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Differential Response and Agency Decision Making: a National Study of Child Neglect Cases

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DIFFERENTIAL RESPONSE AND AGENCY DECISION MAKING: A NATIONAL STUDY OF CHILD NEGLECT CASES

by

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ABSTRACT
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A growing number of child protective service (CPS) agencies have adopted differential response (DR), which allows for the provision of case management and support to moderate-risk CPS cases without launching a formal investigation. Previous research has established that DR does not compromise child safety, and that it promotes family engagement. Yet DR's broader impact on CPS agencies remains largely unknown. Given that DR diverts some cases from traditional investigations, this dissertation explored DR's impact on child neglect cases that do not get diverted. Specifically, the study examined how DR changes the proportion and characteristics of the population of children experiencing investigations, substantiations, and removals from their homes of origin.

Methods: First, using 2010 data from the National Child Abuse and Neglect Data System (NCANDS), a path analysis compared investigation, substantiation, and removal rates in DR counties and non-DR counties while accounting for county-level covariates. Second, using the same 2010 dataset, multilevel logistic regression models were run to test the likelihood that an investigation was substantiated in DR and non-DR counties after accounting for county- and child-level covariates. Finally, a longitudinal analysis of

NCANDS data from 2000-2010 described the degree and rate of change for county-level investigation and substantiation rates coinciding with the launch of DR.

Results: Controlling for county characteristics, the implementation of DR corresponded with significant declines in CPS investigation rates across counties and over time. Further, longitudinal analyses revealed that significant declines in investigation rates occurred during the first three years of DR implementation. In addition, cross-sectional analyses indicated that the rate of substantiated investigations was higher among DR counties than non-DR counties and that this pattern was consistent across children of different racial and ethnic groups. However, the longitudinal analyses showed that DR implementation was not associated with an increase in the proportion of substantiated investigations. DR implementation was also not associated with changes in removal rates.

Conclusion: The reduction of investigations associated with the launch of DR has implications for staffing structures and resource disbursement in CPS agencies and community partners. The findings also inform further discussion about the role of public child welfare agencies beyond investigating maltreatment allegations. Finally, the study reinforces the value of national datasets for assessing widespread system change.

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CHAPTER 1

Introduction

Statement of the Problem

In 2012, child protective services (CPS) agencies in the U.S. responded to allegations of child maltreatment involving 3.8 million children, yet fewer than one-fifth of those allegations were ultimately substantiated (U.S. Department of Health and Human Services, DHHS, 2013). Fewer still presented sufficient risk to warrant removal from the home or court action (7% and 4%, respectively). Although the importance of having a public child protection system to detect and respond to genuine cases of maltreatment cannot be overstated, these statistics show that the majority of maltreatment allegations do not result in substantiation or intensive intervention. Nevertheless, most agencies require a formal investigation for all cases that are not screened out immediately after an initial report of maltreatment. In addition to investigating maltreatment, CPS professionals are also responsible for providing case management and family support. Yet the adversarial nature of the investigation process can make it difficult for workers to develop the rapport and trust needed to provide effective, strengths-based services in their work with CPS-involved families (Conley, 2007; Christenson, Curran, DeCook, Maloney, & Merkel-Holguin, 2008; Waldfogel, 1998).

Differential response (also called alternative response) is a reform that offers CPS agencies an option to provide services (case management and other support) to eligible families without launching a full investigation (National Quality Improvement Center for Differential Response, QIC-DR, 2011). In most CPS systems, a hotline worker or other professional assesses the initial report of maltreatment and either screens the allegation out because it did not meet a state's standard for maltreatment, or screens it in for further assessment. At this point, in an investigation-only system (non-DR), all screened-in

cases usually proceed to an investigation phase, were CPS workers, sometimes in collaboration with law enforcement and other professionals, determine whether there was sufficient harm and evidence to substantiate the allegation of maltreatment (Drake & Jonson-Reid, 2000). In a DR system, CPS professionals assess whether the case should be investigated or diverted to an alternate pathway. Cases in the alternate pathway are still assessed for risk, but are not subject to a formal investigation and do not receive an official judgment corresponding to the maltreatment allegation. Eligibility requirements for diverting families from the investigation pathway vary by state, but DR typically targets families who present with low-to-moderate maltreatment risk. Families may change pathways if risk assessment changes. Proponents of DR emphasize that it still safeguards children, while allowing CPS workers to focus on engaging families and securing early access to services (Merkel-Holguin, Kaplan, & Kwak, 2006; Rycus & Hughes, 2008; Zielewski, Macomber, Bess, & Murray, 2006).

DR's impact extends beyond those families who directly benefit from alternative responses: Because some cases are diverted to alternate pathways in CPS agencies with DR, the number of investigated cases is reduced (Shusterman, Hollinshead, Fluke, & Yuan, 2005). The remaining population of cases referred for investigation may represent a greater concentration of high-risk children, which can help to concentrate the resources of investigation teams and reduce the number of children who are incorrectly deemed to have been maltreated (i.e., false positives, Schene, 2005). To date, however, evidence of these shifts in investigation and substantiation rates have been limited to studies of one state or a small number of states. In addition, no studies have examined DR's impact on removal decisions. These important information gaps are important to address given that

the number of states implementing DR is growing despite the lack of comprehensive analyses of DR's broad impact on the CPS system (QIC-DR, 2011; Yuan, 2005).

Significance of the Problem

Understanding the extent to which DR influences investigation, substantiation, and removal decisions has three significant implications for child welfare systems. First and most directly, knowing the degree and rate of change in CPS decision making that is attributable to DR may promote system reform by helping decision makers in DR counties reallocate staff, services, and other resources. It is not presently known whether DR evokes similar case decision outcomes across counties and states. If outcomes are dissimilar across counties, this information may guide further exploration to identify those features of specific DR initiatives that drive changes in decision-making practices.

Second, if significant changes in overall decision rates occur because of the implementation of DR, it is important to understand if the changes are proportionate for particular subpopulations of CPS-involved children. The three studies presented here focus on two such groups: children reported to be victims of neglect and children who are racial or ethnic minorities. With regard to the first group, a large majority of maltreatment reports, investigations, and substantiations involve neglect (DHHS, 2013). Yet few DR studies have specifically examined neglect, even though DR appears well suited to improve decision making for neglect cases (Trocmé & Chamberland, 2003). For instance, deprivation arising solely from economic hardship should not be considered neglect (Child Welfare Information Gateway, 2011), yet poverty and economic instability have been shown to be strong predictors of neglect (Duva & Metzger, 2010; Slack, Holl, McDaniel, Yoo, & Bolger, 2004). The implementation of DR may to help to direct low-

income families to community-based supports rather than drawing families further into the CPS system based on economic factors that correlate with maltreatment (Duva & Metzger, 2010).

DR may also differentially affect children of different races or ethnicities. One hoped-for outcome is that DR reduces racial disparities. This may occur if families with risk factors that are associated with race (e.g., poverty), are more often diverted to alternate, community-based services (Allan & Howard, 2013). On the other hand, DR may reinforce or even worsen pre-existing decision-making biases. For example, African-American children are already overrepresented in the child welfare system. If a greater percentage of higher-risk cases reported to CPS are African American than other races/ethnicities, by selecting out lower-risk cases from investigation, DR might actually exacerbate the problem. Similarly, if racial biases influence a worker's decision to assign a case to either the investigative or alternate pathway, then African American and other minority families may be more likely to be investigated. At a minimum, it is important to know whether DR interacts in some way with the variable of child race/ethnicity, and since no large-scale study has yet addressed that question, this study will seek to do so.

Third, the dearth of empirical evidence regarding DR's system-level impact is symptomatic of the larger challenges associated with assessing and understanding national CPS system reforms. Although several national datasets track information about CPS systems, it is difficult to use these datasets for interstate comparisons because of the large amount of variation in data reporting practices across states (Fallon, et al., 2010). As data improve over time so to do the opportunities to assess practice innovation and policy changes at a national level. This dissertation's three studies aim to broaden our

understanding of outcomes that can be expected from implementing DR, as well as to inform the design of future studies of other major child welfare initiatives.

Theoretical Foundations

The research questions advanced in this dissertation explore the relationship between DR and outcomes such as investigation, substantiation, and removal decisions. Variability across these three decision outcomes operates at two levels: individual-level variability (i.e., different likelihoods of decision outcomes among cases or caseworkers) and higher-level variability (i.e., different likelihoods of decision outcomes among agencies, counties, states, or countries). Herbert Simon's classic conceptualization of bounded rationality (1955) is applicable to individual-level variability. It proposes that individuals make decisions constrained by factors such as limited time and information, and based on their own knowledge, skill, and personal experiences. These constraints are often present in CPS decisions, where the safety of a child is at stake yet information relevant to assessing risk may be limited and difficult to obtain (Bauman, Dalgleish, Fluke, & Kern, 2011; Crea, 2010; Munro, 1999; Stein & Rzepnicki, 1984). Faced with such constraints, individuals employ a variety of heuristics to help make decisions (Gigerenzer, 1991). Sometimes these heuristics lead to biases and errors in decision making, which have been documented in child welfare decision making (DePanfilis & Girvin, 2005; Munro, 1999). For instance, Munro (1999) reports that when assessing risk, caseworkers tend to overemphasize recent or easily verified events (i.e., availability heuristic, Tversky & Tanneman, 1974). Less common, however are CPS decision-making studies that examine higher-level variability, such as patterns of decision making

across county CPS agencies, which may be informed more by agency policy and macro-level sociopolitical forces than by social psychological theories.

The Decision-Making Ecology (DME) is a framework that accounts for both individual and higher levels of variability (Baumann, et al., 2011). The DME is based on elements of individual decision-making theories, such as bounded rationality, but describes forces that influence CPS decision making beyond individual-level factors. The four categories of influences that DME describes are: (1) case factors; (2) decision-maker factors; (3) external factors; and (4) organizational factors.

Risk and protective factors associated with maltreatment should, in theory, be the driving influence when assessing the validity of an allegation and creating case plans. However, other case factors such as a child's race or socioeconomic status, may exert unwarranted influence on the conclusions reached, leading to problems such as the overrepresentation of some children within the CPS system.

Decision-maker factors include qualities such as caseworker experience, skill level, education, job satisfaction, caseload, race, and age. CPS professionals can also be influenced by their own attitudes about parenting, along with past work or personal experiences (Baumann et al., 2011). Prior research has found clear patterns of decision-making variability among workers. For instance, studies have found that caseworkers tend to fall into two groups: those who prefer intensive responses that prioritize safety, and those who prefer less intensive responses that prioritize family preservation (Arad-Davidzon & Benbenishty, 2008; Regehr, Bogo, Shlonsky, & LeBlanc, 2010). Results across studies, however, have not identified any worker characteristics (e.g., race or

experience level) that consistently predict the direction or degree of these preferences (Regehr et al., 2010; Ryan, Garnier, Zyphur, & Zhai, 2006).

Decision making is also likely to be influenced by external factors such as community demographics and resources. Two studies of Canada's child welfare systems found that children (of any race) were more likely to be placed in out-of-home care if they were served by a CPS agency with a larger-than-average population of Aboriginal children (Fallon, et al., 2013; Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010). Given that both Aboriginal and non-Aboriginal children in these agencies experienced high odds of removals, the authors of both papers suggested that the lack of appropriate services in communities with large populations of Aboriginal children may explain the higher chance of removal.

The fourth category of influence, organizational factors, includes agency characteristics such as staffing and supervisory structures, as well as assessment tools, practice models and policies. Some research on organizational factors has found that a lower likelihood of out-of-home placement among CPS cases is related to an agency having a decentralized structure, strong leadership and higher proportion of workers with social work degrees (Chabot et al., 2013; Yoo & Brooks, 2005). However, less attention has been given to the impact of practice and policy reforms on large-scale decision patterns in CPS (Fallon et al., 2010). With the growing interest in evidence-based practice, many CPS practice models have undergone rigorous evaluation, but these have not translated into knowledge of the overall impact of innovations on CPS systems for three primary reasons. First, evaluations of early stages of implementation are often formative and focus on specific program and agency context as well as child or family

factors and outcomes (Aarons, Hurlburt, McCue Horwitz, 2011). These evaluations typically are constrained to one or a small number of sites, making it difficult to draw conclusions of CPS system changes that can be generalized to other localities. In addition, many practice innovations target a small number of children or are designed to improve outcomes that would be difficult to detect across a national sample of cases without expending significant resources for research. Finally, the adoption of CPS reforms is often difficult to track across jurisdictions over time. In contrast to other CPS innovations, however, DR represents a large-scale systemic change that provides new ways to respond to low- to moderate-risk cases at critical decision points within the early phases of CPS involvement. This should make it possible to detect its impact using administrative data. Among other advantages, its adoption can be tracked more easily across jurisdictions than other types of reforms because it typically requires codification in statutes. Accordingly, DR is the type of agency change from which effects on decision making, as articulated by the DME, can be assessed using available information.

The impact of decision maker and case factors on decision making has been the subject of far more studies than the impact of external or organizational factors. Yet without knowing the extent to which community or agency context may influence case decisions the relationships between individual risk factors and child decision outcomes may be obscured by unmeasured county or agency effects. The studies in this dissertation apply multiple approaches to exploring these macro-level influences on decision making.

Overview of the Literature

CPS Decision Making

This research examines three critical decision points within CPS cases: investigation, substantiation, and removal. The decision outcomes are intended to represent characteristics of agencies, not meaningful measures of child risk or child developmental outcomes. Decision outcomes measure how a child welfare agency carries out its primary function of protecting at-risk children, and substantial variation exists across states in these outcomes. For example, in 2010, investigation, substantiation, and removal rates across states varied by a factor of two, seven, and eleven respectively (U.S. Department of Health and Human Services, DHHS, 2011). While differences in population density, racial composition, and poverty levels may account for some of this variation (Wulczyn & Brunner Hislop, 2003), it seems likely that different decision-making policies and practices also play a role.

Differential Response

Missouri and Florida launched the first U.S. differential response initiatives in 1993, and by 2013, at least 24 states had implemented DR in one or more counties (National Quality Improvement Center on Differential Response in CPS, QIC-DR, 2013). Differential response is not a discrete initiative but a set of reforms designed to enhance the response options for low- to moderate-risk cases. Because it usually requires changes to states' statutes, DR is integrated into existing CPS systems in different ways, yet key commonalities exist. For the purposes of this research, DR is defined as a system using the following core elements: (1) At least two pathways are available for screened-in cases; (2) Decisions to divert cases to alternate pathways are determined by risk protocols and case characteristics; (3) A case can change pathways when risk levels increase or decrease; (4) Protocols for alternate responses are codified in statute or explicitly stated

in policy; (5) Families in alternate pathways can refuse services; (6) Cases in alternate pathways do not result in a maltreatment disposition; and (7) No perpetrators of maltreatment are identified for those cases receiving an alternate response (Kaplan and Merkel-Holguin, 2008). Some states and counties offer tiered response systems that are similar to DR but do not incorporate all elements of a full DR system. For example, California has an initiative called "Differential Response" that embraces many of the components of DR, but moderate-risk cases still require an investigation and disposition. In the current studies, initiatives such as these are not considered DR.

Prior studies have found that the rates of CPS investigations and substantiations among county populations are smaller in DR counties than in non-DR counties (Loman & Siegel, 2004; Virginia Department of Social Services, 2007; Westat, 2009). Shusterman and her colleagues (2005) summarized results from several evaluations of established DR initiatives and reported that these studies found between 40-70% of children were diverted from traditional investigations. Other evaluations of DR implementation in Virginia and Missouri indicated that DR implementation was associated with a higher proportion of investigated cases receiving substantiations. This supports the presumption that as lower-risk cases in DR counties get diverted to alternative responses, those remaining constitute a smaller but higher-risk child population (Shusterman et al., 2005; Loman, & Siegel, 2004; Virginia Department of Social Services, 2007).

All of the studies were limited to a single state or a few states (Loman & Siegel, 2004; Shusterman et al., 2005; Westat, 2009), and none sought to make comparisons between DR and non-DR counties or among a large number of DR counties. Also, none

was able to establish the temporal order of changes in decision-making patterns arising from DR implementation across a sample of DR counties in different states.

The Application of DR to Neglect

The three studies described here focus on neglect cases, the most common type of child maltreatment. Although over three-fourths of all child maltreatment victims are neglected (DHHS, 2011), the complexity of assessing neglect may lead to significant differences in decision outcomes across cases and agencies. Compared to other maltreatment types that are defined by acts of harm, neglect is defined by an omission of care, which may make risk assessment particularly difficult (Dubowitz, 2007; Straus & Kantor, 2005). A further concern is that poverty, parental incapacity, or other circumstances lead some children to experience conditions similar to neglect, despite no intent to harm on the part of the caregiver (DePanfilis, 2006). This has produced ongoing debate and lack of consensus among scholars as to whether the intent to harm is a necessary element of child neglect (Dubowitz, 2007; Hearn, 2011).

Neglect, Poverty, and Race

The picture is further clouded by the fact that child neglect is strongly associated with indicators of family poverty such as low income, unemployment, the use of public assistance, housing instability, and a range of other measures associate with economic risk (Mersky, Topitzes, & Reynolds, 2009; Sedlak et al., 2010; Slack et al., 2011). Also, CPS decision making appears to be affected by poverty not only at the family level, but also at the neighborhood and community levels. Drake and Pandey (1996) found that neglect, more than other forms of maltreatment, is strongly associated with neighborhood poverty. In addition, Jantz, Rolock, Leathers, Dettlaff, & Gleeson (2012) reported that

children residing in counties with high poverty rates and other indicators of social disorganization were more likely to enter substitute care during a maltreatment investigation. The extent to which poverty produces elevated risk for neglect or induces circumstances of disadvantages that are mistaken for neglect may be difficult to ascertain, and this ambiguity can lead to inconsistent CPS decision making across staff and agencies. By focusing on service needs rather than investigations, DR can help address neglect-like circumstances in low-income families without requiring a neglect investigation.

Another important variable is the race/ethnicity of the child. Rates of poverty, neglect, and more restrictive decision making have been associated with a child's racial or ethnic status, and at present, there is conflicting evidence regarding whether racial differences indicate bias in the CPS system or some other confounding factor. As an example, two studies that examined child welfare practices in Texas found that, when compared to cases of White children with similar risk scores and poverty levels, cases of African American children were more likely to be substantiated (Dettlaff et al., 2011) and result in removal of the child from the home (Rivaux et al., 2008). In contrast, other research suggests that high rates of CPS involvement among African American children may be due to the high occurrence of family and community risk factors in minority populations (Bartholet, 2009; Drake et al., 2011; Font, Berger, & Slack, 2012; Putnam-Hornstein, Needell, King, & Johnson-Motoyama, 2013).

Proponents of DR have suggested that because of its emphasis on community-based service provision, DR may mitigate differential decision making associated with race (Allan & Howard, 2013; Loman & Siegel, 2012). The three studies described here

were designed to determine whether patterns of CPS decision making are different for counties with high proportions of African American children or children living in poorer counties; whether children of different races and ethnicity experience different likelihoods of decision making; and if the apparent relationships among poverty, race, and decision making in neglect cases are weaker in DR counties than in others.

Summary of Research Questions and Methods

Chapters 2-4 report results from three discrete yet conceptually related studies of the influence of DR on CPS decision making. All three employ data from the National Child Abuse and Neglect Data System (NCANDS). Although NCANDS data includes records from all CPS investigations in nearly every state, issues related to data quality and depth resulted in the exclusion of records from many states. Exclusion criteria varied slightly across the three studies based on the measures examined and research questions explored. The table in Appendix A lists the states excluded by study, along with a brief explanation of the exclusion decisions. The methods of each analysis are described in detail within each chapter and are summarized below.

Chapter 2: The Influence of Differential Response on Decision Making in CPS Agencies

Given findings from past studies that suggest DR may affect significant changes in the population of investigated cases, this study's chief aim was to use a national dataset to assess the magnitude of DR's influence on investigation, substantiation, and out-of-home placement rates.

Research questions. Two primary questions were addressed: (1) After accounting for select community characteristics, to what extent does DR lead to different

investigation, substantiation, and removal rates among cases with neglect allegations? (2) If significant relationships exist between decision outcomes and county-level characteristics, does DR moderate these relationships? The analysis also explored a methodological question regarding what effects occur from using population-based versus decision-based enumeration approaches when modeling the influence of predictors on aggregate rates of investigation, substantiation, and removal.

Methods. The study used information from the 2010 NCANDS dataset to examine the relationship between DR implementation and investigation, substantiation, and removal rates in 297 U.S. counties and 994,045 cases. Two different types of decision rates were calculated, based on techniques described in Rolock (2011). These were: (1) *Population-based* rates (i.e., investigation/population; substantiation/population; and removal/population), which used the county population as the denominator for all three decision outcomes, and (2) *Decision-based* rates (i.e., substantiation/investigation and removal/substantiation), which used the population from the preceding decision point as the denominator in order to isolate the unique effects of each decision point. Three covariates were created from other data sources to account for 2010 county population characteristics. These were the percentage of children living below the federal poverty line, the percentage of African Americans children, and population density per square mile.

Two multivariate approaches were used compare DR (n= 81) to non-DR counties (n= 216). First, sets of ordinary least square regression models were tested for each of the three decision outcomes. These models used decision-based rates as dependent variables in order to control for effects accumulated from prior decision points. For each

outcome, a reduced model without DR was compared to a model with DR. Second, path analyses were conducted to identify mediating effects of prior decision points and moderating effects of DR on the influence of poverty and race/ethnicity on decision outcomes. Because path analyses allow all three decision outcomes to be modeled simultaneously, the dependent variables used population-based rates.

Chapter 3: How Differential Response has Changed Decision Making for Investigated Cases: A Multilevel Analysis

This study extended the analysis from Chapter 2 by integrating child-level information into a multilevel analysis of substantiation decisions. The dependent variable was the likelihood that a child's investigation would result in substantiation. Child-level racial/ethnic categories were included in the model to further investigate differential decision making by race and assess whether DR mitigates the effect of race/ethnicity on decision making. One notable limitation of this study is the lack of measures of child risk factors and family poverty in the NCANDS dataset. Although county-level poverty measures were included, additional child- and family-level information would have helped provide a better understanding of case-level decision making.

Research questions. (1) Do child racial/ethnic characteristics, county DR implementation, county poverty rates, and county racial diversity influence the probability of an investigated neglect case receiving a substantiated disposition? (2) Does the effect of child race/ethnicity on substantiation decisions vary across counties? (3) Do county-level predictors help to explain any differential effect of race on substantiation across counties?

Methods. This study used 2010 NCANDS data (284 counties, representing 997,512 cases) and employed multilevel logistic regression to assess the relationship between substantiation decisions and child- and county-level factors. Child-level predictors included age, race/ethnicity (African American, Asian, Hispanic, White, and Other), sex, and whether the child was a prior victim (i.e., had ever received a previous substantiation or "indicated" disposition). County-level predictors included population density, White child rate (to measure racial diversity at the county level), child poverty rates, and DR implementation. Model testing proceeded in five iterative blocks: (1) the null model; (2) child-level fixed effects; (3) county-level fixed effects; (4) random effects for child-level race; and (5) interactions to test moderation between race and county-level effects.

Chapter 4: Moving Mountains: A Longitudinal Analysis of Changes in Investigation and Substantiation Rates in U.S. Counties Associated with Differential Response Implementation.

