing the composition of the populations served by child welfare agencies. There is little empirical evidence at the national level to support this claim, so one of the objectives of this study is to provide an analysis of some of the circumstances associated with children placed in foster care, including demographic characteristics at the individual level, circumstances associated with the maltreatment leading to removal from home, as well as characteristics specific to states, including the rates of children living below the poverty line. These analyses will supplement the

existing body of literature so that we may more critically and thoughtfully interpret national trends in child maltreatment and placement in foster care.

Research Questions

The following three specific research questions are explored in this thesis:

1. What characteristics, **at the child or state level**, increase the likelihood of placement in foster care?
2. Given the decreasing rates of foster care placement in recent years, has the degree to which certain characteristics influence foster care placement **changed over time**?
3. Are these characteristics somewhat **consistent across States** so that we may generalize findings to the national level, or is there so much variability between States that there is no cohesive national trend over time?

It is important to note that while the outcome of interest is measured at the individual level, we are not examining individual behavior. Professionals within child welfare agencies make decisions to remove children from their homes, and those agencies operate within a structural framework guided by policies and practices that suggest consistencies within these groups, whether they are local or state agencies. Therefore, the primary unit of analysis in this study is the state level, to determine how individual characteristics may have different degrees of influence depending on the state in which the child welfare agency is located. Because of this, careful consideration will

be given to how individual states define child maltreatment and how their reporting of these data have changed over time, which is sometimes misleading and must be analyzed and interpreted with caution. One goal of this thesis is to begin to explore, through secondary datasets, the popular hypothesis that children entering foster care exhibit a more challenging array of circumstances than children entering care in the past. Anecdotally and through some limited research, there is support for these claims, but there is a need to garner greater evidence in support of this, in light of the trends indicating a failing economy and increased child poverty while child maltreatment and the use of foster care seems to be on the decline. If we cannot support these claims, we must take a more critical look at how the child welfare system is changing, and whether these changes are in the best interests of the highly vulnerable children and families that are in need of services.

Limitations

There are a host of important indicators that are important to consider when evaluating the reasons children are placed into foster care that are not available in the datasets utilized in this study. For example, we would like to know the severity of the maltreatments children suffered, not just what types of maltreatment. We would like to know more about their family characteristics: what was the family's income level, what type of neighborhoods do they live in, what are their levels of access to resources and support, either formal or informal? How do other parental or child related risk factors impact the likelihood of placement? This analysis does not capture all of this, but in the

review of existing literature I will highlight those variables that other studies have found to be significant indicators. The unique contribution of this study is that it provides a more nuanced and careful treatment of the data in a multilevel statistical model using national data, and includes an analysis of more recent data than most other studies have utilized. Researchers may use this approach to analyze other datasets in a similar way and determine how other variables may influence the findings.

Nature of the Study

While efforts have been made to contextualize the research question and findings within the existing body of literature and synthesize the results in a meaningful way, this is a quantitative study. There are advantages and disadvantages to doing quantitative analysis over qualitative studies. Because the social sciences are so complex and nuanced, there are contextual factors or latent variables that are unaccounted for in a statistical model. This means that great caution should be used in making inferences. Statistics may indeed identify important relationships, but do not always tell the whole story. As with any study, results may be framed to support a particular agenda. Child welfare advocates have good reason to selectively present statistics to highlight the deficiencies of the child welfare system, so that social programs continue to be funded and progress continues to be made. On the other hand, professionals want to acknowledge and applaud the great improvements and reforms that have transpired, so studies may be framed to highlight the achievements of the system.

Acknowledging that no researcher is completely without bias, I am interested neither in demonstrating the failures or highlighting the achievements of the child welfare system. Sadly, there is no dearth of social problems in this country and child maltreatment remains among them. Child welfare practice and policy is dynamic and evolving, frequently driven by research studies and data to inform practice. The intention of this research project is to better understand what the data are telling us now about the children entering the foster care system. If data informs practice and policy, it is of critical importance that we interpret it correctly and recognize its limitations as well as its strengths. Some of the methods by which we can analyze data vastly outpace the quality of the data feeding into them, which paves the way for misleading results. Without consistency in reporting and attention to data quality, we will misunderstand trends and pathways for change could be misguided.

CHAPTER TWO: REVIEW OF LITERATURE ON CHILD MALTREATMENT AND FOSTER CARE PLACEMENT

A prerequisite to correctly understanding and interpreting the existing research related to child abuse and neglect and foster care placement is to define what we mean by these terms. Next, we explore structural causes for variation, such as state laws or policies that influence the likelihood of placement in foster care. This first chapter of the review of literature will focus on those factors found to be related to child abuse and neglect and placement in care, and this will be followed by a chapter reviewing the literature related to multilevel types of data analysis, as this is a central component of this study.

Defining child maltreatment

What constitutes child abuse and neglect? At a minimum, federal legislation defines child maltreatment as "any recent act or failure to act on the part of a parent or caretaker which results in death, serious physical or emotional harm, sexual abuse or exploitation; or an act or failure to act which presents an imminent risk of serious harm" (The Federal Child Abuse Prevention and Treatment Act (CAPTA), (42 U.S.C.A. §5106g)). States have the latitude to define child abuse and neglect beyond these minimum criteria, and as a result, there are some significant inconsistencies between them. Most States do differentiate between four major types of maltreatment: physical abuse, neglect, sexual abuse, and emotional abuse. Although child maltreatment can be

limited to one type, often multiple maltreatment types are co-occurring. In many states, abandonment and parental substance abuse are considered forms of child abuse or neglect. Neglect is the maltreatment category that provides the greatest variation between states, but most states consider neglect to encompass physical (e.g., failure to provide necessary food or shelter, or lack of appropriate supervision), medical (e.g., failure to provide necessary medical or mental health treatment); educational (e.g., failure to educate a child or attend to special education needs); or emotional (e.g., inattention to a child's emotional needs, failure to provide psychological care, or permitting the child to use alcohol or other drugs). (Child Welfare Information Gateway, 2008).

To provide an example of how differently states may define neglect and how it may impact the rates of child abuse and neglect, consider these two examples. In 2010, the District of Columbia had the highest rates of child victims in the country, at 23.4 per 1,000 (counting each child only once). Pennsylvania had the lowest rate, at 1.3 per 1,000. Taking this at face value, one might assume they are comparable, and that Pennsylvania must truly be one of the safest places for children, and Washington, D.C., the most dangerous. This sort of assumption is dangerous, because it leads people to jump immediately to speculation about the causes for the disparity, comparing social and economic issues rather than first taking a closer look at how those rates are defined and calculated.

In fact, according to the law, the District of Columbia defines neglect as the following:

"'Neglected child' means a child:

- Whose parent, guardian, or custodian has failed to make reasonable efforts to prevent the infliction of abuse upon the child
- Who is without proper parental care or control, subsistence, education, or other care or control necessary for his or her physical, mental, or emotional health
- Whose parent, guardian, or other custodian is unable to discharge his or her responsibilities to and for the child because of incarceration, hospitalization, or other physical or mental incapacity
- Whose parent, guardian, or custodian refuses or is unable to assume responsibility for the child's care, control, or subsistence and the person or institution providing for the child states an intention to discontinue such care
- Who is in imminent danger of being abused and another child living in the same household has been abused
- Who has received negligent treatment or maltreatment
- Who has resided in a hospital located in the District of Columbia for at least 10 calendar days following its birth, despite a medical determination that the child is ready for discharge from the hospital, and the parent has not taken any action or made any effort to maintain a parental, guardianship, or custodial relationship or contact with the child
- Who is born addicted or dependent on a controlled substance or has a significant presence of a controlled substance in his or her system at birth
- In whose body there is a controlled substance as a direct and foreseeable consequence of the acts or omissions of the child's parent
- Who is regularly exposed to illegal drug-related activity in the home.

'Negligent treatment' or 'maltreatment' means failure to provide adequate food, clothing, shelter, or medical care that includes medical neglect, and the deprivation is not due to the lack of financial means of his or her parent, guardian, or other custodian."

In contrast, Pennsylvania defines neglect much more narrowly, as simply:

"The term 'child abuse' includes serious physical neglect by a perpetrator constituting prolonged or repeated lack of supervision or the failure to provide essentials of life, including adequate medical care, that endangers a child's life or development or impairs the child's functioning" (Child Welfare Information Gateway[2], 2008).

This is not to say there wouldn't be a disparity in the rates of child maltreatment if the definitions were the same. The rates could very well be higher in Washington, D.C. But the differences in definitions render this comparison problematic, even if one were to

[2] www.childwelfare.gov/systemwide/laws_policies/statutes/define.cfm

control for other differences between the two locations, such as the demographic composition of the population, socioeconomic levels, etc.

Responding to child maltreatment

In addition to differences in definitions of child maltreatment, there is also variation in the ways state Child Protective Services (CPS) respond to alleged maltreatment. The initial notification to a child welfare agency is called a referral, and this may include more than one child. Referrals that do not meet specific agency criteria are screened out or diverted to other agencies, so the levels of criteria used is the first decision point where states may vary in their response. In 2010, there was a tremendous range among states in the percentage of screened-in referrals, between 25.2 and 98.7 percent (Child Maltreatment, 2010). Screened-in referrals are considered reports, and the majority of them receive an investigation. Some states employ a practice known as alternative or differential response, which takes lower-risk cases and offers voluntary services, rather than an investigation. Differential response has been a growing practice, spreading to more and more states, so rates of child maltreatment may be impacted by these changes in practice.

For the majority of reports that do receive an investigation, the state proceeds to determine if the child was, in fact, maltreated by state definitions and then determine the appropriate course of action by the agency. The determinations they make are called dispositions, and they are generally termed either substantiated (founded) or unsubstantiated (unfounded) based on state law or policy.

States have different levels of evidence required before substantiating alleged maltreatment. To continue using the same two states as examples, D.C. requires "credible" evidence, and Pennsylvania requires "substantial evidence or clear and convincing/beyond reasonable doubt" (Child Maltreatment, 2010). The latter is considered more stringent, so fewer cases may be substantiated. Further, Pennsylvania refers many neglect cases for services offered under Temporary Assistance for Needy Families (TANF), which is a less common practice not shared by other state agencies.

Another important phenomenon to consider when looking for differences in the way state agencies respond to alleged maltreatment is the impact that a particularly tragic or horrific event covered heavily by the media may have on child welfare practice. Practice can be very sensitive in that if a child dies as a result of child abuse, child welfare workers may become more vigilant in response, either informally through enforcement of existing protocols, or formally through legislative changes. These types of changes would be observed within states, over time, and may show up as spikes at various stages along the way, in the numbers of children reported, investigated, determined victims, or placed in foster care. A 2009 study titled, "Media coverage of agency-related child maltreatment fatalities: Does it result in state legislative change intended to prevent future fatalities?" examined the effect of news stories, specific state characteristics, and child welfare policy has on initiating new child welfare legislation. The results of this study suggest that a high degree of media attention is associated with new preventative child welfare policies. In addition, state child welfare policy practice

characteristics are also significantly related to the passage of new child maltreatment fatality-related legislation (Douglas, 2009).

Systemic differences

From an administrative perspective, child welfare systems are partitioned into various domains: family courts, juvenile justice, child protective services, permanency planning, mental health, education, and so on. State to state variation (and even county to county variation) in child welfare laws and policy, and variation in the structure, interoperability and communication between these respective domains may also impact the likelihood of foster care placement. This may affect service delivery; for example, a child is referred for mental health services and an individualized education plan is made, and separate units must work together to get the appropriate paperwork, staff and resources together to meet the child's needs. Some states may provide a wide array of in-home services and family strengthening programs to prevent foster care placement, while others may not and may more readily place a child in foster care. Some states have state-administered child welfare agencies and some are county-administered, which may mean they are less homogenous across the state with respect to practice and policy. Whether or not States have a centralized reporting system for reports of child maltreatment (e.g. one hotline number everyone in the state would call), or if it is decentralized to local agencies may also affect the consistency in which cases are screened in for an investigation.

There are also differences in the way the administrative datasets are managed. Some states have a statewide child welfare information system[3], in which CPS data and foster care data are all housed within the same system, and other states have a series of separate systems with varying degrees of interoperability. Even for those who do have a single, integrated system, there are often data quality problems which can complicate analysis of trends related to child outcomes.

But despite these variations, the administrative datasets have dramatically improved in terms of data quality over the years, and generally are an excellent source of information in identifying variables related to foster care placement and child maltreatment. Child welfare practice has become much more data-driven in recent years as a result, and there are now more analytical tools and techniques available, leading the child welfare field toward using data to inform practice and policy more effectively and reliably than ever before.

National Statistics on Child Abuse and Neglect

Between 2006 and 2010, while the numbers of children referred to Child Protective Services (CPS) for child abuse and neglect have changed very little and involve about six million children each year, there has been a slight decrease in victimization rates. The victimization rate is defined as the number of children age 17 or younger with at least one substantiated or indicated report of maltreatment, divided by the number of children age 17 or younger in the general population. This is multiplied by

[3] Such information systems that receive Federal funding support are referred to as Statewide Automated Child Welfare Systems (SACWIS).

1,000 to get a rate per thousand. In 2006, about 12 per 1,000 children in the general population were found to be victims of child abuse or neglect and this decreased slightly to about 10 per 1,000 in 2010 (Child Maltreatment 2010).

This does not mean, however, that all types of maltreatment have shown a similar rate of decline. There appear to be different national trends depending on the type of maltreatment. Finkelhor and Jones (2012) recently released a research brief compiling the evidence to show that rates of sexual abuse have been declining steadily since the 1990's. NCANDS data show a 62% decline between 1990 and 2010, with the raw numbers dropping from over 150,000 to 63,000 cases. Many in the field have questioned this drop, with concerns it may only reflect changes in reporting. In response, multiple studies and sources have investigated and confirmed this trend. The National Incidence Study (NIS) of Child Abuse and Neglect found a 47% decline between 1993 and 2005, using different data sources and measurement than NCANDS. The National Crime Victimization Survey measures rates of sexual assault on adolescents age 12 to 17, and found a 69% decline between 1993 and 2008. The National Survey of Family Growth reported a 39% decline in first sexual intercourse prior to age 15 with someone at least 3 years older. The Minnesota Student Survey of sixth, ninth, and twelfth graders found a 28 to 29 percent decline in sexual abuse between 1992 and 2010. FBI rape statistics show a 35% decrease between the same years, and over half of rapes reported to the FBI occur in minors under the age of 18. Victim self-report surveys also confirm a similar decline in sexual abuse among juveniles.

Concerns about the normalization of sexual abuse have been raised in response; driven by the theory that sexual abuse may not be classified as such by youth as frequently, but the surveys showing the decline did not use terms such as abuse or assault, but simply asked about sexual behavior and later classified them as assault, when it fit those criteria (Finkelhor & Jones, 2012).

Physical abuse has not followed such a clear pattern of decline, as different sources of data suggest different trends. While NCANDS and NIS data indicate a decline in physical abuse by caregivers, two national surveys did not. NCANDS data alone shows a 56% decline in physical abuse between 1990 and 2009, but NCANDS does not assess the severity of the abuse. The NIS found a 29% decrease between 1993 and 2005. Hospital data, however, found no such declines in the numbers of children admitted due to injuries sustained as a result of physical abuse, and in some cases, they even reported increased numbers, pertaining to infants less than 1 year of age. There are different reasons to which we may be able to attribute the decreases or increases in different studies; some of which have to do with data collection and reporting, but this is still an area in need of further study and no conclusive trends can be cited (Finkelhor & Jones, 2012).

Neglect is the most common form of child maltreatment, and is also the broadest category. As described earlier in the example definitions provided by the District of Columbia and Pennsylvania, neglect may be physical, emotional, involve exposure to drugs and alcohol, among other things. The proportion of child victims with substantiated neglect has increased over time, from 64% of victims in 2006 to 78% in 2010 (Child

Maltreatment 2006 and Child Maltreatment 2010, respectively). While some may be quick to label neglect among the most benign types of maltreatment, studies show that victims of neglect have worse outcomes than other types of maltreatment. Neglected children are more likely to be placed in foster care than children who were victims of other maltreatment types (Child Maltreatment 2006).

As mentioned earlier, the practice of diverting children from an investigative agency response to a voluntary services response (Differential Response) may have had some impact on the numbers of children found to be victims of child maltreatment, but it is difficult to quantify its impact on the data, as the existing data elements in the primary source for child maltreatment data (NCANDS) do not adequately address this issue.

Variables associated with Child Maltreatment and Foster Care Placement

Because of the economic recession of the past decade, we might have expected an increase in rates of child maltreatment. Data released by the Census Bureau indicates that the poverty rate increased for children under the age of 18, from 19.0 percent in 2008 to 20.7 percent in 2009, and the family poverty rate and the number of families in poverty were 11.1 percent and 8.8 million in 2009, respectively, up from 10.3 percent and 8.1 million in 2008[4]. Studies have shown that indicators of economic hardship (unemployment, low socioeconomic status) significantly increase rates of child maltreatment (National Incidence Study of Child Abuse and Neglect, 2010). Parents with

[4] DeNavas-Walt, Carmen, Bernadette D.Proctor, and Jessica C. Smith,U.S. Census Bureau,Current Population Reports, P60-238,*Income, Poverty, and Health InsuranceCoverage in the United States: 2009*,U.S. Government Printing Office,Washington, DC, 2010.

low socioeconomic status (SES) may be more likely to neglect their children because of inadequate resources enabling them to provide proper care for their children, such as access to health care and basic necessities such as shelter, food, and clothing (Berger, 2004; Rosenfeld et al., 1997). Poverty has long been considered a risk factor for child maltreatment, due either to acute stressors such as loss of a job, health care crises, etc., or long-term stressors such as inadequate housing, living in dangerous neighborhoods, and lack of access to health care or other resources (Vondra, 1993). In some studies, family income has been considered the strongest predictor of a child's placement into foster care (Lindsey, 1991). This finding was reinforced more recently; in 2006, Barth, Wildfire, and Green found that over 50% of children in foster care and a third of the children who receive in-home services were identified by their case workers as having families unable to meet basic needs. Particularly in urban populations, poverty among families is the strongest predictor of repeat maltreatment (Connell, Bergeron, Katz, Saunders, & Tebes, 2007, McGuiness and Schneider, 2007).

Thus, the recent increase in child poverty rates coupled with declining foster care entry rates seems to present a paradox. When confronted with this inconsistency, it is useful to consider there may be some distinction between risk factors for child maltreatment and risk factors for foster care placement. While they certainly do overlap, it is plausible that certain variables do not impact foster care placement in the same way they do for child maltreatment. For example, poverty has been long documented as a risk factor for child maltreatment. But despite the existence of some research drawing the link between poverty and foster care placement (Bath, Richey and Haapala, 1992; Halper and

Jones, 1981), other studies challenge this notion. A 1997 study by Alice Theiman and Paula Dail found that neither low income nor receiving public assistance was predictive of foster care placement, challenging the stereotype of low-income families being at greater risk of a child removed from home. Instead, they found that indices of child-centered and parent-centered risk were more significant predictors (Theiman and Dail, 1997).

More recent longitudinal studies have facilitated a wealth of data about child abuse and neglect and highlight strategies implemented to prevent removal from home and placement into foster care. An increased emphasis on preventive and family preservation services is often touted by the child welfare field as best practice, although some argue these efforts would be better spent on improving the quality of foster care (Duerr Berrick, 2009). In fact, most children who are substantiated victims of maltreatment are not removed from home. Social workers are advised to "invest fully in prevention to promote family functioning at every level of risk and to decrease substantially the incidence of child maltreatment; and coordinate an entire network of professional and lay, as well as formal and informal, services to support and redirect both family and child when maltreatment does occur" (Vondra, 1993). Ramping up in-home services and preventive interventions are intended to alleviate and reduce the use of foster care, which is seen only as a last resort. Despite this, the national data do not show a

national increase in in-home services provided[5], while foster care placement continues to decline (ACF, HHS, 2010).

The Fourth National Incidence Study of Child Abuse and Neglect (NIS-4) emphasizes the importance of examining social characteristics when interpreting rates of child maltreatment. They found that socioeconomic indicators such as parents' labor force participation, household socioeconomic status, family size, and family structure and living arrangement are not only associated with the incidence of maltreatment, but are also correlated with each other. They recommend further analyses to determine their independent relationships to maltreatment. They also found disparities between racial categories in the incidence of maltreatment, with higher incidence rates for Black children, but they recommend future analyses to examine whether these race differences in maltreatment rates would remain when the negative effects of these family circumstances are taken into account (Sedlak et al, 2010).

The overrepresentation of African American children in foster care has been a major issue in child welfare and the focus of many research studies. Findings indicate that even when the effects of poverty and risk are controlled for, race still affects the decision to remove children from home. Workers use standardized risk assessment instruments when investigating homes, intended to remove bias from the decision-making process. These assessments usually provide a summary risk score, used to help guide decisions around placement in foster care. One study argues that rather than the racial bias occurring when assigning risk scores during assessments, there appear to be

[5] National trends from NCANDS on in-home services may be unreliable, as the services fields in the dataset are often underreported.

racial/ethnic differences in the threshold workers use to make the decision to remove children; specifically, the threshold is higher for White children and youth than for African Americans (Rivaux et al, 2008). It seems that in many cases, risk scores alone are not the only indicator used in deciding to remove children from home, and workers do have some discretion in the decision-making process. Indeed, the finding that African American children are more likely to be removed from their homes than White children has been replicated repeatedly (Curtis, Dale & Kendall, 1999; Garland, Hough, et al.,2000; Garland, Landsverk, & Lau, 2003; Hill, 2006; Sedlak & Broadhurst, 1996; Stolzfus, 2005; Texas Health and Human Services Commission and Texas Department of Family and Protective Services, 2006; U.S. Children's Bureau, 2012; U.S. Department of Health and Human Services, 2012; Wulczyn, Barth, Yun, Jones-Harden, & Landsverk, 2005), but Rivaux argues that these studies have not always included or adequately addressed the influence of risk scores. One study looking at California's data claimed that by the time they are seven years old, almost 2 in 5 black children have been referred to the child welfare system and almost 1 in 10 has been removed from his or her parents' care at least once….as compared with less than 1 in 5 white or Hispanic children has been referred and about 1 in 30 has been removed" (Magruder and Shaw, 2008). Nationally, there has been a decrease in recent years in the proportions of African American children and youth entering foster care, from to 30% in 1998 to 23% in 2011 (ACF,HHS, 2012), but this is still disproportionately high, compared to the 14.6% of children who are African American in the general child population (US. Census Bureau, 2011 estimates).

Age is also a very important variable to consider when identifying those most at risk for placement in foster care. The youngest children are the most vulnerable to child maltreatment. More than one third (34%) of child victims in 2010 and almost 80% of the children who died as a result of child abuse and neglect were younger than four years old, and the largest age group was infants (Child Maltreatment 2010). National statistics over time indicate shifting trends over the years. In 1977, 12% of children entering care were infants; by the mid-90's about one quarter (23%) of foster care entries were infants (Barbell & Freundlich, 2001). The proportion of infants entering care decreased through 2000, but in the last several years we have seen the percentage of entries under the age of 1 on the rise again, to almost 16% in 2011 (Children's Bureau, ACF, 2012).

Infants from impoverished areas experience a 2.7 times greater risk of maltreatment (Wulcyn et al., 2005). In fact, because infants are more likely to experience maltreatment than any other age, CAPTA legislation requires early intervention services for infants to minimize the negative effects of maltreatment (McGuiness and Schneider, 2007).

The next most likely age group to enter foster care is older teens, for very different reasons. The most commonly cited reason older youth enter care is behavior problems, while for infants it is neglect (Children's Bureau, ACF, 2012). Older youth may also be more likely to enter foster care due to increased availability of services, such as supervised independent living arrangements. The Fostering Connections Act of 2008 included a provision to continue to provide federal funds for foster care beyond the age of

18, and some states have opted into this. These states may be more likely to have higher rates of entry for older youth than states who do not offer foster care beyond 18.

Other variables likely to affect risk of foster care placement include mental and physical health issues. Studies spanning the past several decades have shown high rates of mental health issues, emotional and behavioral problems among foster care youth; a 1990 study found these problems to be three to six times greater among foster care youth than children not in care (Dubowitz, 1990). Many of the health problems foster care youth experience are a result of the abuse and neglect they suffered prior to foster care placement, such as prenatal exposure to alcohol and drugs, trauma from child abuse or chronic neglect, etc. Once in foster care, often these problems are exacerbated, as the instability of foster care placement often leads to further harm.

Substance abuse, either by parents or by adolescents is an important risk factor for children being placed in foster care. Methamphetamine use became a major issue during the early 2000's and a series of discretionary grants were funded by the Children's Bureau to establish programs to target this population.

