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# Understanding the Decline in Child Victimization: A National-and-State-Level Analysis of Child Abuse and Neglect Trends

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UNDERSTANDING THE DECLINE IN CHILD VICTIMIZATION: A NATIONAL-  
AND STATE-LEVEL ANALYSIS OF CHILD ABUSE AND NEGLECT TRENDS

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the University of Missouri – St. Louis in  
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## ABSTRACT

Figures from the National Child Abuse and Neglect Data System (NCANDS) suggest that national rates of child maltreatment declined during the last decade of the 20<sup>th</sup> century and into the 21<sup>st</sup> century. These data, which are derived from official state child protective service agency record systems, have frequently been used to measure changes in child abuse and neglect in the U.S. and in individual U.S. states. However, because the NCANDS has yet to be assessed for methodological issues surrounding the validity of the data to measure temporal change, it is unknown if the decline revealed in the NCANDS data reflects the true nature of the changes over time from 1990 to 2013 in the occurrence of child maltreatment. Using correlational and cointegration techniques, I find that child physical abuse and child sexual abuse rates at the national level are highly correlated in both level and trend with both national rates of child homicide and children exposed to violence in their home. I also find that most (though not all) states' rates in child maltreatment correspond to state rates in child homicide, and that these two child victimization trends are cointegrated, sharing a significant long-run equilibrium with one another. Once the NCANDS data validity concern has been addressed, this project also assesses how several competing hypotheses (e.g., greater economic prosperity, increased number of agents of social control, increased use of psychiatric medications, higher incarceration rates) might account for state-level variations in child maltreatment trends. Using panel regression models, these findings suggest that at least some of the declines in rates of child victimization over this period are real and not due to artificial declines based on policy and procedural changes over time. I find that various factors are significantly associated with rates of child victimization from 1990 to 2013, with particular factors better suited for explaining trends in certain types of child victimization. Policymakers should be aware of these relationships and recognize that macro-level declines in rates of child victimization may only be possible if these other macro-level conditions are also addressed.

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## CHAPTER ONE: INTRODUCTION

National figures from the National Child Abuse and Neglect Data System (NCANDS) suggest that rates of child abuse and neglect declined during the last decade of the twentieth century and into the twenty-first century. NCANDS rates, which are derived from official record systems of state child protective service (CPS) agencies<sup>1</sup> and have frequently been used to measure changes in child abuse and neglect in the U.S. and within U.S. states, reveal that roughly 15 per 1,000 children nationwide in the early- to mid-1990s were victims of child maltreatment (i.e., child abuse and/or neglect)—a figure more than 60% higher than the rate in 2013 (9.1 per 1,000 children) (U.S. Department of Health and Human Services, 2001, 2015). Although previous research has established this decline using both administrative and survey data (see, e.g., Finkelhor & Jones, 2012; Finkelhor, Saito, & Jones, 2015), few empirical studies have attempted to understand the downward trend in rates of child maltreatment over this period.

Of those scholars that have provided some insight into why national rates of child abuse and neglect may have declined post-1990, David Finkelhor and his colleagues at the University of New Hampshire's Crimes Against Children Research Center have offered the most compelling and comprehensive arguments. Using a variety of secondary sources, Finkelhor and Jones (2006) estimated that various forms of child victimization, including child physical abuse, sexual abuse, homicide, aggravated assault, robbery, and larceny declined between 40% to 70% from 1993 to 2004. A more recent study through 2013 observed national rates of child abuse declined even further (Finkelhor, Saito, & Jones, 2015). Over most of the same period (from 1990 until the early- to mid-2000s),

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<sup>1</sup> Throughout this dissertation, state agencies that deal with child welfare issues will be referred to as CPS agencies, regardless of what individual states formally call their individual state agency responsible for child welfare.

studies have found that significant improvements were also made across a variety of other child welfare indicators, especially measures of social and mental suffering (Land, Lamb, and Fu, 2016). Examples of these indicators include the rate of births to teenage mothers, high school completion rates, teen suicide, and children living in poverty (Finkelhor & Jones, 2006; Land, Lamb, & Fu, 2016).

Various scholars have noted, however, that epidemiological trends in a multitude of indicators of child harm have not simultaneously declined or declined to the same degree. While rates of child abuse declined nationally post-1990 according to NCANDS data (and rates of neglect remained largely stable), certain indicators of child harm (such as the rate of hospital admissions for young children with serious injuries due to physical abuse) actually increased over this same period (see, e.g., Farst, Ambadwar, King, Bird, & Robbins, 2013; Leventhal & Gaither, 2012; Wood et al., 2012).

These disagreements across indicators of child harm have scholars concerned that the decline revealed in the NCANDS data does not reflect the true nature of the changes over time in the occurrence of child abuse and/or neglect. And, because the NCANDS data have yet to be assessed for methodological issues surrounding the validity of the data to measure temporal change, a necessary feature of data used in time-series analyses, the NCANDS data have only been used sparingly, and largely in conjunction with other data sources within and across states and the U.S. to describe trends in child abuse and neglect.

This project investigates the validity of the NCANDS data for describing both national- and state-level changes in child abuse and neglect from 1990 to 2013. The first component (i.e., the measurement component) of the project assesses the NCANDS data

(national- and state-level rates of child physical abuse, child sexual abuse, and child neglect) by comparing them to national- and state-level rates of various other indicators of child victimization. This initial analysis attempts to establish whether the NCANDS data appear to be valid measures of national- and state-trends in the rates of child victimization. Because homicide data are the most reliable crime measure that criminologists have available (Mosher, Miethe, & Hart, 2011), trends in child homicide are used to assess how the NCANDS national- and state-level child maltreatment data are associated with the national- and state-level trends in child homicide.<sup>2</sup> The degree of correspondence between the NCANDS child abuse and neglect rates and child homicides rates is assessed to examine variation across the trends. In addition, the degree of correspondence among NCANDS national-level trends is also compared to a measure of

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<sup>2</sup> Although homicide rates have been found in previous research to be particularly reliable and consistent in level and trend between law enforcement and public health records (see, e.g., Regoeczi & Banks, 2014; Smith & Cooper, 2013), there have been a number of studies on the misclassification and underascertainment of child homicide, particularly child abuse homicide, in official public health records (Bethea, 1999; Crume, DiGuseppi, Byers, Sirotnak, & Garrett, 2002; Herman-Giddens, Brown, Verbiest, Carlson, Hooten, & Howell, 1999). For example, child deaths designated as of “undetermined intent” may likely prove to be intentional homicides after a more thorough investigation into the circumstances surrounding the death has been performed and evidence has been gathered and triangulated by public health, law enforcement, and social service officials (American Academy of Pediatrics, 2006; Bethea, 1999). As states began to invest more resources into the accurate ascertainment of child homicide over the past few decades, state child fatality review boards were formed and tasked with thoroughly investigating all child deaths or all child deaths with a suspicious aura surrounding them (e.g., deaths due to Sudden Infant Death Syndrome). Research suggests that this type of interagency collaboration and data collation processes to build more detailed files on suspicious child deaths has more accurately classified child homicides as homicides. These multi-agency, multi-disciplinary teams were first established at the local level in California in the late 1970s (see Durfee, Parra, & Alexander, 2009 for a detailed history of child fatality review teams in the U.S.). Throughout the 1980s, additional local child fatality review teams were established throughout the country. In 1990, Missouri became the first state to mandate the review of all deaths to children under the age 14. By 2005, child fatality review teams were established in 49 states (and all states by 2012). Because many child fatality review teams exist at both the state and local level (Christian & Sege, 2010; Durfee, Parra, & Alexander, 2009; National Center for Fatality Review and Prevention, no date), it is likely that state child homicide data have become more reliable over time. While the history of underreporting related to child homicide is important to note and should be considered when assessing the robustness of the child homicide rates, because previous research has established that rates of homicide are the most reliable crime measure that researchers have available, and over this period post-1990, both law enforcement and public health data have reported comparable rates of homicide and child homicide at the national level, I am confident using child homicide rates as the metric from which to test the external validity of NCANDS child maltreatment trends.

children's exposure to violence in the home from the National Crime Victimization Survey (NCVS). Cointegration of the state-level trends is also explored in order to assess how changes in NCANDS state-level rates respond to changes in state-level rates of child homicide. If strong relationships are found, one could argue that the NCANDS data are, in fact, reporting trends in child victimization that have been found in other more established and relied upon sources. This analysis could provide important information about whether (and where) the NCANDS has sufficient validity for studying national- and state-level trends in child victimization, specifically child abuse and neglect.

Over this period, little attention has also been paid to trends in child abuse and neglect at subnational levels. Highlighting this problem, the Committee on Child Maltreatment Research, Policy, and Practice—a panel under the auspices of the Institute of Medicine and the National Research Council within the National Academies of Sciences, Engineering, and Medicine—recently suggested the need for research comparing the rates of child abuse and neglect reporting and substantiation in states across several years, focusing on variation at the state level (Institute of Medicine, 2013, p. 8-24). Because national trends in the rates of child abuse and neglect are an aggregation of all 50 states' rates over time, it is important to examine the variability that exists within and across states over time in rates of child abuse and neglect. The first goal of the state-level analysis is to identify measurement issues and data inconsistencies in the state-specific trends and attempt to correct for them. The second goal of the state-level analysis of trends in rates of child abuse and neglect is to describe the variation that exists within and across states in rates of child abuse and neglect, and demonstrate how relevant state-level variations are to hypotheses about the national decline in child abuse

and neglect. Therefore, the second component of this study (i.e., the substantive component) exploits the availability of the NCANDS data at the state level to better understand child abuse and neglect over time by examining how various macro-level changes in specific hypothesized phenomena are related to state-level trends in child physical abuse, child sexual abuse, and child neglect.

A number of competing hypotheses identified in either the crime trends literature or by Finkelhor and colleagues have been proposed as explanations for why rates of child maltreatment declined post-1990. These hypotheses expound on how societal changes in various measures have potentially had the effect of lowering the rate of child maltreatment over time. These factors include, but are not limited to, changes in: economic conditions; the number of agents of social intervention; state agency-level practices and procedures; rates of incarceration; and the use of psychopharmacology (see, e.g., Finkelhor & Jones, 2006). Despite speculation among scholars that changes in these factors have likely led to declining rates of child abuse and neglect (Finkelhor & Jones, 2006), researchers have yet to directly test the significance of the proposed hypotheses. The substantive component of this project, therefore, aims to fill this gap by being the first to empirically assess these competing explanations for changes in the rates of child physical abuse, child sexual abuse, and child neglect from 1990 to 2013. To the extent that the results of this study explain why rates of abuse and neglect for children fell from 1990 to 2013, these findings have the potential to impact future policies related to child protective services at both the state and agency level. For example, they could likely fill an important gap in both criminological theory and criminal justice policy related to how changing social conditions and/or state-level policy decisions may have accounted for fluctuations in the rates of child abuse and neglect over time.

To establish when, where, and potentially why rates of child abuse and neglect declined from 1990 to 2013, this dissertation proceeds as follows. Chapter Two provides a review of the literature on national trends in child abuse and neglect. Particular attention is paid to the competing hypotheses proposed by various scholars concerning why rates of child maltreatment declined post-1990 and the important definitional and procedural issues that may exist due to the variation in how child maltreatment is defined and reported across states in the U.S. In Chapter Three, a summary of the current study is provided. This summary identifies the research questions that this dissertation addresses as well as how the study may contribute to the current state of research on child victimization and crime trends. Chapter Four introduces the data, measures, and analytic techniques used in this study. Chapter Five presents the national-level trend results of the measurement component of the study. In the discussion that follows this assessment, specific attention is paid to the trends in reports of child maltreatment, child homicide, and children's exposure to violence in their home. Chapter Six presents the state-level trends in reports of child maltreatment. Trends in rates of child maltreatment at the state level are shown to examine outliers and inconsistencies in reporting within each state. The purpose of this state-level measurement analysis is to offer evidence of the degree of validity of the NCANDS for studying state-level trends in child abuse and neglect. Data cleaning methods are described and correlational and convergence techniques are examined and discussed. With the methodological concerns of using the NCANDS data for trend analyses described, Chapter Seven provides the results of the substantive component of the study. Results from various hypothesis tests are reported at the state level for child physical abuse, child sexual abuse, and child neglect. A supplementary

analysis of child homicide and how these hypotheses hold up in predicting state-level rates of child homicide over time is also described in Chapter Seven, followed by a discussion of how these results may impact crime trend theory and criminal justice policy. Finally, a brief summary of the study's main findings are found in the conclusion in Chapter Eight.

## CHAPTER TWO: LITERATURE REVIEW

Over the past few decades, rates of serious violent crime (e.g., homicide and robbery) in the U.S. have shown significant fluctuations, with the greatest declines found during the 1990s after a period of elevated rates in the 1980s (Blumstein & Rosenfeld, 2008). The “great American crime decline” that began at the end of the twentieth century has had criminologists and other crime trends specialists perplexed by the multifaceted circumstances under which the decline occurred (Zimring, 2007). Unfortunately, crime trends research remains relatively limited, and often highly contentious, as to why crime rates exhibited such large declines. This research is further complicated by problems resulting from the comparison of trends across different data sources, and distinguishing short-term from long-term changes in crime rates and in the factors hypothesized to explain those changes (Blumstein & Rosenfeld, 2008). Crime trends research is, however, host to a wide range of hypotheses resulting from recent trend studies about the decline, many of which have been proposed to also explain the declines found in the rates of child abuse and neglect during the same period.

Previous crime trends research emphasizes the significance of mass incarceration, improving economic conditions, changing dynamics of illegal drug markets, and the growth of police and other agents of social control across the nation as factors related to the declines in violent crime that have garnered the greatest empirical support (see, e.g., Blumstein & Rosenfeld, 2009; Blumstein & Wallman, 2006; LaFree, 1999; Zimring, 2007). Because most scholars argue that it is unlikely that any one of these factors accounts for the entire decline in violent crime (Blumstein & Wallman, 2006; Zimring, 2007), crime trends research tends to incorporate not only the abovementioned societal changes, but also others that have taken place in the U.S. during the latter half of the



twentieth century. While some of these explanations have garnered much support, others have been challenged rather frequently (see, e.g., the impact of childhood lead exposure on crime rates in Nevin, 2000 and Reyes, 2007 and its critique in Lauritsen, Rezey, & Heimer, 2016, and McCall & Land, 2004; the effect of legalized abortion on crime rates in Donohue & Levitt, 2001 and its critique in Cook & Laub, 2002 and Zimring, 2007). These macro-level hypotheses about the downward trend in violent crime—some merely speculative, others empirically supported—have been debated by scholars for years, but these hypotheses have yet to be empirically assessed for their relationships with the declining trends in child abuse and neglect.

While there may be important differences between the serious violent crimes of rape, robbery, and aggravated assault and child maltreatment, crimes against both adults and children fell dramatically in the 1990s. Available national-level data suggest that rates of children exposed to violence (direct and indirect exposure), including rates of child abuse and neglect, have been steadily declining since the early 1990s (Finkelhor & Jones, 2012; Finkelhor, Saito, & Jones, 2015). In 2013, 9.1 per 1,000 children (approximately 679,000 children) nationwide were victims of child abuse and/or neglect according to state CPS agencies (U.S. Department of Health and Human Services, 2015). Compared with child abuse and/or neglect rates of roughly 15 per 1,000 children in the early- to mid-1990s (U.S. Department of Health and Human Services, 2001), these figures highlight how much lower the risk for abuse and neglect appears to be for children across the U.S. today compared to twenty years ago.

Over the same period, various other crimes against children also declined in both survey and administrative data. A benefit of having not only administrative data, but also

survey data on crimes against children reveal declines is that some survey data are not subject to changes in administrative operations (e.g., increases in crime recording by officials, computerization of data collection) which have been shown to artificially shift rates of crime over time in administrative data sources (Mosher, Miethe, & Hart, 2011). According to the National Crime Victimization Survey (NCVS), which gathers information from respondents on both reported and unreported victimizations over the previous six months, the rate of violent crime victimizations against youth ages 12 to 17 dropped dramatically from 1994 to 2010. Serious violent victimizations (rape or sexual assault, robbery, or aggravated assault) against teens declined 77% over these years, with the rate of rape or sexual assault declining by 68%, robbery declining by 77%, and aggravated assault declining by 80% (White & Lauritsen, 2012).

Child homicide rates also declined from the early-1990s into the twenty-first century (Cooper & Smith, 2011). The homicide victimization rate for children ages 14 and younger peaked in 1993 at a high of 2.2 homicides per 100,000 children, then declined through 2004 to 1.4 homicides per 100,000 children, and has since remained stable. Similarly, the homicide victimization rate for teens ages 14 to 17 fell nearly 58% from 1993 to 2008, starting at a high of 12.0 homicides per 100,000 teens in 1993 and decreasing to 5.1 homicides per 100,000 teens by 2008 (Cooper & Smith, 2011).

A variety of other child welfare indicators also improved over this period. Births to teenage mothers decreased 56% from 59.9 to 26.5 per 1,000 females ages 15 to 19 from 1990 to 2013 (Martin, Hamilton, & Ventura, 2015). Suicide rates for children under age 17 dropped nearly 40% from 1990-2007, but have since increased (Centers for Disease Control and Prevention, no date). Similar fluctuations over this period were also

found in the percentage of children living in poverty. Child poverty rates slightly increased from 1990 to 1993 (from 20.6 to 22.7), but then declined through 2000 (to 16.2), only to increase until 2010 (to 22.0) and decline again in the years after the recession through 2013 (to 19.9) (DeNavas-Walt & Proctor, 2014). In addition, declines in past month and lifetime alcohol and drug use among high school students were reported from the mid- to late-1990s through 2013 (Centers for Disease Control and Prevention, 2015).

Not all scholars, however, agree that there has been a decline in all forms of childhood exposure to violence, including abuse and neglect. For example, the rate of hospital admissions for young children with serious injuries due to physical abuse has either increased or remained relatively stable over the period from 1997 to 2009 according to various studies (Farst et al., 2013; Leventhal & Gaither, 2012; Wood et al., 2012). In addition, child neglect has not seen the same steep declines as those found in child physical abuse and child sexual abuse, although some scholars have argued child neglect has declined somewhat (a modest 7%) over this period (Jones, Finkelhor, & Halter, 2006). Most estimates of the declines in child neglect, however, appear to be the result of researchers reporting the start and end date of the trend in a manner that shows a decline. To date, it is unclear why most child welfare indicators have improved while others have worsened.

## THEORETICAL BACKGROUND

Although various scholars have offered possible reasons for the decline in rates of child abuse and neglect, few have posited explanations for it beyond those offered to

account for the more general twenty-year decline in violent crime. Of those scholars that have presented explanations for the decline in child abuse and neglect beyond those typically discussed in relation to violent crime trends, Finkelhor and colleagues have speculated and provided some correlational evidence that various societal changes may have affected rates of child abuse and neglect post-1990 (Finkelhor & Jones, 2006; Jones, Finkelhor, & Halter, 2006). In fact, Finkelhor and Jones (2006) contend that increased economic prosperity, the increased use of psychiatric pharmacology, and the hiring of more police and agents of social intervention are promising explanations for the declines in rates of child abuse and neglect. In contrast, the authors claim that increased incarceration of offenders and the receding crack cocaine epidemic are less likely to have contributed to the decline in child abuse and neglect, but are still plausible hypotheses for explaining juvenile victimization (Finkelhor & Jones, 2006). Although the authors also discuss other explanations to account for the declining trend in child abuse and neglect (e.g., more restrictive gun control laws, changing social norms and practices, dissipation of the side effects of the cultural revolution of the 1960s, reductions in ‘unwanted’ children), only those capable of being measured and empirically tested at the state level during the post-1990 period of the decline, and mentioned above with favorable or modestly favorable endorsement by Finkelhor and associates are discussed below and analyzed in this study.

### *Economic Improvements*

During a time of sustained economic growth, the 1990s in the U.S. saw improved macroeconomic indicators across all regions and sectors of society. The annual unemployment rate progressively dropped to its lowest rate in decades (U.S. Department

of Labor, 2015). Declines were also found in the U.S. poverty rate in the mid- to late-1990s (U.S. Census Bureau, 2015). All of these economic improvements happened alongside declining violent crime rates across the U.S.

Numerous criminologists have cited the economic prosperity/economic stress hypothesis as partially responsible for trends in specific types of violent crime (Arvanites & DeFina, 2006; LaFree, 1999; Lauritsen, Rezey, & Heimer, 2013; Rosenfeld & Fornango, 2007). For example, Messner, Raffalovich, and Sutton (2010) revealed that both the infant mortality rate (i.e., a proxy measure for poverty) and the 'relative' poverty rate (i.e., a measure of poverty set at 60% of the national median adult equivalent income, that is, 'relative' income deprivation as opposed to 'absolute' income deprivation) produced significant positive effects on rates of homicide across 16 western nations from 1993 to 2000. With regard to the effect of economic conditions on children, Land, Lamb, and Mustillo (2001) found support for a relationship between trends in economic indicators and child well-being from 1975 to 1998.

Child maltreatment has been consistently linked to poverty in the U.S. (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007). The interaction between poverty and child maltreatment at both the micro and macro levels has been documented by various scholars from a multitude of disciplines (see, e.g., Berger, 2004, 2005; Drake & Pandey, 1996; Gelles, 1992; Paxson & Waldfogel, 2002; Slack et al., 2011; Yang, 2015). On a micro level, economic factors such as parental unemployment, low family income, single parenthood, and living in a disadvantaged or impoverished neighborhood have been associated with increased risk for child maltreatment (Berger, 2004, 2005; Gelles, 1992). There is also persuasive evidence that macroeconomic indicators (e.g., unemployment

rates, labor force participation rates, child poverty rates) are also strongly associated with rates of child maltreatment across various zip codes, counties, and states (Drake & Pandey, 1996; Eckenrode, Smith, McCarthy, & Dineen, 2014; Paxson & Waldfogel, 2002). Much of this research is cross sectional, however, limiting the claims this body of research can make regarding causality.

A strong relationship between economic indicators and rates of child maltreatment is not always found in aggregate-level studies of economic conditions and crime (see, e.g., Lindo, Schaller, & Hansen, 2013; Millett, Lanier, & Drake, 2011; Seiglie, 2004). For example, Seiglie (2004) found that income, poverty, and female labor force participation rates were not significantly related to state child maltreatment rates from 1990 to 1996, while states' unemployment rates yielded some explanatory power. Lindo, Schaller, and Hansen (2013) also discovered that measures of economic conditions were not strongly related to rates of child abuse from 1996 to 2009 in their single-state county-level study, but argued that overall measures of economic conditions mask strong opposing sex effects in parental unemployment and risk for abuse. The authors argued that higher rates of male layoffs during this period increased rates of abuse, while higher rates of female layoffs reduced rates of abuse, suggesting there are differential risks for child abuse given which parent is home with their children more often. Clearly, the relationship between trends in economic conditions and rates of child abuse and neglect is complex and worthy of further investigation.

#### *Increased Dissemination of Psychiatric Medications*

Finkelhor and colleagues suggest that increases in the dissemination of psychiatric medication to parents and children may have had an effect on rates of child abuse and

neglect in the early- to mid-1990s (Finkelhor & Johnson, 2015; Finkelhor & Jones, 2006). Beginning in the late-1980s and early-1990s, psychotropic medications to treat a variety of mental health problems, including depression, anxiety, attention-deficit disorder (ADD), and attention-deficit hyperactivity disorder (ADHD) were being introduced at rates never before seen in the mental health profession (Mayes, Bagwell, & Erkulwater, 2008; Olfson et al., 2002; Pincus et al., 1998). For example, the rate of outpatient treatment for depression increased more than threefold from 0.73% in 1987 to 2.33% in 1997 (Olfson et al., 2002).

These increases were not limited to adults. In children, the rate of diagnosis for ADD/ADHD increased significantly over the past two decades (Getahun et al., 2013; Mayes, Bagwell, & Erkulwater, 2008; Schwarz, 2013). One study by the Centers for Disease Control and Prevention (2010) reported that the percentage of children ages 14 to 17 in the U.S. with a parent-reported ADHD diagnosis increased 21.8% in four years, from 7.8% in 2003 to 9.5% in 2007. Consequently, the percentage of children and youth prescribed psychotropic medications to treat mental health disorders, especially ADD/ADHD increased dramatically (Olfson et al., 2002; Zito et al., 2000; Zito et al., 2003). One study found that 6% of youth younger than 20 years were using a prescribed psychotropic medication at some point during the past year by 1996—a rate two to three times greater than the percentage of youth using these drugs in 1991 (Zito et al., 2003). Between 2005 and 2013, Jonas, Gu, and Albertorio-Diaz (2013) reported that 3.2% of the adolescent population ages 12 to 19 used ADD/ADHD medications, a 19-fold increase since the early 1990s (Finkelhor & Johnson, 2015).

The increased dissemination of psychiatric medications, which has been termed “the psychopharmacology revolution,” has been linked to decreased rates of violence in various studies over the past decade. Advocates of the psychopharmacology hypothesis contend that psychotropic medications ease the symptoms of mental health disorders which may lead to more mentally stable adults and children in society, potentially resulting in fewer individuals that act out aggressively. For example, Lichtenstein and colleagues (2012) found that patients with ADHD treated for their disorder with psychotropic medications had lower rates of offending than when they were unmedicated. This finding suggests that the use of medication reduces risk of offending among patients with ADHD. This could be the result of patients feeling more in control of their mind and body while medicated instead of inattentive or aggressive when unmedicated. Relatedly, a Dutch study found that when rates of antidepressant use among the Dutch population increased, rates of lethal violence decreased over a 15-year period from 1994 to 2008 (Bouvy & Liem, 2012). A study of the relationship between rates of prescriptions of psychotropic drugs and crime rates in the U.S. from 1997 to 2004 also found evidence that the increased dissemination of psychiatric medications over this period was associated with decreased violent crime rates (Marcotte & Markowitz, 2011).

Moreover, psychiatric medications may also help improve family life and reduce interpersonal stress between parents and children. Prior research has shown that child inattention, aggression, and oppositional-conduct problems (i.e., possible symptoms of ADD/ADHD) significantly contributed to parental stress (Podolski & Nigg, 2001). Studies have also shown a negative relationship between children’s ADHD status and parent’s socioeconomic status, earnings, and relationship stability (i.e., parents of



children with ADHD have a higher probability of low socioeconomic status, lower earnings, and relationship instability), which may cause greater parental stress (Kvist, Nielsen, & Simonsen, 2013). More parental stress could lead to less effective parenting, which in turn, could further lead to increases in child maltreatment. Evidence of the relationship between these behavioral problems and risk for child maltreatment has also been found in previous research (Fuller-Thomson, Mehta, & Valeo, 2014; Ouyang, Fang, Mercy, Perou, & Grosse, 2008). Therefore, under these assumptions, increased dissemination of psychiatric medications could be associated with lower rates of child abuse and neglect over time.

Over the same period, however, some research has also pointed to the likelihood that the effects of ADD/ADHD medication on the conduct disorders of medicated children is likely overestimated, both because of a lack of robustness of most findings due to short treatment interventions and follow-up periods (i.e., the durability of effects), and because of a strong indication of publication bias toward positive findings (Schachter, Pham, King, Langford, & Moher, 2001). As a professor of psychology stated in the *New York Times*, “To date, no study has found any long-term benefit of attention-deficit medication on academic performance, peer relationships or behavior problems...most studies of these drugs ha[ve] not been properly randomized, and some of them ha[ve] other methodological flaws” (Sroufe, 2012). For example, in a multisite, randomized efficacy/effectiveness trial, a team of medical researchers found that ADHD medication status did not predict change in ADHD symptom severity (i.e., hyperactivity and impairment: in school, at home, with their peers, with their self-esteem, or leading to physical injury or risky behavior, etc.) three to six years later for children diagnosed with

ADHD during preschool (Riddle et al., 2013). In one of the most widely known longer term randomized control trials of the effects of ADHD medication on mental, emotional, behavioral, and academic outcomes among ADHD diagnosed children, another team of medical researchers found that at first, medication (or medication plus therapy) produced the best results. However, after three years, these effects diminished, and by eight years post-follow-up there was no evidence that medication produced any behavioral or academic benefits (Molina et al., 2009). In another study, Currie, Stabile, and Jones (2014) found that ADHD medication use among children with ADHD significantly worsened emotional functioning for girls and academic outcomes for boys. Therefore, even with numerous studies pointing to the negative association between psychotropic medications and children's behavioral, academic, and/or emotional outcomes, evidence does in fact exist that this relationship may not be as strong or as meaningful as predicted.

#### *Increased Numbers of Agents of Social Control*

The role of aggressive criminal justice activity at both the state and federal levels, including increased numbers of law enforcement officers and diverse changes in policing strategies and tactics has also been argued to have possibly contributed to the violent crime decline of the 1990s (Blumstein & Rosenfeld, 2009; Zimring, 2007). While there are studies that found little support for this policing hypothesis (e.g., Eck & Maguire, 2006), others have found significant effects of various policing strategies on crime rates in localized environments (e.g., Rosenfeld, Fornango, & Rengifo, 2007).

Aggressive criminal justice activity is not necessarily limited to law enforcement agencies. Agents of social control can also be social workers, child care workers, and other individuals engaged in child abuse prevention activities. Just as the number of law

enforcement personnel increased during the 1990s, so too did the number of individuals employed in social service agencies (U.S. Census Bureau, 1990-2013). The argument that follows is that if the number of agents of social intervention, including law enforcement officers, social workers, and child protection workers increased, and these agents are visible and accessible to the public, then offenders or potential offenders would be deterred from committing crime. The same argument is made when state and federal agencies increase their focus on reducing these crimes beyond just hiring more personnel, largely via changes in prevention and intervention policies and strategies.

While not specific to child abuse, this hypothesis was supported by Dugan, Nagin, and Rosenfeld's (2003) study of intimate partner homicide rates and domestic violence resources and Xie, Lauritsen, and Heimer's (2012) study of the effect of police and social service workforce size on women's risk for nonlethal intimate partner violence. In both studies, the authors found that the accessibility of several types of domestic violence resources were associated with lower rates of lethal or nonlethal intimate partner violence. Finkelhor and Jones (2006) argue that this hypothesis may also account for the timing of declines in child sexual abuse relative to child physical abuse and child neglect. Because more intensive prevention and intervention efforts were made in the early 1990s regarding child sexual abuse compared with other forms of child maltreatment, the authors argue that one would expect rates of child sexual abuse to fall earlier and faster than rates of child physical abuse, which the authors argue did.

### *Mass Incarceration*

One factor that has been widely accepted as an explanation for the violent crime decline is the dramatic expansion of incarceration during the 1990s (Blumstein &

Rosenfeld, 2009; LaFree, 1999; Levitt, 2004; Zimring, 2007). One strength of the incarceration hypothesis is that incarceration rates were also increasing during the 1980s before the violent crime decline began (Blumstein & Rosenfeld, 2009), suggesting a causal relationship is more likely between the two variables as opposed to a concurrent or spurious relationship.

Proponents of the incarceration hypothesis contend that as the prison population increases, the incapacitation of greater numbers of offenders makes society safer, thus reducing crime rates. In a study testing the direct effect of incarceration, Rosenfeld and Fornango (2007) estimated that mass imprisonment during the 1990s accounted for 19% of the decline in U.S. robbery rates and 23% of the decline in U.S. burglary rates between 1992 and 2000, controlling for various other factors. Incarceration is also argued to have a deterrent effect on would-be offenders via the threat of incarceration.

The effect of incarceration on crime rates, however, varies by crime type (Blumstein & Rosenfeld, 2009; Zimring, 2007). Finkelhor and Jones (2006) maintain that offenders of most forms of child abuse or neglect are rarely ever sentenced to prison. Because many crimes against children are never punishable by incarceration, the authors argue it is unlikely that increased prison rates account for the declines in child physical abuse and child neglect. Finkelhor and Jones (2006) do make the case that child sexual abuse *is* likely affected by higher incarceration rates because stricter laws concerning child sex offenses have led to increased rates of incarceration for child sex offenders. It also may be the case that higher female incarceration rates may have serious implications for rates of child maltreatment, as previous micro-level research has found that

incarcerating mothers tends to leave children in unstable and potentially less safe environments (Sharp & Marcus-Mendoza, 2001; Siegel, 2011).

### *Receding Crack Cocaine Epidemic*

During the 1980s and early 1990s, crack cocaine drug markets were at their peak in the U.S. As a replacement for adult dealers who had been arrested and/or sent to prison for drug trafficking, drug possession, or drug possession with the intent to distribute crack cocaine, immature young recruits with little restraint for using violence (including using firearms) began dealing in these markets. Consequently, lethal violence escalated in drug markets across cities in the U.S. (Blumstein & Rosenfeld, 1999, 2008; Cook & Laub, 2002). Numerous criminologists have linked drug market activity, especially the youth gangs that competed within these markets, to higher rates of homicide among young adults in the late 1980s and early 1990s (Blumstein & Rosenfeld, 1999; Blumstein & Wallman, 2000; Levitt, 2004). As the crack cocaine epidemic subsided and drug markets became more stable in the mid- to late-1990s, scholars discovered violent crime also began to decrease (Blumstein & Rosenfeld, 1999, 2008; Cook & Laub, 2002; Levitt, 2004).

The changing dynamics of drug markets over the past thirty years has likely had an effect on trends in homicide. However, scholars have yet to find empirical evidence supporting other types of violent crime having been affected by the decline of the crack market (LaFree, 1999; Zimring, 2007). Moreover, even though the crack epidemic was concentrated primarily in urban and suburban areas, because violent crime also decreased in rural areas in the late-1990s post abatement, several scholars have questioned the

robustness of the receding crack epidemic in explaining aggregate declines in violent crime (e.g., LaFree, 1999; Zimring, 2007).

The drug market hypothesis, as it has been called, has also been linked to child maltreatment. Freisthler, Kepple, and Holmes (2012) examined how drug markets within various Census tracts in Sacramento, California place community children at risk for maltreatment from 2001 to 2008. The authors found that Census tracts with greater incidents of drug sales had significantly higher numbers of substantiations for child maltreatment the following year, even after controlling for spatial dispersion of drug market activity and various demographic factors. Moreover, Albert and Barth's (1996) study on the effects of demographic, social, and economic measures on the number of child maltreatment reports in 18 California counties from 1985 to 1991 found that the number of drug arrests of females in urban, suburban, and rural counties was positively associated with the number of CPS reports for child abuse.

#### *Artifactual Explanations*

It is also possible that declines in the rates of child abuse and neglect may be merely an artifact of measurement—the result of a variety of changes in the data collection and reporting of child abuse and neglect. For example, declines may be due to, among other things, reduced funding, the adoption of more conservative standards within state CPS agencies, changes in the data collection methods or definitions of child abuse or child neglect within state CPS agencies, more nonprofessional versus professional caseworkers investigating reports of alleged child maltreatment, and changes in screening practices when caseload sizes increase (Almeida, Cohen, Subramanian, & Molnar, 2008; Eckenrode, Powers, Doris, Munsch, & Bolger, 1988; Finkelhor & Jones, 2004, 2006;

Wells, Downing, & Fluke, 1991). One such conservative standard could be the use of alternative responses as a way of responding to reports of child abuse and neglect.

Alternative responses—a form of differential response that is usually applied in low- and moderate-risk cases—typically do not require a formal determination or substantiation of child abuse or neglect, but still usually require that a comprehensive family assessment is produced by state CPS workers (Shusterman, Hollinshead, Fluke, & Yuan, 2005). One recent study of the influence of differential response on decision-making in CPS agencies in 297 U.S. counties found that counties that implemented differential response alternatives had significantly lower investigation rates, but higher substantiation rates among investigated cases. These findings suggest that alternative responses may improve the accuracy of CPS responses by reducing the rates of false positives (i.e., fewer families’ experience a CPS investigation, and those that do are more likely to have the allegation of maltreatment substantiated) (Janczewski, 2015). Consequently, rates of substantiated child maltreatment are likely to be positively or negatively influenced by the policies in place within state CPS agencies.

Previous research has also found that substantiation definitions are sometimes unreliable due to intake and investigative decisions made by state CPS caseworkers (Smith Slep & Heyman, 2006). For example, CPS caseworkers may make substantiation decisions based on a variety of factors other than evidence of maltreatment (e.g., a non-offending parent taking protective measures, the lack of child disclosure, parents addressing their problems) (English, Marshall, Coghlan, Brummel, & Orme, 2002). One study found that as many as 10% of physical and sexual abuse reports were misclassified as neglect by CPS agencies (Runyan, Cox, Dubowitz, Newton, Upadhyaya, Kotch, Leeb,

Everson, & Knight, 2005). It is possible then that discrepancies in reports between substantiated maltreatment and unsubstantiated maltreatment or which maltreatment type was substantiated may be the result of human error in data collection, coding, or reporting, or purposive in nature (e.g., if physical abuse cannot be substantiated, a CPS caseworker may recode the charge as neglect, which may have a lower threshold for substantiation).

Furthermore, decreases in child abuse and neglect caseloads may also be the result of CPS caseworkers not investigating reports as often or as thoroughly because of limited financial resources or CPS caseworkers deciding to ‘screen out’ less serious cases due to time constraints. In a study of the impact of CPS caseload size on rate of substantiation over time, Almeida and colleagues’ (2008) state-panel multilevel analysis found that the decline in the rate of child sexual abuse from 1997 to 2002 was not associated with increases in CPS caseload size. However, many of these other societal-level or agency-level changes related to child abuse or neglect have yet to be fully explored for child physical abuse, child sexual abuse, and child neglect separately.

Distinguishing data artifacts from true shifts in crime rates is fundamental to understanding crime trends. If potential artifactual explanations cannot be empirically ruled out, then increases or decreases in the rates of child abuse and neglect may potentially reflect error or change in data measurement and not actual changes in rates over time. Therefore, before any of the above competing explanations can be empirically examined, the child maltreatment data themselves should be free (or as free as possible) from data collection or data measurement errors from the onset. Only after confidence is



established in the data should these proposed hypotheses be empirically tested, shining light on why rates of child abuse and neglect in the U.S. declined post-1990.

## DEFINITIONAL VARIATION

Definitional variation in child abuse and neglect across jurisdictions over time has been, and still is, a constant source of frustration for those attempting to understand both the scope of, and trends in, child maltreatment (Fallon et al., 2010). Up until the Child Abuse Prevention and Treatment Act (CAPTA) of 1974, state lawmakers were responsible for defining what physical injuries constituted child abuse and what conditions were considered neglectful, which inevitably led to definitional variation across state statutes (Davidson, 1995). In response to diverse definitions and procedures across states, the U.S. Congress passed CAPTA in 1974, which stipulated that the federal government provide states with federal dollars to improve and standardize state definitions and responses to child abuse and neglect (Costin, Karger, & Stoesz, 1996). CAPTA also established a minimum set of acts or behaviors that define child abuse and neglect; however, states are able to define additional acts or behaviors as child abuse or neglect at any time and count them in their annual statistics if they so desire.

With the enactment of CAPTA, the federal government set the minimum standard for states to define abuse and neglect as

the physical or mental injury, sexual abuse, negligent treatment, or maltreatment of a child under age 18 by a person who is responsible for the child's welfare under circumstances which indicate the child's health or welfare is harmed or threatened thereby as determined in accordance with regulations prescribed (Child Abuse Prevention and Treatment Act of 1974, Section 3).

Operational definitions of child abuse and neglect were largely driven by state laws

defining the three traditional categories of child maltreatment: physical abuse, sexual abuse, and neglect.<sup>3</sup>

### *Child Physical Abuse*

In essence, child physical abuse is the non-accidental physical injury to a child by a child's caretaker, including fractures, burns, bruises, welts, cuts, and/or internal injuries (Clark & Clark, 1989). However, varying degrees of non-accidental physical injury exist and not all of them are considered child physical abuse, the most notable being physical punishment such as spanking a child. The distinction then between socially accepted normal punishment and child physical abuse usually becomes a matter of the degree of physical injury inflicted as written in state statutes (Coleman, Dodge, & Campbell, 2010). That does not mean, however, that all professionals and laypeople agree to what constitutes reasonable physical punishment. Debates have been going on for years regarding whether spanking is child abuse and whether spanking has long-term physical, mental, emotional, or psychological consequences on children. Unfortunately, there are no signs that this debate will be resolved anytime soon (Coleman, Dodge, & Campbell, 2010; Hines, Malley-Morrison, & Dutton, 2013).

### *Child Sexual Abuse*

CAPTA also required states to include the sexual abuse of a child in their definition of child abuse. Although child sexual abuse statutes vary from state to state, they generally criminalize all adult sexual activity with children under age 14, in addition

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<sup>3</sup> It should be noted that child maltreatment also refers to other types of maltreatment such as child psychological abuse or emotional abuse. Child psychological abuse and emotional abuse are not discussed in this review of the literature because not all states collect and/or report data on these two types of maltreatment. Medical neglect is also often cited as another type of child maltreatment separate from neglect, but for purposes of this study, when referring to neglect, the author is referring to all types of neglect, including medical neglect.

to any kind of incest (Hines, Malley-Morrison, & Dutton, 2013). States also include the sexual exploitation of children in their definitions. Therefore, noncontact acts such as voyeurism, exhibitionism, and exposure to pornography (i.e., forcing a child to witness pornography) are considered forms of child sexual abuse. And, while not expressly stated in most state statutes, most professionals and laypeople maintain that just one instance of sexual contact (or noncontact) is enough to label an act abusive, regardless of the duration of the act itself (Hines, Malley-Morrison, & Dutton, 2013; Trickett, 2006).

The CAPTA Reauthorization Act of 2010 explicitly defined child sexual abuse as

The employment, use, persuasion, inducement, enticement, or coercion of any child to engage in, or assist any other person to engage in, any sexually explicit conduct or simulation of such conduct for the purpose of producing a virtual depiction of such conduct; or the rape, and in cases of caretaker or inter-familial relationships, statutory rape, molestation, prostitution, or other forms of sexual exploitation of children, or incest with children.

### *Child Neglect*

Neglect encompasses a wide variety of behaviors (or lack of behaviors) on the part of a parent or caretaker. Neglect generally includes failure by parents or caretakers to provide adequate food, clothing, shelter, education, supervision/protection, emotional support/nurturance, or medical care to children. Neglect may be willful, as in the case of a parent refusing to feed their child, or unintended, as in the case of a parent suffering from a mental illness rendering them incapable of providing adequate care (Clark & Clark, 1989; Dubowitz, 2006; Hines, Malley-Morrison, & Dutton, 2013).

Distinguishing at what point inadequate care turns into child neglect is a complicated task for social workers based on the broad definitions of neglect in state statutes. Do certain contexts require that the definition of neglect be restricted to only

cases of extreme neglect? For example, because young children in many cultures help care for their younger siblings, both as a necessity and as an important responsibility in their maturation process, is the act of leaving an older child with his or her younger siblings child neglect on the part of the parent or caretaker? There has yet to be a consensus to this debate, and as a result, issues arise when customs clash within the U.S. Many professionals argue that not only does the context of the child's experiences matter, but political, policy, cultural, and economic contexts matter as well in determining a neglectful act from a non-neglectful act (Dubowitz, 2006; Hines, Malley-Morrison, & Dutton, 2013).

Because states can deviate from the standard definitional requirements of CAPTA, macro-level studies of trends within and across states in child abuse and neglect using data from official state sources will undoubtedly contain an element of measurement error. These definitional issues may be an issue because state-level trends may fail to converge if state trends in child maltreatment are capturing entirely different phenomena within and across states. Because states provide their own definitions on child abuse and neglect, variations in definitions exist within and across states and in all years of this analysis.

#### PROCEDURAL VARIATION

Each state has the autonomy to facilitate child welfare services using whatever medium they desire. All states have a CPS agency in charge of child welfare, but the implementation of policies and procedures regarding child maltreatment investigations is up to individual states. With the passing of CAPTA, the federal government established

minimum standards and provided states with federal dollars to improve their responses to child abuse and neglect (Costin, Karger, & Stoesz, 1996). In the years after CAPTA, states attempted to produce standardized protocols for the investigation of child maltreatment reports and data systems capable of reporting dispositions and other child maltreatment data in a timely and efficient manner. However, states varied a great deal in how they investigated and ultimately reported substantiation of abuse or neglect. Under CAPTA, states were able to individually determine many of the specific rules related to not only the definitions of child abuse and neglect, but also who must report child maltreatment, and when maltreatment must be handled through the state CPS agencies or through law enforcement. CAPTA also included provisions for tracking maltreatment data and testing new approaches to addressing child maltreatment.

In the early years of CAPTA, most counties within states collected and reported child maltreatment data using paper records. However, during the 1990s and into the 2000s, nearly all states moved to one of many computerized data systems, the most common being a Statewide Automated Child Welfare Information System (SACWIS)—a federally funded, voluntary, comprehensive, and automated case management tool that the Department of Health and Human Services first supported in 1994 (U.S. General Accounting Office, 2003). The federal government encouraged (and ultimately provided funding for) states to develop SACWIS systems. Public Law 103-66 and 104-193 established general SACWIS requirements and federal funding for the implementation of SACWISs within states, including enhanced funding for states to begin the transition (U.S. Department of Health and Human Services, 2016). The reason for a push to SACWISs was purely for efficiency and accuracy: SACWIS and SACWIS-like systems

are capable of extracting and validating child maltreatment much easier than previous data reporting methods. This is ultimately the tool from which NCANDS data are generated at the state level. As states received more federal funds to standardize data collection methods, they also became more SACWIS compliant, and over time, their NCANDS data collection and data reporting patterns changed (U.S. General Accounting Office, 2003).

These procedural changes have not stopped with the implementation of SACWIS and SACWIS-like data systems. Many child welfare advocates would argue that the most significant change in child welfare policy and greatest impetus for standardizing procedures occurred in 1996 with amendments to CAPTA, and in 1997 with the passage of the Adoption and Safe Families Act. One such amendment to CAPTA in 1996 required that specific data elements be collected by each state (e.g., the collection of information on false reports of abuse and neglect, how long it took to terminate parental rights). The Adoption and Safe Families Act increased the federal role in child welfare services by demanding state accountability and authorizing the U.S. Department of Health and Human Services to develop outcome measures and monitor state performance in providing child welfare services (McGowan, 2014; Peddle & Wang, 2003). This monitoring process includes the use of, at a minimum, state-level NCANDS data and required it as of 2000.

Most states began reporting case-level information to the U.S. Department of Health and Human Services at some point, however, from 1996 into the 2000s (Peddle & Wang, 2003). Throughout this period, states continued to alter their policies related to how they report their child maltreatment data to NCANDS. For the most part, states

collect information on reports of child maltreatment in far greater detail than that which is reported to NCANDS. And, because of the discrepancy in data elements between states and the NCANDS, states decide on their own how to “map” their detailed data into the established NCANDS categories. For more information about state-level procedural changes and a detailed description of select states’ reported definitional and procedural changes from 1990 to 2013 see Appendix A.

Just as definitional variations in child maltreatment over time within and across states could potentially lead to trends being an artifact of data measurement and collection, knowing that data reporting systems within states have improved over time, and across states these improvements have happened at different times, the disentanglement of real increases and decreases in child maltreatment may be difficult to obtain using NCANDS state-level data. In the next chapter, I describe the research questions that this dissertation addresses, as well as how this study contributes to the current state of research on child victimization and crime trends.

### CHAPTER THREE: THE CURRENT STUDY

This dissertation is guided by two general research questions. These research questions drive both the measurement and substantive components of this dissertation, providing the framework for the comprehensive assessment of national- and state-level trends in child abuse and neglect from 1990 to 2013.

The first research question examines whether the NCANDS data are valid for studying national- and state-level trends in child victimization from 1990 to 2013. My expectation is that the NCANDS data will be valid for studying national trends in child victimization because previous research has shown steep declines post-1990 in both NCANDS measures of child maltreatment and measures of child victimization from other national data sources. Unfortunately, I have no expectation regarding the validity of the NCANDS data for studying state-level trends in child victimization because NCANDS state-level rates in child victimization have never before been assessed in this manner. However, whether the NCANDS data do or do not appear to be valid measures of child victimization at either the national or state level, I assess the degree to which the NCANDS trends deviate from the other sources of child victimization trend data.

In order to address the first research question, this dissertation compares national-level trends in the rates of child abuse and neglect from the NCANDS to other national trends in child victimization. The national-level time series analysis of these data series assesses the extent to which the three data series correspond to one another and/or converge with one another in their depictions of childhood exposure to violence trends in the U.S.

The degree of correspondence among the trends in child victimization at the national level is used to statistically assess the similarities and differences among the



respective data sources in both level and trend of child victimization. If strong relationships are found between the national NCANDS trends and other national trends in child victimization, one could argue that the NCANDS data are reporting trends in child victimization that have been found in other more established and relied upon sources (e.g., child homicide). In other words, if any or all of the NCANDS' national-level child abuse or neglect trends are highly correlated with the national-level child homicide trend, for example, it would be reasonable to infer that NCANDS data provide a valid measure for assessing trends in child victimization.<sup>4</sup> This method of assessing the ability of the NCANDS data to measure change in childhood exposure to violence has been used previously by various scholars examining the correspondence in trends in the Federal Bureau of Investigation's (FBI) Uniform Crime Reports (UCR) and NCVS for other types of crime, such as robbery, rape, and motor vehicle theft (see, e.g., Ansari & He, 2012; Berg & Lauritsen, 2016; Lauritsen, Rezey, & Heimer, 2016; Lynch & Addington, 2007; McDowall & Loftin, 2007).