The final study took a different approach from the previous two cross-sectional studies by using eleven years of NCANDS data (2000-2010) to document whether the launch of DR was associated with changes in county-level investigation and substantiation rates. Previous evaluations of DR implementation suggest that the rate of investigations falls over time as DR becomes more established and CPS workers divert an increasingly higher proportion of cases to an alternative response (Loman & Siegel, 2004; Shusterman, et al., 2005; Westat, 2009). This analysis, however, sought to determine if patterns in the rate of change are evident across a national sample of counties and, if so, when those changes are likely to take place.

Research questions. Three main questions were addressed: (1) Is the implementation of DR associated with a decrease in *the proportion of a county's child population* experiencing a neglect investigation or substantiation over time? If DR results in significant changes, when and at what rate do such changes occur? (2) Is the implementation of DR associated with an increase in *the proportion of investigated cases* that result in a substantiation over time? If DR results in significant changes, when and at what rate do changes occur? (3) If DR is associated with significant changes in decision rates, do patterns remain consistent for different racial and ethnic subpopulations of children?

Methods. This longitudinal analysis examined three dependent variables: rates of neglect investigations within the population (investigation/population rates), neglect substantiations within the population (substantiation/population rates), and neglect substantiations within investigations (substantiation/investigation rates). It also employed four phases of analysis. First, descriptive analyses were conducted to compare non-DR counties to DR-counties over time. These used data from eleven years of NCANDS submissions, resulting in a total sample of 295 counties from 42 states, with aggregated data from 7,658,147 neglect investigations. In the second phase, the sample was restricted to counties that had a DR initiative operating at some point within the eleven-year study time frame. This lowered the sample size to 70 counties from 15 states, with aggregated data from 1,142,174 neglect investigations. A piecewise mixed-effect model was then used to compare pre-DR and post-DR decision-making patterns. In the third analysis, the sample was divided across racial/ethnic subpopulations (African American, Hispanic, and White children), and the piecewise mixed-effect equations were

modeled again to detect differences in decision-making patterns based on race/ethnicity. Finally, additional post-hoc descriptive analyses were conducted to investigate unexpected null findings for substantiation/investigation rates found in Phase 2.

Chapter 5: Conclusion

Together, the three studies provide a comprehensive assessment of the national impact of DR on CPS decision making, both cross-sectionally and over time. The fifth and final chapter offers a synthesis of the findings as a cohesive line of inquiry, after which it identifies research and policy implications. It also summarizes the studies' limitations and suggests directions for future research.

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CHAPTER 2

The Influence of Differential Response on Decision Making in Child Protective Service Agencies

Introduction

Public child protective services (CPS) systems make a series of decisions for each child maltreatment allegation they receive, including whether to screen in a referral, to substantiate an allegation of maltreatment, and to remove a child from his or her home when necessary. Although decision making is presumably driven by the same principles across CPS agencies (e.g., assessing risk of harm), substantial variation exists in decision outcomes across states and counties. In 2010, for example, the nation's average rate of CPS cases that resulted in some type of CPS response was about 25 cases per 1,000 children. However, among states, this rate varied by a factor of more than five, ranging from a low of 10 to a high of 51 cases per 1,000 (U.S. Department of Health and Human Services, DHHS, 2011a). Substantiation rates varied even more widely, from 2.2 to 28.8 per 1,000 children, as did the percentage of children with substantiations who were placed into out-of-home care (ranging from a low of 6% to a high of nearly 70%). Some of this variation is due to local factors such as population density, racial composition, and poverty levels, which produce regional clusters of children experiencing high levels of risk (Wulczyn & Brunner Hislop, 2003). Still, at least some of the variation results from different decision-making policies and practices adopted by CPS agencies.

Differential response (DR) is one such policy that may contribute to variations in patterns of county-level decision making. In general terms, DR involves diverting some moderate-risk children to services without launching a formal CPS investigation. DR agencies therefore have different decision options for CPS cases than non-DR agencies, which suggests that DR may lead to changes in agency-wide patterns of CPS involvement across decision points. Although some studies have examined outcomes for

children who receive DR services, little is known about broader system changes that may result from the implementation of DR. This study tests several hypotheses about CPS decision making by examining the influence of DR on county-level rates of investigation, substantiation, and removal decisions while accounting for local demographic characteristics.

Analyzing Differential Response

DR and related terms such as "alternative response" and "family assessments" refer to an array of options offered in the early stages of CPS involvement. Authors such as Merkel-Holguin, Kaplan, and Kwak (2006) have sought to identify the minimal core elements of DR, but for this study the most salient element is that an alternate track is available for eligible families after a case has been screened in and without a formal investigation occurring. Much of the existing DR research has examined the extent to which families receiving an alternate response are as safe as those receiving a traditional investigation, and whether they differ from other families on outcomes such as service receipt and satisfaction (Conley & Berrick, 2010; Loman & Siegel, 2005; Ruppel, Huang, & Haulenbeek, 2011). Studies have also shown that DR reduces the number of investigations (Westat, 2009) and the rate of substantiation (Loman & Siegel, 2005). However, most of these studies evaluated DR within one state or in a small number of states and did not make comparisons among DR agencies or between DR and non-DR agencies. Finally, DR research thus far has given less than full attention to whether child neglect, which is the most commonly reported type of maltreatment and represents the largest portion of cases diverted to DR (U.S. DHHS, 2011b).

Decision Making in Cases of Neglect

Over three quarters of all child maltreatment victims (78%) experience neglect (U.S. DHHS, 2011a), it is the least clearly defined maltreatment type and possibly a major source of decision-making variability (Dubowitz, 2007; Straus & Kantor, 2005). Numerous strategies have been developed to improve the accuracy of decision making in CPS, including family group decision making and algorithmic-based assessments (Chor, McClelland, Weiner, Jordan, & Lyons, 2013; Crea, 2010; DePanfilis, 2006). Still, studies have uncovered undesirable variability in decision making across CPS staff (Munro, 1999; Rossi, Schuerman, & Budde, 1996) and different rates of decision outcomes across agencies (Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010; Yoo & Brooks, 2005). Neglect cases may be particularly difficult to reliably assess because they are characterized by an omission of care, which is distinct from other maltreatment types that are usually defined by acts of harm. One difficulty is that the legal definition of neglect varies by state (Child Welfare Information Gateway, 2011), and there are various subcategories, including physical, medical, educational and emotional neglect that are used in some but not all states (Barnett, Manly, & Cicchetti, 1993; Sedlak et al., 2010).

A further concern is that some children experience conditions similar to neglect that are caused by poverty, incapacity, or other circumstances unrelated to a caregiver's intent to maltreat (DePanfilis, 2006), and, no clear consensus has emerged among scholars as to whether the intent to maltreat is a necessary part of the definition of neglect (Dubowitz, 2007; Hearn, 2011).

Neglect and Poverty

The relationship between child neglect and poverty is well documented in the literature. Longitudinal studies have found poverty, unemployment, public assistance, and other measures of economic risk among cases reported for neglect (Slack et al., 2011) and substantiated or indicated for neglect (Mersky, Topitzes, & Reynolds, 2009). Also, a study of U.S. maltreatment incidence rates found that socioeconomic status was a significant predictor for neglect (Sedlak et al., 2010).

CPS decision making appears to be affected by poverty not only at the family level, but also in the neighborhood and community. Areas with concentrated poverty are more likely to have structural and social problems such as low-quality schools, high incidents of violence and criminal activities, few job opportunities, and high rates of social isolation (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007). One study included poverty among several indicators of social disorganization and reported that children residing in counties with low levels of organization are more likely to enter substitute care during a maltreatment investigation (Jantz, Rolock, Leathers, Dettlaff, & Gleeson, 2012). Similarly, Drake and Pandey (1996) found that neglect, more than other forms of maltreatment, has a particularly strong association with neighborhood poverty.

A further complication is the fact that rates of poverty and neglect differ by race, as does CPS decision making. For example, two studies that examined child welfare practices in Texas found that, when compared to cases of White children with similar risk scores and poverty levels, cases of African American children were more likely to be substantiated (Dettlaff et al., 2011) and result in removal of the child from the home (Rivaux et al., 2008). Other research suggests that high rates of CPS involvement for minority (and particularly African American) children may be driven less by CPS

decision-making practices and more by family and community risk factors that occur at higher rates in minority populations (Bartholet, 2009; Drake et al., 2011; Font, Berger, & Slack, 2012; Putnam-Hornstein, Needell, King, & Johnson-Motoyama, 2013). For instance, poor African American children are more likely to live in areas with high concentrations of poverty than are poor White children (Drake & Rank, 2009).

Due to the complexity of measuring and defining race and its effects, this study does not include an in-depth analysis of racial disparity within CPS agencies. Similarly, because of the limited information about family poverty in National Child Abuse and Neglect Data System records (NCANDS, U.S. DHHS, 2011b), the study is unable to fully address the complex interaction of race, poverty, and neglect at the individual level. Its analysis of race is restricted to African American children because of the low rates of other minorities in many counties (Dettlaff et al., 2011) and evidence that minority groups differ from one another in terms of patterns of decision-making outcomes (Drake et al., 2011; Putnam Hornstein et al., 2013). Still, the study will be able to detect if patterns of CPS decision making are systematically different for counties with high proportions of African American children or children living in poorer counties. If some neglect cases represent families unnecessarily involved in CPS for reasons related to poverty rather than child safety issues, then DR, with its emphasis on community-based service provision, offers an alternate way to provide resources to these families (Loman & Siegel, 2012). Therefore, it is anticipated that relationships between poverty, race, and decision making in neglect cases will be weaker in DR counties than in others.

Measuring Decision Making

A final area of scholarship salient to this analysis is how best to measure decision making in CPS agencies. Recent studies examining racial disparity have made substantial conceptual and methodological contributions to measuring decisions as interrelated points along a case trajectory (Drake et al., 2011; Rolock, 2011; Shaw, Putnam-Hornstein, Magruder, & Needell, 2008). Most researchers construct some sort of proportion or index to compare decision outcomes between minority children and White children. When using a proportion, however, the choice of denominator is critical to capturing the decision of interest. Rolock (2011) identifies two ways to measure CPS decision outcomes: *Population-based enumeration* uses the full population as the denominator and captures effects that have accumulated during prior decision-making points. *Decision-based enumeration* uses the population from the preceding decision point as the denominator, and captures only those effects that are unique to the specific decision point. In addition to their use in studying racial disparities, these measures can be applied to a more general examination of decision making among agencies.

This paper addresses two substantive research questions: first, after accounting for community characteristics such as poverty and proportion of African American children, to what extent does DR lead to different investigation, substantiation, and removal rates among cases with neglect allegations? Second, if significant relationships exist between decision outcomes and county-level characteristics, does DR moderate these relationships? In answering these questions, the study will also seek to determine the effect of using population-based versus decision-based enumeration approaches when modeling the influence of predictors on aggregate rates of investigation, substantiation, and removal.

Methods

Data and Study Population

Data were drawn from the 2010 National Child Abuse and Neglect Data System (NCANDS) child file (U.S. DHHS, 2011b). The file contains information about screened-in CPS referrals (reports) that received a disposition decision between October 1, 2009, and September 30, 2010. Each child may have more than one report in a given year and approximately 12% of children in the study sample had more than one report in 2010. Accordingly, the rates for investigation, substantiation, and removal used in this analysis represent rates that include duplicate children.

The national scope of NCANDS makes it well suited for studying county-level variation, but such a broad representation of U.S. counties also creates challenges to ensuring the integrity of NCANDS data. Accordingly, a significant number of counties were eliminated from the study in order to address two issues related to the diversity and volume of counties contained in the data file: data quality and county representativeness.

Data quality. NCANDS is a voluntary reporting system, and some states report items inconsistently or not at all (Fallon et al., 2010; Woodruff, 2006). These state-specific reporting aberrations result in large amounts of data that are systematically missing from certain counties or states. Differences in reporting procedures can produce clustering effects that may skew findings, particularly for studies such as this where counties are the unit of analysis. The author conducted extensive exploration on key indicators to find state- or county-level clusters of missing data or deviations from expected values. When these clusters were detected, the author contacted state data administrators whenever possible to determine the source of the aberration. This quality

assurance process resulted in the removal of data from all counties in Connecticut, New Jersey, New York, Pennsylvania, Puerto Rico, and Oregon, along with two counties in Virginia. Additionally, all ten counties in Georgia were missing information on child removals and so were excluded from the OLS regression and path analyses that used child removal as a dependent variable.

County representativeness. Some counties were also eliminated from the final analysis to ensure that those remaining in the study sample were comparable. Specifically, counties with small overall child populations and extremely small proportions of African American children were eliminated from the study. With regard to overall child populations, all counties with less than 38,000 children were excluded in the study because many small counties were not identified in the original NCANDS sample. To protect the identity of children, NCANDS policy requires that the county identifier be removed from any record that originated from a county with less than 1,000 reports. Therefore, the only reports containing county identifiers from small counties are those from small counties with relatively high rates of CPS involvement. To avoid misrepresenting small counties, the author chose to include only those counties with large enough populations to have at least 1,000 reports even if their CPS report rate was slightly lower than average. This was operationalized by creating a population size restriction: only reports from counties with screened-in child populations of at least one standard deviation below the national mean of 4.96 screened-in responses per 1,000 children were included.

Five additional counties in three different states were removed from the study because of extremely low proportions of African American children (i.e., <1% of the

child population). As discussed above, the racial composition of a county may influence CPS decision making, and counties with a low presence of African American children may be unique in other, unmeasured ways (Ards, Myers, Malkis, Sugruc, & Zhou, 2003). Moreover, estimates for subpopulations that represent such a small proportion of the total population are less precise and can lead to inaccurate incidence rates, especially when calculating rates by subpopulation for events such as CPS involvement that affect only a small number of children in the overall population (McMorrow, 2009).

In addition to eliminating entire counties from the sample, some child-level records used to calculate the county-level measures were also excluded. Specifically, only *neglect* reports with a disposition of *substantiated*, *indicated*, or *unsubstantiated* were retained. NCANDS has two neglect maltreatment types: *neglect or deprivation of necessities* and *medical neglect*. This analysis included only cases with "neglect or deprivation of necessities." The majority of states only use *substantiated* and *unsubstantiated* categories, but six states also use *indicated*, which, for the purposes of NCANDS reporting, applies to cases where there was reason to suspect maltreatment but an allegation could not be substantiated (U.S. DHHS, 2011a). Four other dispositions tracked by NCANDS—*intentionally false*, *closed with no finding*, *alternative response victim*, and *alternative response nonvictim*—are not used by all states. By only including those neglect records with dispositions of substantiated, indicated, or unsubstantiated, the analyses were able to focus on the most important and reliably comparable dispositions. Following the exclusion protocols described above, the final data set included information from 297 counties from 42 states, incorporating 994,045 neglect investigation records.

Measures

Dependent variables. The three dependent variables in this analysis are investigation, substantiation, and removal rates. An *investigated report* refers to any allegation of neglect that received a disposition of substantiated, indicated, or unsubstantiated, including reports in which neglect co-occurred with other forms of maltreatment. Approximately 30% of neglect cases in this analysis had at least one other type of maltreatment indicated. *Substantiated reports* are those in which the allegation of neglect resulted in a disposition of substantiated or indicated. If neglect was unsubstantiated, but another type of maltreatment was substantiated, the case was considered unsubstantiated for this analysis. *Removal* refers to those substantiated or indicated neglect reports that resulted in an out-of-home placement during the reporting period. Removals include both formal out-of-home care (i.e., foster care) and brief removals. Because removals represent a variety of responses, in this analysis the term *removal* is best understood as a decision that represents one form of increased CPS involvement, whether or not traditional out-of-home care occurs. Further, removal rates could not account for removals that occurred beyond the NCANDS reporting period.

To address the additional research question regarding measurement approaches to decision making, the study applies decision- and population-based enumeration methods from Rolock (2011). The three population-based rates are calculated as the incidence per 1,000 children within a county. Decision-based substantiation rates are a percentage of investigated reports, and decision-based removal rates are a percentage of substantiated reports. Because investigation represents the earliest decision captured in the NCANDS

child file, the investigation rate in the decision-based enumeration was the same as the rate in the population-based approach.

Predictors. This analysis included DR implementation and four additional county-level covariates.

A county was categorized as implementing DR if its model aligned with the DR elements described by Merkel-Holguin and colleagues (2006). Data about DR implementation were gathered through resources available from the Quality Improvement Center for Differential Response and verified through documentation in written state policies and statutes or direct communication with CPS representatives in the state.

Three covariates were created from other data sources to account for 2010 county population characteristics: (1) the percentage of children living below the federal poverty line (U.S. Department of Agriculture, 2012), (2) the percentage of African Americans among all persons age 18 and under (National Cancer Institute, NCI, 2013), and (3) population density per square mile (NCI, 2012; U.S. Census Bureau, 2010). These covariates were included to control for demographic differences in county population and test whether the implementation of DR moderated the relationship between the covariates and decision outcomes. The final covariate, prior victim status, was the percent of investigated reports for children with previous substantiated or indicated incidents of maltreatment out of all investigated reports. Previous literature suggests that children who were victims of a prior CPS report represent a subpopulation of CPS-involved children with multiple risk factors, including poverty and parental substance abuse (Connell, Bergeron, Katz, Saunders, & Kraemer Tebes, 2007).

Analysis Plan

Descriptive analyses. Exploratory analysis was conducted to assess the distributional properties of the variables. To determine the extent to which the sample counties represented U.S. counties, *t*-tests were calculated to compare demographic characteristics among the following subpopulations: (1) all U.S. counties to large U.S. counties (i.e., with at least 38,000 children), (2) all U.S. counties to sample counties, and (3) large U.S. counties to sample counties. Finally, a second set of *t*-tests were employed to identify differences between DR and non-DR counties.

Multivariate Analyses. Multivariate ordinary least square (OLS) regression models were constructed for each of the three decision-making outcomes to isolate the effects of DR and other county characteristics on decision-based investigation, substantiation, and removal rates. The influence of DR implementation was tested by examining two models for each decision point: a reduced model without DR implementation and a full model with DR as a predictor. *F*-tests with Bonferroni corrections were used to determine if there was a significant difference in *R*-square values between the reduced and full models at each decision point (Cohen, Cohen, West, & Aiken, 2003).

Accumulated effects across decision points were analyzed using path analysis. Unlike the decision-based enumeration used for substantiation and removal rates in the regression analysis, the three decision-making outcomes in the path model used population-based enumeration. Population enumeration was appropriate because the path analysis accounted for the influence of prior decision points by allowing earlier decision rates to predict later decision rates. Model fit was assessed by a χ^2 test, Root Mean

Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMSR).

Path Model 1 tested the direct effects of DR implementation, child poverty rates, proportions of African American children, prior victim rates, population density, and any earlier decision outcome (i.e., investigation, substantiation) on each of the three decision outcomes. This model also tested potential mediation effects of (1) investigation rates on substantiation and removal rates and (2) substantiation rates on removal rates. A bootstrap resampling method was used to provide accurate confidence intervals (CIs) and standard errors for assessing mediation effects (MacKinnon, Lockwood, & Williams, 2004). Path Model 2 tested moderation effects of DR by conducting a multiple-group path analysis where group invariance was tested for each predictor of interest through χ^2 difference tests (Muthén & Muthén, 1998-2012). Descriptive analyses and OLS regressions were conducted using SPSS 21, whereas the path analyses were conducted using M-Plus 7 (Muthén & Muthén, 1998-2012).

Results

Descriptive Analysis

Exploratory analysis revealed that none of the five decision outcomes (population-based investigation, substantiation, and removal rates, and decision-based substantiation and removal rates) were normally distributed. To address this, each dependent variable was transformed using its square root (Cohen et al., 2003). Other procedures were used to produce more robust heteroscedasticity-consistent estimates that adjusted standard errors in the regression models (Hayes & Cai, 2007). The descriptive results (Tables 2.1 and 2.2) use non-transformed values for dependent variables, and the

multivariate results (Tables 2.3-2.5 and Figure 2) use transformed values and standardized coefficients.

Table 2.1 compares covariate descriptive information among all U.S. counties (*n*= 3,141), all counties with at least 38,000 children ("large counties," *n* = 387), and the sample counties used (*n* = 297). The population of all U.S. counties is distinct from the populations of both large counties and sample counties for every descriptor. However, sample counties did not differ significantly on any characteristics from large U.S. counties, suggesting that the sample is representative of large counties in the U.S.

[Table 2.1]

Differences exist, however, between DR and non-DR counties. Compared to non-DR counties, those with DR had smaller populations and larger proportions of African American children (see Table 2.2), which supports the use of multivariate statistics to control for covariates. Without accounting for other predictors, DR counties had significantly lower population-based rates of investigation, substantiation, and removal than non-DR counties. In contrast, DR counties had higher decision-based substantiation rates (i.e., rates of substantiation among investigated cases) compared to non-DR counties, but no significant differences were present in decision-based removal rates.

[Table 2.2]

Multivariate Regression

To assess the influence of DR on decision outcomes in a multivariate context, a regression model without DR implementation (reduced model) was compared to a model with DR implementation (full model) for each outcome. Tolerance statistics (.68 — .95) and Variance Inflation Factors (1.5 — 1.1) indicated no concerns with multicollinearity.

Regression models for substantiation and removal rates used decision-based enumeration to isolate unique contributions of predictors at these decision points (Rolock, 2011).

[Table 2.3]

Table 2.3 presents results from the regression models. The values for R-square diminished across the three decision points (*R*-square = .50, .26, .09, respectively), suggesting that county-level predictors contributed to more variance in counties at early decision points than at later decision points. Higher county-level child poverty rates were associated with higher investigation and removal rates, but lower substantiation rates. Once DR was introduced into the models, the effects of higher proportions of African American children in the population became non-significant for investigation and remained non-significant for substantiation rates. Higher population density was related to higher substantiation rates, but it was not significantly predictive of investigation or removal rates. Prior victim rates were positively associated with investigation rates but had no significant effects for the two subsequent decision points. DR implementation significantly improved the *R*-square statistic for each decision outcome, as indicated by *F*-tests, although the effect was smallest at removal.

Path Analysis

As an early attempt to identify important county-level variables that contribute to variation in decision rates, the *a priori* model included every conceivable recursive relationship of potential interest. Since no parameters were constrained, this initial model is "just identified," and its fit is impossible to test (Wang & Wang, 2012). In the path models presented, the number of parameters was reduced by constraining the pathway of prior victim rates to investigation rates, as supported by the regression findings. This

constraint did not change the relationships of the predictors in any meaningful way from the just-identified *a priori* model, but it allowed tests of model fit. Indices showed good model fit, $\chi^2[2] = .86$, $p = .65$; RMSEA = .00; CFI = 1.00; SRMR = .004.

[Figure 2]

Figure 2 depicts the pathways for the non-moderated model, and the coefficients are presented in Table 2.4. Compared to the results from the regression analysis, two important effects are not significant in the path analysis: county-level child poverty at substantiation and DR at removal. The differences in results produced by the two multivariable analysis methods are due to the strong mediation of preceding decision points in the path model, shown in Table 2.4.

[Table 2.4]

The extent to which DR moderated the influence of other county characteristics on the decision outcomes was tested by assessing multiple-group invariance (Byrne, 2004). Although the full path model has 287 counties, which is an acceptable sample size (Wang & Wang, 2011), the multiple-group analysis generates separate path analysis for DR- and non-DR subgroups (n = 86 and 206, respectively). Significant results from preliminary analysis of possible moderation effects are shown in Table 2.5, but because of the low and unbalanced sample sizes, these findings should be interpreted with caution. DR significantly reduced the effects of county child poverty rates and increased the effects of prior victim rates at investigation. Higher investigation rates were more strongly associated with higher substantiation rates in DR counties. The *R*-square values indicate that the model performed better for DR counties, suggesting that there may be

other, unmeasured variables that influence decision making, especially in non-DR counties.