In the Child Maltreatment 2006 report, a multivariate analysis was performed to look at indicators that would predict foster care placement (Child Maltreatment 2006, ACF, HHS). The analysis included the following child-level variables: the type of maltreatment, whether the child was a first-time victim or had prior victimizations, whether the child has a disability, child's age, race or ethnicity, the source of the report of alleged abuse, and the relationship of the perpetrator to the victim. Based on the odds ratios associated with these variables, they found that prior child victims were 64% more

likely to enter foster care than those with no prior victimizations. Child victims with disabilities were two and a half times more likely to be placed in foster care and victims of multiple maltreatments were 79 percent more likely to be placed in foster care than those with physical abuse alone. African American victims were 23 percent more likely and children of multiple races were 52 percent more likely than White victims to be placed in foster care. Children victimized by their fathers were half as likely to be placed as children victimized by their mothers, and victims referred by mental health or educational personnel were about half as likely to be placed in foster care as those referred by social services. One limitation to this study was it was only done on one year's worth of data, so it does not reveal how these predictors may change over time. The fact that the analysis has not been updated since 2006 also raises the question of how these results may change with more recent data, since we have observed such a reduction in the numbers of children entering foster care since then. Further, it used only data relevant to the child and none of the community characteristics that could also influence placement in foster care, such as poverty rates or other variables at the State level. There is an inherent hierarchical structure to the data, in that they may influence observations at the child level. Single-level regression assumes that observations are independent, but the observations of children within each State are not independent. When the hierarchical nature of such data is ignored, the estimates of the standard errors can be too small which results in spuriously "significant" results (Hox, 2010). In essence, this study violated assumptions of independence in the data, in that it treated all subjects the same and ignored the hierarchical structure of the data.

A recent study (Horwitz, et.al, 2011) titled, “Predictors of placement for children who initially remained in their homes after an investigation for abuse or neglect,” also used single-level logistic regression models to identify predictors of foster care placement, using data from the National Survey of Child and Adolescent Well-being (NSCAW). As the title suggests, in this study, they limited the risk set to a sample of children who had already been referred to child welfare and received an investigation in late 1999 or 2000 and were *not* placed in foster care as a result, and the study looks to see if the child experiences a foster care placement during the follow-up period. They found that if there were prior maltreatment reports, children were over 2 to over 3 times as likely to be placed in foster care. Similarly, if there was documentation of family risk factors, children were far more likely to be removed from home. In their initial model, which included only the maltreatment report variables, there were no characteristics they found to be statistically significant predictors of out of home placement; however, family variables such as income, domestic violence, and high risk scores were all found to be significant predictors of placement in foster care.

Geographical and Structural Framework

Given that so many of the variables that lead to foster care placement are tied to resources that can be linked to the external environment, such as the communities in which people live, income levels, and connections with social and programmatic supports, it follows that ‘place’ matters. Whether a family is in an urban or rural setting,

what county or state they are in may weigh heavily on likelihood for placement in foster care.

While national statistics show an overall decline in the numbers of children in foster care, individual states sometimes tell a different story. An analysis of all States between 2003 and 2011 shows that 37 states exhibited a decline in the numbers of children entering foster care each year, seven states showed no continuous pattern or remained relatively stable, and eight states actually increased the numbers of children brought into foster care. Just between 2009 and 2011, Texas increased their numbers of children entering foster care by 32%. Between 2003 and 2011, Mississippi increased their number of entries by over 50%, while Hawaii decreased theirs by over 50%. These are important observations because very different policies and practice may be guiding these state child welfare agencies. It demonstrates that studies at the national level may not be relevant or applicable to the state level, without somehow taking into account this variation. This can be done through stratification and consideration of each state independently, or it can be handled statistically through a multilevel model.

CHAPTER THREE: REVIEW OF LITERATURE ON MULTILEVEL MODELING

The study of the social sciences often reveals the existence of hierarchical data structures; that is, social phenomenon often have a nested structure, in recognition of the organizational structures that affect individual components. This is true in clinical studies as well as the social sciences. For example, if a research study intends to evaluate patient outcomes after certain types of treatment options, it may be very important not to ignore the effect of the hospital in which a patient was treated. Or if you wish to study students' academic achievement, you would want to take into account the classroom or school effects on their individual growth. Traditional single-level models may have treated these as direct interaction effects in the model, but the resulting estimates are less accurate than treating them as a higher order variable.

Within multilevel models (also known as hierarchical linear models, random effects models, mixed models, etc.) each of the levels is represented by its own submodel. Statistically, these submodels express the relationships between variables within each level and also specify how variables at one level can influence relationships on another level (Raudenbush & Bryk, 2002). To utilize these structures in a statistical model allows you to improve the estimation of the effects within each group or cluster, better test hypotheses about cross-level effects (e.g. how school size could affect academic achievement within schools), and partition the variance and covariance components

among the levels (understanding the differences within and between groups). In addition, you have improved estimation of the individual direct fixed effects of the model, by accounting for the variation both within and between groups.

Multilevel vs. single level logistic regression

Traditional logistic regression requires a dichotomous outcome, but in the case where a single-level model has been implemented that ignores a nested structure of the data, the odds-ratios predicting the likelihood of the event of interest occurring may be inaccurate. Khan and Shaw (2011) demonstrate this by using the 2004 Bangladesh Demographic and Health Survey (BDHS) to model the likelihood of contraceptive use among women in Bangladesh. They point out that it is much easier to interpret the odds ratios in a single-level model, but this requires the data fit the following assumptions: first, that there is independence of the observations conditional on the explanatory variables, and that there are uncorrelated residual errors. When data are nested, they are likely to violate these assumptions. Comparing the results from a single-level logistic regression and a multilevel logistic regression is not simple, because the odds ratios are not comparable. Converting parameter estimates into odds ratios for multilevel logistic regression is very difficult due to the structure of the data. Khan and Shaw advocate either simply stating estimates increase or decrease the log odds of an outcome, or converting the log odds into probabilities. Once they had a reasonable metric for comparison, Khan and Shaw found that the standard logistic model overestimated the odds-ratio by about 43% compared to a three-level model taking into account the effect of clusters and divisions on the outcome. Their primary assertion is that standard logistic

regression models "seriously bias the parameter estimates of observed covariates when analyzing multilevel data" (Khan and Shaw, 2011). This exemplifies the important point that it is not only the data that are nested within structures, but the organization of the data often reflects the hierarchical nature (or clustering effect) of underlying social processes. It is important to take these into account when estimating effects in a statistical model.

Support for use of Multilevel Modeling

Many researchers in the field of child welfare have encouraged longitudinal analyses (particularly the use of discrete time analysis methods) to measure change over time in outcomes related to children in foster care. Some researchers, such as Fred Wulcyzn, of the University of Chicago, also emphasize the importance of including social structural characteristics at the community level to better understand outcomes (Wulcyzn, Chen & Courtney , 2010). Citing Coleman (1988), this 2010 study works with the hypothesis that family structure and poverty may lead to a reduction in access to social capital, and includes predictors such as whether a child lives in a female-headed household, the poverty rates of the community, and whether the area was designated as urban or rural in measuring the rates of reunification with their families for children in foster care, as well as time to reunification. Using hierarchical linear modeling (HLM), their analysis incorporated child-level characteristics at level 1 (child's age, sex, county of residence, race/ethnicity, foster care placement type) and community-level characteristics at level 2 (county family poverty rate, county proportion of families headed by females, county foster care placement rate per 1,000 children, county's

proportion of children that are African-American, indicator of whether the county is the major metropolitan area of the state). The findings of this analysis show that social structural factors are most important during the first 6-month period after the child is placed into foster care. Family structure, placement rate, and racial composition all influenced reunification in different ways (Wulcyzn, Chen & Courtney, 2010). Surprisingly, poverty rates had little impact on rates of reunification in this study.

In June, 2010, the *Social Science Review* published a study from Denmark that utilized multilevel models to examine children's risk of maltreatment and placement in foster care. They cited earlier research that identifies variables that increase the risk of out of home care, including family's place of residence and whether they are from urban or rural areas (Courtney 1994; Glisson, Bailey and Post, 2000). They used multilevel models to examine the effect of variables at the municipality level. Municipalities in Denmark are self-governing local authorities and child welfare agencies have autonomy in implementation of policy, but follow national legislation on out of home placement, similar to the way states operate in the United States. This study considered municipal level variables, such as formal supports such as spending on social policies, social supports such as aid to volunteering organizations, social disorganization factors such as rates of unemployment and crime, and political factors, such as proportions of democrat vs. conservative party members in the local councils. These variables were chosen under the theory that social structures in which families reside matter for child outcomes. The ecological model postulates that there is an exosystem (made up of neighborhood, community structures as well as governance) which impacts individual actions

(Bronfenbrenner, 1977). Anderson points out that while prior research supports the claim that these exogenous factors impact rates of child maltreatment, there was little that examined whether they also affect out of home placement rates. Because the decision to place a child relies on additional factors beyond maltreatment, there is "no deterministic correlation between a community's child maltreatment and placement rates….one cannot automatically infer that child maltreatment affects out of home placement rates" (Anderson, 2010).

The method Anderson used was a multilevel logistic regression model, with an individual level outcome variable (likelihood of out of home placement) and municipal factors as the second tier, or Level 2 variable, to account for variation in the factors described earlier.

Individual characteristics related to the child included age, birth weight, gender, whether the mother smoked during pregnancy, and ethnicity. Variables associated with the parents were socioeconomic status, criminal behavior, health, age, income, education, and family structure (single parent or two parent households, number of children, etc.).

In addition to confirming individual level direct effects on likelihood of placement out of home, this study claims that municipal level factors such as formal and social supports and social disorganization indicators *do* explain variation between municipalities (Anderson, 2010). Therefore, these types of structural contextual variables are important to keep in mind when exploring predictors of out of home placement.

Specifying a multilevel model with binary outcome

A special case of the binomial distribution is known as the Bernoulli distribution; this is used when modeling dichotomous outcomes. This is used when the dependent variable can have only two responses, usually coded as 0 and 1. A two-level model for proportions is specified so that there is no assumption of normality, and rather, the probability distribution is binomial (μ,η_{ij}) with a mean μ. There is a specific logistic regression equation, and the link function for binomial data is the *logit* function. The logistic function transforms predictions between $-\infty$ to $+\infty$ to values between 0 and 1. This can be interpreted as the predictive probability of the outcome of interest occurring.

Specification of a multi-level model can be a very tricky task; it requires a number of decisions to be made both about how the variables are conceptually 'nested' and should be treated statistically. First, you must determine the number of levels in the hierarchy; determine whether there is any cross-classification, which means that some units may not belong exclusively to one group at a given level; figure out the explanatory variables at each level of the hierarchy, the probability distributions of the units at each level, and the most appropriate link function to use (in the case of the Bournoulli distribution, the logit log link function). Then, given the model specifications, you determine the appropriate estimation method.

Typical estimation methods are full maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian methods. In the case of a non-normal distribution such as Bernoulli, there are some other alternatives to implementing the estimation method, because an integral must be approximated (Raudenbush and Bryk, 2002). There is the Gauss-Hermite quadrature method, in which the variable of

integration (the higher order variables) are centered around the posterior mode rather than a mean of 0; there are non-adaptive quadrature methods, which are slightly less accurate but more efficient. Laplace's method is efficient, faster to compute, and convergence of the model is more easily attained.

Longitudinal Multilevel Models

Among the existing longitudinal multilevel analyses in the literature, by far the most common are repeated measures at the child level, to measure either a growth model to track individuals' change over time; or discrete time survival curves based on individual observations over time (Singer and Willett, 2003). The nature of the research question at hand lends itself to a cross-sectional comparative longitudinal design, where the micro-level units (e.g. child-level observations) are not repeated, but observations at a macro-level (e.g. state) are repeated over time. Fewer studies exist that are structured in this way, despite the growing number of datasets that lend themselves toward this type of analysis.

A frequent concern is how to handle time-varying covariates associated with a macro-level indicator (i.e. a variable may change at each observation period). Rather than the more commonly understood time-varying covariates at the child-level, these would be indicators that change over time at a higher-order level in the model. The concern is that there would be autocorrelation, which would produce a biased estimate of the coefficient

on that covariate. This can be addressed by group-centering[6] the time-varying covariate and including it in the model (Fairbrother, 2012).

DiPrete and Grusky (1990) point out that these types of cross-sectional longitudinal design studies should become more prevalent with datasets such as the General Social Survey (GSS) and the Current Population Survey (CPS) from the Census Bureau lending themselves to this type of sampling design, and we can now "describe the trends in individual-level processes over extended periods of time and…carry out single-context analyses to estimate the effects of structural forces on these year-by-year fluctuations" (DiPrete and Grusky, 1990).

In standard hierarchical linear models, the data are sometimes cross-classified, but usually are nested within each level. Repeated measures on a higher level variable may complicate the 'nesting' effect. For example, if one were to study change over time on school policies affecting student test scores with different students in the sample at each time of data collection, this is a repeated measure at the school level rather than the student level, and the level one units are not the same from one data collection point to the next. One way to model this is through a three-level model where the third level may either be nested or non-nested, depending on the research question and data structure. The three-level specification is appropriate whenever one is interested in allowing the covariates at higher level (e.g. school policies) to vary depending on the cohort (e.g. 2005

[6] Centering predictor variables is a way of making the estimates easier to interpret, and also removes high correlations between the random intercept and slopes and high correlations between first- and second-level variables and cross-level interactions (Kreft and de Leeuw, 1988). Group-mean centering is done by calculating the mean of the group; e.g. state, and then subtracting this from every value of the predictor variable for each case included in the analysis. For example, if the mean age for a state was 6.7, a child who was 8 years old would be group mean centered to (8-6.7=1.3). Grand mean centering is done in a similar fashion, but the overall mean across all groups is used rather the group-specific averages.

vs. 2007). Comparing results between a two-level and a three-level model specification, DiPrete and Grusky found "a twofold increase in the federal employment effect on female racial stratification…and a nearly fourfold increase in the corresponding effect on female educational returns" and they go on to claim that "a standard two-level specification can mute the effects of macrolevel variables" (DiPrete and Grusky, 1990). This lends support to the idea that the better one can identify structures and conceptually order their importance hierarchically in a model, the more accurate the estimates produced from the analysis.

Conclusion

The past two chapters have explored prior research to identify important predictors of child maltreatment and out of home placement, and demonstrate the advantages of using multilevel models to carry out this type of analysis. Some of the most important indicators are measures of risk that are captured in scaled scores as a result of in home assessments. Other important sources of variation in understanding foster care placement have to do with geography, for ecological reasons (e.g. community characteristics and social supports) as well as for differences in governance (e.g. state statutes vary widely in classification of and response to child maltreatment). Because of these structural differences, we build the case for using a multilevel model to analyze the data to answer the research questions put forth in this paper.

CHAPTER FOUR: METHODS

This chapter begins with a review of the research questions and specifies how this study will address them. The source data and software used for the analysis will be identified and the rationale provided for choice of source data and sample selection. A detailed description of variables included in the analysis will follow, as well as the study design. It concludes with the details of the analysis.

Research questions

In Chapter One, the research questions posited were as follows:

1. What characteristics, **at the child or state level**, increase the likelihood of placement in foster care?
2. Given the decreasing rates of foster care placement in recent years, has the degree to which certain characteristics influence foster care placement **changed over time**?
3. Are these characteristics somewhat **consistent across States** so that we may generalize findings to the national level, or is there so much variability between States that there is no cohesive national trend over time?

Study Design

These three research questions can be simultaneously addressed through a multilevel model that is structured longitudinally as a cross-sectional repeated measures comparative design. It is longitudinal in that it studies change over time, but not at the individual level, as most traditional longitudinal models do. The repeated measures are at the state level, as state-level indicators such as poverty rates vary over time. This method allows an assessment of how the direct effects at the individual level change over time, but they are for unique individuals each year rather than a more common growth model which measures the same individuals at different data collection points. The indicator of 'time' is the year each child was reported to Child Protective Services as a victim of child abuse or neglect. Lastly, the study is a 'comparative' longitudinal design because children are nested within states, the higher level unit, and this allows a comparison of states over time.

The outcome variable of interest is whether or not children are placed in foster care, and because it has the Bernoulli (binary) distribution, this is a multilevel logistic regression. As a preliminary step, a single level logistic regression analysis is provided as well.

Defining the Risk Set

To answer the research questions, we must first define the risk set for the study. Who is at risk of placement in foster care? In reality, the children and youth 'at risk' of foster care placement may be any child or youth in the United States, from newborn infants to youth as old as (in some States) 21 years of age. For most children and youth who live in safe and nurturing environments, the risk is almost none. And as discussed in

the literature review, teens often enter foster care for very different reasons than infants and young children. Not all children who enter foster care are first reported to CPS. Some of them may never have a report of child maltreatment at all, and come into the system through juvenile justice or due to severe physical or emotional disabilities that their own parents are ill-equipped to care for properly. Some young children enter into foster care this way, too, but it is more likely that teens would enter care without a report of alleged maltreatment.

That said, a large proportion of children do come to the attention of child welfare agencies through reports of child abuse or neglect. The majority is left in their homes, but some enter foster care as a result. For that reason, the risk set for this study is limited to children under the age of 18[7] who were victims of substantiated or indicated reports of maltreatment.

Sources of Data

This analysis required merging several secondary datasets available through restricted access to researchers through the National Data Archive on Child Abuse and Neglect (NDACAN) at Cornell University[8] and data from the U.S. Census Bureau.

The datasets most heavily utilized in this study were those reported through the National Child Abuse and Neglect Data System (NCANDS), from 2007 through 2010. It

[7] Even though some young adults between the ages of 18 and 21 are included in reports of maltreatment and are sometimes provided foster care services, States have varying policies on service provision beyond the age of 18. Further, Federal reporting guidelines for AFCARS and NCANDS datasets limit reporting populations to children and youth under 18 years of age, so this study will be limited in the same way.

[8] Although I am a research analyst with the Office of Data, Analysis, Research, and Evaluation within the Administration for Children, Youth and Families and have access to these datasets in that capacity, I applied for the secondary datasets as a student researcher through the National Data Archive and utilized the datasets housed there. In doing so, it ensures that this study may be replicated to other researchers who might follow the same channels for access.

also utilized an element from the Adoption and Foster Care Analysis and Reporting System (AFCARS) files, also from 2007 through 2010.

NCANDS data are reported by States by Federal Fiscal Year (October 1 through September 30), and retained in separate files. Through what is known as the Child File, case-level detail is provided on all referrals of child abuse or neglect that were screened in for a CPS response. They include information on the children involved, the types of maltreatment that are alleged, the dispositions of the CPS responses, the risk factors of the child and caregivers, services provided to the family or child, perpetrator data, dates associated with the maltreatment incident, removal date from home if applicable, among others. This is administrative data collected from all states and jurisdictions, including the District of Columbia and Puerto Rico. NCANDS is a voluntary data collection system, in that there is no Federal legislation requiring the reporting of these data, but all States now participate and provide data. In the most recent data collection effort (FY2011), only Oregon provided aggregate data instead of the Child File. Each report in the Child File may contain multiple children, and each child may be included in multiple reports. There are identifiers associated with both the report and with the child, so they may be combined to form unique Report-Child pairs. The national Child Files differentiated by year were merged together to create one large multiyear file.

AFCARS is a federally mandated data collection system, and data are reported by all 52 states and jurisdictions. The Foster Care file provides case-level data on all children under the care and supervision of the child welfare agency. Data elements include dates of removal from home, reasons for removal, age and race/ethnicity of the

child, child diagnosed conditions or disabilities, as well as case plan goals, discharge reasons and dates of discharge, when applicable. The two data sources (AFCARS and NCANDS) maintain a common encrypted child identifier that allows children in both files to be linked for analytic purposes. Not all states have successfully provided matching IDs, but most can be linked in this way.

Because a review of the NCANDS data revealed some data quality problems with the dependent variable (foster care services), it was prudent to link the AFCARS data with the NCANDS data because it is a more accurate source of information on foster care. Thus, the foster care services field was "corrected" using pertinent information from a multiyear AFCARS file, whenever the data were missing from the NCANDS file. This process will be described in greater detail in the next section of this chapter.

Data from the U.S. Census Bureau on the overall population by State were downloaded from the Census Bureau's website, using their Population Estimates by State, Age, Sex, Race and Ethnicity. The 2010 estimates are available through the 2010 Decennial Census, and a vintage 2009 file with population estimates by year projected from the 2000 Census provided estimates for 2005 through 2009. This file was then limited to only include individuals under the age of 18 to determine the child population, for use in calculating rates of foster care entry per the general child population by state and year.

The American Community Survey (ACS) was the data source for rates of children living below the poverty level, by state and year, also available through the U.S. Census Bureau.

Constructing the Sample

There were two issues that arose when preparing the NCANDS data for analysis:

Sampling issue #1:

My initial intention was to use six years of data from NCANDS Child Files, and include a complete national file to examine the outcome of interest: whether or not a child was placed in foster care. I encountered some data quality issues that would have led to inaccurate conclusions relying on these data alone, so the data cleaning and recoding component became a very large piece of this study. Even though 51 States/jurisdictions (including Puerto Rico and Washington, D.C.) reported a Child File containing case-level data, some States have been inconsistent in the reporting of particular data elements over the years. The dependent variable for this analysis (FosterCr) reflected inconsistencies in reporting and mapping/coding practices between states, and across years. I recoded the responses where the intention was clear, but those states who incorrectly indicated they had no children in foster care or for which there was simply too much missing data were removed from the analysis completely. Even after recoding and removing problematic states, the numbers and percentages of children entering foster care were still lower than to be expected. Since these findings ran contrary to more reliable estimates of foster care entries available in the AFCARS data, this is most likely due to underreporting of this element in NCANDS. To reconcile this and impute missing data, the multiyear NCANDS file was merged with the multiyear AFCARS foster care files between 2007 and 2010, and matches were found using

AFCARS IDs, within States[9]. When the records matched and the date in the AFCARS file indicated the removal date was after the report date from NCANDS, the foster care field in the NCANDS file was corrected to a value of '1' if it did not already indicate the child entered foster care. This 'correction' was limited to only those removals that occurred within two years of the report date[10]. This was done for two reasons: to alleviate bias in the observation period for removal from home, and also to disassociate that particular maltreatment report from the removal from home, under the theoretical assumption that a removal more than two years later may no longer be related to the same incident. A cross-tabulation on the corrected Foster Care field by State and by Year yielded more plausible results, as shown in Table 1 below. 'Original' represents the data as reported to the Child File; 'Corrected' is with the correction gained by matching with AFCARS.

Table 1: Percent of Child Victims who Entered Foster Care, by Year of Victimization (Unadjusted vs. Adjusted)

	Original		Corrected	
Year	Number	Percent	Number	Percent
2007	16788	20.9%	23,768	29.6%
2008	17044	20.6%	23,663	28.6%
2009	17080	20.9%	21,286	26.1%
2010	16219	22.5%	18,093	25.1%

[9] I began by analyzing years 2005 to 2010, but AFCARS IDs were only provided for 2007 through 2010, so this limited the analysis to just three years.

[10] Over 95% of the foster care episodes found were within the next two years of the report; only 4.3% were three years or more. These 839 cases in the sample were coded as not having been placed in care, for purposes of the analysis.

Sampling issue #2:

Because of the nature of the multilevel analysis chosen for this thesis, it was also important to have independent, unique counts of children at the lowest unit of analysis in this study. Because the study design is intended to look at repeated samples over time at the state level, I wanted to count children only once and not look at repeated events by child. Measuring change over time would be more complicated if children were duplicated in the sample, because not only would you try to interpret the model to determine how repeated measures at the higher order variables affect the outcome, you would also have repeated measures at the individual level and these would be cross-correlated in such a way that the findings would be more convoluted and harder to interpret.

As mentioned earlier, the structure of the Child Files is such that children may be duplicated in files, reported in multiple reports both within and across years. In order to simplify the analysis, I chose to keep only one record for each child. To do this, I initially merged all Child Files together and de-duplicated the file by retaining only the most recent report on each child, across years. As a result, I found that the percentages of children placed in foster care did not decrease over time as expected. This was due to the fact that children with a report in an earlier year and possibly a removal and placement in foster care at that time had their records superseded by more recent reports of maltreatment, skewing the results. Taking the first instance of each child's report would create a bias in the other direction, leading to false conclusions about the first year in the study.