NCANDS state-level trends in rates of child abuse and neglect are also compared to trends in state-level child homicide data in a fashion similar to the analysis of national trends in child victimization. In addition, cointegration and error correction mechanisms are analyzed. The goal of using cointegration techniques is to examine if the series converge, i.e., a "long-run equilibrium" exists among the series. It is expected that the various trends of child victimization will periodically depart from one another due to the unique measurement features of each data system, however, they will "tend to move

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<sup>4</sup> There is always the possibility that only specific types of child maltreatment would pass this correlational test (e.g., child abuse trends are highly correlated with trends in child homicide, but child neglect trends are not). If discordant findings are found among child maltreatment types and child homicide, explanations for these differences are discussed.

together in concert, varying together in an equilibrium relationship” (McDowall & Loftin, 2007, p. 105). A lack of cointegration implies no long-run equilibrium in the series, signaling arbitrary movements away from one another without any tendency to return to a long-run relationship (McDowall & Loftin, 2007; Thome, 2014). Evidence of cointegration indicates that the data series share an underlying stochastic process, which would support the notion that the NCANDS state-level data are capable of measuring the same trend in child victimization at the state level that other data sources measure. Cointegration analyses have been previously used by various scholars interested in examining the convergence/divergence of the UCR and NCVS (see, e.g., Ansari & He, 2012; Berg & Lauritsen, 2016; McDowall & Loftin, 2007), but have yet to be used to explain convergence/divergence of child maltreatment trends from the NCANDS and child homicide data.

Fortunately, the availability of state-level NCANDS data increases the analytic possibilities for longitudinal analyses of child victimization data with relatively short time series. Because national trends in the rates of child abuse and neglect are an aggregation of all 50 states’ rates over time, it is also important to examine the variability that exists within and across states over time in rates of child victimization. By decomposing the national rates of child abuse and neglect by state using state-level substantiated reports of child physical abuse, sexual abuse, and child neglect from the NCANDS from 1990 to 2013, I examine the potential measurement error in data points across the series for each state, as well as describe the variation that exists within and across states in rates of child abuse and neglect. This analysis shows the degree of consistency in the child maltreatment trends across states and demonstrates how relevant

state-level variations are to hypotheses about the national decline in child abuse and neglect from 1990 to 2013. These robust time-series analyses at both the national and state level should provide important information about whether (and where) the NCANDS has sufficient validity for studying trends in childhood exposure to violence.

The second research question this study addresses investigates competing factors that may be associated with the declines in the rates of child maltreatment from 1990 to 2013. The various possible and wide-ranging hypotheses that have been identified in the crime trends literature and by Finkelhor and colleagues guides this analysis. The primary hypotheses (i.e., promising explanations) include: increased economic conditions; increased numbers of agents of social intervention; and the increased use of psychopharmacology. Secondary hypotheses (i.e., plausible explanations) include: increased incarceration rates; and the receding crack cocaine epidemic. The final hypothesis to be tested looks at potential artifactual explanations for the decline. Specifically, the substantive component of this dissertation questions whether changes in these macro-level factors predict trends in child abuse and neglect at the state level from 1990 to 2013. Ultimately, the principal motivation of this analysis is to better understand why rates of child abuse and neglect changed over the past 24 years in an effort to inform researchers and policymakers about the correlates of child abuse and neglect rate reduction. Furthermore, given that there is too little statistical power in a 24-year national-level time series analysis to obtain robust results in such an analysis, by using state-level panel data, the number of observations in the analysis increases considerably, producing the statistical power necessary for examining several of the competing hypotheses simultaneously.

## POTENTIAL IMPACT

This dissertation adds to the existing body of knowledge about trends in child abuse and neglect by: 1) Establishing whether the NCANDS data are valid over time and place, and thus suitable for studying trends in child victimization; 2) Examining trends in childhood exposure to violence at both the national and state levels using new and robust techniques in crime trends research; and 3) Empirically assessing the various proposed hypotheses regarding why child abuse and neglect declined over the past two decades.

This study has the potential to provide evidence for or against using the NCANDS data for studying trends in child abuse and neglect. Currently, most analyses using the NCANDS are either state-specific or national in scope but limited to a few years. By exposing the methodological ability of the NCANDS to study trends in child abuse and neglect, this study may inform researchers and practitioners around the U.S. who use the NCANDS data to measure rates of child abuse and neglect from year to year in their respective jurisdictions or for the advancement of knowledge in child abuse and neglect research.

In addition, while victimization scholars have speculated that certain hypotheses may explain declines in rates of child abuse and neglect post-1990, none have empirically assessed the relevant and testable hypotheses over the entire period. To the extent that the results of this dissertation explain why rates of abuse and neglect for children fell from 1990 to 2013, these findings have the potential to impact future policies related to child protective services at both the state and agency level. If, for instance, certain measures are shown to be related to the declines in child abuse and neglect over this series, federal, state, and local policymakers should take heed of these measures and attempt to address

them. This study does not likely settle this issue once and for all, but it is a good first step in attempting to understand why child maltreatment declined post-1990.

The potential impact of this study, however, goes beyond the field of child victimization by also adding to the scant literature on crime trends. Not only is crime trends research host to a wide range of hypotheses about the decline in crime at the end of the twentieth century that have yet to be rectified, but crime trends research is also challenged by problems resulting from the comparison of trends across different data sources. Child abuse and neglect trend research is not any different. This study adds to the crime trends literature by establishing when, where, and potentially why child abuse and neglect declined post-1990. Furthermore, this examination of trends in child victimization, and more specifically, trends in child abuse and neglect, should also provide scholars with additional violent crime trends (at both the national and state level) for future comparisons with trends in other crimes (e.g., intimate partner violence).

To address the research questions outlined above, national- and state-level data from multiple sources are used. Various statistical modeling techniques are utilized to determine the nature of national- and state-level trends in child abuse and neglect from 1990 to 2013. The data and methods used in this dissertation are discussed next in Chapter 4, followed by an outline of the statistical analyses described above.

## CHAPTER FOUR: RESEARCH DESIGN

### DATA AND MEASURES

This study uses multiple secondary data sources to provide a comprehensive examination of trends in child abuse and neglect at the national and state level. The main dataset, the NCANDS, provides this study with annual state-level counts of child abuse and neglect used to create both state-level and national-level data files. Additional variables were added to the state-level panel dataset from a variety of data sources to conduct the state-level measurement and substantive analyses. National rates of child abuse and neglect were calculated from the NCANDS state-level data files to produce the national-level dataset.<sup>5</sup> National rates of child homicide and exposure to violence were then appended to national-level file. All of the data used in these analyses are generalizable to all persons (or in some cases to all children) in either U.S. states or the country as a whole. The NCANDS, Supplementary Homicide Reports (SHR), and the NCVS and their corresponding measures are used in the national-level measurement analysis. The NCANDS and SHR are used in the state-level measurement analysis. The NCANDS, SHR and all remaining secondary data sources are used in the state-level substantive theoretical analysis.

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<sup>5</sup> When calculating the national rates of child maltreatment and missing data existed for a given state in a given year, that state's child population that year was removed from the denominator (i.e., the total population of children across the states that submitted reports of substantiated maltreatment that year). In other words, NCANDS national rates of child abuse or neglect in a given year are not necessarily the sum of all 50 states' reports of child maltreatment, but rather, they are the sum of only those states that reported non-missing sensible data in a given year. On average, two states were excluded from the national rates due to missing data in a given year. The median number of states missing in a given year was one. The minimum and mode number of states missing was zero. The maximum number of states missing in a given year was nine (understandably in 1990, the first year of NCANDS data collection).

### *Child Abuse and Neglect*

National- and state-level rates of child abuse and neglect were collected from the NCANDS. The NCANDS is a federally-sponsored national data collection and analysis system created for the purpose of tracking the incidence, prevalence, and nature of child maltreatment reports each year within the U.S. The NCANDS data are stored at the Bronfenbrenner Center for Translational Research at Cornell University and distributed by the federally-funded National Data Archive on Child Abuse and Neglect (NDACAN). NCANDS data have been provided by the NDACAN at Cornell University and are used in this study with permission.

NCANDS data are official reports of child abuse and neglect as recorded by state CPS agencies. These data have been collected annually from state CPS agencies since 1990 and report key child abuse and neglect statistics from all states, including data on reports, investigations, victims, and perpetrators.

The NCANDS consists of both case-level and state-level components. The Detailed Case Data Component, which became known as the Child File in 2000, reports case-level information from state CPS agencies on each reported case of child abuse or neglect. Aggregate state-specific data on all investigated reports of maltreatment to state CPS agencies, as well as statewide administrative data are available in the Summary Data Component (SDC) from 1990 to 1999, and the annual Combined Aggregate Files (CAF) from 2000 to 2008. The CAFs are available annually until 2008, at which point the NDACAN no longer distributed aggregate state-level case data. However, state-specific data on aggregate cases of child maltreatment from 2009 to 2013 were constructed using the annual Child Files. NDACAN provided these files after a special license was

obtained. The Child Files from 2009 to 2013 were aggregated by state to produce state counts of the number of reports and investigations by disposition for each year. State-level administrative data from 2009 to 2013 were available in the NCANDS State Files. This study used data from the SDC from 1990 to 1999, the annual CAFs from 2000 to 2008, and both the annual NCANDS State Files and state data from the aggregated Child Files from 2009 to 2013 (U.S. Department of Health and Human Services, no date a, no date b, no date c, no date d).

Annual state-level NCANDS files were merged from 1990 to 2013.

Documentation provided by NDACAN was used to ensure that the correct variables were joined across the data series using the SDC, CAFs, and NCANDS State Files and Child Files. For example, unlike the CAFs where identical structures and variables were used allowing for an easy merge across the CAF years, a variable crosswalk from the SDC to the CAF datasets must be used to ensure accurate merging.

Additional weighting adjustments were made to the NCANDS data because a change was made in the reporting time frame of the NCANDS data in 2003. While NCANDS data were reported annually by calendar year from 1990 to 2002, starting in 2003, states began submitting data according to the federal fiscal year. Because the federal fiscal year starts on October 1<sup>st</sup> of one year and ends on September 30<sup>th</sup> of the next, fiscal year data from the 2003 NCANDS were weighted in order to estimate counts and rates for a twelve month period that did not overlap with data from 2002 (i.e., in 2003, data were collected from October 1, 2002 to September 30, 2003, rather than the January 1, 2003 to December 31, 2003 calendar year). Therefore, the number of child maltreatment reports for each child maltreatment type for 2003 is composed of 75% of



the reports in fiscal year 2003 (representing reports for nine of the 12 months in 2003) multiplied by one-quarter of those 75% (representing the other three months in 2003). This estimation procedure was necessary in order to account for the overlapping data in 2002 and 2003. Because NCANDS data post-2003 are composed of data from non-overlapping twelve month periods, the aggregation of reports from these federal fiscal years represents the aggregation of reports for that calendar year. The estimation procedure describe above can be represented as:

$$NCANDS\ Count_{2003} = (NCANDS\ Count_{FY2003} * .75) + \frac{(NCANDS\ Count_{FY2003} * .75)}{4}$$

This weighting procedure assumes no seasonal variation in a state’s reported count of child abuse and neglect or other CPS agency-level data. Though previous research has argued there appears to be an annual pattern to homicide and other forms of violent crime, where aggregate patterns arise during certain seasons of the calendar year (see, e.g., Carbone-Lopez & Lauritsen, 2013; Hipp, Bauer, Curran, & Bollen, 2004; Lauritsen & White, 2014; McDowall & Curtis, 2015), none of these studies looked specifically at seasonal fluctuations in child abuse and neglect or crimes against young children. The most relevant study by Carbone-Lopez and Lauritsen (2013) found that rates of violence in the home for youth ages 12 to 17 (the closest measure of child abuse and neglect reported in previous research) did not vary across winter, fall, and summer months from 1993 to 2008, and while rates appear to be slightly lower in the spring than in the summer, this effect was not significant after stochastic nonstationarity in the trends and autocorrelated standard errors were corrected using first-differenced models. Due to these conflicting findings, there is insufficient evidence to garner any accurate measurement of error that may have been brought into the NCANDS data by using this

weighting procedure. However, because recent evidence suggests that there was no significant seasonal variation in violent crimes against children ages 12 to 17 in their home from 1993 to 2008 (i.e., a period within the confines of this study's timeframe), there is little reason to believe that child abuse or neglect, which also often takes place in a child's home, has any substantial seasonal rhythm in the NCANDS data.

NCANDS child maltreatment data can be reported as the unique count or duplicate count of child reports. In a given year, if the unique count is reported, a child is only counted once regardless of how many reports were filed for him or her. In contrast, the duplicate count counts a child as many times as a report has been filed. This study uses state reports of the number of the duplicate count of children (i.e., the number of reports of maltreatment that have been substantiated in a given year for each state) because it is the most consistently reported for all child maltreatment types from 1990 to 2013. Using the duplicate count of children produces an incident rate (i.e., a victimization rate) of child physical abuse, child sexual abuse, and child neglect, as opposed to a prevalence rate (i.e., a victim rate).

NCANDS rates of child abuse and neglect are a combination of both *substantiated* and *indicated* dispositions of child maltreatment investigations. The disposition of each investigation depends on the classification system used by each state. Some states categorize an allegation as either *substantiated* or *unsubstantiated*. Other states include both *substantiated* and *unsubstantiated*, as well as a third disposition, *indicated*. In these states, maltreatment is *indicated* if there is sufficient reason to suspect that the child may have been maltreated or is at risk of maltreatment, but the level of evidence required by state law to substantiate an allegation is not available. To

accommodate this variation among states, *indicated* allegations are treated as *substantiated* in the rates of child maltreatment in this study.

NCANDS classifies child maltreatment into six categories: physical abuse, sexual abuse, neglect, medical neglect, psychological maltreatment, and ‘other’. As a result of missing data across many states from 1990 to 2013 on cases of psychological maltreatment and ‘other’, these maltreatment types are not analyzed.<sup>6</sup> In addition, some states do not classify medical neglect cases as their own category. Rather, these states report cases of medical neglect in the broader neglect category. Therefore, in order to be consistent and capture medical neglect for all states, the medical neglect category has been incorporated into the neglect measure.

NCANDS trends in the national rates of substantiated reports of child physical abuse, sexual abuse, and child neglect for children ages 17 or younger from 1990 to 2013 are included in the analysis. National rates were calculated using the state-level file, which excludes all non-U.S. states (e.g., the District of Columbia (DC), Puerto Rico, U.S. Virgin Islands, Guam). The final state-level panel dataset contains NCANDS annual data for all 50 states across 24 years (i.e., 1,200 observations).<sup>7</sup>

Trends in child abuse and neglect from the NCANDS are captured using 1990 to 2013 state rates of child physical abuse, child sexual abuse, and child neglect per 1,000

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<sup>6</sup> On average across all states and the 24 years of this study, substantiated psychological or emotional abuse/maltreatment accounted for 3% of all reports investigated by state CPS agencies. On average, substantiated maltreatment recorded as “other” accounted for almost 7% of all reports investigated by state CPS agencies. The percentage of all reports that were in these categories varied from a high of 15% of all report investigations in the late 1990s to a low of around 6% in all years post-2007. Therefore, by including child physical abuse, child sexual abuse, and child neglect categories, this analysis accounts for, on average, between 85% to 94% of all CPS investigations leading to substantiated maltreatment reports each year of this study.

<sup>7</sup> DC has been excluded from the analysis because of its unique makeup as a large U.S. urban jurisdiction. The nature of DC’s small geographical area and urban-type population makes it incomparable to the 50 U.S. states which are all comprised of urban, suburban, and rural jurisdictions. Furthermore, nearly all panel studies of state-level social science research have also excluded DC from their analyses because of DC’s status as an extreme outlier (see, e.g., Arvanites & DeFina, 2006; Jacobs & Carmichael, 2002).

children 17 years or younger. State rates of child physical abuse, child sexual abuse, and child neglect are calculated by dividing the total number of substantiated cases of child physical abuse, child sexual abuse, or child neglect in each state by the total number of children under age 18 in each state for each year, and multiplying by 1,000. National rates of child abuse and neglect are calculated by summing the total number of substantiated cases of child physical abuse, child sexual abuse, or child neglect across all reporting states in a given year and dividing by the total population of children in the reporting states in that year, then multiplying by 1,000. Any states with discernable problematic data (e.g., an improbable 'zero' value) for the total number of substantiated cases of child physical abuse, child sexual abuse, or child neglect in a given year has been recoded to 'missing' to ensure that the overall rates of child physical abuse, child sexual abuse, or child neglect in a given year are not artificially low and that the state trend in the rates remains stable over the series. Many of those 'missing' values were later interpolated according to the rules established and described below.

The dependent variables in the substantive analysis are state rates of child physical abuse, child sexual abuse, and child neglect per 1,000 children 17 years or younger. Supplementary analyses were also run using the state rates of child homicide as the dependent variable to see how these model coefficients compare to coefficients estimated from child physical abuse, child sexual abuse, and child neglect models.

### *Child Homicide*

Trends in child homicide are also used in the national- and state-trend analysis of childhood exposure to violence. It is essential to this analysis to compare the child maltreatment trends from the NCANDS to trends in child homicide because homicide

data are particularly well-measured at the national level and have been shown to be very similar in level and trend to other mortality data (see, e.g., Regoeczi & Banks, 2014; Smith & Cooper, 2013). Annual national- and state-level child homicide data from 1990 to 2013 from both the FBI's SHR and the Centers for Disease Control and Prevention's (CDC) National Vital Statistics System (NVSS) are used. Annual SHR data were available online through the Office of Juvenile Justice and Delinquency Prevention and NVSS data were available online using the Web-based Injury Statistics Query and Reporting System (WISQARS).

National- and state-level child homicide rates were calculated by dividing the total number of children 17 years or younger who were victims of homicide by the total population of children 17 years or younger and multiplying by 100,000. SHR rates are the primary source of child homicide trends. However, if SHR child homicide rates were 'missing' or appeared problematic (i.e., the SHR showed a rate of '0', but the NVSS showed a rate greater than '0'), SHR rates were replaced with NVSS rates. Given the high degree of correlation in the homicide trends between the SHR and NVSS (Regoeczi & Banks, 2014; Smith & Cooper, 2013), this replacement procedure seems reasonable. NVSS rates replaced 7.3% of all missing or problematic SHR child homicide rates.<sup>8,9</sup>

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<sup>8</sup> In this analysis, 6.75% (81/1,200) of SHR child homicide rates were replaced by NVSS rates because SHR rates were 'missing'. An additional .58% (7/1,200) of all SHR child homicide rates were replaced by NVSS rates because they were reported as '0' when the NVSS reported more than '0'.

<sup>9</sup> It was suggested that this measure be restricted to child homicides by family members in the SHR as this measure is much closer conceptually to child victimization in the maltreatment sense than child homicides in general. Unfortunately, the sheer amount of missing data and '0' data points at the state-level in rates of child homicide by family members compared with rates of all child homicides made this alternate homicide measure unfeasible in this analysis. Additional homicide measures were also considered, including infanticide, rates of child homicide for children ages 1 to 4, and rates of child homicide for children ages 1 to 14. Rates of teenage homicide were not examined because previous research suggests that teenage homicide is typically peer related, not family related, and therefore the result of different circumstances and processes than homicides of young children. Interestingly, correlations among these measures were high regardless of the age group comprising the homicide rate. Rho was greater than .78 for all homicide

### *Children's Exposure to Violence in the Home*

A measure of childhood exposure to violence in the home from the NCVS is also included in the national time-series analysis. The NCVS is a nationally representative household-based survey conducted by the U.S. Census Bureau on behalf of the Bureau of Justice Statistics (BJS). Over the last few decades, the NCVS has been the nation's primary source of information on the frequency, characteristics, and consequences of criminal victimization in the U.S. A major purpose of the NCVS is to capture information on victimizations both reported and unreported to the police, complementing official data sources that may be affected by changes over time in victim reporting rates (Baumer & Lauritsen, 2010), administrative data recording practices (Mosher, Miethe, & Hart, 2011), and participation in national data collection systems (Lynch & Jarvis, 2008; Maltz & Targonski, 2002). National rates of children's exposure to violence in the home were collected and analyzed from publicly available NCVS annual data files from 1992 to 2013 following the procedures used by BJS and reported in Truman and Smith (2012).<sup>10</sup>

The rate of children's exposure to violence in their home in the NCVS is defined as the rate of children age 17 or younger living in households where at least one household member age 12 or older experienced one or more nonfatal violent victimizations in the past year. Nonfatal violent victimizations include rape, sexual assault, robbery, aggravated assault, or simple assault. This measure, as reported by Truman and Smith (2012), estimates the number of children in the home, not the number of victimizations or number of adults victimized in the home. Thus, this measure shows

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measures except correlations with infanticide, where the correlations were between .41 and .68. Therefore, in order to be all encompassing, all child victims of homicide are included in the child homicide rate.

<sup>10</sup> The measures required to calculate the rate of children exposed to violent victimization in their home were not available in the 1990 and 1991 NCSs.

the extent to which children have direct or indirect exposure to violent victimization against persons in their home. Because the victimization of one household member may affect all other members of the household (e.g., emotionally, financially, logistically), this measure is an important factor in understanding childhood exposure to violence.

#### *Additional State-Level Data*

Several variables have also been collected and added to the NCANDS state-panel dataset in order to examine the hypothesized covariates of trends in state-level rates of child abuse and neglect. The data for these explanatory measures were compiled from the NCANDS and other secondary data sources for as many years as available from 1990 to 2013.

Trends in the level of people below the poverty threshold were included in order to test the importance of the economic prosperity hypothesis. Annual state poverty rates were collected from 1990 to 2013 from the U.S. Census Bureau.<sup>11</sup>

Annual state incarceration rates from the U.S. Department of Justice's Bureau of Justice Statistics were also included in order to assess the incarceration hypothesis from 1990 to 2013 (i.e., whether incarceration rates had any association with rates of child maltreatment). To account for the likely lagged effect of incarceration rates on rates of child victimization, incarceration rates were lagged one year in all models.

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<sup>11</sup> Originally, gross state product (GSP) was proposed to be used to capture economic conditions at the state level. However, following the work of Messner, Raffalovich, and Sutton (2010), I decided that the poverty rate was a much better construct to measure the importance of the economy and economic conditions on rates of child maltreatment because these measures directly involve the state's resident population—the population that is largely responsible for the reports of child maltreatment across the state. In addition, state unemployment rates collected from the U.S. Bureau of Labor Statistics were also used as an additional measure of state-level economic conditions but showed no significant differences from annual state poverty rates because of their high correlation to one another ( $\rho=.83$  at the national level from 1990 to 2013). I chose poverty rates over unemployment rates due to criticism that unemployment rates do not accurately reflect the rate at which people are truly unemployed because they do not consider everyone who does not have a job (e.g., discouraged workers ultimately give up on finding jobs and are not counted as potential labor force participants), while the percent of people below the poverty line captures the entire population's economic condition.

In order to examine the influence of increases in police and other agents of social control, annual data on the percentage of full-time law enforcement officers and CPS workers in each state were collected. The percentage of full-time law enforcement officers per capita in each state was calculated based on data available from the FBI's UCR from 1990 to 2013. The ratio of CPS workers to children in a state was calculated based on data available in the NCANDS from 1997 to 2013. Both the contemporaneous and lagged effects of these two social control measures are included in the analyses. By including same year and previous year rates of agents of social control, I am able to account for both the concurrent effect of personnel on rates of child victimization and the time needed for changes in the percent of personnel to potentially have an effect on rates of child victimization.

To examine the drug market hypothesis (i.e., the effect of the drug epidemic and the changing nature of drug markets on child maltreatment over time), a proxy measure 'annual state rates of drug violation arrests' was compiled from 1990 to 2013 from the FBI's UCR. This measure includes arrests for the unlawful cultivation, manufacture, distribution, sale, purchase, use, possession, transportation, or importation of any controlled drug or narcotic substance. Controlled drugs include: opium or cocaine and their derivatives (e.g., morphine, heroin, codeine); marijuana; synthetic narcotics—manufactured narcotics that can cause true addiction (e.g., methadone); and dangerous nonnarcotic drugs (e.g., barbiturates).

The psychopharmacology hypothesis is tested by including annual statewide use of psychopharmacological drugs. Consumption of psychotropic drugs by children was gauged using the proxy measure 'statewide rate of retail methylphenidate distribution (in



grams)'. In children and young adolescents, ADHD and other disruptive disorders account for a substantial proportion (37.8%) of psychopharmacological use (Olfson, Blanco, Liu, Moreno, & Laje, 2006). Stimulants are the main class of drug and methylphenidate is the main drug prescribed for the treatment of ADHD in children. One study found that roughly 63% of children were prescribed stimulants to treat their ADHD (Riddle et al., 2013). Therefore, measuring methylphenidate use over time seems to be the best way to capture changes in psychopharmacological use in children. Statewide methylphenidate consumption was assembled from the Automation of Reports and Consolidation Orders System (ARCOS) data which are collected by the U.S. Department of Justice's Drug Enforcement Administration (DEA). ARCOS data report annual retail drug distribution (in grams) by state and drug type. These data were only available from 1997 to 2013.

One potential artifactual explanation for the decline has been examined using statewide data from the NCANDS. This measure, 'the average caseload size of state CPS workers each year', was available from 1997 to 2013.

Because previous research has suggested that there are significant racial differences in reporting to CPS agencies (Fluke, Yuan, Hedderson, & Curtis, 2003; Hussey, Chang, & Kotch, 2006; Putnam-Hornstein, Needell, King, & Johnson-Motoyama, 2013), where blacks have higher reporting rates than non-blacks (Flaherty et al., 2008), it is important that a measure of race was included in the analyses. As a control variable, the percentage of a state's population that is black each year from 1990 to 2013 was also added to the dataset for use in the regression analyses. These demographic data are from the U.S. Census Bureau. Fixed-effects for time have also been controlled in all

models that diagnostics showed required these yearly effects. When individual fixed-effects for year were not needed, the yearly trend was included.

When a data source provided only counts of a measure for each state each year, rates, ratios, or percentages were created using U.S. Census Bureau population data for each state each year. See Table 1 for a list of these dependent, independent, and control variables and their data sources. Measures were included in analyses for either or both the long series (1990 to 2013) or the short series (1997 to 2013), depending on data availability. While all of the child victimization measures were available from 1990 to 2013, some of the independent variables were only available from 1997 to 2013. In order to test these hypotheses, it was necessary to conduct two separate analyses (and run two different models for each victimization type). Hypotheses with measures collected back to 1990 are included in both the 1990-2013 and the 1997-2013 models. Hypotheses with measures only available post-1997 are only included in the 1997-2013 models.

Table 1. List of Measures and Data Sources

<u>Measures</u>	<u>Data Source</u>
<b><i>National-Level Trends</i></b>	
Rate of Child Physical Abuse	National Child Abuse and Neglect Data System
Rate of Child Sexual Abuse	National Child Abuse and Neglect Data System
Rate of Child Neglect	National Child Abuse and Neglect Data System
Percentage of Children Exposed to Violence in their Home	National Crime Victimization Survey, Bureau of Justice Statistics
Rate of Child Homicide	Supplementary Homicide Report, Federal Bureau of Investigation
<b><i>State-Level Trends</i></b>	
<b><i>Dependent Variables</i></b>	
Rate of Child Physical Abuse	National Child Abuse and Neglect Data System
Rate of Child Sexual Abuse	National Child Abuse and Neglect Data System
Rate of Child Neglect	National Child Abuse and Neglect Data System
Rate of Child Homicide	Supplementary Homicide Report, Federal Bureau of Investigation National Vital Statistics System, Centers for Disease Control and Prevention
<b><i>Independent Variables</i></b>	
<b><i>Economic Hypothesis</i></b>	
Poverty Rate	U.S. Census Bureau
<b><i>Psychopharmacology Hypothesis</i></b>	
Rate of Retail Methylphenidate Distribution	Automation of Reports and Consolidation Orders System, U.S. Drug Enforcement Administration
<b><i>Agents of Social Control Hypothesis</i></b>	
Law Enforcement Officers (per capita)	Uniform Crime Report, Federal Bureau of Investigation
CPS Workers (per child)	National Child Abuse and Neglect Data System
<b><i>Incarceration Hypothesis</i></b>	
Incarceration Rate	Bureau of Justice Statistics
<b><i>Drug Market Hypothesis</i></b>	
Arrest Rates for Drug Abuse Violations	Uniform Crime Report, Federal Bureau of Investigation
<b><i>Artifactual Explanation</i></b>	
Average Caseload Size of CPS Workers	National Child Abuse and Neglect Data System
<b><i>Control Variable</i></b>	
Percent Black	U.S. Census Bureau

## ANALYTIC STRATEGY

### *Measurement Component*

The measurement component of this study is broken up into two parts—the national-level measurement analysis and the state-level measurement analysis. The national-level measurement analysis attempts to understand the national trends in child victimization from 1990 to 2013 using both agency and survey data sources. Comparing different modes of data collection processes in the trend in child victimization allows for an assessment of potential administrative agency biases in data collection and reporting of child victimization. In order to assess the degree of correspondence NCANDS national-level trends in child abuse and neglect have with other measures of child victimization, national-level trends in the NCANDS rates of child physical abuse, child sexual abuse, and child neglect are compared to the SHR national rates of child homicide and the NCVS national trend in the rate of children living in households that experienced a violent victimization from 1990 to 2013. The national-level trend analysis uses correlational techniques to examine the relationship among the NCANDS, SHR, and NCVS national trends in child victimization. Correlations among each of the national-level trends from the NCANDS, SHR, and NCVS are presented in both level and trend. Correlations in trend (i.e., first-difference correlations) are presented to show how short-term year-to-year fluctuations may covary among the measures.

The state-level measurement analysis is more in-depth and descriptive than the national-level measurement analysis owing to the use of state-level panel data. The advantage of using panel data is that panel data provide a large number of data points for analysis. Having more data points in a regression analysis, for example, increases the

degrees of freedom and reduces collinearity among the explanatory measures, which in turn improves the efficiency of the estimates. In addition, having data grouped into panels (in this case, by state) allows for multiple trends to occur at the same time across the years of the analysis.

One of the first measurement issues to be resolved before any trend comparisons are made is the problem of missing data in state-level variables, especially the NCANDS measures. Because many of these measures are state administrative agency data, and reporting is not compulsory or enforced by the federal government, a number of states have missing data points in the years of this analysis. Therefore, state-level trends are reviewed and the validity of data points is questioned. Some missing data points are interpolated and a number of states are removed from future analyses. Trends in the rates of these measures with missing data in the remaining states are described and statistical testing is performed to show if the interpolated data are statistically similar to the original non-interpolated data. This data cleaning process produces complete data in the majority of states on the various measures in the analysis.

Once the state-level panel data are clean, the state-level measurement analysis compares state-level trends in rates of child victimization from the NCANDS and rates of child homicide from 1990 to 2013. State trends in the rates of child physical abuse, child sexual abuse, child neglect, and child homicide are examined separately to visually inspect variation in these rates within and across states. Similar to the national-level measurement analysis, the state-level trend analyses also use correlational techniques in both levels and first-differences to examine the relationship between NCANDS state-level rates of child physical abuse, child sexual abuse, and child neglect, and state-level

rates of child homicide. In addition, convergence methods, including the use of error correction mechanisms, are used to show how changes in state rates of child homicide respond to changes in the rates of child physical abuse, child sexual abuse, and child neglect at the state level.<sup>12</sup> Taken together, the correlational and cointegration techniques provide complimentary information about the degree of convergence between sources of data on child victimization.

Tests of cointegration apply the generalized error correction model approach used by Bannerjee et al. (1993), which allows for both stationary and nonstationary time series analyses. Additional Augmented Dickey Fuller tests revealed that a number of the state panels contained a unit root (i.e., they are nonstationary time series). The coefficient  $b_0$  produces the error correction rate in the following error correction equation:

$$\Delta Y_t = a + b_0 Y_{t-1} + b_1 \Delta X_t + b_2 X_{t-1} + e_t$$

Using state-level panel data with obvious high degrees of autocorrelation within and across panels, linear regressions accounting for correlated panels and corrected standard errors were modeled following the general error correction equation. In these linear regressions, the first difference of the outcome ( $\Delta Y_t$ ) is modeled as a linear function of a constant ( $a$ ), the lag of  $Y$  ( $b_0 Y_{t-1}$ ), the first difference of  $X$  ( $b_1 \Delta X_t$ ), the lag of  $X$  ( $b_2 X_{t-1}$ ), and an error term ( $e_t$ ). The coefficients  $b_1$  and  $b_2$  capture, respectively, the instantaneous effect of  $X_t$  on the change in  $Y_t$  (referred to as the “short term effect”) and the effect of  $X_t$  on the change in  $Y_t$  during the next period (i.e.,  $t+1$ , referred to as the “long term

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<sup>12</sup> While it would also be interesting to also see how changes in the national-level NCANDS rates respond to changes in the rates of child homicide and childhood exposure to violence, cointegration analyses were not possible at the national level. With a small number of years (24) in the national-level time-series, the results of the error correction models would be biased. To identify long-run relationships among variables via cointegration tests, research suggests that there is a need for at least 30 observations (and at best more than 50 observations) used in cointegration analyses.

effect”). Dividing  $b_2$  by  $-b_0$  produces the long run multiplier (LRM), which calculates the distribution of the long term effect of  $X_t$  over subsequent time periods.

### *Substantive Component*

The substantive component of this study uses various techniques and models capable of describing and estimating NCANDS state-level panel data. In order to address the abovementioned hypotheses regarding the decline in child victimization from 1990 to 2013, empirical tests are run using panel data regression models. Model diagnostics are performed on the data for each dependent variable of interest—rates of child physical abuse, child sexual abuse, or child neglect—in order to assess if any issues are present in the data prior to model selection. Panel model diagnostics include tests for: specification, cross-sectional dependence (also known as contemporaneous correlation), heteroscedasticity, auto-correlation, and stationarity. The results of various panel regression models are observed on each dependent variable for the years 1990-2013 and 1997-2013 depending on which independent variables are included in the model. After accounting for diagnostic issues present in the various panel models, and how these models compare to one another after correcting or not correcting for these issues using different model specifications, a final model is selected for each dependent variable.

Panel regression models are used because panel datasets (i.e., a dataset including observations over time) are a more complicated dataset design to analyze and their structure cannot be ignored. These data are a short panel—observations across many individual units (i.e., 50 states) and fewer time periods (i.e., 24 years). A linear panel-data model approach is used because it allows for an examination of the within-state and across-state variations in the rates of child victimization. Panel models are particularly

useful for this kind of analysis because they are designed for analyzing repeated measurements at different points in time on the same individual units (e.g., states). Moreover, panel models are capable of adjusting the standard errors of the estimates due to highly correlated errors. Because each additional year of data for each state is not independent of previous years (i.e., they are serially correlated), panel models are necessary to accurately estimate the variation in rates within and across states in this analysis. While panel models incorporate both state and year effects to capture unmeasured time-invariant and time-varying influences on the outcome variables, this study includes only time-varying effects on rates of child victimization.

Each explanatory factor or group of factors that operationalize a given hypothesis was tested both individually and in the full model to discern its/their base effect on rates of child physical abuse, sexual abuse, and neglect, as well as its/their effect after holding all other explanatory measures constant. A supplementary analysis was also completed using child homicide as the dependent variable. This additional check on the validity of the NCANDS trends to measure trends in child victimization is conducted in order to compare the hypothesis test results across NCANDS measures of child maltreatment and child homicide.

In Chapter Five, the results of the national-level measurement component of this study are reported. These visual and statistical findings are followed by a discussion of how this measurement analysis may offer evidence of the validity of the NCANDS for studying national trends in child maltreatment.



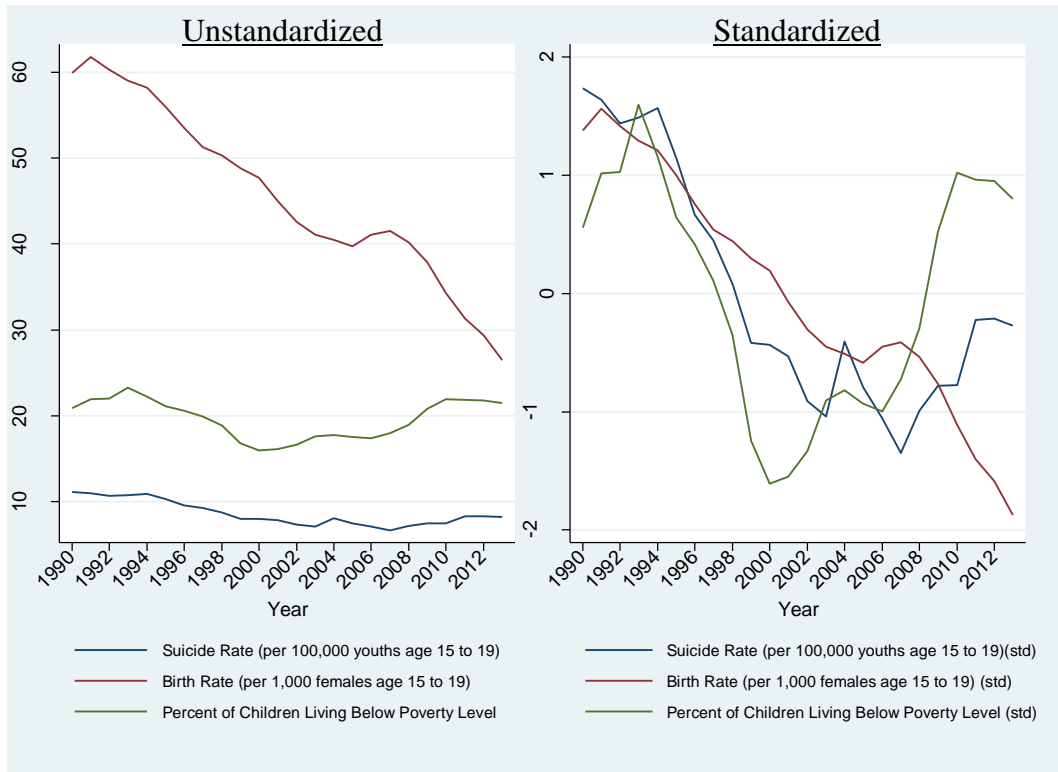
## CHAPTER FIVE: MEASURING THE VALIDITY OF NATIONAL-LEVEL TRENDS IN CHILD MALTREATMENT

Similar to issues in criminology regarding the decline in violent crime, there has been some debate about the validity of the NCANDS rates in depicting trends in child maltreatment accurately. David Finkelhor and colleagues maintain that there appears to be correlational evidence supporting the argument that the declines are real, especially for child sexual abuse (Finkelhor & Jones, 2006, Finkelhor & Jones, 2012). These scholars found that during the 1990s and up through the early- to mid-2000s, significant improvements were made across a variety of other child welfare indicators. As shown in Figure 1, the rate of births to teenage mothers, teen suicide, and children living in poverty improved throughout the 1990s and up until the early- to mid-2000s. When the trends are standardized (i.e., rescaled to have a mean of zero and a standard deviation of one), all three of these measures in the 1990s show nearly parallel steep declines. However, these improvements, while substantial throughout the 1990s, did not last for all three indicators into the twenty-first century. For example, the declines in the percent of children living in poverty in the 1990s were largely eliminated by the substantial increases that followed in the 2000s.

In addition, a number of other child welfare measures have not simultaneously declined or declined to the same degree over this period. This contradiction, coupled with the fact it is possible that the declines may reflect procedural and/or methodological changes in the collection and reporting of child maltreatment by state CPS agencies over time, has made some scholars skeptical of the NCANDS ability to accurately measure change over time in child victimization. Consequently, these contradictions and

uncertainties suggest that it is likely that at least some of the decline in child maltreatment may, in fact, be an artifact of measurement.

Figure 1. Unstandardized and Standardized Trends in Indicators of Child Welfare, 1990-2013



This chapter attempts to shine light on the NCANDS ability to measure temporal change in child victimization at the national level. It is essential in understanding the usefulness of the NCANDS data for measuring trends over time to know if the declines in the NCANDS child maltreatment data reflect the true nature of the changes over time in the occurrence of child victimization. By empirically evaluating the NCANDS validity against other agency and survey sources of child victimization trend data, this measurement assessment focuses on national-level trends in child victimization from 1990 to 2013 before moving on to explore the state-level trends.

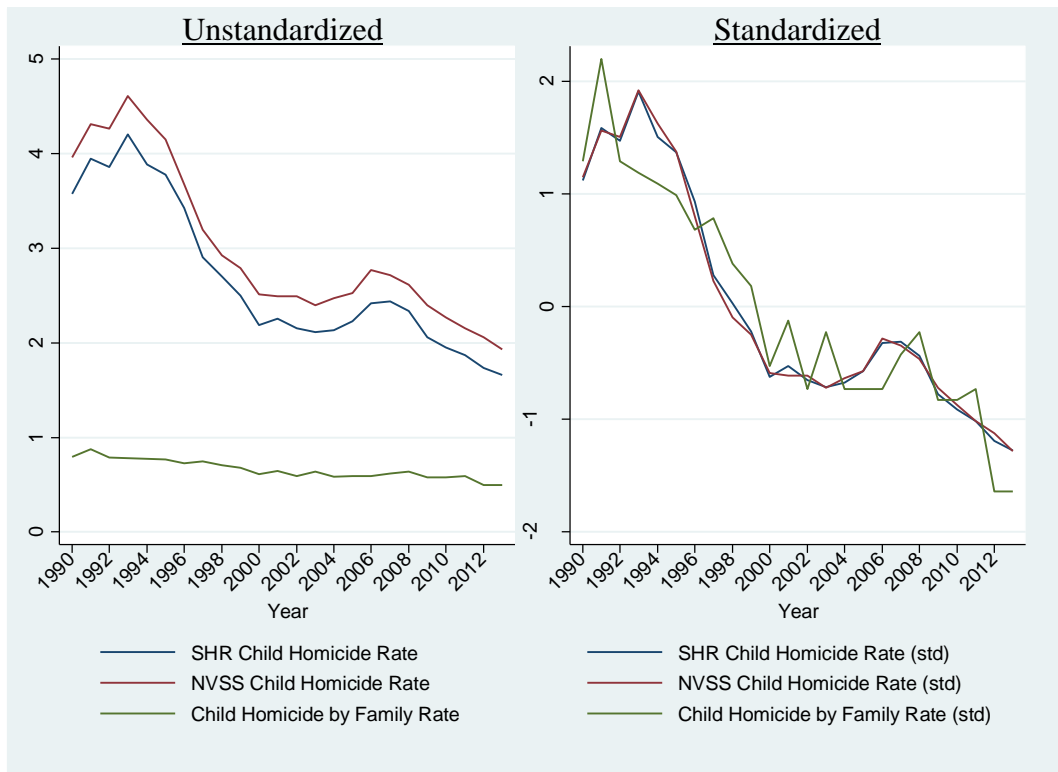
## NATIONAL-LEVEL TREND RESULTS

An important assumption of this measurement analysis is that trends in homicide rates are as close to the “gold standard” of reliable violent crime trend data as any other data available. However, there are two main sources of homicide data (the SHR and the NVSS) so researchers often need to decide which source is best suited for their research. Rates of child homicide in the SHR are reported by state and local law enforcement agencies, whereas rates of child homicide in the NVSS are derived from the manner of death on the deceased’s death certificate as determined by state coroners and medical examiners. Both sources of homicide are derived from agency data and both sources are reported annually.

As shown in Figure 2, national rates of child homicide, including child homicide by a family member, declined from 1990 to 2013. As anticipated, and comparable to prior research on the relationship between SHR and NVSS aggregate trends in homicide by Smith and Cooper (2013), the SHR and NVSS annual rates show very similar trends in the rate of child homicide over this period ( $\rho=.998$ ). While NVSS rates of child homicide are slightly higher than SHR rates of child homicide (just as Smith and Cooper found in their SHR/NVSS comparison with homicide rates in general), both homicide sources showed declines in child homicide rates from 1990 through the early-2000s, followed by a slight increase through 2006, and further decline through 2013. Even the national rates of child homicide by family members followed a similar trend over this period ( $\rho=.94$  with SHR child homicide,  $\rho=.92$  with NVSS child homicide), as shown in the standardized adjustment in the graph on the right. Given that these sources show very similar national trends in rates of child homicide, SHR child homicide rates are used as a

comparison from this point forward in the national-level measurement assessment of the NCANDS trends.

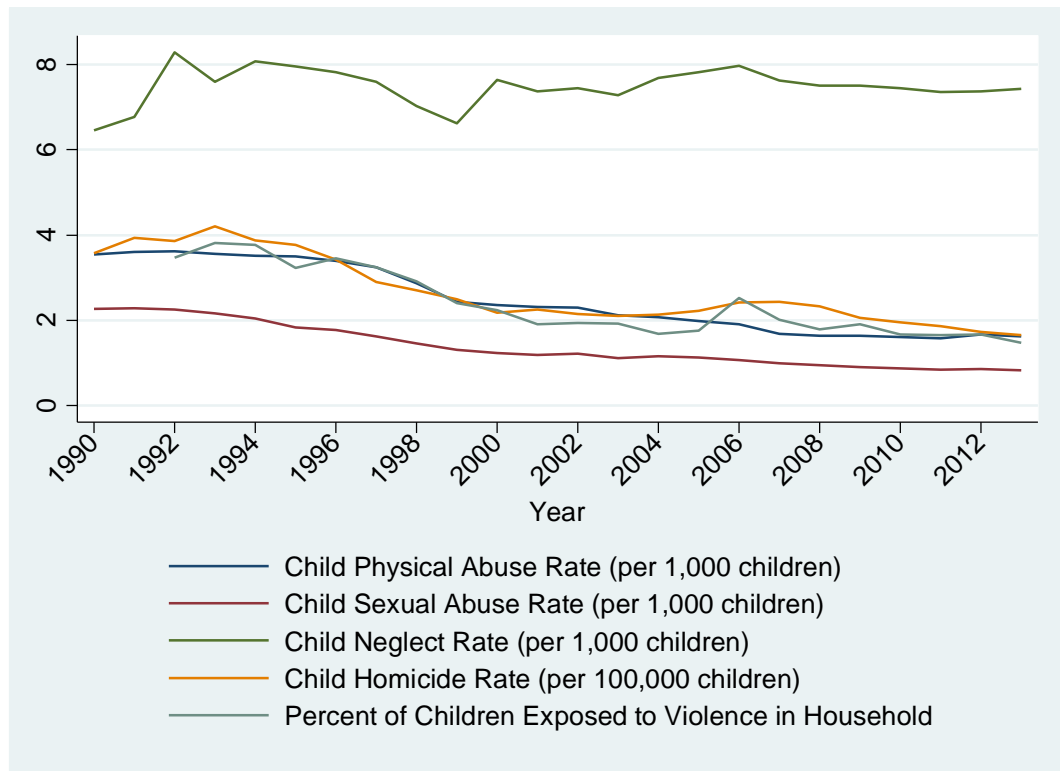
Figure 2. Unstandardized and Standardized U.S. Rates of Child Homicide (per 100,000 children), 1990-2013



Trends in NCANDS rates of child physical abuse, child sexual abuse, and child neglect, as well as trends in the rates of child homicide and the percentage of children exposed to violent victimization in their household from the NCVS can be found in Figure 3. All of the trends except the trend in the rate of child neglect follow the same downward trajectory through the 1990s and into the turn of the century although at slightly different levels. Rate of child neglect are roughly two to three times higher than rates of child physical abuse and child sexual abuse respectively in the early-1990s. By the end of the series, rates of child neglect are 4 to 9 times higher than rates of child

physical and sexual abuse. This change seems to be the result of rates of child neglect neither increasing nor decreasing much across the long trend, while rates of child physical abuse and child sexual abuse declined throughout the entire series.

Figure 3. U.S. Rates of Child Victimization, 1990-2013



NCANDS rates of child physical abuse and child sexual abuse appear to follow a very similar trend to the trend in rates of child homicide and children exposed to violent victimization in their home from 1990 to 2013. The only discernable difference in the trends is the slight increase in the rates of child homicide and children exposed to violence in their home around 2006 while the NCANDS child abuse rates continued to decrease.

After standardizing the rates in order to compare across the different distributions, it is clear that all of the trends besides child neglect did in fact decline in tandem (see Figure 4). Standardized rates of child neglect over this period fluctuated dramatically.