[Table 2.5]

Discussion

Both regression and path analysis results support the claim that DR influences decision-making patterns in child welfare agencies. Specifically, DR implementation is associated with lower investigation rates, which aligns with findings from previous studies (Westat, 2009). As shown in Table 2.2, DR counties also have lower population-based substantiation rates in univariate analysis. In multivariate models that account for other county characteristics and investigation rates, however, DR counties showed higher substantiation rates among investigated cases, suggesting DR may improve the accuracy of CPS responses by reducing the rates of false positives. That is, DR counties may have, on average, fewer families who experience a child welfare investigation that ultimately results in no substantiation of the allegation. Although DR was significantly associated with lower removal rates in the regression analysis, when the mediation effects of prior decision making were taken into account in a path model, the effects of DR on removal rates became non-significant. The smaller effects at removal would be expected given that DR is a system reform that targets earlier decision points.

The results also contribute new information about how county-level poverty rates may predict patterns of decision outcomes among child welfare agencies. In multivariate analyses, higher child poverty rates were associated with higher investigation rates and lower decision-based substantiation rates (although in the path analysis these associations were not significant for substantiation). This offers support for the strong associations

between poverty and investigation rates found in previous studies (Slack et al., 2011). The findings also lend credence to the concern noted in prior literature that families may be inappropriately referred for child welfare investigations due to factors associated with poverty rather than maltreatment (DePanfilis, 2006; Shdaimah, 2009). Findings from the multiple-group path analysis indicate that DR implementation is significantly associated with reductions in the relationship between poverty levels and investigation rates, which suggests that in DR counties, families that come to the attention of CPS because of an unmet need related to poverty may be diverted to an alternative track prior to investigation.

Less clear is the relationship between the proportions of African American children residing in the county and patterns in CPS decision outcomes. Neither of the final multivariate models showed a significant relationship between the proportion of African American children and investigation or substantiation rates. Higher proportions of African American children corresponded with lower removal rates in the regression models, but no significant effects were found in the path models. Further, removal rates were negatively associated with the proportion of African American children in a county, and positively associated with county child poverty rates. Other recent studies have shown complex interactions among poverty, race, and CPS response. In particular, Drake and Rank (2009) found that White children were more likely than African American children to be reported in high-poverty areas and that African American children were more likely to be reported in low-poverty areas. Yet a subsequent study found that moderate levels of community poverty was positively associated with substantiation rates for African American children, but reversed for White children (Jonson-Reid, Drake, &

Zhou, 2013). This mix of findings indicates that future research may be needed to understand the differential effects of community poverty by race on CPS involvement.

This study also did not include measures of racial disparity (e.g., the degree to which African American children were more likely than White children to be involved in CPS, given their representation within a population), which may provide a more nuanced view of how race affects decision making. Racial disparity measures were excluded both to reduce model complexity in this initial, pre-theoretical examination of county characteristics and because race effects may be better measured in an analysis that can account for child characteristics.

NCANDS data provides a unique opportunity to examine CPS decision making on a national scale, but not without limitations. To date, NCANDS data about family risk factors and services are not collected consistently enough to allow meaningful comparisons across counties or states. Additionally, many counties were eliminated from the analysis because of NCANDS reporting issues such as lack of comparability (for small counties) or large amounts of missing data. Therefore, the selection of counties in this study is not random. In fact, the counties do not represent a sample at all, but rather represent a subpopulation of counties that fit the inclusion criteria designed to reduce unwanted clustering effects from state reporting aberrations. Descriptive analysis suggests that the study counties have similar demographic characteristics as large counties in the U.S., but the counties that were eliminated because of data concerns may differ from sample counties in other, unmeasured ways. Like most multi-jurisdictional data collection efforts, the quality of NCANDS datasets improves every year; thus, future research may allow the inclusion of a larger number of counties. A related consideration

is that county DR implementation was not random, and there may be unmeasured confounding factors that relate to both DR implementation and differences in CPS decision making.

Another limitation of this study is that it focused on a small number of county-level effects. For example, measures of agency climate and characteristics of CPS professionals were not available for all counties in this study, and some evidence suggests that these may influence decision making at the case level (Dettlaff et al., 2011). Aggregate measures of poverty and proportion of African American children included in this model cannot be assumed to represent a child's experience of community risk, which is better assessed at the neighborhood level (Aron et al., 2010). Instead, county-level racial composition and poverty measures were hypothesized to contribute to higher aggregate rates of CPS involvement. Thus, the analysis suggests that decision-making rates among large counties are related to several county-level indicators, but the same indicators may only contribute a small part to predicting a child's decision outcome. A multilevel analysis that accounts for child-level factors may help reveal the extent to which DR and county population characteristics influence a child's likelihood of experiencing certain decision outcomes.

Additionally, this analysis included both cases with a single neglect allegation and those with multiple types of maltreatment allegations. Future research may be warranted to determine if decision-making patterns are different for cases that involve a single allegation of neglect compared to cases with co-occurring allegations.

A final limitation is that the investigation stage is the earliest point included in the NCANDS dataset, so it is not possible to isolate predictors of investigation decisions

from those that may drive earlier decisions, such as screening out hotline calls or even a person's decision to make the initial report to CPS. This means that factors such as DR and poverty rates, which were found to influence investigation rates, should be interpreted as predictors that influence decisions up to and including investigation.

Implications

This study makes three significant contributions to current knowledge about CPS decision making and the implementation of DR. First, it highlights the need to integrate county-level population characteristics and agency policy differences into research about decision outcomes. To date, research about CPS decision making has primarily focused on case and staff factors, ignoring broader characteristics such as county population and major CPS system differences. This is because studies that collect in-depth data about child risk factors and staff characteristics are often constrained to one or a few jurisdictions. Many researchers are also reluctant to use national administrative datasets such as NCANDS because of the high degree of variation found across jurisdictions. This study demonstrates that much of this variation is not unmeasurable error, and real differences in county characteristics and agency policy and practices can be explored. As data resources improve, researchers may be able to integrate measures of child risk, staffing, and county-level characteristics within a single model to better predict the experiences of children and families served by complex systems.

Second, this study offers a unique comparison of two methods of aggregating decision rates. By accounting for earlier events, decision-based rates identify the contribution of predictors at a single decision point. Population-based rates may be less meaningful for examining a single decision point because those rates also include the

accumulated effects of prior decisions. When used in a mediation model, however, population-based rates identify the indirect effects of prior decisions that were not fully accounted for in the model using decision-based rates. Many of the results from the decision-based regression models and the population-based path analysis were similar, but two major differences were that the regression analysis found significant effects for child poverty at substantiation and DR at removal, which were both non-significant in the path model. These differences can be attributed to powerful mediation effects from previous decision points within the path model. The divergent results do not indicate a problem with the model; instead, they highlight how rate calculation methods influence findings. The choice of calculation method depends primarily on the research question: Decision-based rates may be most useful for understanding predictors and intervention effects at a discrete decision point, and population-based rates used in mediation models may provide a more complete picture of decision-making systems. This study suggests that caution is needed whenever examining rates of later decision points using non-mediated models. For example, regression results indicated that DR reduced removal rates, but the path model demonstrated that DR's effect on removal is almost entirely indirect and due to DR's larger effect on previous decision points.

Finally, this study supports the notion that DR is a major system reform with effects extending beyond the outcomes of those families who avoid a formal investigation. Prior research has mostly compared the outcomes for families served in an alternate track with those who received a traditional investigation within a single agency (Brown, Merkel-Holguin, & Hahn, 2012; Loman & Siegel, 2012). These works establish DR's appropriateness as part of a CPS response, but they offer little information about

how DR changes systems overall. The current study shows dramatic shifts in the CPS population in DR counties: The agencies are investigating fewer cases, and those they do investigate are more likely to be substantiated. The findings also suggest that DR moderates the impact of poverty on investigation rates. Such changes in the front-end response to CPS-involved families have implications for training, staffing structures, and resource disbursement in public CPS agencies and community service providers. Formative evaluations that address the intended and unintended system changes resulting from the adoption of DR are needed to help guide policy formation.

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Table 2.1

County-level Descriptive Statistics Comparing Study Counties to All U.S. Counties

	All Counties			All Large Counties			Study Counties		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Child population	3,141	23,599	77,102	387	135,399[a]	183,298	297	140,594[a]	20,1863
Child poverty rate	3,137	24%	9	387	20%[b]	8	297	21%[b]	8
African American child rate	3,141	11%	15	387	16%[c]	13	297	18%[c]	16
Population density	3,139	260	1728	387	1434[d]	4659	297	957[d]	1577

Note. Superscripts (a-d) indicate means that are not statistically different from each other ($p > 0.05$) according to 2-tailed *t*-test.

Table 2.2

County-level Descriptive Statistics Comparing DR and non-DR Counties

	All Study Counties			DR Counties			Non-DR Counties		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Child population	297	140,594[a]	201,863	81	108,462	78,850	216	152,643[a]	230,764
Child poverty rate	297	21%[c]	8	81	20%[c]	8	216	21%[c]	7
Proportion of Afr. Am. children	297	18%[b]	16	81	23%	18	216	16%[b]	16
Population density	297	957[d]	1,577	81	1,124[d]	1,565	216	894[d]	1,581
Investigation (pop. based)	297	25.3	19.1	81	12.7	11.9	216	30.1	19.2
Substantiated (pop. based)	297	6.7[e]	5.5	81	5.1	6.3	216	7.3[e]	5.0
Removal (pop. based)	287	1.7	1.5	81	1.1	1.3	216	2.0	1.6
Substantiated (dec. based)	297	30%	17	81	42%	22	216	26%	12
Removal (dec. based)	287	26%[f]	17	81	22%[f]	17	216	28%[f]	17
Prior victim rate	286	25%[g]	16	80	22%[g]	14	206	26%[g]	17

Note. Georgia (10 counties) does not report removal rates. Georgia and Hawaii (1 county) do not report prior victim rates. Superscripts (a-g) indicate means that are not statistically different from each other ($p > 0.05$) according to 2-tailed *t*-test. Population-based rates are per 1000 children in a county. Decision-based substantiation rates are percentages out investigated reports and decision-based removal rates are percentages out of substantiated reports.

Table 2.3

OLS Regression Models Using Decision-based Enumeration

	Investigation		Substantiation		Removal	
	Reduced β (SE)	Full β (SE)	Reduced β (SE)	Full β (SE)	Reduced β (SE)	Full β (SE)
Differential response		-.44* (.19)		.45* (.20)		-.15* (.30)
Child poverty rate	.43* (.01)	.35* (.01)	-.20* (.01)	-.12* (.01)	.21* (.02)	.19* (.02)
Proportion of Afr. Am. children	-.20* (.64)	-.07 (.54)	.09 (.57)	-.05 (.60)	-.30* (.87)	-.25* (.84)
Prior victim rate	.39* (.49)	.35* (.49)	-.01 (.55)	.03 (.45)	-.02 (.56)	-.03 (.55)
Population density	-.06 (.01)	-.05 (.01)	.17* (.01)	.16* (.01)	.05 (.01)	.05 (.01)
R^2	.33	.50	.07	.26	.07	.09
R^2 change[a]		.17*		.19*		.02*

Note. SE= Standard error. Robust heteroscedasticity-consistent SE estimators used.

[a] R-square change used F tests with Bonferroni adjusted alpha to control inflated Type I errors.

* $p < .05$

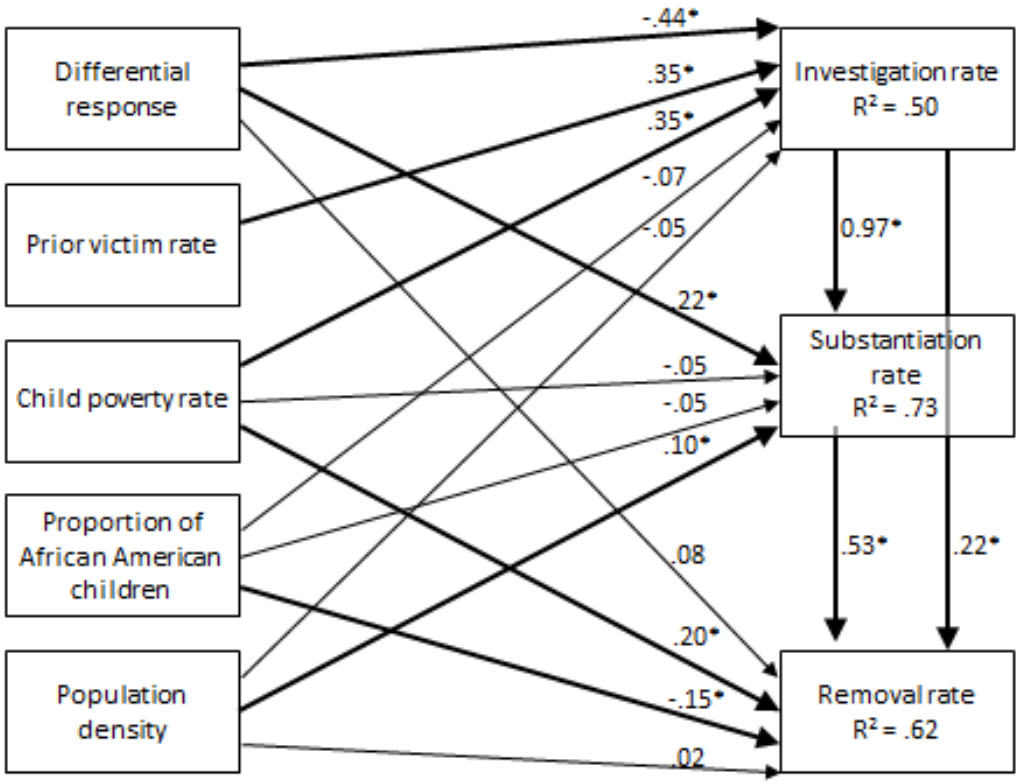

Figure 2: Non-moderated model. Standardized coefficients for direct effects presented.
* $p < .05$

Table 2.4

Results from Non-Moderated Path Model with Significant Mediation Effects

	Invest.	Substantiation		Removal			
	Direct (SE)	Direct (SE)	Inv on Sub [CI]	Direct (SE)	Inv on Rem [CI]	Sub on Rem [CI]	Inv+Sub on Rem [CI]
Differential response	-.44* (.04)	.22* (.04)	-.43 [-.50, -.35]	.08 (.05)	-.10 [-.17, -.03]	.12 [.07, .17]	-23 [-.29, -.16]
Child poverty	.35* (.05)	-.05 (.04)	.34 [.26, .43]	.20* (.05)	.08 [.02, .13]		.18 [.12, .24]
Proportion of Afr. Am. children	-.07 (.05)	-.05 (.04)		-.15* (.05)			
Population density	-.05 (.05)	.10* (.04)		-.02 (.05)		.06 [.01, .10]	
Prior victim rate	.35* (.04)	–		–			
Investigation	–	.97* (.03)		.22* (.01)		.52 [.41, .63]	
Substantiation	–	–		.53* (.08)			
R^2	.50	.73		.62			

Note. Standardized coefficients shown. Bootstrapped resample to better estimate indirect effects. Only significant indirect effects shown (p<.05). SE= Standard Error, CI=Confidence Interval.

* $p < .05$

Table 2.5
Multiple-group Analysis Showing Significant DR Moderation Effects.

	Investigation		Substantiation		Removal	
	DR	Non-DR	DR	Non-DR	DR	Non-DR
Differential response						
Child poverty rate	.22 (.12)	.44* (.06)				
Proportion of African American children						
Population density						
Prior victim rate	.67* (.07)	.32* (.06)				
Investigation rate			.89* (.03)	.83* (.03)		
Substantiation rate						
R^2	.49	.32	.86	.66	.79	.55

Note. Moderation effects tested only for predictors with significant direct effects. Table presents only those moderation effects shown significant through testing multiple-group invariance ($p < .05$, Byrne, 2004).
* $p < .05$

CHAPTER 3

How Differential Response Has Changed Decision Making for Investigated Cases: A Multilevel Analysis

Introduction

When children are reported for suspected maltreatment and the report meets initial screening criteria, child protective services (CPS) professionals must decide whether the case warrants a full investigation. In most CPS agencies, no substitute to investigation exists, but other agencies have Differential Response (DR) tracks that provide alternatives for families that are deemed to present low-to-moderate maltreatment risk. While the definition and implementation of DR varies by jurisdiction, generally this practice offers families the opportunity to receive referrals to community-based services such as parenting support classes, job training, and childcare without a formal investigation or substantiation (Merkel-Holguin, Kaplan, & Kwak, 2006).

Since DR (i.e., dual track, multiple track, alternative response, etc.) programs were first piloted by a few states in the 1990s, the impacts of DR on decision making in CPS agencies have been substantial. For example, when reviewing previous DR evaluations, Shusterman, Hollinshead, Fluke, and Yuan (2005) report that DR agencies diverted 42% to 71% of CPS reports to an alternate, non-investigative track. Over the past two decades, as DR has been disseminated widely throughout the U.S., research has continued to demonstrate that DR significantly alters the gatekeeping function of CPS by reducing the number of investigations and substantiations (Westat, 2009; see National Quality Improvement Center on Differential Response in CPS, QIC-DR, 2011 for review). In addition, as the number of maltreatment investigations decreases, the rate of investigated cases that are substantiated typically increases (Shusterman, 2005; Virginia Department of Social Services, 2007). Presumably, this shift in substantiation rates reflects a change in the composition of the pool of investigated cases. If risk assessment

aligns with decision making, than it would be expected that the rerouting of low-to-moderate risk cases from the investigation track would result in a commensurate increase in the likelihood of substantiation for the remaining higher-risk cases.

Among the factors that are typically incorporated into a CPS risk assessment are any prior CPS decisions related to the child and family in question. Children and families that have a record of substantiated abuse and neglect are logically considered to be at higher risk than those who have never been reported to CPS. However, among families that have been investigated, it is uncertain whether the prior decision to substantiate a maltreatment report is a valid and reliable indicator of subsequent risk. Some studies have shown that substantiated and unsubstantiated cases do differ upon re-report (Fuller & Nieto, 2009; Trocmé, Knoke, Fallon, & MacLaurin, 2009), whereas other studies imply that the distinction lacks any meaningful difference in subsequent risk assessments (Cross & Casanueva, 2008; Kohl et al., 2009).

Evidence suggesting that prior CPS investigation decisions may lack predictive validity underscores a concern in the DR literature, and in the child welfare field broadly, that CPS risk assessments reflect some measure of bias. That is, decisions are based not only on true indicators of risk, but also on extraneous factors that are correlated with risk. Most notably, a large body of research has explored whether the high rates of African American children found across decision points within CPS systems are due to racially biased decision-making (Hill, 2007; Magruder & Shaw, 2008; see Hill, 2008 for review). Two early National Incident Studies (NIS) of child maltreatment within the U.S. population found similar rates of maltreatment among African American and White children (Sedlak, 1991; Sedlak & Broadhurst, 1996). If the rate of child maltreatment for

African American children in the community appears lower than their presence within the CPS system, than racially-based differential decision making within the CPS systems would be a likely contributor to the apparent disproportionality. The most recent NIS, however, found maltreatment rates in the African American subpopulations to be higher than in the White subpopulation (Sedlak, McPherson, & Das, 2010). Other population-based studies have supported the recent NIS results, suggesting that the high proportion of African American children in the CPS system is due largely to socioeconomic and health-related risk factors associated with maltreatment that are present among African American families at disproportionately high levels (Drake, Lee, & Jonson-Reid, 2009; Putnam-Hornstein, Needell, King, Jonson-Motoyaman, 2013; Sedlak, McPherson, & Das, 2010). Proponents of DR suggest that its implementation may mitigate any racial/ethnic disproportionality that might exist by improving access to services that address risk factors (Allan & Howard, 2013). To date, however, little attention has been paid to whether and how the population of investigated cases may be affected by DR and the extent to which these effects may vary across racial/ethnic subpopulations (QIC-DR, 2011).

Using data from the 2010 National Child Abuse and Neglect Data System (NCANDS, U.S. Department of Health and Human Services, DHHS, 2011), this study employed multilevel models to compare the likelihood of substantiation for children in the investigation track in DR county agencies to the likelihood of substantiation for children in the investigation track in non-DR county agencies. The study also focused on cases with allegations of neglect because they are the most commonly reported form of maltreatment (DHHS, 2011). It applied a framework called Decision-Making Ecology

(DME; Baumann, Dalgleish, Fluke, & Kern, 2011) to evaluate the impact of DR implementation on substantiation decisions while taking into account child- and county-level characteristics.

Differential Response Implementation

As the number of children coming to the attention of CPS has grown in recent decades, so too has concern that formal maltreatment investigations may be too adversarial and not appropriate for low- to moderate-risk families (Yuan, 2005). To address this concern, CPS agencies have adopted a variety of strategies to offer a tier of alternate approaches for service provision. There is no universally accepted definition of DR, but for the purposes of this study DR is defined as a system using core elements articulated by Kaplan and Merkel-Holguin (2008). These include: (1) At least two pathways are available for screened-in cases; (2) Decisions to divert cases to alternate pathways are determined by risk protocols and case characteristics; (3) A case can change pathways when risk levels increase or decrease; (4) Protocols for alternate responses are codified in statute or explicitly stated in policy; (5) Families in alternate pathways can refuse services; (6) Cases in alternate pathways do not result in a maltreatment disposition; and (7) No perpetrators of maltreatment are identified for those cases receiving an alternate response.

Most scholars point to legislation passed in Florida and Missouri in 1993 as the beginning of formal DR implementation (QIC-DR, 2011; Schene, 2005). Because of the policy and practice changes associated with such a major CPS system reform, states often initially implement DR in one or a few counties and then expand implementation over

time. In 2002, nine states had adopted DR in at least some of their counties, and by 2012, nearly half of all states (23) were implementing DR.

As would be expected, early evaluations of DR focused on whether it compromised child safety. A 2011 literature review that synthesized results from 15 studies of DR initiatives indicated that reported children in DR pathways were at no higher risk of maltreatment recurrence than those in traditional investigation pathways (QIC-DR, 2011). One large-scale survey of CPS agencies found investigation rates for neglect, medical neglect, and multiple forms of maltreatment were lower in states that had DR tracks than in investigation-only states (Westat, 2009). Another study examined NCANDS data for states that had adopted DR and found that in five of six, the overall number of investigated cases fell while the proportion of investigated allegations that were substantiated increased (Shusterman et al., 2005). These results support the claim that DR allows the investigation pathway to prioritize the most high-risk cases.

Although available research suggests DR offers a better way of serving low- to moderate-risk families by decreasing unnecessary investigations and increasing the accuracy of substantiation decisions, many studies on which these conclusions are based have methodological limitations. For example, most examined DR within a single state or a small number of states and did not compare among DR agencies or compare between DR and non-DR agencies. Others, such as the Westat study in 2009, included a large sample of CPS agencies but were descriptive analyses that did not control for confounding variables. As DR implementation becomes increasingly widespread, more evidence is needed regarding DR's impact on CPS decision making and the population characteristics of children with investigated and substantiated cases.

