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ABSTRACT

Prior research has found that disproportionate minority contact (DMC) is a problem at various decision-making points in the juvenile justice system. Some have argued that this is the result of discriminatory decisions by system actors, while others assert that it is due to legally relevant factors (e.g., differences in offense seriousness). A major challenge in assessing the relationship between race and juvenile justice outcomes is the difficulty in comparing similarly-situated youth from different racial groups.

This dissertation addresses two limitations often found in prior DMC research. First, the majority of prior DMC studies have focused on a single juvenile court and/or a single stage of the court process. Due to the interconnectedness among court outcomes and the variation in decision-making processes across juvenile courts, these studies may under- or overestimate any possible effects of race on decision-making. As such, this dissertation uses a sample of over 50,000 youth referred to seven juvenile courts in Ohio to examine the relationship between race and five juvenile court outcomes: preadjudication detention, case dismissal, adjudication, secure confinement, and waiver to criminal court. Second, to obtain a true depiction of DMC, research must examine White and Non-White youth who are as similarly-situated as possible in all attributes except race. Unfortunately, the statistical analysis most often used to achieve this—multivariate logistic regression—may not be the most effective method to study DMC due to a number of potential limitations. As such, this dissertation compares the strengths and weaknesses of logistic regression and four counterfactual techniques in examining the relationship between race and juvenile court outcomes. The counterfactual methods used in this study are nearest neighbor matching, regression adjustment, inverse-probability weighting, and inverse-probability-weighted regression adjustment.
Results from all five statistical techniques indicated that Non-White youth were significantly more likely than White youth to be detained prior to adjudication, placed in a secure confinement facility post-adjudication, and waived to criminal court. Results were mixed, however, regarding the case dismissal and adjudication outcomes. Two of the five methods indicated that Non-White youth were more likely to have their case dismissed and less likely to be adjudicated delinquent, while the other three methods produced nonsignificant results for these outcomes. Based on the findings—as well as available post-analysis diagnostics, covariate balance, and the fit between the data and the various methodologies—this study posits that nearest neighbor matching with exact matching is the best-equipped statistical technique to produce accurate estimates of the presence and extent of DMC in the juvenile justice system.
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CHAPTER 1
INTRODUCTION TO THE PROBLEM

One of the most often documented aspects of the juvenile justice system over the past 100 years has been the pronounced disproportionality in the processing of White and Non-White juveniles (Bishop, 2005). Research consistently finds that minority youth—primarily African Americans and Hispanics—are overrepresented at every stage in the juvenile court process. More specifically, minority youth are disproportionately petitioned to juvenile court (Leiber, Bishop, & Chamlin, 2011; Leiber & Stairs, 1999; Thomas & Sieverdes, 1975), held in pre-adjudication detention (Guevara, Herz, & Spohn, 2006; Kurtz, Linnemann, & Spohn, 2008; Moak, Thomas, Walker, & Gann, 2012), adjudicated delinquent (Leiber, 2015), committed to secure out-of-home correctional facilities after adjudication (Barton, 1976; Bishop, 2005; Bishop & Leiber, 2011; Davis & Sorensen, 2013), and waived to criminal court (Bishop, 2005; Brown & Sorensen, 2013; Males & Macallair, 2000). This knowledge is so ingrained that the U.S. government, via the Department of Justice’s Office of Juvenile Justice and Delinquency Prevention (OJJDP), has termed the phenomenon disproportionate minority contact (DMC), a designation that refers to the disproportionate number of minority youth who come into contact with the juvenile justice system relative to their representation in the general population (OJJDP, 2009a). Indeed, Platt (1969) argued that the first juvenile court in Chicago, IL was created to address the perceived “urban disenchantment” that contributed to juvenile delinquency in large cities. Because racial minorities and those with little financial resources were—and are—more likely to reside in these urban areas, the underlying philosophies of early juvenile courts essentially guaranteed that Non-White youth would come into contact with the juvenile justice system more frequently than White youth.
Since the early 1990s, there has been a dramatic increase in the amount of research that has examined DMC in the juvenile justice system (see discussion of the Juvenile Justice and Delinquency Prevention Act below; Bishop, Leiber, & Johnson, 2010; Davis & Sorensen, 2012, 2013; Guevara et al., 2006; Kempf-Leonard, 2007; Leiber, 2002; Leiber et al., 2011; McCoy, Walker, & Rodney, 2012; OJJDP, 2009; Piquero, 2008). The results of this research, however, have been mixed at best (Engen, Steen, & Bridges, 2002; McCoy, Walker, & Rodney, 2012). One possible explanation for the mixed findings is that DMC studies often differ in their methodology and statistical techniques (see Engen et al., 2002). Kempf-Leonard (2007) argued that to draw accurate conclusions about DMC, researchers must examine youth who are, at a minimum, “similarly-situated” on all legal and extralegal attributes except race. However, a large portion of DMC research—specifically studies that use multivariate regression—does not do this (Owen & Takahashi, 2014). For example, studies that use multivariate regression may produce biased results if the White and Non-White youth included in the analyses differ among the included covariates, leading to comparisons of nonequivalent groups. This dissertation attempts to address this limitation and others by employing counterfactual statistical approaches to examine the relationship between race and juvenile court outcomes among similarly-situated youth (see Chapter 3).