To remedy this issue, I reconstructed the sample by returning to the complete population of children reported in the Child Files, then randomly selecting one report for each child. This means that all children were included, but only once. If a child was reported multiple times across years, there would be no sampling bias toward which record in which year was selected. Once a complete unduplicated file was created, I pulled a simple random sample to use in the analysis, complete with AFCARS corrections, and Census data specific to each state and year included. The final sample file contains 317,549 observations, 38 variables, and includes data from 32 states[11]. Table 2 shows how the revision to sampling methodology changed the numbers and proportions of children entering foster care. The 'Revised Sample' results are more plausible and consistent with other data sources reports of trends over time in foster care placement.

Table 2. Percent of Child Victims who Entered Foster Care, by Year of Victimization (Original vs. Revised Samples)

	Original Sample		Revised Sample	
Year	Number	Percent	Number	Percent
2007	33,008	24.7%	23,768	29.6%
2008	33,847	24.2%	23,663	28.6%
2009	39,256	24.2%	21,286	26.1%
2010	31,124	25.0%	18,093	25.1%

[11] The following states were removed due to inadequate data: AL, AR, AZ, DE, DC, GA, IL, IN, MD, MI, MT, NY, NC, ND, OK, OR, PA, VT, WA, and Puerto Rico.

Software

The Statistical Package for the Social Sciences (SPSS 20) was used to prepare the data, compute and recode new variables and merge AFCARS and NCANDS, select the sample, and produce descriptive statistics. The single-level logistic regression was implemented using SPSS, as well. Hierarchical Linear Modeling (HLM 7) was used for the multilevel models.

Child level variables

The Child File contains many variables that may impact the likelihood of foster care placement. To strike a balance between accounting for most of the variation and not overloading the model with too many variables, the variables selected for this analysis were those cited frequently in the literature as being related to foster care placement, as well as some basic demographic characteristics: child's age, sex, whether the child was a prior victim or not, race/ethnicity, maltreatment type, whether the child has a diagnosed disability, and the relationship of the perpetrator to the victim. Data on services provided were generally poor, as well as data on whether the caretaker(s) had substance abuse problems, so these variables were omitted from the model.

In order to simplify and make the analysis more interpretable, many of these variables were recoded to consolidate multiple variables and simplify analysis.

Age

The probability of entering foster care is not normally distributed according to age. Infants are by far the most likely group to enter foster care, and rates of foster care placement tend to decrease as children get older. When looking at entries to foster care in

AFCARS, there is another smaller spike for teenagers, as the foster care entry rates go up for older youth around 15 to 17 years of age, but a smaller proportion of these would have a record in NCANDS to indicate a report of maltreatment. Because of this bimodal distribution, age was recoded into three dummy variables (<2 years, 2-14 years, and 15-17 years), and the model only includes Infants/Toddlers and Teens, leaving those children in the middle as the reference group.

Prior Victim

This data element refers to whether or not there exist previous substantiated or indicated incidents of maltreatment of the child victim. This is a binary variable; the child either has prior allegations of child abuse or neglect that have been substantiated or indicated, or not. It does not take into account the number of prior victimizations. Whenever this data element was unknown, it was recoded to missing.

Race and ethnicity

Race and ethnicity is an area where there are many ways of analyzing the data, due to the overlap of multiple categories in the datasets. The frequency of foster care placement is quite low for some races (American Indian/Alaska Native, Native Hawaiian, and Asian). While actual rates in the general population for some of these groups indicates they are sometimes overrepresented (American Indians in particular), the numbers are so small that for this analysis, they are grouped together into “Other.” This analysis treats race and ethnicity by creating mutually exclusive categories for race; i.e. children identifying with more than one race category are coded as having more than one race, and then this is grouped within “Other.” If race was coded as ‘Unable to

Determine', it was recoded to missing. Children of Hispanic ethnicity may be included in any racial category that applies, consistent with Federal reporting guidelines that recognize that Hispanic ethnicity is a distinct construct from race. This coding schema to make the dummy variables mutually exclusive is done for ease of analysis and interpretation, but it should be acknowledged that this overlooks the important membership of individuals to multiple racial and ethnic identities. Further studies could focus on how the results of the model would vary depending on different classification schema for these variables.

Maltreatment types

The NCANDS dataset allows the following categories of maltreatment types: physical abuse, neglect or deprivation of necessities, medical neglect, sexual abuse, psychological or emotional maltreatment, or other. The NCANDS files allow up to four maltreatment types to be specified for each report-child pair, and each has a related disposition level that corresponds to the allegation (substantiated, indicated or reason to suspect, unsubstantiated, alternative response, etc.). For this analysis, only substantiated or indicated dispositions were counted, and the maltreatment types were coded and consolidated into four binary variables indicating whether or not the child was a victim of the following types of maltreatment: 1) physical abuse, 2) neglect, 3) sexual abuse, and 4) other. The 'Other' category was expanded to be inclusive of emotional abuse and medical neglect, as well. An additional category to show if children were victims of multiple maltreatments was also created.

Because children may be victims of different types of abuse, these variables are not mutually exclusive of one another. Because multiple types of abuse may occur simultaneously on a report for a particular child, the child will be indicated as a victim of all types of abuse that apply. An alternative coding schema could have been applied to force the categories to be mutually exclusive; i.e., 'Neglect Alone', 'Physical Abuse alone', 'Multiple Maltreatment Types'. This is how some analyses have handled it (Child Maltreatment 2006), and it addresses any potential for correlation between those variables. However, this analysis does not treat them as a dummy set, but leaves them as distinct variables in their own right so that we may assess the full impact of each maltreatment type, rather than artificially imposing a mutually exclusive schema upon them. Some studies exploring maltreatment have not removed children from categories of maltreatment when another type applies (Attar-Schwartz & Shalhevet, 2011), while other studies explore more closely the interactions between various combinations of maltreatment types (Hahm, Lee, Ozonoff & Wert, 2009). There are advantages and disadvantages to each approach, but this study simply focuses on the most frequently examined types of abuse: neglect, sexual abuse and physical abuse, coded such that children may be victims of more than one category.

Child disabilities

There is strong evidence in the literature that children with disabilities or diagnosed conditions are more likely to be placed in foster care. Because of this, efforts were made to utilize the data related to child disabilities available in NCANDS.

Because the NCANDS data have numerous variables related to diagnosed conditions, these were consolidated into one field, so that if the child had a condition apply in any of the related fields, he or she is classified as having a disability. In addition, if the variable indicating the child had an alcohol or drug problem *and* the age of the child was less than 1, this was re-coded as a child disability, assuming that this represents exposure in utero. This is consistent with Federal reporting guidelines for AFCARS, as well. Remaining fields include: mental retardation, a clinical diagnosis that there are "significantly sub-average general cognitive and motor functioning existing concurrently with deficits in adaptive behavior manifested during the developmental period that adversely affect a child's/youth's socialization and learning"; child is emotionally disturbed, characterized by an "inability to build or maintain satisfactory interpersonal relationships; inappropriate types of behavior or feelings under normal circumstances; a general pervasive mood of unhappiness or depression; or a tendency to develop physical symptoms or fears associated with personal problems. The term includes persons who are schizophrenic or autistic"; visually or hearing impaired to the extent to which it may significantly affect functioning or development; learning disabilities, including conditions such as "perceptual disability, brain injury, minimal brain dysfunction, dyslexia, and developmental aphasia; physical disabilities, such as cerebral palsy, spina bifida, multiple sclerosis, orthopedic impairments", etc.; some other medical condition not included in the other categories, such as children with chronic illnesses such as a diagnosis of HIV-positive or AIDS; and behavior problems to the extent to which it may adversely affect

socialization, learning, growth, and moral development. (National Data Archive on Child Abuse and Neglect: NCANDS User's Guide and Codebook, 2011).

However, the data elements related to child disabilities and diagnosed conditions are not reported with as much consistency and accuracy to NCANDS as most other elements, so the percentage of unknown or missing values in this item was very high (over 40% were missing in the sample). In order to investigate whether the elimination of missing cases from the analysis skews the results, a model is run including this variable and another model run excluding it, to examine the impact it has on other variables and variation in the model.

As will be discussed in the Results section, this variable is ultimately removed from the analysis due to inadequate data that resulted in the list-wise deletion of too large a proportion of the sample. Some descriptive statistics will still be provided, as it is an important variable to consider.

Perpetrator relationship to victim

A variable was also created to represent biological mothers and fathers as perpetrators, consolidating information from the Perpetrator Sex field and the Perpetrator Relationship field (1=parent). These were coded into four mutually exclusive dummy variables, including the following: Perpetrator is mother only; Perpetrator is father only; Perpetrators include both parents; Perpetrator is not a parent. These will be included in the model with the hypothesis that children may be more likely to be removed from home if the perpetrator includes a parent, particularly the mother.

Time

The indicator of time was the year each child was most recently reported to CPS (i.e., report date). Although children may be reported multiple times, the sampling method used only the most recent report for each child, so children are unduplicated but represent the most recent reporting year. There were a number of options on selecting the time variable. In addition to report date, I considered incident date, disposition date, and date of removal from home (for children placed in foster care). Incident date (the date the alleged maltreatment occurred) would have been the most appropriate choice but it is not available for all states. The disposition date is the date on which the determination is made as to whether an alleged maltreatment is substantiated, indicated or unsubstantiated, but there is frequently a long lag time between when a report of alleged child maltreatment is made and the date a determination is made. Often, this can even occur after the child is placed in foster care. The date of removal from home was not used because many children included in the analyses are not removed from home.

The outcome variable of interest was whether the child received foster care services (yes or no). It was adjusted to count only those foster care placements where the date of removal from home occurred after the reported date of maltreatment, but only up to two years afterward.

Covariates Specific to State and Year

For every state, by year, data from the US Census Bureau were retrieved on the percentages of children living below the poverty line. Foster Care Entry Rates were also calculated by year and by state, and they represent the number of children entering foster care in the state during the year divided by the number of children under 18 in the general

population of that state, multiplied by 1,000. These were selected to test the hypothesis that states with higher poverty rates might have higher foster care placement rates. Likewise, states with higher entry rates should also have higher rates of foster placement. Because the rates of foster care entry have changed so dramatically over time, it was necessary to make these rates specific to each year in the model.

Building the Model

Single-level Logistic Regression

As a preliminary analysis, a single-level logistic regression analysis is performed. This provides a foundation on which we can understand what the significant variables may be in the model and serves as the foundation on which we build a multilevel model.

Testing for whether a multilevel model is needed

Even though there are sound theoretical grounds for assuming a hierarchical structure to the data, it is important to test this assumption with the data. The assumption is that there are no higher level effects (effects of state or year) on the likelihood of placement in foster care. Likelihood ratio tests are used when performing hypothesis tests on variance parameters, rather than Wald tests. P-values and 95% confidence intervals should also not be utilized for this purpose, as they assume a normal sampling distribution. The LR test statistic is then compared against a chi-squared distribution with degrees of freedom equal to the number of extra parameters in the more complex model. The resulting *p*-value is then used to assess whether a two- or three-level model fits the data significantly better than a single-level model (Leckie, 2012). Once the null hypothesis can be rejected, the next step is to properly classify and fit a multilevel model.

Classification of the Multilevel Model

Classification of the multilevel model was an iterative process, initially driven by theory and then refined by testing various nesting structures to determine the best fit. This section shows each model classification explored through this iterative process, and although some results are shared here, they were only preliminary exploratory findings that helped shape the selection of the final two models included in this analysis.

Since one goal was to examine the overall national impact of time on each predictor and only account for between-state variation in the model as a "nuisance" parameter, the first conceptualization was a three-level model classified as in Figure 2:

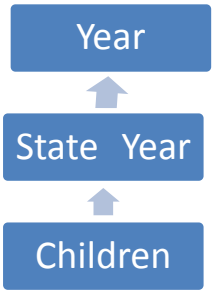

Figure 2. Three-level Model classification diagram: Year at Level 3

The intention was to explain all of the state variation as an interaction with year, and assess year overall. While all of the coefficients related to year indicated that foster care placement was less likely with more recent years, the model results showed that Year as a random effect at Level 3 was not significant at $p<.05$, and the model was not a good fit. Various treatments of the year variable were implemented; it was entered as a continuous variable and as a dummy variable; it was included as a child-level fixed effect

as well as a higher-level random effect in two- and three-level models. But the results consistently suggested that year alone does not have a statistically significant effect on the variability in likelihood of foster care placements. Further, the reliability estimates pertaining to the intercept when year was at a higher level were so low that they suggest it should not be treated as a random effect in the model.

Instead, it seems the effects of time are more nuanced. While trends at the national level indicate a reduction over time, the data must be examined in a way that allows each State to be measured on its own trajectory. As mentioned in the Literature Review, although many States have shown a decrease in foster care placement over time, some states have actually increased their entries into foster care.

Instead of the three tiered model with Year as the top level, the third level might more appropriately be State, classified as follows:

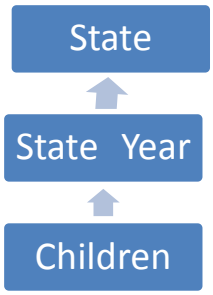

Figure 3. Three-level Model classification diagram: State at Level 3

The combination of State and year is essentially an interaction effect between the State and the time variable to look at each one as its own unit. This unit of observation

proved most effective in the model to explain variation in likelihood of foster care placement. In fact, it explained so much of the variation that there is no need for an additional 'Year' variable to be included as a separate effect.

Therefore, the model was refined further to a two-level classification structure, where all of the variation was explained by State and Year combinations. Results from this model will be discussed in the next section, referred to later as 'Model 1'.

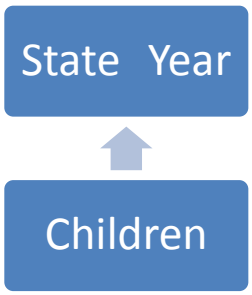

Figure 4. Two-level Model classification diagram; State and Year as Level 2

Next, the model was simplified even further to a two-level classification structure, where children were nested within states, and year was used as a Level 1 fixed effect. This allows the impact of Year to be nested within States, and overall trends over time in the likelihood of foster care placement can be assessed. This will be referred to as 'Model Two'.

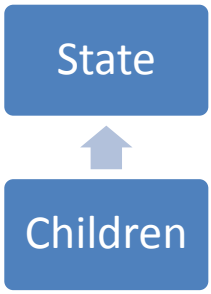

Figure 5. Two-level Model classification diagram: State at Level 2

Analysis

Some suggest the use of group mean centering covariates of interest to estimate simultaneously the cross-sectional relationship between covariates and placement in foster care as well as the longitudinal effects (Fairbrother, 2012). This is done by first calculating the mean of each variable across all years for each state. This state mean allows a cross-sectional comparison of states, regardless of time. To assess the longitudinal effect, each state mean is subtracted from the state and year combination. The cross-sectional component (state mean for the variable) and the longitudinal component (the state-year level variable) are orthogonal to one another and their effects can be measured separately. It provides "a direct investigation of social change without assuming that the longitudinal relationship is the same as the cross-sectional one" (Fairbrother, 2012). Other statisticians advise grand mean centering for ease in interpretability (Hox, 2010); this means that each individual's value is subtracted from the overall mean (not specific to the group).

In these models, the dichotomous covariates will be left uncentered, and Year will be grand-mean centered for ease in interpretation of the coefficients.

Limitations

The dataset is not a fully representative national sample, so conclusions may not necessarily be generalized to the national scale. Even though individual states were excluded due to data quality issues and not randomly sampled, there is no systematic bias in terms of which states were selected, and the sample does include the majority of states in the country.

Also, as discussed in the sampling section, the outcome of interest is right-censored in that the observation time to allow the event of interest to occur (foster care placement) is shorter for children maltreated in 2010 than for children maltreated in 2007. To mitigate this bias, a time constraint was applied to how long after the reported maltreatment the child entered foster care, so that if it exceeded two years, we do not link that foster care episode with that maltreatment report. However, children maltreated in 2010 do not have the same two year observation period included, so all children who subsequently were removed and placed in care during 2011 will be censored in this analysis.

CHAPTER FIVE: RESULTS

This chapter begins by exploring simple descriptive statistics within the sample, to form a basic understanding of the relationships between the variables included in the analysis. This is followed by the results of a single level logistic regression model, and concludes with the results and interpretation of the multilevel model.

Descriptive Statistics

The sample consists of child level information from 32 states and contains 317,549 records; each record representing one unique child's substantiated report of child abuse or neglect. The sample includes reports of maltreatment made between 2007 and 2010. Across all years, of these child victims, the average age at the time of the maltreatment report was 7.1 (*SD*=7.6), but is not normally distributed across ages; infants and toddlers are by far the largest age group.

The two figures below compare the age distribution between child victims as a whole (Figure 6) to the subset of those victims who are placed in foster care (Figure 7). The two exhibit very similar trends in age for all age groups except for infants, for whom there is a remarkably higher proportion of those children and youth placed in foster care.

The two Figures also demonstrate how these patterns have shifted over time. They both show that the proportion of infants and toddlers is continuing to increase across the four years shown, and proportions of older youth are stable or declining.

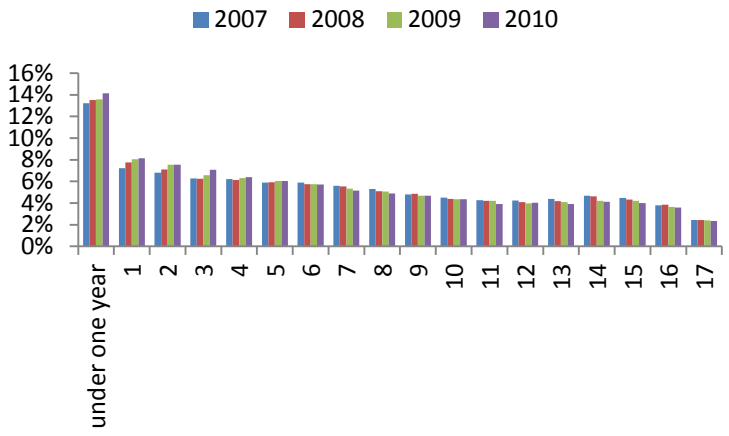

Figure 6. Percent of Child Victims by Age at time of Report (2007-2010)

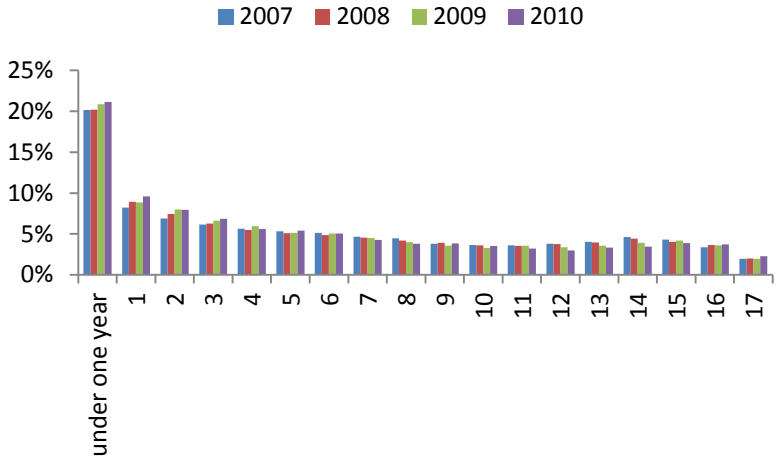

Figure 7. Percent of Child Victims by Age Entering Foster Care (2007-2010)

As discussed in the literature review, whether the child has been a victim of substantiated abuse or neglect in the past is also an important risk factor for placement in foster care. In this sample, almost a third (31.2%) of victims had a prior victimization

(*SD*=.47). Of those children who were prior victims, 32.4% were placed in foster care, as compared to a placement rate of 21.7% for those children who were first-time victims.

Race is also a variable with a large number of missing or unknown values, with almost 17% of the sample missing this information. However, it is of critical importance to retain this variable in the model, because the disparity in rates of foster care placement between these groups is so great. Child victims who are white had the lowest rates of foster care placement, at 26.8% in 2007 and it declined to 23.7% in 2010. African-American child victims had higher placement rates, from 31.4% in 2007 to 27.2% in 2010. The highest placement rates (42.4% in 2007 to 36.9% in 2010) were for child victims classified as "Other" race, which was driven largely by children identified as Alaska Native or American Indian, a group with very small numbers but the highest foster care placement rates of all. It also includes children of Asian and Pacific Islander descent. All races include children of Hispanic origin. What we learn about these statistics by race is that not only is there a great amount of variation between these groups, but there has also been a fair amount of change over time.

Examining the rates of foster care placement by age groups within each racial category, we learn that they depend largely on the age of the child. African-American infants and young children have similar placement rates as White infants and young children, but Black teenagers have much higher placement rates than White teenagers. Rates are higher across all age groups within the 'Other' race category, but are particularly higher for infants, who had the highest placement rate of all at 58% in 2008. See Table below for all rates by age and race. Note that percentages do not total 100%

because, for each group, we consider all victims with the same age/race combination as the denominator and the number entering foster care as the numerator.

Table 3: Proportion of Child Victims entering Foster Care, by Race and Age (2007-2010)

Race, by Age	2007	2008	2009	2010
Black	31.4%	31.5%	28.4%	27.3%
under one year	42.6%	42.7%	41.0%	37.1%
1-5	28.9%	30.2%	26.9%	25.4%
6-10	27.2%	25.9%	23.3%	22.9%
11-15	32.7%	31.3%	27.6%	25.8%
16-17	29.8%	32.8%	29.4%	32.8%
Other	42.4%	41.4%	38.9%	36.9%
under one year	56.3%	58.0%	53.9%	49.9%
1-5	43.7%	42.6%	36.8%	38.3%
6-10	35.8%	34.1%	32.8%	29.4%
11-15	40.1%	37.0%	37.8%	33.8%
16-17	33.3%	34.9%	39.8%	30.2%
White	26.9%	27.4%	24.4%	23.7%
under one year	43.3%	42.5%	40.0%	36.9%
1-5	27.6%	27.9%	25.4%	24.7%
6-10	21.9%	22.7%	19.3%	19.5%
11-15	24.0%	24.6%	20.7%	18.9%
16-17	21.6%	23.3%	21.7%	23.1%

Maltreatment types are also a very important factor when considering the likelihood of placement in foster care. Of all types of child maltreatment reported, neglect is the most common. This was true in all years, but there is a clear trend showing that neglect is increasing as a proportion of all substantiated child victims, as well as of all child victims placed in foster care. Figure 3 illustrates that of all child victims, 69.3% were neglected in 2007, and this increased to 71.9% in 2010. Of those placed in foster

care (a subset of the former), 80.4% were neglected in 2007 and this increased to 82.8% in 2010. Thus, the majority of children placed in foster care have been neglected, and we can consider this a likely candidate as a predictor for foster care placement.

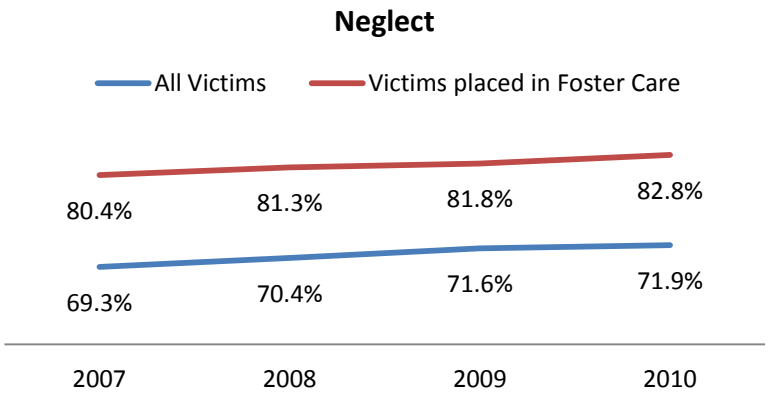

Figure 8. Percent of Child Victims Neglected, All Victims vs. those Placed in Foster Care

Despite common assumptions that most child abuse is physical, physical abuse comprises a very small proportion of child maltreatment; around 17% of all child victims (*SD*=.38). Note that while it has been relatively flat across the past several years as a proportion of victims, the percentage of victims placed in foster care showed a slight increase in those who were physically abused, from 15.5% in 2007 to 16.7% in 2010.

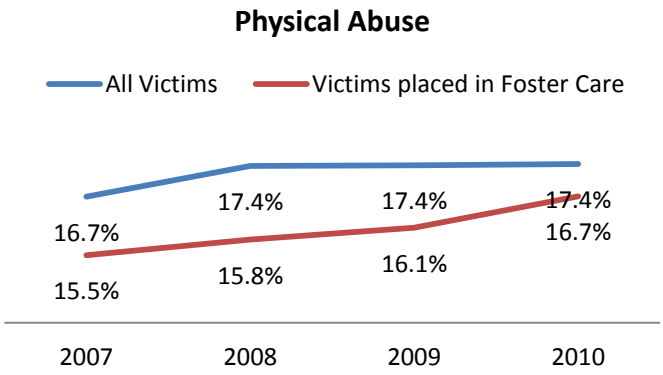

Figure 9. Percent of Child Victims Physically Abused, All Victims vs. those Placed in Foster Care

The least frequent maltreatment type is sexual abuse, but because of its very serious implications, this category is almost always isolated and not grouped into 'Other'. As reported in the literature review, sexual abuse appears to be declining, from 8.9% in 2007 to 7.9% in 2010, as a percentage of all child victims. Of those victims placed in foster care, it has remained relatively flat, around 5% each year.