Differential Response in Neglect Cases

This study focused on neglect cases for three reasons. First, some DR agencies mandate investigations for certain types of maltreatment (e.g., sexual abuse) while other DR agencies do not, but none have mandated investigations for neglect cases. Accordingly, decision making with regard to neglect cases is more comparable across states and counties than for cases involving other types of maltreatment. Second, child characteristics such as age, race, and gender are distributed differently across various types of maltreatment (Sedlak, Mettenburg, Basena, Petta, McPherson, Greene, & Li, 2010), and the inclusion of all maltreatment types in the analyses may attenuate the relationship between predictors and the likelihood that an allegation will be substantiated. A third reason for focusing on neglect is the challenge it presents for decision making. Despite being the most common form of maltreatment, neglect is often considered the least studied and least understood type of maltreatment (Dubowitz, 1994, 2007; Kaplan, Pelcovitz, & Labruna, 1999; McSherry, 2007). It also spans a broad range of omissions of care, either deliberate or passive (Dubowitz, 2007). Moreover, the strong relationship between neglect and poverty is well documented in the literature (Mersky, Berger, Reynolds, & Gromoske, 2009; Sedlak, Mettenburg, Basena, Petta, McPherson, Greene, & Li, 2010; Slack et al., 2011), and the frequent co-occurrence of neglect and poverty raises concerns about whether neglect is a function of parental behavior or parental circumstances. It has also sparked debate as to whether the intent to harm matters in addressing the needs of children who experience severe omissions of care (Dubowitz, 2007; McSherry, 2007).

Some scholars have suggested that DR may be particularly appropriate for cases that are reported at least in part because of poverty (Duva & Metzer, 2010; Kyte, Trocmé, & Chamerland, 2013). In one longitudinal study of a state's DR system, families were randomly assigned to either traditional investigations or an alternate track to services (Loman & Siegel, 2012). Those with low socioeconomic status (SES) in the alternate track were significantly more likely to obtain anti-poverty services than low-SES families in the investigation track. Moreover, the receipt of those services was related to fewer re-reports and removals over time.

Substantiation Decisions

The determination of whether a child has been harmed has traditionally represented a central function of CPS agencies. In recent years, however, the role of CPS has broadened from investigation-focused responses to family-driven service provision (Bell & Sanders, 2013). This evolution has called into question how substantiation decisions are made, what the consequences are for families, and if it is even appropriate for CPS agencies to classify cases as substantiated or unsubstantiated (Fluke, 2009; Kohl, Jonson-Reid, & Drake, 2009). Also at issue is whether substantiation predicts future maltreatment. One national study reported that substantiated cases had no higher rates of recidivism than unsubstantiated cases (Kohl et al., 2009); consequently, the authors suggested that if no clear relationship between substantiation and risk of recurrence exists, CPS agencies should categorize CPS-involved families by the types of service they need rather than the case disposition they receive. Other studies, however, reported elevated rates of recurrence among substantiated cases (Fuller & Nieto, 2009; Hindley, Ramchandani, & Jones, 2006; Lipien & Forthofer, 2004) as well as differential

relationships between recurrence and substantiation based on maltreatment types (Child Welfare Information Gateway, 2003; Connell, Bergeron, Katz, Saunders, & Kramer Tebes, 2007).

Two additional concerns regarding substantiation have relevance for understanding the potential impact of DR. First, some states require a case to be substantiated in order for services to be provided, but even in CPS agencies without such requirements, substantiated cases receive services more often than unsubstantiated cases (Fluke, 2009; Kohl et al., 2009). Linking service receipt to substantiation has raised concerns that CPS professionals might substantiate neglect allegations simply to access resources for poor families (Shdaimah, 2009). DR directly addresses this concern by uncoupling services from the investigative function (Yuan, 2005).

The second concern regarding substantiation was voiced by Kohl and colleagues (2009), who noted that unsubstantiated cases are commonly assumed to represent families who come to the attention of CPS in error. However, whereas some portion of unsubstantiated cases represent families with no past maltreatment or future risk, another portion is likely to comprise high-risk cases with insufficient evidence to substantiate. Some findings suggest that DR implementation may decrease the overall number of investigations while increasing the proportion of substantiations among cases that are investigated (Shusterman et al., 2005). This means that if low-risk cases are diverted to alternate responses, more investigative resources may be directed toward cases that are potentially high-risk. An example of this was offered by a formative evaluation of one state's DR implementation (Loman, 2005). Results showed that investigations fell by 70% when DR was implemented. The DR agencies also provided supplemental training

about forensic casework to staff who worked those cases in the investigation pathway. The evaluators found that significantly more arrests occurred in demonstration sites compared to control sites. Although the present study could not directly determine whether changes in CPS investigation practices underlie any changes associated with substantiation rates in DR counties, it is important to consider that higher proportions of substantiations may be associated with both a decreased likelihood of low-risk cases receiving an investigation and an increased likelihood of high-risk cases receiving a substantiated disposition.

Applying the Decision-Making Ecology Framework

The DME is a conceptual framework that acknowledges that CPS case decisions are often made amidst a high degree of uncertainty (Baumann et al., 2011). In an ideal world, CPS workers would base their assessments solely on maltreatment risk and then choose a decision outcome based on evidence-based practice standards. The DME, however, makes explicit the exogenous variables that may also influence decision outcomes. These include four categories of influences: (1) case factors; (2) decision-maker factors; (3) external factors; and (4) organizational factors.

Case factors related to a child's risk and associated strengths should, in theory, be the driving influence for decisions around maltreatment allegations and service provision. But there are other case factors that, in combination with decision-maker factors, could potentially exert unwarranted influence on decision making. Most notably, racial and socioeconomic biases may influence a caseworker's perception of risk. For example, two studies of the CPS system in Texas found that even when African American children and White children received similar scores on a standardized risk assessment tool, the African

American children were more likely to have their cases substantiated (Dettlaff et al., 2011) and to be removed from home (Rivaux et al., 2008). Another study reported that workers who had higher proportions of African American or Hispanic children on their caseload were less likely to remove minority children at disproportionately high rates (Texas Department of Family and Protective Services, 2010). The author suggested that this might be because greater exposure mitigated racial/ethnic bias in decision makers. Yet evidence of bias is not ubiquitous in the literature, and several studies suggest that the over-inclusion of African American in CPS is primarily due to higher levels of risk factors rather than biased decision making in CPS systems (Drake et al., 2011; Font, Berger, & Slack, 2012; Putnam-Hornstein et al., 2013).

The influence of decision makers extends beyond possible racial and socioeconomic biases. Several studies have shown that CPS workers' preferences result in two different decision maker profiles: those who generally prefer intensive responses that prioritize safety, and those who generally prefer less intensive responses that prioritize family preservation (Arad-Davidzon & Benbenishty, 2008; Regehr, Bogo, Shlonsky, & LeBlanc, 2010). Some studies have addressed whether worker characteristics, such as age or race, affected decision making, but the findings are mixed and most studies found no direct effect (Regehr et al., 2010; Ryan, Garnier, Zyphur, & Zhai, 2006). Still, some studies have found that caseworker characteristics such as age (Ryan, et al., 2006) and race (Font et al., 2012; Ryan et al., 2006) moderated case decisions. In addition, there is evidence that these preferences are not easily changed even through training or the use of standardized assessment tools (Regeher et al., 2010).

No information about caseworker characteristics is available in NCANDS child files, so the current study was not able to assess the impact of decision-maker factors. However, the data do allow examination of child racial/ethnic categories in order to identify potential racial bias in decision making.

According to Baumann and colleagues (2011), the third category of influence on decision making, external factors, includes laws that may constrain or influence agency policy, resources available within communities, and the demographic characteristics of community populations. Demographic characteristics operate on two levels of influence: First, factors such as residing in a neighborhood with high poverty, crime, or other characteristics of disorganization may elevate the maltreatment risk of individual children (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Jantz, Rolock, Leathers, Dettlaff, & Gleeson, 2012; Merritt, 2009). This level of influence is more closely associated with case-level characteristics and is best measured by studies in which the unit of analysis is smaller than counties so neighborhoods are more precisely represented (Aron et al., 2010).

Second, community characteristics may influence the CPS system's response although fewer studies explicitly link community characteristics, such as racial composition, socioeconomic features, and population density with agency patterns of decision making. One characteristic that has been associated with differences in removal decisions is higher proportions of minority children in communities and in CPS agencies (Fallon, et al., 2013; Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010). These studies also uncovered complex multilevel interaction effects, where high proportions of minority children affected the decision outcomes for children of specific races or

ethnicities. For example, a Canadian study found that high overall rates of CPS-involved Aboriginal children were associated with a higher likelihood of Aboriginal children being removed from their homes (Fluke et al., 2010). Drake, Lee, and Jonson-Reid (2009) found that White children were more likely than African American children to be referred to CPS in high-poverty areas and that African American children were more likely to be referred in low-poverty areas. Similarly, Wulczyn (2011) found that states and counties with higher poverty rates had lower racial/ethnic disparity rates for placement. Studies have also compared communities of varying population density levels and have found little to no association between population size and CPS decisions about substantiation (English, Marshall, Coghlan, Brummel, & Orme, 2002), removals (Fluke et al., 2010), or service referrals (Jud, Fallon, & Trocmé, 2012).

Although there are many other possible external factors, this study included three variables—county rates of child poverty, proportion of White children (as a measure of racial/ethnic homogeneity), and population density—as county factors to be examined for their possible influence on decision making.

Organizational factors, the fourth category of influence in the DME, has been the subject of less inquiry, although characteristics such as decentralized structure, strong leadership, and higher proportion of workers with social work degrees have been associated with decision outcomes that result in less intensive CPS involvement (Chabot et al., 2013; Yoo & Brooks, 2005). Organizational factors also include agency policy and practice models, but it is difficult to test the impact of most CPS reforms in a national sample since there is usually no way to track implementation across a large number of agencies. DR, however, represents a large-scale CPS reform and typically requires

codification in statute. Thus, its implementation is usually well documented. Further, DR specifically targets decision options, so its adoption should lead to measurable shifts in decision-making patterns that are easily tracked in CPS administrative data.

Chabot and colleagues (2013) noted that studies examining the impact of organizational or community-level factors on child outcomes have been limited by measurement issues. For instance, datasets that contain detailed child-level measures rarely contain adequate measures about agencies and communities, and researchers may include measures based on availability rather than theory. The current study faced similar challenges. The 2010 NCANDS dataset contains CPS information on a large number of children in a large sample of U.S. counties and, because NCANDS child files identify counties, census and other sources of county-level data can easily be merged to provide more information on community characteristics. However, as will be discussed, data about child and family risk factors from NCANDS are inconsistently collected. This means the study was not able to include child-level data about poverty and other risk factors, such as parental substance abuse and mental health issues that may offer a more complete understanding of decision making. Despite these limitations, this study offers an opportunity to expand upon the empirical support for the DME by testing the impact of well-established CPS reform on a national scale.

In sum, this study was guided by the following research questions: *(1a) Accounting for other child and county characteristics, are investigated cases in DR counties more likely to be substantiated than cases in non-DR counties? (1b) What other important county- and child-level characteristics influence substantiation decisions? (2a) Do child-level race/ethnicity effects matter more in some counties than in others?*

(2b) Are the effects of race/ethnicity on substantiation decisions mitigated by the implementation of DR?

Methods

Data and Study Population

This study used the 2010 National Child Abuse and Neglect Data System (NCANDS) child file, which is comprised of voluntary data submissions by state public child welfare agencies. The system contains information about screened-in CPS referrals (reports) that received a disposition decision between October 1, 2009 and September 30, 2010 (DHHS, 2011). A child may have more than one report in a given year; therefore, some children have multiple reports. This was true of approximately 12% of children in the study sample (DHHS, 2011). Although this paper uses the terms *report*, *case*, and *child* interchangeably, the unit of analysis in this study is an investigated CPS report, and an individual child may be represented more than once in the sample.

Because NCANDS is a voluntary system, the quality of data varies by state and by measure. For example, many states choose not to report information about service or risk factor measures in NCANDS because they do not collect this information in an easily transmissible way in their state systems. In other instances, a state's information about a measure may not be comparable with other states because of a unique reporting characteristic within that state. State-to-state variations have the potential to produce clustering that represents differences in data recording practices, rather than real differences in populations or agencies. The variations can also skew county- and state-level analyses, so multiple approaches were used to reduce the potential impact of data recording differences among state NCANDS submissions. For example, contacts with

state data administrators by the author resulted in the removal of cases from all counties in Connecticut, Hawaii, Missouri, New Jersey, New York, Pennsylvania, Puerto Rico, and Oregon, along with two counties in Virginia. This was based on information indicating that each of these jurisdictions had one or more of the following: atypical decision pathways, such as having all reports screened-in and investigated; missing data, such as lacking case-level information about unsubstantiated cases; or data quality concerns, such as errors related to county identification.

Also removed from the analyses were cases from small counties because NCANDS does not identify the county from which a case originated if that county has less than 1,000 total NCANDS reports. Therefore, the only counties with low overall populations that are identified in NCANDS are those with higher than average CPS reporting rates, so including these counties in the analysis would misrepresent others of their size. Accordingly, the sample was reduced to include only counties that have a large enough child population to be included in the original NCANDS dataset, even if their NCANDS reporting rate was one standard deviation below the mean U.S. reporting rate (4.96 per 1,000 children). This produced a sample in which no county with fewer than 38,000 children was included. Establishing a population threshold improved the comparability across sample counties and reduced the risk of misrepresenting small counties, but it also resulted in the exclusion of many small rural counties. It also led to the exclusion of two states, Montana and North Dakota, which had no counties that met the population threshold.

Exclusions were made not only based on county characteristics but also because of three case-specific criteria. First, the final sample excluded a small number of

NCANDS cases represented individuals 18 and over (.04% of the sample). Second, although NCANDS collects data on several types of maltreatment, only cases involving neglect were included. In 2010, this accounted for 79% of substantiated cases (DHHS, 2011). NCANDS allows a single record to include up to four different types of maltreatment to capture co-occurring abuse and neglect. Nearly one-third (30%) of the neglect cases in this study also identified at least one other type of maltreatment. The final case-specific criterion for inclusion was that the case had to have a substantiated, indicated, or unsubstantiated disposition outcome. NCANDS includes four other disposition categories: *intentionally false*, *closed with no finding*, *alternative response victim*, and *alternative response nonvictim.* These categories are not used by all states and so were excluded from the sample. A final issue also relates to the use of alternative response disposition categories. Because not all states that implemented DR in 2010 included DR cases in their NCANDS submission, this study used a different method (described below) was used to identify agencies that implement DR. After applying each exclusion criterion, the study including 997,512 neglect investigation records with either a substantiated, indicated, or unsubstantiated disposition from 284 counties in 39 states.

Measures

Outcome. Cases dispositions were divided into two categories: (1) unsubstantiated or (2) substantiated or indicated. Among cases with co-occurring maltreatment types, the disposition was considered to be unsubstantiated if the neglect allegation was classified as unfounded, regardless of the disposition decision for other maltreatment types.

Child level-covariates. Four covariates from NCANDS were included in the multilevel models to account for important child characteristics. These were age, sex, race/ethnicity, and prior victim status.

The *age* of children in the sample ranged from 0-17 and the *sex* of the child was coded dichotomously, with males as the reference category.

NCANDS allows children to be included in multiple racial and ethnic categories. To simplify the analysis, ethnicity was combined with race to create five categories: Hispanic (all children identified as Hispanic regardless of racial categories); African American (all non-Hispanic identified as African American, even if other race categories were also indicated); Asian (non-Hispanic children identified exclusively as Asian); White (non-Hispanic children identified exclusively as White); Other (non-Hispanic children identified exclusively as American Indian or Alaskan Native; non-Hispanic, non-African American children with multiple race categories; and children with "undetermined," "unknown," or "missing" race categories). NCANDS does not include American Indian and Alaskan Native children served by tribal CPS agencies (National Indian Child Welfare Association, 2008), and as a result, Earle and Cross (2001) estimated that the dataset may capture only about 60% of American Indian/Alaskan Native children who experience child maltreatment. The category American Indian/Alaskan Native is included in the descriptive table, but because the records do not fully capture the experience of American Indian children in the child welfare system, this category was combined with "other" in multivariate analyses.

The category of *prior victim* includes children who had been the subject of a past CPS report that resulted in a disposition of substantiated or indicated. Because few states

consistently report risk factors such as parental substance abuse or mental health issues, prior victim status is the only child-level risk factor available for this analysis. Although this measure does not capture the full range of risks associated with maltreatment cases, children who have had prior reports are more likely to be from families with multiple stressors, including parental substance abuse and low SES (Connell, et al., 2007; Fluke, Shusterman, Hollinshead, Yuan, 2008).

County-level predictors. In addition to the three case-level covariates, the study also examined four county-level predictors. These came from other data sources that were merged with NCANDS through county identifiers (FIPS codes). Applying the DME framework, three of the measures are county demographic characteristics that represent external influences on decision making: child poverty rate, population density, and the proportion of White children. The final county-level predictor, DR implementation, is an organizational factor.

Child poverty rate was measured as the percentage of children living below the federal poverty line in 2010, according to criteria from the U.S. Department of Agriculture (2012). *Population density* was calculated by dividing each county's population, using 2010 population estimates from the National Cancer Institute (NCI, 2013) by the total square miles in the county, as reported by the U.S. Census Bureau (2012). *Proportion of White children* represented the percentage of non-Hispanic White children who resided in a given county, again using NCI data (2012). This rate was used as an approximate measure of county racial/ethnic diversity. The NCI dataset provides county-level population estimates, based on U.S. census data, by age, race, and sex.

The fourth county-level predictor, *DR implementation*, was determined by creating a database to document DR implementation for every U.S. county, as described by Janczewski (in press). DR was coded dichotomously, where DR indicated a county that was implementing DR in 2010 in accordance with the core elements of differential response as described by Merkel-Holguin and colleagues (2006).

Analysis plan

Descriptive analyses. Results of analyses designed to assess the distributional properties among variables revealed that population density had a strong positive skew (6.18) and was highly kurtotic (49.91). As a result, a log transformation was performed on this measure for the multilevel analysis (Cohen, Cohen, West, & Aiken, 2003). Also, age, which was the only continuous level-one variable, was grand-mean centered for the multilevel analysis (Bell, Ene, Smiley, & Scheneberger 2013; Enders & Tofighi, 2007). Finally, 4,117 cases (representing less than five-tenths of one percent of all cases in the final dataset) were excluded from the final sample because they had missing values on one or more predictors.

Multilevel Analysis. The primary outcome measure for the study – the decision of whether to substantiate a case – is dichotomous; therefore, the analysis used a multilevel logistic equation with a logit link function between the dichotomous outcome and a linear regression equation (Hedeker, 2005). Due to the binomial distribution of the outcome, the level-one error term in multilevel logistic regression is part of the error distribution and is estimated to be a constant ($\sigma_e^2 = \pi^2/3$). This has implications for the estimation methods available for logistic regression and the selection of appropriate fit indices, as discussed below.

To address the research questions, model testing proceeded in five iterative blocks, following an approach proposed by Hox (2010). The equations for each of the five models are presented in Appendix B. First, the null model (Model 1) estimated the clustering effects of counties without the inclusion of predictors. An interclass correlation coefficient (ICC) was calculated using the covariance estimate (i.e., the random effect of counties) to test the underlying assumption that substantiation decisions cluster by county (Guo & Zhao, 2000). The second model included child-level predictors (race/ethnicity, age, sex, and prior victim status), and the third model added county-level predictors (DR status, child poverty rate, population density, and the proportion of White children in the county). Results from Model 3 were used to assess the relationship between substantiation decisions and child- and county-level racial characteristics and DR implementation (Research Question 1). Models 2 and 3 only allowed examination of fixed effects, meaning that the influence of predictors was restricted to the intercept. Research Question 2, however, explored the possibility that the effect of child racial characteristics may be different among counties. To address this question, the next equation allowed the slope of child race to vary by adding a new random effect into the model (Model 4). Finally, a series of models tested whether level-two predictors explained the random effects of child race through cross-level interactions (Models 5a-d). For instance, prior literature suggests that the relationship of child racial characteristics and CPS decision making may be moderated by community racial composition and poverty levels (Drake, et al., 2009).

The models used Laplace estimation procedures, which have been shown to perform well in two-level dichotomous random effects models (Raudenbush, Yang, &

Yosef, 2000), and which allow comparisons of model fit using the log likelihood ratio tests (LLRTs; Snijders & Bosker, 2012). In Model 4, random effects were assessed using a test similar to LLRTs, but with conditional log likelihoods (Shun, 1997; Snijders & Bosker, 2012). LLRTs determine whether nested models are significantly different from one another through chi-square tests. The alpha level was set *a priori* ($\alpha = .05$), with Bonferroni adjustments to account for multiple comparisons.

Although significant values from Wald tests of fixed effects are reported, the large sample size means that significance tests are not particularly useful without additional statistics to better interpret effect sizes. Accordingly, odds ratios (ORs) will be the primary statistic used for interpretation of effects. A pseudo R^2 statistic was calculated by measuring the reduction in the level-2 error term that occurred when level-2 predictors were added (Snijders & Bosker, 2012). As with any pseudo R^2 statistic, the test is only an approximation of the amount of variance explained by predictors, and results should be interpreted with caution. Descriptive analyses including the plots were conducted using SPSS 21, whereas the multilevel models were analyzed using SAS software, Version 9.2.

Results

Descriptive Analysis

Roughly a quarter (25.8%) of the 997,512 neglect investigations were substantiated. Table 3.1 presents descriptive information for child-level predictors in the total sample of investigated cases, along with child- and county-level predictors by county. The range of means for child-level predictors across counties suggests clustering effects. For instance, although Hispanic children comprise approximately 28% of the

sample, their proportions across counties range from zero to 97%. The rate of substantiation (2% to 75%) also varies widely by county. These large county differences support the use of multilevel analysis to identify whether the odds of substantiation are dependent on the characteristics of the county in which a child is served.

[Table 3.1]

Multilevel Analysis

Modeling proceeded in five blocks, with results from Models 1 and 2 shown in Table 3.2. The ICC in the null model (Model 1) indicated that approximately 12.6% of the variance found in the likelihood of substantiation occurs at the county-level.

All child-level predictors introduced in Model 2 were found to be significantly related to the likelihood of a case being investigated, but the ORs were relatively small in most cases. The strongest child-level predictor was prior victim status, where prior victims were 1.34 times more likely to experience substantiation than children with no prior substantiated or indicated maltreatment case. The effects for race/ethnicity were statistically significant, but the effect sizes, as measured by odds ratios, were so small that the likelihood of substantiation for minority children was not meaningfully different from White children. Specifically, compared to White children, African American, Hispanic, and Asian children had only slightly higher odds of having a substantiated case (OR= 1.01, 1.06, and 1.15 respectively). Females were slightly more likely than males to experience a substantiation (OR =1.02) while the odds of substantiation were less for older children than for younger children (OR = .95). The ICC increased from the null model (from 12.5% to 13%), and this was most likely due to clustering associated with the child-level predictors. The log likelihood fell sharply with the introduction of child-

level predictors, resulting in a significant LLRT and indicating an improved fit over the null model.

[Table 3.2]

Four county-level predictors were introduced in Model 3 (Table 3.3). Investigated neglect cases in counties with DR were 2.19 times more likely to be substantiated than cases in counties without DR, which was the strongest effect in the model. County child poverty rates and the proportion of White children were not associated with a significant change in the likelihood of case substantiation. Similarly, children from counties with larger population densities were only slightly more likely to receive an investigation (OR=1.09), although the effect was small (OR= 1.09). The fixed effects for child-level predictors remained similar to Model 2. Based on the reduction of the ICC, the pseudo R^2 statistic found that 15.2% of county-level variance in the null model was explained with the introduction of level-2 predictors. The LLRT indicated that Model 3 was a better fit than Model 2.