Figure 4. Unstandardized and Standardized U.S. Rates of Child Victimization, 1990-2013

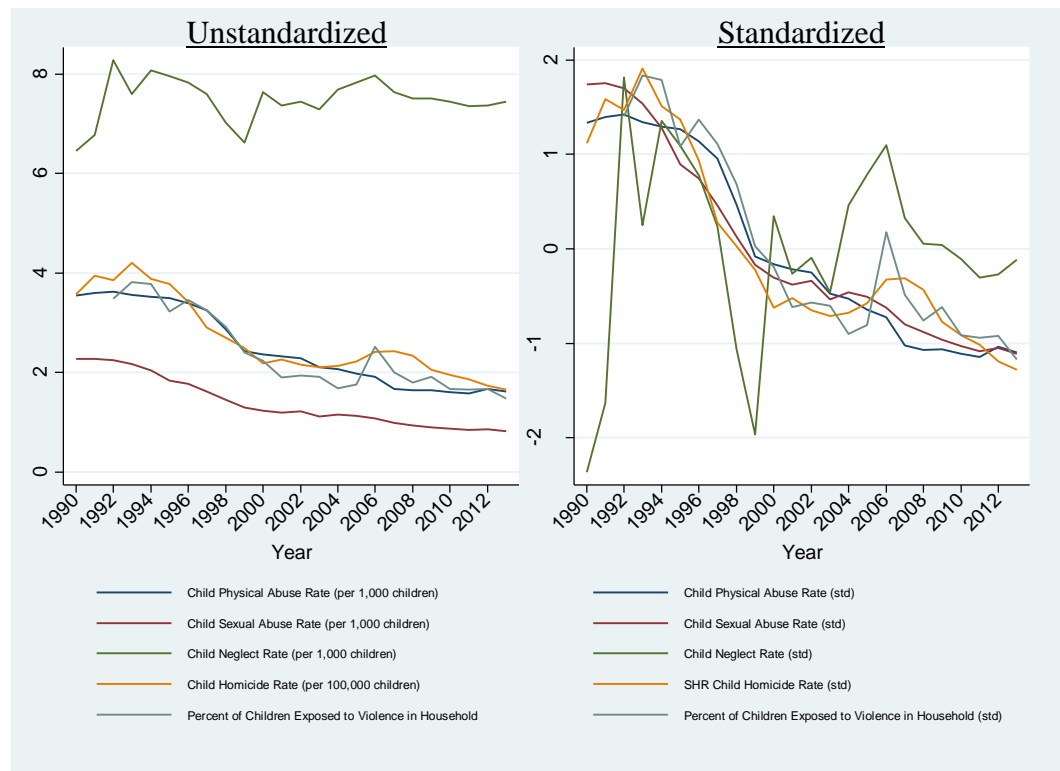


Figure 5 reveals the NCANDS trend in rates of child physical abuse compared with the SHR and NCVS trends in child victimization from 1990 to 2013. Aside from the marked increase in the child homicide rate and the percent of children exposed to violence in their home from 2004 to 2007<sup>13</sup>, the rates of child physical abuse over time consistently trend with both measures of child victimization. Year-to-year changes in the

<sup>13</sup> As shown in Appendix B, national rates of child homicide increased over this period largely because of increased homicide rates among teenagers, as opposed to younger children. Because the NCVS trend in children exposed to violence in their home corresponds to the national homicide trend from 2004 to 2007, this measure may be capturing higher rates of older children exposed to violence in their home as opposed to younger children.

rates of child physical abuse followed a slightly similar trend to year-to-year changes in the rates of child homicide and children exposed to violence in the home, where sizable decreases occurred most years from the mid-1990s through early-2000s in all measures (see Figure 6). However, consistent and steep declines occurred each year in the child physical abuse trend from the early-1990s until 2011, while year-to-year declines were not as steady in the other measures.

Figure 5. Comparison of National Trends for Child Physical Abuse Analysis, 1990-2013

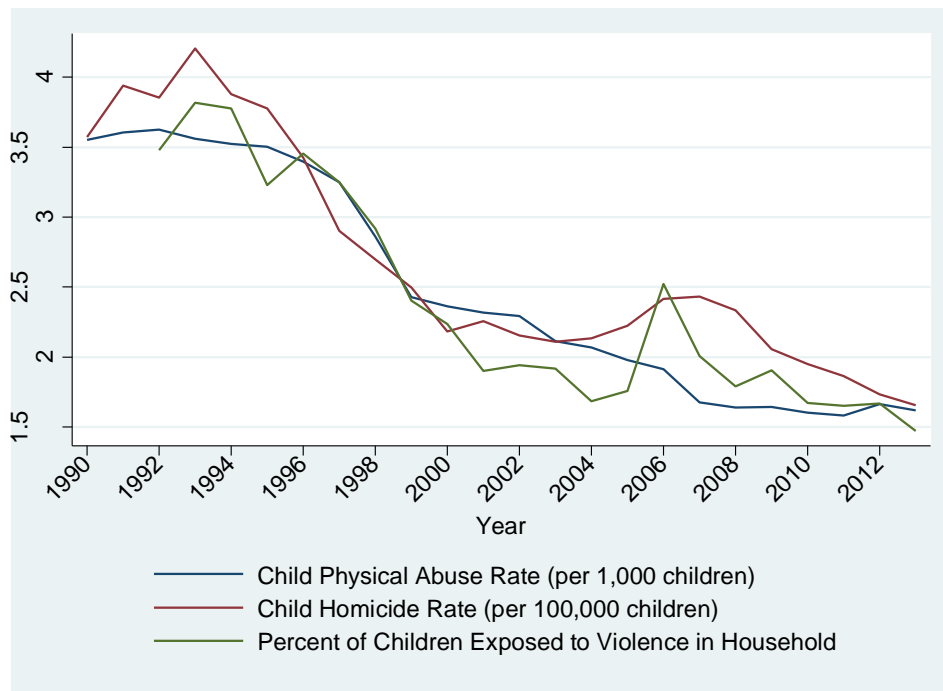


Figure 6. Comparison of National Trends (in Levels and First Differences) for Child Physical Abuse Analysis, 1990-2013



NOTE: \*Rates are first differenced.

NCANDS national rates of child sexual abuse from 1990 to 2013 also followed the same downward trend as the other rates of child victimization (see Figure 7). Similar to trends in child physical abuse, trends in child sexual abuse largely mirrored those of child homicide and children exposed to violence in their home across the series, excluding the aforementioned 2004 to 2006/2007 increase. As shown in Figure 8, year-to-year changes in the rates of child sexual abuse were negative in every year throughout the series except three (2002, 2004, and 2012). Unlike trends in child homicide and children exposed to violence in their home where declines were consistent only in the mid- to late-1990s, child sexual abuse rates declined every year for more than a decade (from 1991 until 2002).



Figure 7. Comparison of National Trends for Child Sexual Abuse Analysis, 1990-2013

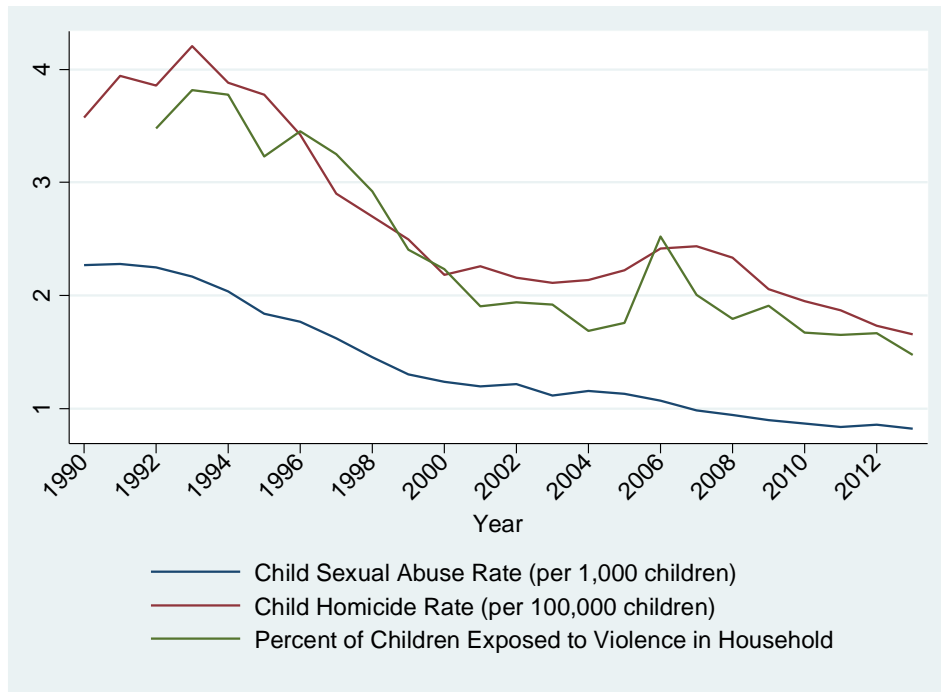
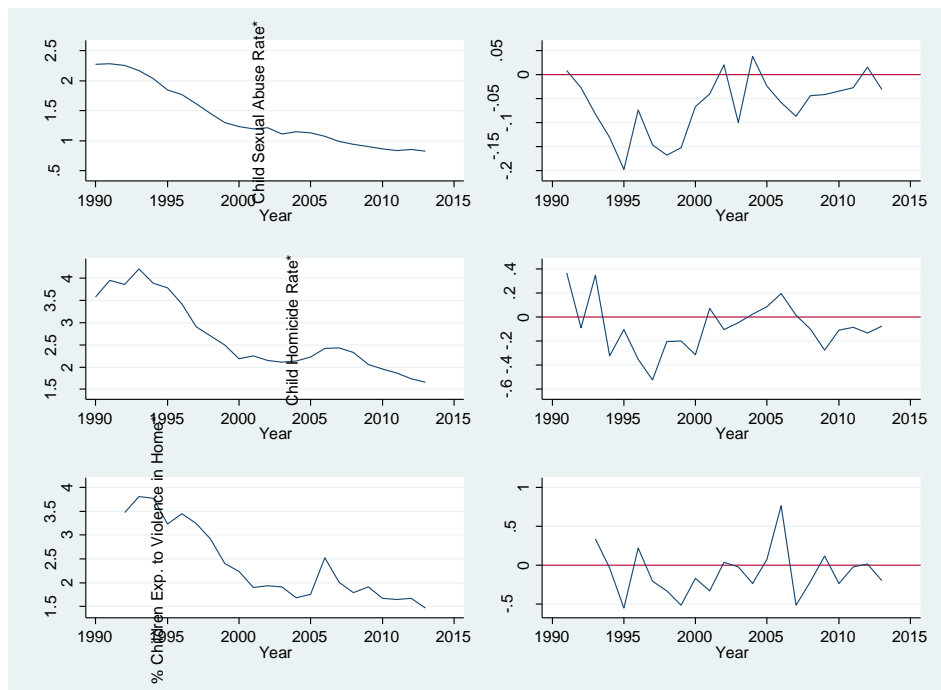


Figure 8. Comparison of National Trends (in Levels and First Differences) for Child Sexual Abuse Analysis, 1990-2013



NOTE: \*Rates are first differenced.

As shown in previous figures, NCANDS rates of child neglect did not decline in the same way as the NCANDS rates of child abuse (see Figure 9). In fact, rates of child neglect decreased over just a few years of the series and none of those declines were long lasting. The inconsistent trend in rates of child neglect over this period in both levels and first differences diverges frequently from the trends in rates of child homicide and children exposed to violent victimization in their home (see Figure 10). However, all three trends had a short-term increase in and around 2006.

Figure 9. Comparison of National Trends for Child Neglect Analysis, 1990-2013

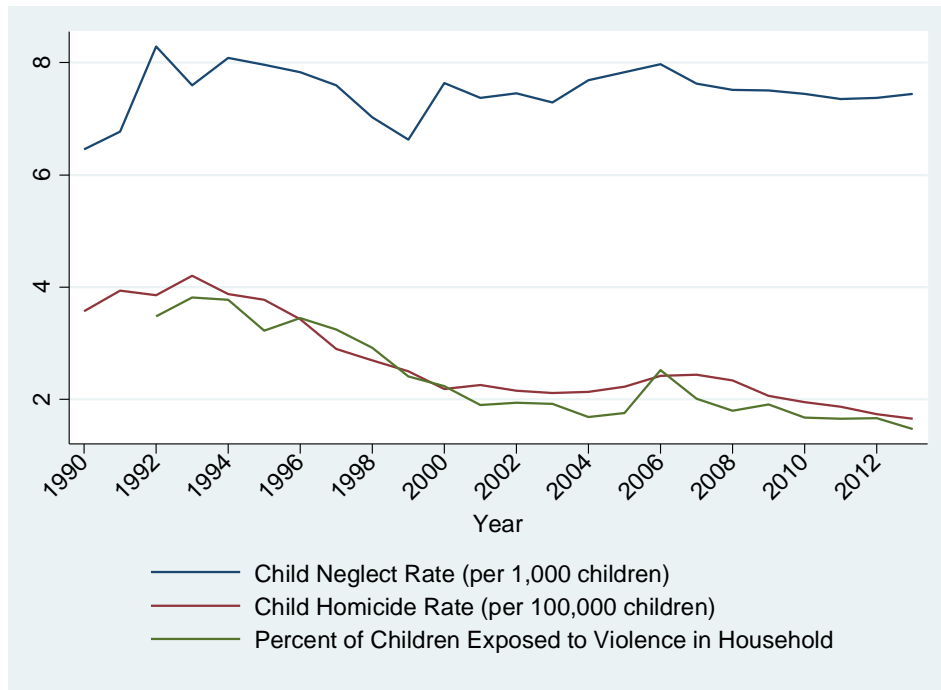
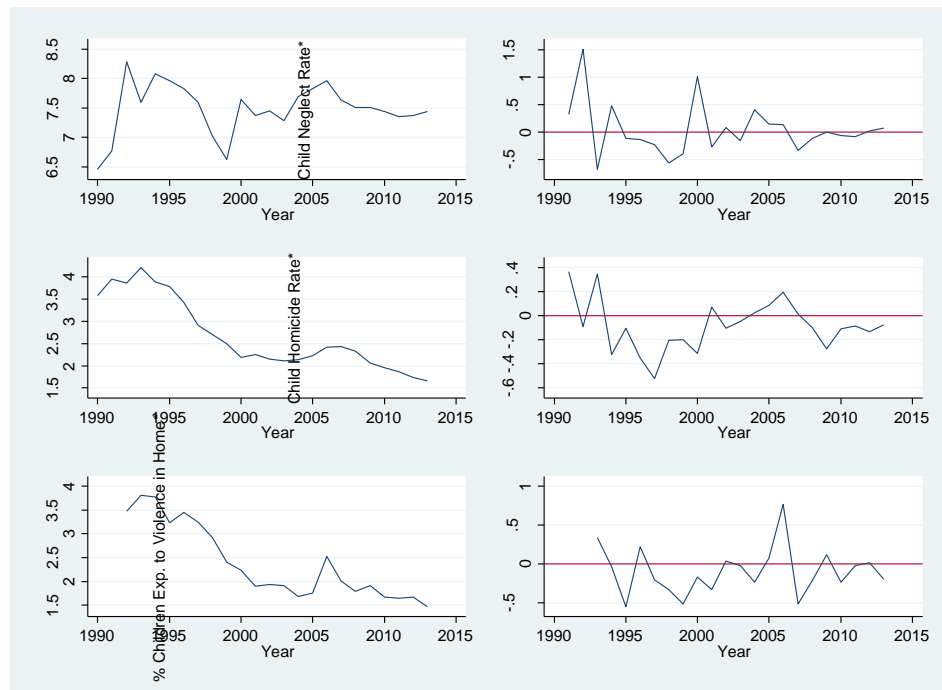


Figure 10. Comparison of National Trends (in Levels and First Differences) for Child Neglect Analysis, 1990-2013



NOTE: \*Rates are first differenced.

In addition to the visual depictions of the trends, a statistical assessment using correlations between the trends in both levels and first differences is provided in Table 2. Here, it is clear that the trend in the rates of child physical abuse is highly correlated with the trends in the rates of child homicide and children exposed to violence in their home ( $\rho=.94$  for both correlations). Correlations between rates of child sexual abuse and these two other indicators of child victimization from 1990 to 2013 are just as strong, if not stronger than trends in child physical abuse ( $\rho=.94$  and  $\rho=.96$ ). Trends in the rates of child homicide and children exposed to violence in their home are also highly correlated with one another ( $\rho=.95$ ). First-differenced NCANDS trends in rates of child physical abuse and child sexual abuse are moderately (though not significantly) correlated with the

other trends. As visually demonstrated, NCANDS trends in child neglect are the least correlated with the other measures of child victimization in this study.

Table 2. National-Level Correlations Between Child Victimization Trends, 1990-2013

	Child Physical Abuse Rate	Child Sexual Abuse Rate	Child Neglect Rate	Child Homicide Rate	Percentage of Children Exposed to Violence in their Home
Child Physical Abuse Rate	1.00				
Child Sexual Abuse Rate	.97 (.62)	1.00			
Child Neglect Rate	.02 (.47)	-.02 (.36)	1.00		
Child Homicide Rate	.94 (.23)	.96 (.39)	.11 (-.10)	1.00	
Percentage of Children Exposed to Violence in their Home	.94 (.38)	.94 (.34)	.42 (.13)	.95 (.31)	1.00

NOTE: Correlations in levels and first-differences (in parentheses). Any  $p > .41$  when  $n=24$  is significant at  $p < .05$  (two-tailed).

## DISCUSSION

Do NCANDS rates of child physical abuse, child sexual abuse, and child neglect at the national level adequately reflect U.S. trends in child victimization? This visual and statistical test of the validity of the NCANDS trends provides evidence that the national trends in the rates of child physical abuse and child sexual abuse correspond rather robustly to trends in the rates of child homicide and children exposed to violence in their home (i.e., they were all largely declining over this period). Trends in rates of child neglect, however, fluctuated greatly and were vastly distinct from the other measures of

child victimization, including the other types of child maltreatment. Correlation coefficients between rates of child physical abuse and child sexual abuse were extremely high compared to these two more established and relied upon sources of child victimization. Because strong relationships were found between trends in the rates of child physical abuse and child sexual abuse, it appears that these trends are measuring a similar phenomenon occurring over this period.

Trends in the rates of child homicide and children exposed to violence in their home were also highly correlated with one another, providing even greater confidence in the validity of these trends to measure trends in child victimization. Their high degree of correspondence with one another provides evidence that using these two measures for comparison purposes is a reasonable and compelling test of the validity of the NCANDS trends to measure temporal change at the national level.

The robustness of these correlations is important given that the NCANDS trends are just as highly correlated with survey data as they are with administrative agency data. NCVS measures are not subject to potential changes in administrative operations so the similarity of the national trends in child homicide, child physical abuse, child sexual abuse, and children exposed to violence in their home makes these findings convincing. Even the high degree of correlation between two independent sets of agency data (the NCANDS and the SHR) is significant because of the potential for these agencies to use disparate data collection and recording systems. Moreover, all three data sources (the NCANDS, SHR, and NCVS) reported a short-term increase in rates of child victimization in and around 2006. Given that this unusual fluctuation was observed across all three

sources, the evidence suggesting strong validity of the NCANDS national trends for measuring temporal change is even more suggestive.

Finkelhor and Jones (2012) came to a slightly similar conclusion related to the decline in rates of child sexual abuse beginning in the early-1990s following their assessment of several national trends in victimization from a variety of sources. While the authors did not necessarily argue that the NCANDS is a valid measure for studying national trends in child victimization, they did argue that the declines in the NCANDS child sexual abuse data appeared to be sufficiently supported by other independent sources of agency and survey data. Therefore, they argued that the declines in child sexual abuse likely occurred as opposed to being an artifact of measurement. Interestingly enough, however, they were unable to conclusively validate the decline in child physical abuse due to the existence of contradictory trends in physical abuse from other data sources. Their analysis compared the percent change in rates over time as opposed to using correlational techniques as those used in this study.

Even with strong evidence that the NCANDS rates of child physical abuse and child sexual abuse are sufficiently valid for studying temporal change in child victimization at the national level, little evidence was found that NCANDS rates of child neglect were an effective gauge of trends in child victimization. It seems somewhat reasonable, however, that rates of child neglect did not trend similarly to the other four measures of child victimization because there is something inherently different about the omission vs. the commission of violence. Child physical abuse, child sexual abuse, child homicide and children exposed to violence in their home are all indicators that measure the commission of violence, where physical or sexual violence was acted upon an

individual, and in most of these cases, upon a child. While child neglect is a crime and could lead to serious consequences for children, it is not necessarily violent behavior. Finkelhor and colleagues suggest that it could also be that child neglect has not received the same level of political attention and public awareness as physical and sexual abuse post-1990, which may be one reason national rates failed to decline like rates of child abuse. Moreover, it is also possible that the identification of new forms of child neglect over time (e.g., drug-affected newborns) may have masked a decline in other conventional types of neglect in the NCANDS data, when in fact one occurred (Finkelhor, Saito, & Jones, 2016).

In Chapter Six, the results of the state-level measurement component of this study are reported. These results are followed by a discussion of how this measurement analysis may offer evidence of the validity of the NCANDS for studying state-level trends in child maltreatment.

## CHAPTER SIX: MEASURING THE VALIDITY OF STATE-LEVEL TRENDS IN CHILD MALTREATMENT

Strong correlations between NCANDS national trends in rates of child abuse and both sets of well-established survey and agency collected trends in child victimization do not necessarily mean that all state-level NCANDS trends are equally valid measures of temporal trends in child victimization and suitable for purposes of measuring and assessing explanations for the declines. In other words, just because the national rates of child maltreatment are the sum of all state rates of child maltreatment, does not mean that all state trends on their own meet the standards for assessing hypotheses about trends in child maltreatment. For this reason, it is necessary to investigate the consistency, reliability, and ultimately the validity of state-level trends in child maltreatment.

Before the any analyses could take place, however, a significant investigation was required into all state-level administrative agency data sources because many of these data sources were wrought with missing or unexplainable data points. Therefore, a number of data verification and cleaning methods were employed to remove obvious or confirmed erroneous data from the trends. In addition, data estimation techniques were used to fill in missing data where applicable to produce trends in these state-level measures from 1990 to 2013. The main measurement and substantive analyses use the complete estimated data. However, additional robustness tests using the original data are also conducted and reported in the substantive component of this study.

This chapter investigates the NCANDS ability to measure temporal change in child victimization at the state level. The same correlational techniques using state-level trends in the rates of child homicide are explored to identify the utility of the NCANDS state-level data for measuring temporal trends in child victimization. Additionally,



cointegration techniques are also used to see at what point trends in state-level rates of child maltreatment return to equilibrium after deviating from their long-term or short-term trend. Through the use of error correction models, it is also possible to decipher if, and when, NCANDS state-level trends converge with trends in rates of child homicide and if they share an underlying long-run equilibrium with state-level child homicide trends.

The analytical methods used in this chapter provide evidence of how useful the NCANDS state-level data are for measuring state-level trends in child victimization over time. In addition, within and across state trend comparisons are reported both visually and empirically for NCANDS child maltreatment measures. Extreme variations within and across states in these measures may lead to these state-level trends being incapable or at the very least inefficient in measuring temporal trends in child victimization. Without confidence in the validity and reliability of the state-level trends, one should be skeptical of the results of hypothesis tests done at the state level.

## DATA CLEANING

As with all research, the quality of the data used is paramount in trusting the accuracy of research findings. Therefore, it was very important that the state-level data used in this analysis were as accurate and complete as possible across the series. Without complete data (i.e., balanced data: a data point entered for each year in each state for all measures entered into an analysis), many analyses, including the correlational analyses, were not possible over the entire period for all states. Because the state-level dataset was composed of data from a collection of official federal data sources, who in turn requested

their data from individual state agencies, it is understandable why the data in the state-level file were not error-free and balanced. In some cases, state agencies are not required to submit data to the federal government, but rather they voluntarily submit their data to their federal counterpart. For these reasons, a few methods of data verification and cleaning were employed prior to all of the main state-level analyses.<sup>14</sup>

To examine the reliability and validity of the state-level NCANDS data, three verification methods were conducted prior to any analyses. First, NCANDS counts of reports by disposition and number of investigations were checked against the NCANDS data provided in the annual Child Maltreatment Reports published by the Administration for Children and Families, a branch of the U.S. Department of Health and Human Services. When counts were missing for any state in a given year, but available in the annual report, the data point from the report was entered into the dataset. At times, data points were updated based on updated trends tables available in more recent annual reports. Second, state trends in each measure of interest were graphed to observe outlier data points. To better understand these trends, I contacted representatives at state CPS agencies in 16 states that had questionable data in order to verify the accuracy of the NCANDS trends and to inquire about any state-specific circumstances that may explain the questionable trends. This process, as well as reviewing notes regarding the state data available in the back of the annual Child Maltreatment Reports, provided a much better understanding of the state-level NCANDS trends. These inquiries revealed that most outlier data points were the result of definitional or procedural changes at the state level in a given year (see Appendix A for a description of select states' trend inquiries). Third,

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<sup>14</sup> The state-level measurement analysis and main hypothesis tests of the substantive analysis were all conducted using the estimated state-level data. The original data were also included in hypothesis tests as a test of the robustness of the estimated data in the final panel models.

because some data points were extreme outliers and the information necessary to understand why these points deviated from the normal trend was not obtained, any data points that were four or more standard deviations from the mean of all states on each NCANDS measure were recoded as missing.<sup>15</sup>

Due to the presence of missing state data on a number of the dependent and independent measures across the years of this analysis, techniques to deal with missing data were employed. List-wise deletion, a typical way of dealing with missing data on measures, removes an entire record (or in this case, a state) from the analysis if any single value is missing. Unfortunately, using list-wise deletion removed all states from the analyses for many reasons; one reason being that one year of data was missing across all states on an independent variable. Therefore, it was necessary to use estimation techniques to fill in as many missing data points as possible with estimated values so that entire state panels or whole years would not have to be removed from the analyses.<sup>16</sup>

When data were missing data on a measure for a particular state, interpolation (i.e., estimating values based on a linear function between two or more known values) was used to keep as many states in the analyses as possible. Interpolation procedures differed for dependent and independent variables and occurred according to the following rules. If NCANDS data were missing for a given state in more than three years in the

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<sup>15</sup> Data points that were four or more standard deviations above the mean included: rates of child physical abuse - 11 data points (10 from Alaska), rates of child sexual abuse - 6 data points (5 from Alaska), and rates of child neglect - 1 data point (from Alaska). Consequently, because Alaska had a number of data points with extreme values in the rates of child physical and child sexual abuse that were recoded as missing, Alaska was dropped from all state-level analyses for child physical abuse and child sexual abuse because an investigation into their data revealed that they only reported child-based counts during these years instead of report based counts. Therefore, there was one report, per child, per incident, instead of one report per incident, regardless of the number of children. No data points were more than four standard deviations from the aggregate mean in the rate of child homicide.

<sup>16</sup> It should be noted that the missing data in this study are not likely missing at random. This issue will be discussed later in the dissertation. In addition, multiple imputation of the missing data seems like a feasible option to create balanced data as long as the clustering of the years within states are accounted for, however, this dissertation does not utilize imputation procedures.

series, the entire state was removed from the analysis of that dependent variable. Therefore, data were never interpolated for more than three years in a given state in the rates of child physical abuse, child sexual abuse, child neglect, and child homicide. For the most part, if any of the abovementioned independent variables in a given state had more than 5 missing years of data (i.e., just over 20% of the data were missing), that state was removed from all analyses (see Appendix C for information about the states removed from the analyses due to excessive missing data).

The only exception to this rule occurred when interpolation could be performed between two known data points in a given state with five or more years of nonconsecutive missing data. This exception was made in order to keep a state in the analysis.<sup>17</sup> Interpolation was never performed in a given state when more than four consecutive years of data were missing at the beginning, middle, or end of the series. In addition, if one year of state data was missing at the beginning or end of the series, the closest year of data was duplicated in the missing year (e.g., if 1990 was missing in a given dependent or independent measure, the 1991 value would be copied into the 1990 data point for that measure). This rule was established because it was the most conservative way of maintaining the average trend in each measure while still allowing for the analyses to extend back to 1990.<sup>18</sup> Interpolation processes kept a number of states in the analysis that would have otherwise been removed entirely from some of the analyses. However, between one and fifteen states were ultimately removed from the

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<sup>17</sup> This exception was made only once (with Montana), in the case of six missing rates of drug abuse violation arrests. A few of these six missing rates were between two known rates so the average was entered as the missing rate in order to keep Montana in the analyses.

<sup>18</sup> Extrapolation of these data points was deemed too extreme a technique as many missing data points would have been replaced to create an unreliable steep trend when the linear trend fluctuated between the first two or last two real data points.

analyses because data cleaning and interpolation techniques did not produce complete data for the entire long or short series (i.e., there was still excessive missing data on at least one dependent or independent variable).<sup>19</sup> Table 3 provides the counts and percentages of the state panels included in the final regression models after this data cleaning procedure. Across the long series (1990-2013), 90% or more of the 50 U.S. states were included in the models for each dependent variable. This percentage dropped to 72% to 78% across the short series (1997-2013) because a number of states were missing NCANDS data for CPS measures (i.e., the ‘ratio of CPS workers per child’ and ‘average caseload size’).

Table 3. Descriptive Statistics for State Panels Included in the Regression Models

<i>Dependent Variable</i>	<u>1990-2013</u>		<u>1997-2013</u>	
	Number	Percentage	Number	Percentage
Rates of Child Physical Abuse	45	90%	36	72%
Rates of Child Sexual Abuse	45	90%	36	72%
Rates of Child Neglect	45	90%	36	72%
Rates of Child Homicide	49	98%	39	78%

Descriptive statistics were examined to determine if the data cleaning and interpolation procedures produced any significant differences between the state panel data directly from their source and the final state panel data post-interpolation. Difference in means t-tests for correlated samples were performed to compare the difference between mean rates across the original source data and the final data on each measure

<sup>19</sup> The states removed from the state-level analysis were still included in calculating annual U.S. rates of child victimization for each victimization type.

(i.e., the original rates as they came from their data source or the original rates as they came from their data source but only for the states included in the analysis, and the final data after all data cleaning and interpolation has been performed on source data for the states included in the analysis) in both the long and short series by state and across all states. This t-test determines the internal validity of the clean and interpolated final data (i.e., whether the clean interpolated final data are statistically different from the original data and the original data for only the years and states in the analyses). If the final data are statistically different from the original source data, it increases the likelihood that the data cleaning and interpolation procedures produced bias trends in the final estimated data.

The final estimated data are composed of 90% or more of the original data for each dependent variable in the long series analyses and 72% or more of the original data for each dependent variable in the short series analyses. Aggregated state average mean rates varied only slightly across the rates for each outcome measure in both the long and short series (see Table 4). After examining the difference in means t-tests, no combination of the original source data and the final interpolated data across all outcome variables revealed statistically significant differences across the aggregated state panels.

Table 4. Aggregate Sample Descriptive Statistics for the Outcome Variables in Long and Short Series Analyses

	<u>1990-2013 Analysis</u>					<u>1997-2013 Analysis</u>				
	No. of States: Rates	Percent of Rates Available (N=1,200)	Mean Rate	Min Rate	Max Rate	No. of States: Rates	Percent of Rates Available (N=850)	Mean Rate	Min Rate	Max Rate
<i>Dependent Variables</i>										
Rates of Child Physical Abuse										
Original Data	50: 1,144	.953	2.59	.13	18.54	50: 831	.978	2.17	.13	18.54
Original Data: States Removed Excluded*	45: 1,055	.879	2.47	.13	10.63	36: 605	.712	2.01	.13	9.52
Final Data**	45: 1,080	.90	2.51	.13	10.07	36: 612	.72	2.02	.13	9.52
Rates of Child Sexual Abuse										
Original Data	50: 1,141	.951	1.44	.17	7.90	50: 831	.978	1.17	.17	7.90
Original Data: States Removed Excluded*	45: 1,052	.876	1.42	.17	6.96	36: 605	.712	1.17	.17	4.57
Final Data**	45: 1,080	.90	1.42	.17	5.87	36: 612	.72	1.16	.17	4.57
Rates of Child Neglect										
Original Data	50: 1,144	.953	7.42	.04	49.08	50: 831	.978	7.24	.06	49.08
Original Data: States Removed Excluded*	45: 1,055	.879	7.30	.04	26.93	36: 605	.712	6.73	.06	26.93
Final Data**	45: 1,080	.90	7.36	.04	26.93	36: 612	.72	6.77	.06	26.93
Rates of Child Homicide										
Original Data	50: 1,197	.997	2.24	0	7.73	50: 847	.996	1.93	0	7.73
Original Data: States Removed Excluded*	49: 1,173	.978	2.23	0	7.73	39: 662	.779	1.87	0	7.73
Final Data**	49: 1,176	.98	2.24	0	7.73	39: 663	.78	1.87	0	7.73

NOTE: \*Only the states included in the long and short series analyses are included. Between 1 to 15 states were dropped because interpolation techniques did not create complete data for the entire long or short series. Interpolation was not conducted on this sample.

\*\*The final data are the post-data cleaning, post-interpolation data.

Difference in means t-tests also revealed no statistically significant difference in mean rates between the source data and final data on all dependent variables within each state as well (see Table 5 and Table 6).<sup>20</sup> The more data points interpolated in a state trend tended to produce rates a bit further away from the original data mean rate, however, the interpolation processes did not produce a significantly different mean rates of child physical abuse, sexual abuse, and neglect. Interestingly, though, there is great variation across states in their mean rates on each of the three outcomes. Higher rates are typically found for child neglect, although regardless of the series (1990-2013 or 1997-2013), the minimum and maximum mean state rates of each outcome are significantly different.

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<sup>20</sup> State rates of child homicide as an outcome variable are not included in this table because these rates only had to be interpolated in two states (three rates in total) across all years. Difference in means t-tests revealed no statistically significant differences in the original child homicide rates and the final child homicide rates in these two states used in the supplementary analysis.



Table 5. Original/Final Mean Rates of Child Maltreatment Trends by State, 1990-2013

	<u>Rates of CPA</u>		<u>Rates of CSA</u>		<u>Rates of CN</u>	
	Original Data Mean	Final Data Mean (N=24)	Original Data Mean	Final Data Mean (N=24)	Original Data Mean	Final Data Mean (N=24)
Alabama	*	4.65	*	2.63	*	5.71
Arizona	*	1.76	*	0.91	*	4.95
Arkansas	2.94 <sup>a</sup>	2.93	3.17 <sup>a</sup>	3.15	7.91 <sup>a</sup>	7.85
California	2.85 <sup>a</sup>	2.95	1.58 <sup>a</sup>	1.64	6.97 <sup>a</sup>	6.87
Colorado	1.74 <sup>a</sup>	1.79	1.07 <sup>a</sup>	1.12	5.58 <sup>a</sup>	5.52
Connecticut	*	2.38	0.83 <sup>b</sup>	0.89	*	12.28
Delaware	*	2.41	*	0.96	*	4.53
Florida	*	3.51	*	1.51	*	10.23
Georgia	2.51 <sup>a</sup>	2.55	1.34 <sup>a</sup>	1.38	11.95 <sup>a</sup>	11.77
Hawaii	*	1.49	*	0.61	*	1.68
Idaho	3.45 <sup>a</sup>	3.26	1.99 <sup>a</sup>	1.83	6.17 <sup>a</sup>	6.03
Illinois	*	1.83	*	1.47	*	6.59
Indiana	*	2.71	*	2.95	*	10.62
Iowa	2.98 <sup>b</sup>	3.03	1.29 <sup>b</sup>	1.32	11.60 <sup>b</sup>	11.26
Kentucky	*	4.25	*	1.44	*	15.51
Louisiana	*	2.48	*	0.76	*	7.53
Maine	*	3.16	*	1.79	*	8.09
Massachusetts	3.85 <sup>b</sup>	3.92	0.96 <sup>b</sup>	0.95	18.28 <sup>b</sup>	18.31
Michigan	2.36 <sup>a</sup>	2.35	0.66 <sup>a</sup>	0.66	7.81 <sup>a</sup>	7.88
Minnesota	*	1.83	*	0.73	*	4.77
Mississippi	2.09 <sup>a</sup>	2.09	1.40 <sup>a</sup>	1.38	5.50 <sup>a</sup>	5.46
Missouri	*	1.79	*	1.55	*	4.29
Montana	2.91 <sup>c</sup>	3.56	1.10 <sup>c</sup>	1.33	6.96 <sup>c</sup>	7.69
Nebraska	*	2.20	*	1.02	*	7.68
Nevada	2.43 <sup>c</sup>	2.64	0.54 <sup>c</sup>	0.59	7.74 <sup>c</sup>	8.48
New Hampshire	*	0.71	*	0.81	*	2.16
New Jersey	*	1.46	*	0.49	*	3.44
New Mexico	*	2.71	*	0.85	*	8.98
New York	2.44 <sup>c</sup>	2.67	0.73 <sup>c</sup>	0.81	13.33 <sup>c</sup>	12.61
North Carolina	*	0.79	*	0.75	*	12.90
North Dakota	2.80 <sup>b</sup>	2.84	0.84 <sup>c</sup>	0.83	8.03 <sup>b</sup>	8.03
Ohio	4.50 <sup>b</sup>	4.57	2.76 <sup>b</sup>	2.82	8.69 <sup>b</sup>	8.89
Oklahoma	*	3.32	*	1.22	*	11.32
Oregon	*	1.77	*	1.77	*	4.43
Pennsylvania	*	0.75	*	1.02	*	0.11
Rhode Island	*	3.69	*	1.26	*	12.43
South Carolina	*	2.93	*	0.95	*	7.31
South Dakota	*	2.23	*	1.04	*	8.95
Tennessee	*	2.03	*	2.07	*	4.33
Texas	*	2.42	*	1.23	*	6.30
Utah	*	2.67	*	2.91	*	3.84
Vermont	*	2.70	*	3.73	*	1.68
Virginia	*	1.39	*	0.78	*	3.40
Wisconsin	*	1.86	*	3.04	*	3.12
Wyoming	1.62 <sup>a</sup>	1.68	1.04 <sup>a</sup>	1.07	5.21 <sup>a</sup>	5.23

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect.

NOTE: \*There were no missing data in original source data so the original data are the final data.

The number of years used to calculate the original mean state rate: <sup>a</sup>N=23, <sup>b</sup>N=22, <sup>c</sup>N=21.

Alaska, Kansas, Maryland, Washington, and West Virginia are not included in table because they were removed from the long series analyses on these outcomes.

Table 6. Original/Final Mean Rates of Child Maltreatment Trends by State, 1997-2013

	Rates of CPA		Rates of CSA		Rates of CN	
	Original Data Mean	Final Data Mean (N=17)	Original Data Mean	Final Data Mean (N=17)	Original Data Mean	Final Data Mean (N=17)
Alabama	*	4.08	*	2.19	*	4.05
Arizona	*	1.19	*	0.30	*	3.92
Arkansas	2.60 <sup>a</sup>	2.61	3.31 <sup>a</sup>	3.27	8.69 <sup>a</sup>	8.56
California	*	1.84	*	1.01	*	7.27
Delaware	*	2.50	*	0.91	*	4.34
Florida	*	3.05	*	1.11	*	9.03
Hawaii	*	0.98	*	0.50	*	1.36
Idaho	1.85 <sup>a</sup>	1.78	0.87 <sup>a</sup>	0.83	4.40 <sup>a</sup>	4.30
Illinois	*	1.95	*	1.41	*	5.88
Indiana	*	2.07	*	2.48	*	10.78
Iowa	2.55 <sup>a</sup>	2.58	1.06 <sup>a</sup>	1.08	13.42 <sup>a</sup>	13.05
Kentucky	*	3.09	*	1.03	*	15.11
Louisiana	*	2.30	*	0.69	*	7.28
Maine	*	3.25	*	1.74	*	9.34
Massachusetts	3.37 <sup>b</sup>	3.53	0.70 <sup>b</sup>	0.72	20.17 <sup>b</sup>	19.98
Minnesota	*	1.30	*	0.69	*	4.57
Mississippi	*	1.77	*	1.28	*	5.39
Missouri	*	1.53	*	1.41	*	3.11
Montana	*	2.05	*	0.80	*	5.83
Nevada	2.00 <sup>a</sup>	2.06	0.43 <sup>a</sup>	0.44	6.06 <sup>a</sup>	6.34
New Hampshire	*	0.58	*	0.61	*	2.35
New Jersey	*	0.98	*	0.40	*	3.14
New Mexico	*	2.38	*	0.61	*	8.83
North Carolina	*	0.80	*	0.72	*	12.04
North Dakota	1.54 <sup>a</sup>	1.59	0.66 <sup>a</sup>	0.66	7.05 <sup>a</sup>	7.03
Oklahoma	*	3.16	*	1.00	*	12.17
Oregon	*	1.35	*	1.28	*	4.57
Pennsylvania	*	0.58	*	0.91	*	0.09
Rhode Island	*	2.50	*	0.87	*	12.43
South Dakota	*	1.98	*	0.60	*	8.80
Tennessee	*	2.03	*	2.02	*	4.45
Texas	*	2.07	*	1.04	*	6.57
Utah	*	2.44	*	2.75	*	3.52
Vermont	*	2.78	*	3.33	*	1.26
Virginia	*	1.12	*	0.59	*	2.61
Wyoming	*	1.04	*	0.65	*	4.47

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect.

NOTE: \*There were no missing data in original source data so the original data are the final data.

The number of years used to calculate the original mean state rate: <sup>a</sup>N=16, <sup>b</sup>N=15.

Alaska, Colorado, Connecticut, Georgia, Kansas, Maryland, Michigan, Nebraska, New York, Ohio, South Carolina, Washington, West Virginia, and Wisconsin are not included in table because these states were removed from the short series analyses on these outcomes.

The same method was used to check whether the data cleaning and interpolation procedure used may have created biased rates for independent variables across the aggregated panels (see Table 7) and within each state (see Table 8). Data interpolation was not necessary for three of the key independent variables (poverty rates, incarceration rates, and the rate of methylphenidate distribution) and the control variable (percent black) because the original source data were complete. Significant differences between means of the original source data and the final data were not found for any of the remaining four independent variables across the aggregated panels. In the case of the percent of law enforcement officers per capita, data were missing for an entire year (1990), so 1991 data were replicated in 1990 producing no mean rate differences or altered trend between 1990 and 1991. This was done to keep 1990 in the analysis. Interpolated arrest rates for drug abuse violations, the number of CPS caseworkers per child, and the average size of a CPS workers' caseload were found across various states and years of the analysis.

In addition, difference in means t-tests for correlated samples were calculated between the original data and the final data for each state for each of the outcomes in the long and short series. None of those differences were statistically significant. Similar to the variation found in the mean state rates of NCANDS measures, there is significant variation in the final mean state rates of these independent variables as well.

With the state-level data cleaned and no significant differences were found across the original and interpolated data, state-level trends in the various measures of child victimization can be visually and empirically examined. As shown in the previous tables, most states are included in the state-level trend analyses that follow. For example, 45 of

50 states are included in the child maltreatment trend analyses from 1990 to 2013, while 49 of 50 states are included in the child homicide trend analyses during this same period.

Table 7. Aggregate Descriptive Statistics for Independent Variables in Long and Short Series Analyses

	<u>1990-2013 Analysis</u>				<u>1997-2013 Analysis</u>			
	No. of Rates (Max N=1,200)	Mean Rate	Min Rate	Max Rate	No. of Rates (Max N=850)	Mean Rate	Min Rate	Max Rate
<b><i>Independent Variables</i></b>								
Poverty Rate*								
Original Data	1,200	12.73	4.5	26.4	850	12.45	4.5	25.75
Incarceration Rate*								
Original Data	1,200	361.01	67.06	885.56	850	392.08	110.05	885.56
Female Incarceration Rate*								
Original Data	1,200	49.07	4.07	140.47	850	56.28	6.95	140.47
Law Enforcement Officers per capita								
Original Data	1,150	.002	.001	.004	850	.002	.001	.004
Final Data**	1,200	.002	.001	.004	850	.002	.001	.004
Arrest Rates for Drug Abuse Violations								
Original Data	1,118	4.94	.32	21.23	832	5.28	.32	21.23
Final Data**	1,200	4.81	.32	21.23	850	5.25	.32	21.23
CPS Caseworkers per child								
Original Data					706	.0005	.00003	.0016
Final Data**					748	.0005	.0001	.0017
CPS Worker Caseload								
Original Data					694	69.12	7.38	222.07
Final Data**					748	68.74	7.38	275.72
Rate of Methylphenidate Distribution*								
Original Data					850	52.26	12.09	125.18
<b><i>Control Variable</i></b>								
Percent Black*								
Original Data	1,200	10.26	.30	37.42	850	10.42	.31	37.42

NOTE: \*These variables had no missing data in either series so data cleaning was not necessary.

\*\*The final data are the post-data cleaning, post-interpolation data.

Descriptive statistics for the final data on a measure include all states with complete data on that measure, regardless of whether the state is included or excluded in a specific analysis because it is missing on another variable. The number of states in the final interpolated data is not consistent across all of the variables in the short series because descriptive statistics across all states with complete data are shown in this table. Because each outcome model includes a different number of states for both the long and short series, descriptive statistics for all states with available data are examined.

Table 8. Original and Final Mean Rates for CPS-Related and Drug-Related Trends by State, 1990-2013 and 1997-2013

	<u>Arrest Rates for Drug Abuse Violations</u>				<u>Average CPS Worker Caseload Size</u>		<u>Ratio of CPS Workers to Children</u>	
	1990-2013		1997-2013		1997-2013		1997-2013	
	Original Data Mean	Final Data Mean (N=24)	Original Data Mean	Final Data Mean (N=17)	Original Data Mean	Final Data Mean (N=17)	Original Data Mean	Final Data Mean (N=17)
Alabama	3.64 <sup>a</sup>	3.57	*	3.96	*	70.33	*	.00038
Arizona	5.63 <sup>a</sup>	5.56	*	5.82	*	39.12	*	.00057
Arkansas	4.70 <sup>a</sup>	4.62	*	5.06	*	55.47	*	.00066
California	7.44 <sup>a</sup>	7.43	*	7.30	58.88 <sup>aa</sup>	57.65	*	.00043
Colorado	4.11 <sup>a</sup>	4.04	*	4.23	-	-	-	-
Connecticut	5.37 <sup>a</sup>	5.33	-	-	-	-	-	-
Delaware	4.85 <sup>a</sup>	4.80	*	5.41	74.87 <sup>aa</sup>	76.36	.00043 <sup>aa</sup>	.00043
Florida	7.61 <sup>d</sup>	7.36	8.18 <sup>aa</sup>	8.17	*	87.01	*	.00043
Georgia	6.53 <sup>a</sup>	6.44	-	-	-	-	-	-
Hawaii	2.87 <sup>c</sup>	2.86	2.81 <sup>bb</sup>	2.81	43.74 <sup>cc</sup>	46.32	.00024 <sup>cc</sup>	.00024
Idaho	3.65 <sup>a</sup>	3.56	*	4.11	29.08 <sup>cc</sup>	27.95	.00072 <sup>bb</sup>	.00072
Illinois	15.46 <sup>c</sup>	13.79	*	17.58	*	83.14	*	.00026
Indiana	3.96 <sup>a</sup>	3.86	*	4.54	99.41 <sup>bb</sup>	110.60	.00033 <sup>aa</sup>	.00032
Iowa	3.05 <sup>b</sup>	2.84	*	3.46	105.64 <sup>aa</sup>	106.67	.00033 <sup>aa</sup>	.00032
Kentucky	8.51 <sup>a</sup>	8.32	*	9.37	*	45.09	*	.00059
Louisiana	6.84 <sup>a</sup>	6.71	*	7.46	*	109.97	*	.00021
Maine	3.56 <sup>b</sup>	3.49	4.08 <sup>aa</sup>	4.07	*	38.90	*	.00053
Massachusetts	3.10 <sup>a</sup>	3.14	*	2.64	*	114.54	*	.00025
Michigan	3.58 <sup>a</sup>	3.56	-	-	-	-	-	-
Minnesota	3.27 <sup>a</sup>	3.18	*	3.60	47.89 <sup>cc</sup>	47.14	.00032 <sup>cc</sup>	.00031
Mississippi	7.48 <sup>a</sup>	7.34	*	8.05	*	48.43	*	.00056
Missouri	6.58 <sup>a</sup>	6.46	*	7.12	93.99 <sup>cc</sup>	85.14	.00049 <sup>bb</sup>	.00059
Montana	1.45 <sup>f</sup>	1.35	1.62 <sup>bb</sup>	1.65	40.16 <sup>dd</sup>	41.70	.00097 <sup>dd</sup>	.00096
Nebraska	5.60 <sup>a</sup>	5.48	-	-	-	-	-	-
Nevada	5.71 <sup>a</sup>	5.65	5.57 <sup>aa</sup>	5.48	90.88 <sup>aa</sup>	91.38	.00026 <sup>aa</sup>	.00026
New Hampshire	3.21 <sup>c</sup>	3.16	3.44 <sup>aa</sup>	3.45	*	93.92	*	.00029
New Jersey	6.37 <sup>a</sup>	6.34	*	6.43	44.23 <sup>aa</sup>	43.29	.00058 <sup>aa</sup>	.00058
New Mexico	4.24 <sup>a</sup>	4.15	*	4.44	*	66.21	*	.00049

New York	6.39 <sup>a</sup>	6.39	-	-	-	-	-	-
North Carolina	4.92 <sup>a</sup>	4.88	*	5.10	85.73 <sup>cc</sup>	90.58	.00047 <sup>bb</sup>	.00046
North Dakota	2.42 <sup>a</sup>	2.35	*	2.91	34.19 <sup>ee</sup>	34.88	.00077 <sup>ee</sup>	.00073
Ohio	4.15 <sup>a</sup>	4.13	-	-	-	-	-	-
Oklahoma	5.17 <sup>b</sup>	5.10	5.79 <sup>aa</sup>	5.81	98.85 <sup>aa</sup>	96.58	*	.00042
Oregon	4.96 <sup>a</sup>	4.89	*	5.18	*	67.41	*	.00043
Pennsylvania	4.25 <sup>a</sup>	4.18	*	4.51	*	8.63	*	.00100
Rhode Island	3.72 <sup>a</sup>	3.66	*	3.79	*	99.39	*	.00032
South Carolina	5.63 <sup>a</sup>	5.55	-	-	-	-	-	-
South Dakota	3.80 <sup>a</sup>	3.68	*	4.34	*	41.36	*	.00065
Tennessee	6.12 <sup>a</sup>	6.10	*	6.48	97.53 <sup>cc</sup>	96.71	.00042 <sup>aa</sup>	.00043
Texas	5.11 <sup>a</sup>	5.05	*	5.42	48.60 <sup>bb</sup>	46.87	.00053 <sup>bb</sup>	.00053
Utah	4.16 <sup>a</sup>	4.08	*	4.25	*	140.26	*	.00018
Vermont	2.01 <sup>c</sup>	1.89	2.34 <sup>aa</sup>	2.27	39.31 <sup>bb</sup>	40.65	.00060 <sup>aa</sup>	.00060
Virginia	4.10 <sup>a</sup>	4.04	*	4.29	80.70 <sup>aa</sup>	81.53	*	.00027
Wisconsin	4.19 <sup>d</sup>	4.23	-	-	-	-	-	-
Wyoming	4.68 <sup>a</sup>	4.52	*	5.57	*	24.67	*	.00101

NOTE: \*No missing data in original source data so the original source data are the final data.