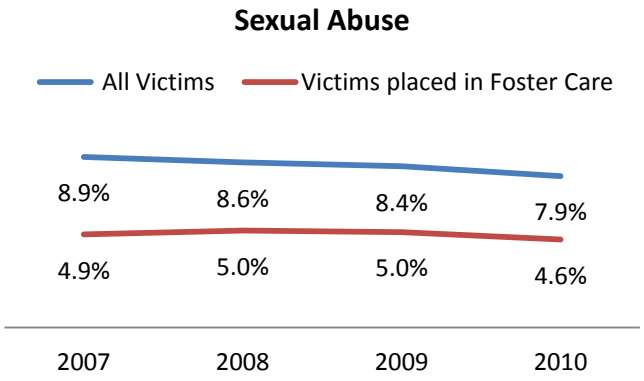

Figure 10. Percent of Child Victims Sexually Abused, All Victims vs. those Placed in Foster Care

For the purposes of this analysis, children who were victims of emotional abuse and medical neglect were also included in the 'Other' category, along with those children reported as victims of Other abuse. Other forms of maltreatment increased across the four years shown, among all victims (from 15% in 2007 to 17.4% in 2010), as well as for those victims placed in foster care (from 14.1% in 2007 to 16.4% in 2010). There was not much disparity between the two groups, suggesting that Other maltreatment forms are not likely to be meaningful predictors of foster care entry.

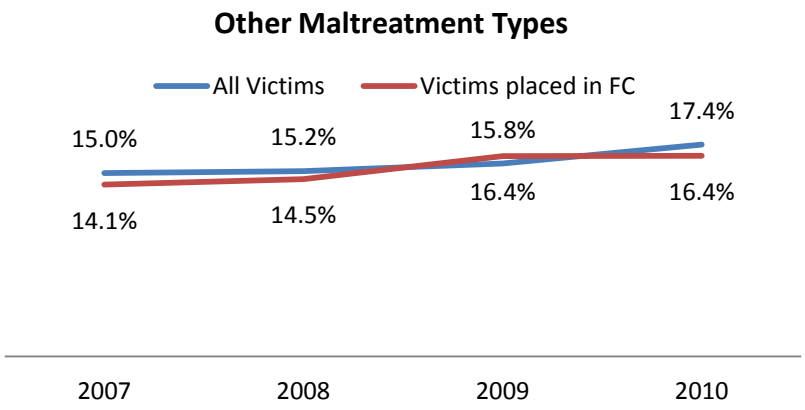

Figure 11. Percent of Child Victims of some Other type of Maltreatment, All Victims vs. those Placed in Foster Care

Children may be victims of multiple forms of maltreatment, so the categories discussed in this paper are not mutually exclusive of one another. Children who suffered multiple maltreatment types have been on the rise; of all victims of maltreatment, just 13.8% suffered multiple forms in 2007, and by 2010 this increased to 18.7%. Those victims placed in foster care exhibited a similar trend; 9.6% of child victims placed in foster care had multiple forms of maltreatment in 2007, and this increased to 13.7% in 2010. In the absence of information on the severity of abuse, this is one way we might validate anecdotal claims from the child welfare field that the thresholds seem to be rising on determination of children as victims and use of foster care as a last resort for only the toughest of cases.

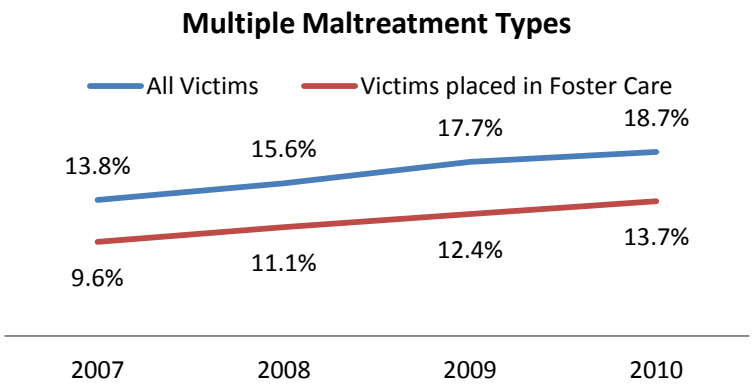

Figure 12. Percent of Child Victims of Multiple types of Maltreatment, All Victims vs. those Placed in Foster Care

Disabilities and special needs are an important characteristic to consider when looking at predictors of placement in foster care. Unfortunately, data on child and caretaker disabilities are woefully underreported; over 40% of the file was missing this information. Because of this, this variable will not be included in the statistical models. It is, however, worth exploring as a descriptive statistic in its own right.

Although there are nine distinct data elements in NCANDS that capture various types of child disability information, these were collapsed for this analysis into one all-inclusive dummy variable indicating whether or not the child was diagnosed with any of them (including mental and physical health problems). Of child victims, approximately 13.1% were diagnosed with a disability in 2007; 10.5% in 2008, and 10.1% in 2009 and 2010. Of those who were placed in foster care, 26.7% had a disability in 2007. This number declined thereafter, and fluctuated between 22 and 23 percent in 2008 to 2010.

This would indicate that having a disability places children at greater risk of foster care placement.

Likewise, children whose primary caretakers have disabilities, mental health issues and/or substance abuse problems may be more likely to be placed in foster care. NCANDS provides twelve distinct data elements that capture various types of caretaker risk factors, including financial indicators such as having financial problems, receiving public welfare assistance, inadequate housing including homelessness, the presence of domestic abuse in the household, as well as mental and physical health issues including diagnosed disabilities and alcohol and substance abuse problems. These would be important variables to include in the analyses, but the data are too incomplete to use in the model. Even after collapsing these 12 elements into three variables which I labeled "Caretaker Struggling", "Caretaker Disability" and "Caretaker Substance Abuse", there was too much missing data to utilize the variables. Almost half the sample was missing information on caretaker's disability; over half of the sample was missing data on caretaker substance abuse data, and over a third of the sample was missing data on 'caretaker struggling'. Despite the missing data, it is of interest to compare the two populations (all victims vs. those placed in foster care) on these elements.

Of all child victims who reported data on these elements, 35% had caretakers who were struggling financially. Of those victims placed in foster care, this increased to 48%, suggesting that financial risk factors related to the caretaker is a likely predictor for foster care placement. Similarly, when considering all child victims, 24% had caretakers with substance abuse or alcohol problems, and of those children placed in foster care, this rose

to 36%; more than 1 in 3. Those child victims who had a primary caretaker with a diagnosed disability was around 8.6%, and of those placed in foster care it increased to 14%. Thus, all of these caretaker risk factors are very likely to be correlated with increased probability of placement in foster care, but we will not include them in the statistical model due to inadequate reporting.

These descriptive statistics can be very useful in gaining insight into what variables are likely predictors for foster care placement, but the next section will build on this by considering them together in a one-level statistical model.

Logistic Regression- 1 Level model

As a precursor to a more complex multi-level model, first a single-level logistic regression is conducted to explore those variables that predict the likelihood of placement in foster care. As discussed in the methods section, the risk set is an unduplicated sample of children under the age of 18 who were found to be victims of child abuse or neglect, between the years 2007 and 2010. The dependent variable is whether or not the child victim of maltreatment entered foster care. The independent variables (age of child, race and ethnicity, maltreatment types, perpetrator's relationship to the victim, whether child has a prior substantiated maltreatment, interaction terms between age and maltreatment types, the year the incident was reported, the overall child poverty rate for the state, and the overall entry rate into foster care for the state) are entered in the model to determine if the log of the odds for each variable indicates an increased or decreased probability of entering foster care.

Results show that overall the model is significant at p<.001, and the fit of the model is assessed through the model chi-square, which is 23,778 with 48 degrees of freedom. The -2 Log Likelihood is 248,770, which represents the probability of the observed results given the parameter estimates. The overall fit of the model is good and the strength of the association between the independent variables and the dependent variable is moderate, with Cox and Snell R-square at .095 and Nagelkerke R-square at .140. Given these significance levels, we reject the null hypothesis that the variables tested in the model have no relationship with the likelihood of placement in foster care.

Almost all of the independent variables in the model had a significant (p<.01) effect on the likelihood of foster care placement, with the exception of the State entry rate into foster care and physically abused infants. With this information, we can begin to answer Research Question #1:

Research Question #1: What characteristics, **at the child or state level**, increase the likelihood of placement in foster care?

Among variables included in the model, some of the strongest predictors of foster care placement were related to the state in which the child welfare agency reported the incident, with Idaho being more than seven times more likely to place a child in foster care than Alaska, the reference group (p <.001). Controlling for all other variables in the model, the fact that state alone was significant suggests that there are systemic differences between states (a theory supported by the review of literature). The multilevel

model will more accurately account for the variability between states and treat it as a hierarchical level rather than simply another covariate at the child level.

Also highly significant in the model was the age of the child, with the likelihood of foster care placement over two and a half times greater for infants and toddlers (Exp B=2.890) than for older children, regardless of maltreatment type.

Another important indicator was having a maltreatment type of neglect, with neglected children almost three times more likely to be placed in foster care than others (Exp B=2.201). This is consistent with prior research findings, as well. Since neglect was also included as an interaction term with age, it is an interesting finding that while neglect overall increases the likelihood of placement, neglected babies are approximately 40% less likely to be placed, and neglected teens are not statistically significantly more or less likely to be placed. So it can be inferred that neglected *children*, particularly, are the ones at greatest risk of foster care placement due to neglect.

The perpetrator's relationship to the victim is also a significant variable in influencing the likelihood of foster care placement. Both parents as the perpetrators indicated a higher likelihood of placement in foster care, (Exp B=2.620), but children maltreated by their fathers were 50% less likely to be placed in care than children whose mothers were the perpetrators.

A surprising finding was that the higher the child poverty rate in the state, it was 99% *less* likely the child was placed in foster care ($p<.01$). This finding runs contrary to the hypothesis that higher poverty rates would increase the likelihood of foster care placement, so we must use caution in our interpretation of this finding. A higher overall

entry rate into foster care for the state overall did not have a statistically significant effect on the odds of foster care placement.

Child race also was significant in the model. Children with “Other” race (which includes Native Hawaiian and Pacific Islanders, American Indian and Alaska Native, or multiple races) are 46% more likely than White children to be placed in care. African American children were 20% more likely than White children to be placed in care.

Children with a prior victimization were 70% more likely to be placed in foster care (Exp B=1.704), which is to be expected, given the distributions cited earlier. This means that children who are reported with substantiated maltreatment allegations multiple times are more likely to be removed from home and placed in foster care.

Table 4. Binary Logistic Regression for Predicting Foster Care Placement for Victims of Child Abuse and Neglect (2007-2010)

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Exp(B)	S.E.	Exp(B)	S.E.	Exp(B)	S.E.	Exp(B)	S.E.	Exp(B)	S.E.
Infant	1.904**	.012	1.819**	.012	2.787**	.031	2.749**	.031	2.890**	.032
Teen	1.098**	.016	1.115**	.017	1.144**	.019	1.137**	.019	1.139**	.019
Physical abuse	1.219**	.018	1.198**	.018	1.274**	.021	1.369**	.021	1.301**	.023
Neglect	1.974**	.016	1.744**	.016	2.002**	.019	2.121**	.019	2.201**	.021
Sexual abuse	.881**	.024	.910**	.025	.985	.026	1.053*	.026	.925*	.028
Multiple types of abuse	1.324**	.016	1.342**	.016	1.328**	.016	1.319**	.017	1.459**	.019
Prior Victimization	1.774**	.010	1.782**	.010	1.783**	.010	1.719**	.010	1.704**	.011
Black	1.179**	.011	1.178**	.011	1.179**	.011	1.216**	.012	1.201**	.012
Other race	1.779**	.018	1.777**	.018	1.784**	.018	1.701**	.018	1.462**	.020
Perp Father			.519**	.016	.518**	.016	.498**	.016	.502**	.017
Perp Non-Parent			.793**	.014	.798**	.014	.796**	.014	.817**	.014
Perp Both Parents			2.482**	.019	2.497**	.019	2.617**	.019	2.620**	.020
Neglected Infant					.607**	.032	.612**	.032	.595**	.032
Physically abused Infant					.872**	.034	.920*	.034	.940	.034
Physically abused Teen					.911*	.041	.901*	.041	.908*	.042
Poverty rate							.240**	.107	.006**	.309
Foster Care Entry Rate							1.105**	.003	1.181	.116
Arkansas									2.119**	.097
California									4.281**	.071
Colorado									1.108	.212
Connecticut									.692**	.116
Florida									1.375**	.122
Hawaii									4.801**	.251
Idaho									7.859**	.100
Iowa									.647	.573
Kansas									2.145**	.093
Kentucky									1.603**	.164
Louisiana									3.229**	.196
Maine									1.343	.238
Massachusetts									.771**	.063

Michigan									1.253*	.099
Minnesota									1.871**	.234
Mississippi									3.131**	.240
Missouri									2.897**	.072
Nebraska									1.140	.490
Nevada									4.030**	.123
New Hampshire									2.642*	.325
New Jersey									2.760**	.208
New Mexico									2.551**	.083
Ohio									1.261**	.065
Rhode Island									1.166	.274
South Carolina									2.133**	.194
South Dakota									3.992**	.280
Texas									1.906*	.250
Virginia									1.569	.311
West Virginia									1.882	.329
Wisconsin									3.567**	.070
Wyoming									2.717	.561
Constant	.130**	.017	.156**	.018	.138**	.020	.113**	.036	.106**	.522

-2 (Log-Likelihood)	260571.819	257881.96	257610.020	255989.984	248770.022
Cox & Snell R Square	.049	.060	.061	.067	.095
Nagelkerke R Square	.072	.088	.089	.099	.140
Hosmer & Lemeshow Chi-square	277.847**	200.425**	103.805**	72.924**	33.292**

Note. * $p < .05$; ** $p < .01$.
Omitted reference category for state is Alaska.

This single-level logistic regression adds to our understanding of the predictors for foster care placement, but it does not adequately address the nested nature of the data with states, which is clearly a very important variable in the model. Second, it does not

properly assess change over time in these characteristics. I included interaction effects between the year of report and some of the other independent variables, but the results did not suggest a good fit for the model, and it yielded insignificant results indicating the model was a better fit excluding this level of analysis. For these reasons, we move to multilevel models to explore Research questions #2 and #3, and to refine our findings for Research question #1.

Multilevel models

Now that there is a general understanding of which variables may increase the likelihood of foster care placement, it is time to take into account the nested structure of the data.

The model was specified as having a Bernoulli distribution. This means that the outcome variable (whether or not the child is placed in foster care) is dichotomous, with only two possible outcomes (0 and 1). The probability distribution is binomial, and the link function utilized is the logit, which then allows us to interpret the exponentiated logistic coefficients as odds ratios. Interpretations are made in terms of the log odds of children being placed in foster care, rather than foster care placement itself. Hierarchical Linear Modeling cannot be used, because the outcome is non-linear, which assumes a normal distribution. Instead, we use Generalized Linear Mixed Models (GLMM) to take into account the nature of the dependent variable.

As discussed in Chapter 4, three-level models were tested but were not a good fit for the data. For this reason, results will only be discussed for the final two classification models: first, a two-level model with state and year interactions as the Level 2 grouping

variable; and second, a two-level model with state as the Level 2 grouping variable and Year will be treated as a covariate at Level 1. Chapter 6 will summarize and discuss the differences between these two models, and what we can learn from each of them.

Model 1: Two-level model classified with State and Year interaction effects as the clustering effect, and Children as Level 1.

The first step is to carry out an intercept-only (Null) model to test the null hypothesis that there is no relationship between state and year interaction terms on the likelihood of foster care placement. The default estimation method for the null model is restricted maximum likelihood. The equation for this null model may be written as follows:

Level 1 Model: $\text{Prob}(FOSTERCR_{ij}=1|\beta_j) = \phi_{ij}$, $\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$, $\eta_{ij} = \beta_{0j}$

Level-2 Model: $\beta_{0j} = \gamma_{00} + u_{0j}$

The intercept-only or 'empty' model alone confirms that the intercept of the outcome variable (logistic link of foster care placement) is significantly affected by the Level 2 grouping variable of the state and year in which children were reported ($p<.001$). The variance component model for the random effect intercept (state by year) was .396, with standard deviation of .63. This information tells us that simply by nesting the data within state and year, there is a significant relationship on the likelihood of child victim placement in foster care.

Table 5. Variance Component and Significance test for the Null Model

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	0.62894	0.39556	127	13362.95591	<0.001

Building upon this model, covariates were added in one at a time. This is done so that the impact of each additional variable can be assessed. The final model is specified as follows:

Level-1 Model

$\text{Prob}(FOSTERCR_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(BABY_{ij}) + \beta_{2j}*(TEEN_{ij}) + \beta_{3j}*(PHYSABUSE_{ij}) + \beta_{4j}*(NEGLECT_{ij}) + \beta_{5j}*(SEXABUSE_{ij}) + \beta_{6j}*(PRIORVICTIM_{ij}) + \beta_{7j}*(BLACK_{ij}) + \beta_{8j}*(OTHERRace_{ij}) + \beta_{9j}*(PerpDAD_{ij}) + \beta_{10j}*(PerpOTHER_{ij}) + \beta_{11j}*(PerpBothParents_{ij}) + \beta_{12j}*(NeglectedBaby_{ij})$

Level-2 Model

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(StateFCEntryRATE_j) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30}$

$\beta_{4j} = \gamma_{40}$

$\beta_{5j} = \gamma_{50}$

$\beta_{6j} = \gamma_{60}$

$\beta_{7j} = \gamma_{70}$

$\beta_{8j} = \gamma_{80}$

$\beta_{9j} = \gamma_{90}$

$\beta_{10j} = \gamma_{100}$

$\beta_{11j} = \gamma_{110}$

$\beta_{12j} = \gamma_{120}$

Note: StateFCEntryRATE has been centered around the grand mean.

Using the State and Year interaction as the Level 2 variable, Foster Care Entry Rates and Poverty rates specific both to the year and the state were included as level 2 covariates. This was one of the primary advantages to using the state and year interaction term as the level 2 grouping variable; that the entry rates and poverty rates could be tested as random effects variables in the model. A preliminary model fitted included poverty rates, but they were not significant in the model and the overall fit was improved by deleting it. This will be discussed more in Chapter 6. The final model includes entry rates as level 2 covariate because it was a significant predictor of foster care entry ($p<.001$), where every unit increase in the overall state entry rate into foster care indicated a 13% greater likelihood of foster care placement. Note that in the single-level logistic regression, entry rates were not found to be significant predictors, but poverty rates were.

The overall model as well as all fixed effects included were found to be significant at $p<.001$. The variance component is 0.37 and SD is 0.61.

Table 6. Model 1: Two-level Logistic Regression Predicting Foster Care Placement, 2007-2009: Model Statistics

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	0.61522	0.37849	126	11323.84249	<0.001

HLM provides the transformed odds ratios (OR) for each independent variable that can be interpreted as the predicted probability that foster care placement will occur if that variable applies, controlling for all other covariates. The 95% confidence intervals (CI) show the precision of the odds ratio, by providing the range in which we can be confident the true value lies. The final assessment of the transformed odds ratios showed that in this model, the following fixed effects still remain predictors of foster care entry: Infants are more than two and a half times more likely to enter foster care (OR=2.746, CI=2.457, 3.070); teens were also slightly more likely to be placed in foster care than children at other ages (OR=1.108, CI=1.053, 1.166). Neglected children were two and a half times more likely to be placed in care (OR=2.576; CI=2.396, 2.770). However, as found in the single-level logistic regression, neglected infants were about 40% *less* likely to be placed in care (OR=.603; CI=.535,.680).

Both parents as the perpetrators of maltreatment increased the likelihood of placement by almost two and a half times; children having a perpetrator who was not the child's biological parent were 20% less likely to be placed in foster care (OR=.835, CI=.777, .898), and children having the biological father as the perpetrator were 50% less likely to be placed in care (OR=534, CI=.506, .564).

Having a prior victimization placed children at a 67% greater chance of foster care placement than first-time victims. Children who were physically abused were 55% more likely to be placed in care than other types of abuse (OR=1.554, CI=1.468, 1.645); children victims of sexual abuse were also slightly more likely to be placed in care (OR=1.138, CI=1.046, 1.237).

Children as Other race were 44% more likely to be placed in care than White children (OR=1.442, CI=1.367, 1.520), and Black children were 19% more likely (OR=1.187, CI=1.143, 1.232).

The following table shows the coefficients, odds ratios and confidence intervals for each of these variables in the model. Note that all of these variables were statistically significant at p<.001, with the exception of sexual abuse, which was still statistically significant at p=.002.

Table 7. Model 1: Two-level Logistic Regression Results on Likelihood of Foster Care Placement for Victims of Maltreatment, 2007-2009.

	Coefficient	Robust S.E.	Odds Ratio	Confidence Interval
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	-1.748477**	0.069583	0.174039	(0.152,0.200)
ERATE, γ_{01}	0.130165**	0.026223	1.139016	(1.081,1.200)
For Infant slope, β_1				
INTRCPT2, γ_{10}	1.010205**	0.056866	2.746164	(2.457,3.070)
For Teen slope, β_2				
INTRCPT2, γ_{20}	0.102521**	0.025889	1.107960	(1.053,1.166)
For Physical Abuse slope, β_3				
INTRCPT2, γ_{30}	0.440796**	0.029189	1.553944	(1.468,1.645)
For Neglect slope, β_4				
INTRCPT2, γ_{40}	0.946283**	0.036941	2.576116	(2.396,2.770)
For Sexual Abuse slope, β_5				
INTRCPT2, γ_{50}	0.128917**	0.042616	1.137595	(1.046,1.237)
For Prior Victim slope, β_6				
INTRCPT2, γ_{60}	0.511935**	0.042523	1.668516	(1.535,1.814)
For Black slope, β_7				
INTRCPT2, γ_{70}	0.171123**	0.019280	1.186637	(1.143,1.232)
For Other Race slope, β_8				
INTRCPT2, γ_{80}	0.365914**	0.027043	1.441831	(1.367,1.520)
For Perp Father slope, β_9				
INTRCPT2, γ_{90}	-0.626621**	0.027667	0.534395	(0.506,0.564)

For Perp NonParent slope, β_{10}				
INTRCPT2, γ_{100}	-0.180279**	0.036939	0.835037	(0.777,0.898)
For Perp Both Parents slope, β_{11}				
INTRCPT2, γ_{110}	0.909474**	0.049776	2.483017	(2.252,2.737)
For Neglected Infant slope, β_{12}				
INTRCPT2, γ_{120}	-0.506039**	0.061057	0.602879	(0.535,0.680)

Note. * $p < .05$; ** $p < .01$.

This model provides information that refines and builds on our findings to answer Research Question #1. We now have a better understanding of which characteristics are more likely to predict children will be removed from home and placed in foster care.

It does not, however, give us a clear understanding of how the likelihood of foster care placement has changed over time. By treating each year as a unique characteristic coupled with states, it tells us that there is, indeed, variability across the groups, but does not inform as to the direction of the change.

Thus, we move into the final model, specified more simply as state as the level 2 grouping unit, and individual children at level 1.

Model 2: Two-level model classified with State as Level 2, and Children as Level 1.

The preliminary step to test the null model where state is the level 2 unit of analysis and children the level 1 revealed that, apart from an interaction with year, we can still reject the null hypothesis that the state in which a child is reported a victim of maltreatment has no effect on likelihood of foster care placement. With a variance component of 0.37651, the model is significant at p<.001. The variance explained is

slightly less than that of the state and year interaction model, but this model will be simpler to interpret and also fits the data well.

Year was added as a level 1 predictor, and was grand mean centered, meaning that each individual value of year was subtracted from the overall average year, so that the values could be more easily interpreted. The main finding gained from the model classified this way is that we are able to address Research Question #2, which asks how the likelihood of foster care placement has changed over time, and how have certain predictors changed over time. We see from this model that the more recent the year, the less the likelihood of foster care placement. As a precursor to the final model, I iteratively tested individual interaction effects with year and all of the other direct effects in this model, but none were found to be significant. This finding is important, because it suggests that the degree to which each individual predictor impacts the likelihood of foster care placement has not changed significantly over time.