[Table 3.3]

Model 4 tested whether the effect of a child's race/ethnicity varied across counties. Results found significant random effects for child race/ethnicity, suggesting that a child's race or ethnicity may matter more in substantiation decisions in some counties than in others (Table 3.4). The random effects for race/ethnicity were small (covariance estimate = .07, with an ICC of just 2%), which is unsurprising given the small fixed effects for race/ethnicity found across Models 2-4. Model fit, as tested by the likelihood ratio tests for mixed-effect models, showed improved fit compared to previous models.

[Table 3.4]

The final set of analyses (Model 5) examined the interaction of child-level race and the four county-level predictors. Each interaction was modeled separately and none of the cross-level interactions were found to significantly improve model fit (log likelihood scores were higher than in Model 4, results not presented). These findings suggest that DR implementation, population density, child poverty rates, and the proportion of White children in a county do not explain the differential effects of child race on substantiation decisions between counties in this sample. Ancillary analyses were carried out to test whether a parsimonious model without non-significant predictors (child poverty and White child rate) would enhance model fit from Model 4. However, fit indices shrank in this trimmed model, indicating that Model 4 represents the best-fitting model.

Discussion

Results from the null model indicate that county-level effects accounted for nearly 13% of the variance in substantiation decisions for neglect investigations, which supports the application of a multilevel model. The remainder of this discussion explores answers to the three research questions that this analysis pursued.

Research Question 1

The first research question applied the DME framework to address the extent to which county DR implementation effects substantiation decisions while accounting for a child's prior victim status, racial/ethnic characteristics, age, and sex, as well as county poverty rates, and racial diversity.

Children served by a county with DR had a greater likelihood of having the investigation substantiated than children in a non-DR county. The association between DR and higher substantiation rates is not surprising, as this has been demonstrated in previous studies (Loman & Siegel, 2004; Shusterman et al., 2005; Virginia Department of Social Services, 2007; Westat, 2009). However, the magnitude of the relationship (OR = 2.3), after accounting for other child- and county-level factors, is notable, particularly in comparison to other variables in the model. Despite the large amount of heterogeneity that exists within CPS agencies and the communities they serve, these findings suggest that decision making in CPS systems is driven largely by the policies and practices operating within each agency.

Among child-level variables, there was a small (OR=1.34) yet statistically significant association between prior victim status and substantiation. This result provides some support from past studies that reported higher risk among children with prior substantiations (Fuller & Nieto, 2009; Hindley, Ramchandani, & Jones, 2006; Lipien & Forthofer, 2004). It also provides evidence that decision making in CPS cases aligns with expectations about responding to risk found in previous research (Trocmé et al., 2009). Results from models 2-4, relations between child-level racial and ethnic categories and substantiation remained statistically significant, yet the small size of the odds ratios (range = 1.01-1.18) imply that the differences are trivial. In general, the lack of robust effects for race/ethnicity is consistent with previous findings that overrepresentation of minority children is most evident at decision points in CPS earlier than substantiation (Drake, et al., 2011; Fluke, Yuan, Hedderson, & Curtis, 2003). Although not directly tested, the absence of race/ethnicity effects also supports the claim

that most of racial disproportionality evident in CPS is not due to biased decision making on the part of CPS staff, but rather differential distributions of risk and protective factors across racial and ethnic subpopulations (Drake et al., 2011; Putnam-Hornstein & Needell, 2013).

In the final model (Model 4), the rate of child poverty, population density, and the proportion of White children within a county were not found to significantly influence the likelihood of whether an investigation received a substantiation. The results are inconsistent with other studies that found effects between child outcomes and population demographic characteristics related to poverty (Aron et al., 2010; Jantz, Rolock, Leathers, Dettlaff, & Gleeson, 2012). The contradictory results may be because the present study measured population characteristics at the county-level. These measures served as control variables to account for some of the county-level heterogeneity found across the national sample. Previous studies employed more localized approaches to measuring population characteristics in order to demonstrate the strong association between poverty and other community-risk factors and child outcomes.

In total, the introduction of level-two variables explained about 14% of the county-level variance (pseudo R^2). Although this suggests that DR represents a non-trivial portion of the difference in substantiation rates in counties, it also indicates that there is a great deal of county level variation unaccounted for in the model. DR was the only agency factor included in this analysis, and its strong effect on decision making suggests that exploring the influence of other organizational factors may help identify additional sources of county-level variation. At present, however, it remains difficult to

obtain county-level data from a large sample of agencies on factors informed by the DME such as staffing, funding, or practice models.

Research Question 2

The large sample of U.S. counties in this study and the nested structure of the data provide opportunities to explore whether the influence of child racial and ethnic characteristics on substantiation decisions varied across counties. Model 4 uncovered significant random effects for child racial and ethnic characteristics. Despite the statistical significance, the random effects for the race/ethnicity categories were small (accounting for approximately 2% of the county variation) and should not be overstated. The second research question also addressed whether DR moderated the impact of race and ethnicity on substantiation decisions. The model fit indices were poor, suggesting the model became over-fitted with the addition of the complex interactions (Babyak, 2004).

Results imply that child race/ethnicity influences substantiation decisions, but to a greater extent in some counties than in others. The multilevel models, however, were unable to discern important county characteristics that may influence these effects. Additionally, similar to the fixed-effect results, the random race/ethnicity effects are most likely different across racial categories, although the random coefficient model was not constructed to distinguish among categorical differences. Moderation effects may also exist in counties with higher race/ethnic effects that are not observable in the 284 counties included here. Nonetheless, findings suggest that when analyses examine CPS decision making in a large, geographically diverse data set such as NCANDS, they should address the heterogeneity of effects among race/ethnicity categories and the

differential effects that may be operating at the county or local level. Further examination of a subsample of counties with strong race/ethnic effects may help identify county-level characteristics that contribute to disparate decision-making practices among groups of minority children.

Limitations

The study had some important limitations. First, although NCANDS is a valuable tool for understanding national patterns in CPS data, but it is essentially a distillation of CPS data from 50 different state information systems. This heterogeneity contributes to a number of concerns regarding missing data and measurement error. Key indicators about child-level risk and poverty, for example, were missing or not consistently collected from a large number of counties. . Likewise, the inclusion of specific indicators of risk such as parental mental health, substance abuse, and family poverty would have enabled more comprehensive analyses of how risk shapes CPS decision making.

A number of states and counties were excluded because of NCANDS data quality concerns or unique data-reporting practices. Eliminating these counties from the sample reduced the likelihood of unwanted clustering effects due to reporting differences, but it also reduced the generalizability of the results. The 284 counties included in the final analysis do not represent a random sample of U.S. counties. Those that met selection criteria and therefore remained in the sample had relatively large child populations and no observable reporting aberrations in their 2010 NCANDS child data file.

Another limitation of this study is that it is cross-sectional in nature. Although the findings suggest significant differences between DR and non-DR counties in 2010, a

longitudinal analysis would more definitively demonstrate that increases in the likelihood of substantiation correspond with the launch of DR.

Finally, despite statistical advances in multilevel modeling, the field continues to deliberate certain aspect of how these approaches are applied and interpreted. For example, in this study a pseudo-R^2 statistic was presented as an approximate measure of effect size for the random coefficient model (Model 3, Snijders & Bosker, 2012), and the LLRT was used to test the fit of nested models (Shun 1997). Yet, there are other ways to interpret the variance terms and an abundance of strategies for model testing. In addition, further research is warranted to determine the extent of county clustering effects within states. This study did not include states as a third level because it is intended to serve as an early attempt to describe the relationship between substantiation and some of the most theoretically promising predictors in a multilevel context. Adding a third level to the model might have added to the precision of the results, but it would have also heightened complexity and reduced the ability to interpret important relationships. In particular, the effects of county-level variables such as the implementation of DR may operate at both the state- and county-level, and their total contribution to the variance of substantiation decisions would have been more ambiguous in a three-level model. Future studies may build off this more primitive two-level model with the addition of state-level effects.

Conclusion

By using a national sample, this study has demonstrated Differential Response's impact on substantiation decisions on a larger scale than previous research. Results from the multilevel model also suggest that DR's influence on decision making remains strong even when accounting for important child-level variables such as prior victim status and

race/ethnicity, along with other county-level factors such as poverty rates and racial diversity. Findings support the hypothesis that DR implementation increases the proportion of investigated cases receiving a substantiation decision. Further, prior victim status remains a strong child-level indicator of substantiation. Accordingly, results do not suggest that DR implementation affects the association between risk and substantiation. There were no indications that a child's race or ethnicity meaningfully contributed to the likelihood of substantiation in the large sample. Still, there is some indication that this likelihood varies by county and that future exploration about why race/ethnicity matters in the subsample of counties with high race effects may be warranted. A previous study of 2010 NCANDS data found an overall reduction in the number of investigations in DR counties (Janczewski, in press), and these findings in tandem support the premise that, by diverting low- and moderate-risk children prior to investigation, DR implementation may reduce both false positives and false negatives at the substantiation decision point.

A second contribution of this study is that it demonstrates the influence of a major CPS practice/policy variable on decision making. Although past studies applying the DME framework have tried to account in some way for practice models (Maguire-Jack & Font, 2014), the heterogeneity of the models have made it difficult to identify clear effects. DR is relatively well-documented in state and county CPS policies. It also fundamentally alters decision options for a significant portion of cases and its effects on decision making are thus more direct than other CPS system innovations and practice models. The clear influence of DR on decision making highlights the importance of

organizational context whenever system decision making is studied (Baumann et al., 2011).

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Table 3.1

Descriptive Statistics for Investigated Neglect Cases

	Total Cases (N = 997,512 cases)		Aggregated By County (N = 284 counties)		
	Percent or Mean	S.D.	Mean	S.D.	Range
Child-Level					
Substantiated	25.8%		28.1%	0.13	2 - 75%
Race/ethnicity					
African American	26.2%		25.5%	0.19	0 - 90%
American Indian/ Alaskan Native	0.7%		1.0%	0.04	0 - 43%
Asian	0.9%		0.8%	0.01	0 - 10%
Hispanic/Latino	27.6%		18.6%	0.20	0 - 97%
White	37.9%		46.3%	0.19	0 - 94%
Other	6.6%		7.8%	0.09	0 - 54%
Prior victim	26.5%		25.0%	0.16	0 - 72%
Female	49.3%		49.3%	0.02	42 - 60%
Child age	7.0	5.11	6.8	0.62	5 - 9
County-level					
DR status			25.7%		
White child rate			56%	0.2	2 - 94%
Ch. poverty rate			20.9%	0.07	4 - 49%
Pop. density			930	1597	15 - 17181

Note. SD= Standard deviation

Table 3.2

Fixed and Random Effects for Null (1) and Child-level Predictor Models (2)

	Mode1 1					Model 2 (Child-level predictors)				
	Estimate		*S.E.*	*O.R.*	*95% (LL)*	*C.I. (UL)*	*Estimate*		*S.E.*	*O.R.*	*95% (LL)*	*C.I. (UL)*
						Fixed effects						
Intercept	-1.04	*	0.04	0.35	0.33	0.38	-0.83	*	0.04	0.43	0.40	0.47
Level 1 Predictors												
Race (White is reference category)												
Asian							0.14	*	0.02	1.15	1.09	1.20
Af. American							0.01	*	0.01	1.01	1.00	1.03
Hispanic							0.06	*	0.01	1.06	1.05	1.08
Other							-0.42	*	0.01	0.65	0.64	0.67
Prior victim							0.29	*	0.01	1.34	1.32	1.35
Female							0.02	*	0.00	1.02	1.01	1.03
Age							-0.05	*	0.00	0.95	0.95	0.95
						Random effects						
County	0.475		0.04				0.50		0.04			
ICC	12.6%						13.0%					
LLRT							20972	*				

Note: SE= Standard error; OR= Odds ratio; CI= Confidence interval; ICC= Interclass correlation; LLRT=Log likelihood ratio test. LLRT used Bonferroni correction.

*$p < .05$

Table 3.3
Fixed Effects of County-level Predictors (Model 3)

	Model 3					
	Estimate		S.E.	O.R.	95% CI (LL)	(UL)
			Fixed Effects			
Intercept	-1.21	*	0.38	0.30	0.14	0.63
Level 1 (Child)						
Race (White is reference category)						
Asian	0.14	*	0.02	1.15	1.09	1.21
African American	0.01	*	0.01	1.01	1.00	1.03
Hispanic	0.06	*	0.01	1.06	1.05	1.08
Other	-0.42	*	0.01	0.65	0.64	0.67
Prior Victim	0.29	*	0.01	1.34	1.32	1.35
Female	0.02	*	0.00	1.02	1.01	1.03
Age	-0.05	*	0.00	0.95	0.95	0.95
Level 2 (County)						
DR implementation	0.82	*	0.09	2.28	1.90	2.72
Child Poverty	-0.01		0.01	0.99	0.98	1.00
Density	0.07		0.04	1.08	1.00	1.16
White Child Rate	0.00		0.00	1.00	0.99	1.00
			Random effects			
County	0.41		0.04			
Race						
ICC (County)	0.11					
LLRT	70	*				

Note: SE= standard error; OR= Odds ratio; CI= Confidence Interval; ICC= Interclass Correlation; LLRT=Log Likelihood Ratio Test. LLRT used Bonferroni correction.
**p> .05.*

Table 3.4
Random Effects of Race/Ethnicity (Model 4)

	Model 4					
	Estimate		S.E.	O.R.	95% CI (LL)	(UL)
Intercept	-1.21	*	0.38	0.30	0.14	0.63
Level 1 (Child)						
Race (White is reference category)						
Asian	0.16	*	0.04	1.17	1.08	1.28
African American	0.05		0.03	1.05	1.00	1.10
Hispanic	0.08	*	0.03	1.08	1.03	1.14
Other	-0.32	*	0.03	0.73	0.69	0.77
Prior Victim	0.28	*	0.01	1.32	1.30	1.33
Female	0.02	*	0.00	1.02	1.01	1.03
Age	-0.05	*	0.00	0.95	0.95	0.95
Level 2 (County)						
DR implementation	0.82	*	0.09	2.26	1.89	2.71
Child Poverty	-0.01		0.01	0.99	0.98	1.00
Density	0.08	*	0.04	1.08	1.00	1.16
White Child Rate	0.00		0.00	1.00	0.99	1.00
County	0.40		0.04			
Race	0.07		0.01			
ICC (County)	0.11					
ICC (Race)	0.02					
LLRT	4490	*				

Note: SE= standard error; OR= Odds ratio; CI= Confidence Interval; ICC= Interclass Correlation; LLRT=Log Likelihood Ratio Test. LLRT used Bonferroni correction.
*$p > .05$.

CHAPTER 4

Moving Mountains: A Longitudinal Analysis of Changes in Investigation and Substantiation Rates in U.S. Counties Associated with Differential Response Implementation

Introduction

Child protective services (CPS) systems are often seen as entrenched bureaucracies that are resistant to reform. In reality, however, these systems are anything but static: CPS agencies are in a state of constant flux, responding to internal and external pressures to adopt policy and practice changes in the name of system improvement. This longitudinal study examines the impact of a single system reform, differential response (DR), on child welfare outcomes in a multistate sample of counties in the U.S. It expands on previous work (Janczewski, in press) that found differences in 2010 neglect investigation and substantiation rates between CPS agencies in counties with DR and their non-DR counterparts. Other studies have documented changes in investigation and substantiation rates associated with the introduction of DR (Loman & Siegel, 2004; Shusterman, Fluke, Hollinshead, & Yuan, 2005; Westat, 2009), but the timing and rate of change has not been explored across a large sample of county agencies. Using data from the National Child Abuse and Neglect Data System (NCANDS) child files for 2000-2010, the goal of this analysis is to determine whether changes in rates corresponded with the launch of DR.

Ordinarily, when an allegation of maltreatment is reported to a CPS agency, a case undergoes some kind of initial and immediate screening, where a decision is made to either screen out the case because it does not meet the agency's criteria for maltreatment or screen in the case for an investigation (DePanfilis, 2006). The second phase consists of a formal investigation that concludes with a disposition, or finding for the maltreatment allegation. The disposition categories vary by states, but minimally include *substantiated* or its equivalent (i.e., sufficient evidence of maltreatment), and

unsubstantiated. Differential response, also called alternative response, provides one or more tiered response options in lieu of the formal investigation phase. Although the implementation of DR is different in each state, these alternate responses typically emphasize family-driven, community-based services and target low- to moderate-risk children whose cases were initially screened in for further assessment (Merkel-Holguin, Kaplan, & Kwak, 2006). The adoption of DR has come about in part as a way to support CPS-involved families who may present significant needs for services, but for whom an investigation of child maltreatment may not be necessary or appropriate (Schene, 2005).

The first differential response initiatives in the U.S were launched by Missouri and Florida in 1993, and by 2013, at least 24 states had implemented DR in one or more counties (National Quality Improvement Center on Differential Response in CPS, QIC-DR, 2013). Research suggests that among states with established DR initiatives, roughly 40-70% of children are diverted from traditional investigations (Shusterman, et al., 2005). Also, the overall rates of CPS investigations and substantiations appear to be smaller in DR counties than in non-DR counties (Janczewski, in press; Loman & Siegel, 2004; Virginia Department of Social Services, 2007; Westat, 2009). Another benefit is that the proportion of investigated cases receiving substantiations has been found to be higher among DR counties than in non-DR counties, supporting the hypothesis that as lower-risk cases in DR counties get diverted to alternative responses, investigations focus on a smaller, but higher-risk, child population (Janczewski, in press; Shusterman et al., 2005).

To date, however, the studies have consisted of cross-sectional comparisons between DR and non-DR counties (Janczewski, in press; Westat, 2009) or those within a single or a few states over time (Loman & Siegel, 2004; Shusterman et al., 2005). The

temporal order of changes to investigation and substantiation trends as they relate to DR implementation has not been established across a large sample of DR counties. This study seeks to describe when, and at what rate, changes in the frequency of investigations and substantiations have occurred in relation to the start of DR implementation, using a sample of 295 counties in 42 states.

Measuring and Predicting CPS Decisions

Although patterns of investigation and substantiation rates generally align with national child maltreatment incidence studies (Sedlak et al., 2010), some cases of maltreatment are never investigated or substantiated (false negatives) and some investigated and substantiated cases do not represent true maltreatment risk (false positives). Accordingly, a maltreatment investigation or even a substantiated case is not a precise measure of child maltreatment or risk (Kohl, Jonson-Reid, & Drake, 2009). Rather, substantiations and investigations represent decision points within CPS cases. In aggregate, these decision rates are useful metrics to identify differences in CPS decision-making practices across agencies and provide insight into the effect of large-scale policy and practice innovations.

Conceptual models of CPS decision making have focused on describing and improving the way caseworkers determine the validity of an allegation in situations where information is imperfect and the risk associated with making a mistake is high (Baumann, Dalgleish, Fluke, & Kern, 2011; Crea, 2010; Munro, 1999; Platt, Dendy, & Turney, 2013). Most models are based on the concept of bounded rationality that acknowledges that constraints such as limited time and information, along with personal factors such as skill and experience, influence the way decisions are made. Research

about CPS decision making often uses such models to explore the risk of potential bias and decision-making errors that may occur when CPS professionals make difficult case decisions (Gambrill, 2005; Mansell, 2006).

This study applies one such decision-making model, the Decision-Making Ecology (DME), proposed by Baumann and colleagues (2011). The DME articulates four different kinds of influences on CPS decision making, including case factors, decision-maker factors, external factors, and organizational factors. Similar to other models, the DME uses concepts from bounded rationality to explain the influence of case and decision-maker factors. It has been used to examine whether the characteristics of CPS worker lead to biases that contribute to increased likelihoods of investigations and removals for minority children (Dettlaff et al., 2011; Rivaux et al., 2008). Yet the DME also contends that, because CPS decision making occurs within complex systems, organizational and external forces such as policies, practice models, laws, and political climates can influence decision making. For instance, one study applied the DME to examine whether staff vacancies and the geographic location of an organization influenced the likelihood that an Aboriginal child had a CPS case that resulted in a substantiation (Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010). Another study found that county-level socioeconomic disorganization was related to increased risk of removal, especially among African American children (Jantz, Rolock, Leathers, Dettlaff, & Gleeson, 2012). Although the DME suggests that agency practices and policies represent another area of influence for decision making, few studies have examined the extent to which CPS policy and practice differences are related to decision-making variations across agencies. DR is a reform that educes widespread policy and practice

changes within CPS systems. This study focuses on the impact of DR implementation on CPS decision making, as measured by investigation and substantiation rates.

History Effects

Events that affect CPS decision making and that occur over the same period of time as states' adoption of DR may interfere with the ability to isolate the impact of DR implementation. This is a "history effect," as described by Shadish, Cook, and Campbell (2002). One example of an event that may have influenced investigation and substantiation rates is federally mandated Child Family Service Reviews (CFSRs), which officially began in 2000 and led to the adoption of a standard set of child safety, permanency, and well-being outcomes across public CPS agencies (JBS International, 2011). The CFSRs are designed both to measure the current state of CPS systems and to affect long-term system reform. Certain CFSR measures, such as timeliness of investigations, repeat maltreatment, and risk assessment, may prompt state improvements in these areas that also affect investigation and substantiation rates. To date, however, no empirical studies have examined the impact of CFSR on decision-making practices.

Beyond the child welfare system, other forces that may have also affected investigation and substantiation rates include demographic shifts that can change the concentration of risk in certain regions of the country over time. For example, the U.S. Hispanic population grew by 43% in the decade between 2000 and 2010 (U.S. Census Bureau, 2010), and Dettlaff and his colleagues (2011) have shown that first-generation immigrants may have different risk and protective factors than other Hispanic families. Further, the early years of the study period were a time of relative economic prosperity, but this changed dramatically with the onset of the Great Recession in late 2007 (National

Bureau of Economic Research, 2010). Whether this might also affect child maltreatment reporting is unclear. Although higher rates of hospital admissions for physical abuse were found to be related to mortgage delinquency and unemployment (Wood et al., 2012), state-level unemployment rates and other economic indicators were not predictive of CPS referrals (Millett, Lanier, & Drake, 2011).

These macro-level forces may confound the relationship between DR implementation and substantiation and investigation rates, but it is difficult to anticipate the direction and strength of the potential of history effects, and it is not possible to include all history effects in a single statistical model. Rather than attempting to identify and account for all potential confounding effects, the analyses will address history threats by including the effect of each reporting year, as described below.

Unique Characteristics of Neglect

The three primary types of child maltreatment—physical abuse, neglect, and sexual abuse—have different incidence rates and elicit different agency responses. Information from the Third and Fourth National Incidence Studies indicates that between 1993 and 2006, incidence rates for physical and sexual abuse declined in the U.S., but neglect rates showed no discernible decline and also greater volatility (Sedlak et al., 2010). Similarly, since the 1990s the rates of sexual and physical abuse investigations that result in a substantiation have declined while neglect rates have remained relatively unchanged (Finkelhor & Jones, 2006). Neglect is also far more common than other maltreatment types, with incidence rates more than twice as high as the rate for physical and sexual abuse combined (DePanfilis, 2006). The same is true of substantiated or

indicated reports of neglect, which in 2010 accounted for 78% of all such reports (U.S. Department of Health and Human Services, DHHS, 2011).

The fact that the number of neglect reports is not declining and that these reports continue to far outnumber those of other maltreatment types may reflect the true incidence of the problem in the U.S. population. However, it is also possible that it represents a growing sensitivity to child neglect by reporters or a loosening or expansion of the definition of neglect over time (Jones, Finkelhor, & Halter, 2006). Given that national trends for neglect are, for whatever reason, dissimilar to trends for other types of maltreatment, and that the majority of CPS cases involve neglect, this study will focus specifically on neglect cases.