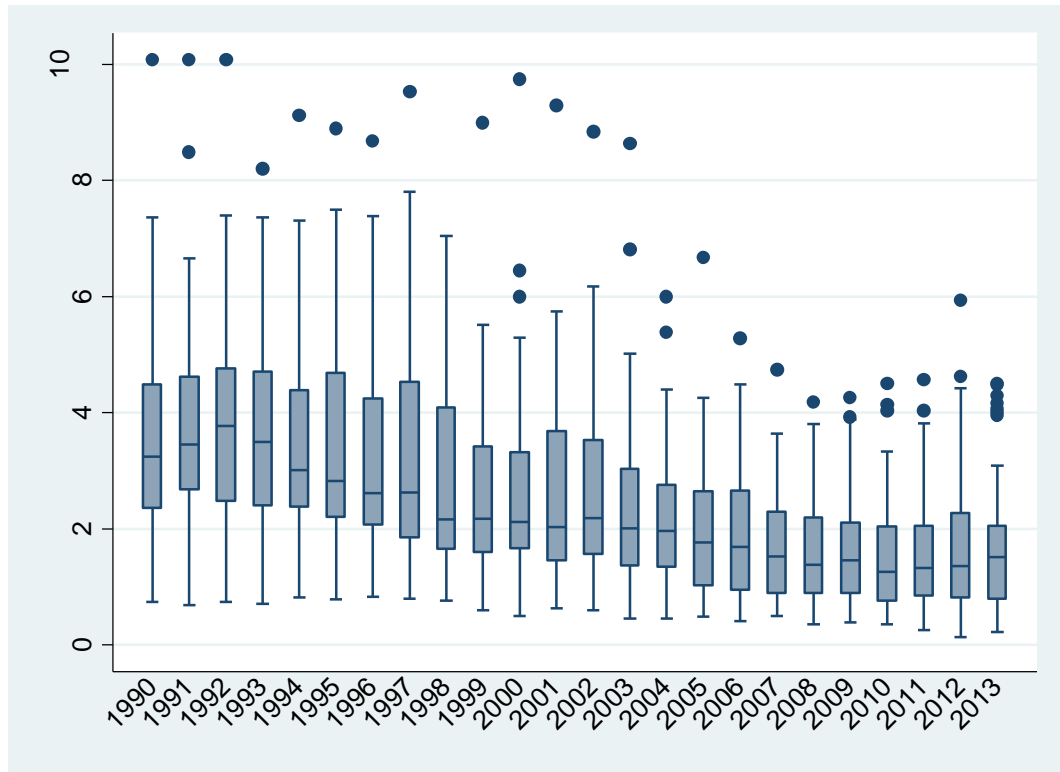
The number of years used to calculate the mean of the original source data is 24 or 17 depending on the length of the analysis unless otherwise noted. <sup>a</sup>N=23, <sup>b</sup>N=22, <sup>c</sup>N=21, <sup>d</sup>N=20, <sup>e</sup>N=19, <sup>f</sup>N=18. <sup>aa</sup>N=16, <sup>bb</sup>N=15, <sup>cc</sup>N=14, <sup>dd</sup>N=13, <sup>ee</sup>N=12.

Alaska, Kansas, Maryland, Washington, and West Virginia are not included in the table because they were removed from the long series analyses. Colorado, Connecticut, Georgia, Kansas, Maryland, Michigan, Nebraska, New York, Ohio, South Carolina, and Wisconsin are missing data in the short series because these states had either excessive or completely missing data on any of the independent variables, usually the CPS-related measures, and therefore were dropped from the short series analyses.

## STATE-LEVEL TREND RESULTS

Trends in the national rates of child physical abuse declined from around 3.5 reports per 1,000 children in 1990 to around 1.5 reports per 1,000 children in 2013. However, as shown in Figure 11, a few states had rates in a given year significantly higher (though less than four standard deviations higher) than the majority of all states. The middle 50% of state rates varied by about 1 to 1.5 reports of child physical abuse per 1,000 children every year from 1990 to 2013. There was also significant variation in the rates of child physical abuse across the series. In any given year, a handful of state rates were also outliers (more than 1.5 interquartile ranges above the upper quartile) compared to all other state rates.

Figure 11. Aggregate State Trend in Child Physical Abuse, 1990-2013

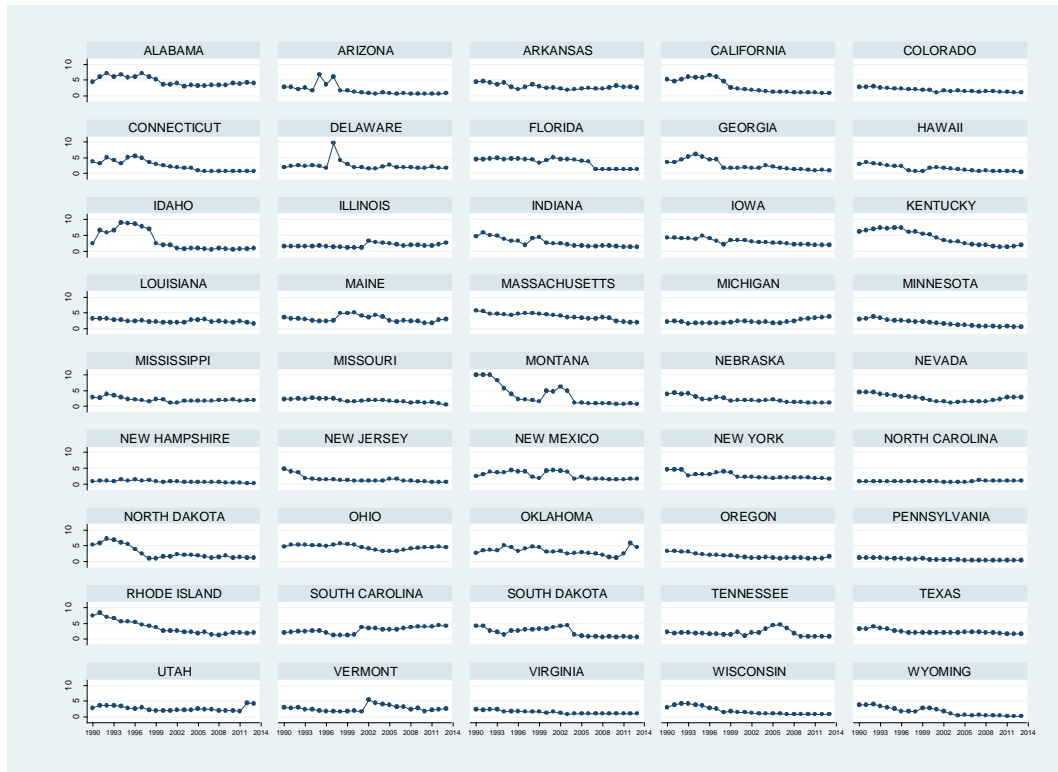


NOTE: States not included in the long series analysis of the trend in child physical abuse are not included in the figure. See Appendix D for a description of how to interpret this box plot.

State-level trends in rates of child physical abuse were also not uniform across all states (see Figure 12). Many states' rates decreased over the entire period from 1990 to 2013, while some states were stable over time. There were also states with a few outlier data points in their trend. Nearly all increases in rates were followed by a gradual decline, producing a few state trends that fluctuated throughout the series (e.g., Georgia, Kentucky, Montana). For the most part, however, most states show a decrease in the rate of child physical abuse from 1990 to 2013, albeit with some movement in the beginning or middle of the trend. A few states had increased rates toward the end of the series (e.g., Michigan, Oklahoma).



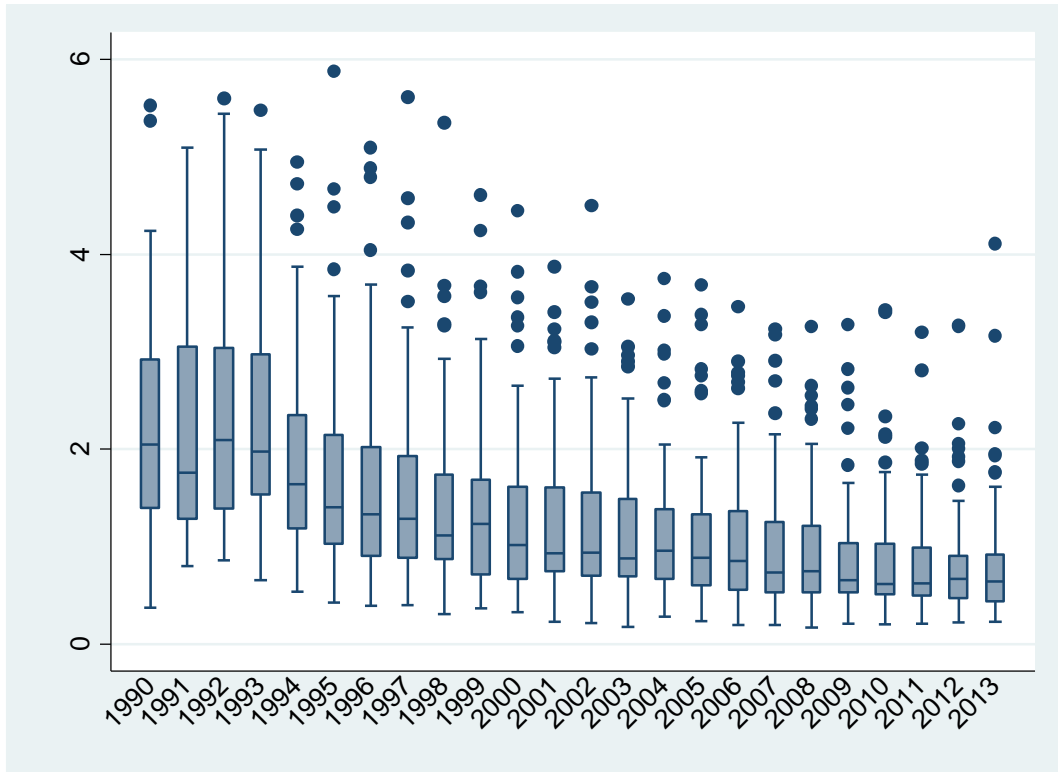
Figure 12. Trends in Rates of Child Physical Abuse by State, 1990-2013



NOTE: States not included in the long series analysis of the trend in child physical abuse are not included in the figure.

Using aggregated NCANDS state-level data, trends in the national rates of child sexual abuse declined from 1990 to 2013. Individual state trends in child sexual abuse also varied, however, as shown in Figure 13. Many more rates fell outside above the upper quartile rate for child sexual abuse than for child physical abuse. The middle 50% of states varied by about 1 report of child sexual abuse per 1,000 children in 1990, but only one-half of a report of child sexual abuse per 1,000 children by 2013. Even in the aggregate, there was significant variation in state rates of child sexual abuse from 1990 to 2013, although a general decline occurred throughout this period in the median state rate.

Figure 13. Aggregate State Trend in Child Sexual Abuse, 1990-2013

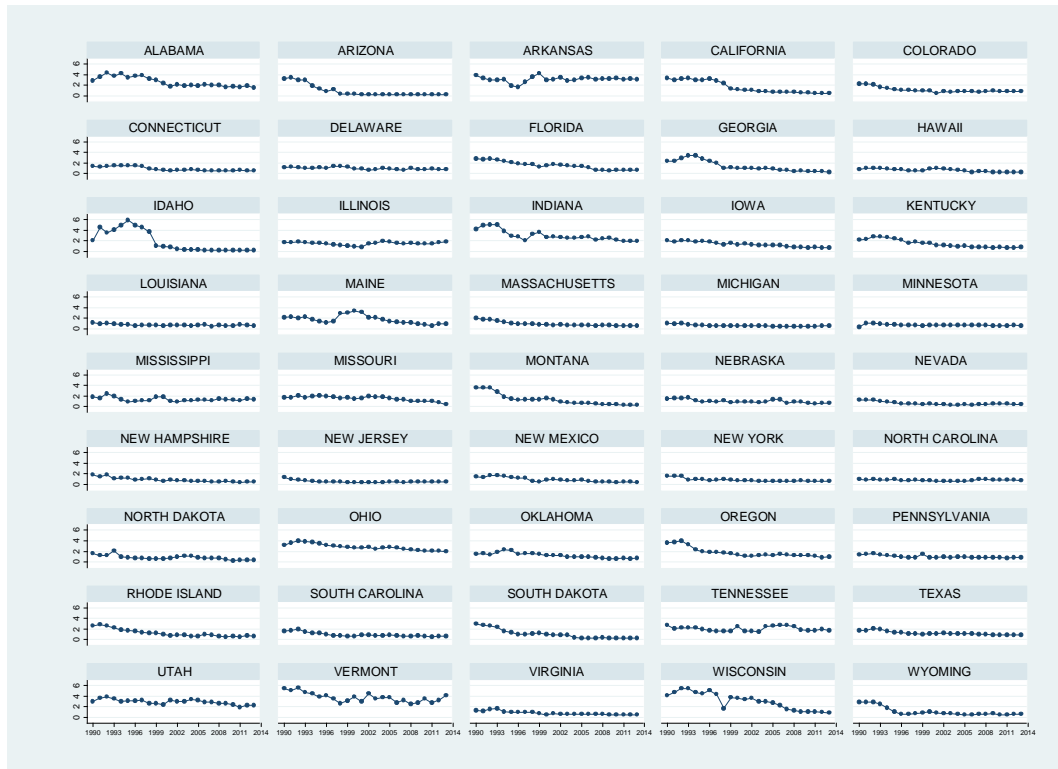


NOTE: States not included in the long series analysis of the trend in child sexual abuse are not included in the figure. See Appendix D for a description of how to interpret this box plot.

States do not necessarily follow similar trends in the rates of child sexual abuse either (see Figure 14). Similar to trends in the rates of child physical abuse, most state trends in the rates of child sexual abuse decreased from 1990 to 2013, and any increase was followed by a decline. A few state trends were also stable over the period (e.g., Michigan, North Carolina). State rates of child sexual abuse had fewer outlier data points than rates of child physical abuse. Interestingly, Idaho, Georgia, and to an extent, Indiana, and Montana appear to have child physical abuse and child sexual abuse trends that mirror one another in a few fluctuations over the period. These similar trends may be the

result of data measurement and reporting procedures in these states and not real increases or decreases in rates (as discussed later).

Figure 14. Trends in Rates of Child Sexual Abuse by State, 1990-2013

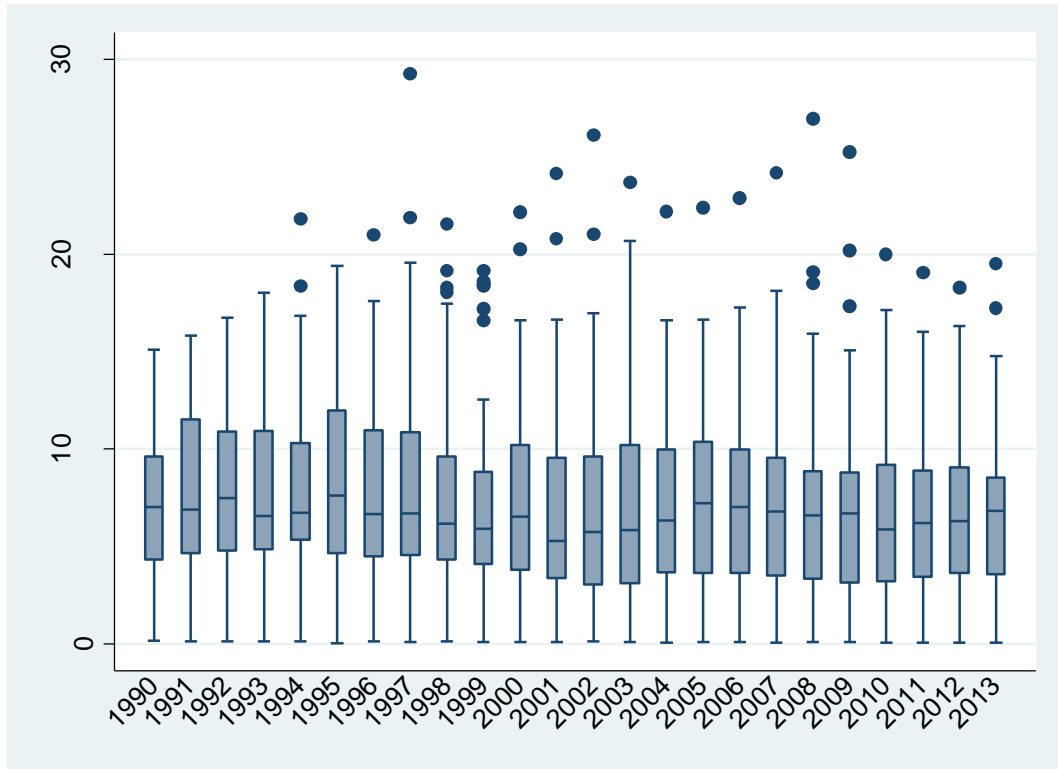


NOTE: States not included in the long series analysis of the trend in child sexual abuse are not included in the figure.

As described in Chapter 5, national rates of child neglect did not consistently decline from 1990 to 2013, but rather fluctuated throughout the trend. Individual state trends in child neglect also varied as shown in Figure 15. Any state rates that fell above the upper quartile rate were found only in the middle and end of the series. In addition, the middle 50% of states differed by roughly 5 reports of child neglect per 1,000 children throughout the entire period. As shown, the trend rose and fell nearly every year,

increasing then decreasing then increasing again, with no consistent trend noticeable from 1990 to 2013.

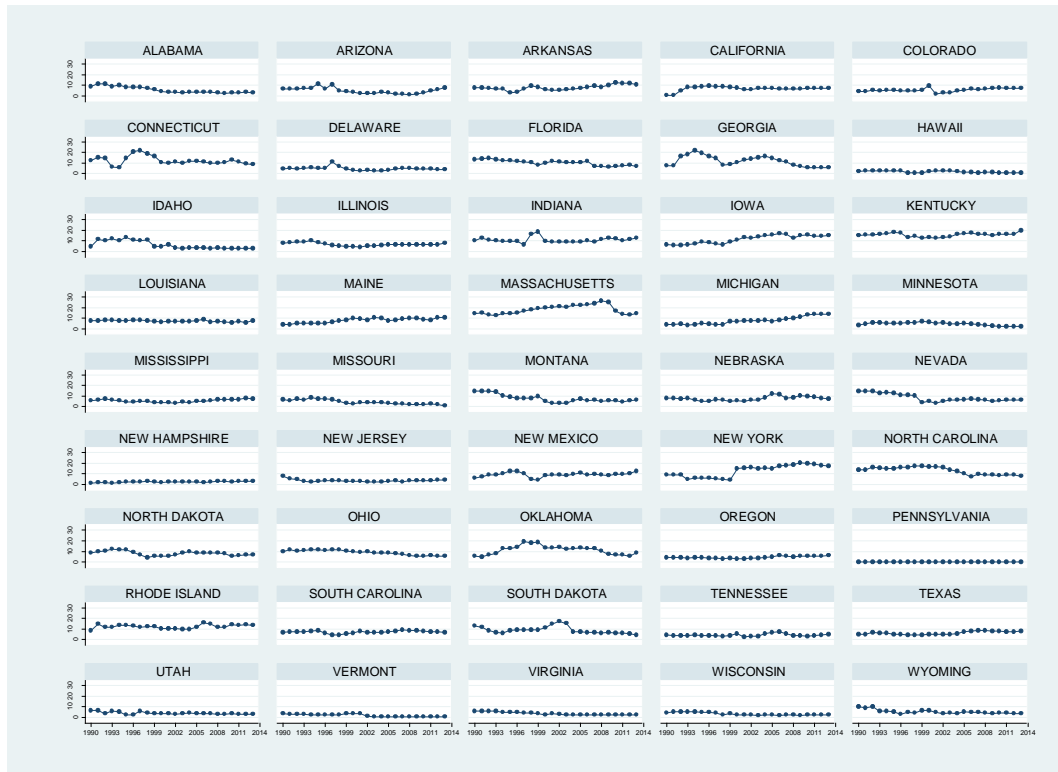
Figure 15. Aggregate State Trend in Child Neglect, 1990-2013



NOTE: States not included in the long series analysis of the trend in child neglect are not included in the figure. See Appendix D for a description of how to interpret this box plot.

There is much more variation in the state trends of child neglect than the other state trends in child abuse measures (see Figure 16). A few state trends were stable over the period (e.g., Minnesota, Tennessee), but many showed gradual increases throughout the series or upward and downward movements within the series (e.g., Massachusetts, Oklahoma). Only a few states had largely steady declines throughout the period (e.g., Alabama, North Carolina).

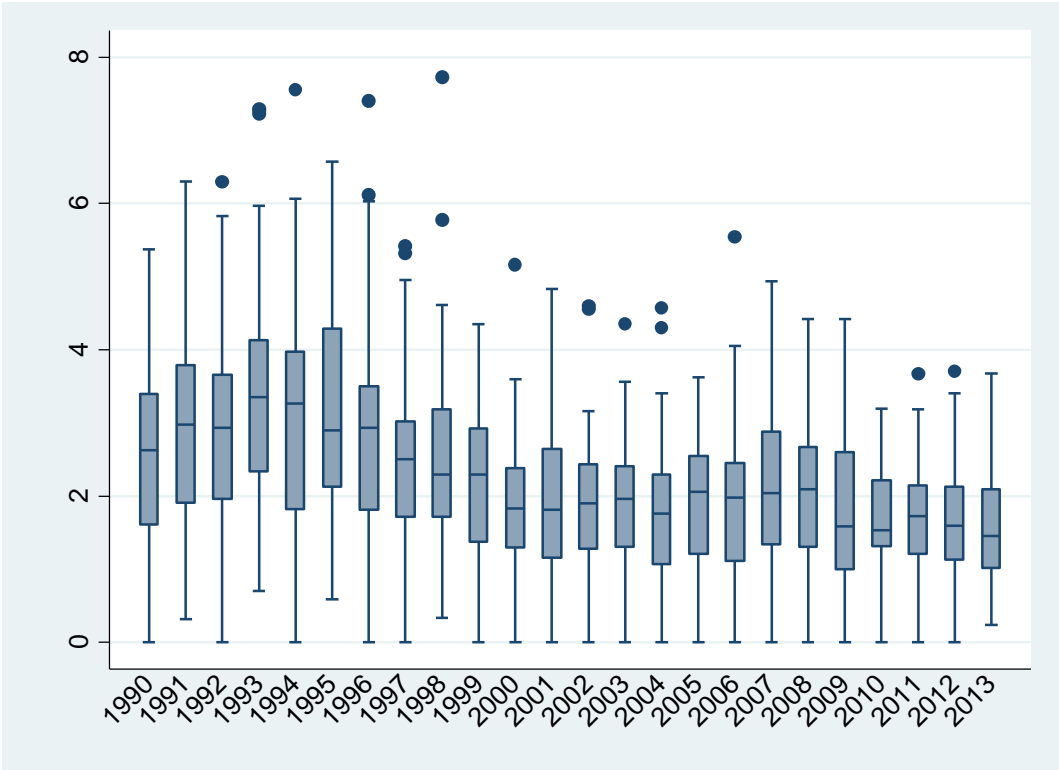
Figure 16. Trends in Rates of Child Neglect by State, 1990-2013



NOTE: States not included in the long series analysis of the trend in child neglect are not included in the figure.

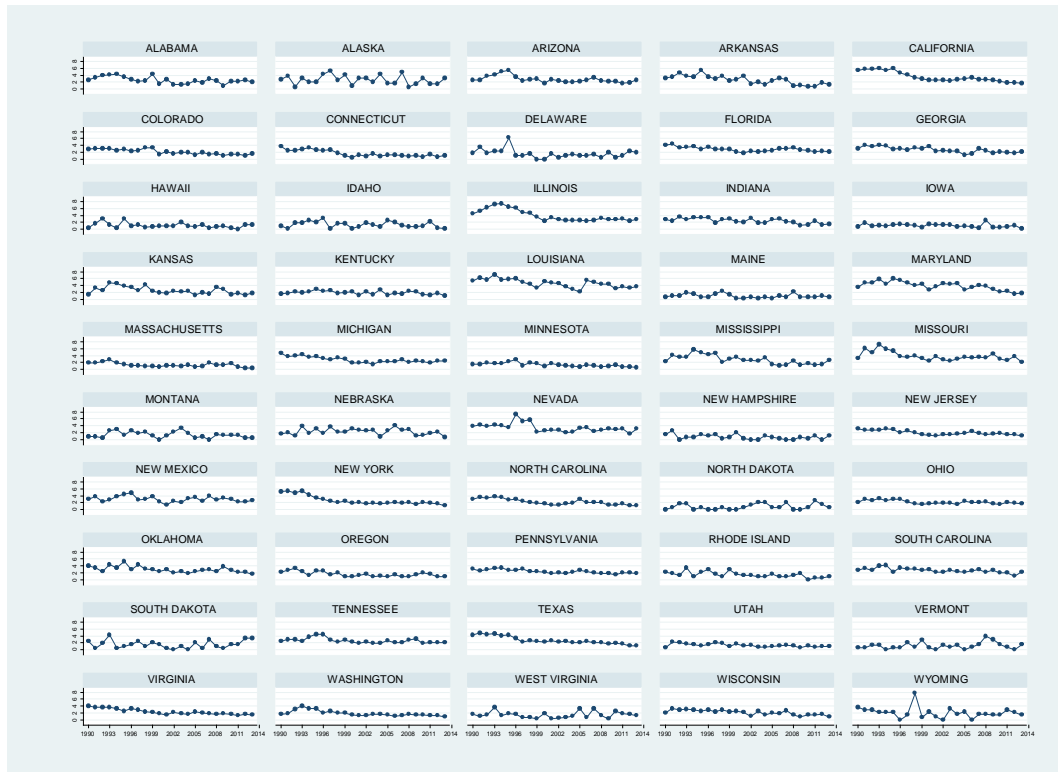
Visually, the majority of the state rates of child physical abuse and child sexual abuse from 1990 to 2013 appear to decline; however, variation exists within and across states in their rates of both abuse types over time. State rates of child neglect varied as well, although very few states had declines over the period. As shown in Figure 17, rates of child homicide also declined over this period, although the decline appears to begin in the mid-1990s as opposed to the early-1990s. Similar to the trends in child maltreatment, states varied in their rates of child homicide each year from 1990 to 2013 as evident by the large dispersion of rates in Figure 17. The majority of states' rates of child homicide did, however, either remain stable or decline over time as shown in Figure 18.

Figure 17. Aggregate State Trend in Child Homicide, 1990-2013



NOTE: All 50 states are included in figure.  
See Appendix D for a description of how to interpret this box plot.

Figure 18. Trends in Rates of Child Homicide by State, 1990-2013



NOTE: All 50 states are included in figure.

In order to examine the validity of the child maltreatment trends to measure temporal trends in child victimization, correlation and cointegration techniques comparing state-level trends in child maltreatment to state-level trends in child homicide were examined. As shown in Table 9, the majority of states' NCANDS trends in child physical abuse and child sexual abuse were very highly correlated ( $p > .80$ ), and many more were highly correlated ( $p > .60$ ). Nearly all state correlations (41 out of 46) between trends in child physical abuse and child sexual abuse were significant. In fact, the majority of all state correlations between NCANDS measures (including child neglect) were significant.

Table 9. State-Level Correlations Between Child Maltreatment and Child Homicide Rates by State, 1990-2013

<i>State</i>	<u>CPA/CSA</u>	<u>CSA/CN</u>	<u>CPA/CN</u>	<u>CPA/CH</u>	<u>CSA/CH</u>	<u>CN/CH</u>
Alabama	0.94	0.96	0.90	0.67	0.69	0.68
Arizona	0.47	0.54	0.83	0.54	0.46	0.51
Arkansas	0.30	0.56	0.14	0.42	-0.37	-0.63
California	0.98	-0.13	0.04	0.89	0.93	-0.22
Colorado	0.90	-0.16	-0.29	0.79	0.65	-0.49
Connecticut	0.90	0.33	0.59	0.77	0.92	0.23
Delaware	0.63	0.63	0.86	-0.04	0.24	0.11
Florida	0.84	0.96	0.89	0.25	0.61	0.50
Georgia	0.97	0.69	0.77	0.65	0.75	0.35
Hawaii	0.89	0.89	0.84	0.44	0.42	0.41
Idaho	0.99	0.97	0.96	0.35	0.30	0.29
Illinois	0.55	0.67	-0.05	-0.47	0.12	0.69
Indiana	0.94	0.23	0.34	0.59	0.57	-0.003
Iowa	0.94	-0.84	-0.73	0.25	0.19	-0.33
Kansas	0.95	0.89	0.93	0.04	0.22	-0.01
Kentucky	0.96	0.06	-0.08	0.44	0.35	-0.02
Louisiana	0.82	0.57	0.60	0.45	0.51	0.52
Maine	0.89	-0.15	0.15	0.02	0.07	-0.21
Massachusetts	0.79	-0.53	-0.16	0.48	0.69	-0.21
Michigan	-0.19	-0.61	0.86	-0.35	0.79	-0.65
Minnesota	0.52	0.36	0.62	0.68	0.33	0.53
Mississippi	0.83	0.39	0.42	0.43	0.11	-0.17
Missouri	0.93	0.79	0.93	0.60	0.40	0.64
Montana	0.91	0.89	0.69	0.12	0.01	-0.02
Nebraska	0.88	0.21	-0.15	0.13	0.18	-0.07
Nevada	0.91	0.86	0.87	0.50	0.37	0.60
New Hampshire	0.69	-0.68	-0.44	0.23	0.29	-0.28
New Jersey	0.93	0.89	0.80	0.71	0.67	0.43
New Mexico	0.69	0.08	0.20	-0.07	0.20	0.15
New York	0.94	-0.57	-0.74	0.74	0.84	-0.63
North Carolina	0.73	-0.15	-0.57	-0.21	0.32	0.38
North Dakota	0.78	0.68	0.79	-0.02	0.16	0.12
Ohio	0.50	0.86	0.54	0.26	0.75	0.51
Oklahoma	0.50	0.33	0.26	0.09	0.64	0.08
Oregon	0.96	-0.28	-0.37	0.70	0.76	-0.21
Pennsylvania	0.89	0.63	0.70	0.79	0.67	0.58
Rhode Island	0.98	-0.03	-0.07	0.54	0.52	-0.25



South Carolina	-0.32	0.09	0.70	-0.61	0.43	-0.23
South Dakota	0.64	0.37	0.90	-0.20	0.12	-0.39
Tennessee	0.76	0.76	0.81	-0.11	-0.04	-0.17
Texas	0.98	-0.32	-0.19	0.93	0.93	-0.42
Utah	0.22	0.44	0.26	0.27	0.44	0.39
Vermont	0.26	0.44	-0.42	-0.05	-0.27	-0.21
Virginia	0.95	0.97	0.98	0.89	0.91	0.93
Wisconsin	0.88	0.85	0.98	0.72	0.70	0.69
Wyoming	0.86	0.90	0.82	0.19	0.27	0.28
<i>Aggregate Statistics</i>						
Average $-\rho/+\rho$	-0.26/0.79	-0.37/0.61	-0.33/0.67	-0.21/0.49	-0.23/0.48	-0.26/0.44
Min/Max	-0.19/0.99	-0.03/0.97	0.04/0.98	$\pm 0.02/0.93$	0.01/0.93	-0.003/0.93
# (%) of States $\rho > .41$	41 (89%)	29 (63%)	30 (65%)	26 (57%)	24 (52%)	19 (41%)
# (%) of States $\rho > .60$	36 (78%)	22 (48%)	25 (54%)	15 (33%)	17 (37%)	9 (20%)
# (%) of States $\rho > .80$	28 (61%)	13 (28%)	16 (35%)	3 (7%)	5 (11%)	1 (2%)

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect; CH=Child Homicide.

NOTE: Alaska, Maryland, Washington, and West Virginia are not included in table because these states were removed from the analyses due to missing or questionable data. Therefore, the number and percentage of states is out of 46.

Any  $\rho > .41$  when  $n=24$  is significant at  $p < .05$  (two-tailed).

As for correspondence between NCANDS rates and the child homicide rates, trends in child homicide were more likely to be significantly correlated with NCANDS state trends in child physical abuse and child sexual abuse than trends in child neglect. More than half of all state trends in child physical abuse and child sexual abuse were significantly correlated with trends in child homicide. Correlations, when significant, were overwhelmingly positive, indicating that state trends in child physical abuse and child sexual abuse followed the same downward trend as state trends in child homicide. Fewer state trends in child homicide were significantly correlated with state trends in child neglect. However, the average of all positive correlation coefficients across all trend comparison groups was significant (i.e., all average positive correlations were greater than 0.41), while the average of all negative correlation coefficients across all trend

comparisons groups was nonsignificant (i.e., all average negative correlations were less than 0.41). The minimum and maximum correlations across the states varied from insignificant to near perfect correlation for all correlations between measures.

When comparing the correlation coefficients of the detrended rates of child victimization by state (see Table 10), year-to-year changes in the NCANDS state rates of child physical abuse, child sexual abuse, and child neglect are largely positive and highly correlated with one another. Nearly all first-differenced correlation coefficients between child maltreatment groups are positive and significantly correlated. In contrast, detrended correlation coefficients between child maltreatment indicators and child homicide are weak and nonsignificant. These findings suggest that state rates of child physical abuse, child sexual abuse, and child neglect are likely to increase or decrease from one year to the next within a state in tandem across maltreatment types. For example, state policies and practices within state CPS agencies likely impact the substantiation of all three types of child maltreatment from one year to the next, not just the substantiation of one maltreatment type compared to another. Therefore, if child physical abuse rates go up from one year to the next in a state due to changes in intake procedures, for example, then it is also likely that rates of child sexual abuse and child neglect would increase over that period as well. On the other hand, positive or negative year-over-year changes in state rates of child maltreatment rarely complemented positive or negative year-over-year changes in rates of child homicide. One reason for this could be that the variables that effect changes in the rates of child maltreatment from one year to the next (whether agency related or societal in scope) are not likely to be the same factors that effect changes in the rates of child homicide from one year to the next. Another potential reason

for these low first-differenced correlation coefficients between state child maltreatment trends and state child homicide trends is the possibility that there are limits to the use of state child homicide trends in trying to validate year-to-year trends in child maltreatment. Clearly, state child homicide trends do not perform well as a measure of triangulation when looking at year-over-year changes in state rates of child abuse and neglect.<sup>21</sup>

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<sup>21</sup> Unfortunately, there are no state-level child victimization trend data available in other data sources, including the NCVS.

Table 10. State-Level Correlations Between Detrended Child Maltreatment and Child Homicide Rates by State, 1990-2013

<i>State</i>	<u>CPA/CSA</u>	<u>CSA/CN</u>	<u>CPA/CN</u>	<u>CPA/CH</u>	<u>CSA/CH</u>	<u>CN/CH</u>
Alabama	0.83	0.82	0.88	0.31	0.18	0.33
Arizona	0.37	0.47	0.89	0.09	-0.27	0.07
Arkansas	0.66	0.71	0.73	0.05	-0.35	-0.19
California	0.95	0.44	0.56	0.11	0.10	0.13
Colorado	0.81	0.58	0.66	-0.28	-0.19	-0.56
Connecticut	0.45	0.09	0.56	-0.002	0.25	-0.21
Delaware	0.47	0.36	0.91	0.01	0.23	-0.09
Florida	0.83	0.88	0.90	-0.32	-0.37	-0.28
Georgia	0.90	0.83	0.78	-0.11	-0.01	-0.13
Hawaii	0.76	0.66	0.83	0.09	0.09	0.01
Idaho	0.92	0.85	0.77	-0.02	-0.21	-0.20
Illinois	0.75	0.56	0.37	-0.15	-0.01	0.46
Indiana	0.88	0.76	0.91	0.20	0.24	0.27
Iowa	0.57	0.42	0.54	-0.06	-0.38	-0.58
Kansas	0.96	0.93	0.87	-0.37	-0.23	-0.24
Kentucky	0.74	0.62	0.67	0.07	-0.16	-0.01
Louisiana	0.60	0.59	0.44	-0.03	-0.04	0.27
Maine	0.77	0.54	0.75	0.14	0.22	0.02
Massachusetts	0.17	0.12	0.75	-0.19	0.01	-0.13
Michigan	0.72	0.49	0.65	-0.20	0.14	-0.05
Minnesota	0.48	0.38	0.58	-0.05	-0.05	-0.13
Mississippi	0.91	0.51	0.59	0.07	0.01	-0.02
Missouri	0.71	0.63	0.71	0.08	-0.24	-0.32
Montana	0.49	0.33	-0.31	-0.06	-0.51	-0.25
Nebraska	0.61	0.73	0.65	0.32	0.33	0.24
Nevada	0.66	0.32	0.43	0.13	-0.09	0.33
New Hampshire	0.17	0.14	0.51	-0.25	-0.61	-0.03
New Jersey	0.70	0.86	0.79	0.18	0.26	0.21
New Mexico	0.65	0.70	0.69	-0.38	-0.39	0.05
New York	0.91	0.23	-0.08	-0.40	-0.48	-0.32
North Carolina	0.64	0.30	0.11	-0.30	-0.20	-0.12
North Dakota	0.20	0.34	0.65	0.21	0.33	0.16
Ohio	0.07	0.34	0.29	-0.06	0.29	0.31
Oklahoma	0.46	0.40	0.28	-0.01	0.28	-0.01
Oregon	0.50	0.37	0.17	-0.11	0.40	0.20
Pennsylvania	0.93	-0.04	-0.19	-0.001	0.13	0.15
Rhode Island	0.65	0.64	0.63	0.19	0.06	-0.21

South Carolina	0.52	0.37	0.72	-0.28	-0.41	-0.26
South Dakota	0.46	0.26	0.85	0.11	0.33	-0.05
Tennessee	0.72	0.80	0.88	-0.15	-0.15	-0.03
Texas	0.88	0.73	0.88	0.18	-0.05	0.16
Utah	0.48	0.05	0.24	0.28	0.15	0.21
Vermont	0.60	-0.32	-0.75	0.19	0.13	-0.09
Virginia	0.80	0.84	0.87	-0.04	0.10	0.02
Wisconsin	0.70	0.76	0.81	-0.09	-0.23	-0.11
Wyoming	0.60	0.49	0.64	-0.39	0.12	0.03
<i>Aggregate Statistics</i>						
Average $-\rho/+p$	0.64	-0.18/0.53	-0.33/0.65	-0.17/0.15	-0.24/0.19	-0.18/0.18
Min/Max	0.07/0.96	-0.04/0.93	-0.08/0.91	-0.001/-0.40	$\pm 0.01/-0.61$	$\pm 0.01/-0.58$
# (%) of States $\rho > .42$	41 (89%)	29 (63%)	37 (80%)	0	3 (7%)	3 (7%)
# (%) of States $\rho > .60$	31 (67%)	18 (39%)	29 (63%)	0	1 (2%)	0
# (%) of States $\rho > .80$	13 (28%)	8 (17%)	12 (26%)	0	0	0

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect; CH=Child Homicide.

NOTE: Alaska, Maryland, Washington, and West Virginia are not included in table because these states were removed from the analyses due to missing or questionable data. Therefore, the number and percentage of states is out of 46.

Rates are detrended through the process of first differencing.

Any  $\rho > .42$  when  $n=23$  is significant at  $p < .05$  (two-tailed).

In order to determine if the states that had significantly large correlations between trends in child abuse measures and trends in child homicide had other underlying properties in common, aggregate correlations in the trends were calculated for states grouped by state population size and geographic region of the U.S. Table 11 aggregates and summarizes these correlational statistics by state population size. Stronger correlations were found across trends in child physical abuse and child sexual abuse for large population states compared with states of smaller population size. Groupings by population size do not appear, however, to have any relevance for comparing correlations between trends in child sexual abuse and child neglect. As for the correspondence between NCANDS measures and child homicide, population size has little bearing on the

relationship between the trend over time in rates of all child maltreatment measures and child homicide. All four aggregate trend correlations by state population size were weak and nonsignificant for NCANDS indicators and child homicide.

Table 11. State-Level Trend Correlations by State Population Size, 1990-2013

<i>Population Size</i>	<u>CPA/CSA</u>	<u>CSA/CN</u>	<u>CPA/CN</u>	<u>CPA/CH</u>	<u>CSA/CH</u>	<u>CN/CH</u>
< 2 million	0.61	0.09	0.55	0.12	-0.05	0.22
2-5 million	0.50	-0.07	0.41	0.22	0.05	-0.03
5-10 million	0.48	0.02	0.52	0.16	0.28	-0.15
> 10 million	0.81	0.14	0.39	0.23	0.32	-0.08

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect; CH=Child Homicide.

NOTE: Alaska, Maryland, Washington, and West Virginia are not included in the correlations because these states were removed from the analyses due to missing or questionable data.

Any  $\rho > .41$  when  $n=24$  is significant at  $p < .05$  (two-tailed).

State population size is based on the 2000 Census population.

The location of a state within the U.S. is also of little importance in differentiating the correspondence between trends in child maltreatment and child homicide. As shown in Table 12, all four regions have weak, nonsignificant correlation coefficients between trends in child physical abuse, sexual abuse, and neglect, and trends in child homicide.<sup>22</sup>

<sup>22</sup> These findings are less of a challenge to the validity of the state-level analyses and more of evidence that state CPS agencies function in extremely similar ways regardless of the number of reports that are handled by the agency or where the agency is located. While it may seem like these two factors matter in determining how a state agency functions, it does not appear to be the case with regard to trends in child abuse. The strength of the significant correlation coefficients is remarkable given the higher likelihood that significant correlation coefficients have been canceled out by aggregating state correlation coefficients into categories, regardless of their significance. Therefore, because states with both negative and positive correlation coefficients for child maltreatment trends and child homicide trends have been grouped into the same categories, it is not surprising that nonsignificant negative correlations between these two trends in states have canceled out most of the effects of states with positive and significant correlation coefficients, especially given just half of all states had a positive and significant  $\rho$  between trends in child maltreatment and child homicide.

Table 12. State-Level Trend Correlations by Region of the U.S., 1990-2013

<i>Region</i>	<u>CPA/CSA</u>	<u>CSA/CN</u>	<u>CPA/CN</u>	<u>CPA/CH</u>	<u>CSA/CH</u>	<u>CN/CH</u>
Northeast	0.41	-0.24	0.49	0.20	-0.07	-0.06
South	0.59	0.12	0.33	0.16	0.14	0.02
Midwest	0.71	0.27	0.59	0.27	0.09	0.38
West	0.51	0.13	0.51	-0.07	0.23	-0.16

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect; CH=Child Homicide.

NOTE: Alaska, Maryland, Washington, and West Virginia are not included in the correlations because these states were removed from the analyses due to missing or questionable data.

See Appendix E for information about the classification of states into these four U.S. regions.

Any  $\rho > .41$  when  $n=24$  is significant at  $p < .05$  (two-tailed).

Additionally, tests of convergence of the trends were also examined to see if the trend in child homicide shared a short run or long run effect with trends in child physical abuse, child sexual abuse, and child neglect. Through the use of cointegration techniques, it was possible to decipher if, and when, NCANDS state-level trends converged with trends in state rates of child homicide or if they shared an underlying stochastic process with the state-level child homicide trends. All four child victimization trends were determined to be  $I(1)$ , otherwise known as integrated (of order one). An integrated measure (of order one) is a measure whose first difference is stationary regardless of whether the actual values of the measure are stationary (i.e., if  $Y_t$  is  $I(1)$ , then  $\Delta Y_t$  is  $I(0)$ ).  $I(1)$  denotes an integrated variable (of order one), while  $I(0)$  denotes a stationary variable. Diagnostic analyses determined that all four trends were stationary when first differenced.

Three error correction models were examined. Each model used the rates of child homicide as the dependent variable (Y) and the rates of a type of child maltreatment as the independent variable (X) (see Table 13). The beta coefficients of error correction

terms serve as important indicators in understanding how quickly a series moves back to its equilibrium with another series after it is pushed away by an external shock. The beta coefficient of the rate of child homicide in the previous period ( $Y_{t-1}$ ) represents the cointegration parameter, or return rate at which the set of independent variables (i.e., rates of child maltreatment) return to equilibrium after this shock to the system. Return rates hovering around -.28 reveal relatively slow returns to equilibrium after deviating from their long-term or short-term trend. In essence, a return rate of -.28 shows that, after one year, the trends made it roughly 28% back to equilibrium. Each additional year thereafter added an additional bump back to equilibrium. By the 14<sup>th</sup> and 15<sup>th</sup> year of the series the rates asymptotically converge (i.e., they never fully converge but reach the point at which the deviation from equilibrium is negligible). The duration of these long-run effects are graphically displayed in Figures 19-21. Just over one-quarter of the cumulative long-run effect of child physical abuse and child sexual abuse on change in child homicide rates occurs in the first year beyond the current period and that long-run effect persists for more than a decade.



Table 13. Error Correction Model Results

1. Trends in CPA and CH	
	$\Delta$ Rate of Child Homicide
Rate of Child Homicide <sub>t-1</sub>	-.285*** (.043)
$\Delta$ Rate of Child Physical Abuse	.030 (.047)
Rate of Child Physical Abuse <sub>t-1</sub>	.049* (.020)
Short Run Effect	ns
Long Run Effect	+
2. Trends in CSA and CH	
	$\Delta$ Rate of Child Homicide
Rate of Child Homicide <sub>t-1</sub>	-.282*** (.042)
$\Delta$ Rate of Child Sexual Abuse	-.031 (.088)
Rate of Child Sexual Abuse <sub>t-1</sub>	.063* (.029)
Short Run Effect	ns
Long Run Effect	+
3. Trends in CN and CH	
	$\Delta$ Rate of Child Homicide
Rate of Child Homicide <sub>t-1</sub>	-.276*** (.042)
$\Delta$ Rate of Child Neglect	-.013 (.019)
Rate of Child Neglect <sub>t-1</sub>	.002^ (.005)
Short Run Effect	ns
Long Run Effect	ms(+)

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect.

NOTE: Standard errors are in parentheses.

+ = significant positive effect, ms = marginal significant effect (direction), ns = no significant effect.