There were no state-level covariates included in this model, because the state entry rates and poverty rates varied by year, and to average them across years would lose too much of the specificity that there was no value added by doing this.

All other level 1 covariates were added to the model one by one, and the results showed that two of the variables that were considered significant predictors in the last model (Sexual abuse and Victim is a Teenager) are now no longer significant at $p<.05$.

The odds ratios related to the variables that do significantly increase the likelihood of foster care placement are consistent with those found in Model #1: Infants still have the greatest odds of foster care placement and the OR only slightly decreased

from 2.74 to 2.70; the OR for Neglect went from 2.56 to 2.54; the OR for Both Parents as Perpetrators went from 2.483 to 2.466, etc. The fact that we are controlling for year as a direct effect at level 1 rather than a nesting effect at level 2 and the odds ratios for all other direct effects did not substantively change further supports the claim that the impact of various indicators on foster care placement has not changed significantly across the four years included in these models.

Table 8. Two-level Logistic Regression Predicting Foster Care Placement, 2007-2009: Model Statistics

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	0.65356	0.42714	31	13923.73557	<0.001

Table 9. Model 2: Two-level Logistic Regression Predicting Foster Care Placement for Victims of Maltreatment, 2007-2010

	Coefficient	Robust S.E.	Odds Ratio	Confidence Interval
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	-1.709501**	0.137185	0.180956	(0.137,0.239)
For YEAR slope, β_1				
INTRCPT2, γ_{10}	-0.071368**	0.012962	0.931120	(0.908,0.955)
For Infant slope, β_1				
INTRCPT2, γ_{10}	0.994845**	0.095037	2.704304	(2.245,3.258)
For Teen slope, β_2				
INTRCPT2, γ_{20}	0.101474*	0.041131	1.106801	(1.021,1.200)
For Physical Abuse slope, β_3				
INTRCPT2, γ_{30}	0.432393**	0.045931	1.540940	(1.408,1.686)
For Neglect slope, β_4				
INTRCPT2, γ_{40}	0.932590**	0.063399	2.541082	(2.244,2.877)

For Sexual Abuse slope, β_5				
INTRCPT2, γ_{50}	0.128878	0.067937	1.137551	(0.996,1.300)
For Prior Victim slope, β_6				
INTRCPT2, γ_{60}	0.495822**	0.078184	1.641848	(1.409,1.914)
For Black slope, β_7				
INTRCPT2, γ_{70}	0.166743**	0.029675	1.181451	(1.115,1.252)
For Other Race slope, β_8				
INTRCPT2, γ_{80}	0.355384**	0.039977	1.426728	(1.319,1.543)
For Perp Father slope, β_9				
INTRCPT2, γ_{90}	-0.625215**	0.033648	0.535146	(0.501,0.572)
For Perp NonParent slope, β_{10}				
INTRCPT2, γ_{100}	-0.173745**	0.064583	0.840511	(0.741,0.954)
For Perp Both Parents slope, β_{11}				
INTRCPT2, γ_{110}	0.902867**	0.085228	2.466665	(2.087,2.915)
For Neglected Infant slope, β_{12}				
INTRCPT2, γ_{120}	-0.503171**	0.108258	0.604610	(0.489,0.748)

Note. * $p < .05$; ** $p < .01$.

Conclusion

This chapter provided the results of the analyses conducted on a sample of victimized children reported to NCANDS between 2007 and 2010. The descriptive statistics provided an important exploratory analysis to identify the relationships between variables and the outcome of interest: foster care placement. Due to missing data, some variables had to be dropped from the analysis. Next, the results of a single-level logistic regression were presented, followed by two multilevel models, each providing a unique contribution to our understanding of what predicts foster care placement and how that has (or has not) changed in recent years. Finally, it can be inferred from these models that aggregate national statistics may sometimes cloud the picture; differences between states

are so great that acknowledging the hierarchical structure imposed by states is an important exercise in determining the likelihood of foster care placement.

CHAPTER SIX: DISCUSSION

This chapter begins by summarizing the findings from each of the three research questions put forth in this thesis, and places the results within the broader context of prior research in this area. Next is a discussion of the strengths and limitations of this study, and what inferences can be made. A discussion of data systems and analysis will follow, with a call to action for strengthening data quality for research purposes as well as recognizing the importance of using multilevel models in the social sciences. Finally, I will put forth suggestions for how this may be expanded into a broader study or supplemented by additional research.

Summary of Findings

This thesis explored three research questions. We begin with the first: What characteristics, **at the child or state level**, increase the likelihood of placement in foster care? Considering all children who were victims of child abuse and neglect between 2007 and 2010 as the set of children at risk of foster care placement, we were able to identify specific child-level variables associated with greater odds of foster care placement. These variables include age at time of maltreatment, type of maltreatment, relationship of perpetrator to victim, prior-victimization, and race.

Age at time of maltreatment. Infants were almost three times as likely as older children to be placed in care, and teenagers were slightly more likely to be placed in care than younger children.

Maltreatment type. Neglected children are far more likely than children with other types of abuse to be placed in care, with the exception of infants. This finding has been found to be true in other research studies as well, as discussed in the Literature review. It runs contrary to some commonly held beliefs that neglect is more benign than other types of abuse; when it comes to likelihood of removal from home, it's a significant predictor.

Relationship of perpetrator to victim. When the perpetrators include both of the child's biological parents, the chances are much greater for removal from home, as opposed to perpetrators as biological fathers only, or non-parental perpetrators, where there is a reduced likelihood of foster care placement. We may surmise that this is because children may be more likely to live with their mothers following a victimization by someone other than the mother. Mothers are actually the most frequent type of perpetrator, which also may be surprising to some.

Prior victimization. Having been a victim before is also a strong predictor of foster care placement. Many children are reported multiple times over the course of their childhoods, and sometimes it takes multiple interventions and efforts for family preservation in the home before a more drastic measure like foster care placement is enacted. For this reason, children with prior victimizations are more likely to be removed from home and placed in foster care than children who are first-time victims.

Child race. Children of ‘Other’ race were over 40% more likely to be placed in foster care than White children. Even though percentages of children of ‘Other’ race are low in terms of foster care entries, the odds are greater that they will be placed in care. Disaggregation of the Other category shows this is predominantly true for American Indian/Alaska Native children. Black or African American children were also more likely to be removed from home than White children, even though White children comprise the largest proportion of the foster care population.

State level characteristics examined included the percent of children living below the poverty line, by year, as well as the rate of children in the general population entering foster care each year (per 1,000). While it was puzzling that higher poverty rates at the state level seemed to significantly predict a reduced likelihood of foster care entry in the single-level logistic regression, the two-level model with state and year as Level 2 revealed no statistical significance between these poverty rates and the likelihood of foster care placement. This would suggest that the statewide poverty rates for children are not a suitable indicator for answering research questions about how poverty affects likelihood of foster care placement. It may need to be captured at the individual or community level. The rates of children placed in foster care by state and year did show the anticipated outcome of having a significant effect on increased likelihood of foster care placement.

The second research question asked: Given the decreasing rates of foster care placement in recent years, has the degree to which certain characteristics influence foster care placement **changed over time**? The year in which children were reported for alleged

maltreatment was the metric by which time was measured in this analysis, and data from the Federal Fiscal Years (October 1st through September 30) 2007 through 2010 were utilized. The direct impact of year was measured as a level 1 covariate in the final model, and it had a significant relationship on the likelihood of foster care placement, in that the likelihood of placement decreased with more recent years. This comports with our expectations, given the reduced numbers of children entering foster care each year, but it should be noted that there was a slight limitation in the sampling methodology which meant that children who were maltreated in 2010 were not allowed the same amount of observation time (two years) as those children from the earlier years, to see if they were placed in care. This issue is known as right censored data, and although most of the foster care entries were likely to fall within the first year, there were some that would have been missed. That said, we can still assess the impact of year on the likelihood of foster care placement to a lesser degree. Interaction terms of year with each other predictor variable in the model were tested, and none were found to be significant. This would suggest that the extent to which each of the variables found to be significant predictors has *not* significantly changed over the years.

Finally, the third research question asked: Are these characteristics somewhat **consistent across States** so that we may generalize findings to the national level, or is there so much variability between states that there is no cohesive national trend over time? The findings from the multilevel analyses confirm that the likelihood of a victim of child abuse or neglect being placed in foster care varies tremendously depending on which state agency investigates and handles the case. Therefore, researchers must be very

cautious about making inferences based on national statistics; the differences between states is best handled through a multilevel model where the variation can be accounted for in a hierarchical manner, to acknowledge the structural impact that states impose. Further, national aggregate statistics are often driven by sample size; large states such as California often dominate the trends, while smaller states such as Massachusetts are eclipsed. This is why disaggregating data to the state level or presenting results in a multilevel national model is superior to simply collapsing all the data together to infer national trends and statistics.

Strengths, Caveats and Limitations

One of the main strengths of this thesis is that large, national administrative datasets were used in a way that allowed for a comprehensive, multilevel statistical analysis to better understand what indicators are associated with increased likelihood of removal from home and placement in foster care. I linked the AFCARS and NCANDS datasets using the common identifier, to enhance the quality of the data on the dependent variable. This has rarely been done in research studies, though it is one of the goals of these administrative datasets and serves as the basis for why the common identifier is provided; but only very recently has the common identifier been provided to the research community. There is great potential for further analysis using this sort of linkage; there is much more than can be learned to further our understanding of children's experience in the child welfare system, from beginning (initial referral to CPS) to end-ultimately, a permanent discharge from foster care.

Another strength is that this thesis provides an example for how multilevel analysis might be used in other contexts, to tease out differences in social structures in place that may confound results. States are not the only hierarchical layer to consider; if one were interested in examining county-to-county variation for either research initiatives or performance management, this is a technique that could be applied. It also enables one to statistically control for, or adjust for various differences in the composition of populations, to arrive at a more equitable comparison.

One of the limitations of this thesis, however, is that the variables available in the administrative datasets utilized do not capture the full range of important indicators to consider for likelihood of foster care placement. This limitation was mentioned in the first chapter, but it is important to remember that variables such as risk assessment scores, the severity of abuse, more complete information on caretaker characteristics such as maternal health and well-being, age, economic indicators at the family level, and community characteristics may be critical to understanding what makes children more or less likely to be removed from home.

This study was also limited to only consider children who were victims of child abuse and neglect as at risk for foster care placement. This is the appropriate choice, but it should be noted that some children and youth come into foster care through channels other than child abuse and neglect. This is particularly salient because there most likely exists a bias toward older ages. Some teens may enter foster care not because they were found to be victims on a particular report, but because they may be in the juvenile justice system and subsequently enter foster care, they may enter care because of their own

behavior problems with substance abuse, mental health issues, etc., and the foster care system may provide services and independent living programs that are more appropriate for youth than their other alternatives. This is a caveat to bear in mind when thinking through all of the reasons children are placed in foster care, but it does not introduce a bias in the results of this study, because I only counted foster care entries of those children who were in fact determined to be victims, so the phenomenon is controlled for in the risk set.

Another potential limitation is that the study was not as long-range as originally intended. This sort of analysis could have been enhanced by including more years in the datasets, but this was not possible due to reasons described in Chapter 4. For this reason, caution is warranted in concluding there have been little meaningful changes over time in effect that each independent variable had on the likelihood of foster care placement; we may only conclude that using 2007 to 2010 alone, it did not appear to have changed significantly.

Finally, the biggest impediment to this study was not in the methods, but in the quality of the data. Because of so much missing data on child- and caretaker- level disabilities, mental health issues, substance abuse, and economic indicators, these potentially very important variables were unable to be included in the model. Further, the dependent variable on whether the child was placed in foster care revealed inconsistent patterns of reporting across states, and many states had to be removed from the analysis completely due to inadequate data. The NCANDS data are not a legislatively mandated reporting effort, as AFCARS is, but almost all states voluntarily provide NCANDS data .

Great efforts are made to improve the quality of the data and encourage consistency in reporting, but there is still much room for improvement.

Opportunities for Further Research

The study presented in this thesis is intended as a critical stepping stone in understanding the trends in predictors for what leads state child welfare agencies to remove children from homes and place them in foster care. It is not, however, the final answer. My personal plan is to build upon this study for my dissertation project by supplementing it with more qualitative analysis, as well as integrating findings from the National Survey of Child and Adolescent Well-Being (NSCAW) and the National Incidence Study (NIS). Both of these studies provide a wealth of data that could better inform and contextualize these findings.

It would also be interesting to explore the potential relationship between new initiatives in child welfare policy and its impact on foster care placement. Particularly, the Fostering Connections Act of 2008 which allows states the option of providing foster care beyond the age of 18. Also critical to a fuller understanding of this phenomenon would be an examination of the growing implementation of Differential Response in state child welfare systems, and the impact it may have on victimization rates and potentially foster care placement.

Conclusion

The child welfare system in the United States is actually a complex network of systems that operate in a dynamic environment, responding to changes in social climate, changes in policy and law, and changes in the populations served. This thesis provides a statistically robust method for handling the variation between state agencies, and arrives at some conclusions with implications for the field in gaining a greater understanding of what characteristics are most strongly associated with removal from home and placement in foster care. It would be of interest to build on this study longitudinally, and add new years of data to the analysis to see whether we can observe meaningful changes over time in the extent to which certain variables play a key role.

APPENDIX A

Single-Level Logistic Regression: Final Model

Notes

Output Created		12-Mar-2013 16:11:48
Comments		
Input	Data	C:\thesis\FinalSample 2-16-13b withLvl2vars.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	317549
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing

Syntax		LOGISTIC REGRESSION VARIABLES FosterCr /METHOD=ENTER baby teen physabs neglect sexabs multiplemal ChPrior Black_D Other_D /METHOD=ENTER Biodad PerOther BothParents /METHOD=ENTER BabyNeglect Babyphysabs Teenphysabs /METHOD=ENTER Poverty ERate /METHOD=ENTER state /Contrast (state)=Indicator(1) /CLASSPLOT /PRINT=GOodfit /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).
Resources	Processor Time	00 00:00:11.875
	Elapsed Time	00 00:00:13.029

```
[DataSet1] C:\thesis\FinalSample 2-16-13b withLvl2vars.sav
```

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	237759	74.9
	Missing Cases	79790	25.1
	Total	317549	100.0
Unselected Cases		0	.0
Total		317549	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
No	0
yes	1

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted: Foster Care Services No	yes	Percentage Correct
Step 0	Foster Care Services	No	175918	0	100.0
		yes	61841	0	.0
	Overall Percentage				74.0

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.045	.005	50010.076	1	.000	.352

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	baby	3020.530	1	.000
		teen	65.277	1	.000
		physabs	63.940	1	.000
		neglect	4087.280	1	.000
		sexabs	1365.844	1	.000
		multiplemal	1572.168	1	.000
		ChPrior	2600.307	1	.000
		Black_D	57.775	1	.000
		Other_D	1243.208	1	.000
	Overall Statistics		11816.851	9	.000

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	11976.543	9	.000
	Block	11976.543	9	.000
	Model	11976.543	9	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	260571.819[a]	.049	.072

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	277.847	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Foster Care Services = No		Foster Care Services = yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19419	18933.260	1922	2407.740	21341
	2	21349	21208.271	3779	3919.729	25128
	3	3129	3284.858	958	802.142	4087
	4	36506	36613.591	9470	9362.409	45976
	5	13077	13504.648	4281	3853.352	17358
	6	17828	18073.549	5968	5722.451	23796
	7	21644	21701.628	9679	9621.372	31323
	8	15066	15122.336	7336	7279.664	22402
	9	15294	15371.879	8545	8467.121	23839
	10	12606	12103.979	9903	10405.021	22509

Classification Table[a]

	Observed		Predicted: Foster Care Services No	Predicted: Foster Care Services yes	Percentage Correct
Step 1	Foster Care Services	No	173933	1985	98.9
		yes	59807	2034	3.3
	Overall Percentage				74.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	baby	.644	.012	3089.690	1	.000	1.904
	teen	.093	.016	32.136	1	.000	1.098
	physabs	.198	.018	127.611	1	.000	1.219
	neglect	.680	.016	1789.793	1	.000	1.974
	sexabs	-.127	.024	27.632	1	.000	.881
	multiplemal	.281	.016	302.204	1	.000	1.324
	ChPrior	.573	.010	3118.692	1	.000	1.774
	Black_D	.165	.011	210.510	1	.000	1.179
	Other_D	.576	.018	1001.577	1	.000	1.779
	Constant	-2.044	.017	15000.249	1	.000	.130

a. Variable(s) entered on step 1: baby, teen, physabs, neglect, sexabs, multiplemal, ChPrior, Black_D, Other_D.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2689.854	3	.000
	Block	2689.854	3	.000
	Model	14666.397	12	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	257881.965[a]	.060	.088

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	257881.965[a]	.060	.088

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	200.425	7	.000

Contingency Table for Hosmer and Lemeshow Test

		Foster Care Services = No		Foster Care Services = yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	22560	22230.704	2239	2568.296	24799
	2	20542	20315.835	3161	3387.165	23703
	3	19872	19825.156	4458	4504.844	24330
	4	23577	23512.423	6303	6367.577	29880
	5	17525	17983.204	6048	5589.796	23573
	6	17041	17533.677	6856	6363.323	23897
	7	18447	18443.996	8576	8579.004	27023
	8	16266	16463.365	8991	8793.635	25257
	9	20088	19609.637	15209	15687.363	35297

Classification Table[a]

			Predicted		
			Foster Care Services		
	Observed		No	yes	Percentage Correct
Step 1	Foster Care Services	No	172573	3345	98.1
		yes	58392	3449	5.6
	Overall Percentage				74.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	baby	.598	.012	2604.658	1	.000	1.819
	teen	.109	.017	43.226	1	.000	1.115
	physabs	.181	.018	104.255	1	.000	1.198
	neglect	.556	.016	1151.432	1	.000	1.744
	sexabs	-.094	.025	14.228	1	.000	.910
	multiplemal	.294	.016	321.793	1	.000	1.342
	ChPrior	.577	.010	3123.555	1	.000	1.782
	Black_D	.164	.011	204.109	1	.000	1.178
	Other_D	.575	.018	982.756	1	.000	1.777
	Biodad	-.657	.016	1644.451	1	.000	.519
	PerOther	-.232	.014	287.333	1	.000	.793
	BothParents	.909	.019	2205.680	1	.000	2.482
	Constant	-1.856	.018	11097.552	1	.000	.156

a. Variable(s) entered on step 1: Biodad, PerOther, BothParents.

Block 3: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	271.946	3	.000
	Block	271.946	3	.000
	Model	14938.343	15	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	257610.020[a]	.061	.089

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	103.805	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Foster Care Services = No		Foster Care Services = yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	22055	21901.769	2227	2380.231	24282
	2	20735	20579.155	3135	3290.845	23870
	3	19590	19552.395	4306	4343.605	23896
	4	24676	24651.064	6697	6721.936	31373
	5	16917	17086.444	5586	5416.556	22503
	6	16410	16625.808	6467	6251.192	22877
	7	13528	13986.368	6857	6398.632	20385
	8	15712	15673.326	7896	7934.674	23608
	9	14783	14618.805	8747	8911.195	23530
	10	11512	11242.865	9923	10192.135	21435

Classification Table[a]

			Predicted		
			Foster Care Services		
	Observed		No	yes	Percentage Correct
Step 1	Foster Care Services	No	173320	2598	98.5
		yes	59089	2752	4.5
	Overall Percentage				74.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	baby	1.025	.031	1088.979	1	.000	2.787
	teen	.135	.019	52.320	1	.000	1.144
	physabs	.242	.021	128.370	1	.000	1.274
	neglect	.694	.019	1346.663	1	.000	2.002
	sexabs	-.015	.026	.342	1	.559	.985
	multiplemal	.284	.016	298.200	1	.000	1.328
	ChPrior	.578	.010	3126.360	1	.000	1.783
	Black_D	.165	.011	205.228	1	.000	1.179

	Other_D	.579	.018	994.850	1	.000	1.784
	Biodad	-.657	.016	1640.397	1	.000	.518
	PerOther	-.225	.014	270.137	1	.000	.798
	BothParents	.915	.019	2232.728	1	.000	2.497
	BabyNeglect	-.500	.032	249.077	1	.000	.607
	Babyphysabs	-.137	.034	16.721	1	.000	.872
	Teenphysabs	-.093	.041	5.228	1	.022	.911
	Constant	-1.980	.020	10029.396	1	.000	.138

a. Variable(s) entered on step 1: BabyNeglect, Babyphysabs, Teenphysabs.

Block 4: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1620.036	2	.000
	Block	1620.036	2	.000
	Model	16558.379	17	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	255989.984[a]	.067	.099

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	72.924	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Foster Care Services = No		Foster Care Services = yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	21727	21598.912	2050	2178.088	23777
	2	20718	20539.710	3058	3236.290	23776
	3	19627	19666.175	4145	4105.825	23772
	4	18773	18921.515	5006	4857.485	23779
	5	18409	18290.018	5371	5489.982	23780
	6	17219	17532.167	6580	6266.833	23799
	7	16493	16652.837	7289	7129.163	23782
	8	15856	15778.404	7918	7995.596	23774
	9	14553	14677.945	9223	9098.055	23776
	10	12543	12260.318	11201	11483.682	23744

Classification Table[a]

			Predicted		
			Foster Care Services		
	Observed		No	yes	Percentage Correct
Step 1	Foster Care Services	No	172455	3463	98.0
		yes	57961	3880	6.3
	Overall Percentage				74.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	baby	1.011	.031	1057.146	1	.000	2.749
	teen	.128	.019	46.892	1	.000	1.137
	physabs	.314	.021	213.554	1	.000	1.369
	neglect	.752	.019	1556.955	1	.000	2.121
	sexabs	.051	.026	3.893	1	.048	1.053
	multiplemal	.277	.017	281.045	1	.000	1.319
	ChPrior	.542	.010	2707.747	1	.000	1.719
	Black_D	.195	.012	285.081	1	.000	1.216
	Other_D	.531	.018	826.035	1	.000	1.701

	Biodad	-.698	.016	1826.120	1	.000	.498
	PerOther	-.229	.014	275.819	1	.000	.796
	BothParents	.962	.019	2437.321	1	.000	2.617
	BabyNeglect	-.492	.032	240.353	1	.000	.612
	Babyphysabs	-.083	.034	6.112	1	.013	.920
	Teenphysabs	-.104	.041	6.433	1	.011	.901
	Poverty	-1.428	.107	176.467	1	.000	.240
	ERate	.100	.003	1045.851	1	.000	1.105
	Constant	-2.182	.036	3600.535	1	.000	.113

a. Variable(s) entered on step 1: Poverty, ERate.