Race and DR Implementation

The over-representation of African American children within the CPS system is well documented in the literature (Fluke, Yuan, Hedderson, & Curtis, 2003; Gryzlak, Wells, & Johnson, 2005; Hill, 2007). In addition, a smaller but growing body of research indicates that Hispanic children's rate of investigation is at or below average, a phenomenon sometimes referred to as the "Hispanic paradox" (Fluke et al., 2003; Putnam-Hornstein, Needell, King, Johnson-Motoyama, 2013). To date, there is no consensus among observers about whether these differential rates of CPS involvement across racial/ethnic subpopulations can be attributed to biased decision making or other systemic mechanisms operating within the CPS system or to actual differences in maltreatment risk across racial/ethnic categories (Bartholet, 2009; Dettlaff et al., 2011; Drake et al., 2011; Putnam-Hornstein, et al., 2013).

Allan and Howard (2013) posit that DR may mitigate the higher rate of reporting and substantiation experienced by African American children. As evidence, they point to the connection between poverty and CPS involvement among African American families (see Putnam-Hornstein, et al., 2013). They also cite a state evaluation that found that African American families in the DR pathway were more likely to receive poverty-related services than White children in the DR pathway or African American children in the investigation pathway (Siegel, Filonow, & Loman, 2010). Although findings such as those cited by Allan and Howard suggest that African American families may be differentially impacted by DR due to their overall higher representation in CPS, the findings do not necessarily imply that DR directly reduces racial disparity experienced by African American children. This study will examine that question by determining whether the implementation of DR reduces investigation or substantiation rates among African American families beyond its effect on the overall CPS population.

To summarize, the goal of this study is to analyze changes in decision-making patterns over time that may be associated with DR implementation. In this context, its aims are primarily descriptive: given that nearly half of all states are currently implementing DR, it is important that CPS decision makers and researchers have access to empirical results documenting changes in the population of CPS-involved children in the U.S that may be associated with DR. The measures addressed here will be county-level investigation and substantiation rates of neglect cases. Specific questions addressed are:

(1) Is the implementation of DR associated with a decrease in the proportion of a county's child population experiencing a child neglect investigation or substantiation

over time? If DR results in significant changes, when and at what rate do such changes occur?

(2) Is the implementation of DR associated with an increase in the proportion of investigated cases that result in a substantiation over time? If DR results in significant changes, when and at what rate do changes occur?

(3) If DR is associated with significant changes in decision rates, are these patterns consistent for different racial and ethnic subpopulations of children?

Methods

Data and Study Population

The study uses data from NCANDS child files from the 2000-2010 reporting periods. NCANDS is a federally sponsored data collection system to which states voluntarily submit child-level data about CPS referrals that received a response from the agency (i.e., screened-in cases). A child may have more than one NCANDS report in a given twelve-month period. For example, in 2010 approximately 12% of children had more than one report (DHHS, 2011). The number of states included in NCANDS child files has grown over the years, from 34 in 2000 to 49 in 2010, including Puerto Rico and the District of Columbia (DHHS, 2001-2011).

Data reduction strategies. Despite improvements in NCANDS data submissions over time, many states still had large amounts of missing data within and across the eleven reporting periods used in this study. A variety of exploratory analyses were used to identify patterns of missing data and unexpected values, including a review of state-specific NCANDS data documentation (DHHS, 2001-2011). In some instances, state data administrators were contacted to clarify reporting aberrations.

Three issues emerged from this initial phase of data exploration. First, seven states and territories—Connecticut, Missouri, New Jersey, New York, Oregon, Pennsylvania, and Puerto Rico—were unable to report, or did not report in a comparable way, information about the measures used in this study during any reporting period. For example, Oregon and Missouri submissions were missing child-level information for unsubstantiated cases, thus investigation rates in these two states could not be calculated. Six other states—Delaware, Kansas, Louisiana, Michigan, North Carolina, and Ohio—were excluded in one or a limited number of reporting periods due to uncertainty about data consistency.

Second, in order to protect the identity of children, NCANDS datasets contain no county identifiers for any reports originating from a county with less than 1,000 reports. This means that small counties with high CPS reporting rates are identified but small counties with average or low reporting rates are not. Because there was no other way to avoid misrepresenting small counties, all small counties were excluded from the sample. The exclusion threshold was defined as those counties with fewer than 38,000 children—the minimum child population needed for a county to be included in NCANDS even if the county's reporting rate was one standard deviation below the national CPS reporting average (4.96 reports per 1,000 children). This produces a less heterogeneous sample and limits the potential generalizability of the findings to counties with relatively large child populations, but it removes a source of systemic error that could seriously distort the results.

Finally, despite the data reduction strategies designed to increase the comparability within sample counties as described above, exploratory analyses revealed

many outliers in the data. For example, NCANDS documentation noted that several states collected information only on substantiated cases in the 2000 reporting period, and so these states were excluded from the sample. Despite their exclusion, investigation and substantiation rates from the 2000 reporting period still contained a higher amount of variation than other reporting periods. It is unknown whether the remaining variation was due to reporting aberrations or real differences decision practices at the agencies, and so outliers that were not explained by documentation about reporting aberrations were left in the sample. The mixed-effect analyses were conducted on transformed data that reduced the influence of extreme values. When possible, these outliers are identified and described in the results discussion.

Dataset construction. Merging the full NCANDS data files from 2000-2010 resulted in a single dataset with 849 counties from all states, the District of Columbia, and Puerto Rico that submitted data in at least one of the study's reporting years. The merged dataset contained investigation and substantiation rates by county and year, and included 11,425,441 discrete investigations of neglect cases. After the data-reduction steps described above, the final sample included 295 counties from 42 states, with aggregated data from 7,658,147 neglect investigations across eleven years. This sample was used for most of the descriptive analyses described below. A piecewise mixed-effect analysis restricted the sample further to counties that were within five years of starting a differential response initiative (see *Analysis Plan, primary model* section). This dataset included 70 counties from 15 states, with aggregated data from 1,142,174 neglect investigations.

In addition to NCANDS, county population information was obtained from the National Cancer Institute (NCI, 2013), which provides an epidemiological dataset based on U.S. Census data with refined county population estimates by year, by race, by age. The descriptive analyses also used county child poverty rates from U.S. Department of Agriculture (2012).

Measures

Investigation and substantiation rates. Three dependent variables were examined in the analyses: (1) rates of neglect investigations within the population (investigation/population rates), (2) neglect substantiations within the population (substantiation/population rates), and (3) neglect substantiations within investigations (substantiation/investigation rates). A single report in NCANDS can contain up to four different maltreatment allegations, each with its own disposition outcome. Investigation and substantiation rates included those cases with co-occurring maltreatment, comprising approximately one-third of all neglect reports.

In the dataset, *investigations* refers to any allegation of neglect that received a disposition of substantiated, indicated, or unsubstantiated. *Substantiated cases* are those in which the allegation of neglect resulted in a disposition of "substantiated" or "indicated." If the neglect allegation was not substantiated but another allegation involving a different type of maltreatment was substantiated, the case was still considered unsubstantiated for this study's purposes. Four other disposition categories that NCANDS tracks are *intentionally false*, *closed with no finding*, *alternative response victim*, and *alternative response nonvictim.* Cases with these dispositions were not included because the categories are not used in every state.

With regard to child race/ethnicity, three NCANDS categories were used in the subanalysis: (1) White, Non-Hispanic; (2) African American, Non-Hispanic; and (3) Hispanic children of any racial category. Although other racial categories are identified in NCANDS, it was possible that the low numbers of children in these categories in many counties could lead to distortions in the results, so the subanalysis were conducted only on children from the three largest racial/ethnic groups. In all other analyses, however, children of all racial/ethnic categories were included. Substantiation rates for each racial/ethnic category in the subanalysis were constructed in a similar way as rates for the full analysis. For example, the investigation rate for African American children represents the proportion of African American children who received investigations out of the total county population of African American children.

DR measures. A database was created to document DR implementation for every U.S. county for each of the eleven reporting periods (Janczewski, 2014). DR implementation was defined using the core elements of DR articulate by Merkel-Holguin and colleagues (2006).

Two measures of DR implementation were *DR implementation* and *time implementing DR*. DR implementation was a dichotomous measure indicating whether a county was implementing DR for at least six months within a given NCANDS reporting period. Time implementing DR was a continuous variable representing the number of years a county had implemented DR. This variable was centered at zero, which represented the baseline year prior to implementation. Counties that did not implement DR within any of the eleven reporting periods were not included in the analyses that examined time implementing DR. In some counties, DR implementation started,

stopped, and later resumed. In the final sample, only three counties from two states (Alaska and Arizona) experienced these interruptions of DR implementation. Given that DR interruptions are unique events that may result in unanticipated changes in decision outcomes, it was unclear how best to classify the gap years and so for these data points the variable of time implementing DR was coded as missing. When DR was re-launched, the value restarted at one.

Year. Another measure of time used in this study was y*ear*, which represents the NCANDS reporting period. Prior to 2003, NCANDS reporting periods were based on the calendar year, but from 2003 through the present, periods correspond with federal fiscal years (October through September). This change resulted in a three-month overlap of data within the 2002 and 2003 files. The *years* measure was included to control the influence of history on the effects of DR implementation. Changes in CPS policies, demographic patterns, and the economy may have influenced investigation and substantiation rates, and these are examples of the potential history effects noted earlier. Although this study could not include specific measures of all such possible threats, by including years in the model, the relationship between the dependent variables and DR years measures the effect of DR implementation after adjusting for other temporal trends.

Analysis Plan

Data analyses proceeded in three phases. First, the distributional properties of the three dependent variables—investigation/population, substantiation/population and substantiation/investigation rates—were assessed. Second, descriptive analyses were used to identify possible trends in the three rates and DR implementation over time.

Finally, a piecewise mixed-effect equation was modeled to compare changes in the three dependent variables for DR counties pre- and post-implementation.

The initial analysis indicated that investigation and substantiation rates had a high degree of inter- and intra-county variability over time and that the distribution of rates was positively skewed. In general, mixed-effect models are robust to many violations of normality including heteroscedasticity and non-Gaussian distributions (Jacqmin-Gadda, Sibillot, Proust, Molina, & Thiébaut, 2006). Initial testing of model fit indices, however, revealed that log transformed dependent variables were more stable in the models than non-transformed, and so the piecewise mixed-effect models used transformed values (Cohen, Cohen, West, & Aiken, 2003).

In the second phase of the analysis, DR and non-DR counties were compared in terms of population characteristics and investigation and substantiation rates of DR using *t* tests. Next, the unadjusted means of investigation and substantiation rates were plotted by reporting years and length of time before and after DR implementation. These plots were used to inform the construction of piecewise mixed-effect model.

Third, the piecewise mixed-effect models examined the impact of DR implementation on investigation and substantiation rates over time. In a true experimental design, the timing of both the measurement and intervention is controlled. The dataset in this study, however, is observational and unbalanced because counties launched DR at different points in time over the eleven-year study period. This means that some counties have more pre-implementation data points and some have more post-implementation data points. In addition, missing data points were more likely to occur in early years of the study period, which also contributed to unbalanced data. Piecewise

mixed-effect models have a number of advantages for testing slope changes in observational studies (Naumova, Must, & Laird, 2001), which are often unbalanced. Mixed-effect models can accommodate multiple random effects, and the effects are robust to both collinearity associated with repeated measures and to unbalanced clustering of effects across time (Naumova, et al., 2001). The *years* variable was also added to account for confounding history effects.

Primary models. This analysis used a subsample of counties that had implemented DR at any point during the eleven-year study period (n=70). The dataset consisted of a row for each of the eleven reporting periods for each county. Two dummy-coded variables designated rows as pre-DR (one or more years prior to the baseline year) or post-DR (one or more years after baseline). This grouping technique is used to identify slope changes in piecewise mixed-effect models (Wu, 2010). The baseline year (i.e., the year before DR implementation) served as the point to define the groups based on the descriptive plots. These indicated evidence of a spline trend for investigation/population and substantiation/population rates, where the slope changed at the first year of implementation (Figures 4.1 & 4.2). Similar trends were not visible in the descriptive plots for substantiation/investigation rates, but given that the initial plots did not control for history, tests were performed for slope changes of substantiation/investigation rates at the baseline year in a multilevel, multivariate context.

After creating grouping variables, piecewise mixed-effect models were fitted to test whether the slopes of the two groups (pre- and post-DR) were different. For each of the dependent variables, three nested models were tested: Model A only included the effects of the pre- and post-DR slopes; Model B included reporting year; Model C

included a quadratic term for post-DR effects to explore whether post-DR slopes were non-linear. Quadratic terms for pre-DR slopes and cubic effects for post-DR tests were also tested, but these did not improve model fit and their results are not presented. Due to concerns that earlier data submissions lacked quality or were dissimilar to submissions in later years, the robustness of the findings were assessed by testing a series of Model C equations using a reduced subsample that excluded data from 2000-2002 reporting years. Results from the reduced sample were comparable to the full sample in terms of significant fixed effects and differences in slope, so further reporting will address only the full sample.

Because of the longitudinal nature of the data, several possible covariance structures were tested. Results showed that the best fit was associated with an autoregressive covariance structure (Gurka, Edwards, & Muller, 2011). Likelihood ratio tests were used to assess the fit of the nested models. Significant fixed effects were found using tests with *a priori* alpha levels set at $p < .05$. Finally, contrasts using *t* tests with Bonferroni corrections were performed to determine if pre- and post-DR slopes were significantly different.

Racial subanalysis. In response to the research question addressing the possibility that the impact of DR implementation may vary by race, separate versions of Model C were fit with investigation and substantiation rates for White, African American, and Hispanic subpopulations. Pairwise comparisons using *t* tests compared estimates for intercepts, fixed effects, and slope differences across the three racial/ethnic subgroups.

Post hoc analysis. As will be discussed, models for the third dependent variable, substantiation/investigation rates, yielded null results. In light of these unexpected findings, average DR-county investigation and substantiation rates were calculated excluding post-DR data points. These pre-DR rates were then compared to rates in non-DR counties in order to determine whether DR-counties decision rates were significantly different from non-DR counties before DR was implemented.

Results

Descriptive Analysis

Figure 4.1 displays the total number of DR and non-DR counties by NCANDS reporting period. This figure highlights two important characteristics of the data. First, a much larger number of counties are included in later years than in earlier years. Second, the proportion of counties employing DR has increased over time. These results support using a robust multilevel method to address the uneven distribution of data points over time.

[Figure 4.1]

Figure 4.1 also illustrates that even at the peak of DR implementation (in the final year), non-DR counties outnumbered DR counties more than two to one. On available county characteristics, the two groups appeared to be comparable. For example, no significant differences were found between DR and non-DR counties relative to child poverty rates, population density, and the proportion of White children residing in the county (Table 4.1). Likewise, DR and non-DR counties did not show, on average, significantly different investigation/population and substantiation/population rates.

However, differences did appear with regard to substantiation/investigation rates, which were significantly higher (about 1.3 times) in DR than non-DR counties.

[Table 4.1]

With regard to dependent variables, results shown in Figure 4.2 suggest that the average rate of neglect investigations increased over time in non-DR counties while decreasing in DR counties. Substantiation/population rates also trended downward across all counties over time, but more so for DR counties. The trend line for substantiation/population rates for neglect appears uneven, with a sharp increase in 2009. Analyses suggest that this fluctuation was primarily due to the implementation of DR in Massachusetts in 2009, which consistently reported a higher rate of investigation and substantiation/population than other states (DHHS, 2000-2010). Changes in neglect substantiation/investigation rates were inconsistent over time in both groups, although DR counties had higher rates of substantiation for every reporting period except 2000.

[Figure 4.2]

The final descriptive analyses explored substantiation and investigation rates within the subsample of counties that implemented DR at any point during the study timeframe. In Figure 4.3, time was measured as length of time implementing DR, where "0" represents the year prior to implementation. The dotted vertical lines indicate the time parameters used in the mixed-effect model. These plots suggest a dramatic reduction in both investigation and substantiation/population rates during the first three years of DR implementation, with rates stabilizing in later years. The rates at the far end of the chart start to increase again and show a high degree of variability, but this may be due to the small number of counties implementing DR for long periods of time. Results

for substantiation/population rates drop at Year 0 but then appear relatively stable over the length of time implementing DR. Without controlling for history effects, results shown in Figure 4.3 offer support for the hypotheses that investigation/population and substantiation/population rates decrease during the early years of DR implementation. However, they do not support the hypothesis that DR implementation corresponds with an increase in the proportion of investigated neglect cases that receive a substantiated disposition.

[Figure 4.3]

Mixed-Effect Analysis

Primary Analysis. Three primary models were tested in the piecewise mixed-effect analysis for each of the three outcome variables. As shown in Table 4.2, investigation rates were significantly lower after the implementation of DR across all three models (Models A-C). When *year* was added in Model B to control for history effects, the pre-DR slope became insignificant, while the effects of post-DR strengthened. The quadratic effect of post-DR further improved model fit (Model C), suggesting that the slope of post-DR is nonlinear. More complex nonlinear functions were also tested, but these effects degraded model fit.

[Table 4.2]

DR implementation had similar effects on substantiation/population rates, as shown in Table 4.3. The average rate was lower after DR implementation, with a negative and significantly steeper slope than for rates prior to DR implementation. Although Model B for substantiation/population rates found non-significant differences between pre- and post-DR slopes, the difference became significant once again when the

quadratic effect for post-DR was added (Model C). The addition of a quadratic effect for post-DR improved model fit most likely because it more accurately estimated the reduction in slope after Year 3 of implementation, as also shown in Figure 4.3.

[Table 4.3]

Table 4.4 shows results for the piecewise mixed-effect model for substantiation/investigation rates, and these do not reveal significant differences between the slopes before and after implementation. In fact, the fixed effects of DR implementation and reporting year did not contribute significantly to substantiation/investigation rates for any of the models. These results and the findings presented in Figure 4.3 suggest that the proportion of investigated neglect cases that receive a substantiated disposition did not change with implementation of DR, contrary to expectations articulated in Research Question 2. Further analyses of these null findings are presented in the *Post hoc analysis* section.

[Table 4.4]

Race/ethnicity subanalysis. Model C was estimated for White, African American, and Hispanic subpopulations to determine whether DR's influence on investigation and substantiation rates varied by race or ethnicity. For this subanalysis, three pairwise comparisons among racial groups were conducted using *t* tests to detect significant differences in (1) intercepts; (2) fixed effects of the post-DR slope; and (3) estimated change of slopes before and after DR implementation.

[Table 4.5]

Although the dependent variables were transformed, which limits the direct interpretation of the estimates, the results shown in Table 4.5 reveal significant

differences in the intercepts (i.e., adjusted average) in two of the three outcomes among the three racial/ethnic subpopulations. Compared to White children, African American children experienced significantly higher rates of investigation and substantiation within county populations. Conversely, Hispanic children's adjusted average rates were significantly lower than rates for White or African American children. There were no significant racial/ethnic differences among intercepts for the third dependent variable, the proportion of investigations that received substantiations. This rate, which used the preceding decision point as a denominator, better identifies new effects associated with the substantiation decision (Rolock, 2011). Therefore, the findings suggest that the non-significant results regarding racial differences that were found for substantiation/population rate, were related to the disproportionate representation of racial/ethnic subpopulations introduced at or before the investigation stage rather than the effect of differential decision making introduced at the point of substantiation.

Pairwise contrasts among racial/ethnic groups for the other two comparisons of interest (*Post-DR slope* and *Difference in pre/post slopes*) revealed no significant racial differences. These findings suggest that although pre-existing racial disproportionality is evident in the adjusted average investigation rates, DR's effect was similar across racial/ethnic subpopulations. That is, DR implementation decreased investigations and substantiations within a county population at approximately the same rate across racial/ethnic groups.

Post hoc analysis. Prior research suggests that DR increased the proportion of investigated cases that were substantiated (Loman & Siegel, 2004), yet the piecewise mixed-effect models showed no such relationship across counties. One possible

explanation for this result is that DR counties had, on average, higher substantiation rates than non-DR counties even prior to implementation. To test this possibility, average rates of investigation, substantiation/population, and substantiation/investigation were calculated for DR counties prior to DR implementation (i.e., excluding post-DR data points). These rates were then compared to average rates for non-DR. Results, which are shown in Table 4.6, support the *post hoc* explanation. They reveal significant differences in substantiation/investigation rates between pre-DR counties and non-DR counties, but no significant differences in investigation or substantiation/population rates. This suggests that on average, DR-counties substantiated a higher proportion of investigated cases than non-DR counties before DR was initiated. The pre-existing difference highlights the importance of conducting longitudinal studies to rule out possible selection effects when assessing changes associated with system reforms.

[Table 4.6]

Discussion

The implementation of DR was associated with significant reductions in investigation and substantiation/population rates, as suggested by prior literature (Janczewski, in press; Shusterman et al., 2005; Virginia Department of Social Services, 2007). These relationships remained significant even after introducing the control variable to adjust for yearly variation in trends. Further, differences in pre/post slopes suggest that not only were DR investigation and substantiation/population rates lower after the DR implementation but the rates of decline in these measures were also significantly different as evident by the contrast tests conducted for each model between pre- and post-DR slopes. It is also supported by both descriptive plots and the quadratic

effects in the mixed-effect models show that the rate of decline for both investigation and substantiation/population rates was steepest in the first three years of DR implementation.

The mixed-effect models, however, did not find significant differences in pre- and post-substantiation/investigation rates (Research Question 2), which was unexpected based on past findings. Previous studies were either cross-sectional comparisons between DR and non-DR counties (Janczewski, in press) or single state evaluations (Loman & Siegel, 2004; Virginia Department of Social Services). Notably, post hoc analyses suggest that DR-counties had significantly higher rates of substantiated investigations even prior to the launch of DR compared to non-DR counties. This finding raises concerns regarding possible selection biases in previous cross-sectional studies. Since findings from two single-state evaluations indicate that substantiation/investigation rates did increase over time, more analyses may be needed to understand the effects of DR implementation on substantiated investigations and to determine whether there are effect differences across states.

The subanalysis did not reveal any differential effects of DR implementation on investigation or substantiation rates for racial/ethnic subgroups. DR may not directly reduce disproportionality experienced by CPS-involved African American children; however, because African American children tend to be overrepresented within the CPS system they may be most affected by the decreased investigations and increased access to service provision that may result from DR.

The current study has two major limitations related to selection effects that may have influenced findings. First, states submitting NCANDS data consistently over time had more data points in the analysis, and these states may differ in substantively

meaningful ways from those with missing data. For example, early and consistent NCANDS reporting may be associated with more CPS resources in general, and more resources may be associated with the availability of certain types of services that also influence CPS decision making.

Second, counties in states that choose to implement DR or that were early adopters may not be comparable to other counties. Despite *t* tests indicating no significant differences in population characteristics between DR and non-DR counties, there may be other, unmeasured differences. This concern is particularly salient given that the post-hoc analysis found DR and non-DR counties to be significantly different relative to substantiation/investigation rates prior to the implementation of DR. Currently, about half the states in the U.S. have initiated DR. If early adopters of DR are different from others, then the generalizability of this study's findings may be limited in terms of predicting future trends of newly launched DR services.