^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Figure 19. Cumulative Percentage Distribution of Long-Term Effect of Child Physical Abuse on Child Homicide

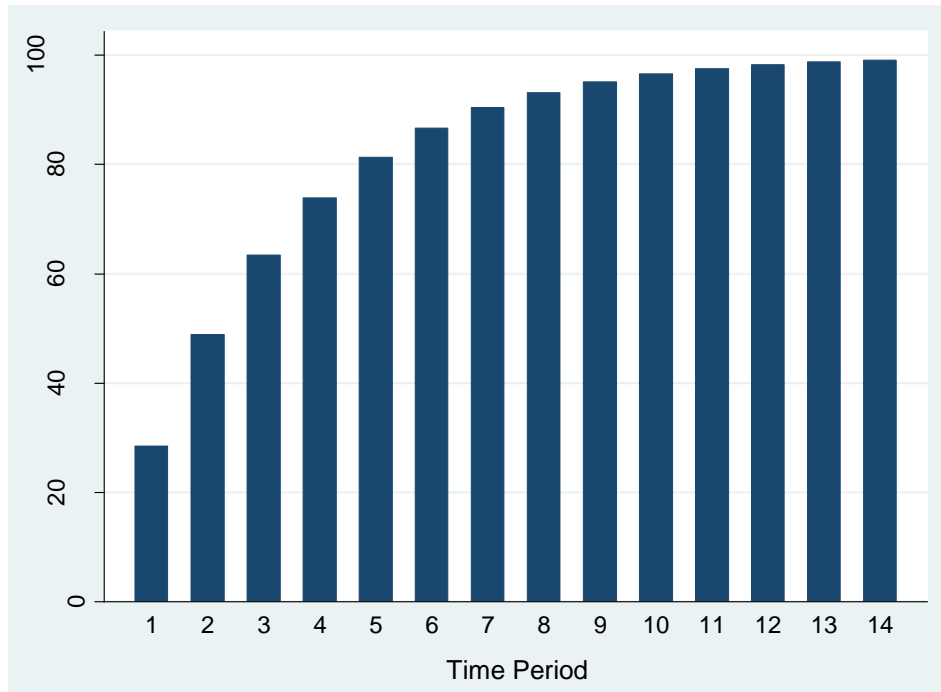


Figure 20. Cumulative Percentage Distribution of Long-Term Effect of Child Sexual Abuse on Child Homicide

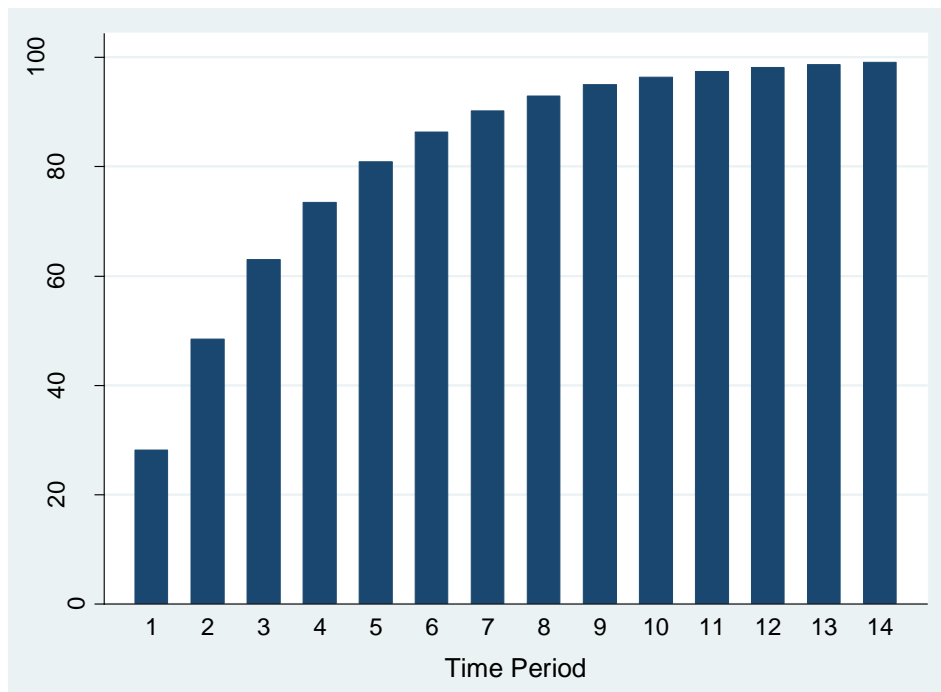
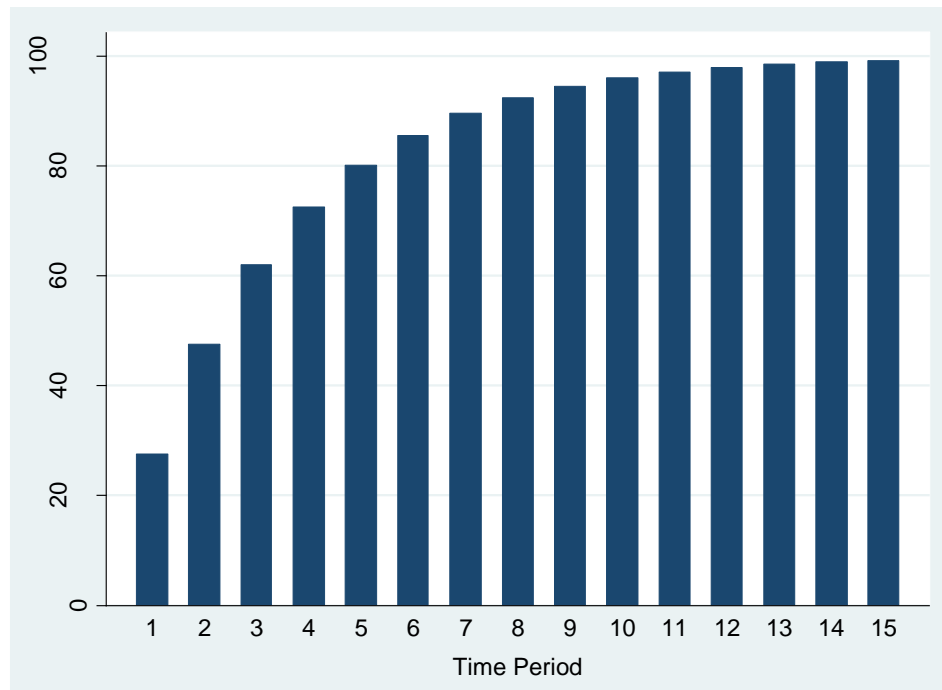


Figure 21. Cumulative Percentage Distribution of Long-Term Effect of Child Neglect on Child Homicide



Bewley transformation regressions provided the precise standard errors and confidence intervals needed to determine the statistical significance of the long-run effects of rates in child maltreatment in the previous period ( $X_{t-1}$ ) on rates in child homicide ( $Y$ ). Using these results, the error correction mechanism returned a significant long-run effect of both child physical abuse and child sexual abuse rates on trends in child homicide between 1990 and 2013. While these models yielded significant long-run effects ( $p < .05$ ), the other model, trends in child neglect on child homicide, had a marginally significant long-run effect ( $p = .09$ ).

The beta coefficient for the change in  $X$  (i.e., the change in rates of each type of child maltreatment) gives important information about the short-run effects or immediate shocks/immediate effects of  $X$  on  $Y$ . In all three models, no significant short-run effects

were found. The non-significance of the short-run effect is not unexpected, as cointegration is established when two or more  $I(1)$  variables (i.e., variables whose first difference is stationary) obey an equilibrium relationship in the long-run, even if they diverge substantially from that equilibrium in the short run.

Therefore, state-level in child maltreatment trends and child homicide are cointegrated with either significant or marginally significant long-run relationships between each set of two trends, with asymptotic convergence in the long-run trends occurring at around year 14 or 15. This dynamic relationship between the NCANDS state-level trends and the state-level trend in child homicide provides evidence that these two data sources are generally measuring a similar phenomenon over time, even though trends from the two sources occasionally depart from one another in the short term.

## DISCUSSION

A measurement assessment of the state-level data unearthed some very important data concerns that needed to be addressed before the data, especially the NCANDS data, could be used to examine trends at the state level. After a visual review of the state-level data, it was obvious that different state-level measures had varying degrees of data quality issues. Even though the quality of the NCANDS data for depicting national-level trends was good (and these data were the aggregate of the state-level data), individual state-level data appeared to vary in their validity. Therefore, data adjustments were made prior to examining the trends and issues of validity at the state level. These adjustments (i.e., data removal or replacement, and data interpolation) were necessary to produce

balanced state panel data capable of studying trends in child victimization in as many states and years as possible.

A review of state-level trends revealed considerable variation in the trends in child physical abuse, child sexual abuse, and child neglect. For the most part, however, state-level trends in child abuse appeared to decline for most states from 1990 to 2013, especially at the beginning of the series. State-level trends in child neglect were much more varied, with some states showing both increases and decreases, while others showed stability over time. Outlier data points or parallel increases and decreases were found in some states in a given year within all of the NCANDS trends, which gives some credence to the notion that definitional or procedural changes within state agencies related to data collection and data reporting were responsible for higher or lower rates in a given year. For example, after reviewing the state NCANDS commentary in the appendices of the annual Child Maltreatment reports and reaching out to state agency officials, it was disclosed that the CPS agency in Delaware was significantly impacted by the death of three children in 1997 (mostly through a very high and steady scrutiny by the media). Therefore, the Delaware Title 16 (Abuse of Children) statute was largely rewritten as the Child Abuse Prevention Act of 1997, which revamped most CPS investigation policies and implemented many new ones. It became clear that one of the outcomes of these child deaths was a revitalized emphasis on reporting child abuse and concern among agency staff that they were not holding parents accountable. This explanation (afforded by further investigating the trend in Delaware) is very compatible with the data, considering this outlier year was noticeable in both the child physical abuse and child neglect trends in 1997. It is also because of this explanation that the data point remained in the analysis

because it was obviously not reported in error. These kinds of procedural explanations were available (and documented in Appendix A) for a number of states that had unusual trends mirroring each other across the three maltreatment types.

Interestingly, even though great variation existed across states in rates of child sexual abuse from 1990 to 2013, state trends in child sexual abuse appeared to have less outlier rates in a given year. This could be due to the fact that, of the three types of child maltreatment, child sexual abuse is the least common among the maltreatment types and substantiation is often more difficult for state CPS workers. Substantiation is more complicated largely due to physical evidence of sexual assault being less likely to exist compared with tangible evidence resulting from physical abuse or neglect. For example, some acts, such as fondling and oral sex, leave no physical traces. Even injuries from penetration typically heal very quickly in children and thus abnormal genital findings are not common, especially if the child is examined more than 48 hours post-abuse (Adams, Harper, Knudson, & Revilla, 1994; Heger, Ticson, Velasquez, & Bernier, 2002; Kellogg, Menard, & Santos, 2004). Moreover, children usually have to disclose to someone that sexual abuse occurred, which many are afraid to report, as opposed to adults or peers reporting signs of abuse with or without the child's knowledge. Therefore, large increases or decreases within consecutive years in the rate of child sexual abuse within a state are not likely to occur, unless the number of CPS investigative workers at state agencies changes considerably from year to year, providing caseworkers with more or less time to complete thorough investigations. Almeida and colleagues (2008) found that there was, in fact, an increase in the total number of investigation workers and caseworkers between 1997 and 2002, and at the same time, a decrease in the number of substantiated

investigations of child sexual abuse during this period, providing support for the argument that increasing caseload sizes had little to nothing to do with the decline in child sexual abuse. Therefore, it could be that any significant deviations from the average state trend in subsequent years are likely due to changes in agency policies, including what is or is not defined as child sexual abuse. It would seem logical then that long-term upward or downward trends are likely representative of actual increases or decreases in rates of child sexual abuse.

The visual assessment also revealed that trends in child homicide at the state level largely mimicked those of child physical abuse and child sexual abuse, where declines were noticeable across most states during this period, especially during the 1990s. Also visible when inspecting the state trends in rates of child homicide is the rather choppy fluctuations from one year to the next in a number of states. While states with larger population sizes had smooth trends, states with smaller population sizes were more likely to have notable movements from one year to the next. This is likely because state rates of child homicide are very heavily influenced by small counts of child homicides in the rate calculation, due to the fact that child homicide is a statistically rare crime in many states. One additional child homicide in a state with a low child population is going to disproportionately increase the rate of child homicide compared with a state that has a greater child population (and equally larger counts of child homicide). This introduces the possibility that rates of child homicide in certain states (i.e., those with small population sizes) are more prone to movement because rates show great instability when calculated with small numerators.

With a visual understanding of the trends in rates of child abuse and neglect and child homicide, a statistical assessment of these state-level trends was also examined. Even though the validity of the trends was established using correlational analyses between trends in child maltreatment and child homicide at the national level, establishing validity at the state-level is a bit more challenging. How does one establish validity when there are 50 unique correlation coefficients that often tell a different story? While it is not possible to definitively determine the validity of the NCANDS trends using these correlation coefficients, one can argue that the aggregate statistics tell a consistent story.

The overwhelming majority of NCANDS state-level trends in child physical abuse and child sexual abuse were highly correlated ( $\rho > .60$ ), and the majority of all state correlation coefficients among trends in child physical abuse, child sexual abuse, and child neglect were statistically significant. The fact that all of the NCANDS state-level trends are highly correlated with one another is telling, especially because most of the declining state trends in child physical and child sexual abuse are significantly correlated with the trends in child neglect, which appear more erratic and less likely to decline over the series. This is likely the result of each state having a unique child protection system set up to investigate and report substantiated abuse to the NCANDS system. These state systems clearly function in a similar fashion regardless of the maltreatment type under investigation. And while it visually appeared that there was sizeable within-state variation in rates of child abuse and neglect, the variation within states across the maltreatment types was less than expected, given more than 63%, and as high as 89% of states had significant correlation coefficients between NCANDS trends. This finding is made more



convincing after examining the high percentages of correlation coefficients on the first-differenced trend within states that are statistically significant between NCANDS measures. Clearly, year-to-year changes in state rates of child maltreatment had underlying commonalities not yet explored.

Aggregate statistics also revealed that more than half of all state trends in child physical abuse and child sexual abuse were positive and significantly correlated with state trends in child homicide. Even the average positive correlation coefficient was statistically significant, indicating that when the correlation in trends was positive, it was more likely to be significant than nonsignificant. Those correlation coefficients that were negative between state-level trends in child abuse and neglect and child homicide were, on average, nonsignificant. These results should, however, be accepted with some skepticism because strong positive trends of correlation appear to diminish when the detrended series are used in the correlational analysis.

First-differenced comparisons in the state rates of child maltreatment and state rates of child homicide were very weakly correlated. Apparently year-over-year changes did not correspond between child homicide and child maltreatment, suggesting one of three issues could have resulted in this finding. First, the uniqueness of the NCANDS and SHR state data collection and reporting systems may have had a profound influence on year-to-year state trends. Second, the factors that affect change in child maltreatment rates in a given year could be distinct from the factors that affect change in child homicide rates in a given year at the state level. And third, it could be that state-level child homicide data are not likely the best data to use to establish validity of the state-level NCANDS trends. This latter problem is again largely the result of the instability of

the child homicide rates at the state level and associated error that is brought into the correlational tests because of the unreliability of year-over-year fluctuations in unstable rates.

In order to test whether the size or location of a state mattered in producing rates of child maltreatment or child homicide, correlation coefficients were also examined for groups of states by population size and regional location. For example, it could be that states with larger populations have higher or lower rates of both child maltreatment and child victimization over time because their state systems differ from smaller population states because they deal with higher volumes of cases reported. A strained or funding-deficient state child welfare system in a large state could also potentially have consequences on rates of child maltreatment or child homicide. In addition, rates of child maltreatment and child homicide calculated from small state child populations as opposed to large state child populations have a higher chance of being instable each year due to the higher likelihood of small numerators in the calculation. It could also be that people from states located in certain areas of the country are more lax about reporting of child maltreatment, mainly due to differences in cultural norms surrounding the acceptable treatment and punishment of children. However, this analysis showed that population size and regional location had little bearing on the relationship between the trend over time in the rate of NCANDS measures and child homicide.

Conflicting evidence of the validity of the NCANDS state-level data to measure temporal change in rates of child victimization using correlational analyses between NCANDS trends and trends in child homicide demonstrates the need for additional tests of external validity beyond correlational techniques. The goal of using cointegration

techniques was to examine if the NCANDS child physical abuse, child sexual abuse, and child neglect trends converge (i.e., a long run equilibrium exists) with the trends in child homicide at any point throughout the series. It is expected that the various trends of child victimization will periodically depart from one another due to the unique measurement features of each data system, however, these cointegration analyses were conducted to understand if they “tend to move together in concert...[and vary] together in an equilibrium relationship,” which would suggest that two data series share an underlying stochastic process, supporting the notion that the NCANDS state-level data are capable of measuring the same trend in child victimization at the state level that the child homicide state-level data measure (McDowall & Loftin, 2007, p. 105).

According to the criteria for the cointegration tests, the NCANDS trends and the trend in child homicide do move together throughout the period from 1990 to 2013. Two of the three error correction models yielded significant long-run effects, but no significant short-run effects were found between the trend in child physical abuse and child sexual abuse on the trend in child homicide. The error correction mechanism returned a significant, albeit relatively slow long-run significant effect of both child physical abuse and child sexual abuse on trends in child homicide. All in all, the convergence of NCANDS state-level trends and trends in child homicide at the state level based on cointegration tests revealed significant or marginally significant cointegration between the two data sources, with convergence in the long-run trend occurring at around year 14 in the series for each child maltreatment type and child homicide. This dynamic relationship between the NCANDS state-level trends and the state-level trend in child

homicide provides evidence that the two data sources on child victimization are generally measuring a similar phenomenon.<sup>23</sup>

Therefore, for the first time, through the use of correlational and cointegration techniques, this study provides visual and statistical evidence that the NCANDS state-level data are reasonably valid measures of temporal trends in child victimization at the state level. In the previous chapter, it was also established that the NCANDS national-level trends are also valid indicators of child victimization at the national level. Having reasonable confidence in the validity of the NCANDS data at both the national and state level permits further analysis of these data. In Chapter Seven, the results of the substantive component of the study are reported and discussed. Results from various hypothesis tests are reported examining what factors are associated with the trend in child maltreatment. A supplementary analysis of child homicide and how these hypotheses hold up in predicting state-level rates of child homicide over time is also described, followed by a discussion of how these results may impact crime trend theory and criminal justice policy.

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<sup>23</sup> The cointegration analyses reported assume that, if a causal association between child maltreatment and child homicide exists, the direction is from child maltreatment to child homicide and not from child homicide to child maltreatment. This assumption is why rates in child homicide were entered into the error correction models as the dependent variable and each trend in child maltreatment was entered as the independent variable. Child maltreatment, especially child physical abuse and child neglect, while not always, can be precursors to child homicide. While it seems counter intuitive that rates of child homicide in a given year would have an effect on rates of child maltreatment, my analysis of Delaware's trend proved this was statistically (though not necessarily theoretically) possible as a handful of child homicides in a year increased the rate of substantiation for child maltreatment. However, this effect is only in the classification of child maltreatment reports as substantiated, not necessarily in the occurrence of maltreatment itself. This is an important distinction worth noting.

## CHAPTER SEVEN: WHAT FACTORS ARE ASSOCIATED WITH THE TREND IN CHILD MALTREATMENT?

Crime trends research is host to a wide range of competing hypotheses about the decline in crime at the end of the twentieth century. This study has already added to the crime trends literature by establishing *when* and *where* child maltreatment declined post-1990 using valid measures of national- and state-level trends in child victimization. Next, I examine these state-level trends and try to establish *why* rates of child physical abuse, child sexual abuse, and child neglect changed from 1990 to 2013. A number of hypotheses proposed by scholars, and in particular, David Finkelhor and colleagues, have been assessed for their role in the declines in the rates of child physical abuse and child sexual abuse, as well as in the fluctuating trends in rates of child neglect.

The six hypotheses examined in this component of the study capture various explanations proposed by crime trends and victimization scholars. Measures operationalizing these six hypotheses (the economic, psychopharmacology, agents of social control, incarceration, drug market, and artifactual hypotheses), which represent the independent variables of these regression models, were collected at the state level and, as previously mentioned, went through the same rigorous data cleaning processes as the dependent measures of child victimization when necessary. See Appendix F for visual representations of the aggregate and state-level trends in these independent variables and Appendix G for the aggregate trend correlations between these explanatory measures.

Linear panel regression model approaches are used because they allow for an examination of the within-state and across-state variations in the rates of child maltreatment after accounting for the effects of these explanatory measures. As mentioned previously, panel regression models are particularly useful for this kind of

analysis because they are designed for analyzing repeated measurements at different points in time on the same individual units (in this case, states across years). There are a number of panel data model approaches, all of which estimate parameters based on various assumptions regarding the distribution of error within the model. Critical to these analyses, panel models are capable of adjusting the standard errors of the estimates due to highly correlated errors in the measures.

Diagnostic tests were run on each model before a final panel model was chosen for inclusion in this study. See Appendix H for a summary of the diagnostic testing performed and the results of those tests on the regression models. After diagnostic testing, the final panel regression models chosen for each outcome and series corrected for any issues of groupwise heteroscedasticity, cross-sectional dependence, serial autocorrelation, or stationarity present in the model.<sup>24</sup> Without corrections for these issues, the errors in the model would not be *iid* (independent and identically distributed), which is a requirement for hypothesis testing.

Final panel models were selected based on the unique issues present in each individual model. Based on prior research describing the consequences of serial autocorrelation within panels over time and cross-sectional dependence across panels over time, certain panel models have been proposed as more efficient or accurate in panel

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<sup>24</sup> A Hausman Specification Test was conducted to determine the efficiency of using a fixed-effects model over a random-effects model (see Hausman, 1978). Because each individual model is specified differently (fixed-effects, random-effects, fixed-effects autoregressive, or random-effects autoregressive), I decided to use panel-corrected standard error (PCSE) models as opposed to various models for each outcome and series. Groupwise heteroscedasticity was tested using a Modified Wald Test (see Greene, 2000, p.598). Cross-sectional dependence (also known as contemporaneous correlation) was tested using Pesaran's Test (see De Hoyos & Sarafidis, 2006). Serial correlation was tested using the Wooldridge Test (for a summary of the Wooldridge Test for autocorrelation in panel data see Drukker, 2003). Issues of stationarity within panels were tested using the following three tests: the Fisher Test (see Maddala & Wu, 1999), the Levin-Lin-Chu Test (see Levin, Lin, & Chu, 2002), and the Im-Pesaran-Shin Test (see Im, Pesaran, & Shin, 2003).

regression analyses. For example, according to Reed and Ye (2007, 2011), when the primary concern of the regression is constructing accurate confidence intervals for hypothesis testing (as it is in this study), and both serial correlation and cross-sectional dependence are present in the model, Beck and Katz's (1995) panel-corrected standard errors (PCSE) estimator should be used. Much of this research has to do with the problems caused when  $N > T$  (i.e., the number of cross-sectional panels is greater than the number of time periods) as opposed to  $N \leq T$  (i.e., the number of cross-sectional panels is less than or equal to the number of time periods).<sup>25</sup> In this current analysis, the number of states is greater than the number of time periods, so Beck and Katz's (1995) PCSE estimators (which has the ability to correct for heteroscedasticity, cross-sectional dependence, and first-order serial autocorrelation if present) are used.<sup>26</sup> These estimators use linear regression with parameters estimated by either Prais-Winsten (when serial correlation is present) or pooled ordinary least squares (when serial autocorrelation is not present). Serial autocorrelation has been corrected, when present, with panel-specific first-order autocorrelation adjustments (i.e., panel-specific AR(1) processes). When tests for stationarity suggest unit roots were present in the panels, non-stationarity was corrected by detrending the variables in the model.

The significance of these hypotheses for explaining declines (and other changes) in rates of child physical abuse, child sexual abuse, and child neglect are reported below.

While it may seem almost counterintuitive to discuss explanations related to the decline

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<sup>25</sup> A number of previous studies have suggested that feasible generalized least squares (FGLS) estimators should not be trusted when  $N > T$  because this estimator is known to have deflated standard errors under these conditions (Beck & Katz, 1995; Chen, Lin, & Reed, 2010; Reed & Ye, 2007, 2011).

<sup>26</sup> While fixed-effects and random-effects panel models are also reasonable models to use with these data to accurately gauge the results of hypothesis tests, as a way of comparing the results across models, linear panel regressions using either Prais-Winsten estimators or pooled ordinary least squares estimators that correct for the various diagnostic issues present in each model are used throughout these analyses (see Appendix H).

in child victimization on a measure of child maltreatment (i.e., child neglect) that evidence suggests did not decline over this period, inspecting the significance of these hypotheses on both declining and non-declining trends allows for a complete understanding of the effect of these hypotheses on trends in child victimization. In addition, a supplementary analysis using rates of child homicide was conducted in order to compare the results of the child maltreatment models with another known state-level indicator of child victimization. These juxtapositions allow for an evaluation of whether these hypotheses, if significant, function in ways that lead to divergent trends in the types of child victimization.

#### CHILD PHYSICAL ABUSE

Panel regression models depicting the relationship between rates of child physical abuse and the six competing hypotheses displayed groupwise heteroscedasticity, first-order serial autocorrelation, and non-stationary panels. Therefore, the first difference of the series of child physical abuse rates and other independent variables was taken and the results shown below are differenced-stationary. This was the only outcome that was not stationary in levels, so comparisons with other indicator models are not as straightforward. First-differenced regression estimators for all child victimization indicators in both the long and short series models are available in Appendix I.

Year-to-year changes in the rates of child physical abuse were regressed on year-to-year changes in the various hypotheses and are reported in Table 14. Linear regressions with panel-specific first-order serial autocorrelation adjustments and heteroscedastic panels corrected standard errors estimated by Prais-Winsten regression



were used in Model 1 (i.e., the long series model) and Model 2 (i.e., the short series model).

Table 14. Panel Regressions of Year-to-Year Changes in the Rates of Child Physical Abuse

	DV = Annual Change in the Rate of Child Physical Abuse <u><math>\Delta</math>Rate of Child Physical Abuse</u>	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Prais-Winsten (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
$\Delta$ Poverty Rate	-.002 (.012)	-.008 (.015)
$\Delta$ Incarceration Rate $t_{-1}$	-.0008 (.0013)	-.002 (.002)
$\Delta$ Percent of Law Enforcement Officers	-.819 (2.24)	-2.34 (2.61)
$\Delta$ Percent of Law Enforcement Officers $t_{-1}$	-.419 (2.60)	-1.49 (2.56)
$\Delta$ Rate of Drug Abuse Violation Arrests	.008 (.024)	-.022 (.024)
$\Delta$ Ratio of CPS Caseworkers to Children		-171.58 (339.66)
$\Delta$ Ratio of CPS Caseworkers to Children $t_{-1}$		-102.08 (251.32)
$\Delta$ Average CPS Worker Caseload		.003 (.001)*
$\Delta$ Rate of Methylphenidate Distribution		.004 (.005)
<i>Control Variable</i>		
$\Delta$ Percent Black	-.13 (.18)	-.22 (.12)^
Year	a	.012 (.006)^
$R^2$	.0473	.0420

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for a number of years in the model. Year-to-year changes from 1991 to 1992 served as the reference category for Model 1.

^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Annual change in the measures used to operationalize these six competing hypotheses account for less than 5% of the variation in the annual change in the rates of child physical abuse from 1997 to 2013. Annual change in four of the hypotheses with complete data for the entire series also account for less than 5% of the variation in the

annual change in the rates of child physical abuse from 1990 to 2013. This finding is likely because very few of these detrended measures are significantly associated with changes in the rates of child physical abuse. In fact, none of the variables in the long series are statistically significant, and only one measure, year-to-year changes in the average CPS worker caseload size, is statistically significant in the short series.

As increases occurred from one year to the next in the average size of CPS workers' caseload from 1997 to 2013, year-to-year increases also occurred in rates of child physical abuse. In other words, year-to-year decreases in average caseload size were associated with year-to-year decreases in the rate of child physical abuse. If this was an artifactual finding, one would expect that as the average caseload size increased from one year to the next, CPS workers would become too busy to investigate reports of abuse, therefore leading to lower rates of abuse in the following year. However, the positive association between year-to-year changes in the size of worker caseload and rates of child physical abuse does not support this hypothesis and may instead give some support to the presence of a true decline in rates of child physical abuse from 1997 to 2013.

## CHILD SEXUAL ABUSE

A Prais-Winsten linear regression with panel-specific first-order autocorrelation adjustments and heteroscedastic panels corrected standard errors was used in Model 1 for the rate of child sexual abuse regressed on the various hypotheses (see Table 15). In Model 2, parameters were estimated by Prais-Winsten regression with panel-specific first-order autocorrelation adjustments and panel-corrected standard errors (corrections

made for both cross-sectional dependence and heteroscedasticity). State-level panels are stationary in these models so results are presented in levels.

Table 15. Panel Regressions of Rates of Child Sexual Abuse

	<u>DV = Rate of Child Sexual Abuse</u>	
	MODEL 1	MODEL 2
	Prais-Winsten	Prais-Winsten
	(1990-2013)	(1997-2013)
	Coef. (Std. Err.)	Coef. (Std. Err.)
<i>Independent Variables</i>		
Poverty Rate	-.004 (.006)	.006 (.007)
Incarceration Rate $t_{-1}$	-.00003 (.0003)	-.0007 (.0003)*
Percent of Law Enforcement Officers	-2.28 (.85)**	-2.70 (1.13)*
Percent of Law Enforcement Officers $t_{-1}$	-.78 (.83)	-.101 (1.02)
Rate of Drug Abuse Violation Arrests	.006 (.007)	.015 (.01)
Ratio of CPS Caseworkers to Children		374.24 (153.76)*
Ratio of CPS Caseworkers to Children $t_{-1}$		116.14 (112.66)
Average CPS Worker Caseload		.004 (.001)***
Rate of Methylphenidate Distribution		.001 (.002)
<i>Control Variable</i>		
Percent Black	-.002 (.007)	.02 (.007)**
Year	a	-.04 (.006)***
$R^2$	.3905	.5731

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the model. The year 1991 served as the reference category.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Models 1 and 2 show that the poverty rate, the lagged percent of law enforcement officers per capita, the arrest rate for drug abuse violations, the lagged ratio of CPS caseworkers to children, and rate of methylphenidate distribution do not seem to have any relationship to rates of child sexual abuse during these periods. There is little evidence that these factors had any association to rates of child sexual abuse, just as their first-

differenced equivalents had no statistical relationship with trends in child physical abuse (as shown in Table I2 of Appendix I).

Some of these findings are consistent with scholars' understanding of the decline in the national child sexual abuse trend. For example, Finkelhor and colleagues (2006) argued that the incarceration rate, a possibly significant factor for the decline, is likely only important for child homicide and child sexual abuse because murders and child sex offenders are more likely to get prison time than those convicted of child physical abuse or neglect. This notion is supported for the decline in rates of child sexual abuse from 1997 to 2013, but not from 1990 to 2013 (i.e., the lagged incarceration rate is significantly associated with lower rates of child sexual abuse from 1997 to 2013, but there is no significant relationship between the two rates from 1990 to 2013). This discrepancy may be due to the timing of the various federal and state laws requiring mandatory minimum sentences for convicted sex offenders. Most of these laws<sup>27</sup> were enacted in the mid-2000s (U.S. Sentencing Commission, 2011). Not only did these laws enact or increase mandatory minimums for sex offenses, but they also created new offenses relating to failing to register as a sex offender, which also came with mandatory minimum sentences under certain conditions. The enactment of these laws may have produced a stronger association between the lagged incarceration rate and rates of child sexual abuse in the short series than in the long series, given a greater proportion of years in the short series would have had these increased penalties compared to the proportion in the long series. The same argument can be made for mandatory minimums for non-sex-

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<sup>27</sup> At the federal level, these laws include the Prosecutorial Remedies and Other Tools to end the Exploitation of Children Today (PROTECT) Act of 2003 and the Adam Walsh Child Protection and Safety Act of 2006, which included the Sex Offender Registration Notification Act (SORNA). State laws incorporating the conditions of these federal laws at the state level were enacted shortly thereafter.

related offenses as well, increasing the overall incarceration rate and taking potentially violent offenders off of the streets.

Increases in the two proxy measures for agents of social control also seemed to significantly affect the rate of child sexual abuse, albeit in different directions and only concurrently. An increase in the percent of police officers in a given state was associated with significantly lower rates of child sexual abuse. What this suggests is that greater percentages of police officers in states may also mean that those states have higher odds of also having specialized units that focus on child sexual abuse and/or exploitation, such as a special victims unit devoted to sex crimes or crimes against children. In addition, it could be that more manpower in police departments may lead to more monitoring of sex offender registries. In both of these scenarios, the more police on the street, the more they are likely working to prevent child sex abuse by deterring and/or monitoring offenders of child sex abuse.

However, the greater the ratio of CPS workers to children, the higher state rates of child sexual abuse. This significant finding is obviously in the opposite direction than anticipated. It could be, however, that the more CPS workers there are in the state CPS agency, the more likely they are to detect and investigate reports, and ultimately find evidence of substantiation. This explanation seems reasonable and may be why greater numbers of agents of social control could have both a positive and negative effect on rates of child sexual abuse.

Similarly, the average caseload size of CPS workers was significantly associated with higher rates of child sexual abuse. As caseload size increased over time, so too did the rate of child sexual abuse. In other words, each decrease in caseload size was

associated with a decrease in the rate of child sexual abuse. If this was an artifactual finding as mentioned earlier, one would expect that as the average caseload size increased for CPS workers, they would become too busy to investigate reports of abuse, which would likely lead to lower rates of abuse. Similar to the findings in Model 2 of the child physical abuse analysis, the positive relationship between average size of a CPS worker's caseload and the rate of child sexual abuse may provide additional support to the existence of a true decline in the incidence of substantiated child sexual abuse cases from 1997 to 2013.

Unlike the low explained variance in the detrended child physical abuse models, these models account for 39% and 57% of the variation in rates of child sexual abuse from 1990 to 2013 and 1997 to 2013, respectively.

## CHILD NEGLECT

Groupwise heteroscedasticity and panel-specific first-order autocorrelation were present in Models 1 and 2 for the rate of child neglect regressed on the various independent variables (see Table 16). Both issues were corrected using Prais-Winsten regressions with heteroscedastic panels corrected standard errors.

Table 16. Panel Regressions of Rates of Child Neglect

	DV = Rate of Child Neglect	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Prais-Winsten (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
Poverty Rate	.04 (.027)	.114 (.036)**
Incarceration Rate <sub>t-1</sub>	-.005 (.002)**	-.005 (.002)**
Percent of Law Enforcement Officers	-6.03 (3.43)^	-10.65 (3.52)**
Percent of Law Enforcement Officers <sub>t-1</sub>	1.89 (4.06)	2.14 (3.95)
Rate of Drug Abuse Violation Arrests	.02 (.04)	.073 (.056)
Ratio of CPS Caseworkers to Children		3660.7 (621.8)***
Ratio of CPS Caseworkers to Children <sub>t-1</sub>		-415.3 (445.8)
Average CPS Worker Caseload		.038 (.004)***
Rate of Methylphenidate Distribution		.013 (.01)
<i>Control Variable</i>		
Percent Black	.06 (.03)^	.04 (.02)^
Year	.01 (.03)	-.05 (.04)
<i>R</i> <sup>2</sup>	.3860	.5261

NOTE: ^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

As shown in the measurement component of this study, rates of child neglect did not consistently trend downward over the period from 1990 to 2013. Instead, rates of child neglect fluctuated considerably and varied within and across states over this period. It is curious, then, that a number of the hypotheses proposed to explain the decline in child maltreatment are statistically significant in explaining fluctuating rates of child neglect. While the arrest rate for drug abuse violations, the two lagged proxy measures for agents of social control, and the rate of retail methylphenidate distribution do not have any relationship to rates of child neglect, the poverty rate, lagged incarceration rate, percent of law enforcement officers per capita, ratio of CPS caseworkers to children, and average size of a CPS worker's caseload all have statistically significant associations with

rates of child neglect in either the long or short series, controlling for all other measures in the respective models. Altogether, these variables (and the corresponding hypotheses they represent) account for roughly 39% and 53% of the variance in rates of child neglect over these periods.

Over both the long and short series, the lagged incarceration rate had a negative and significant association with rates of child neglect. In other words, increases in the imprisonment rate the year before were associated with decreases in the child neglect rate in the following year. This is inconsistent with Finkelhor and colleagues (2006) argument about the impact of the incarceration rate on trends in child maltreatment. Because parents and caretaker who are found guilty of child neglect are less likely to be given prison sentences than those found guilty of child abuse, and in particular child sexual abuse or child homicide, the fact that the incarceration rate has any relationship to rates of child neglect is remarkable.

Poverty rates also appear to have a statistically significant relationship with rates of child neglect from 1997 to 2013. This finding is compatible with prior micro- and macro-level research that has often found significant and positive associations between child neglect and poverty indicators (Berger, 2004, 2005; Drake & Pandey, 1996; Gelles, 1992; Paxson & Waldfogel, 2002). Economic factors such as parental unemployment, low family income, and living in a disadvantaged or impoverished neighborhood (all potential contributors to one's poverty status) have been shown to be associated with increased risk for child neglect in these previous studies. At the individual level, when children are born into a family without the ability to afford basic needs, they may be less likely to have those needs met. Of all of the maltreatment types, child neglect (or the



failure to provide a child with basic care and basic needs) is arguably the most likely to have some underlying connection to economic resources. The results of this analysis strengthen this argument at the macro level.

Furthermore, state poverty rates were only associated with rates of child neglect in Model 2 during the 1997 to 2013 period, even though this model controlled for more of the hypotheses and found many of them significant. This finding suggests that the recession of the latter half of the 2000s may have had a more influential effect on increasing rates of child neglect during the shorter series, where the positive economic conditions of the 1990s are not as strongly accounted for considering the trend begins in 1997.

Increases in the contemporaneous effect of the two measures of agents of social control were significantly associated with rates of child neglect, but again in opposite directions, and only from 1997 to 2013. A negative and marginally significant association between the percent of law enforcement officers per capita and the rates of child neglect was also found in the long series ( $p=.079$ ). While an increase in the percent of police officers in a given state was associated with significantly lower rates of child neglect, greater ratios of CPS workers to children were associated with significantly higher the rates of child neglect. As mentioned in the child sexual abuse section, increases in the percent of law enforcement officers per capita in states may provide a deterrent effect on crimes against children, as larger police departments have more resources, specialized units are more common, and officers and investigators can spend more time on cases of maltreatment and their presence is more likely to be felt in community. In contrast, it

could be that the more CPS workers there are in the state CPS agency, the more likely they are to detect, investigate, and substantiate reports of neglect that year.

The average caseload size of CPS workers was also significantly associated with higher rates of child neglect. Even though rates of child neglect did not uniformly decline for the majority of states, similar results were found in terms of how caseload size affects rates of all types of child maltreatment. As caseload size increased over time, rates of child maltreatment, including child neglect, also increased, suggesting that the more overwhelmed caseworkers were with reports of child maltreatment, the more likely they were to find substantiation. This positive relationship is counterintuitive and ultimately provides additional evidence that trends in substantiation are less a factor of resources available to CPS caseworkers and more a function of actual decreasing or increasing rates of child maltreatment.

#### SUPPLEMENTARY ANALYSIS OF CHILD HOMICIDE

As a way of comparing the hypothesis test results from the child maltreatment models to another trend in child victimization, a supplementary analysis using rates of child homicide as the dependent variable was also conducted. A Prais-Winsten regression using PCSEs was used in Model 1 of child homicide regressed on the various hypotheses as cross-sectional dependence between panels, panel-specific first-order serial autocorrelation within panels, and heteroscedastic errors were present. Because cross-sectional dependence between panels and serial autocorrelation was not present from 1997 to 2013 among these variables, an ordinary least squares regression with heteroscedastic errors was instead used in Model 2 (see Table 17).

Table 17. Panel Regressions of Rates of Child Homicide

	DV = Rate of Child Homicide	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Ordinary Least Squares (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
Poverty Rate	-.012 (.011)	.027 (.015) <sup>^</sup>
Incarceration Rate <sub>t-1</sub>	.003 (.0004) <sup>***</sup>	.003 (.0003) <sup>***</sup>
Percent of Law Enforcement Officers	-1.14 (2.04)	-1.39 (3.56)
Percent of Law Enforcement Officers <sub>t-1</sub>	3.12 (2.08)	4.89 (3.53)
Rate of Drug Abuse Violation Arrests	.091 (.019) <sup>***</sup>	.081 (.01) <sup>***</sup>
Ratio of CPS Caseworkers to Children		737.32 (361.14) <sup>*</sup>
Ratio of CPS Caseworkers to Children <sub>t-1</sub>		-768.11 (344.86) <sup>*</sup>
Average CPS Worker Caseload		.002 (.001) <sup>^</sup>
Rate of Methylphenidate Distribution		-.004 (.002) <sup>^</sup>
<i>Control Variable</i>		
Percent Black	.01 (.005) <sup>^</sup>	-.016 (.006) <sup>**</sup>
Year	a	a
<i>R</i> <sup>2</sup>	.5158	.4017

NOTE: <sup>a</sup>Separate year effects were included in the models but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the models. The year 1991 served as the reference category in Model 1 and the year 1998 served as the reference category in Model 2.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

These models account for roughly 52% and 40% of the variation in rates of child homicide from 1990 to 2013 and 1997 to 2013, respectively. The contemporaneous and lagged effect of the percent of law enforcement officers per capita in states was not statistically significant in both the long and short series. Moreover, similar to findings in the child neglect outcome, the poverty rate was also not associated with rate of child homicide from 1990 to 2013, but was marginally significant from 1997 to 2013 (p=.072). Again, this could likely be due to the stronger effects of the recession of the latter half of the 2000s in the short series than in the long series.

The prior years' incarceration rate had a positive and statistically significant relationship with rates of child homicide. This relationship is contrary to deterrence theory, which would suggest that imprisonment acts as a general and specific deterrent for offenders to commit crime, especially a crime such as homicide which nearly always comes with a sentence of incarceration for convicted offenders. Instead, higher rates of incarceration in the previous year are associated with higher rates of child homicide in the current year from 1990 to 2013 (and 1997 to 2013).

Interestingly, the rate of drug abuse violation arrests, the measure representing changes in illegal drug markets and the receding crack cocaine epidemic of the 1990s was positive and significant in predicting rates of child homicide in both models. As arrest rates for drug abuse violations increased from 1990 to 2013 (and 1997 to 2013), rates of child homicide increased, controlling for the effects of all other variables in the respective models. This finding is again in the opposite direction than expected based on the proposed hypothesis, but may likely represent the confounding effects of drug use, abuse, and sales with lethal and nonlethal violent crime. Because this measure includes both arrests for drug consumption and drug distribution/sales (i.e., possession with the intent to distribute), its effect may be tapping into the lethal violence associated with the illegal drug market and/or drug-involved parenting, as opposed to declines in drug consumption.<sup>28</sup>

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<sup>28</sup> In order to ascertain if the inclusion of drug abuse violation arrests was suppressing the effects of law enforcement activity and the influence of the police and other agents of social control on child homicide, this measure was also removed from these models. When arrests for drug abuse violations were removed from the child homicide models, the contemporaneous and lagged effects of the percent of law enforcement per capita remained nonsignificant. In addition, when arrest rates for drug abuse violations were removed from the other outcome models, very small changes were found in the beta coefficients of the agents of social control measures, but the significance of each beta coefficient remained largely the same.

Unlike the previous analyses where the rate of statewide retail methylphenidate distribution was nonsignificant for all child maltreatment outcomes, this proxy measure for the psychopharmacological hypothesis is negative and significantly associated with rates of child homicide from 1997 to 2013. Therefore, as rates of retail methylphenidate distribution increase, rates of child homicide decrease. This finding is compatible with the arguments made by Finkelhor and colleagues that the increased use of psychopharmaceuticals among parents and children may have an ameliorating effect on rates of child victimization in the home (Finkelhor & Johnson, 2015; Finkelhor & Jones, 2006). While this hypothesis failed to be significant in predicting rates of child maltreatment, it seems to have some relationship at the macro level with the most severe form of child victimization—child homicide.

The ratio of CPS caseworkers to children, both in the same year and in the previous year was significantly associated with rates of child homicide, but in different ways. While increases in the lagged ratio of CPS caseworkers to children were related to lower rates of child homicide the next year, increases in the ratio of CPS caseworkers in a given year were associated with higher rates of child homicide in that year. Interestingly, the effects seem almost identical albeit in opposite directions. This finding is consistent with previous research that has analyzed the effects of law enforcement activity on crime rates. For example, Rosenfeld and Fornango (2014) found that the contemporaneous effect of police stops was positive and nearly always significant in its relationship to precinct burglary rates across various panel regression models, while the two-year lagged effect of police stops, though not always significant in all models, was associated with lower precinct burglary rates. The authors conveyed similar substantive findings when

examining precinct robbery rates as well. These results imply that there may be an enduring effect of previous years' law enforcement activity on lowering crime rates, while increased law enforcement activity in a given year may be concurrent with higher crime rates due to the problem of endogeneity.

Endogeneity exists when the predictor variable is correlated with the error term of the regression equation used to estimate the effect of the predictor variable on the outcome (Wooldridge, 2010). This means that the predictor is a function (in whole or in part) of the outcome. It is reasonable that the number of state CPS caseworkers would increase or decrease depending on the rates of child maltreatment and child homicide in a state in a given year. Therefore, personnel changes within CPS agencies are likely to be concurrent with higher or lower rates of reported child victimization, and these changes could have lasting impacts. Lagging the predictor variable tends to help account for the problem of endogeneity in regression models. Interestingly, significant and opposite effects of the contemporaneous and lagged CPS social control measure were only found in its relationship to child homicide rates, not rates of the three types of child maltreatment. This finding suggests higher rates of child homicides within a state have a greater impact on decisions related to state spending on child welfare (through increasing the number of CPS personnel) than higher rates of child maltreatment, and these decisions over time may lower rates of child homicide (though not rates of child maltreatment) in the short term.

Relatedly, the average caseload size of a CPS caseworker was also associated with higher rates of child homicide. As caseload size increased over time, rates of child homicide also increased, suggesting that the more overwhelmed caseworkers were with

reports of child maltreatment, the higher the rates of child homicide were that year. This finding, while marginally significant ( $p=.079$ ), suggests that the connection between overworked CPS caseworkers and rates of child homicide in a state may, in fact, be causal, and worthy of attention in future research.

The rate of child physical abuse was also added to these models (results not shown) to see if rates of child physical abuse were associated with rates of child homicide given one could argue child physical abuse could be a precursor to child homicide. Even though the average size of a CPS workers' caseload was positive and significant, rates of child physical abuse were nonsignificant in all models, suggesting higher rates of child physical abuse are not significantly coupled with higher rates of child homicide once other factors are taken into account.<sup>29</sup>

## DISCUSSION

The importance of these findings should be qualified, but not understated. This study is the first of its kind to empirically test the hypotheses that have been proposed by child victimization and crime trends experts on why rates of child victimization, and in particular child maltreatment, declined post-1990. While this substantive analysis does not offer conclusive evidence as to the importance of these hypotheses for explaining macro-level trends in child victimization, it does help to differentiate whether the state-level measures used to represent these hypotheses have significant relationships with

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<sup>29</sup> Interestingly, the beta coefficient of the rate of child physical abuse modeled on its own as a predictor of rates of child homicide was positive and statistically significant ( $b=.086$ ,  $p=.001$ ,  $R^2=.3774$ ). Therefore, it is likely that the various other significant factors in the multivariate model explain the same variation in rates of child homicide that the rates of child physical abuse explain when these other factors are not taken into account.

state-level rates of (and state-level trends in) child physical abuse, child sexual abuse, child neglect, and child homicide.

After correcting for the presence of various diagnostic concerns in the models, all of the measures used to operationalize the six competing hypotheses related to the decline in child victimization were significantly associated with the different types of child maltreatment and child homicide. Interestingly, year-over-year changes in the rates of not only child physical abuse, but child sexual abuse, child neglect, and child homicide as well (as shown in Appendix I), had much less explanatory power in describing the variance in year-over-year changes in rates of these types of child victimization. Regression models predicting levels, as opposed to trends in rates of child victimization, were much more effective in explaining variations in rates of child victimization. The coefficient of determination (i.e.,  $R^2$ ) was consistently large in magnitude regardless of which outcome model was assessed in levels using these measures. For the most part, these independent variables account for roughly 40% to 57% of the variation in rates of child sexual abuse, child neglect, and child homicide. Considering there are a few hypotheses not included in this analysis due to the lack of data measuring other important phenomenon (e.g., changing norms and values across society), coefficients of determination that comprise nearly half of the variability in these rates is remarkable.

The results of the child neglect models are very thought-provoking. While child neglect trends did not decline in the same way that child physical abuse, child sexual abuse, and child homicide did post-1990, the factors proposed to help explain these declines appear to carry some weight in explaining the largely fluctuating, but relatively stable rates of child neglect over this period just as much as they explained the largely



declining rates of child sexual abuse and child homicide. Because neglect is unique in that it is an act of omission as opposed to an act of commission, these findings are even more intriguing.

One would expect the results of these models to differ across the child victimization outcomes largely because each victimization type is unique in the risk and protective factors typically associated with its occurrence. For example, higher poverty rates were significantly associated with higher rates of child neglect from 1997 to 2013, but failed to reach statistical significance in explaining rates of child sexual abuse, and were only marginally significant in explaining rates of child homicide over the short series. In addition, the arrests rates for drug abuse violations had no significant relationship to rates of child maltreatment, but were significantly associated with rates of child homicide. As mentioned previously, given the breadth of drug-related arrest charges captured by this measure, especially those consistently linked to neighborhood violence, the significance of this measure in predicting the most violent form of child victimization only is more reasonable, especially given higher rates of child homicides occur among teenagers who are more likely to be involved in drug-activity on the streets than younger children.

One consistent finding throughout these hypothesis tests was the apparent contradiction in the direction of the effect between the two types of agents of social control modeled: the percent of law enforcement officers per capita and the ratio of CPS caseworkers to children. While both act as state agents of social control, the conflicting direction of the significant contemporaneous relationship each had on rates of child victimization was not anticipated. Increases in the percent of law enforcement officers

per capita had the concurrent effect of lowering rates of child sexual abuse and child neglect. Even though one would expect rates of child victimization to decline as the number of agents of social control increases, these analyses find that the ratio of CPS caseworkers to children in a given year actually corresponds to increases in rates of child maltreatment in the same year. However, understanding how funding and intake procedures have changed over time in each state's CPS agency makes this finding less alarming. As various federal laws created additional funding streams for child welfare services in states throughout the 1990s, more CPS workers were hired, and more policies and procedures were established to investigate reports of abuse and neglect. With greater resources in these agencies, it is plausible then that CPS workers would be better able to perform their jobs and efficiently investigate reports, potentially leading to greater rates of substantiation. This argument, if true, means artifactual explanations for trends in rates of child maltreatment cannot be completely discounted. While the ratio of CPS caseworkers to children was expected to measure the effect of social control mechanisms on rates of child maltreatment, it may have, in fact, revealed the effect of policy changes at the state agency level on rates of child maltreatment (i.e., and hence the problem of endogeneity between CPS activity and rates of child maltreatment). Interestingly, however, the one-year lagged effect of the percent of law enforcement officers per capita never reached significance in its association with rates of child sexual abuse, child neglect, and child homicide, but the lagged ratio of CPS caseworkers to children only showed an enduring significant effect on rates of child homicide.