Block 5: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	7219.961	31	.000
	Block	7219.961	31	.000
	Model	23778.340	48	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	248770.022[a]	.095	.140

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	33.292	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Foster Care Services = No		Foster Care Services = yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	22011	21901.003	1767	1876.997	23778
	2	20848	20837.049	2928	2938.951	23776

3	19466	19398.942	3564	3631.058	23030
4	19533	19466.460	4427	4493.540	23960
5	18532	18592.866	5257	5196.134	23789
6	17575	17839.521	6213	5948.479	23788
7	16788	16919.809	6957	6825.191	23745
8	15947	15890.579	7861	7917.421	23808
9	14492	14367.866	9285	9409.134	23777
10	10726	10703.903	13582	13604.097	24308

Classification Table[a]

	Observed		Predicted: Foster Care Services No	yes	Percentage Correct
Step 1	Foster Care Services	No	169374	6544	96.3
		yes	52092	9749	15.8
	Overall Percentage				75.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	baby	1.061	.032	1121.850	1	.000	2.890
	teen	.130	.019	46.201	1	.000	1.139
	physabs	.263	.023	128.205	1	.000	1.301
	neglect	.789	.021	1412.436	1	.000	2.201
	sexabs	-.078	.028	8.099	1	.004	.925
	multiplemal	.378	.019	396.586	1	.000	1.459
	ChPrior	.533	.011	2237.175	1	.000	1.704
	Black_D	.183	.012	231.738	1	.000	1.201
	Other_D	.380	.020	352.716	1	.000	1.462
	Biodad	-.689	.017	1686.253	1	.000	.502
	PerOther	-.202	.014	206.260	1	.000	.817
	BothParents	.963	.020	2338.224	1	.000	2.620
	BabyNeglect	-.519	.032	257.684	1	.000	.595
	Babyphysabs	-.062	.034	3.208	1	.073	.940
	Teenphysabs	-.096	.042	5.320	1	.021	.908

	Poverty	-5.098	.309	272.725	1	.000	.006
	ERate	.166	.116	2.072	1	.150	1.181
	state			7067.016	31	.000	
	state(1)	.751	.097	59.622	1	.000	2.119
	state(2)	1.454	.071	423.177	1	.000	4.281
	state(3)	.102	.212	.232	1	.630	1.108
	state(4)	-.369	.116	10.176	1	.001	.692
	state(5)	.318	.122	6.861	1	.009	1.375
	state(6)	1.569	.251	39.189	1	.000	4.801
	state(7)	2.062	.100	426.551	1	.000	7.859
	state(8)	-.435	.573	.575	1	.448	.647
	state(9)	.763	.093	67.956	1	.000	2.145
	state(10)	.472	.164	8.268	1	.004	1.603
	state(11)	1.172	.196	35.750	1	.000	3.229
	state(12)	.295	.238	1.528	1	.216	1.343
	state(13)	-.260	.063	17.249	1	.000	.771
	state(14)	.225	.099	5.192	1	.023	1.253
	state(15)	.627	.234	7.191	1	.007	1.871
	state(16)	1.141	.240	22.658	1	.000	3.131
	state(17)	1.064	.072	220.948	1	.000	2.897
	state(18)	.131	.490	.071	1	.790	1.140
	state(19)	1.394	.123	128.738	1	.000	4.030
	state(20)	.971	.325	8.927	1	.003	2.642
	state(21)	1.015	.208	23.903	1	.000	2.760
	state(22)	.936	.083	128.366	1	.000	2.551
	state(23)	.232	.065	12.581	1	.000	1.261
	state(24)	.153	.274	.313	1	.576	1.166
	state(25)	.758	.194	15.230	1	.000	2.133
	state(26)	1.384	.280	24.361	1	.000	3.992
	state(27)	.645	.250	6.635	1	.010	1.906
	state(28)	.450	.311	2.095	1	.148	1.569
	state(29)	.632	.329	3.687	1	.055	1.882
	state(30)	1.272	.070	331.095	1	.000	3.567
	state(31)	.999	.561	3.172	1	.075	2.717
	Constant	-2.244	.522	18.490	1	.000	.106

Classification Table[a]

	Observed		Predicted: Foster Care Services: No	Predicted: Foster Care Services: yes	Percentage Correct
Step 1	Foster Care Services	No	169374	6544	96.3
		yes	52092	9749	15.8
	Overall Percentage				75.3

a. Variable(s) entered on step 1: state.

APPENDIX B: FIRST CLASSIFICATION OF MULTILEVEL MODEL

Specifications for this Bernoulli HLM2 run

Problem Title: Final Model specified with State*Year as Level 2

The data source for this run = LR 3-11-13.mdm
The command file for this run = C:\thesis\HLM final models\3-10-13\FinalModel3-11b.hlm
Output file name = C:\thesis\HLM final models\3-10-13\Model8.html
The maximum number of level-1 units = 236365
The maximum number of level-2 units = 128
The maximum number of micro iterations = 14

Method of estimation: full maximum likelihood via EM-Laplace 2
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is FOSTERCR

Summary of the model specified

Level-1 Model

$\text{Prob}(FOSTERCR_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(BABY_{ij}) + \beta_{2j}*(TEEN_{ij}) + \beta_{3j}*(PHYSABS_{ij}) + \beta_{4j}*(NEGLECT_{ij}) + \beta_{5j}*(SEXABS_{ij}) + \beta_{6j}*(CHPRIOR_{ij}) + \beta_{7j}*(BLACK\_D_{ij}) + \beta_{8j}*(OTHER\_D_{ij}) + \beta_{9j}*(BIODAD_{ij}) + \beta_{10j}*(PEROTHER_{ij}) + \beta_{11j}*(BOTHPARE_{ij}) + \beta_{12j}*(BABYNEGL_{ij})$

Level-2 Model

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(ERATE_j) + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30}$

$\beta_{4j} = \gamma_{40}$

$\beta_{5j} = \gamma_{50}$

$\beta_{6j} = \gamma_{60}$

$\beta_{7j} = \gamma_{70}$

$\beta_{8j} = \gamma_{80}$

$\beta_{9j} = \gamma_{90}$
$\beta_{10j} = \gamma_{100}$
$\beta_{11j} = \gamma_{110}$
$\beta_{12j} = \gamma_{120}$

ERATE has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$

Mixed Model

$\eta_{ij} = \gamma_{00} + \gamma_{01}*ERATE_j$
$+ \gamma_{10}*BABY_{ij}$
$+ \gamma_{20}*TEEN_{ij}$
$+ \gamma_{30}*PHYSABS_{ij}$
$+ \gamma_{40}*NEGLECT_{ij}$
$+ \gamma_{50}*SEXABS_{ij}$
$+ \gamma_{60}*CHPRIOR_{ij}$
$+ \gamma_{70}*BLACK\_D_{ij}$
$+ \gamma_{80}*OTHER\_D_{ij}$
$+ \gamma_{90}*BIODAD_{ij}$
$+ \gamma_{100}*PEROTHER_{ij}$
$+ \gamma_{110}*BOTHPARE_{ij}$
$+ \gamma_{120}*BABYNEGL_{ij}$
$+ u_{0j}$

The value of the log-likelihood function at iteration 5 = -1.292933E+005

Results for Non-linear Model with the Logit Link Function Unit-Specific Model, PQL Estimation - (macro iteration 5)

τ
INTRCPT1,β_0 0.37849

Standard error of τ
INTRCPT1,β_0 0.04847

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.976

The value of the log-likelihood function at iteration 2 = -3.353387E+005

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					

INTRCPT2, γ_{00}	-1.853535	0.057925	-31.999	126	<0.001
ERATE, γ_{01}	0.134504	0.027840	4.831	126	<0.001
For BABY slope, β_1					
INTRCPT2, γ_{10}	1.069156	0.025660	41.666	236225	<0.001
For TEEN slope, β_2					
INTRCPT2, γ_{20}	0.108866	0.017316	6.287	236225	<0.001
For PHYSABS slope, β_3					
INTRCPT2, γ_{30}	0.464451	0.016143	28.770	236225	<0.001
For NEGLECT slope, β_4					
INTRCPT2, γ_{40}	0.995559	0.017887	55.658	236225	<0.001
For SEXABS slope, β_5					
INTRCPT2, γ_{50}	0.137201	0.025234	5.437	236225	<0.001
For CHPRIOR slope, β_6					
INTRCPT2, γ_{60}	0.546143	0.011383	47.979	236225	<0.001
For BLACK_D slope, β_7					
INTRCPT2, γ_{70}	0.182438	0.012073	15.111	236225	<0.001
For OTHER_D slope, β_8					
INTRCPT2, γ_{80}	0.392325	0.020236	19.388	236225	<0.001
For BIODAD slope, β_9					
INTRCPT2, γ_{90}	-0.666649	0.016784	-39.718	236225	<0.001
For PEROTHER slope, β_{10}					
INTRCPT2, γ_{100}	-0.192458	0.014214	-13.540	236225	<0.001
For BOTHPARE slope, β_{11}					
INTRCPT2, γ_{110}	0.970140	0.019951	48.627	236225	<0.001
For BABYNEGL slope, β_{12}					
INTRCPT2, γ_{120}	-0.530015	0.028340	-18.702	236225	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.853535	0.156682	(0.140,0.176)
ERATE, γ_{01}	0.134504	1.143969	(1.083,1.209)
For BABY slope, β_1			
INTRCPT2, γ_{10}	1.069156	2.912921	(2.770,3.063)
For TEEN slope, β_2			
INTRCPT2, γ_{20}	0.108866	1.115013	(1.078,1.154)
For PHYSABS slope, β_3			
INTRCPT2, γ_{30}	0.464451	1.591140	(1.542,1.642)
For NEGLECT slope, β_4			
INTRCPT2, γ_{40}	0.995559	2.706235	(2.613,2.803)
For SEXABS slope, β_5			

INTRCPT2, γ_{50}	0.137201	1.147059	(1.092,1.205)
For CHPRIOR slope, β_6			
INTRCPT2, γ_{60}	0.546143	1.726580	(1.688,1.766)
For BLACK_D slope, β_7			
INTRCPT2, γ_{70}	0.182438	1.200140	(1.172,1.229)
For OTHER_D slope, β_8			
INTRCPT2, γ_{80}	0.392325	1.480419	(1.423,1.540)
For BIODAD slope, β_9			
INTRCPT2, γ_{90}	-0.666649	0.513426	(0.497,0.531)
For PEROTHER slope, β_{10}			
INTRCPT2, γ_{100}	-0.192458	0.824929	(0.802,0.848)
For BOTHPARE slope, β_{11}			
INTRCPT2, γ_{110}	0.970140	2.638314	(2.537,2.744)
For BABYNEGL slope, β_{12}			
INTRCPT2, γ_{120}	-0.530015	0.588596	(0.557,0.622)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.853535	0.073760	-25.129	126	<0.001
ERATE, γ_{01}	0.134504	0.026835	5.012	126	<0.001
For BABY slope, β_1					
INTRCPT2, γ_{10}	1.069156	0.066606	16.052	236225	<0.001
For TEEN slope, β_2					
INTRCPT2, γ_{20}	0.108866	0.031016	3.510	236225	<0.001
For PHYSABS slope, β_3					
INTRCPT2, γ_{30}	0.464451	0.033658	13.799	236225	<0.001
For NEGLECT slope, β_4					
INTRCPT2, γ_{40}	0.995559	0.044006	22.623	236225	<0.001
For SEXABS slope, β_5					
INTRCPT2, γ_{50}	0.137201	0.050997	2.690	236225	0.007
For CHPRIOR slope, β_6					
INTRCPT2, γ_{60}	0.546143	0.047864	11.410	236225	<0.001
For BLACK_D slope, β_7					
INTRCPT2, γ_{70}	0.182438	0.022796	8.003	236225	<0.001
For OTHER_D slope, β_8					
INTRCPT2, γ_{80}	0.392325	0.029934	13.106	236225	<0.001
For BIODAD slope, β_9					

INTRCPT2, γ_{90}	-0.666649	0.034948	-19.076	236225	<0.001
For PEROTHER slope, β_{10}					
INTRCPT2, γ_{100}	-0.192458	0.044365	-4.338	236225	<0.001
For BOTHPARE slope, β_{11}					
INTRCPT2, γ_{110}	0.970140	0.057513	16.868	236225	<0.001
For BABYNEGL slope, β_{12}					
INTRCPT2, γ_{120}	-0.530015	0.071551	-7.408	236225	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.853535	0.156682	(0.135,0.181)
ERATE, γ_{01}	0.134504	1.143969	(1.085,1.206)
For BABY slope, β_1			
INTRCPT2, γ_{10}	1.069156	2.912921	(2.556,3.319)
For TEEN slope, β_2			
INTRCPT2, γ_{20}	0.108866	1.115013	(1.049,1.185)
For PHYSABS slope, β_3			
INTRCPT2, γ_{30}	0.464451	1.591140	(1.490,1.700)
For NEGLECT slope, β_4			
INTRCPT2, γ_{40}	0.995559	2.706235	(2.483,2.950)
For SEXABS slope, β_5			
INTRCPT2, γ_{50}	0.137201	1.147059	(1.038,1.268)
For CHPRIOR slope, β_6			
INTRCPT2, γ_{60}	0.546143	1.726580	(1.572,1.896)
For BLACK_D slope, β_7			
INTRCPT2, γ_{70}	0.182438	1.200140	(1.148,1.255)
For OTHER_D slope, β_8			
INTRCPT2, γ_{80}	0.392325	1.480419	(1.396,1.570)
For BIODAD slope, β_9			
INTRCPT2, γ_{90}	-0.666649	0.513426	(0.479,0.550)
For PEROTHER slope, β_{10}			
INTRCPT2, γ_{100}	-0.192458	0.824929	(0.756,0.900)
For BOTHPARE slope, β_{11}			
INTRCPT2, γ_{110}	0.970140	2.638314	(2.357,2.953)
For BABYNEGL slope, β_{12}			
INTRCPT2, γ_{120}	-0.530015	0.588596	(0.512,0.677)

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	0.61522	0.37849	126	11323.84249	<0.001

Results for Unit-Specific Model, EM Laplace-2 Estimation Iteration 3

τ
INTRCPT1,β_0 0.37952

Standard error of τ
INTRCPT1,β_0 0.06622

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.976

The log-likelihood at EM Laplace-2 iteration 3 is -3.411069E+005

Final estimation of fixed effects (Unit-specific model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.854267	0.074437	-24.911	126	<0.001
ERATE, γ_{01}	0.134527	0.031274	4.302	126	<0.001
For BABY slope, β_1					
INTRCPT2, γ_{10}	1.069821	0.017954	59.588	236225	<0.001
For TEEN slope, β_2					
INTRCPT2, γ_{20}	0.108930	0.014024	7.767	236225	<0.001
For PHYSABS slope, β_3					
INTRCPT2, γ_{30}	0.464673	0.012125	38.325	236225	<0.001
For NEGLECT slope, β_4					
INTRCPT2, γ_{40}	0.996128	0.011616	85.757	236225	<0.001
For SEXABS slope, β_5					
INTRCPT2, γ_{50}	0.137169	0.018896	7.259	236225	<0.001
For CHPRIOR slope, β_6					
INTRCPT2, γ_{60}	0.546456	0.004039	135.284	236225	<0.001
For BLACK_D slope, β_7					
INTRCPT2, γ_{70}	0.182543	0.007539	24.212	236225	<0.001
For OTHER_D slope, β_8					
INTRCPT2, γ_{80}	0.392653	0.018475	21.253	236225	<0.001
For BIODAD slope, β_9					
INTRCPT2, γ_{90}	-0.667044	0.011459	-58.210	236225	<0.001
For PEROTHER slope, β_{10}					

INTRCPT2, γ_{100}	-0.192546	0.008684	-22.173	236225	<0.001
For BOTHPARE slope, β_{11}					
INTRCPT2, γ_{110}	0.970757	0.012163	79.813	236225	<0.001
For BABYNEGL slope, β_{12}					
INTRCPT2, γ_{120}	-0.530355	0.017594	-30.144	236225	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.854267	0.156568	(0.135,0.181)
ERATE, γ_{01}	0.134527	1.143995	(1.075,1.217)
For BABY slope, β_1			
INTRCPT2, γ_{10}	1.069821	2.914856	(2.814,3.019)
For TEEN slope, β_2			
INTRCPT2, γ_{20}	0.108930	1.115084	(1.085,1.146)
For PHYSABS slope, β_3			
INTRCPT2, γ_{30}	0.464673	1.591494	(1.554,1.630)
For NEGLECT slope, β_4			
INTRCPT2, γ_{40}	0.996128	2.707776	(2.647,2.770)
For SEXABS slope, β_5			
INTRCPT2, γ_{50}	0.137169	1.147021	(1.105,1.190)
For CHPRIOR slope, β_6			
INTRCPT2, γ_{60}	0.546456	1.727122	(1.714,1.741)
For BLACK_D slope, β_7			
INTRCPT2, γ_{70}	0.182543	1.200266	(1.183,1.218)
For OTHER_D slope, β_8			
INTRCPT2, γ_{80}	0.392653	1.480905	(1.428,1.536)
For BIODAD slope, β_9			
INTRCPT2, γ_{90}	-0.667044	0.513223	(0.502,0.525)
For PEROTHER slope, β_{10}			
INTRCPT2, γ_{100}	-0.192546	0.824856	(0.811,0.839)
For BOTHPARE slope, β_{11}			
INTRCPT2, γ_{110}	0.970757	2.639942	(2.578,2.704)
For BABYNEGL slope, β_{12}			
INTRCPT2, γ_{120}	-0.530355	0.588396	(0.568,0.609)

Statistics for the current model
Deviance = 682213.884822
Number of estimated parameters = 15

Results for Population-Average Model

The value of the log-likelihood function at iteration 3 = -3.163455E+005

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.748477	0.057533	-30.391	126	<0.001
ERATE, γ_{01}	0.130165	0.027870	4.670	126	<0.001
For BABY slope, β_1					
INTRCPT2, γ_{10}	1.010205	0.023632	42.748	236225	<0.001
For TEEN slope, β_2					
INTRCPT2, γ_{20}	0.102521	0.015865	6.462	236225	<0.001
For PHYSABS slope, β_3					
INTRCPT2, γ_{30}	0.440796	0.015036	29.317	236225	<0.001
For NEGLECT slope, β_4					
INTRCPT2, γ_{40}	0.946283	0.016295	58.072	236225	<0.001
For SEXABS slope, β_5					
INTRCPT2, γ_{50}	0.128917	0.022952	5.617	236225	<0.001
For CHPRIOR slope, β_6					
INTRCPT2, γ_{60}	0.511935	0.010505	48.730	236225	<0.001
For BLACK_D slope, β_7					
INTRCPT2, γ_{70}	0.171123	0.011153	15.344	236225	<0.001
For OTHER_D slope, β_8					
INTRCPT2, γ_{80}	0.365914	0.019177	19.081	236225	<0.001
For BIODAD slope, β_9					
INTRCPT2, γ_{90}	-0.626621	0.014977	-41.840	236225	<0.001
For PEROTHER slope, β_{10}					
INTRCPT2, γ_{100}	-0.180279	0.012932	-13.940	236225	<0.001
For BOTHPARE slope, β_{11}					
INTRCPT2, γ_{110}	0.909474	0.018150	50.108	236225	<0.001
For BABYNEGL slope, β_{12}					
INTRCPT2, γ_{120}	-0.506039	0.026261	-19.270	236225	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.748477	0.174039	(0.155,0.195)
ERATE, γ_{01}	0.130165	1.139016	(1.078,1.204)

For BABY slope, β_1			
INTRCPT2, γ_{10}	1.010205	2.746164	(2.622,2.876)
For TEEN slope, β_2			
INTRCPT2, γ_{20}	0.102521	1.107960	(1.074,1.143)
For PHYSABS slope, β_3			
INTRCPT2, γ_{30}	0.440796	1.553944	(1.509,1.600)
For NEGLECT slope, β_4			
INTRCPT2, γ_{40}	0.946283	2.576116	(2.495,2.660)
For SEXABS slope, β_5			
INTRCPT2, γ_{50}	0.128917	1.137595	(1.088,1.190)
For CHPRIOR slope, β_6			
INTRCPT2, γ_{60}	0.511935	1.668516	(1.635,1.703)
For BLACK_D slope, β_7			
INTRCPT2, γ_{70}	0.171123	1.186637	(1.161,1.213)
For OTHER_D slope, β_8			
INTRCPT2, γ_{80}	0.365914	1.441831	(1.389,1.497)
For BIODAD slope, β_9			
INTRCPT2, γ_{90}	-0.626621	0.534395	(0.519,0.550)
For PEROTHER slope, β_{10}			
INTRCPT2, γ_{100}	-0.180279	0.835037	(0.814,0.856)
For BOTHPARE slope, β_{11}			
INTRCPT2, γ_{110}	0.909474	2.483017	(2.396,2.573)
For BABYNEGL slope, β_{12}			
INTRCPT2, γ_{120}	-0.506039	0.602879	(0.573,0.635)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.748477	0.069583	-25.128	126	<0.001
ERATE, γ_{01}	0.130165	0.026223	4.964	126	<0.001
For BABY slope, β_1					
INTRCPT2, γ_{10}	1.010205	0.056866	17.765	236225	<0.001
For TEEN slope, β_2					
INTRCPT2, γ_{20}	0.102521	0.025889	3.960	236225	<0.001
For PHYSABS slope, β_3					
INTRCPT2, γ_{30}	0.440796	0.029189	15.101	236225	<0.001
For NEGLECT slope, β_4					

INTRCPT2, γ_{40}	0.946283	0.036941	25.616	236225	<0.001
For SEXABS slope, β_5					
INTRCPT2, γ_{50}	0.128917	0.042616	3.025	236225	0.002
For CHPRIOR slope, β_6					
INTRCPT2, γ_{60}	0.511935	0.042523	12.039	236225	<0.001
For BLACK_D slope, β_7					
INTRCPT2, γ_{70}	0.171123	0.019280	8.876	236225	<0.001
For OTHER_D slope, β_8					
INTRCPT2, γ_{80}	0.365914	0.027043	13.531	236225	<0.001
For BIODAD slope, β_9					
INTRCPT2, γ_{90}	-0.626621	0.027667	-22.649	236225	<0.001
For PEROTHER slope, β_{10}					
INTRCPT2, γ_{100}	-0.180279	0.036939	-4.880	236225	<0.001
For BOTHPARE slope, β_{11}					
INTRCPT2, γ_{110}	0.909474	0.049776	18.271	236225	<0.001
For BABYNEGL slope, β_{12}					
INTRCPT2, γ_{120}	-0.506039	0.061057	-8.288	236225	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.748477	0.174039	(0.152,0.200)
ERATE, γ_{01}	0.130165	1.139016	(1.081,1.200)
For BABY slope, β_1			
INTRCPT2, γ_{10}	1.010205	2.746164	(2.457,3.070)
For TEEN slope, β_2			
INTRCPT2, γ_{20}	0.102521	1.107960	(1.053,1.166)
For PHYSABS slope, β_3			
INTRCPT2, γ_{30}	0.440796	1.553944	(1.468,1.645)
For NEGLECT slope, β_4			
INTRCPT2, γ_{40}	0.946283	2.576116	(2.396,2.770)
For SEXABS slope, β_5			
INTRCPT2, γ_{50}	0.128917	1.137595	(1.046,1.237)
For CHPRIOR slope, β_6			
INTRCPT2, γ_{60}	0.511935	1.668516	(1.535,1.814)
For BLACK_D slope, β_7			
INTRCPT2, γ_{70}	0.171123	1.186637	(1.143,1.232)
For OTHER_D slope, β_8			
INTRCPT2, γ_{80}	0.365914	1.441831	(1.367,1.520)
For BIODAD slope, β_9			

INTRCPT2, γ_{90}	-0.626621	0.534395	(0.506,0.564)
For PEROTHER slope, β_{10}			
INTRCPT2, γ_{100}	-0.180279	0.835037	(0.777,0.898)
For BOTHPARE slope, β_{11}			
INTRCPT2, γ_{110}	0.909474	2.483017	(2.252,2.737)
For BABYNEGL slope, β_{12}			
INTRCPT2, γ_{120}	-0.506039	0.602879	(0.535,0.680)

APPENDIX C: SECOND CLASSIFICATION OF MULTILEVEL MODEL

Specifications for this Bernoulli HLM2 run

Problem Title: Model Classified with State only at Level 2

Specifications for this Bernoulli HLM2 run

Problem Title: FinalModel2

The data source for this run = C:\thesis\HLM final models\3-10-13\FileforSTATEonly2.mdm
The command file for this run = C:\thesis\HLM final models\3-10-13\FinalModel2 3-13-13.hlm
Output file name = C:\thesis\HLM final models\3-10-13\hlm2FinalModel2.html
The maximum number of level-1 units = 236365
The maximum number of level-2 units = 32
The maximum number of micro iterations = 14

Method of estimation: full maximum likelihood via EM-Laplace 2
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is FOSTERCR

Summary of the model specified

Level-1 Model

$\text{Prob}(FOSTERCR_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(YEAR_{ij}) + \beta_{2j}*(BABY_{ij}) + \beta_{3j}*(TEEN_{ij}) + \beta_{4j}*(PHYSABS_{ij}) + \beta_{5j}*(NEGLECT_{ij}) + \beta_{6j}*(SEXABS_{ij}) + \beta_{7j}*(CHPRIOR_{ij}) + \beta_{8j}*(BLACK\_D_{ij}) + \beta_{9j}*(OTHER\_D_{ij}) + \beta_{10j}*(BIODAD_{ij}) + \beta_{11j}*(PEROTHER_{ij}) + \beta_{12j}*(BOTHPARE_{ij}) + \beta_{13j}*(BABYNEGL_{ij})$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20}$

$\beta_{3j} = \gamma_{30}$
$\beta_{4j} = \gamma_{40}$
$\beta_{5j} = \gamma_{50}$
$\beta_{6j} = \gamma_{60}$
$\beta_{7j} = \gamma_{70}$
$\beta_{8j} = \gamma_{80}$
$\beta_{9j} = \gamma_{90}$
$\beta_{10j} = \gamma_{100}$
$\beta_{11j} = \gamma_{110}$
$\beta_{12j} = \gamma_{120}$
$\beta_{13j} = \gamma_{130}$