Implications

This study demonstrates the system-wide impact of DR using a national sample of counties and comports with other literature that has suggested that DR reduces CPS investigations. Specifically, the models found large reductions in investigation rates generally occurring within approximately three years DR of implementation. Knowing the degree and rate of change in CPS decision making that is attributable to DR may help decision makers plan for its impact in terms of reallocation of staff, services, and other resources. The findings also highlight the importance of understanding large-scale policy changes, such as DR implementation, when studying CPS decision outcomes. The unexpected null results pertaining to the effects of DR on substantiation/investigation

rates conflicts with prior single-state evaluations and suggests the need for more exploration.

DR is a system reform that targets the decision-making process in the early stages of CPS-involvement, which has also been touted as the best point for addressing racial disparities (Allan & Howard, 2013). Results of this study, however, did not suggest the presence of a direct effect for DR on reducing racial disparity, as measured by reducing the rate at which allegations involving African American children are investigated or substantiated more so than children of other races. But DR's potential benefits to African American children may still be real. As discussed previously, studies suggest that higher-than-average exposure to family- and community-based risk factors experienced by African American children may significantly contribute to their over-representation in CPS (Putnam-Hornstein, et al., 2013). With its emphasis on family-driven, community-based service provision, DR may represent a secondary prevention strategy that can mitigate some of these risks. Clearly, DR's potential in this area is dictated by the ability of CPS agencies to secure high quality services—a challenge for DR and traditional investigative pathways alike.

A final implication of the study's findings is that the need remains for more longitudinal studies using robust, multivariate methods to assess the impact of child welfare policy and identify large-scale shifts in decision making and other systemic outcomes. Currently, much of the information about national trends in child welfare data is synthesized in federally sponsored reports (e.g., DHHS 2000-2010; JBS, 2011; Sedlak et al., 2010). Although these documents serve as good starting points for policy analysis, they are intended for a wide audience. This means the questions they address are broad

and their methods are limited in scope. Disciplines such as public health and economics use a variety of innovative methods, such as the piecewise mixed-effect model used in this paper, to achieve more informative, fine-grained analyses of change over time, and these approaches are currently underutilized in social service policy analysis. As the quality of national CPS datasets improves, these techniques could help improve our understanding of child welfare reform at the local and national levels.

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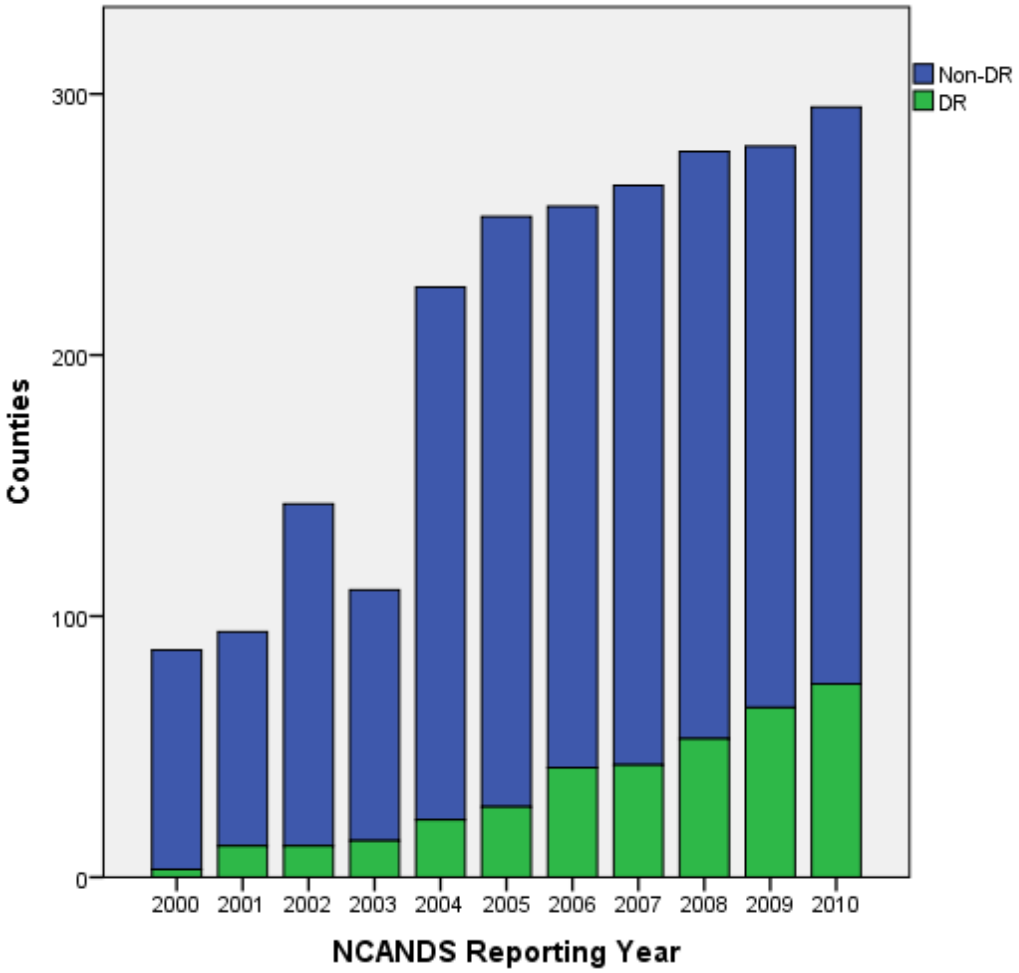

Figure 4.1: Number of DR and non-DR counties in sample over time.

Table 4.1
Comparisons between DR and Non-DR Counties

	Non-DR Counties (n = 199)			DR Counties (n = 96)		
	Mean (SD)	95% CI LL	UL	Mean (SD)	95% CI LL	UL
Density[a]	916 (1649)	683	1148	1004 (1419)	717	1292
% Child Poverty[a]	20.72 (8.2)	19.57	21.87	20.86 (6.9)	19.47	22.25
% White Child Pop	58.89 (22.3)	55.78	62.01	60.94 (17.1)	57.48	64.41
Investigation/Pop Rate[a]	25.47 (14.9)	23.22	27.72	22.03 (16.2)	19.00	25.06
Substantiation/Pop Rate[a]	6.95 (4.5)	6.32	7.57	7.74 (7.1)	6.29	9.18
% Substantiation/Invest	29.53 (11.4)	27.94	31.12	37.79* (14.5)	34.85	40.72

Note: Superscript (a): uses 2010 data only. All other variables use 2000-2010 data. Investigation and population rates are out of 1,000 children in the county population. * $p < .05$

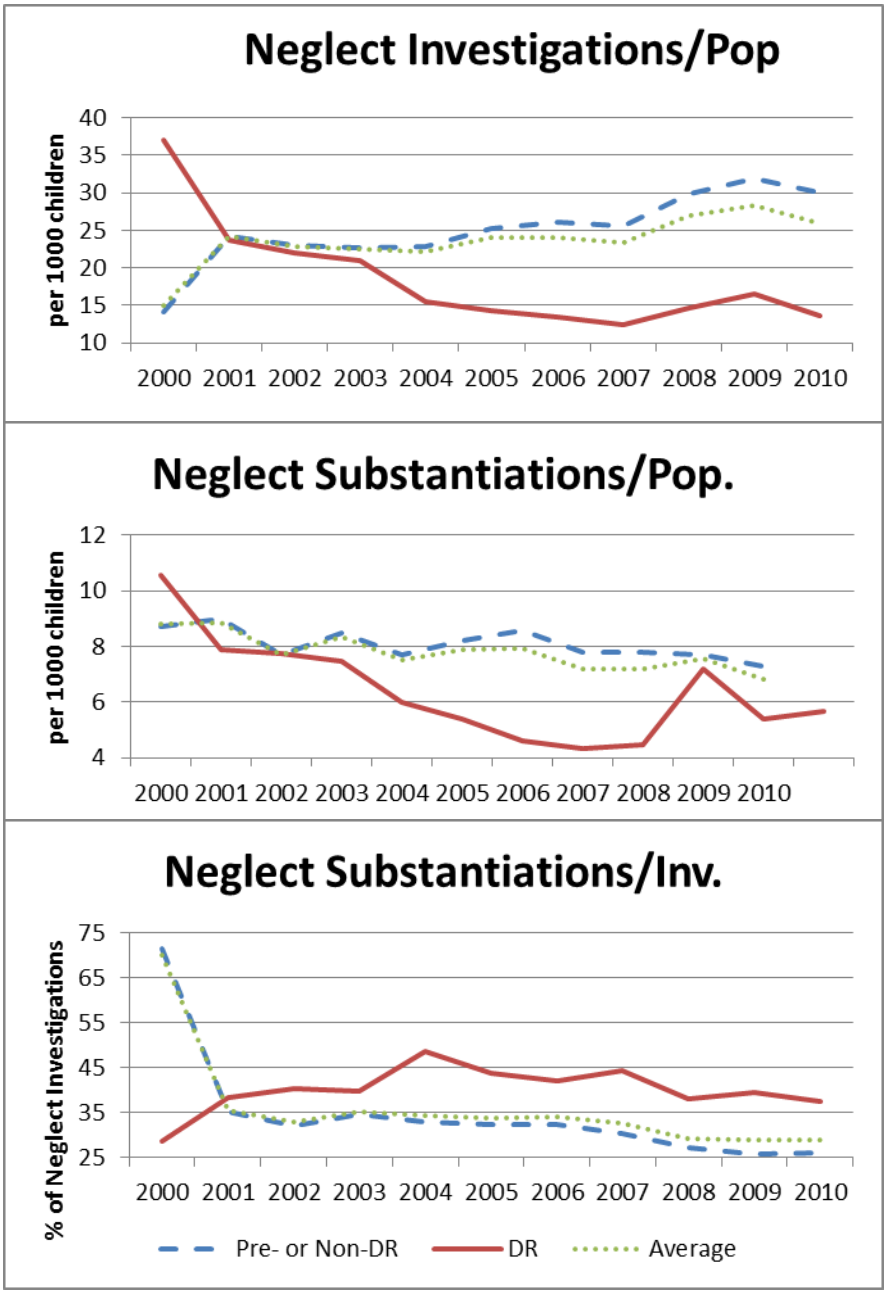

Figure 4.2: Investigation and substantiation rates over time.

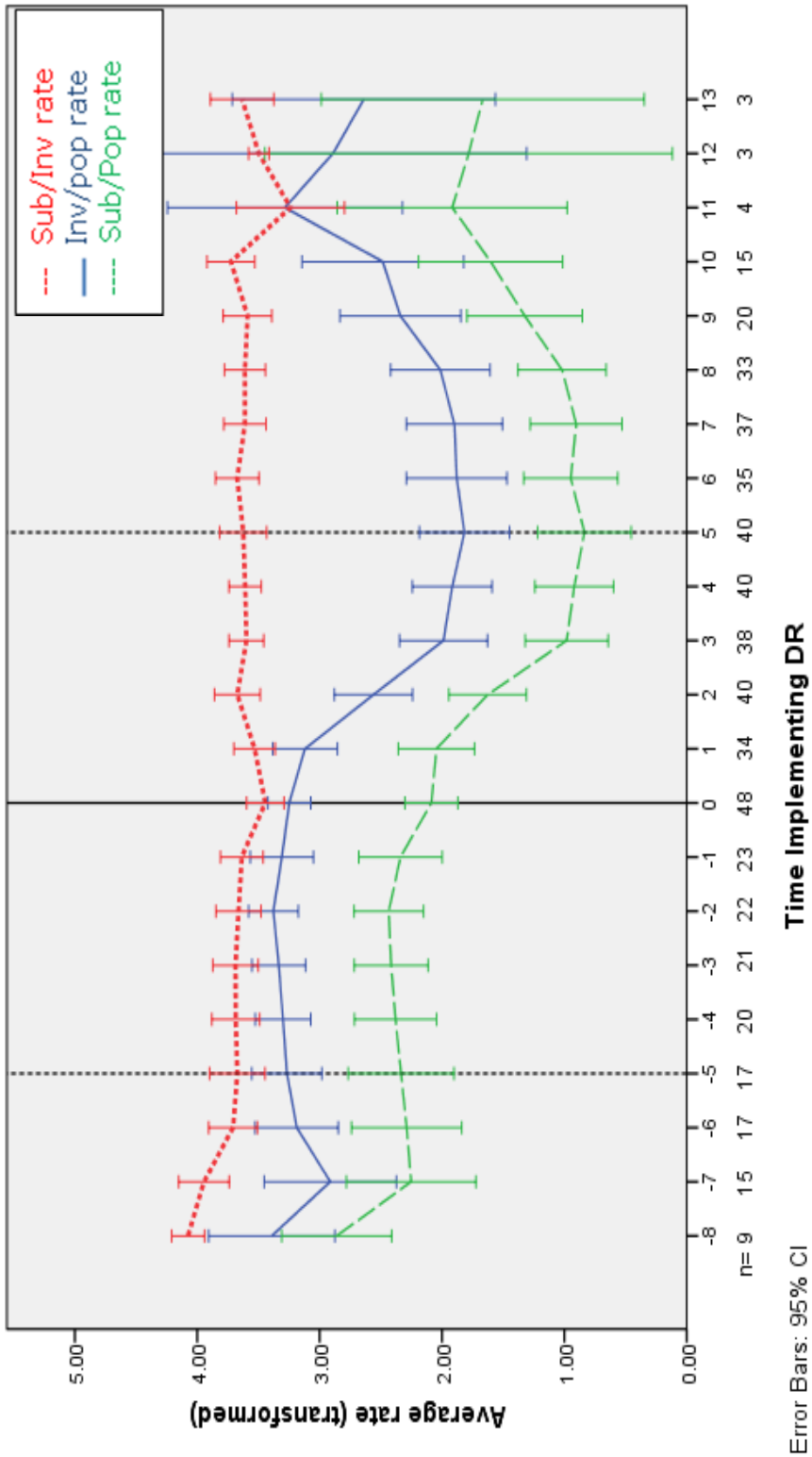

Figure 4.3: Average investigation and substantiation rates pre- and post- DR implementation. Solid vertical line indicates the year before DR started. Dotted vertical lines represent time period used for mixed-effect model. The X-axis also includes the number of counties at each time point.

Table 4.2

Piecewise Mixed-effect Models for Investigation/Population Rates

	Model A			Model B			Model C		
	Estimate		SE	Estimate		SE	Estimate		SE
Intercept	2.971	*	0.07	2.237	*	0.12	2.720	*	0.18
Pre-DR slope	0.122	*	0.05	-0.083		0.06	0.062		0.10
Post-DR slope	-0.162	*	0.04	-0.275	*	0.05	-0.487	*	0.08
Year				0.143	*	0.02	0.086	*	0.03
Quadratic post-DR slope							0.054	*	0.01
Difference in Pre/Post slopes	-0.284	*	0.08	-0.192	*	0.08	-0.55	*	0.14
-2 log likelihood	488.9			447.4	*		433.2	*	

Note: Estimates are transformed.

*$p < .05$, Bonferroni correction used in slope tests and likelihood ratio tests.

Table 4.3
Piecewise Models for Substantiation/Population Rates

	Model A			Model B			Model C		
	Estimate		SE	Estimate		SE	Estimate		SE
Intercept	1.829	*	0.08	1.226	*	0.13	1.966	*	0.18
Pre-DR slope	0.148		0.10	-0.074		0.07	0.130		0.09
Post-DR slope	-0.133	*	0.06	-0.248	*	0.05	-0.558	*	0.07
Year				0.133	*	0.02	0.053	*	0.03
Quadratic post-DR slope							0.073	*	0.01
Difference in Pre/Post slopes	-0.281	*	0.13	-0.17		0.09	-0.69	*	0.13
-2 log likelihood	495.9			464.1			436.0		

Note: Estimates are transformed.
*$p < .05$, Bonferroni correction used in slope tests and likelihood ratio tests.

Table 4.4
Piecewise Models for Substantiation/Investigation Rates

	Model A		Model B		Model C	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.559 *	0.04	3.616 *	0.08	3.760 *	0.11
Pre-DR slope	-0.019	0.04	-0.021	0.04	0.004	0.04
Post-DR slope	0.015	0.03	0.021	0.03	-0.048	0.05
Year			-0.011	0.01	-0.02	0.01
Quadratic post-DR slope					0.015	0.01
Difference in pre/post slopes	0.034	0.05	0.0417	0.05	-0.05	0.07
-2 log likelihood	202.1		208.7		213.2	

Note: Estimates are transformed.
*$p < .05$, Bonferroni correction used in slope tests and likelihood ratio tests.

Table 4.5

Piecewise Models for Race/Ethnicity Subanalysis

	White			African Am.			Hispanic		
	Estimate		SE	Estimate		SE	Estimate		SE
Investigation/Population Rate									
Intercept† a, b, c	2.340	*	0.18	3.435	*	0.18	1.395	*	0.26
Pre-DR slope	0.047		0.07	0.094		0.08	-0.062		0.10
Post-DR slope†	-0.558	*	0.08	-0.486	*	0.07	-0.325	*	0.11
Year	0.107	*	0.01	0.050		0.02	0.210	*	0.03
Quadratic post-DR slope	0.055	*	0.02	0.054	*	0.01	0.014		0.02
Difference in pre/post slopes†	-0.605	*	0.13	-0.579	*	0.13	-0.263		0.18
Substantiation/Population Rate									
Intercept† a, b, c	1.505	*	0.18	2.804	*	0.20	0.820	*	0.00
Pre-DR slope	0.090		0.07	0.161		0.10	-0.038		0.10
Post-DR slope†	-0.604	*	0.08	-0.643	*	0.09	-0.517	*	0.13
Year	0.085		0.02	0.010		0.03	0.1763	*	0.04
Quadratic post-DR slope	0.072	*	0.01	0.090	*	0.01	0.057		0.02
Difference in pre/post slopes†	-0.694	*	0.13	-0.804	*	0.15	-0.478	*	0.21
Substantiation/Investigation Rate									
Intercept†	3.737	*	0.11	3.904	*	0.13	3.887	*	0.17
Pre-DR slope	0.018		0.04	0.034		0.05	-0.005		0.05
Post-DR slope†	-0.051		0.05	-0.145	*	0.06	-0.169		0.09
Year	-0.015		0.01	-0.029		0.02	-0.013		0.02
Quadratic post-DR slope	0.016		0.01	0.030	*	0.01	0.032		0.02
Difference in pre/post slopes†	-0.069		0.08	-0.180		0.09	-0.163		0.13

Note: Estimates are transformed. † indicates pairwise comparisons performed among racial/ethnic groups. Significant differences ($p < .05$, Bonferroni adjusted) designated by the following superscripts: a = White and African American; b = White and Hispanic; c = African American and Hispanic.

*$p < .05$

Table 4.6

Post hoc analysis: Comparison of Investigation and Substantiation Rates Between Pre-DR and Non-DR Counties

	Sum of Squares	df	Mean Square	F	Sig.	Eta-squared
Investigation/population	162.173	1	162.173	.634	.427	0.003
Substantiation/population	723.068	1	723.068	24.760	< .001	0.098
Substantiation/investigation	5044.671	1	5044.671	36.873	< .001	0.14

CHAPTER 5

Conclusion

Discussion

The following discussion synthesizes the results of the three studies in two sections. The first section examines DR's overall impact on investigation, substantiation, and removal decisions in neglect cases, while the second discusses poverty and race in decision making for neglect cases and whether DR moderates this relationship.

DR's Overall Impact on Investigation, Substantiation, and Removal Decisions

The studies presented in Chapters 2 and 4 found that DR implementation was associated with fewer CPS investigations, as previous findings have suggested (Loman & Siegel, 2004; Shusterman, Fluke, Hollinshead, & Yuan, 2005; Westat, 2009). This relationship was consistent even when controlling for the following characteristics: county characteristics such as child poverty rates, proportions of White and African American children, and population density. Similar trends were evident when examining substantiation rates as proportions of the child population (substantiation/population rates), which is not surprising given that substantiation/population rates are a subset of investigation rates. The results from the longitudinal analysis in Chapter 4 showed the presence of rapid declines in these rates beginning within the first year of launching DR and continuing through the third year of implementation (Table 4.3). By the fourth year, the rates of decline diminished, suggesting that the policy has reached maturation. Based on these results, DR appears to be a fast-acting policy that leads to significant changes in child welfare decision making. , suggesting the most substantial changes in investigation and substantiation/population rates occur within the first three years after DR implementation. Because the sample of counties with more than five years of DR

implementation was small, the post-five-year trends were erratic and should not be used for interpretation.

In contrast, the analyses of DR's influence on substantiation decisions within the population of investigated cases (substantiation/investigation rates) yielded inconsistent results across the three studies. Substantiation/investigation rates use decision-based enumeration (Rolock, 2011), so these rates represent discrete effects that occur during the substantiation decision point. Proponents of DR have posited that the proportion of investigated cases that result in substantiation increases when an agency adopts DR because many of the moderate risk cases are diverted to an alternate pathway (Schene, 2005; Shusterman et al., 2005). This assumption necessarily implies that moderate-risk cases are less likely to be substantiated. An evaluation of DR in Virginia supported this hypothesis and found that substantiation rates increased from 23% in 2001 (the baseline year of DR implementation) to 41% in 2004 (Virginia Department of Social Services, 2007).

The cross-sectional results from analyses of 2010 data reported in Chapters 2 and 3 also support this claim: The aggregate analysis in Chapter 2 found significantly higher substantiation/investigation rates in DR counties than in non-DR counties, and the multilevel model in Chapter 3 found that investigations in DR counties were more than twice as likely to result in substantiations. These findings, coupled with the decrease in overall investigation rates, led to the conclusion in Chapter 2 that DR counties have, on average, fewer families who experience a child welfare investigation that results in non-substantiation.

Results from the longitudinal study in Chapter 4, however, contradicted findings from the cross-sectional studies. The piecewise mixed-effect models found no change in substantiation rates coinciding with DR adoption. Initial descriptive analyses indicated that although DR counties had consistently higher rates of substantiation among investigations than non-DR counties (Figure 4.2), the rates did not change between pre- and post-DR implementation (Figure 4.3). Post-hoc analysis revealed significant differences between DR and non-DR counties prior to the launch of DR. This suggests the presence of a selection bias caused by DR counties having significantly higher substantiation/investigation rates than non-DR counties before DR was launched.

The unanticipated results raise two questions: First, why did counties that implemented DR consistently have higher substantiation/investigation rates than counties that did not? Perhaps counties that choose to implement DR are those that already have other practices in place that lead to higher substantiation rates, such as more thorough assessment practices during very early in the course of a case. There may be other unmeasured factors that distinguish non-DR counties from DR counties that could potentially lead to spurious conclusions about its impact. A cluster analysis, in which DR-counties are grouped by high, medium, and low substantiation/investigation rates, may help uncover patterns in subsamples of DR-counties. It should also be noted that typically states rather than individual counties decide to launch DR initiatives, although implementation is often initiated within a few counties before expanding across the state over time. Therefore, although DR is not entirely state-driven, it is not solely county-driven either, and its effect may be more precisely modeled by accounting for both state and county effects.

Second, even if substantiation rates were generally higher in pre-DR counties than in non-DR counties, why did these rates remain relatively stable even after a large portion of moderate-risk cases were diverted? If the findings from this analysis reflect true stability in substantiation/investigation rates (i.e., changes in rates were not obscured by cluster effects), the results suggest that the rate of substantiation in high- and moderate-risk cases is more similar than previously thought. Some evidence suggests that CPS workers may substantiate low- to moderate-risk cases in order to ensure that children receive needed services (Fluke, 2009; Kohl, Jonson-Reid, & Drake, 2009; Shdaimah, 2009), and this might account for at least part of the higher-than-expected substantiation rate in moderate-risk cases. It is also important to note that the purpose of substantiation is to indicate that an investigation found evidence of maltreatment. In principle, there is no reason why a moderate-risk case would be less likely to be substantiated than a high risk case if they both meet the standards for maltreatment. The hypothesis that DR will reduce substantiation/investigation rates because it diverts moderate risk cases may confound substantiation decisions with risk assessment (Drake & Jonson Reid, 2000). Prior literature has found that substantiation represents a poor proxy for risk (Kohl, et al., 2009). The conflicting findings in these analyses reveal much additional research is needed to understand DR's relationship with substantiation. Should future research replicate the results of this study, this may lead to the conclusion that DR's most significant impact on decision making is to help keep service provision distinct from the investigative functions of CPS (Yuan, 2005).