Finkelhor and colleagues (2006) also argued that the incarceration rate, a possibly significant factor for the decline, is likely important for child homicide and child sexual

abuse because murders and child sex offenders are more likely to get prison time than those convicted of child physical abuse or neglect.<sup>30</sup> This notion is only supported in the short series for child sexual abuse rates. One reason the lagged incarceration rate may not be significant throughout the entire series for child sexual abuse may be due to the timing of the various federal and state laws requiring sex offender registries, many of which were enacted in the mid-1990s. Interestingly, incarceration rates lagged one year also have an association with lower rates of child neglect. Contrary to previous research which suggests incarceration breaks up families and produces unstable environments for children, this inverse relationship suggests that children may, in fact, be protected from child sexual abuse and child neglect at increased rates when incarceration rates are higher. In contrast, higher rates of incarceration in the previous year are associated with higher rates of child homicide in the following year from 1990 to 2013 (and 1997 to 2013).

As stated earlier, these hypotheses tests were conducted using the balanced data created via the estimation procedures described in Chapter 6. The interpolation of these data was required in order to produce complete data, a necessity when calculating correlation coefficients across the entire period for any two unique trends. However, the

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<sup>30</sup> Interestingly, when the lagged total incarceration rate was replaced with the lagged female incarceration rate in the child sexual abuse 1997-2013 model (results not shown), the beta coefficient for the female incarceration rate was negative and significantly associated with rates of child sexual abuse ( $p \leq .001$ ). This suggests that higher rates of female incarceration from 1997 to 2013 in states may serve as a protective factor for children in their risk for child sexual abuse, contrary to arguments made in previous research that higher rates of female incarceration place children in unstable and riskier situations at home. Similar to the findings in the child neglect models, female-specific lagged incarceration rates also had a negative and significant association with rates of child neglect over both series, where higher rates of female incarceration in the prior year were associated with lower rates of child neglect in the current year from 1990 to 2013. In addition, the positive and significant relationship between the lagged incarceration rate and rates of child homicide also held for the prior years' female incarceration rate on rates of child homicide. Year-over-year changes in the lagged female incarceration rate (when modeled instead of the detrended total incarceration rate) had a statistically significant negative association with year-over-year changes in the rates of child physical abuse.

PCSE models can also be performed using the original (non-interpolated) data from all of the data sources. As a test of the robustness of these models, additional models were run using the original source data for all outcomes. A comparison of the models reported above and the models using the original unbalanced data can be found in Appendix J. The p-values of the estimated (interpolated) and original (non-interpolated) beta coefficients of certain factors do differ in a few of the models. For the most part, the factors significant using the interpolated data are also significant using the original data. There are instances, however, where the estimated trends in the models are nonsignificant when the original measures are statistically or marginally significant and vice versa. On most of these occasions, the original data produces even more robust beta coefficients for the factors in the four outcome models. Their standard errors are a bit larger, yet their t-statistics are even more significant. Therefore, it seems the interpolation procedure was largely conservative in estimating rates across the dependent and independent variables. This is likely because taking the linear average of two adjacent rates to fill in a missing year lost any fluctuations in the trends from year to year that may have been present and estimated in the regression models using the unbalanced data. This check of the robustness of these models is an assurance that the strength of the magnitude of these effects using the estimated data is large and should not be discounted.

## CHAPTER EIGHT: CONCLUSION

In 2013, years after rates of child abuse declined by more than half, the Committee on Child Maltreatment Research, Policy, and Practice suggested the need for research comparing the rates of child abuse and neglect reporting and substantiation in states across several years, focusing on the variability at the state level (Institute of Medicine, 2013, p. 8-24). This study responds to this need in two ways. First, the measurement component evaluates the validity of the NCANDS data—the nation’s leading data source for information on national-level rates of child maltreatment—for studying trends in child maltreatment at both the national and state level using correlational and cointegration techniques. After the question of the validity of these data for studying temporal trends has been addressed, this study also examined the empirical relevance of factors related to trends in child maltreatment using state panel models. In sum, this analysis provided evidence of when and where rates of child victimization largely declined post-1990, and the factors associated with these declines.

As often as temporal trends in child maltreatment using the NCANDS data have been reported and used by state CPS agencies for evaluation purposes, researchers and officials do not know if, and why, the rates trended downward. These questions arise because state-level trends in child maltreatment post-1990 had not been extensively assessed for issues of validity and reliability. Because artificial declines based on policy and procedural changes are possible (and this study points to evidence of these changes have had an effect on rates), the magnitude of any actual increases or decreases has been unknown.

According to the NCANDS data trends, children's risk for child maltreatment, and in particular physical and sexual abuse, is much lower now than it was just a few decades ago. These declines mirror declines found in other more relied upon administrative and survey data sources. At the national level, rates of child homicide and rates of children exposed to violence in their home were highly correlated with child physical abuse and child sexual abuse in both levels and trends, providing some evidence of the validity of the NCANDS measures to study national trends in child victimization. Having not only administrative data, but also survey data reveal significant correlations among these declining trends in child victimization is important because survey data are not subject to changes in administrative operations, such as crime recording or the computerization of data collection processes, which may artificially affect agency trends. Furthermore, all three data sources (the NCANDS, SHR, and NCVS) reported a short-term increase in rates of child victimization in and around 2006. Given that this unusual fluctuation was observed across all three sources, the evidence suggesting strong validity of the NCANDS trends for measuring temporal change is even more suggestive. These findings provided greater confidence in the NCANDS national-level rates of child maltreatment to depict the reality of children's risk for child victimization.

The measurement assessment of the NCANDS state-level data unearthed some very important data reliability concerns that needed to be addressed before these data could be used to study trends at the state level. I found the NCANDS state-level data have varying degrees of data quality issues (e.g., missing data, extreme outliers, problematic data points) which had to be addressed before proceeding with analyses. Therefore, various data cleaning and interpolation techniques were implemented. Even

though statistical tests revealed that the mean of the aggregate state trends and individual state trends were not significantly different after interpolation, there is the possibility that these techniques, while critical to moving forward with some of the analyses, may have potentially produced significant bias in the trends that could have affected the results of this study. However, a robustness check using the original source data showed that the interpolated data were largely conservative in their estimation of rates using PCSE models so I am confident that any biases produced are limited in scope.

And while this study provided some evidence of validity in the state-level NCANDS trends using both correlational and cointegration analyses, state-level child homicide data were not likely the best data to use to establish validity of the state-level maltreatment trends. This concern is largely attributable to the instability of state child homicide rates that were based on low counts in small population states and the associated error that is brought into the statistical tests because of this instability. Part of the challenge is the need to rely on child homicide data at the state level because it is the only measure available that measures child victimization consistently at the state level over this period. Official statistics are generally better for homicide than any other crime and homicide has been known to be reliable measured over time. On the one hand, the low counts of child homicide in small population states may have biased the findings of the state-level correlational and cointegration analysis. On the other hand, because of the rarity of child homicide, using these trends as the barometer from which to test the external validity of NCANDS child maltreatment trends is fundamentally a tough test in and of itself.

High correspondence between the national trends in child victimization does not necessarily mean that all state-level data trends are equally valid for purposes of measuring and assessing explanations for the trends. Visual assessments found that the majority of states' rates of child abuse declined from 1990 to 2013, while rates of child neglect fluctuated considerably within and across states. This study found that the majority of state trends in child physical abuse and child sexual abuse were highly correlated with one another and with rates of child homicide. The population size of a state and the region the state was located in within the U.S. had little bearing on correlations among trends over time in the rates of NCANDS measures and child homicide. Further analyses of these child maltreatment trends found that they were all in fact cointegrated with child homicide, where the trends move together in concert and share a long-run effect. These results further suggest that the NCANDS state-level trends appear to be generally valid measures of temporal trends in child victimization.

This study is also the first of its kind to empirically test the relevance of multiple factors potentially contributing to trends in child maltreatment post-1990. I found that year-to-year changes in the rates of child victimization had much less explanatory power in describing the variance in year-to-year changes in rates of child victimization than the magnitude of rates of these independent variables in explaining the magnitude of rates of child victimization. The measures representing the six different hypotheses tested in these models accounted for roughly 40% to 50% of the variation in rates of child sexual abuse, child neglect, and child homicide. Interestingly, a few of these hypotheses (e.g., the economic hypothesis, the agents of social control hypothesis) were significantly associated with rates of child neglect, even though rates of child neglect did not decline



over this period. Therefore, these hypotheses may likely have important bidirectional effects on rates and trends in child victimization.

Moreover, the results of these models also differed across the child victimization outcomes. Increases in agents of social control and the average size of a CPS worker's caseload had significant relationships with rates of child sexual abuse and child neglect. While more police officers tend to be associated with lower rates of child maltreatment, more CPS workers tend to be associated with increased rates. In contrast, more police officers were associated with higher rates of child homicide, suggesting increased resources within police agencies may have also had the effect of artificially increasing rates of child homicide. Also, the larger a CPS worker's caseload was, the higher the rates of child maltreatment were, providing support that at least some of the declines in child abuse are real and not an artifact of the data.

It is also worth noting the potential that the average caseload size of a CPS caseworker may be confounded with the ratio of CPS caseworkers to children in the short series models. Because the average caseload size of a CPS caseworker and the ratio of CPS caseworkers to children are both a function of the total number of CPS caseworkers in a state in a given year, trends in these two measures have moderately high correlations (in levels  $\rho = -.654$ , in first-differences  $\rho = -.554$ ). Trends in the average caseload size of a CPS caseworker and the lagged ratio of CPS caseworkers to children are also significantly correlated ( $\rho = -.596$ ). The possible confounding nature of these measures may have had an effect on the results of these analyses.<sup>31</sup> Therefore, caution should be

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<sup>31</sup> Additional checks on this confounding issue found that the average caseload size of a CPS caseworker remained significant across all outcome measures when both the contemporaneous and lagged ratios of CPS caseworkers to children were removed from the models. However, when the average caseload size of a CPS caseworker was removed, the contemporaneous effect of the ratio of CPS caseworkers to children

taken when interpreting the effect of these measures, especially the contemporaneous ratio of CPS caseworkers to children, on all four trends in child victimization.

As with all research, this study is not without its limitations. A number of limitations are especially worth noting. First, the results of the hypothesis tests are only as convincing as the measures and data used to operationalize the hypotheses. Had drug consumption data been available, especially past year crack cocaine use among state residents, for example, this hypothesis would have been operationalized and tested in a more precise fashion. The same goes for the operationalization of the psychopharmacological hypothesis. Ideally, had I been able to measure the consumption of psychopharmaceuticals instead of the distribution of them, and had I been able to also include anti-depressive and anti-anxiety medications also, the measurement of this hypothesis and the findings of this analysis would likely have been more robust. Furthermore, there are a number of hypotheses that I was unable to find reliable and consistent empirical data at the state level to measure (e.g., changes in norms and values related to the acceptable treatment of children), limiting the ability of this substantive analysis to speak to all hypotheses related to the decline in rates of child victimization post-1990. Similar to violent crime trends in general, explanations for the decline in child victimization are almost certainly multidimensional in nature. As shown in this analysis, even though the factors considered here account for roughly half of the variation in the rates of child maltreatment and child homicide, they do not account for much of the variation in year-over-year changes in the trends in rates of child maltreatment and child homicide. This is an issue that should be explored further in future research.

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went from significant to nonsignificant in the child sexual abuse, child neglect, and child homicide models. The lagged effect of the ratio of CPS caseworkers to children did not vary in the direction of the effect or significance when the average CPS caseload size measure was removed from all models.

Second, as mentioned earlier, the missing data in state-level measures, especially the state-level child maltreatment rates, were not missing at random. When a state was missing data in a particular year, that state was more than likely also missing data in additional years, many of which were adjacent to one another. There are likely important, systematic reasons these states were missing these data which cannot be ignored. This is an obvious limitation of this analysis, and one that requires that caution be taken when interpreting the results of this study. More rigorous case studies detailing the methodological and procedural changes made within state agencies during this period, especially for those states with missing or questionable NCANDS data should be attempted in order to understand the historical motivations and rationales driving decisions within state CPS agencies, which ultimately may have had an effect on their NCANDS data. Attempts to minimize measurement issues related to the NCANDS data quality in some states should be made as the quality of the NCANDS data will almost certainly have implications on any future trend research using these data.

Third, it could also be that state-level aggregation masks significant variation in rates among all dependent and independent variables, providing much less variation than necessary to understand the important effects of these variables in explaining reasons for the trends over time. Had data been available for an even smaller geographic panel (e.g., cities or metropolitan statistical areas), more variation may have been present and the results of the analyses may have been different. It should be pointed out, however, that the utilization of data from even smaller geographic units than states comes with a whole host of other data quality and reliability issues not necessarily dealt with in the current study. Future research should attempt to uncover the differences between geographic

units over time, as this more detailed type of analysis may be preferable in studying the when, where, and why trends in child victimization varied over time.

Fourth, the findings of the substantive component of this study are not generalizable to every state. The regression models used to convey the relationship between the various hypotheses and rates of child victimization reveal average patterns shown in the state-level data, not state-specific patterns. It should be noted that patterns and trends are different in every state and while all of these macro-level factors appear to matter for one or more trends in child victimization, they may not matter for a particular state or over a particular period within a particular state.

Fifth, it is worth noting that there is a lack of complete comparability of the child homicide and child abuse measures in both magnitude and trend. Aside from the apparent difference of fatal and non-fatal violence between the two victimization types, the child homicide measure obviously includes many child homicides that are not in any way related to family violence, while child abuse and neglect largely measures violence within families. As mentioned, homicide is more common among children ages 12 to 17, while child abuse and neglect tends to be a crime committed against young children. And, the circumstances related to the homicidal incident vary widely across children of different ages. Therefore, by including homicides to children in their teenage years, these child homicide trends are likely also measuring an additional set of victimization circumstances beyond those that are more comparable to the victimization of younger children. The inability to disaggregate the child homicide rates by age groups across all states and still produce non-zero rates capable of being used for all states over these years

is a major limitation of this analysis and one that should be addressed in future analyses of trend comparisons between types of child victimization.

Finally, with the influx of state child abuse and neglect registries and child fatality review teams across states, as well as newer and more efficient SACWIS-type case-management systems, changes in intake procedures and data reporting methods within state CPS agencies continue to change on an annual basis. Future research in child maltreatment trends should attempt to control for these additional shifts in policies and procedures, as these changes will always likely have an effect on substantiation and rates of child maltreatment over time.

This study has provided strong evidence that the NCANDS data are sufficiently valid for studying national trends in child victimization, and reasonable evidence that the NCANDS data are sufficiently valid for studying state trends in child victimization. Therefore, researchers and practitioners around the U.S. who use the NCANDS data to measure rates of child abuse and neglect from year to year in their respective jurisdictions or for the advancement of knowledge in child abuse and neglect research should be informed of their potential for more advanced analyses of temporal trends in child victimization.

Unfortunately, some state NCANDS data are problematic. I found that a number of states implemented policy and/or procedural changes over time which hindered my ability to fully understand why some state rates of child maltreatment appeared to trend as they did. And, many of the reasons for these changes were not available in published reports or through communicative efforts with current employees at state CPS agencies. Furthermore, it was also obvious to me in my efforts to uncover these unique state

explanations that some state officials were uncomfortable with my question about the trends because their honesty about their state system and/or process for investigating reports of child maltreatment could come back to haunt them and their agency in potential legal proceedings. This is likely because state CPS agencies are tasked with protecting our children from harm, any departure they (or their staff) make from the approved upon regulations detailing how allegations of child maltreatment should be handled could be cause for civil (or even criminal) action. This leads to many unanswered questions in the state-level trends that unfortunately may never be known to researchers. It is recommended that state CPS agencies be as transparent as possible about the changes and/or processes that take place within their agencies in order to fully understand why rates of child maltreatment vary over time. Because agencies spend considerable time and resources collecting these data, they should also be invested in making sure these data are useful and comprehensible to those who use them.

These findings also revealed that certain measures do, in fact, have significant relationships with rates of child victimization. Therefore, federal, state, and local policymakers should be aware of these relationships and recognize that macro-level declines in child victimization may only be possible if these other macro-level conditions are also addressed. For example, states should be proactive by expanding funding to CPS agencies in order to hire more CPS caseworkers when caseload sizes get unmanageable. Because greater average sizes of a CPS workers' caseload were associated with higher rates of child maltreatment and child homicide, states should heed the warnings and streamline resources into agencies ahead of time to lower caseload sizes and relieve the pressures of mounting caseloads on CPS staff. Although this study does not provide

definitive proof of the importance of any of these six hypotheses and their associated factors in explaining trends in rates of child victimization, it is arguably a strong first step in attempting to understand why child victimization declined post-1990.

## REFERENCES

- Adams, Joyce A., Katherine Harper, Sandra Knudson, and Juliette Revilla. 1994. Examination findings in legally confirmed child sexual abuse: It's normal to be normal. *Pediatrics* 94:310–317.
- Albert, Vicky N., and Richard P. Barth. 1996. Predicting growth in child abuse and neglect reports in urban, suburban, and rural counties. *Social Services Review* 70:58–82.
- Almeida, Joanna, Amy P. Cohen, S.V. Subramanian, and Beth E. Molnar. 2008. Are increased worker caseloads in state child protective service agencies a potential explanation for the decline in child sexual abuse? A multilevel analysis. *Child Abuse & Neglect* 32:367–375.
- American Academy of Pediatrics. 2006. Distinguishing sudden infant death syndrome from child abuse fatalities. *Pediatrics* 118:421–427.
- Arvanites, Thomas M., and Robert H. DeFina. 2006. Business cycles and street crime. *Criminology* 44:139–164.
- Banerjee, Anindya, Juan J. Dolado, John W. Galbraith, and David Hendry. 1993. *Cointegration, Error Correction, and the Econometric Analysis of Non-Stationary Data*. Oxford, England: Oxford University Press.
- Baumer, Eric, and Janet L. Lauritsen. 2010. Reporting crime to the police, 1973-2005: A multivariate analysis of long term trends in the National Crime Survey (NCS) and National Crime Victimization Survey (NCVS). *Criminology* 48:131–185.
- Beck, Nathaniel, and Jonathan N. Katz. 1995. What to do (and what not to do) with time series cross-section data. *American Political Science Review* 89:634–647.
- Berg, Mark T., and Janet L. Lauritsen. 2016. Telling a similar story twice? NCVS/UCR convergence in serious violent crime rates in rural, suburban, and urban places (1973-2010). *Journal of Quantitative Criminology* 32:61–87.
- Berger, Lawrence M. 2005. Income, family characteristics, and physical violence toward children. *Child Abuse & Neglect* 29:107–133.
- Berger, Lawrence M. 2004. Income, family structure, and child maltreatment risk. *Children and Youth Services Review* 26:725–748.
- Bethea, Lesa. 1999. Primary prevention of child abuse. *American Academy of Family Physicians* 69:1577–1591.



- Blumstein, Albert, and Richard Rosenfeld. 2009. Factors contributing to U.S. crime trends. In A. Goldberger and R. Rosenfeld (eds.) *Understanding Crime Trends*. Washington, DC: National Academies Press.
- Blumstein, Albert and Richard Rosenfeld. 1998. Explaining recent trends in U.S. homicide rates. *Journal of Criminal Law and Criminology* 88:1175–1216.
- Blumstein, Albert, and Joel Wallman. 2006. *The Crime Drop in America* (revised). New York, NY: Cambridge University Press.
- Bouvy, Paul F., and Marieke Liem. 2012. Antidepressants and lethal violence in the Netherlands 1994-2008. *Psychopharmacology* 222:499–506.
- Carbone-Lopez, Kristin, and Janet Lauritsen. 2013. Seasonal variation in violent victimization: Opportunity and the annual rhythm of the school calendar. *Journal of Quantitative Criminology* 29:399–422.
- Centers for Disease Control and Prevention. 2015. Trends in the prevalence of alcohol and marijuana, cocaine, and other illegal drug use, National YRBS: 1991-2013. Retrieved from: <http://www.cdc.gov/healthyyouth/data/yrbs/results.htm>
- Centers for Disease Control and Prevention. 2010. Increasing prevalence of parent reported Attention-Deficit/Hyperactivity Disorder among children—United States, 2003 and 2007. *MMWR Morbidity and Mortality Weekly Report* 59:1439–1443
- Centers for Disease Control and Prevention. no date. National Vital Statistics System, National Center for Injury Prevention and Control. Retrieved from: [http://webappa.cdc.gov/sasweb/ncipc/mortrate10\\_us.html](http://webappa.cdc.gov/sasweb/ncipc/mortrate10_us.html)
- Chen, Xiujian, Shu Lin, and W. Robert Reed. 2010. A Monte Carlo evaluation of the efficiency of the PCSE estimator. *Applied Economics Letters* 17:7–10.
- Child Abuse Prevention and Treatment Act of 1974. Pub. L. No. 93-247, 88 Stat. 4.
- Child Abuse Prevention and Treatment Act Reauthorization Act of 2010. Pub. L. No. 111-320, 124 Stat. 3459.
- Child Protection Accountability Commission. 2016. Children’s Justice Act: Annual progress report and grant application. State of Delaware, Wilmington, DE.
- Christian, Cindy W., and Robert D. Sege. 2010. Child fatality review. *Pediatrics* 126:592–596.
- Clark, Robin E., and Judith Freeman Clark. 1989. *The Encyclopedia of Child Abuse*. New York, NY: Facts on File, Inc.

- Coleman, Doriane Lambelet, Kenneth A. Dodge, and Sarah Keeton Campbell. 2010. Where and how to draw the line between reasonable corporal punishment and abuse. *Law and Contemporary Problems* 73:107–65.
- Cook, Phillip J., and John H. Laub. 2002. After the epidemic: Recent trends in youth violence in the United States. *Crime and Justice* 29:1–37.
- Cooper, Alexia, and Erica L. Smith. 2011. *Homicide trends in the United States, 1980–2008*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 236018.
- Costin, Lela B., Howard Jacob Karger, and David Stoesz. 1996. *The politics of child abuse in America*. New York, NY: Oxford University Press.
- Coulton, Claudia J., David S. Crampton, Molly Irwin, James C. Spilsbury, and Jill E. Korbin. 2007. How neighborhoods influence child maltreatment: A review of the literature and alternative pathways. *Child Abuse & Neglect* 31:1117–1142.
- Cox, Nicholas. 2009. Speaking Stata: Creating and varying box plots. *The Stata Journal* 9:478–496.
- Crume, Tessa L. Carolyn DiGuiseppi, Tim Byers, Andrew P. Sirotnak, and Carol J. Garrett. 2002. Underascertainment of child maltreatment fatalities by death certificates, 1990-1998. *Pediatrics* 110:e18.
- Currie, Janet, Mark Stabile, and Lauren Jones. 2014. Do stimulant medications improve educational and behavioral outcomes for children with ADHD? *Journal of Health Economics* 37:58–69.
- Davidson, Scott A. 1995. When is parental discipline child abuse? – The vagueness of child abuse laws. *University of Louisville Journal of Family Law* 34:403–19.
- De Hoyos, Rafael E., and Vasilis Sarafidis. 2006. Testing for cross-sectional dependence in panel-data models. *The Stata Journal* 6:482–496.
- DeNavas-Walt, Carmen, and Bernadette D. Proctor. 2014. *Income and Poverty in the United States: 2013*. U.S. Census Bureau, Current Population Reports, P60-249. Washington, DC: U.S. Government Printing Office.
- Donohue, John J., and Steven D. Levitt. 2001. The impact of legalized abortion on crime. *The Quarterly Journal of Economics* 116:379–420.
- Drake, Brett, and Shanta Pandey. 1996. Understanding the relationship between neighborhood poverty and specific types of child maltreatment. *Child Abuse & Neglect* 20:1003–1018.

- Drukker, David M. 2003. Testing for serial correlation in linear panel-data models. *The Stata Journal* 3:168–177.
- Dubowitz, Howard. 2006. Defining child neglect. In M. Feerick, J. Knutson, P. Trinkett, and S. Flanzer (eds.) *Child Abuse and Neglect: Definitions, Classifications, and a Framework for Research*. Baltimore, MD: Paul H. Brookes Publishing Co.
- Dugan, Laura, Daniel S. Nagin, and Richard Rosenfeld. 2003. Exposure reduction or retaliation? The effects of domestic violence resources on intimate partner homicide. *Law & Society Review* 37:169–198.
- Durfee, Michael, Juan M. Parra, and Randell Alexander. 2009. Child fatality review teams. *Pediatric Clinics of North America* 56:379–387.
- Eck, John, and Richard Maguire. 2000. Have changes in policing reduced violent crime? An assessment of the evidence. In A. Blumstein and J. Wallman (eds.) *The Crime Drop in America*. New York, NY: Cambridge University Press.
- Eckenrode, John, Jane Powers, John Doris, Joyce Munsch, and Niall Bolger. 1988. Substantiation of child abuse and neglect reports. *Journal of Consulting and Clinical Psychology* 56:9–16.
- Eckenrode, John, Elliot G. Smith, Margaret E. McCarthy, and Michael Dineen. 2014. Income inequality and child maltreatment in the United States. *Pediatrics* 133:454–461.
- Engle, Robert F., and C. W. J. Granger. 1987. Cointegration and error correction: Representation, estimation, and testing. *Econometrica* 55:251–276.
- English, Diana J., David B. Marshall, Laura Coghlan, Sherry Brummel, and Matthew Orme. 2002. Causes and consequences of the substantiation decision in Washington State child protective services. *Children and Youth Services Review* 24:817–851.
- Fallon, Barbara, Nico Trocmé, John Fluke, Bruce MacLaurin, Lil Tonmyr, and Ying Ying Yuan. 2010. Methodological challenges in measuring child maltreatment. *Child Abuse & Neglect* 34:70–79.
- Farst, Karen, Pratibha B. Ambadwar, Andrew J. King, T. M. Bird, James M. Robbins. 2013. Trends in hospitalization rates and severity of injuries from abuse in young children, 1997-2009. *Pediatrics* 131:e1796–e1802.
- Finkelhor, David, and Melanie Johnson. 2015. Has psychiatric medication reduced crime and delinquency? *Trauma, Violence, & Abuse*. Advance online publication.

- Finkelhor, David, and Lisa Jones. 2012. *Have Sexual Abuse and Physical Abuse Declined Since the 1990s?* Durham, New Hampshire: Crimes against Children Research Center, University of New Hampshire.
- Finkelhor, David, and Lisa Jones. 2006. Why have child maltreatment and child victimization declined? *Journal of Social Issues* 62:685–716.
- Finkelhor, David, and Lisa M. Jones. 2004. *Explanations for the decline in child sexual abuse cases.* Washington, DC: U.S. Department of Justice, Office of Juvenile Justice and Delinquency Prevention.
- Finkelhor, David, Kei Saito, and Lisa Jones. 2015. *Updated trends in child maltreatment.* Durham, New Hampshire: University of New Hampshire, Crimes Against Children Research Center.
- Flaherty, Emalee G., Robert D. Sege, John Griffith, Lori Lyn Price, Richard Wasserman, Eric Slora, Niramol Dhepyasuwan, Donna Harris, David Norton, Mary Lu Angelilli, Dianna Abney, and Helen J. Binns. 2008. From suspicion of physical child abuse to reporting: Primary care clinician decision-making. *Pediatrics* 22:611–619.
- Fluke, John D., Ying-Ying T. Yuan, John Hedderson, and Patrick A. Curtis. 2003. Disproportionate representation of race and ethnicity in child maltreatment: Investigation and victimization. *Children and Youth Services* 25:359–373.
- Freisthler, Bridget, Nancy J. Kepple, and Megan R. Holmes. 2012. The geography of drug market activities and child maltreatment. *Child Maltreatment* 17:144–152.
- Fuller-Thomson, Esme, Rukshan Mehta, and Angela Valeo. 2014. Establishing a link between Attention Deficit Disorder/Attention Deficit Hyperactivity Disorder and childhood physical abuse. *Journal of Aggression, Maltreatment & Trauma* 23:188–198.
- Gelles, Richard J. 1992. Poverty and violence toward children. *The American Behavioral Scientist* 35:258–274.
- Getahun, Darios, Steven J. Jacobsen, Michael J. Fassett, Wansu Chen, Kitaw Demissie, and George G. Rhoads. 2013. Recent trends in childhood Attention-Deficit/Hyperactivity Disorder. *JAMA Pediatrics* 167:282–288.
- Greene, William H. 2000. *Econometric Analysis.* New York: Prentice-Hall.
- Hausman, J. A. 1978. Specification tests in econometrics. *Econometrica* 46:1251–1271.

- Heger, Astrid, Lynne Ticson, Oralia Velasquez, and Raphael Bernier. 2002. Children referred for possible sexual abuse: Medical findings in 2384 children. *Child Abuse & Neglect* 26:645–659.
- Herman-Giddens, Marcia E., Gail Brown, Sarah Verbiest, Pamela J. Carlson, Elizabeth G. Hooten, Eleanor Howell, and John D. Butts. 1999. Underascertainment of child abuse mortality in the United States. *JAMA* 282:463–467.
- Hines, Denise A., Kathleen Malley-Morrison, and Leila B. Dutton. 2013. *Family violence in the United States: Defining, understanding, and combating abuse*. 2<sup>nd</sup> Ed. Washington, DC: SAGE Publications, Inc.
- Hipp, John R., Daniel J. Bauer, Patrick J. Curran, Kenneth A. Bollen. 2004. Crimes of opportunity or crimes of emotion? Testing two explanations of seasonal change in crime. *Social Forces* 82:1333–1372.
- Hussey, Jon M., Jen Jen Chang, and Jonathan B. Kotch. 2006. Child maltreatment in the United States: Prevalence, risk factors, and adolescent health consequences. *Pediatrics* 118:933–942.
- Im, Kyung So., M. Hashem Pesaran, and Yongcheol Shin. 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115:53–74.
- Institute of Medicine. 2013. *New directions in child abuse and neglect research*. Washington, DC: The National Academy of Sciences, National Research Council.
- Jacobs, David, and Jason T. Carmichael. 2002. The political sociology of the death penalty: A pooled time-series analysis. *American Sociological Review* 67:109–131.
- Janczewski, Colleen E. 2015. The influence of differential response on decision-making in child protective service agencies. *Child Abuse & Neglect* 39:50–60.
- Johnston, Janet M. 2001. *Kids Count in Nebraska: 2001 Report*. Omaha, Nebraska: Voices for Children in Nebraska.
- Johnston, Janet M. 2000. *Kids Count in Nebraska: 2000 Report*. Omaha, Nebraska: Voices for Children in Nebraska.
- Jonas, Bruce S., Qiuping Gu, and Juan R. Albertorio-Diaz. 2013. *Psychotropic medication use among adolescents: United States, 2005-2010*. NCHS data brief, no. 135. Hyattsville, MD: National Center for Health Statistics.
- Jones, Lisa M., David Finkelhor, and Stephanie Halter. 2006. Child maltreatment trends in the 1990s: Why does neglect differ from sexual and physical abuse? *Child Maltreatment* 11:107–20.

- Jones, Lisa M., David Finkelhor, Kathy Kopiec. 2001. Why is sexual abuse declining? A survey of state child protection administrators. *Child Abuse & Neglect* 25:1139–1158.
- Kellogg, Nancy D., Shirley W. Menard, and Annette Santos. 2004. Genital anatomy in pregnant adolescents: “Normal” does not mean “nothing happened”. *Pediatrics* 113:e67–e69.
- Kvist, Anette Primdal, Helena Skyt Nielsen, and Marianne Simonsen. 2013. The importance of children’s ADHD for parents’ relationship stability and labor supply. *Social Science & Medicine* 88:30–38.
- LaFree, Gary. 1999. Declining violent crime rates in the 1990s: Predicting crime booms and busts. *Annual Review of Sociology* 25:145–68.
- Land, Kenneth C., Vicki L. Lamb, and Qiang Fu. 2016. Measuring trends in child well being and child suffering in the United States, 1975-2013. *Social Indicators Research* 60:23–41.
- Land, Kenneth C., Vicki L. Lamb, and Sarah Kahler Mustillo. 2001. Child and youth well-being in the United States, 1975-1998: Some findings from a new index. *Social Indicators Research* 56:241–320.
- Lauritsen, Janet L., Maribeth L. Rezey, and Karen Heimer. 2016. When choice of data matters: Analyses of U.S. crime trends, 1973-2012. *Journal of Quantitative Criminology* 32:335–355.
- Lauritsen, Janet L., Maribeth L. Rezey, and Karen Heimer. 2013. Violence and economic conditions in the United States, 1973-2011: Gender, race, and ethnicity patterns in the National Crime Victimization Survey. *Journal of Contemporary Criminal Justice* 30:7–28.
- Lauritsen, Janet L., and Nicole White. 2014. *Seasonal patterns in criminal victimization trends*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 245959.
- Leven, Andrew, Chien-Fu Lin, and Chia-Shang James Chu. 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics* 108:1–24.
- Leventhal, John M., and Julie R. Gaither. 2012. Incidence of serious injuries due to physical abuse in the United States: 1997 to 2009. *Pediatrics* 130:847–852.
- Levitt, Steven D. 2004. Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not. *Journal of Economic Perspectives* 18:163–90.

- Lichtenstein, Paul, Linda Halldner, Johan Zetterqvist, Arvid Sjölander, Eva Serlachius, Seena Fazel, Niklas Långström, and Henrik Larsson. 2012. Medication for Attention Deficit–Hyperactivity Disorder and criminality. *The New England Journal of Medicine* 367:2006–2014.
- Lindo, Jason M., Jessamyn Schaller, and Benjamin Hansen. 2013. *Economic conditions and child abuse*. NBER Working Paper Series 18994. Cambridge, MA: National Bureau of Economic Research.
- Lynch, James P., and Lynn A. Addington, eds. 2007. *Understanding Crime Statistics: Revisiting the Divergence of the NCVS and UCR*. Cambridge, MA: Cambridge Press.
- Lynch, James P., and John P. Jarvis. 2008. Missing data and imputation in the Uniform Crime Reports and the effects on national estimates. *Journal of Contemporary Criminal Justice* 24:69–85.
- Maddala, G. S., and Shaowen Wu. 1999. A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economic and Statistics* 61:631–652.
- Maltz, Michael D., and Joseph Targonski. 2002. A note on the use of county-level UCR data. *Journal of Quantitative Criminology* 18:297–317.
- Marcotte, Dave E., and Sara Markowitz. 2011. A cure for crime? Psycho-pharmaceuticals and crime trends. *Journal of Policy Analysis and Management* 30:29–56.
- Martin, Joyce A., Brady E. Hamilton, and Stephanie J. Ventura. 2015. *Births: Final data for 2013*. Hyattsville, MD: National Center for Health Statistics.
- Mayes, Rick, Catherine Bagwell, and Jenifer Erkulwater. 2008. ADHD and the rise in stimulant use among children. *Harvard Review of Psychiatry* 16:151–166.
- McCall, Patricia L., and Kenneth C. Land. 2004. Trends in environmental lead exposure and troubled youth, 1960-1995: An age-period-cohort characteristic analysis. *Social Science Research* 33:339–359.
- McDowall, David, and Karise M. Curtis. 2015. Seasonal variation in homicide and assault across large U.S. cities. *Homicide Studies* 19:303–325.
- McDowall, David, and Colin Loftin. 2007. What is convergence and what do we know about it? In *Understanding Crime Statistics: Revisiting the Divergence of the NCVS and UCR*, edited by J. Lynch and L. Addington. Cambridge, MA: Cambridge Press.

- McGowan, Brenda G. 2014. Historical evolution of child welfare services. In G. P. Mallon, and P. M. Hess (eds.) *Child Welfare for the Twenty-first Century: A Handbook of practices, Policies, and Program*, 2<sup>nd</sup> ed. New York: Columbia University Press.
- Messner, Steven F., Lawrence E. Raffalovich, and Gretchen M. Sutton. 2010. Poverty, infant mortality, and homicide rates in cross-national perspective: Assessments of criterion and construct validity. *Criminology* 48:509–537.
- Millett, Lina, Paul Lanier, and Brett Drake. 2011. Are economic trends associated with child maltreatment? Preliminary results from the recent recession using state level data. *Children and Youth Services Review* 33:1280–1287.
- Molina, Brooke S. G., Stephen P. Hinshaw, James M. Swanson, L. Eugene Arnold, Benedetto Vitiello, Peter S. Jensen, Jeffrey N. Epstein, Betsy Hoza, Lily Hechtman, Howard B. Abikoff, Glen R. Elliot, Laurence L. Greenhill, Jeffrey H. Newcorn, Karen C. Wells, Timothy Wigal, Robert D. Gibbons, Kwan Hur, and Patricia R. Houck. 2009. The MTA at 8 years: Prospective follow-up of children treated for combined-type ADHD in a multisite study. *Journal of the American Academy of Child and Adolescent Psychiatry* 48:484–500.
- Mosher, Clayton J., Terance D. Miethe, and Timothy C. Hart. 2011. *The Mismeasure of Crime* (2<sup>nd</sup> ed.). Thousand Oaks, CA: Sage Publications.
- National Center for Fatality Review and Prevention. no date. History of child death review in the U.S. Retrieved from:  
<https://www.childdeathreview.org/cdr-programs/history-of-cdr-in-the-us/>
- Nevin, Rick. 2000. How lead exposure relates to temporal changes in IQ, violent crime, and unwed pregnancy. *Environmental Research* 83:1–22.
- North Dakota Supreme Court Review. 1997. Raboin v. North Dakota Department of Human Services. *North Dakota Law Review* 73 N.D.L. Rev. 545.
- North Dakota Supreme Court Opinions. 1996. Walton v. North Dakota Department of Human Services. Retrieved from:  
<https://www.ndcourts.gov/court/opinions/950382.htm>
- Olfson, Mark, Carlos Blanco, Linxu Liu, Carmen Moreno, and Gonzalo Laje. 2006. National trends in the outpatient treatment of children and adolescents with antipsychotic drugs. *Archives of General Psychiatry* 63:679–685.
- Olfson, Mark, Steven C. Marcus, Benjamin Druss, Lynn Elinson, Terri Tanielian, and Harold Alan Pincus. 2002. National trends in the outpatient treatment of depression. *JAMA* 287:203–209.



- Ouyang, Lijing, Xiangming Fang, James Mercy, Ruth Perou, and Scott D. Grosse. 2008. Attention-Deficit/Hyperactivity Disorder symptoms and child maltreatment: A population-based study. *The Journal of Pediatrics* 153:851–856.
- Paxson, Christina, and Jane Waldfogel. 2002. Work, welfare, and child maltreatment. *Journal of Labor Economics* 20:435–474.
- Peddle N. A., and C. T. Wang. 2003. The evolution of a national reporting system on child maltreatment: 25 years of progress. Presentation given at the 14<sup>th</sup> National Conference on Child Abuse and Neglect. Retrieved from: [https://www.acf.hhs.gov/sites/default/files/cb/nccan14\\_workshop\\_42.pdf](https://www.acf.hhs.gov/sites/default/files/cb/nccan14_workshop_42.pdf)
- Pincus, Harold Alan, Terri L. Tanielian, Steven C. Marcus, Mark Olfson, Deborah A. Zarin, James Thompson, and Julie Magno Zito. 1998. Prescribing trends in psychotropic medications. *JAMA* 279:526–531.
- Podolski, Cheryl-Lynn, and Joel T. Nigg. 2001. Parent stress and coping in relation to child ADHD severity and associated child disruptive behavior problems. *Journal of Clinical Child Psychology* 30:503–513.
- Putnam-Hornstein, Emily, Barbara Needell, Bryn King, and Michelle Johnson Motoyama. 2013. Racial and ethnic disparities: A population-based examination of risk factors for involvement with child protective services. *Child Abuse & Neglect* 37:33–46.
- Reed, W. Robert, and Haichun Ye. 2011. Which panel data estimator should I use? *Applied Economics* 43:985–1000.
- Reed, W. Robert, and Haichun Ye. 2007. A Monte Carlo evaluation of some common panel data estimators when serial correlation and cross-sectional dependence are both present. Working Paper, Department of Economics, University of Canterbury. Retrieved from: <https://ir.canterbury.ac.nz/handle/10092/740>
- Regoeczi, Wendy, and Duren Banks. 2014. *The nation's two measures of homicide*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 247060.
- Reyes, Jessica Wolpaw. 2007. Environmental policy as social policy? The impact of childhood lead exposure on crime. Working Paper 13097, National Bureau of Economic Research.

- Riddle, Mark A., Kseniya Yershova, Deborah Lazzaretto, Natalya Paykina, Gayane Yenokyan, Laurence Greenhill, Howard Abikoff, Benedetto Vitiello, Tim Wigal, James T. McCracken, Scott H. Kollins, Desiree W. Murray, Sharon Wigal, Elizabeth Kastelic, James J. McGough, Susan dosReis, Audrey Bauzó-Rosario, Annamarie Stehli, and Kelly Posner. 2013. The Preschool Attention-Deficit/Hyperactivity Disorder Treatment Study (PATs) 6-year follow-up. *Journal of the American Academy of Child and Adolescent Psychiatry* 52:264–278.
- Rosenfeld, Richard, and Robert Fornango. 2014. The impact of police stops on precinct robbery and burglary rates in New York City, 2003-2010. *Justice Quarterly* 31:96–122.
- Rosenfeld, Richard, and Robert Fornango. 2007. The impact of economic conditions on robbery and property crime: The role of consumer sentiment. *Criminology* 45:735–769.
- Rosenfeld, Richard, Robert Fornango, and Andres F. Rengifo. 2007. The impact of order maintenance policing on New York City robbery and homicide rates: 1988-2001. *Criminology* 45:355–383.
- Runyan, Desmond K., Christine E. Cox, Howard Dubowitz, Rae R. Newton, Mukund Upadhyaya, Jonathan B. Kotch, Rebecca T. Leeb, Mark D. Everson, and Elizabeth D. Knight. 2005. Describing maltreatment: Do child protective service reports and research definitions agree? *Child Abuse & Neglect* 29:461–477.
- Schwarz, Alan. 2013. The selling of Attention Deficit Disorder. *The New York Times*. December 15, 2013.
- Seiglie, Carlos. 2004. Understanding child outcomes: An application to child abuse and neglect. *Review of Economics of the Household* 2:143–160.
- Sharp, Susan F., and Susan T. Marcus-Mendoza. 2001. It's a family affair: Incarcerated women and their families. *Women & Criminal Justice* 12:21–49.
- Shusterman, Gila R., Dana Hollinshead, John D. Fluke, and Ying-Ying T. Yuan. 2005. Alternative responses to child maltreatment: Findings from NCANDS. Washington, DC: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation.
- Siegel, Jane A. 2011. *Disrupted Childhoods: Children of Women in Prison*. New Brunswick, NJ: Rutgers University Press.

- Slack, Kristen Shook, Lawrence M. Berger, Kimberly DuMont, Mi-Youn Yang, Bomi Kim, Susan Ehrhard-Dietzel, and Jane L. Holl. 2011. Risk and protective factors for child neglect during early childhood: A cross-study comparison. *Children and Youth Services Review* 33:1354–1363.
- Smith, Erica L., and Alexia Cooper. 2013. *Homicide in the U.S. known to law enforcement, 2011*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 243035.
- Smith Slep, Amy M., and Richard E. Heyman. 2006. Creating and field-testing child maltreatment definitions: Improving the reliability of substantiation determinations. *Child Maltreatment* 11:217–236.
- Spigel, Saul. 2004. Juan F. Consent Decree. Connecticut General Assembly. Retrieved from: <https://www.cga.ct.gov/2004/rpt/2004-R-0352.htm>
- Sroufe, L. Alan. 2012. Ritalin gone wrong. *The New York Times*, pp. SR1. January 29, 2012.
- Thome, Helmut. 2014. Cointegration and error correction modelling in time-series analysis: A brief introduction. *International Journal of Conflict and Violence* 8:199–208.
- Trickett, Penelope K. 2006. Defining child sexual abuse. In *Child Abuse and Neglect: Definitions, Classifications, and a Framework for Research*, edited by M. Feerick, J. Knutson, P. Trinkett, & S. Flanzer. Baltimore, MD: Paul H. Brookes Publishing Co.
- Truman, Jennifer L., and Erica L. Smith. 2012. *Prevalence of violent crime among households with children, 1993-2010*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 238799.
- Tukey, John W. 1977. *Exploratory Data Analysis*. Reading, MA: Addison-Wesley.
- U.S. Census Bureau. 1990-2013. Tables 616. Employed civilians by occupation, sex, race, and Hispanic origin. Retrieved from: [http://www.census.gov/prod/www/statistical\\_abstract.html](http://www.census.gov/prod/www/statistical_abstract.html)
- U.S. Census Bureau. 2015. Current Population Survey, 1960 to 2014. Annual Social and Economic Supplements. Retrieved from: <https://www.census.gov/hhes/www/poverty/data/incpovhlth/2013/figure4.pdf>
- U.S. Department of Health and Human Services. 2016. *SACWIS/TACWIS information*. Children’s Bureau, Administration on Children, Youth and Families. Retrieved from: <https://www.acf.hhs.gov/cb/research-data-technology/state-tribal-info-systems/managers>

- U.S. Department of Health and Human Services. 2015. *Child maltreatment 2013*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2014. *Child maltreatment 2012*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2013. *Child maltreatment 2011*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2012. *Child maltreatment 2010*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2011. *Child maltreatment 2009*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2010. *Child maltreatment 2008*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2009. *Child maltreatment 2007*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2008. *Child maltreatment 2006*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2007. *Child maltreatment 2005*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2006. *Child maltreatment 2004*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2005. *Child maltreatment 2003*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.

- U.S. Department of Health and Human Services. 2004. *Child maltreatment 2002*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2003. *Child maltreatment 2001*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2002. *Child maltreatment 2000*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. 2001. *Child maltreatment 1999*. Administration on Children, Youth and Families, Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. No date a. Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. National Child Abuse and Neglect Data System (NCANDS) Summary Data Component, 1990-1999 [Dataset]. National Data Archive on Child Abuse and Neglect Dataset Number 98.
- U.S. Department of Health and Human Services. No date b. Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. National Child Abuse and Neglect Data System (NCANDS) Combined Aggregate File, 2000-2002 [Dataset]. National Data Archive on Child Abuse and Neglect Dataset Number 102.
- U.S. Department of Health and Human Services. No date c. Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. National Child Abuse and Neglect Data System (NCANDS) Combined Aggregate File, 2003, 2004, 2005, 2006, 2007, and 2008 [Dataset]. National Data Archive on Child Abuse and Neglect Dataset Number 115, 120, 129, 141, 146, and 151.
- U.S. Department of Health and Human Services. No date d. Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. National Child Abuse and Neglect Data System (NCANDS) Child File, 2009, 2010, 2011, 2012, and 2013 [Dataset]. National Data Archive on Child Abuse and Neglect Dataset Number 156, 165, 169, 178, and 188.
- U.S. General Accounting Office. 2003. Child welfare: Most states are developing statewide information systems, but the reliability on child welfare data could be improved. Report to Congressional Requesters, Washington, DC: U.S. General Accounting Office. GAO-03-809.

- U.S. Sentencing Commission. 2011. *Report to the Congress: Mandatory minimum penalties in the federal criminal justice system, 2011*. Washington, DC: U.S. Sentencing Commission.
- Wells, Susan J., Jane Downing, and John D. Fluke. 1991. Responding to reports of child abuse and neglect. *Child & Youth Services* 15:63–72.
- White, Nicole, and Janet L. Lauritsen. 2012. *Violent crime against youth, 1994-2010*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics. NCJ 240106.
- Wood, Joanne N., Sheyla P. Medina, Chris Feudtner, Xianqun Luan, Russell Localio, Evan S. Fieldston, and David M. Rubin. 2012. Local macroeconomic trends and hospital admissions for child abuse, 2000-2009. *Pediatrics* 130:e358–e364.
- Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data (2<sup>nd</sup> ed.)*. Cambridge, MA: MIT Press.
- Xie, Min, Janet L. Lauritsen, and Karen Heimer. 2012. Intimate partner violence in the U.S. metropolitan areas: The contextual influences of police and social services. *Criminology* 50:961–991.
- Yang, Mi-Youn. 2015. The effect of material hardship on child protective service involvement. *Child Abuse & Neglect* 41:113–125.
- Zimring, Franklin E. 2007. *The Great American Crime Decline*. New York, NY: Oxford University Press.
- Zito, Julie Magno, Daniel J. Safer, Susan dosReis, James F. Gardner, Myde Boles, and Frances Lynch. 2000. Trends in the prescribing of psychotropic medications to preschoolers. *JAMA* 283:1025–1030.
- Zito, Julie Magno, Daniel J. Safer, Susan dosReis, James F. Gardner, Laurence Magder, Karen Soeken, Myde Boles, Frances Lynch, and Mark A. Riddle. 2003. Psychotropic practice patterns for youth: A 10-year perspective. *Archives of Pediatrics and Adolescent Medicine* 157:17–25.

## APPENDIX A

### NCANDS State-Level Data Verification

Inquiries revealed that most outlier data points or abnormal trends were the result of definitional or procedural changes at the state level. The information that follows is material I gathered from various sources on potential reasons for outlier data points within a state trend, or abnormal trends over time with a state. States that provided valuable commentary in the back of the annual *Child Maltreatment* reports on definitional or procedural changes that impacted their state NCANDS trends, or states that responded to the author's inquiries for information about their NCANDS data trends are described below.