YEAR has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$

Mixed Model

$\eta_{ij} = \gamma_{00}$
$+ \gamma_{10}*YEAR_{ij}$
$+ \gamma_{20}*BABY_{ij}$
$+ \gamma_{30}*TEEN_{ij}$
$+ \gamma_{40}*PHYSABS_{ij}$
$+ \gamma_{50}*NEGLECT_{ij}$
$+ \gamma_{60}*SEXABS_{ij}$
$+ \gamma_{70}*CHPRIOR_{ij}$
$+ \gamma_{80}*BLACK\_D_{ij}$
$+ \gamma_{90}*OTHER\_D_{ij}$
$+ \gamma_{100}*BIODAD_{ij}$
$+ \gamma_{110}*PEROTHER_{ij}$
$+ \gamma_{120}*BOTHPARE_{ij}$
$+ \gamma_{130}*BABYNEGL_{ij}$
$+ u_{0j}$

The value of the log-likelihood function at iteration 4 = -1.293677E+005

Results for Non-linear Model with the Logit Link Function Unit-Specific Model, PQL Estimation - (macro iteration 5)

τ
INTRCPT1,β_0 0.42714

Standard error of τ
INTRCPT1,β_0 0.10736

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.995

The value of the log-likelihood function at iteration 2 = -3.352217E+005

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.834424	0.117226	-15.649	31	<0.001
For YEAR slope, β_1					
INTRCPT2, γ_{10}	-0.077369	0.004551	-17.001	236320	<0.001
For BABY slope, β_2					
INTRCPT2, γ_{20}	1.069481	0.025638	41.714	236320	<0.001
For TEEN slope, β_3					
INTRCPT2, γ_{30}	0.109586	0.017298	6.335	236320	<0.001
For PHYSABS slope, β_4					
INTRCPT2, γ_{40}	0.464294	0.016109	28.823	236320	<0.001
For NEGLECT slope, β_5					
INTRCPT2, γ_{50}	0.993086	0.017867	55.583	236320	<0.001
For SEXABS slope, β_6					
INTRCPT2, γ_{60}	0.137176	0.025181	5.448	236320	<0.001
For CHPRIOR slope, β_7					
INTRCPT2, γ_{70}	0.536375	0.011284	47.534	236320	<0.001
For BLACK_D slope, β_8					
INTRCPT2, γ_{80}	0.181113	0.012056	15.022	236320	<0.001
For OTHER_D slope, β_9					
INTRCPT2, γ_{90}	0.386494	0.020235	19.100	236320	<0.001
For BIODAD slope, β_{10}					
INTRCPT2, γ_{100}	-0.669817	0.016752	-39.984	236320	<0.001
For PEROTHER slope, β_{11}					
INTRCPT2, γ_{110}	-0.187774	0.014057	-13.358	236320	<0.001
For BOTHPARE slope, β_{12}					
INTRCPT2, γ_{120}	0.974932	0.019909	48.969	236320	<0.001
For BABYNEGL slope, β_{13}					
INTRCPT2, γ_{130}	-0.533854	0.028311	-18.857	236320	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.834424	0.159706	(0.126,0.203)
For YEAR slope, β_1			
INTRCPT2, γ_{10}	-0.077369	0.925548	(0.917,0.934)
For BABY slope, β_2			

INTRCPT2, γ_{20}	1.069481	2.913866	(2.771,3.064)
For TEEN slope, β_3			
INTRCPT2, γ_{30}	0.109586	1.115817	(1.079,1.154)
For PHYSABS slope, β_4			
INTRCPT2, γ_{40}	0.464294	1.590891	(1.541,1.642)
For NEGLECT slope, β_5			
INTRCPT2, γ_{50}	0.993086	2.699552	(2.607,2.796)
For SEXABS slope, β_6			
INTRCPT2, γ_{60}	0.137176	1.147030	(1.092,1.205)
For CHPRIOR slope, β_7			
INTRCPT2, γ_{70}	0.536375	1.709798	(1.672,1.748)
For BLACK_D slope, β_8			
INTRCPT2, γ_{80}	0.181113	1.198550	(1.171,1.227)
For OTHER_D slope, β_9			
INTRCPT2, γ_{90}	0.386494	1.471812	(1.415,1.531)
For BIODAD slope, β_{10}			
INTRCPT2, γ_{100}	-0.669817	0.511802	(0.495,0.529)
For PEROTHER slope, β_{11}			
INTRCPT2, γ_{110}	-0.187774	0.828802	(0.806,0.852)
For BOTHPARE slope, β_{12}			
INTRCPT2, γ_{120}	0.974932	2.650988	(2.550,2.756)
For BABYNEGL slope, β_{13}			
INTRCPT2, γ_{130}	-0.533854	0.586341	(0.555,0.620)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.834424	0.143662	-12.769	31	<0.001
For YEAR slope, β_1					
INTRCPT2, γ_{10}	-0.077369	0.015561	-4.972	236320	<0.001
For BABY slope, β_2					
INTRCPT2, γ_{20}	1.069481	0.121148	8.828	236320	<0.001
For TEEN slope, β_3					
INTRCPT2, γ_{30}	0.109586	0.051067	2.146	236320	0.032
For PHYSABS slope, β_4					
INTRCPT2, γ_{40}	0.464294	0.052075	8.916	236320	<0.001
For NEGLECT slope, β_5					

INTRCPT2, γ_{50}	0.993086	0.074289	13.368	236320	<0.001
For SEXABS slope, β_6					
INTRCPT2, γ_{60}	0.137176	0.080329	1.708	236320	0.088
For CHPRIOR slope, β_7					
INTRCPT2, γ_{70}	0.536375	0.090536	5.924	236320	<0.001
For BLACK_D slope, β_8					
INTRCPT2, γ_{80}	0.181113	0.037239	4.864	236320	<0.001
For OTHER_D slope, β_9					
INTRCPT2, γ_{90}	0.386494	0.044417	8.701	236320	<0.001
For BIODAD slope, β_{10}					
INTRCPT2, γ_{100}	-0.669817	0.043421	-15.426	236320	<0.001
For PEROTHER slope, β_{11}					
INTRCPT2, γ_{110}	-0.187774	0.078708	-2.386	236320	0.017
For BOTHPARE slope, β_{12}					
INTRCPT2, γ_{120}	0.974932	0.087117	11.191	236320	<0.001
For BABYNEGL slope, β_{13}					
INTRCPT2, γ_{130}	-0.533854	0.131532	-4.059	236320	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.834424	0.159706	(0.119,0.214)
For YEAR slope, β_1			
INTRCPT2, γ_{10}	-0.077369	0.925548	(0.898,0.954)
For BABY slope, β_2			
INTRCPT2, γ_{20}	1.069481	2.913866	(2.298,3.695)
For TEEN slope, β_3			
INTRCPT2, γ_{30}	0.109586	1.115817	(1.010,1.233)
For PHYSABS slope, β_4			
INTRCPT2, γ_{40}	0.464294	1.590891	(1.437,1.762)
For NEGLECT slope, β_5			
INTRCPT2, γ_{50}	0.993086	2.699552	(2.334,3.123)
For SEXABS slope, β_6			
INTRCPT2, γ_{60}	0.137176	1.147030	(0.980,1.343)
For CHPRIOR slope, β_7			
INTRCPT2, γ_{70}	0.536375	1.709798	(1.432,2.042)
For BLACK_D slope, β_8			
INTRCPT2, γ_{80}	0.181113	1.198550	(1.114,1.289)
For OTHER_D slope, β_9			
INTRCPT2, γ_{90}	0.386494	1.471812	(1.349,1.606)

For BIODAD slope, β_{10}			
INTRCPT2, γ_{100}	-0.669817	0.511802	(0.470,0.557)
For PEROTHER slope, β_{11}			
INTRCPT2, γ_{110}	-0.187774	0.828802	(0.710,0.967)
For BOTHPARE slope, β_{12}			
INTRCPT2, γ_{120}	0.974932	2.650988	(2.235,3.145)
For BABYNEGL slope, β_{13}			
INTRCPT2, γ_{130}	-0.533854	0.586341	(0.453,0.759)

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	0.65356	0.42714	31	13923.73557	<0.001

Results for Unit-Specific Model, EM Laplace-2 Estimation Iteration 2

τ

INTRCPT1,β_0 0.42751

Standard error of τ

INTRCPT1,β_0 0.17758

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.995

The log-likelihood at EM Laplace-2 iteration 2 is -3.412143E+005

Final estimation of fixed effects (Unit-specific model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.834607	0.196302	-9.346	31	<0.001
For YEAR slope, β_1					
INTRCPT2, γ_{10}	-0.077381	0.002036	-37.998	236320	<0.001
For BABY slope, β_2					
INTRCPT2, γ_{20}	1.069650	0.015689	68.180	236320	<0.001
For TEEN slope, β_3					
INTRCPT2, γ_{30}	0.109604	0.016130	6.795	236320	<0.001
For PHYSABS slope, β_4					
INTRCPT2, γ_{40}	0.464351	0.012284	37.801	236320	<0.001
For NEGLECT slope, β_5					

INTRCPT2, γ_{50}	0.993229	0.010784	92.101	236320	<0.001
For SEXABS slope, β_6					
INTRCPT2, γ_{60}	0.137170	0.022050	6.221	236320	<0.001
For CHPRIOR slope, β_7					
INTRCPT2, γ_{70}	0.536453	0.003197	167.816	236320	<0.001
For BLACK_D slope, β_8					
INTRCPT2, γ_{80}	0.181138	0.006591	27.482	236320	<0.001
For OTHER_D slope, β_9					
INTRCPT2, γ_{90}	0.386576	0.022485	17.193	236320	<0.001
For BIODAD slope, β_{10}					
INTRCPT2, γ_{100}	-0.669919	0.015474	-43.294	236320	<0.001
For PEROTHER slope, β_{11}					
INTRCPT2, γ_{110}	-0.187796	0.013208	-14.219	236320	<0.001
For BOTHPARE slope, β_{12}					
INTRCPT2, γ_{120}	0.975090	0.019243	50.671	236320	<0.001
For BABYNEGL slope, β_{13}					
INTRCPT2, γ_{130}	-0.533941	0.017702	-30.163	236320	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.834607	0.159676	(0.107,0.238)
For YEAR slope, β_1			
INTRCPT2, γ_{10}	-0.077381	0.925537	(0.922,0.929)
For BABY slope, β_2			
INTRCPT2, γ_{20}	1.069650	2.914358	(2.826,3.005)
For TEEN slope, β_3			
INTRCPT2, γ_{30}	0.109604	1.115836	(1.081,1.152)
For PHYSABS slope, β_4			
INTRCPT2, γ_{40}	0.464351	1.590981	(1.553,1.630)
For NEGLECT slope, β_5			
INTRCPT2, γ_{50}	0.993229	2.699940	(2.643,2.758)
For SEXABS slope, β_6			
INTRCPT2, γ_{60}	0.137170	1.147023	(1.099,1.198)
For CHPRIOR slope, β_7			
INTRCPT2, γ_{70}	0.536453	1.709932	(1.699,1.721)
For BLACK_D slope, β_8			
INTRCPT2, γ_{80}	0.181138	1.198581	(1.183,1.214)
For OTHER_D slope, β_9			
INTRCPT2, γ_{90}	0.386576	1.471933	(1.408,1.538)

For BIODAD slope, β_{10}			
INTRCPT2, γ_{100}	-0.669919	0.511750	(0.496,0.528)
For PEROTHER slope, β_{11}			
INTRCPT2, γ_{110}	-0.187796	0.828784	(0.808,0.851)
For BOTHPARE slope, β_{12}			
INTRCPT2, γ_{120}	0.975090	2.651406	(2.553,2.753)
For BABYNEGL slope, β_{13}			
INTRCPT2, γ_{130}	-0.533941	0.586290	(0.566,0.607)

Statistics for the current model

Deviance = 682428.554222

Number of estimated parameters = 15

Results for Population-Average Model

The value of the log-likelihood function at iteration 3 = -3.133461E+005

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.709501	0.117022	-14.608	31	<0.001
For YEAR slope, β_1					
INTRCPT2, γ_{10}	-0.071368	0.004137	-17.252	236320	<0.001
For BABY slope, β_2					
INTRCPT2, γ_{20}	0.994845	0.023352	42.602	236320	<0.001
For TEEN slope, β_3					
INTRCPT2, γ_{30}	0.101474	0.015601	6.504	236320	<0.001
For PHYSABS slope, β_4					
INTRCPT2, γ_{40}	0.432393	0.014857	29.103	236320	<0.001
For NEGLECT slope, β_5					
INTRCPT2, γ_{50}	0.932590	0.016051	58.100	236320	<0.001
For SEXABS slope, β_6					
INTRCPT2, γ_{60}	0.128878	0.022388	5.757	236320	<0.001
For CHPRIOR slope, β_7					
INTRCPT2, γ_{70}	0.495822	0.010325	48.023	236320	<0.001
For BLACK_D slope, β_8					
INTRCPT2, γ_{80}	0.166743	0.010963	15.210	236320	<0.001
For OTHER_D slope, β_9					
INTRCPT2, γ_{90}	0.355384	0.019074	18.632	236320	<0.001
For BIODAD slope, β_{10}					
INTRCPT2, γ_{100}	-0.625215	0.014729	-42.447	236320	<0.001
For PEROTHER slope, β_{11}					

INTRCPT2, γ_{110}	-0.173745	0.012576	-13.816	236320	<0.001
For BOTHPARE slope, β_{12}					
INTRCPT2, γ_{120}	0.902867	0.017874	50.512	236320	<0.001
For BABYNEGL slope, β_{13}					
INTRCPT2, γ_{130}	-0.503171	0.025970	-19.375	236320	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.709501	0.180956	(0.143,0.230)
For YEAR slope, β_1			
INTRCPT2, γ_{10}	-0.071368	0.931120	(0.924,0.939)
For BABY slope, β_2			
INTRCPT2, γ_{20}	0.994845	2.704304	(2.583,2.831)
For TEEN slope, β_3			
INTRCPT2, γ_{30}	0.101474	1.106801	(1.073,1.141)
For PHYSABS slope, β_4			
INTRCPT2, γ_{40}	0.432393	1.540940	(1.497,1.586)
For NEGLECT slope, β_5			
INTRCPT2, γ_{50}	0.932590	2.541082	(2.462,2.622)
For SEXABS slope, β_6			
INTRCPT2, γ_{60}	0.128878	1.137551	(1.089,1.189)
For CHPRIOR slope, β_7			
INTRCPT2, γ_{70}	0.495822	1.641848	(1.609,1.675)
For BLACK_D slope, β_8			
INTRCPT2, γ_{80}	0.166743	1.181451	(1.156,1.207)
For OTHER_D slope, β_9			
INTRCPT2, γ_{90}	0.355384	1.426728	(1.374,1.481)
For BIODAD slope, β_{10}			
INTRCPT2, γ_{100}	-0.625215	0.535146	(0.520,0.551)
For PEROTHER slope, β_{11}			
INTRCPT2, γ_{110}	-0.173745	0.840511	(0.820,0.861)
For BOTHPARE slope, β_{12}			
INTRCPT2, γ_{120}	0.902867	2.466665	(2.382,2.555)
For BABYNEGL slope, β_{13}			
INTRCPT2, γ_{130}	-0.503171	0.604610	(0.575,0.636)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	-1.709501	0.137185	-12.461	31	<0.001
For YEAR slope, β_1					
INTRCPT2, γ_{10}	-0.071368	0.012962	-5.506	236320	<0.001
For BABY slope, β_2					
INTRCPT2, γ_{20}	0.994845	0.095037	10.468	236320	<0.001
For TEEN slope, β_3					
INTRCPT2, γ_{30}	0.101474	0.041131	2.467	236320	0.014
For PHYSABS slope, β_4					
INTRCPT2, γ_{40}	0.432393	0.045931	9.414	236320	<0.001
For NEGLECT slope, β_5					
INTRCPT2, γ_{50}	0.932590	0.063399	14.710	236320	<0.001
For SEXABS slope, β_6					
INTRCPT2, γ_{60}	0.128878	0.067937	1.897	236320	0.058
For CHPRIOR slope, β_7					
INTRCPT2, γ_{70}	0.495822	0.078184	6.342	236320	<0.001
For BLACK_D slope, β_8					
INTRCPT2, γ_{80}	0.166743	0.029675	5.619	236320	<0.001
For OTHER_D slope, β_9					
INTRCPT2, γ_{90}	0.355384	0.039977	8.890	236320	<0.001
For BIODAD slope, β_{10}					
INTRCPT2, γ_{100}	-0.625215	0.033648	-18.581	236320	<0.001
For PEROTHER slope, β_{11}					
INTRCPT2, γ_{110}	-0.173745	0.064583	-2.690	236320	0.007
For BOTHPARE slope, β_{12}					
INTRCPT2, γ_{120}	0.902867	0.085228	10.594	236320	<0.001
For BABYNEGL slope, β_{13}					
INTRCPT2, γ_{130}	-0.503171	0.108258	-4.648	236320	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	-1.709501	0.180956	(0.137,0.239)
For YEAR slope, β_1			
INTRCPT2, γ_{10}	-0.071368	0.931120	(0.908,0.955)
For BABY slope, β_2			
INTRCPT2, γ_{20}	0.994845	2.704304	(2.245,3.258)
For TEEN slope, β_3			

INTRCPT2, γ_{30}	0.101474	1.106801	(1.021,1.200)
For PHYSABS slope, β_4			
INTRCPT2, γ_{40}	0.432393	1.540940	(1.408,1.686)
For NEGLECT slope, β_5			
INTRCPT2, γ_{50}	0.932590	2.541082	(2.244,2.877)
For SEXABS slope, β_6			
INTRCPT2, γ_{60}	0.128878	1.137551	(0.996,1.300)
For CHPRIOR slope, β_7			
INTRCPT2, γ_{70}	0.495822	1.641848	(1.409,1.914)
For BLACK_D slope, β_8			
INTRCPT2, γ_{80}	0.166743	1.181451	(1.115,1.252)
For OTHER_D slope, β_9			
INTRCPT2, γ_{90}	0.355384	1.426728	(1.319,1.543)
For BIODAD slope, β_{10}			
INTRCPT2, γ_{100}	-0.625215	0.535146	(0.501,0.572)
For PEROTHER slope, β_{11}			
INTRCPT2, γ_{110}	-0.173745	0.840511	(0.741,0.954)
For BOTHPARE slope, β_{12}			
INTRCPT2, γ_{120}	0.902867	2.466665	(2.087,2.915)
For BABYNEGL slope, β_{13}			
INTRCPT2, γ_{130}	-0.503171	0.604610	(0.489,0.748)

APPENDIX D: SPSS SYNTAX FOR DATA TRANSFORMATIONS AND FILE PREPARATION

*Prior to this syntax, I did the following to create a sample:

From 2005 through 2010 Child Files, I selected only the IDs, then I identifed those children with only one record, and saved them out as Unduplicated.

* Then I saved out those with more than one report, and randomly selected a report within each ID group. Then I merged these back into the Unduplicated file, with a final merged sample from 05 to 10. Then I matched these IDs back into the original full Child Files to get the whole records.

* Then I did some analysis and discovered that I only have AFCARS IDs for 2007 forward. So I deleted 2005 and 2006 from my sample. This syntax begins with that sample file.

```
****.

GET

  FILE='C:\thesis\Sample 2-1-13\Child2007to2010_Unduplicatedsample2-12-13.sav'.

DATASET NAME DataSet15 WINDOW=FRONT.

*Run some initial descriptives to analyze variables.


do if staterr="AK" or staterr="CA" or staterr="HI" or staterr="MI".

recode FosterCr (9=2).

end if.

do if staterr="MI" or staterr="NE" or staterr="NJ" .

recode FosterCr (0=2).

end if.

exe.


select if staterr ne "GA".

sel if staterr ne "NY".

sel if staterr ne "NC".
```

```
sel if staterr ne "AL".
sel if staterr ne "AZ".
sel if staterr ne "DC".
sel if staterr ne "IL".
sel if staterr ne "IN".
sel if staterr ne "MD".
sel if staterr ne "ND".
sel if staterr ne "OK".
sel if staterr ne "OR".
sel if staterr ne "PA".
sel if staterr ne "PR".
sel if staterr ne "WA".
sel if staterr ne "DE".
sel if staterr ne "MT".
sel if staterr ne "VT".
exe.

*Clean up missing data and 0's.
recode FosterCr (9=sysmis) (0=sysmis).
exe.
recode FosterCr (2=0).
exe.
value labels FosterCr
0 'No'
1 'Yes'.
exe.

CROSSTABS
```

```
  /TABLES=Year BY FosterCr
  /FORMAT=AVALUE TABLES
  /CELLS=COUNT ROW
  /COUNT ROUND CELL.

do if Rptdt ge date.mdy(10,01,2004) and Rptdt le date.mdy(09,30,2005).
compute Year=2005.
end if.
do if Rptdt ge date.mdy(10,01,2005) and Rptdt le date.mdy(09,30,2006).
compute Year=2006.
end if.
do if Rptdt ge date.mdy(10,01,2006) and Rptdt le date.mdy(09,30,2007).
compute Year=2007.
end if.
do if Rptdt ge date.mdy(10,01,2007) and Rptdt le date.mdy(09,30,2008).
compute Year=2008.
end if.
do if Rptdt ge date.mdy(10,01,2008) and Rptdt le date.mdy(09,30,2009).
compute Year=2009.
end if.
do if Rptdt ge date.mdy(10,01,2009) and Rptdt le date.mdy(09,30,2010).
compute Year=2010.
end if.
exe.

*Select only Victims.
select if IsVictim=1.
EXECUTE.
```

```
*Since TN and UT only have AFCARS IDs for 2007 and 2008 but not 2009 or 2010, remove them.
sel if staterr ne "TN".
sel if staterr ne "UT".
EXECUTE.

Select if Year ge 2007.
exe.

iF  ( staterr = "AL") staterr_num=1.
IF  ( staterr = "AK") staterr_num=2.
IF  ( staterr = "AZ") staterr_num=4.
IF  ( staterr = "AR") staterr_num=5.
IF  ( staterr = "CA") staterr_num=6.
IF  ( staterr = "CO") staterr_num=8.
IF  ( staterr = "CT") staterr_num=9.
IF  ( staterr = "DE") staterr_num=10.
IF  ( staterr = "DC") staterr_num=11.
IF  ( staterr = "FL") staterr_num=12.
IF  ( staterr = "GA") staterr_num=13.
IF  ( staterr = "HI") staterr_num=15.
IF  ( staterr = "ID") staterr_num=16.
IF  ( staterr = "IL") staterr_num=17.
IF  ( staterr = "IN") staterr_num=18.
IF  ( staterr = "IA") staterr_num=19.
IF  ( staterr = "KS") staterr_num=20.
IF  ( staterr = "KY") staterr_num=21.
IF  ( staterr = "LA") staterr_num=22.
```

```
IF  ( staterr = "ME") staterr_num=23.
IF  ( staterr = "MD") staterr_num=24.
IF  ( staterr = "MA") staterr_num=25.
IF  ( staterr = "MI") staterr_num=26.
IF  ( staterr = "MN") staterr_num=27.
IF  ( staterr = "MS") staterr_num=28.
IF  ( staterr = "MO") staterr_num=29.
IF  ( staterr = "MT") staterr_num=30.
IF  ( staterr = "NE") staterr_num=31.
IF  ( staterr = "NV") staterr_num=32.
IF  ( staterr = "NH") staterr_num=33.
IF  ( staterr = "NJ") staterr_num=34.
IF  ( staterr = "NM") staterr_num=35.
IF  ( staterr = "NY") staterr_num=36.
IF  ( staterr = "NC") staterr_num=37.
IF  ( staterr = "ND") staterr_num=38.
IF  ( staterr = "OH") staterr_num=39.
IF  ( staterr = "OK") staterr_num=40.
IF  ( staterr = "OR") staterr_num=41.
IF  ( staterr = "PA") staterr_num=42.
IF  ( staterr = "RI") staterr_num=44.
IF  ( staterr = "SC") staterr_num=45.
IF  ( staterr = "SD") staterr_num=46.
IF  ( staterr = "TN") staterr_num=47.
IF  ( staterr = "TX") staterr_num=48.
IF  ( staterr = "UT") staterr_num=49.
IF  ( staterr = "VT") staterr_num=50.
IF  ( staterr = "VA") staterr_num=51.
```

```
IF  ( staterr = "WA") staterr_num=53.
IF  ( staterr = "WV") staterr_num=54.
IF  ( staterr = "WI") staterr_num=55.
IF  ( staterr = "WY") staterr_num=56.
IF  ( staterr = "PR") staterr_num=72.
variable labels  staterr_num 'State (numeric)'.
formats staterr_num (F2.0).
execute.

**************************************************
LABEL STATE IDs WITH STATE NAMES
**************************************************.
value labels
 /staterr_num
  01     "Alabama  "
  02    "Alaska  "
  04     "Arizona  "
  05       "Arkansas  "
  06       "California  "
  08       "Colorado  "
  09       "Connecticut  "
  10       "Delaware  "
  11       "District of Columbia  "
  12       "Florida  "
  13       "Georgia  "
  15       "Hawaii  "
  16       "Idaho  "
  17       "Illinois  "
```