The study presented in Chapter 2 also included an analysis of DR's impact on removal decisions. The regression analysis found that DR counties had significantly

lower removal/substantiation rates than non-DR counties, but the mediation model that included prior decision points did not find any significant associations between removal and DR implementation. These results suggest that compared to non-DR agencies, DR agencies may have lower removal rates overall, but that this effect is mainly due to the significantly lower investigation rates in DR counties. Additionally, as would be expected from a front-end system reform, DR's influence appears strongest at early decision points.

A Closer Examination of Poverty, Race, and DR

The studies contribute new information about how county-level poverty rates may predict patterns of decision outcomes among child welfare agencies. In the cross-sectional study in Chapter 2, higher county-level child poverty rates were associated with significantly higher investigation rates in both the regression and path models, along with higher substantiation rates in the regression model. The study also tested whether DR moderated the effects of poverty on decision outcomes through a multiple-group path analysis. Results showed that DR implementation was significantly associated with a reduction in the relationship between poverty levels and investigation rates. In the multilevel cross-sectional study presented in Chapter 3, however, county-level child poverty rates were not associated with the likelihood of substantiation in DR and non-DR counties. The study in Chapter 2 supports findings from previous research that a significant association exists between poverty and decision making in neglect cases (Mersky, Topitzes, & Reynolds, 2009; Slack et al., 2011; Sedlak et al., 2010), and it suggests that DR may weaken this association by diverting low- and moderate-cases that would have otherwise been investigated, possibly as a way to procure services. Although

results from the multilevel model in Chapter 3 did not indicate a significant relationship between poverty rates and substantiation, this is most likely because the dependent variable in this analysis was measured at the child level (i.e., the likelihood of substantiation), and county-level poverty may not adequately measure of child-level economic disadvantage. As discussed in the limitation section below, this study would have been enhanced if it had included a measure of child-level poverty as a way of more precisely assessing both the relationship between decision making and poverty in neglect cases and the extent to which DR implementation moderated poverty's association with substantiation.

All three studies included child- and county-level race/ethnicity measures. Consistent with previous research (Drake et al., 2011; Fluke, Yuan, Hedderson, & Curtis, 2003; Hill, 2007), the findings revealed disproportionately high populations of African American children at all three decision points. Results also supported the findings of several recent studies indicating that this disproportionality is most evident at the earliest stages of CPS involvement, and decision making within the CPS system does not contribute substantially to this over-representation when controlling for risk factors (Bartholet, 2009; Drake et al., 2011; Font, Berger, & Slack, 2012; Putnam-Hornstein, Needell, King, & Johnson-Motoyama, 2013). For example, results in Chapter 3 indicated that among children with investigated cases, African American children's odds of substantiation were only 1.04 times more than those of White children, after controlling for a limited set of child- and county-level predictors. Results from the racial/ethnic subanalysis presented in Chapter 4 were similar. The adjusted average investigation and substantiation/population rates were significantly higher for African American children

than White children, but no significant differences were found in substantiation/investigation rates. In tandem, the findings suggest that the relatively high representation of African American children with substantiation is primarily explained by their higher than average presence in earlier stages of CPS involvement.

Hispanic children, in contrast, experienced significantly lower investigation and substantiation/population rates than either White or African American children (Table 4.5), although their substantiation/investigation rates were not significantly different than those of children from other racial groups. Likewise, the multilevel results in Chapter 3 found that the odds of substantiation among Hispanic children were only 1.09 higher than the odds of White children. Relatively lower proportions of Hispanic children entering the CPS system have been reported elsewhere (Dettlaff et al., 2009; Drake, et al., 2011; Putnam-Hornstein & Needell, 2011). Some authors suggest that despite high levels of poverty and other risk factors, Hispanic families may also have more or stronger protective factors that mitigate their risk of CPS outcomes (Drake, et al., 2011; Putnam-Hornstein, et al., 2013). The experiences of Hispanic families in CPS, and the etiology of child maltreatment among this diverse subpopulation is still a nascent field of study. Due to the lack child-level measures, the present analyses were unable to closely examine possible differential distributions of risk and protective factors across racial/ethnic groups, but the results suggest that patterns of decision making among neglect cases for Hispanic families are different than those of either White or African American families.

The studies presented in Chapters 2 and 3 also measured race as a county-level variable. In the mediation model (Table 2.4), a higher proportion of African American children residing in a county was associated with significantly lower rates of removals

but not with outcomes at other decision points. Similarly, in the multilevel models (Table 3.3), the county proportion of White children was not significantly associated with substantiation decisions. County-level racial characteristics have not often been included in studies of CPS decision making, particularly in a multivariate context. The inverse relationship between removal rates and the proportion of African American children seems contrary to findings from a Canadian study where a higher proportion of Aboriginal children was associated with higher odds of a case resulting in removal (Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010). Given that the studies had very different samples, their conflicting findings may simply reinforce the point that decision-making patterns are not generalizable across different minority subpopulations.

DR proponents have hypothesized that differential response may mitigate the over-representation of African American children in the child welfare system (Allan & Howard, 2013; Loman & Siegel, 2012). The findings from the three studies consistently found no evidence to suggest that DR is associated with changes in the effect of child race on system decision making. Specifically, results from the cross-level interactions in Chapter 3 did not improve model fit, most likely because race/ethnicity had a relatively small direct effect on substantiation. Similarly, the longitudinal analysis in Chapter 4 showed that the implementation of DR corresponded with reductions in investigations at approximately the same rate across racial/ethnic subpopulations of children.

Limitations

The most significant limitations across the three studies relate to the challenges of relying on National Child Abuse and Neglect Data System (NCANDS). The NCANDS child file is a national dataset consisting of information collected annually from each

state's administrative reporting system. Chapters 2-4 discuss these limitations and their implications in more detail, but the major issues include: (1) The exclusion of CPS cases from small counties; (2) missing and poor quality data in important child and family measures of risk factors and services; (3) no county-level data about agency and staff characteristics; and (4) no child-level data at the initial point of CPS referral. These limitations mean the studies' findings are not generalizable to small counties and results are limited in terms of their contribution to knowledge about many child and agency factors that may affect decision making in neglect cases. Without child-level information about all referrals, the analyses were also unable to isolate predictors associated with the decision to investigate a CPS referral from predictors common to any CPS referral, including those cases that were never investigated. Accordingly, the significant factors identified in Chapter 2 (e.g., county poverty level and DR implementation) should be interpreted as predictors that influence decision making up to and including investigation.

In addition to the limitations of NCANDS data, two other caveats must be noted. First, the studies did not distinguish between neglect-only allegations and allegations where neglect co-occurred with other types of maltreatment. Cases with multiple types of maltreatment may differ from neglect-only cases, especially in terms of level of risk. Second, much of the information about DR implementation was collected through interpreting agency policy manuals or talking with staff, and although every effort was made to verify information about DR implementation, it is possible that some was not accurate. Further, the decision to classify initiatives as "true" DR was somewhat subjective, although the author adhered as closely as possible to criteria established by Merkel-Holguin, Kaplan, and Kwak (2006).

Implications and Future Directions

The primary purpose of this dissertation was to expand current knowledge about the influence of DR on decision making in neglect cases. The results indicate that DR implementation corresponds with major changes in CPS populations, particularly at the point of investigation. The research has two implications for future scholarship. First, it expands the application of the DME by examining the influence of a CPS reform on decision making. Second, it highlights the need for continued discussion about the provision of services and the dual, and sometimes incompatible, roles of maltreatment investigation and family support in public CPS agencies.

The DME is an intuitive decision-making model that acknowledges the influence of case, decision maker, external, and agency factors on CPS decision making. The influence of DR on investigation rates is not surprising, but the strength of this effect, even when controlling for county- and child-level covariates, highlights the importance of accounting for agency practice and policy differences when studying decision making. To date, little attention has been directed toward understanding how CPS practice reforms may affect the likelihood of important CPS decisions, primarily because it is difficult to track the implementation of initiatives across CPS agencies. While efforts have been made to improve the documentation of CPS innovations, such as the National Study of Child Protective Services Systems and Reform Efforts (U.S. DHHS, 2003) and the online State Child Welfare Policy Database (sponsored by Child Trends and Casey Family Programs), this work is rare because tracking is resource intensive and requires ongoing commitment in order to keep the information current.

In addition to continued efforts to document CPS practices across agencies over time, more research is needed to understand how agency-level characteristics affect change. For example, the reduction in investigations that correspond with DR implementation may be because DR raises the decision threshold for launching a CPS investigation. This would indicate that agency standards largely drive CPS decisions. Alternatively, perhaps lower investigation rates occur because DR adoption includes new training that promotes principles like family engagement, which in turn, could cause a shift in perceptions and assessment of risk among CPS professionals. In reality, it seems likely that both agency-level and decision-maker forces are responsible for some of the reductions in investigation rates that are associated with the initiation of DR. However, decision-making research in CPS is focused almost exclusively on case- and decision-maker factors. Arguably, decision-making research suffers from some of the same biases it is designed to uncover: the human tendency to assume that individuals have more control over their decisions than externalities allow (i.e., the internal attribution bias, Jones & Harris, 1967). Further research about the intended and unintended impact of policy and practice reform on decision making may redirect research and training efforts from approaches that are focused on identifying and reducing individual errors to approaches that seek systemic reform (Gambrill & Shlonsky, 2001; Munro, 2005).

Another area of future research is the assumed connection between the implementation of DR and the improvement of service provision for families. Except for a few states that still require substantiation of maltreatment in order to access services (Kohl, et al., 2009), there is nothing prohibiting service provision for cases in traditional CPS investigative pathways. Likewise, the launch of DR within a CPS agency does not

necessarily translate into improved availability of community resources such as mental health services, safer housing, or help finding employment. However, randomized control trials conducted in three states found differences in service receipt when comparing cases receiving DR to similar ones receiving investigations, including a higher proportion of DR families receiving at least one service (The Quality Improvement Center for Differential Response in Child Protective Services, 2014)

Although DR does not by itself resolve persistent gaps in access to community services for CPS-involved families, it may bolster service provision more generally because it represents a reform that directly addresses the tension between the investigative and supportive functions of CPS. Drake (2013) and Drake and Jonson-Reid (2000) note that CPS investigations are past-oriented activities that align with a law-enforcement perspective, whereas the promotion of safety, permanency and well-being—central tenents of public CPS agencies—are future-oriented goals that align with community-based prevention efforts and a public health perspective. Both Drake (2013) and Yuan (2005) observe that a significant contribution of DR is that it provides a clear distinction between these two CPS perspectives, and its adoption may signify an intentional movement on the part of public agencies to shift more of their energies to prevention and service provision.

Although it has been more than 20 years since the first states implemented DR, its pace of adoption has accelerated within the last decade. Empirical research has also accrued during this time, and results tend to support DR's benefits to moderate-risk families. This dissertation, with its focus on the broader impact of DR on CPS systems,

adds another dimension to DR research that is designed to inform both empirical studies of CPS decision making and CPS reforms.

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APPENDIX A

Documentation of Data Quality Concerns Resulting in Exclusion from Sample

Appendix A

Documentation of Data Quality Concerns Resulting in Exclusion from Sample

State	Reason for Exclusion	Chapter 2	Chapter 3	Chapter 4
CT	Has data quality concerns as documented in NCANDS data files	Dropped	Dropped	Dropped
GA	Does not report "prior victim" or removals	Included	Dropped	Included
HI	Does not report "prior victim"	Included	Dropped	Included
MO	Does not report maltreatment type for unsubstantiated cases	Included	Dropped	Dropped
NJ	Problems with county IDs (FIP codes) for multiple years (including 2010)	Dropped	Dropped	Dropped
NY	Does not report investigated cases (all investigated cases are substantiated)	Dropped	Dropped	Dropped
OR	Does not collect data on unsubstantiated cases	Dropped	Dropped	Dropped
PA	Does not report race; other differences in how state tracks decision making	Dropped	Dropped	Dropped
PR	All screened-in reports are investigated	Dropped	Dropped	Dropped
VA-	Two counties in VA had combined submissions and were dropped.	Dropped	Dropped	Dropped
Number of counties and cases in each analysis		297 (994,045)	284 (997,512)	295 (1,142,174)

APPENDIX B

Equations for Multilevel Models

Appendix B: Equations for Multilevel Models for Chapter 4

Model 1: Null model

Level 1:

$$\ln\left[\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)}\right] = \beta_{oj}$$

Level 2:

$$\beta_{oj} = \gamma_{00} + \mu_{oj}$$

Where y_{ij} is dichotomous response for case *i* in county *j*

Model 2: Added fixed effects of child-level predictors

Level 1:

$$\ln\left[\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)}\right] = \beta_{oj} + \beta_{1j}ASIAN_{ij} + \beta_{2j}AfAM_{ij} + \beta_{3j}HISP_{ij} + \beta_{4j}OTHER_{ij} + \beta_{5j}PRIORVIC_{ij} + \beta_{6j}SEX_{ij} + \beta_{7j}AGE_{ij}$$

Level 2:

$$\beta_{oj} = \gamma_{00} + \mu_{oj}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70}$$

Model 3: Added county-level predictors

Level 1:

$$\ln\left[\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)}\right] = \beta_{oj} + \beta_{1j}ASIAN_{ij} + \beta_{2j}AfAM_{ij} + \beta_{3j}HISP_{ij} + \beta_{4j}OTHER_{ij} + \beta_{5j}PRIORVIC_{ij} + \beta_{6j}SEX_{ij} + \beta_{7j}AGE_{ij}$$

Level 2:

$$\beta_{oj} = \gamma_{00} + \gamma_{01}DR_j + \gamma_{02}POV_j + \gamma_{03}POPDEN_j + \gamma_{04}WHITECHI_j + \mu_{oj}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70}$$

Model 4: Added random effects of race

Level 1:

$$\ln\left[\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)}\right] = \beta_{oj} + \beta_{1j}ASIAN_{ij} + \beta_{2j}AfAM_{ij} + \beta_{3j}HISP_{ij} + \beta_{4j}OTHER_{ij} + \beta_{5j}PRIORVIC_{ij} + \beta_{6j}SEX_{ij} + \beta_{7j}AGE_{ij}$$

Level 2:

$$\beta_{oj} = \gamma_{00} + \gamma_{01}DR_j + \gamma_{02}POV_j + \gamma_{03}POPDEN_j + \gamma_{04}WHITECHI_j + \mu_{oj}$$
$$\beta_{1j} = \gamma_{10} + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \mu_{2j}$$
$$\beta_{3j} = \gamma_{30} + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \mu_{4j}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70}$$

Model 5: Added cross-level interactions.

Note: Single model with all interactions shown below, but moderation effects of four county-level predictors on race were tested separately.

Level 1:

$$\ln\left[\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)}\right] = \beta_{oj} + \beta_{1j}ASIAN_{ij} + \beta_{2j}AfAM_{ij} + \beta_{3j}HISP_{ij} + \beta_{4j}OTHER_{ij} + \beta_{5j}PRIORVIC_{ij} + \beta_{6j}SEX_{ij} + \beta_{7j}AGE_{ij}$$

Level 2:

$$\beta_{oj} = \gamma_{00} + \gamma_{01}DR_j + \gamma_{02}POV_j + \gamma_{03}POPDEN_j + \gamma_{04}WHITECHI_j + \mu_{oj}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}DR_j + \gamma_{12}POV_j + \gamma_{13}POPDEN_j + \gamma_{14}WHITECHI_j + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}DR_j + \gamma_{22}POV_j + \gamma_{23}POPDEN_j + \gamma_{24}WHITECHI_j + \mu_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}DR_j + \gamma_{32}POV_j + \gamma_{33}POPDEN_j + \gamma_{34}WHITECHI_j + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \gamma_{41}DR_j + \gamma_{42}POV_j + \gamma_{43}POPDEN_j + \gamma_{44}WHITECHI_j + \mu_{4j}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70}$$

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Helen Bader School of Social Welfare, UW-Milwaukee,
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- *National Evaluation and Technical Assistance Center for Improving Child Welfare Outcomes Through Systems of Care Demonstration Initiative (US Administration of Children & Families)*
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2004-2006 **Manager of Systems Improvement Methodologies**
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- *Supporting Kinship Care Breakthrough Series Collaborative*
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Malik, N., Ward, K., & **Janczewski, C.** (2008) Coordinated Community Response to Family Violence: The Role of Domestic Violence Service Organizations. *Journal of Interpersonal Violence*, 23(7): 933- 955.

Malik, N., Silverman, J., Wang, K., & **Janczewski, C.** (2008) Domestic violence and dependency courts: The Greenbook demonstration experience. *Journal of Interpersonal Violence*, 23(7): 956-980.

Selected Technical Reports & Monographs

Greenbook National Evaluation Team. (2008) *The Greenbook Initiative: Final Evaluation Report.* Washington, DC: National Institute of Justice. Found at: www.thegreenbook.info/documents/finalreport_combined.pdf

Casey Family Programs. (2007) *Supporting Kinship Care: Promising Practices and Lessons Learned.* Seattle, WA: Casey Family Programs. Found at www.casey.org/Resources/publications/kinshipbsc.htm

National Technical Assistance and Evaluation Center for Systems of Care. (2007- 2010) *A Closer Look* [7-issue series]. Washington, DC: Administration for Children and Families. Found at: www.childwelfare.gov/systemwide/service/soc/communicate/initative/closerlook

Greenbook National Evaluation Team. (2004) *The Greenbook Demonstration Initiative Interim Evaluation Report.* Washington, DC: National Institute of Justice. Found at: www.thegreenbook.info/documents/Greenbook_Interim_Evaluation_Report_2_05.pdf

Awards & Fellowships

2012-present	National Quality Improvement Center for Differential Response Dissertation Research Fellowship. $25,000
2013	Network for Social Work Management, Research To Practice Mentorship. (in-kind travel award)
2010-2013	Graduate Student Travel Award, University of Wisconsin-Milwaukee. (in-kind travel award)
2009-2010	Dean's Doctoral Fellowship, Helen Bader School of Social Welfare, University of Wisconsin-Milwaukee. $20,000

Presentations

Refereed Presentations

Janczewski, C. (2013). *Differential Response: Changing the National Landscape in Child Welfare.* The Kempe Center's Annual Conference on Differential Response, Vail, CO.

Janczewski, C., (2013). *How Child Welfare Agencies Make Decisions in Cases of Neglect*. Research to Practice Institute: The Network for Social Work Managements Institute. Newark, NJ.

Janczewski, C. & Gromoske (2011). *Long-term Foster Care as a Permanency Goal: A Multi-Level Exploration of Child, Population, and Agency Predictors*. The National Child Welfare Evaluation Summit, Washington, DC.

Gromoske, A. & **Janczewski, C.** (2011). *Beginning the program improvement process: A strength-based approach*. National Alliance of Social Workers, Wisconsin Chapter, Madison, WI.

Gromoske, A., **Janczewski, C.,** & Hernandez-Meier (2010). *Empowering Clients Through Evidence Based Choice.* National Alliance of Social Workers, Wisconsin Chapter, Brookfield, WI.

Janczewski, C. & Lutz, L. (2005). *The Breakthrough Series Collaborative*. Child Welfare League of America Conference, Washington, DC.

Johnson, P., Cooper, J. & **Crowley, C**. (2003). *Chafee: The National Youth in Transition Database*. The Children's Bureau: National Child Welfare Data Conference, Arlington, VA.

Cooper, J. & **Crowley, C.** (2002) *The National Youth in Transition Database*. The Children's Bureau: National Child Welfare Data Conference, Crystal City, VA.

Invited Presentations & Trainings

Janczewski, C. (2013). Decision Making in Cases of Neglect. The National Advisory Council of the National Quality Improvement Center on Differential Response, Washington, DC.

Janczewski, C. (2006). Action Planning. Systems of Care Family Involvement, Wichita, KS.

Cooper, J. & **Crowley, C.** (2003). *The National Youth in Transition Database*. The Children's Bureau: Pathways to Adulthood, Chicago IL.

Cooper, J. & **Crowley, C.** (2002). *The National Youth in Transition Database*. The Children's Bureau: Pathways to Adulthood, San Diego, CA.

Teaching Experience

University of Wisconsin-Milwaukee, Helen Bader School of Social Welfare (2013)
Regular Guest Lecturer, School of Social Work, Qualitative Research Methods (3 cr, gr).

University of Wisconsin-Milwaukee, Helen Bader School of Social Welfare (2013)
Guest Lecturer, School of Social Work, Evaluation of Practice(2 cr, gr).

University of Wisconsin-Milwaukee, Helen Bader School of Social Welfare (2012)
Associate Lecturer, Social Systems and Social Work (3 cr, gr).

University of Wisconsin, Oshkosh, School of Social Work (2012)
Lecturer, Social Welfare Policy (3 cr, ugr).

University of Wisconsin-Milwaukee (2011)
Teaching Assistant, Society, Poverty, & Welfare (3 cr. ugr)

Pearson Higher Education (2010-2011)
Contractor. Developed supplemental content for textbook, *Social Work Macro Practice* (Netting, Kettner, McMurtry, &Thomas, 2011, 5th ed.)

Certificates and Professional Development

Proficient in the following statistical and analytic packages:

- Dedoose (qualitative and mixed-method analysis),
- Mplus
- SAS
- SPSS
- Stata

Certificates and Professional Development

2013 *Social Science Analytics Using SAS*, Center for Addiction and Behavioral Health Research, University of Wisconsin-Milwaukee
2013 *Dedoose: Mixed Methods*, Center for Addiction and Behavioral Health Research, University of Wisconsin-Milwaukee
2010 *Applied Multi Level Modeling: Exploring Practical Problems*, Center for Addiction and Behavioral Health Research, University of Wisconsin-Milwaukee
2009 *Teaming: Partnering for Proposal*, ICF International
2006 *Strategy to Action: Client Relation and Opportunities*, ICF International
2005 *Breakthrough Series College*, Institute for Health Care Improvement
2005 *Gay, Lesbian, Bi-sexual, Transsexual, and Questioning Youth Training*, Massachusetts Department of Public Health
2004 *Undoing Racism*, The People's Institute for Survival and Beyond
2003 *Performance Measurement for Government and Nonprofits*, The Evaluators Institute
2003 *Advanced Proposal Training*, Caliber Associates

Professional Affiliations

2013-present American Public Health Association (APHA)
2013-present Extreme Science and Engineering Discovery Environment, NSF (XSEDE)
2012-present The Network for Social Work Management (NSWM)
2009-present Society for Social Work and Research (SSWR)

Service

2011- present Wisconsin Home Visiting Evaluation and Program Improvement Work Group
2011- present Grants & Development Committee Milwaukee French Immersion Foundation
2012-2013 Doctoral Recruitment Committee, Helen Bader School of Social Welfare, Wisconsin- Milwaukee
2011-2012 Doctoral Admissions Committee, Helen Bader School of Social Welfare, Wisconsin- Milwaukee
2005-2006 Tutor and Mentor for Homeless Youth, Project Northstar