#### Alaska

Nearly all of Alaska's NCANDS rates are more than two standard deviations above the average rate of child physical abuse, child sexual abuse, and child neglect. One reason for such high proportions of substantiated dispositions is, as Alaska officials reported in the *Child Maltreatment* reports, their definition is broader than that used by many states and the definition of unsubstantiated is narrower. Another reason is that the state uses child-based reporting, where there is one report or investigation per child, per incident, instead of one report per incident, regardless of the number of children involved in the incident (U.S. Department of Health and Human Services, 2003). Alaska officials caution against comparing data across years.

Alaska officials also admitted that their, "Division of Family and Youth Services has a chronic problem with the timely entering of investigation disposition data into its management information system (U.S. Department of Health and Human Services, 2001, p.70)." During 2000 and 2001, an effort was made to officially close dormant investigations. As a result, officials report that the number of investigations closed during those years may be higher than would be typical (U.S. Department of Health and Human Services, 2002). And, the number of investigations disposed during 2001 that were assigned in previous years was significantly larger than the comparable numbers for 2002. According to the 2002 *Child Maltreatment* report, "the drop in the total number of investigations disposed (and corresponding child victims) reflects a decrease in both the number of reports and in investigations assigned during that year that were completed (U.S. Department of Health and Human Services, 2004, p.114)."

Alaska switched to the SACWIS [Statewide Automated Child Welfare Information System] in 2005 and report that "data submitted from prior years from the state's legacy system are not comparable to data from the SACWIS (U.S. Department of Health and Human Services, 2007, p.123)." However, by 2012, officials again reported a backlog of completed assessment data and cautioned against interpreting year-to-year changes in the numbers of completed assessments, victims, and other NCANDS data (U.S. Department of Health and Human Services, 2014).

### Arizona

According to the 2011 and 2012 *Child Maltreatment* reports, Arizona reported an increase in the number of reports and victims of child maltreatment. State officials revealed that a Social Worker Assessment Team (SWAT) was created to reduce the backlog of reports prior to 2011. This resulted in many reports that were received prior to 2011 being closed during 2011. Officials hypothesize that this may be one reason the report count increased. They also mentioned in 2010, 2011, and 2013 that the “ongoing financial challenge facing many residents” or “on-going socio-economic challenges” also may account for the increase (U.S. Department of Health and Human Services, 2013, p.133; U.S. Department of Health and Human Services, 2015, p.129).” Another potential reason for the increase in victims officials mentioned is a statutory change that requires all children who are removed from their parents or guardians to have at least one substantiated allegation of maltreatment.

### Arkansas

Arkansas state officials report that increases in the number of investigations and victims post-2009 “can be attributed to the state’s economic downturn” (U.S. Department of Health and Human Services, 2011; U.S. Department of Health and Human Services, 2012, p.149).

### California

In 1998, California converted to a statewide case management system for child welfare. Prior to 1998, each of the 58 counties sent monthly reports that the state Department of Social Services summarized. This new method of aggregate data collection prompted state officials to caution against comparing counts of reports provided post-1999 with counts from previous years (U.S. Department of Health and Human Services, 2001). Furthermore, prior to 2003, California defined an associated referral as subsequent referrals and counted them as two separate reports. Post-2004, California began excluded associated (secondary) referrals (U.S. Department of Health and Human Services, 2006).

### Colorado

According to the 1999-2000 *Child Maltreatment* reports, Colorado’s maltreatment report data “come from sources as varied as hand counts by county staff and phone reports from court representatives (U.S. Department of Health and Human Services, 2001, p.72; U.S. Department of Health and Human Services, 2002; p. 98).” In 2001, Colorado switched to the SACWIS and had to estimate one-quarter of its data that year during implementation. Officials caution against comparing their post-2001 state data in trend analyses due to the SACWIS transition (U.S. Department of Health and Human Services, 2003, p.107).

### Connecticut

In 1991, the federal class action suit *Juan F. v. Malloy* brought before U.S. District Court laid the foundation for drastic changes in Connecticut’s Department of Children and Youth Services (DCYS) (now the Department of Children and Families (DCF)). According to Spigel (2004), the suit broadly challenged the department’s “management, policies, practices, operations, funding, and protocols concerning abused and neglected children in its custody and those who might come into its custody.” As part of an



agreement with the plaintiff, in 1996, the state entered into a consent decree (i.e., the Juan F. Consent Decree) ordered by the Court that mandated the agency to provide adequate CPS services, make reasonable efforts to keep families together, provide minimally adequate staffing and appropriate care for children, and be monitored until such changes were deemed sufficient by the court. The consent decree established staffing ratios DCYS had to follow, created a comprehensive set of policy manuals covering all areas of DCYS responsibility, and authorized the court to appoint a monitor to review DCYS' operations to help ensure its compliance with the decree (Dwyer & Della Pietra, 2016; Spigel, 2004).

Over the period from 1991 to 2004, many changes were made to Connecticut's DCF. Budgets increased for DCF, allowing for the hiring of new staff, providing more child welfare services, and enhancing data collection systems. Over this period, NCANDS trends may have fluctuated due to these changes. In 2003, the state admitted in court that it failed to comply with the Juan F. Consent Decree and a stipulation was made giving a task force the legal authority to rule over DCF's commissioner. This stipulation further changed procedures and outcomes within the state agency. Some of these include the time frames for beginning and completing a child abuse investigation, and the required number/interval of case worker visits with children and families. As of 2016, Connecticut is still under the consent decree and federal oversight, as it has yet to meet all of the terms (i.e., outcome measures) of an established (and then modified and revised) exit plan (Dwyer & Della Pietra, 2016; Spigel, 2004).

#### Delaware

The Delaware Division of Family Services was significantly impacted by the deaths of multiple children in 1997, and in particular, the death of a 4-year-old boy named Bryan Martin (Child Protection Accountability Commission, 2016). Delaware's Child Protection Accountability Commission (2016) maintained that Bryan's death demonstrated the need for multidisciplinary collaboration and accountability in Delaware's child protection system. As a result, the Delaware Title 16 (Abuse of Children) statute was largely rewritten as the Child Abuse Prevention Act of 1997, which revamped most CPS investigation policies and implemented many new ones. One of the potential outcomes of these deaths was a revitalized emphasis on reporting child abuse and concern among agency staff to not hold parents accountable.

#### Georgia

In 2005, Georgia officials first submitted their data in child file form to NCANDS. Therefore, they report that 2005 may be a breaking point which may affect the comparability of previous years' data to the 2005 data and beyond (U.S. Department of Health and Human Services, 2007). They also report that a "32.7% decrease in submitted records over 2007 was due to: policy changes in diversionary responses [CPS gives services in cases that do not warrant a full investigation]; a more efficient management style [was] introduced which [included] detailed data collection and monthly review of all relevant data at monthly meetings; and an emphasis [was] placed on the timely completion of pending investigations and the improvement of the intake process (U.S. Department of Health and Human Services, 2010, p.132)."

### Idaho

Idaho moved from submitting the SDC file to the child file in 2001. According to the 2000 *Child Maltreatment* report, “large numbers of investigations...with “unknown” dispositions occurred this year because the SACWIS did not require a disposition to be recorded before closing a case. The numbers were more than double from the 1999 numbers. A disposition is now required before case closure (U.S. Department of Health and Human Services, 2002, p.103).” After the move to the child file, Idaho officials reported that submissions using the child file may undercount the number of reports due to missing dispositions.

### Indiana

Indiana’s fluctuating rates in the few years prior to 2000 may be the result of implementation of their legacy child welfare system (Indiana’s Child Welfare Information System-ICWIS) and the new requirements on jurisdictions after the federal Adoption and Safe Families Act was passed in 1997.

State officials reported in the 2008 *Child Maltreatment* report that Indiana experienced a spike in reports in 2008 due to a massive clean-up of old reports/investigations that had never been disposed. They also revealed that one of their largest counties stopped screening out reports due to a fatality and there was another widely publicized fatality which resulted in greatly increased reports (U.S. Department of Health and Human Services, 2010). Indiana officials verified in the 2013 *Child Maltreatment* report that Indiana saw an increase in the number of screened-in assessments in 2013 (U.S. Department of Health and Human Services, 2015).

### Kentucky

Kentucky officials verified in the 2013 *Child Maltreatment* report that Kentucky saw an increase in reports in 2013 that met their investigation acceptance criteria and an increase in reports resulting in substantiation of child maltreatment (U.S. Department of Health and Human Services, 2015).

### Maine

According to the 1999 *Child Maltreatment* report, Maine had 11,058 referrals not assigned for investigation, although 1,312 were considered appropriate for CPS. The reason CPS did not investigate these referrals was due to a shortage of available CPS staff. More than 3,000 of these referrals were allocated to private agencies (community agencies) to conduct an assessment, however these agencies do not make a determination regarding substantiation and do not provide their information to the NCANDS system (U.S. Department of Health and Human Services, 2001; U.S. Department of Health and Human Services, 2007). Maine continued to contract out investigations to independent private agencies through at least 2007.

Maine officials reported that the increase in the number of reports and assessments during 2012 was largely attributable to an increase in substance abuse (U.S. Department of Health and Human Services, 2014).

### Montana

According to state officials, Montana received 30% more referrals from social service workers in 2005 as an indirect result of methamphetamine abuse (U.S. Department of Health and Human Services, 2007).

### Nebraska

Nebraska implemented the SACWIS between 1998 and 1999. In 2000, Nebraska had a series of child deaths that prompted the review of procedures and the child maltreatment intake system. Two children died of child battering in 2000, compared to none the year before and 13 the entire decade before (Johnston, 2000; Johnston, 2001). Prior to these deaths, there was no standard tool or guide on making decisions on when a report should be accepted. In late 2003, Nebraska CPS workers began using a standardized tool to determine if a report met the requirement for assessment.

According to the 2004 *Child Maltreatment* report, the number of screened-in reports increased 54% from 2003 to 2004. State officials attribute this increase to two factors. “The first was a significant public information campaign to raise awareness of child abuse and neglect and how to report it. The second was a change in the State’s intake hotline protocol to screen more “at risk” referrals into the category of cases to be investigated (U.S. Department of Health and Human Services, 2006, p.148).” In 2005, Nebraska officials found that 1,166 reports that were included in the 2005 data were also included in previous years’ reports. They also revealed that the report counts for 2005 may have been inflated more than they actually would have been because of the monitoring and clean-up effort. They also included “court pending” cases without a final disposition mostly as a substantiated disposition prior to 2007. When these “court pending” cases were no longer included, decreases were found across the board (U.S. Department of Health and Human Services, 2008; U.S. Department of Health and Human Services, 2009). Other fluctuations could be accounted for through policies that require accepting any report that includes allegations of methamphetamine use by a parent or caretaker.

### New Mexico

According to the 2005 *Child Maltreatment* report, with the 2005 NCANDS data submission, New Mexico “made substantial efforts to refine the accuracy of data mapping and coding. All 146 elements were reviewed and the mapping and coding were modified to be consistent with NCANDS definitions (U.S. Department of Health and Human Services, 2007, p.145).” In addition, during 2005, substantial efforts were made in clearing a backlog of investigations that had been pending completion. New Mexico completed approximately 4,000 more investigations in 2005 than in 2004 because of these efforts. As a result of these changes, “there are noticeable differences for many data elements between previous and current data submissions.” In fact, state officials disclose that the numbers of reports and victims appear higher in the 2005 submission compared to previous NCANDS submissions (U.S. Department of Health and Human Services, 2007, p.145-146).

In 2011, New Mexico implemented a new state hotline number and a new short code that can be accessed by cell phone to report suspected child maltreatment. According to state officials, “the accompanying statewide public information campaign contributed to an increase in the number of calls received by Statewide Central Intake, along with increases in the numbers of screened-out referrals, accepted reports, and child victims (U.S. Department of Health and Human Services, 2013, p.192).” While no major policies, programs, or system changes took place in 2012, there was an intensive effort to close backlogged investigations in 2013. Furthermore, “intense media attention on several high profile cases led to a surge in reporting for a period of time” in 2013 (U.S. Department of Health and Human Services, 2015).

#### North Dakota

North Dakota moved from an incident-based investigation method to a service method in 1995. The emphasis is put on what services are available to lower any future risk and focuses on building a family’s capacities and strengths (U.S. Department of Health and Human Services, 2003). In 1996 and 1997, in response to state legislation and decisions passed down from the state Supreme Court, North Dakota’s child protection system underwent a drastic change in philosophy, language, and interpretation. *Raboin v. ND Department of Human Services* and *Walton v. ND Department of Human Services* were decisions handed down by the state Supreme Court that impacted the state’s ability to define child abuse (especially discipline by parents leaving bruises) and shifted the burden of proof to the state in cases of suspected child maltreatment (North Dakota Supreme Court Review, 1997; North Dakota Supreme Court Opinions, 1996).

#### Oklahoma

Oklahoma officials verified in the 2012 *Child Maltreatment* report that Oklahoma saw a 20 percent increase in substantiated reports of abuse or neglect over 2011 counts (i.e., a 17% increases in the percentage of reports substantiated (U.S. Department of Health and Human Services, 2014). Oklahoma passed legislation regarding mandatory investigations for “drug-endangered children” and added more CPS workers in 2013 (U.S. Department of Health and Human Services, 2015).

#### Pennsylvania

According to the 1999-2003 *Child Maltreatment* reports, Pennsylvania “does not accept the Basic State Grant and is not required to submit data to NCANDS.” In subsequent years up until 2007, Pennsylvania did not receive funding through the Child Abuse and Neglect State Grant either (U.S. Department of Health and Human Services, 2006, p.153). Pennsylvania “state policy addresses neglect through a general, protective service investigation rather than a CPS investigation. These neglect cases are not classified as child maltreatment (U.S. Department of Health and Human Services, 2001, p.93).” CPS investigations account for approximately 30% of the total reports investigation by the child welfare system. Pennsylvania also has a narrow definition of child abuse and requires clear and convincing evidence of maltreatment, beyond a reasonable doubt (whereas all other states only require a preponderance of evidence, credible evidence, material evidence, or reasonable evidence). This narrow definition remains through 2013.

### South Carolina

With the implementation of the Statewide Automated Child Welfare Information System (SACWIS) in 1998, there was a 9-percent drop in the number of investigations accepted for investigation in 1999. State officials claim that this can be “partially attributed to ongoing problems experienced at the county level in the use of the new SACWIS. Issues included software and hardware problems, the absence of skilled data entry staff, a lack of familiarity with the use of on-line reports to cross-check entries, and the absence of weekly prompting reports until December 1999 (U.S. Department of Health and Human Services, 2001, p.94-95).” As of 2002, South Carolina no longer reported a large amount of data in the “other maltreatment type” category because new language in the South Carolina Code of Laws more clearly linked injury types to a specific maltreatment type.

### Tennessee

Tennessee state officials reported that the increase in the number subject to an investigation in 2000 compared to 1999 does not reflect an actual increase. Instead, it reflects a more accurate manual count of investigations than previously reported (U.S. Department of Health and Human Services, 2002).

### Utah

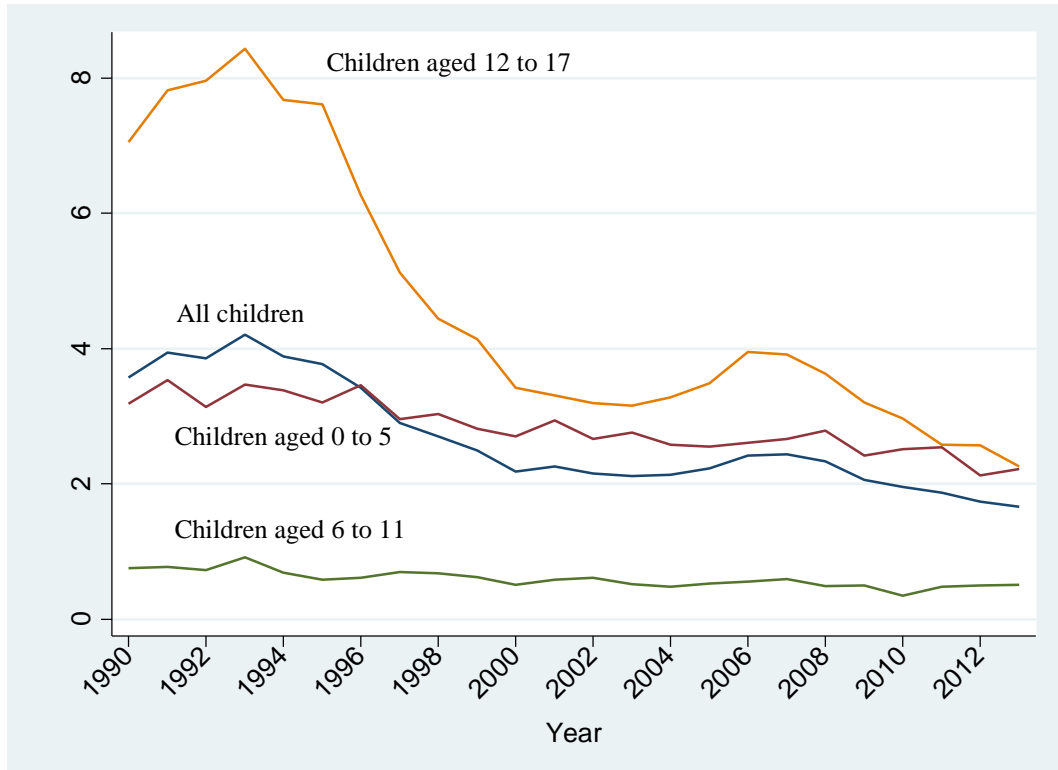
Utah officials verified in the 2012 *Child Maltreatment* report that “child endangerment” was being mapped to the physical abuse category instead of the “other” category after consultation with the feds. This is the reason they report physical abuse increased in 2012. Utah’s definition of child endangerment is “subjecting a child to threatened harm (U.S. Department of Health and Human Services, 2014, p.233).” Utah officials also suspect that increases may occur (and do in 2012 and 2013) after reviewing their state definition of sexual abuse, which they began to review with attorneys in 2012.

### Vermont

According to the 2002 *Child Maltreatment* report, the Vermont Department of Social and Rehabilitative Services (and later the Family Services Division of the Vermont Department of children and Families) investigated cases where a person was at “risk of physical harm” or at “risk of sexual abuse.” Beginning in 2002, however, these two categories were included in NCANDS terms of physical abuse and sexual abuse respectively. In previous years, both were mapped to neglect (U.S. Department of Health and Human Services, 2004).

APPENDIX B

Figure B1. Trends in National Rates of Child Homicide by Age Group, 1990-2013



SOURCE: Puzzanchera, C., Chamberlin, G., & Kang, W. 2016. Easy Access to the FBI's Supplementary Homicide Reports: 1980-2014.

## APPENDIX C

Some states had to be removed from some hypothesis tests due to excessive missing data on both dependent and independent variables. A set of rules were created that outlined an interpolation process that was used to fill in missing data with linear data points. Between 1 and 15 states were removed from the analyses post-interpolation procedures because excessive missing data still existed on a given measure.

Table C1 provides information on whether states were still missing state data on a particular measure post-interpolation. Four states were missing excessive data on the three outcome variables (rates of child physical abuse, sexual abuse, neglect), while one state was missing excessive UCR data on the rate of drug abuse violation arrests, and ten states were missing excess NCANDS data for the two CPS measures. The states that are excluded from the four outcome models (the three child maltreatment models and child homicide) in the long series and in the short series, for the most part, tend to be the same states. This group of states varies considerably in population size, geographic area, and region of the country.

Figures C1 through C7 show the original source data graphed in the states removed from the analyses and the reasons for their removal.

Table C1. States Excluded from the State-Level Analyses (\*1990+ or \*\*1997+)

	<u>Dependent Variables</u>			<u>Independent Variables</u>		<u>Removed from Analyses</u>			
	Rate of CPA	Rate of CSA	Rate of CN	Drug Abuse Violations	CPS Measures	CPA	CSA	CN	CH
Alabama									
<i>Alaska</i>	*/**	*/**	*/**			*/**	*/**	*/**	
Arizona									
Arkansas									
California									
<i>Colorado</i>					**	**	**	**	**
<i>Connecticut</i>					**	**	**	**	**
Delaware									
Florida									
<i>Georgia</i>					**	**	**	**	**
Hawaii									
Idaho									
Illinois									
Indiana									
Iowa									
<i>Kansas</i>				*/**		*/**	*/**	*/**	*/**
Kentucky									
Louisiana									
Maine									
<i>Maryland</i>	*/**	*/**	*/**		**	*/**	*/**	*/**	**
Massachusetts									
<i>Michigan</i>					**	**	**	**	**
Minnesota									
Mississippi									
Missouri									
Montana									
<i>Nebraska</i>					**	**	**	**	**
Nevada									
New Hampshire									
New Jersey									
New Mexico									
<i>New York</i>					**	**	**	**	**
North Carolina									
North Dakota									
<i>Ohio</i>					**	**	**	**	**
Oklahoma									
Oregon									
Pennsylvania									
Rhode Island									
<i>South Carolina</i>					**	**	**	**	**
South Dakota									
Tennessee									
Texas									
Utah									
Vermont									
Virginia									
<i>Washington</i>	*/**	*/**	*/**			*/**	*/**	*/**	
<i>West Virginia</i>	*/**	*/**	*/**			*/**	*/**	*/**	
<i>Wisconsin</i>					**	**	**	**	**
Wyoming									

ABBREVIATION: CPA=Child Physical Abuse; CSA=Child Sexual Abuse; CN=Child Neglect; CH=Child Homicide.  
 NOTE: All non-italicized states are included in all models. Italicized states have been dropped from models on each asterisked measure due to excessive missing data. CPS Measures include 'Ratio of CPS workers per child' and 'Average Caseload Size'.



Figure C1. Trends in Child Victimization in Alaska, 1990-2013

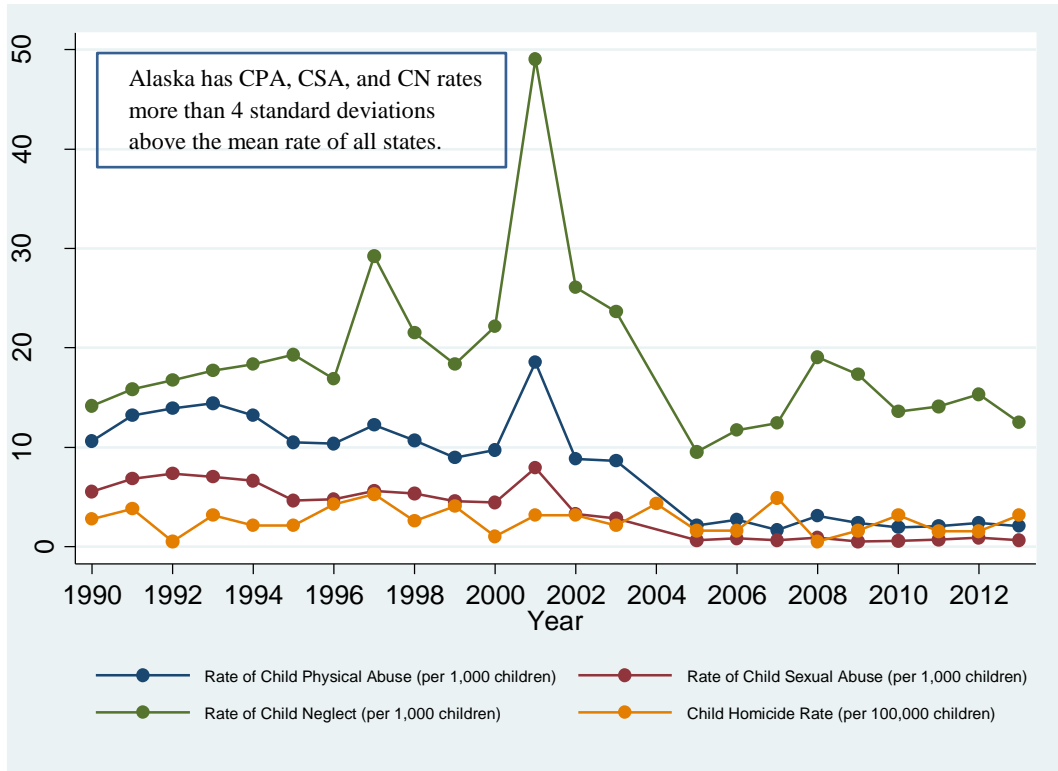


Figure C2. Trends in Child Victimization in Maryland, 1990-2013

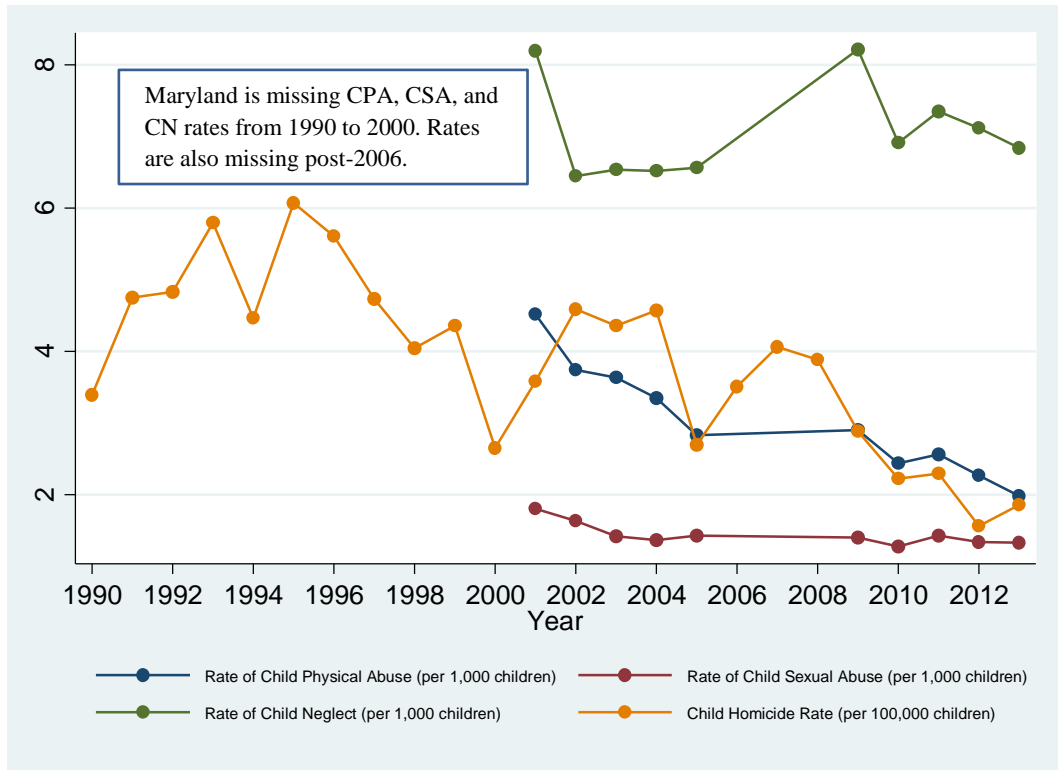


Figure C3. Trends in Child Victimization in Washington, 1990-2013

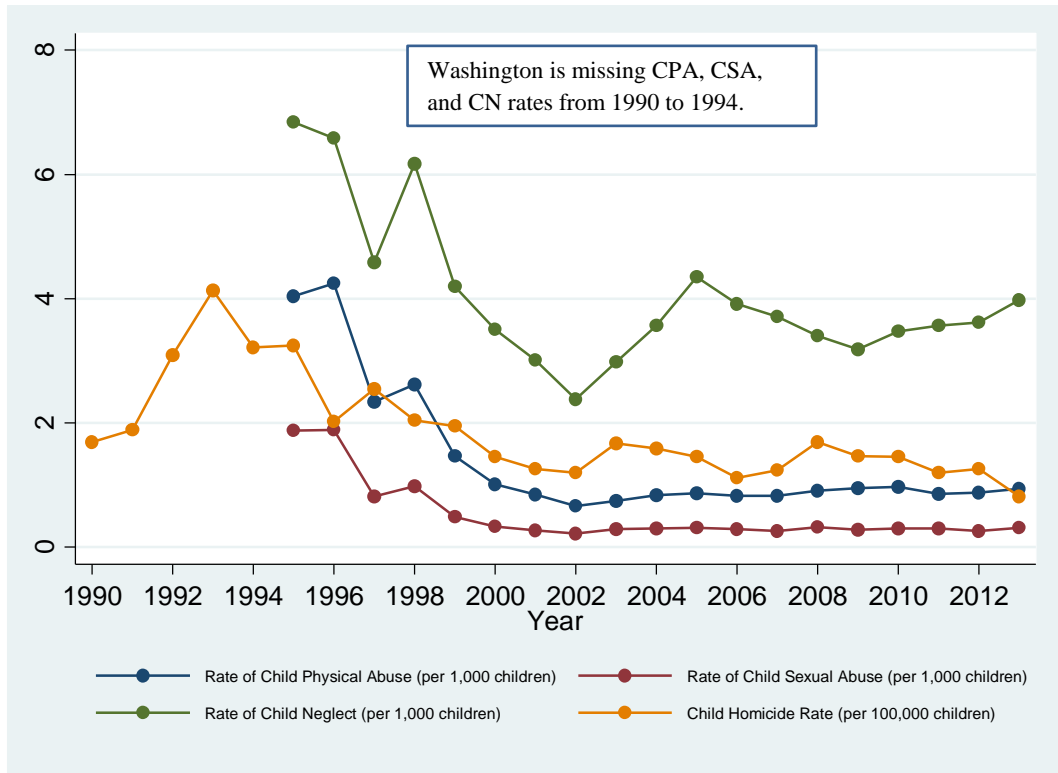


Figure C4. Trends in Child Victimization in West Virginia, 1990-2013

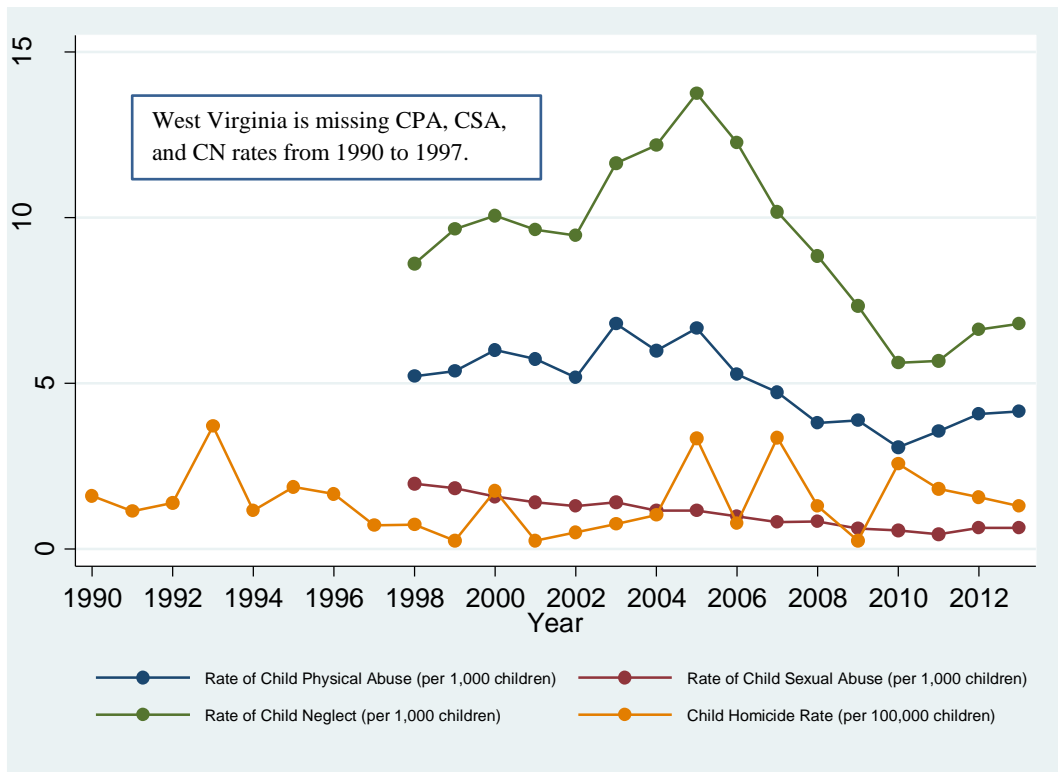
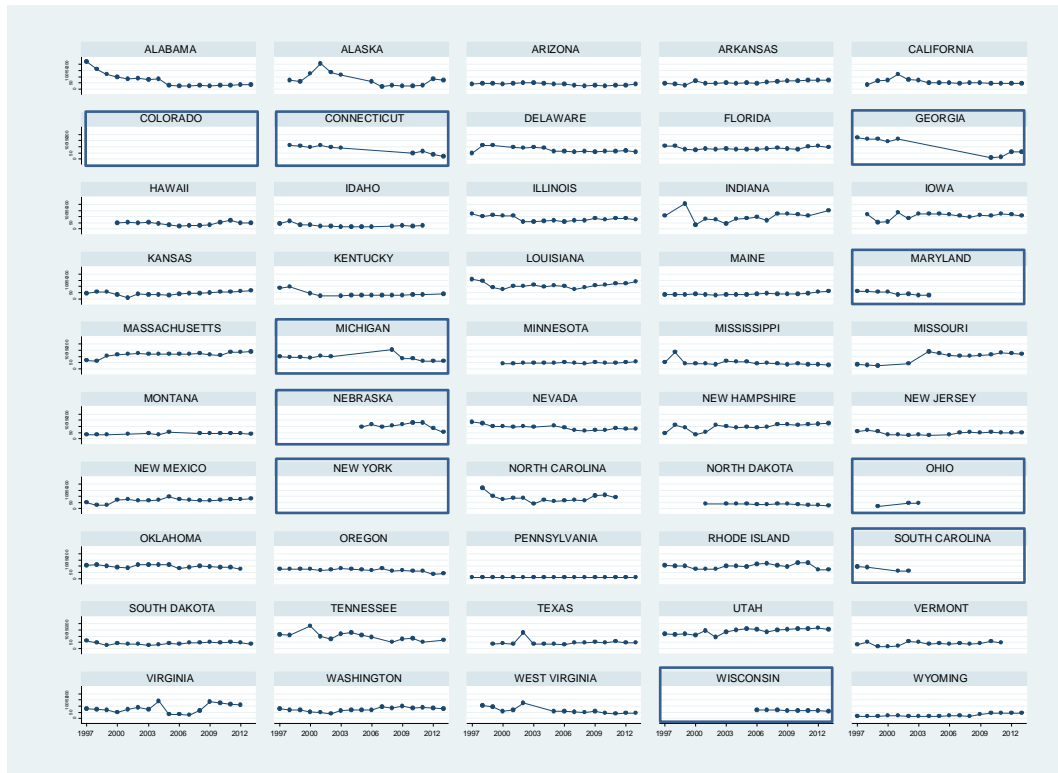
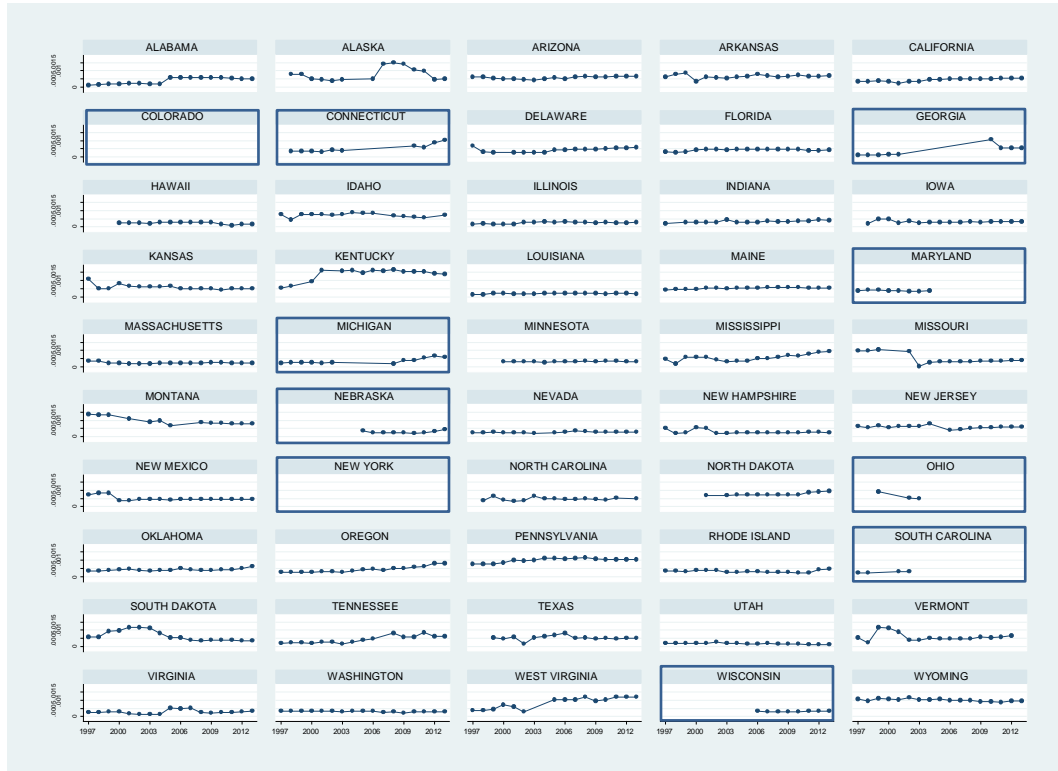


Figure C5. Trends in Average CPS Worker Caseload by State, 1997-2013



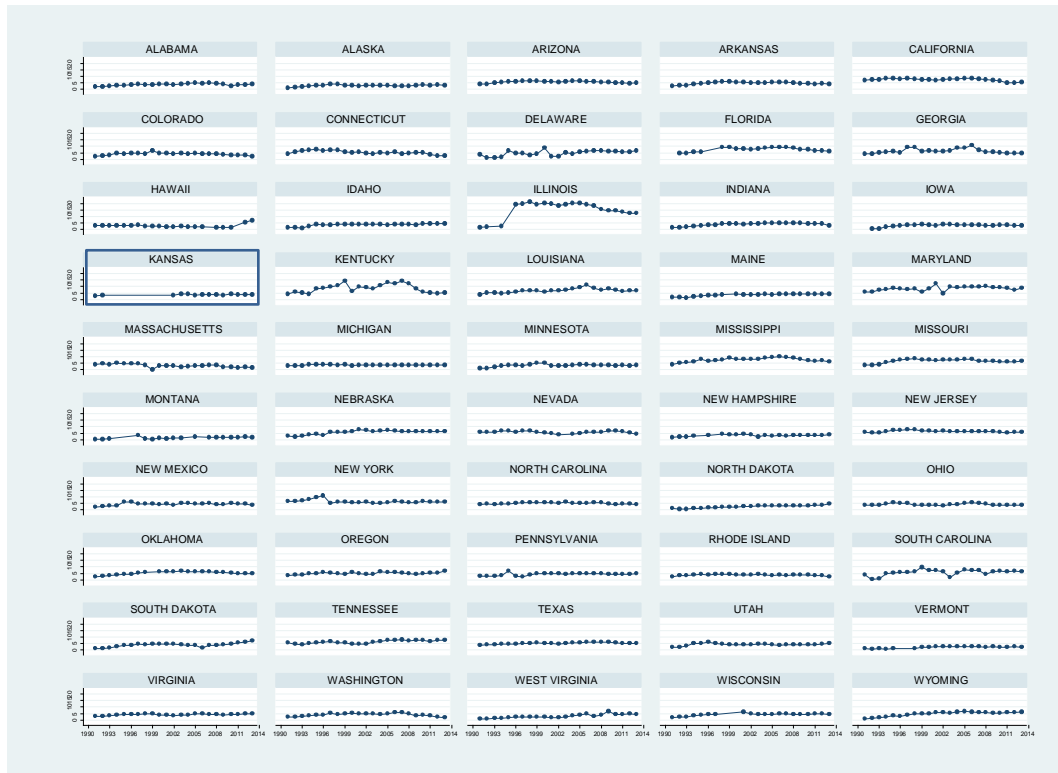
Colorado and New York are missing all data points. Connecticut, Georgia, and Michigan are missing more than 5 data points in the middle of the series. Maryland, Nebraska, Ohio, South Carolina, and Wisconsin are missing data points at the beginning or end of the series.

Figure C6. Trends in Ratio of CPS Caseworkers to Children by State, 1997-2013



Colorado and New York are missing all data points. Connecticut, Georgia, and Michigan are missing more than 5 data points in the middle of the series. Maryland, Nebraska, Ohio, South Carolina, and Wisconsin are missing more than 5 data points at the beginning or end of the series.

Figure C7. Trends in Arrest Rates for Drug Abuse Violations by State, 1990-2013

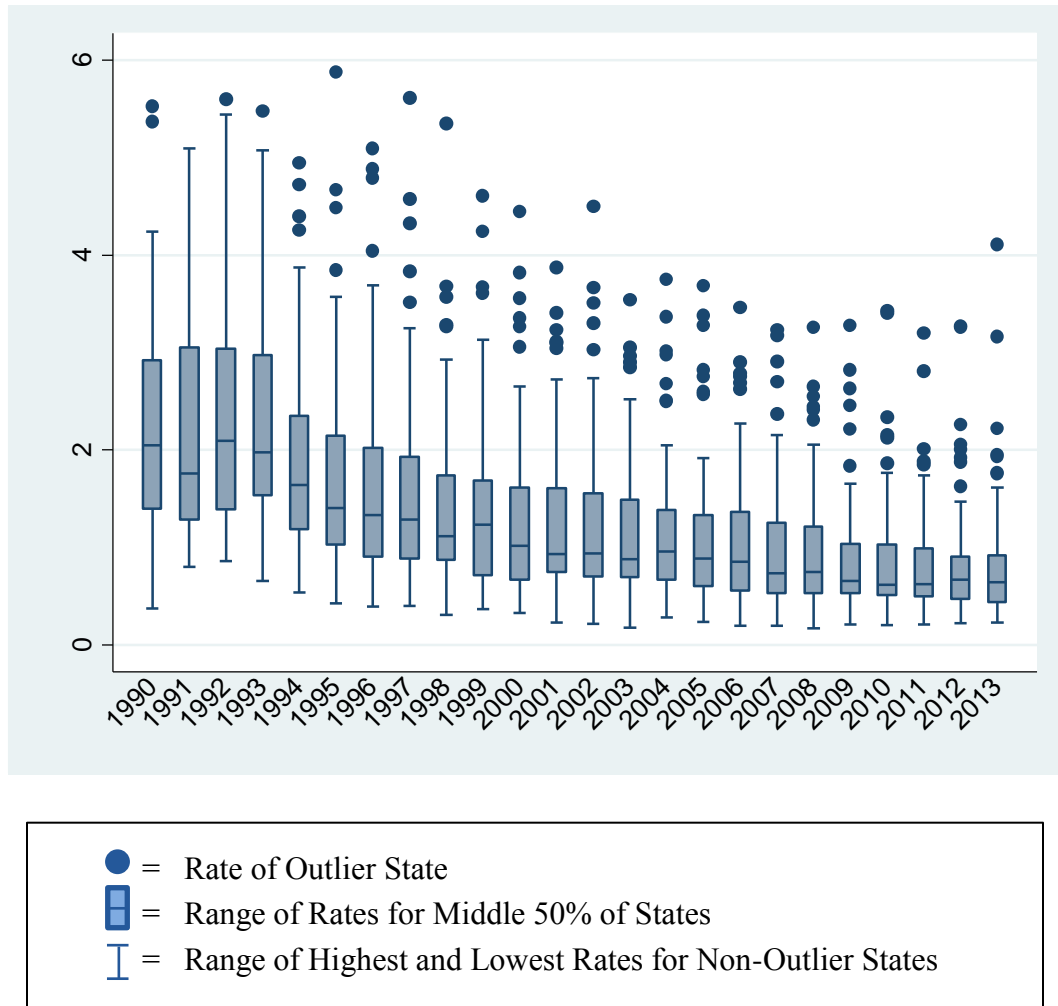


Kansas is missing more than 5 data points in the middle of the series.

## APPENDIX D

Box plots are very useful graphs for showing the level and spread (i.e., the dispersion) of data points. The box plots in Chapter Six can be interpreted according to the example below.

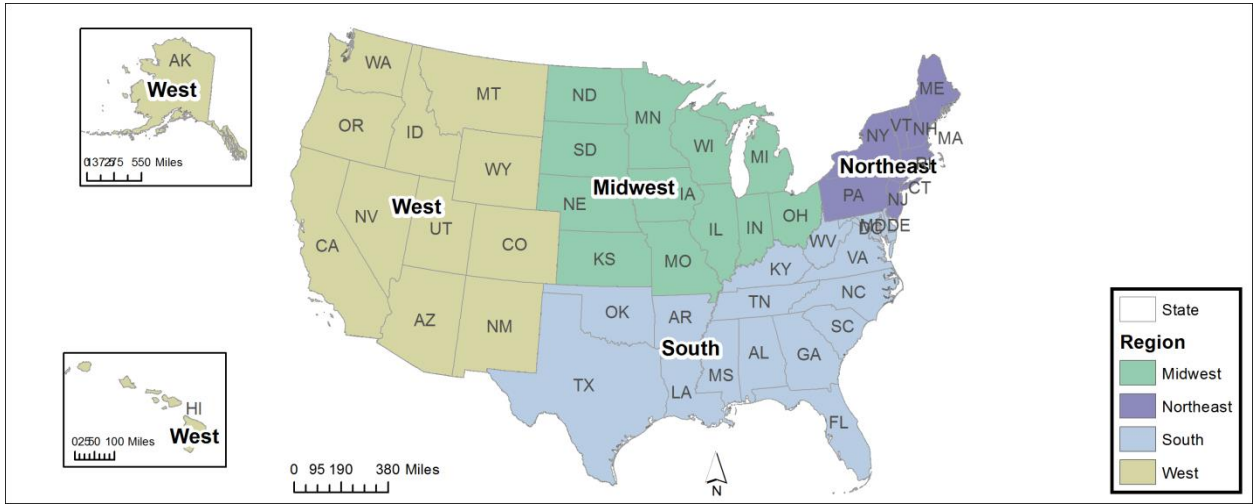
Figure D1. Aggregate State Trend in Child Sexual Abuse, 1990-2013



Each box in a box plot represents the lower and upper quartile rates (i.e., the middle 25% to 75% of state rates fall within the lower and upper quartiles). The length of the box represents the interquartile range (IQR). The median state rate is represented by the line subdividing the box. Lines, often called whiskers, were drawn to span all rates within 1.5 IQR of the nearest quartile. Any rates beyond 1.5 IQR of the lower and upper quartile rates are shown as outlier rates in this graph. Outliers in box plots have not been treated as extreme outliers in the data (i.e., being more than 1.5 IQR of the upper quartile does not mean the rate is more than four standard deviations above the mean). See Cox (2009) and Tukey (1977) for more information about the interpretation of the components of a box plot.

APPENDIX E

Figure E1. Regions of the United States



NOTE: DC was excluded from all analyses.  
SOURCE: U.S. Census Bureau.