18 "Indiana "

19 "Iowa "

20 "Kansas "

21 "Kentucky "

22 "Louisiana "

23 "Maine "

24 "Maryland "

25 "Massachusetts "

26 "Michigan "

27 "Minnesota "

28 "Mississippi "

29 "Missouri "

30 "Montana "

31 "Nebraska "

32 "Nevada "

33 "New Hampshire "

34 "New Jersey "

35 "New Mexico "

36 "New York "

37 "North Carolina "

38 "North Dakota "

39 "Ohio "

40 "Oklahoma "

41 "Oregon "

42 "Pennsylvania "

44 "Rhode Island "

45 "South Carolina "

46 "South Dakota "

```
  47      "Tennessee  "

  48      "Texas  "

  49      "Utah  "

  50      "Vermont  "

  51      "Virginia  "

  53      "Washington  "

  54      "West Virginia  "

  55      "Wisconsin  "

  56      "Wyoming  "

  72      "Puerto Rico  ".

execute.


fre staterr.

*I have 32 states.


*Save a pared down file.

sort cases by staterr_num AFCARSID ChID.

SAVE OUTFILE='C:\thesis\Sample 2-1-13\Child2007to2010_FinalSample2-12-13.sav'

  /DROP=SubYr RptID RptCnty RptFIPS InvDate Notifs ChMil MalDeath JuvPet PetDate CoChRep
Adopt

    CaseMang Counsel Daycare Educatn Employ FamPlan Health Homebase Housing TransLiv InfoRef
Legal

    MentHlth PregPar Respite SSDisabl SSDelinq SubAbuse Transprt OtherSv Per1ID Per2ID Per2Mil
Per3ID

    IsVictim after after2

  /COMPRESSED.
```

```
GET
  FILE='C:\thesis\Sample 2-1-13\FC_Rem_5-10.sav'.
DATASET NAME DataSet2 WINDOW=FRONT.

*****************************************************
CONVERT RECNUMBR TO NUMERIC
*****************************************************
* ... and make it unique across entire file.
* HLM requires numeric IDs..

string statestring (A2).
compute statestring = STRING(state, F2.0).
execute.
string recnumbr2 (A26).
compute recnumbr2=concat(statestring,AFCARSID).
execute.
autorecode VARIABLES=recnumbr2
  /INTO ChildID.
value labels ChildID.
delete variables statestring recnumbr2.

*****************************************************
FIND AND DELETE DUPLICATE RECORDS.
*****************************************************

* [Using AL, AK, and HI as a test, results of dedupping based on original string recnumbr vs. the numeric
ChildID were identical].
```

```
* [Due to DQ problems with TotalRem, we may still end up with duplicate cases that need to be deleted.

* For example, a child may be reported twice in the same file - everything is identical same except for some reason

* the TotalRem value.]


set workspace 200000.


SORT CASES BY State(A) ChildID(A) TotalRem(A).

MATCH FILES

  /FILE=*

  /BY State ChildID TotalRem

  /FIRST=PrimaryFirst

  /LAST=PrimaryLast.

DO IF (PrimaryFirst).

COMPUTE  MatchSequence=1-PrimaryLast.

ELSE.

COMPUTE  MatchSequence=MatchSequence+1.

END IF.

LEAVE  MatchSequence.

FORMAT  MatchSequence (f7).

COMPUTE  InDupGrp=MatchSequence>0.

SORT CASES InDupGrp(D).

MATCH FILES

  /FILE=*

  /DROP=PrimaryFirst InDupGrp.

VARIABLE LABELS  PrimaryLast 'Indicator of each last matching case as Primary' MatchSequence

    'Sequential count of matching cases'.

VALUE LABELS  PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.

VARIABLE LEVEL  PrimaryLast (ORDINAL) /MatchSequence (SCALE).
```

```
FREQUENCIES VARIABLES=PrimaryLast MatchSequence.
execute.

* Retain a record of how many records we deleted (PrimaryLast = 0) due to duplicates.
CROSSTABS
  /TABLES=state BY PrimaryLast
  /FORMAT=AVALUE TABLES
  /CELLS=COUNT ROW
  /COUNT ROUND CELL.

* Keep only the unique (non-duplicate cases).
select if PrimaryLast=1.
execute.

set WORKSPACE 6200.

rename var state=staterr_num.
sort cases by staterr_num AFCARSID.

*Need to remove all duplicates or the match won't work correctly-keep most recent FC record so it's more
likely to follow the malt report..

* Identify Duplicate Cases.
SORT CASES BY staterr_num(A) ChildID(A) TotalRem(A).
MATCH FILES
  /FILE=*
  /BY staterr_num ChildID
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
```

```
DO IF (PrimaryFirst).
COMPUTE  MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE  MatchSequence=MatchSequence+1.
END IF.
LEAVE  MatchSequence.
FORMATS  MatchSequence (f7).
COMPUTE  InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS  PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS  PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL  PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.

select if PrimaryLast=1.
exe.

sort cases by staterr_num AFCARSID.

SAVE OUTFILE='C:\thesis\Sample 2-1-13\FC_Rem_5-10undup.sav'
  /COMPRESSED.
```

```
GET
  FILE='C:\thesis\Sample 2-1-13\Child2007to2010_Unduplicatedsample2-12-13.sav'.
DATASET NAME CFsample WINDOW=FRONT.

*Run the section above that converts state abb to staterr_num.

sort cases by staterr_num AFCARSID Year.

SAVE OUTFILE='C:\thesis\CMSamplesorted.sav'
  /COMPRESSED.

DATASET ACTIVATE CFsample.
MATCH FILES /FILE=*
  /FILE='C:\thesis\Sample 2-1-13\FC_Rem_5-10undup.sav'
  /RENAME (DataYear = d0)
  /BY Staterr_num AFCARSID
  /DROP= d0.
EXECUTE.

sel if staterr gt " ".
exe.

do if (FosterCr ne 1) and (Latremdt ge rptdt).
compute add=1.
end if.
EXECUTE.
fre staterr.
```

```
if add=1 fostercr=1.

exe.


*check records to see how long after report date the child may be placed in foster care, using AFCARS removal field.

 * compute FCYear=xdate.year(LatRemDt).

 * EXECUTE.


do if LatRemDt ge date.mdy(10,01,2004) and LatRemDt le date.mdy(09,30,2005).

compute FCYear=2005.

end if.

do if LatRemDt ge date.mdy(10,01,2005) and LatRemDt le date.mdy(09,30,2006).

compute FCYear=2006.

end if.

do if LatRemDt ge date.mdy(10,01,2006) and LatRemDt le date.mdy(09,30,2007).

compute FCYear=2007.

end if.

do if LatRemDt ge date.mdy(10,01,2007) and LatRemDt le date.mdy(09,30,2008).

compute FCYear=2008.

end if.

do if LatRemDt ge date.mdy(10,01,2008) and LatRemDt le date.mdy(09,30,2009).

compute FCYear=2009.

end if.

do if LatRemDt ge date.mdy(10,01,2009) and LatRemDt le date.mdy(09,30,2010).

compute FCYear=2010.

end if.

exe.
```

```
compute diffyears=(FCYear-Year).

EXECUTE.

fre diffyears.

temp.

sel if add=1.

fre diffyears.


*Since almost 6% of the "corrected" foster care records were placed 3 years or more after the report, I will
recode these back to NOT receiving foster care, since too much time has elapsed to say this was related to
this report. Limiting it to within 2 years.

cross fostercr by year.

do if (add=1 and diffyears gt 2 and missing(rmvdate) and fostercr=1).

compute fostercr=0.

end if.

exe.


SAVE OUTFILE='C:\thesis\Sample 2-1-13\CMSamplewAFCARS 2-16-13.sav'

  /COMPRESSED.

*Run Data Transformations and Compute variables.


* recode chage into a single variable holding the predetermined age groups.

recode chage (0 eq 1) (1 thru 3 eq 2) (4 thru 7 eq 3) (8 thru 11 eq 4)

(12 thru 15 eq 5) (16 thru 17 eq 6)

into chagegrp.
```

```
*Add value labels to 'chagegrp' for categorizing children by age group.
add val lab chagegrp
1 ' <1'
2 '1-3'
3 '4-7'
4 '8-11'
5 '12-15'
6 '16-17' .

*Recode age into 3 categories.
 compute baby=0.
if chage lt 2 baby=1.
compute teen=0.
if chage gt 14 teen=1.
compute kid=0.
if chage ge 2 and chage le 14 kid=1.
exe.

if missing(chage) baby=$sysmis.
if missing(chage) kid=$sysmis.
if missing(chage) teen=$sysmis.
exe.

*create unique ID for state and year.

rename var staterr_num=state.
compute StateYR=state*year.
exe.
```

```
*****************************************************************.

* Create variables to identify maltreatment victims by maltreatment type.


* Create a variable called 'flvictim' to flag all victims of maltreatment. UNNECSSARY..IsVictim already
exists and it's the same.


 * compute flvictim = 0.

 * if (mal1lev >= 1 and mal1lev <=3) flvictim = 1.

 * if (mal2lev >= 1 and mal2lev <=3) flvictim = 1.

 * if (mal3lev >= 1 and mal3lev <=3) flvictim = 1.

 * if (mal4lev >= 1 and mal4lev <=3) flvictim = 1.

 * if (maldeath eq 1) flvictim = 1.

* Obtain frequency counts on the flag variable.

 * var labels flvictim 'Child a Victim'.

 * freq flvictim.


* Create variables for maltreatment type.

* Physical Abuse.

compute physabs = 0.

if ((chmal1 eq 1) and mal1lev >= 1 and mal1lev <=3) physabs = 1.

if ((chmal2 eq 1) and mal2lev >= 1 and mal2lev <=3) physabs = 1.

if ((chmal3 eq 1) and mal3lev >= 1 and mal3lev <=3) physabs = 1.

if ((chmal4 eq 1) and mal4lev >= 1 and mal4lev <=3) physabs = 1.

var labels physabs 'Child Victim of Physical Abuse'.

*freq physabs.


* Neglect.

compute neglect = 0.
```

```
if ((chmal1 eq 2) and mal1lev >= 1 and mal1lev <=3) neglect = 1.
if ((chmal2 eq 2) and mal2lev >= 1 and mal2lev <=3) neglect = 1.
if ((chmal3 eq 2) and mal3lev >= 1 and mal3lev <=3) neglect = 1.
if ((chmal4 eq 2) and mal4lev >= 1 and mal4lev <=3) neglect = 1.
var labels neglect 'Child Victim of Neglect' .
*crosstabs tables isVictim by physabs neglect.

*Sexual Abuse.
compute sexabs = 0.
if ((chmal1 eq 4) and mal1lev >= 1 and mal1lev <=3) sexabs = 1.
if ((chmal2 eq 4) and mal2lev >= 1 and mal2lev <=3) sexabs = 1.
if ((chmal3 eq 4) and mal3lev >= 1 and mal3lev <=3) sexabs = 1.
if ((chmal4 eq 4) and mal4lev >= 1 and mal4lev <=3) sexabs = 1.
var labels sexabs 'Child Victim of Sexual Abuse' .
*crosstabs tables isVictim by physabs neglect sexabs.

*Medical Neglect.
 * compute medneglect = 0.
 * if ((chmal1 eq 3) and mal1lev >= 1 and mal1lev <=3) medneglect = 1.
 * if ((chmal2 eq 3) and mal2lev >= 1 and mal2lev <=3) medneglect = 1.
 * if ((chmal3 eq 3) and mal3lev >= 1 and mal3lev <=3) medneglect = 1.
 * if ((chmal4 eq 3) and mal4lev >= 1 and mal4lev <=3) medneglect = 1.
 * var labels medneglect 'Child Victim of Medical Neglect' .
*crosstabs tables isVictim by physabs neglect sexabs medneglect.

 * compute emoabs=0.
 * if ((chmal1 eq 5) and mal1lev >= 1 and mal1lev <=3) emoabs = 1.
 * if ((chmal2 eq 5) and mal2lev >= 1 and mal2lev <=3) emoabs = 1.
```

```
 * if ((chmal3 eq 5) and mal3lev >= 1 and mal3lev <=3) emoabs = 1.

 * if ((chmal4 eq 5) and mal4lev >= 1 and mal4lev <=3) emoabs = 1.

 * var labels emoabs 'Child Victim of Emotional Abuse' .

* crosstabs tables isVictim by physabs neglect sexabs medneglect emoabs.


*Other Maltreatment type (Medical Neglect, Emotional Abuse, Other).

compute otherabs = 0.

if ((chmal1 eq 3 or chmal1 eq 5 or chmal1 eq 8) and mal1lev >= 1 and mal1lev <=3) otherabs = 1.

if ((chmal2 eq 3 or chmal2 eq 5 or chmal2 eq 8) and mal2lev >= 1 and mal2lev <=3) otherabs = 1.

if ((chmal3 eq 3 or chmal3 eq 5 or chmal3 eq 8) and mal3lev >= 1 and mal3lev <=3) otherabs = 1.

if ((chmal4 eq 3 or chmal4 eq 5 or chmal4 eq 8) and mal4lev >= 1 and mal4lev <=3) otherabs = 1.

var labels otherabs 'Child Victim of Other Abuse' .

*crosstabs tables isVictim by physabs neglect sexabs otherabs.


compute multiplemal=0.

if sum(physabs + neglect + sexabs + otherabs) ge 2 multiplemal=1.

EXECUTE.

*crosstabs tables isVictim by multiplemal.


*Consolidate Child Disabilities/Conditions into one Field.


compute ChDis=0.

do if missing(CdAlc) and missing(CdDrug ) and missing(CdRtrd) and missing(CdEmotnl) and
missing(CdVisual) and missing(CdLearn) and missing(CdPhys)

and missing(CdBehav) and missing(CdMedicl).

compute ChDis=99.

end if.

do if CdAlc=9 and CdDrug=9 and CdRtrd=9 and CdEmotnl=9 and CdVisual=9 and CdLearn=9 and
CdPhys=9 and CdBehav=9 and CdMedicl=9.
```

```
compute ChDis=99.

end if.

do if chAgegrp=1 and (CdAlc=1 or CdDrug=1).

compute ChDis=1.

end if.

do if CdRtrd=1 or CdEmotnl=1 or CdVisual=1 or CdLearn=1 or CdPhys=1 or CdBehav=1 or CdMedicl=1.

compute ChDis=1.

end if.

exe.


*Caretaker Disability.

compute CrtkrDis=0.

do if missing(FCRtrd) and missing(FCEmotnl ) and missing(FCAlc) and missing(FCDrug) and
missing(FCVisual) and missing(FCLearn) and missing(FCPhys)

 and missing(FCMedicl).

compute CrtkrDis=99.

end if.

do if FCRtrd=9 and FCEmotnl=9 and FCAlc=9 and FCDrug=9 and FCVisual=9 and FCLearn=9 and
FCPhys=9 and FCMedicl=9.

compute CrtkrDis=99.

end if.

compute CrtkrSubAbs=0.

do if (FCAlc=1 or FCDrug=1).

compute CrtkrSubAbs=1.

end if.

do if (FCAlc=9 and FCdrug=9) or (missing(FCAlc) and missing(FCdrug)).

compute CrtkrSubAbs=99.

end if.

do if FCRtrd=1 or FCEmotnl=1 or FCVisual=1 or FCLearn=1 or FCPhys=1 or FCMedicl=1.
```

```
compute CrtkrDis=1.
end if.
exe.

compute CrtkrStrug=0.
if (FCHouse=1 or FCMoney=1 or FCPublic=1) CrtkrStrug=1.
exe.


*************************************************************************.
* Generate a variable to categorize reports by professional or non-
professional report source.

* Group all report/child pairs with same Report ID together. Select first in
list only.
 * sort cases by staterr rptid.
 * select if (rptid ne lag(rptid)).

compute rsrcprof = 2.
if (rptsrc le 7) rsrcprof = 1.
var labels rsrcprof 'Professional Status of Report Source'.
val labels rsrcprof
  1 'Professional'
  2 'Non-Professional'.
exe.
```

```
*Race ethnicity syntax.

recode
ChRacAI ChRacAs ChRacBl ChRacNH ChRacWh ChRacUd
(sysmis=0).
exe.
COUNT
  chrace = ChRacAI ChRacAs ChRacBl ChRacNH ChRacWh ChRacUd  (1).
EXECUTE.
do if (chrace=1 and ChRacAI=1).
compute race=3.
else if (chrace=1 and ChRacAs=1).
compute race=3.
else if (chrace=1 and ChRacBl=1).
compute race=2.
else if (chrace=1 and ChRacNH=1).
compute race=3.
else if (chrace=1 and ChRacWh=1).
compute race=1.
else if (chrace=1 and ChRacUd=1).
compute race=9.
else if (chrace>1).
compute race=3.
else if (chrace=0).
compute race=9.
end if.
formats race (f1.0).
value labels race
```

```
1'White'

2'Black'

3'Other'

9'Missing'.

exe.

 * recode

hisorgin

(sysmis=0).

*Create Dummy variables for modeling. Used "_D" to indicate dummy, but mainly to differentiate this variable name from the original.

compute White_D=0.

compute Black_D=0.

compute Other_D=0.

do if race=1.

compute White_D=1.

end if.

do if race=2.

compute Black_D=1.

end if.

do if race=3.

compute Other_D=1.

end if.

do if race=9.

RECODE White_D (ELSE=SYSMIS).

RECODE Black_D (ELSE=SYSMIS).

RECODE Other_D (ELSE=SYSMIS).

end if.

exe.

value labels White_D Black_D Other_D
```

```
0 'No'

1 'Yes'.

exe.


******************.

*Create a new variable to show whether the child/family received any of the following services:

Family Support Services, Family Preservation Services, Case Management Services, Counseling Services,
Day Care Services, Educational and Training Services,

Employment Services, Family Planning Services, Health-Related and Home Health Services, Home Based
Services, Housing Services, IL and Transitional Living services,

Info and Referral services, Legal services, mental health services, pregnancy/parenting services, respite
care services, special services-disabled,

special services-JD, substance abuse services, transportation services, other services.


recode  FamSup FamSup FamPres CaseMang Counsel Daycare Educatn Employ FamPlan Health
Homebase Housing TransLiv InfoRef Legal MentHlth Respite

SSDisabl SSDelinq SubAbuse Transprt OtherSv (sysmis=0) (9=0) (2=0).

count  services=FamSup FamSup FamPres CaseMang Counsel Daycare Educatn Employ FamPlan Health
Homebase Housing TransLiv InfoRef Legal MentHlth Respite

SSDisabl SSDelinq SubAbuse Transprt OtherSv (1).


recode services (1 thru highest=1).

EXECUTE.


**************************.

*Perpetrator relationship to victim.

*Recode so that you have Mother only, Father only, both parents, mother and other, father and other,
nonparental perp, perp relationship unknown.


compute Biomom=0.

compute Biodad=0.
```

```
compute PerOther=0.

compute BothParents=0.

if (Per1Prnt=1 and Per1Sex=1) or (Per2Prnt=1 and Per2Sex=1) or (Per3Prnt=1 and Per3Sex=1) Biodad=1.

if (Per1Prnt=1 and Per1Sex=2) or (Per2Prnt=1 and Per2Sex=2) or (Per3Prnt=1 and Per3Sex=2)
Biomom=1.

if (Per1Rel gt 1) and (Per1Rel ne 99) PerOther=1.

if (Per2Rel gt 1) and (Per2Rel ne 99) PerOther=1.

if (Per3Rel gt 1) and (Per3Rel ne 99) PerOther=1.


if Biodad=1 and Biomom=1 BothParents=1.

 * if PerBiodad=1 and PerBiomom=$sysmis and PerOther=$sysmis PerDadOnly=1.

 * if PerBiomom=1 and PerBiodad=$sysmis and PerOther=$sysmis PerMomOnly=1.

EXECUTE.


do if (Per1Rel=99 or missing(Per1Rel)) and ((Per2Rel ne 1) and (Per3Rel ne 1)).

compute Biomom=$sysmis.

compute Biodad=$sysmis.

compute BothParents=$sysmis.

compute PerOther=$sysmis.

end if.

exe.


RECODE chprior (0=SYSMIS) (1=1) (2=0) (9=SYSMIS).

EXECUTE.

fre chprior.

cross year by chprior.

RECODE chprior (99=SYSMIS).


value labels chprior
```

```
0 'No'
1 'Yes'.
exe.
fre chprior.

fre ChDis.
RECODE ChDis (99=SYSMIS).
EXECUTE.

fre chsex.

DATASET ACTIVATE DataSet1.
RECODE chsex (0=SYSMIS) (1=0) (2=1) (9=SYSMIS).
EXECUTE.
value labels chsex
0 'Male'
1 'Female'.
exe.

fre chsex.

rename var chsex=female.
exe.
```

```
*recode 99s to blank.


RECODE ChDis CrtkrDis CrtkrSubAbs CrtkrStrug rsrcprof multiplemal otherabs sexabs

   neglect physabs (99=SYSMIS).

EXECUTE.


*Make sex, race fields dummy variables by recoding 2's of no to 0, and 9's to sysmis.


 * RECODE chsex chracai chracas chracbl chracnh chracwh chracud cethn (2=0) (9=SYSMIS).

 * EXECUTE.


 * recode perbiomom perbothparents perbiodad (1=1) (SYSMIS=0).

 * exe.


SAVE OUTFILE='C:\thesis\Sample 2-1-13\FinalSample 2-16-13b.sav'

  /DROP=SubYr StaTerr RptID RptCnty RptFIPS RptDt InvDate RptSrc RptDisp RpDispDt Notifs
ChRacAI

   ChRacAs ChRacBl ChRacNH ChRacWh ChRacUd CEthn ChLvng ChMil ChMal1 Mal1Lev ChMal2
Mal2Lev

   ChMal3 Mal3Lev ChMal4 Mal4Lev MalDeath CdAlc CdDrug CdRtrd CdEmotnl CdVisual CdLearn
CdPhys CdBehav

   CdMedicl FCAlc FCDrug FCRtrd FCEmotnl FCVisual FCLearn FCPhys FCMedicl FCViol FCHouse
FCMoney

   FCPublic PostServ ServDate FamSup FamPres JuvPet PetDate CoChRep Adopt CaseMang Counsel
Daycare

   Educatn Employ FamPlan Health Homebase Housing TransLiv InfoRef Legal MentHlth PregPar Respite

   SSDisabl SSDelinq SubAbuse Transprt OtherSv Per1ID Per1Rel Per1Prnt Per1Cr Per1Age Per1Sex
P1RacAI

   P1RacAs P1RacBl P1RacNH P1RacWh P1RacUd Per1Ethn Per1Mil Per1Pior Per1Mal1 Per1Mal2
Per1Mal3
```

```
   Per1Mal4 Per2ID Per2Rel Per2Prnt Per2Cr Per2Age Per2Sex P2RacAI P2RacAs P2RacBl P2RacNH
P2RacWh

   P2RacUd Per2Ethn Per2Mil Per2Pior Per2Mal1 Per2Mal2 Per2Mal3 Per2Mal4 Per3ID Per3Rel
Per3Prnt

   Per3Cr Per3Age Per3Sex P3RacAI P3RacAs P3RacBl P3RacNH P3RacWh P3RacUd Per3Ethn Per3Mil
Per3Pior

   Per3Mal1 Per3Mal2 Per3Mal3 Per3Mal4 AFCARSID IsVictim after after2 LatRemDt ChildID
PrimaryLast add

   diffyears chrace

  /COMPRESSED.


**Prep files for single level Logistic Regression.


*Merge in the State level characterisitics (Poverty and Entry Rates).

sort cases by state year.


MATCH FILES /FILE=*

  /TABLE='C:\thesis\Level2data05-10 9-25-12.sav'

  /BY state Year.

EXECUTE.


SAVE OUTFILE='C:\thesis\FinalSample 2-16-13b withLvl2vars.sav'

  /COMPRESSED.


**Single level Logistic Regression.


GET

  FILE='C:\thesis\FinalSample 2-16-13b withLvl2vars.sav'.

DATASET NAME Sample WINDOW=FRONT.
```

```
* DATASET ACTIVATE Sample.

* LOGISTIC REGRESSION VARIABLES FosterCr

  /METHOD=ENTER Year baby teen female physabs sexabs neglect multiplemal chprior Black_D
Other_D Biodad

    PerOther BothParents Poverty ERate

  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

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