# APPENDIX F

## Trends in Independent Measures

Figure F1. Aggregate State Trend in the Percent of People Below Poverty, 1990-2013

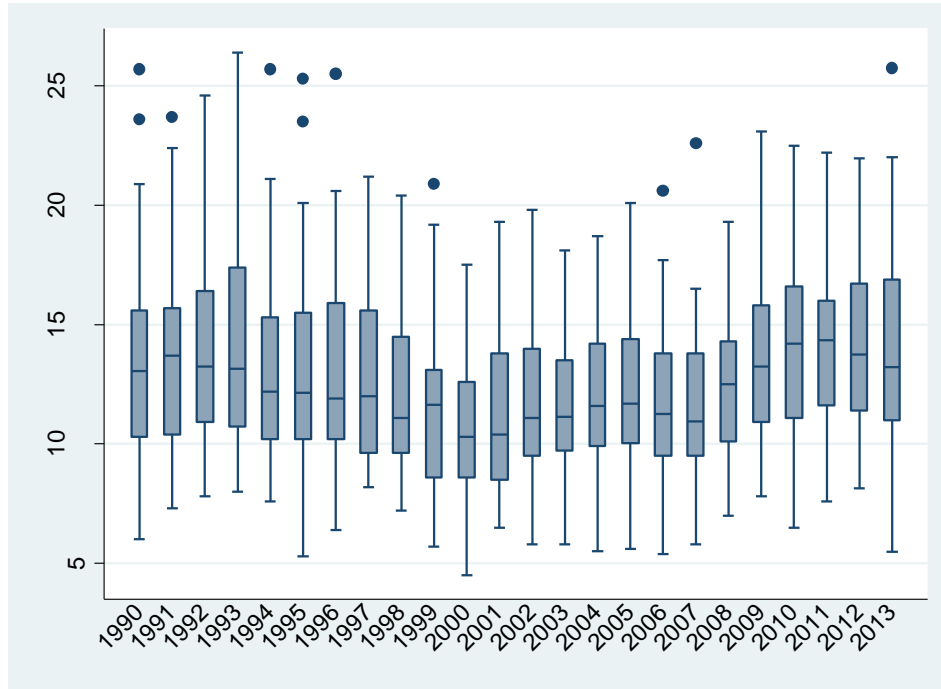


Figure F2. Trends in the Percent of People Below Poverty by State, 1990-2013

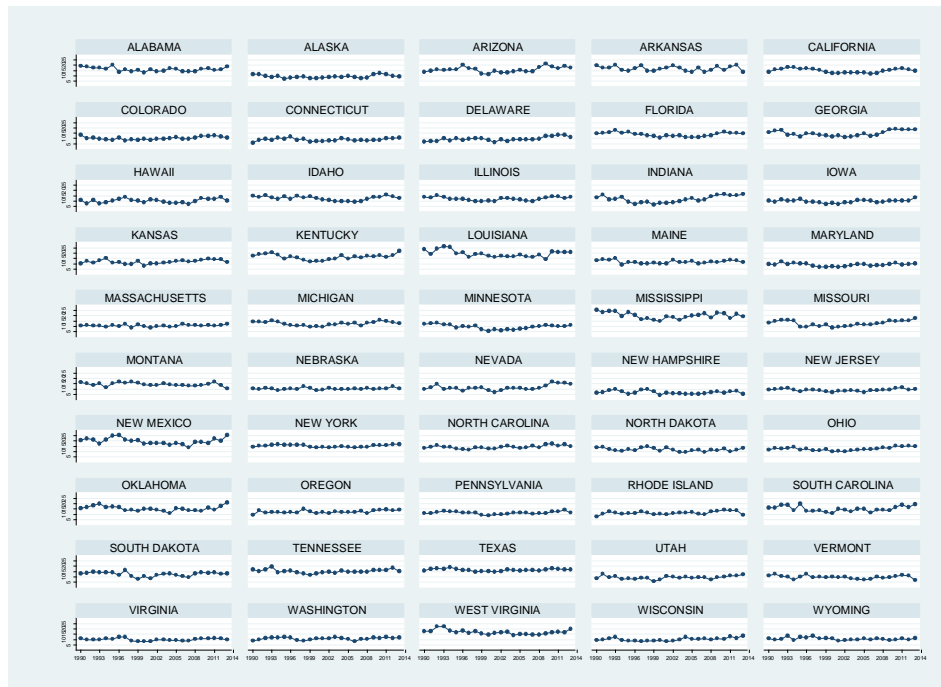




Figure F3. Aggregate State Trend in the Incarceration Rate, 1990-2013

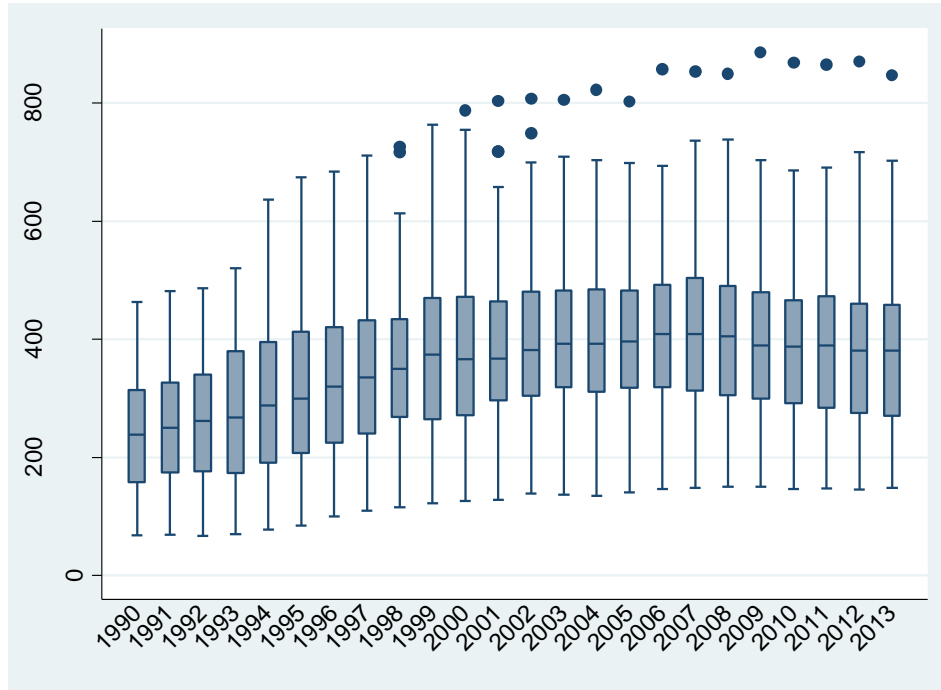


Figure F4. Trends in the Incarceration Rate by State, 1990-2013

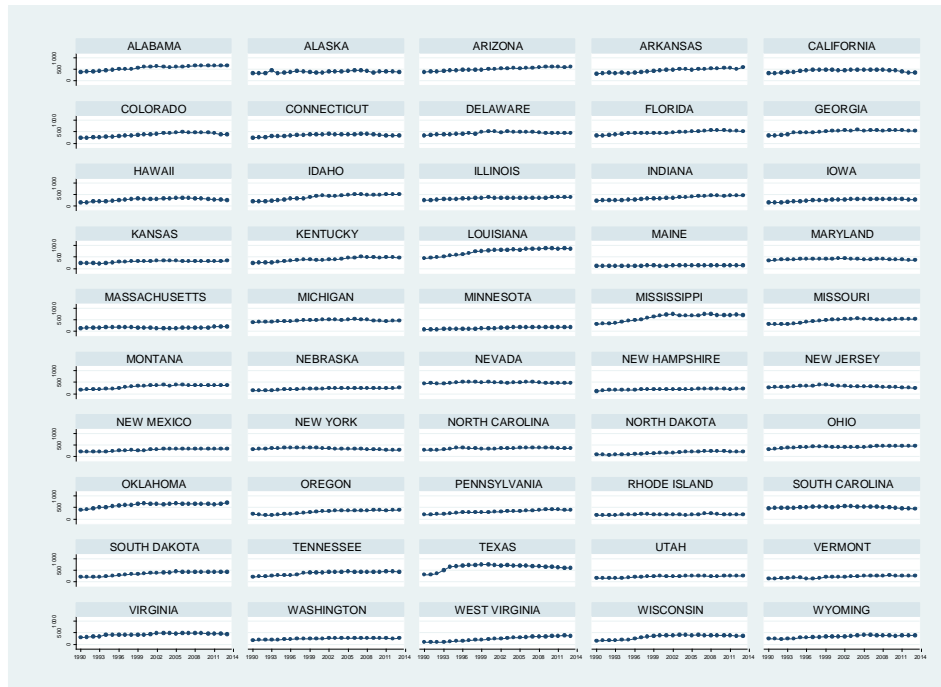


Figure F5. Aggregate State Trend in Arrest Rates for Drug Abuse Violations, 1990-2013

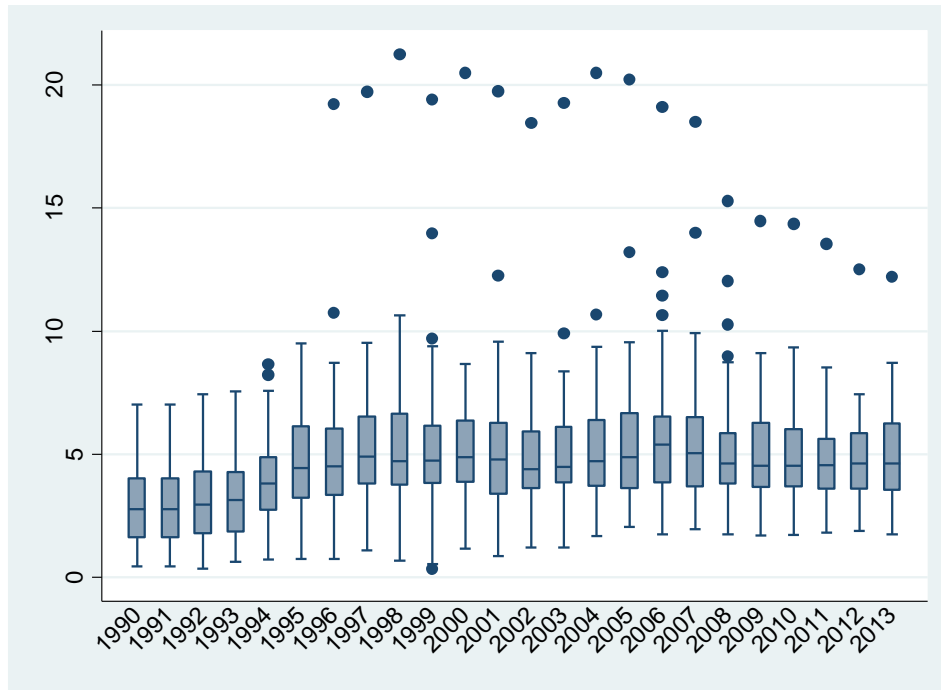


Figure F6. Trends in Arrest Rates for Drug Abuse Violations by State, 1990-2013

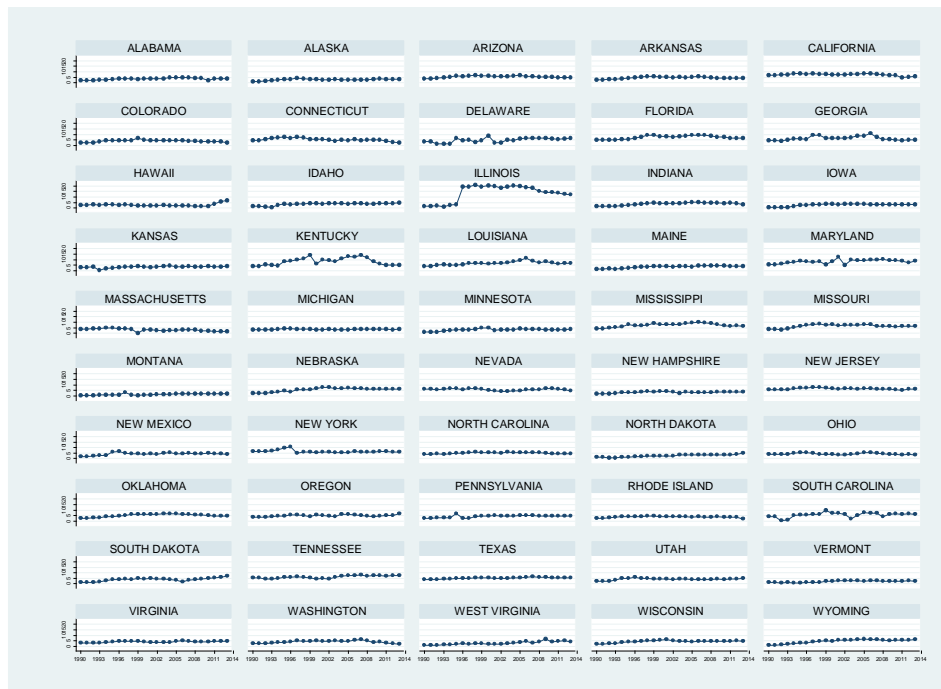


Figure F7. Aggregate State Trend in the Percent of Police Officers per Capita, 1990-2013

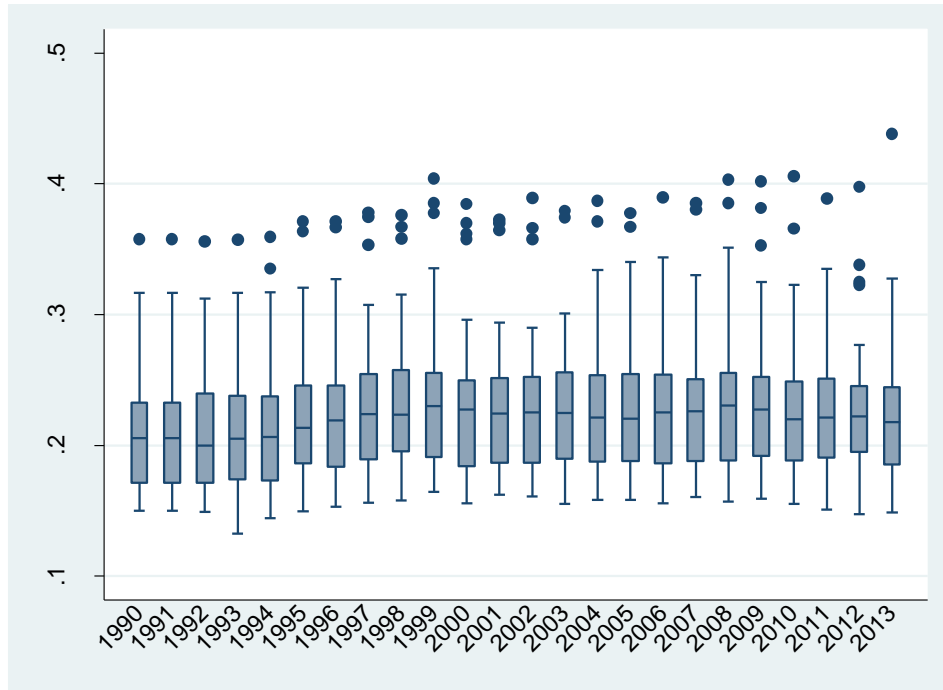


Figure F8. Trends in the Percent of Police Officers per Capita by State, 1990-2013

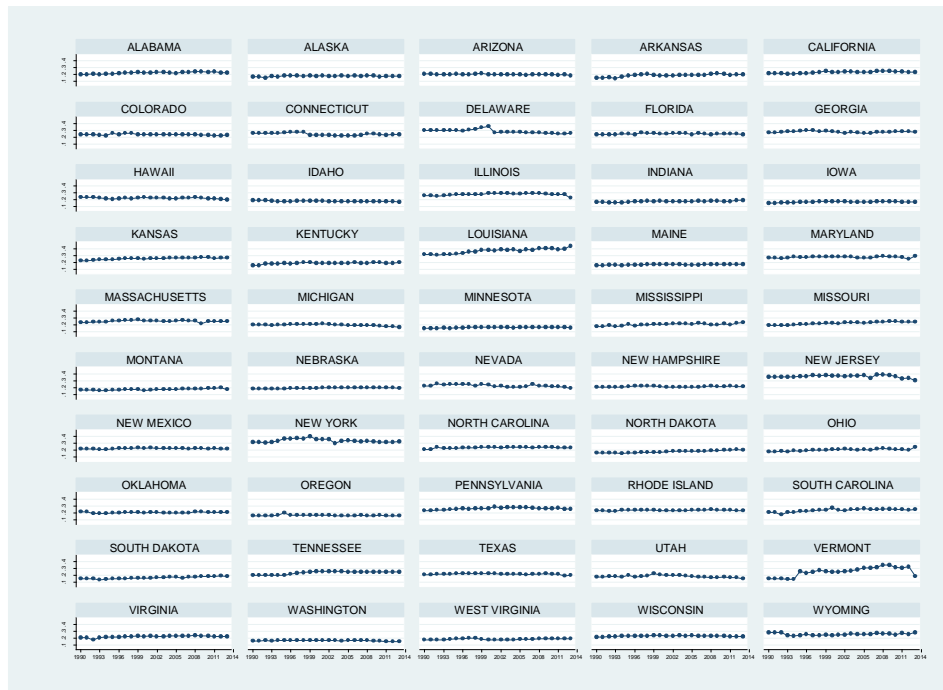


Figure F9. Aggregate State Trend in Percent Black, 1990-2013

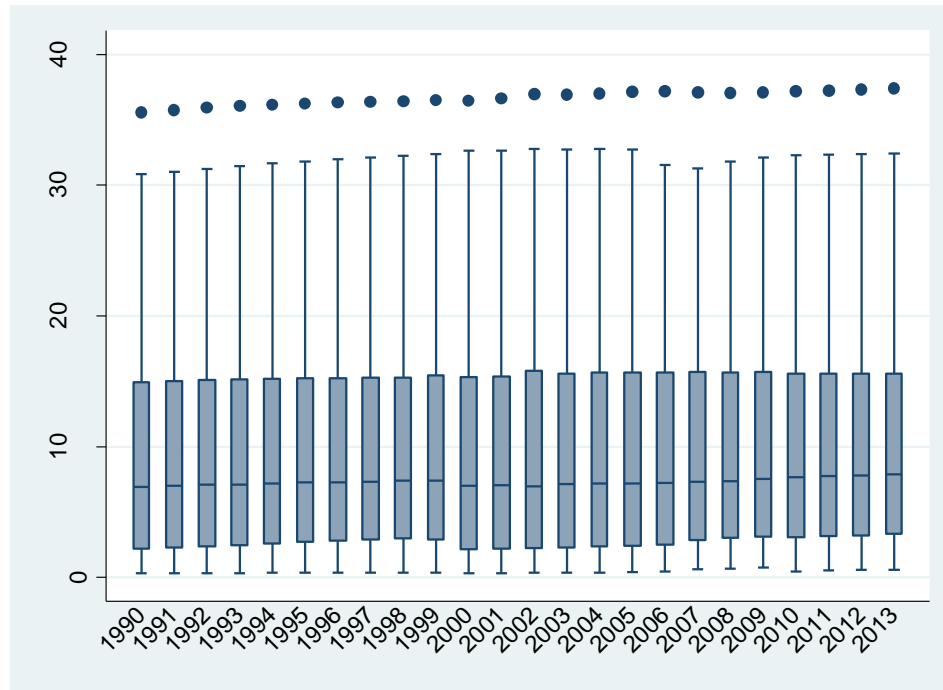


Figure F10. Trends in the Percentage of the Population that is Black by State, 1990-2013

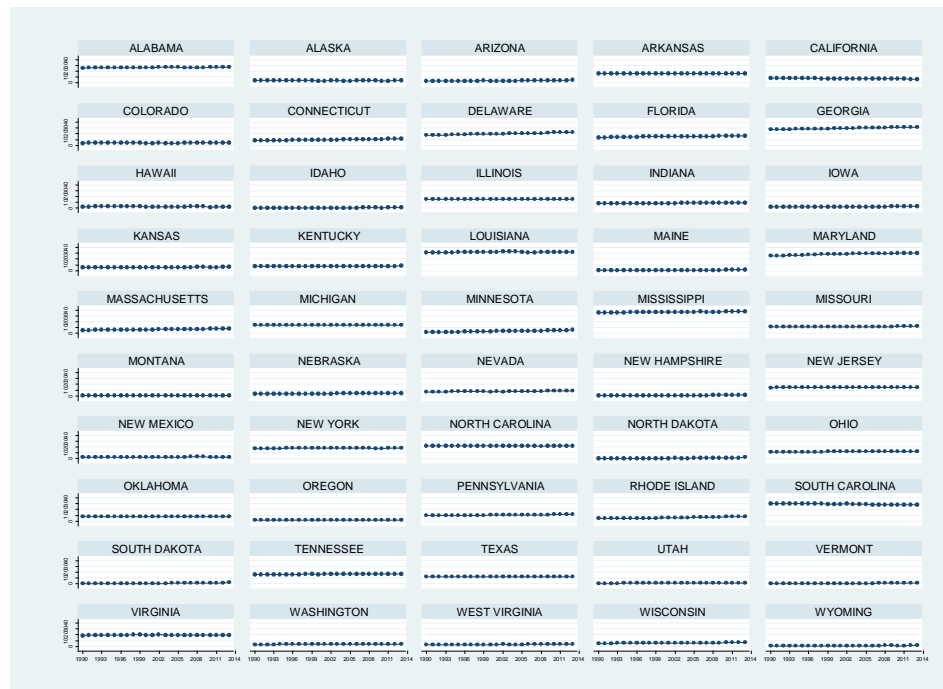


Figure F11. Aggregate State Trend in the Average CPS Worker Caseload, 1997-2013

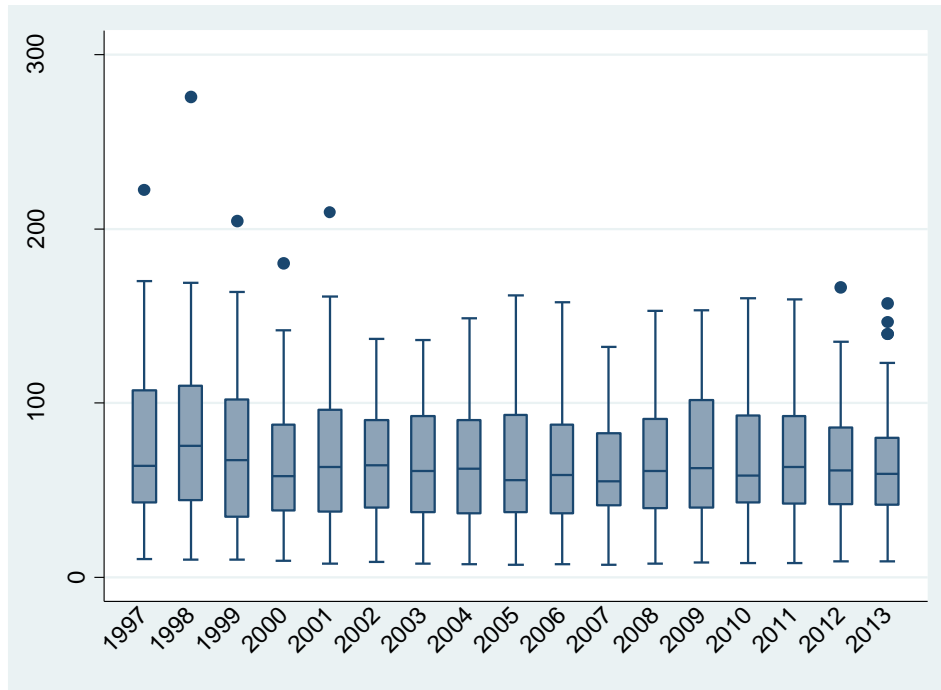


Figure F12. Trends in the Average CPS Worker Caseload by State, 1997-2013

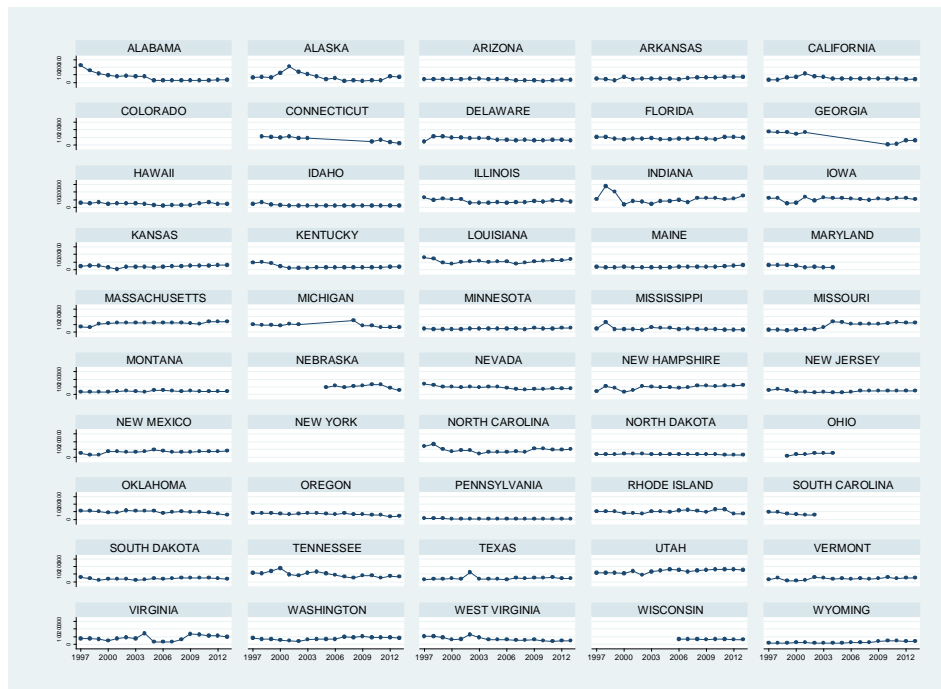


Figure F13. Aggregate State Trend in the Ratio of CPS Workers to Children, 1997-2013

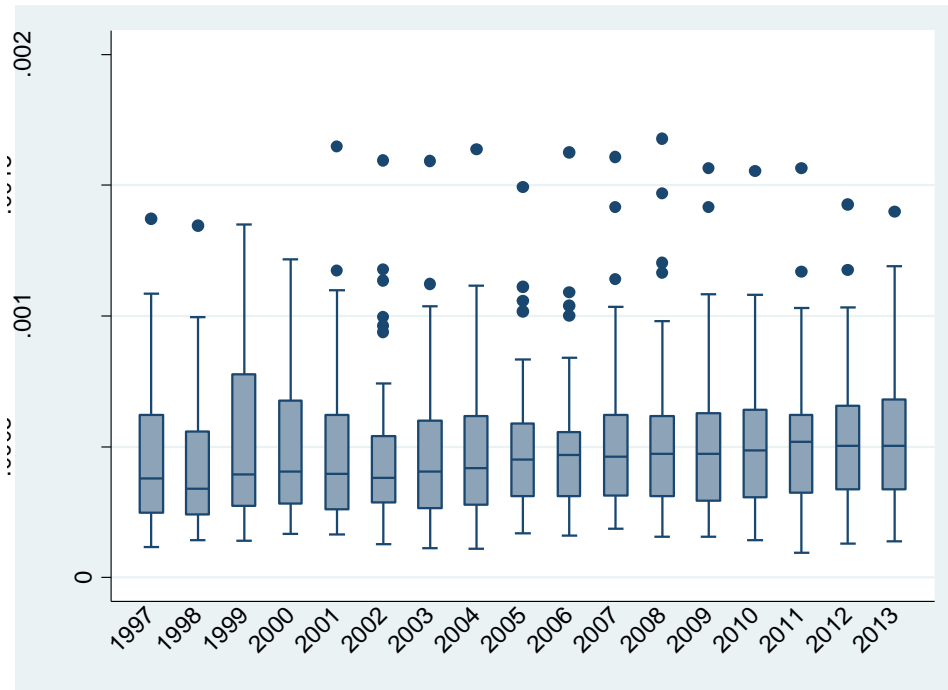


Figure F14. Trends in the Ratio of CPS Workers to Children by State, 1997-2013

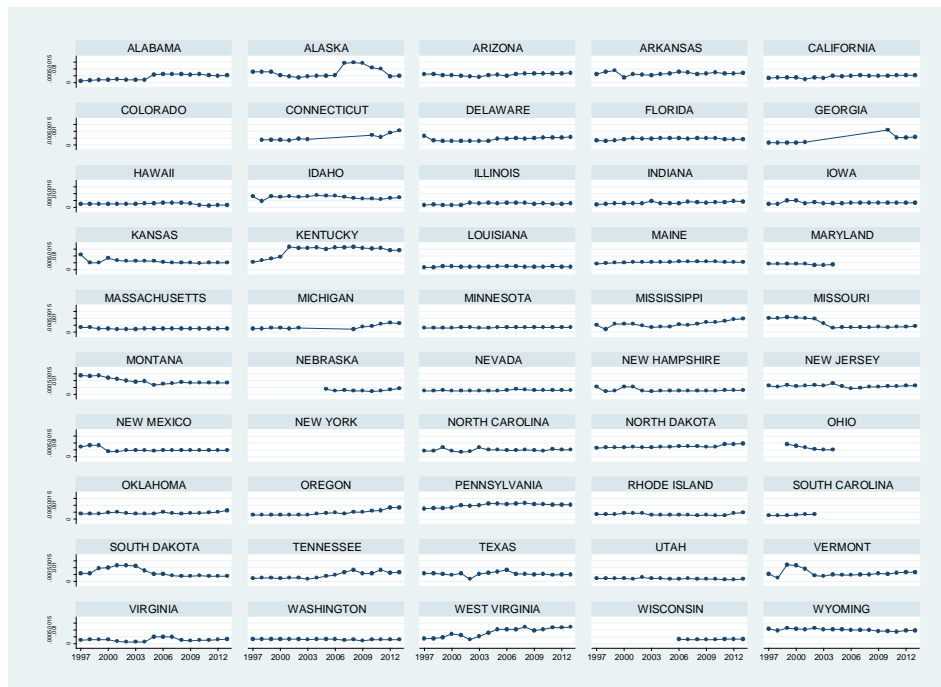


Figure F15. Aggregate State Trend in Rate of Methylphenidate Distribution, 1997-2013

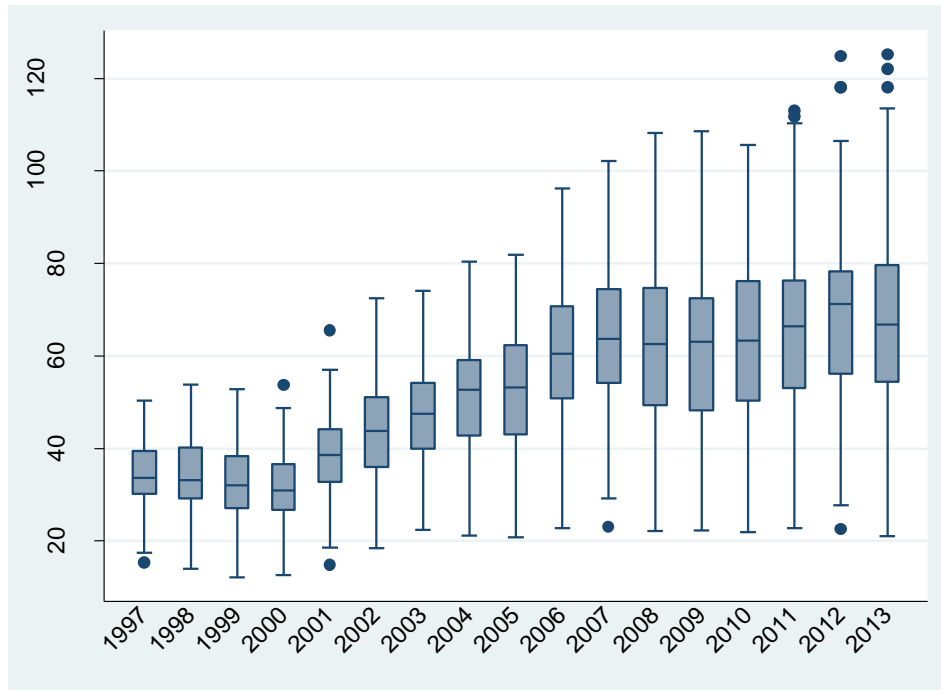
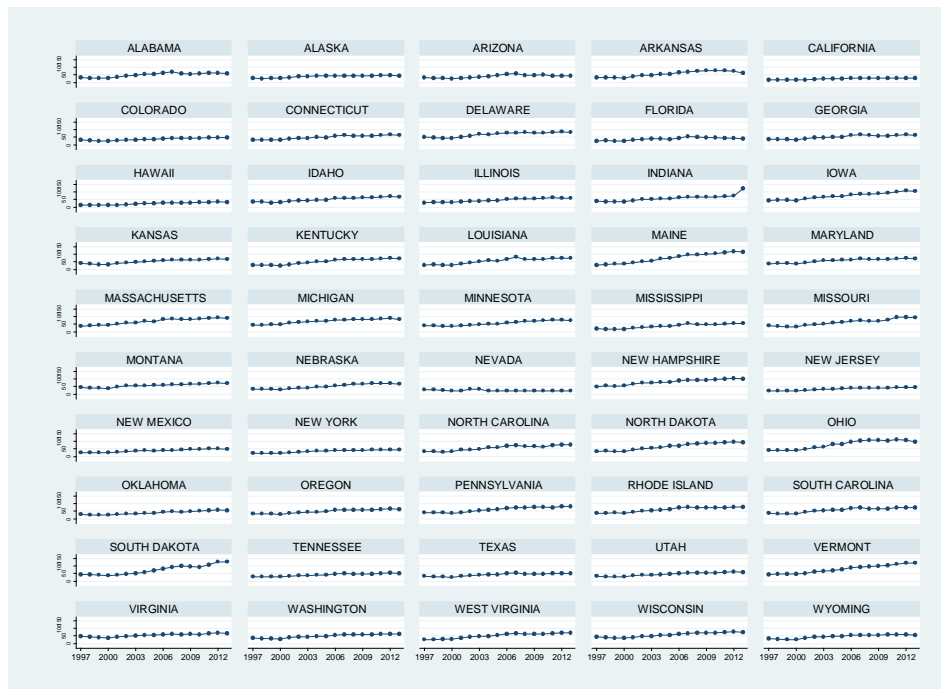


Figure F16. Trends in Rate of Methylphenidate Distribution by State, 1997-2013



APPENDIX G

Table G1. Correlation Matrix between Aggregated State Measures in Levels (1990+ or \*1997+)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.*	11.*	12.*	13.*	14.
1. Child Physical Abuse Rate	1.00													
2. Child Sexual Abuse Rate	.570	1.00												
3. Child Neglect Rate	.482	.113	1.00											
4. Homicide Rate	.147	.145	.053	1.00										
5. Poverty Rate	.150	.010	.125	.283	1.00									
6. Incarceration Rate <sub>t-1</sub>	-.128	-.190	-.028	.276	.387	1.00								
7. Law Enforcement Officers per Capita	-.142	-.208	-.080	.247	.010	.313	1.00							
8. Law Enforcement Officers per Capita <sub>t-1</sub>	-.146	-.200	-.081	.224	.006	.314	.975	1.00						
9. Drug Violation Arrest Rate	-.120	-.172	.021	.275	.096	.389	.383	.373	1.00					
10. Average Worker Caseload Size*	.183	.150	.314	.084	-.055	.007	.062	.061	.058	1.00				
11. Ratio of CPS Workers to Children*	.032	-.005	.084	-.061	.170	.027	-.128	-.131	-.034	-.654	1.00			
12. Ratio of CPS Workers to Children <sub>t-1</sub> *	.020	-.011	.075	-.071	.167	.024	-.123	-.131	-.040	-.596	.920	1.00		
13. Rate of Methylphenidate Distribution*	-.140	-.045	-.011	-.260	-.016	-.104	-.099	-.090	-.188	.012	.061	.058	1.00	
14. Percent Black	-.024	-.072	.043	.388	.361	.601	.496	.490	.403	.150	-.182	-.193	-.047	1.00



Table G2. Correlation Matrix between Aggregated State Measures in First-Differences (1990+ or \*1997+)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.*	11.*	12.*	13.*	14.
1. Child Physical Abuse Rate	1.00													
2. Child Sexual Abuse Rate	.588	1.00												
3. Child Neglect Rate	.558	.463	1.00											
4. Homicide Rate	-.026	-.031	-.041	1.00										
5. Poverty Rate	-.022	.007	-.010	-.068	1.00									
6. Incarceration Rate <sub>t-1</sub>	-.032	-.028	-.011	-.018	-.033	1.00								
7. Law Enforcement Officers per Capita	-.014	-.068	-.022	-.024	.026	.066	1.00							
8. Law Enforcement Officers per Capita <sub>t-1</sub>	-.033	-.004	.034	-.015	-.028	.111	-.237	1.00						
9. Drug Violation Arrest Rate	.026	-.019	.031	.011	-.069	-.013	.109	.018	1.00					
10. Average Worker Caseload Size*	.103	.196	.263	-.067	.053	-.048	.023	.024	-.043	1.00				
11. Ratio of CPS Workers to Children*	.057	.085	.088	.068	-.051	.067	-.013	-.025	.089	-.554	1.00			
12. Ratio of CPS Workers to Children <sub>t-1</sub> *	-.010	.054	.091	-.106	-.001	.022	-.031	-.010	-.033	.043	-.069	1.00		
13. Rate of Methylphenidate Distribution*	.054	.021	.030	.059	.056	-.030	-.020	-.005	.056	.104	-.067	.003	1.00	
14. Percent Black	-.019	.003	-.040	-.028	.063	.011	.029	-.022	.038	-.020	.090	-.022	-.006	1.00

APPENDIX H

Table H1. Summary of Regression Diagnostics

	Needs Time-Fixed Effects	Groupwise Heteroscedasticity	Cross-Sectional Dependence/ Contemporaneous Correlation	Serial Correlation	Non-Stationary	Final Panel Regression Model
<i>Rates of Child Physical Abuse</i>						
MODEL 1	x	x		x	x	
MODEL 2		x		x	x	
ΔMODEL 1	x	x		x		PCSE–Prais-Winsten
ΔMODEL 2		x		x		PCSE–Prais-Winsten
<i>Rates of Child Sexual Abuse</i>						
MODEL 1	x	x		x		PCSE–Prais-Winsten
MODEL 2		x	x	x		PCSE–Prais-Winsten
<i>Rates of Child Neglect</i>						
MODEL 1		x		x		PCSE–Prais-Winsten
MODEL 2		x		x		PCSE–Prais-Winsten
<i>Rates of Child Homicide</i>						
MODEL 1	x	x	x	x		PCSE–Prais-Winsten
MODEL 2	x	x				PCSE–Pooled Ordinary Least Squares
Test Used:	-	Modified Wald Test	Pesaran’s Test	Wooldridge Test	Fisher Test, Levin-Lin-Chu Test, Im-Pesaran-Shin Test	

ABBREVIATION: PCSE=Panel-Corrected Standard Errors

NOTE: Model 1 is the long series model (1990-2013). Model 2 is the short series model (1997-2013).

ΔModel 1 and ΔModel 2 are the first-differenced (detrended) stationary models.

Fisher-type unit-root tests based on Phillips-Perron tests and augmented Dickey-Fuller tests.

APPENDIX I

Table II. Panel Regressions of Year-to-Year Changes in the Rates of Child Physical Abuse

	DV = Annual Change in the Rate of Child Physical Abuse <u>ΔRate of Child Physical Abuse</u>	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Prais-Winsten (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
ΔPoverty Rate	-.002 (.012)	-.008 (.015)
ΔIncarceration Rate <sub>t-1</sub>	-.0008 (.0013)	-.002 (.002)
ΔPercent of Law Enforcement Officers	-.819 (2.24)	-2.34 (2.61)
ΔPercent of Law Enforcement Officers <sub>t-1</sub>	-.419 (2.60)	-1.49 (2.56)
ΔRate of Drug Abuse Violation Arrests	.008 (.024)	-.022 (.024)
ΔRatio of CPS Caseworkers to Children		-171.58 (339.66)
ΔRatio of CPS Caseworkers to Children <sub>t-1</sub>		-102.08 (251.32)
ΔAverage CPS Worker Caseload		.003 (.001)*
ΔRate of Methylphenidate Distribution		.004 (.005)
<i>Control Variable</i>		
ΔPercent Black	-.13 (.18)	-.22 (.12)^
Year	a	.012 (.006)^
<i>R</i> <sup>2</sup>	.0473	.0420

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for a number of years in the model. Year-to-year changes from 1991 to 1992 served as the reference category for Model 1.

^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Table I2. Panel Regressions of Year-to-Year Changes in the Rates of Child Sexual Abuse

	DV = Annual Change in the Rate of Child Sexual Abuse <u>ΔRate of Child Sexual Abuse</u>	
	MODEL 1	MODEL 2
	Prais-Winsten (1990-2013)	Prais-Winsten (1997-2013)
	Coef. (Std. Err.)	Coef. (Std. Err.)
<i>Independent Variables</i>		
ΔPoverty Rate	-.003 (.005)	-.008 (.006)
ΔIncarceration Rate <sub>t-1</sub>	.00005 (.0005)	.0002 (.0006)
ΔPercent of Law Enforcement Officers	-1.70 (.97) <sup>^</sup>	-3.38 (1.30)**
ΔPercent of Law Enforcement Officers <sub>t-1</sub>	-.124 (.98)	-.593 (1.14)
ΔRate of Drug Abuse Violation Arrests	.009 (.007)	.013 (.011)
ΔRatio of CPS Caseworkers to Children		338.39 (156.96)*
ΔRatio of CPS Caseworkers to Children <sub>t-1</sub>		157.62 (107.58)
ΔAverage CPS Worker Caseload		.003 (.001)***
ΔRate of Methylphenidate Distribution		.0006 (.002)
<i>Control Variable</i>		
ΔPercent Black	.016 (.045)	-.019 (.047)
Year	a	.003 (.002)
$R^2$	.0904	.0889

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the model. Year-to-year changes from 1991 to 1992 served as the reference category for Model 1.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Table I3. Panel Regressions of Year-to-Year Changes in the Rates of Child Neglect

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	DV = Annual Change in the Rate of Child Neglect <u><math>\Delta</math>Rate of Child Neglect</u>	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Prais-Winsten (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
$\Delta$ Poverty Rate	.016 (.026)	-.024 (.031)
$\Delta$ Incarceration Rate $_{t-1}$	-.003 (.003)	-.002 (.003)
$\Delta$ Percent of Law Enforcement Officers	-4.03 (3.86)	-6.00 (3.76)
$\Delta$ Percent of Law Enforcement Officers $_{t-1}$	6.55 (4.78)	6.87 (4.96)
$\Delta$ Rate of Drug Abuse Violation Arrests	.050 (.045)	.023 (.064)
$\Delta$ Ratio of CPS Caseworkers to Children		3461.91 (593.53)***
$\Delta$ Ratio of CPS Caseworkers to Children $_{t-1}$		1116.48 (422.08)**
$\Delta$ Average CPS Worker Caseload		.027 (.003)***
$\Delta$ Rate of Methylphenidate Distribution		.004 (.012)
<i>Control Variable</i>		
$\Delta$ Percent Black	-.528 (.306)^	-.617 (.243)*
Year	.007 (.008)	.018 (.012)
$R^2$	.0113	.1547

---

NOTE: ^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Table I4. Panel Regressions of Year-to-Year Changes in the Rates of Child Homicide

	DV = Annual Change in the Rate of Child Homicide <u>ΔRate of Child Homicide</u>	
	MODEL 1 Prais-Winsten (1990-2013) Coef. (Std. Err.)	MODEL 2 Ordinary Least Squares (1997-2013) Coef. (Std. Err.)
<i>Independent Variables</i>		
ΔPoverty Rate	-.042 (.018)*	-.052 (.025)*
ΔIncarceration Rate <sub>t-1</sub>	.0002 (.002)	.0003 (.003)
ΔPercent of Law Enforcement Officers	-3.50 (2.59)	-4.52 (4.08)
ΔPercent of Law Enforcement Officers <sub>t-1</sub>	1.37 (2.90)	3.09 (4.58)
ΔRate of Drug Abuse Violation Arrests	.023 (.024)	-.058 (.048)
ΔRatio of CPS Caseworkers to Children		708.35 (547.11)
ΔRatio of CPS Caseworkers to Children <sub>t-1</sub>		-969.56 (403.03)*
ΔAverage CPS Worker Caseload		-.002 (.003)
ΔRate of Methylphenidate Distribution		.009 (.011)
<i>Control Variable</i>		
ΔPercent Black	-.314 (.14)*	-.369 (.236)
Year	a	a
<i>R</i> <sup>2</sup>	.0654	.0748

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. Year-to-year changes from 1991 to 1992 served as the reference category for Model 1 and year-to-year changes from 1998 to 1999 served as the reference category for Model 2.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

APPENDIX J

Table J1. Panel Regressions of Year-to-Year Changes in the Rates of Child Physical Abuse (Estimated and Original Data)

	MODEL 1 (1990-2013)		MODEL 2 (1997-2013)	
	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)
<i>Independent Variables</i>				
ΔPoverty Rate	-.002 (.012)	.003 (.013)	-.008 (.015)	.004 (.015)
ΔIncarceration Rate <sub>t-1</sub>	-.0008 (.0013)	-.00004 (.001)	-.002 (.002)	-.001 (.002)
ΔPercent of Law Enforcement Officers	-.819 (2.24)	-1.18 (2.47)	-2.34 (2.61)	-1.44 (2.90)
ΔPercent of Law Enforcement Officers <sub>t-1</sub>	-.419 (2.60)	-1.85 (2.90)	-1.49 (2.56)	-3.75 (3.10)
ΔRate of Drug Abuse Violation Arrests	.008 (.024)	.026 (.036)	-.022 (.024)	.019 (.036)
ΔRatio of CPS Caseworkers to Children			-171.58 (339.66)	78.15 (449.64)
ΔRatio of CPS Caseworkers to Children <sub>t-1</sub>			-102.08 (251.32)	44.50 (284.96)
ΔAverage CPS Worker Caseload			.003 (.001)*	.003 (.002)^
ΔRate of Methylphenidate Distribution			.004 (.005)	.004 (.006)
<i>Control Variable</i>				
ΔPercent Black	-.13 (.18)	-.17 (.18)	-.22 (.12)^	-.16 (.12)
Year	a	a	.012 (.006)^	.017 (.006)**
R <sup>2</sup>	.0473	.0537	.0420	.0454

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for a number of years in the model. Year-to-year changes from 1991 to 1992 served as the reference category for Model 1.

^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Table J2. Panel Regressions of Rates of Child Sexual Abuse (Estimated and Original Data)

	MODEL 1 (1990-2013)		MODEL 2 (1997-2013)	
	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)
<i>Independent Variables</i>				
Poverty Rate	-.004 (.006)	-.007 (.006)	.006 (.007)	.008 (.008)
Incarceration Rate $t_{-1}$	-.00003 (.0003)	-.0003 (.0003)	-.0007 (.0003)*	-.001 (.0004)**
Percent of Law Enforcement Officers	-2.28 (.85)**	-2.61 (.88)**	-2.70 (1.13)*	-2.16 (1.04)*
Percent of Law Enforcement Officers $t_{-1}$	-.78 (.83)	-1.70 (.74)*	-.101 (1.02)	-1.30 (1.13)
Rate of Drug Abuse Violation Arrests	.006 (.007)	.013 (.01)	.015 (.01)	.03 (.015)*
Ratio of CPS Caseworkers to Children			374.24 (153.76)*	240.4 (189.88)
Ratio of CPS Caseworkers to Children $t_{-1}$			116.14 (112.66)	62.41 (139.17)
Average CPS Worker Caseload			.004 (.001)***	.003 (.001)***
Rate of Methylphenidate Distribution			.001 (.002)	.003 (.002)
<i>Control Variable</i>				
Percent Black	-.002 (.007)	.004 (.007)	.02 (.007)**	.02 (.005)***
Year	a	a	-.04 (.006)***	a
$R^2$	.3905	.4920	.5731	.6189

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the model. The year 1991 served as the reference category in Model 1 and the year 1998 served as the reference category in Model 2.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.



Table J3. Panel Regressions of Rates of Child Neglect (Estimated and Original Data)

	MODEL 1 (1990-2013)		MODEL 2 (1997-2013)	
	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)
<i>Independent Variables</i>				
Poverty Rate	.04 (.027)	.05 (.03)*	.114 (.036)**	.12 (.04)**
Incarceration Rate <sub>t-1</sub>	-.005 (.002)**	-.005 (.002)**	-.005 (.002)**	-.005 (.001)**
Percent of Law Enforcement Officers	-6.03 (3.43)^	-8.37 (3.63)*	-10.65 (3.52)**	-14.13 (5.78)**
Percent of Law Enforcement Officers <sub>t-1</sub>	1.89 (4.06)	1.58 (4.59)	2.14 (3.95)	1.92 (5.71)
Rate of Drug Abuse Violation Arrests	.02 (.04)	.08 (.06)	.073 (.056)	.11 (.051)*
Ratio of CPS Caseworkers to Children			3660.7 (621.8)***	3849.6 (751.6)***
Ratio of CPS Caseworkers to Children <sub>t-1</sub>			-415.3 (445.8)	-131.7 (465.0)
Average CPS Worker Caseload			.038 (.004)***	.036 (.005)***
Rate of Methylphenidate Distribution			.013 (.01)	.024 (.008)**
<i>Control Variable</i>				
Percent Black	.06 (.03)^	.08 (.03)**	.04 (.02)^	.03 (.01)*
Year	.01 (.03)	-.03 (.03)	-.05 (.04)	-.09 (.04)*
<i>R</i> <sup>2</sup>	.3860	.4219	.5261	.5758

NOTE: <sup>a</sup>Separate year effects were included in the model but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the model.

^ p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.

Table J4. Panel Regressions of Rates of Child Homicide (Estimated and Original Data)

	MODEL 1 (1990-2013)		MODEL 2 (1997-2013)	
	<u>Estimated</u> Prais-Winsten Coef. (Std. Err.)	<u>Original</u> Prais-Winsten Coef. (Std. Err.)	<u>Estimated</u> Ordinary Least Squares Coef. (Std. Err.)	<u>Original</u> Ordinary Least Squares Coef. (Std. Err.)
<i>Independent Variables</i>				
Poverty Rate	-.012 (.011)	-.005 (.01)	.027 (.015) <sup>^</sup>	.033 (.011)**
Incarceration Rate <sub>t-1</sub>	.003 (.0004)***	.003 (.0004)***	.003 (.0003)***	.003 (.0003)***
Percent of Law Enforcement Officers	-1.14 (2.04)	-1.83 (1.89)	-1.39 (3.56)	-.56 (3.18)
Percent of Law Enforcement Officers <sub>t-1</sub>	3.12 (2.08)	3.38 (1.95) <sup>^</sup>	4.89 (3.53)	4.52 (2.99)
Rate of Drug Abuse Violation Arrests	.091 (.019)***	.11 (.02)***	.081 (.01)***	.077 (.01)***
Ratio of CPS Caseworkers to Children			737.32 (361.14)*	707.44 (376.32) <sup>^</sup>
Ratio of CPS Caseworkers to Children <sub>t-1</sub>			-768.11 (344.86)*	-961.19 (375.67)*
Average CPS Worker Caseload			.002 (.001) <sup>^</sup>	.001 (.002)
Rate of Methylphenidate Distribution			-.004 (.002) <sup>^</sup>	-.005 (.002)*
<i>Control Variable</i>				
Percent Black	.01 (.005) <sup>^</sup>	.008 (.004)*	-.016 (.006)**	-.02 (.008)**
Year	a	a	a	a
<i>R</i> <sup>2</sup>	.5158	.5227	.4017	.4369

NOTE: <sup>a</sup>Separate year effects were included in the models but are not shown for ease of viewing. There was a negative and significant beta coefficient for nearly all years in the models. The year 1991 served as the reference category in Model 1 and the year 1998 served as the reference category in Model 2.

<sup>^</sup> p<.10, \* p<.05, \*\* p<.01, \*\*\* p<.001.