Before discussing the history of minority overrepresentation in the juvenile justice system, it is important to note the difference between the terms overrepresentation and disparity, although the two are often (erroneously) used interchangeably (National Council on Crime and Delinquency, 2007). Overrepresentation is defined as when a larger proportion of a certain group is seen in the juvenile justice system than would be expected given their representation in the general population. Disparity, on the other hand, refers to the differing probability of
receiving a certain outcome among members of different groups (i.e., race). This dissertation—as well as most research regarding race and juvenile justice processing—focuses on the potential causes of the disparities in the juvenile court: whether any identified racial disparities are the result of primarily legitimate factors (e.g., minority youth commit more crimes and/or more serious crimes) or suggest underlying racial biases by court actors.

**HISTORY OF RACIAL DISPARITIES IN THE JUVENILE JUSTICE SYSTEM**

As early as the 1930s, research has noted the differential representation and treatment of minorities at different stages of the criminal justice system (Kempf-Leonard, 2007; Sellin, 1935). For example, African Americans accounted for 11% of the U.S. population in 1910 but 31% of the prison population (Rosich, 2007). Sellin found in 1935 that African American males were incarcerated for longer periods of time, on average, compared to their White counterparts. Between 1930 and 1972, 89% of the convicted rapists who received the death penalty were African American (Bureau of Justice Statistics, 2000). Although most of these early studies examined overrepresentation among adult offenders, similar results were found regarding juvenile offenders (e.g., see Ward, 2012).

Despite the early identification of overrepresentation in both the adult and juvenile justice systems, the problem persists today. Indeed, contemporary research suggests that DMC exists—to varying degrees—in at least one stage of the juvenile justice process in every state (Kempf-Leonard, 2007). For example, from 1987 to 1996, the proportion of African American youth in detention facilities in the U.S. increased from 28% to 40%, despite the fact that they represented only 15% of the national juvenile population (Stahl, 2003). In 2011, the rate of placement in secure residential facilities for African American youth was five times higher than the rate for
White youth, while Hispanic youth were twice as likely to be placed in secure confinement relative to White youth (Hockenberry, 2014).

Despite statistical evidence that minority overrepresentation had been occurring essentially since the creation of the first juvenile court in 1899, it was not until the latter half of the 20th century that it was recognized as a legitimate national problem (Leiber, Bishop, & Chamlin, 2011). In the 1980s, the National Council on Crime and Delinquency brought the topic of racial disparity in juvenile confinement to the attention of state and federal lawmakers (Krisberg, Fishman, Eisikovits, Guttman, & Joe, 1987; Owen & Takahashi, 2014). As the statistics regarding disproportionate minority confinement began fueling national concern, legislatures began developing efforts to reduce minority confinement (Engen, Steen, & Bridges, 2002). Among these efforts were three amendments to the Juvenile Justice and Delinquency Prevention Act of 1974 (Public Law 114-22, 42 U.S.C. 5601 et seq.) aimed at compelling states to address DMC-related issues (Sickmund & Puzzanchera, 2014).

The Juvenile Justice and Delinquency Prevention Act of 1974

The Juvenile Justice and Delinquency Prevention Act (JJDPA) created the Office of Juvenile Justice and Delinquency Prevention, housed within the U.S. Department of Justice, to support states in reducing delinquency and improving juvenile justice systems. As part of this charge, OJJDP was authorized to provide Formula Grants to states in an effort to achieve these goals. These Formula Grants are provided to support “state and local delinquency prevention and intervention efforts and juvenile justice system improvements … based on detailed studies of needs in their jurisdictions” (OJJDP, 2009b, p. 1).

Since its inception, the JJDPA has undergone three major amendments. In 1988, the first amendment to the JJDPA was a direct result of the copious amount of research showing that
minority youth were consistently overrepresented in secure confinement facilities compared to their proportion of the general population (e.g., see Barton, 1976). This amendment required that a portion of the Formula Grant funding awarded to each state go toward programs and policies specifically focused on reducing the disproportionate number of minority youth placed in secure detention and confinement facilities (Kempf-Leonard, 2007; OJJDP, 2009a).

The second amendment to the JJDPA, approved by Congress in 1992, elevated efforts to address disproportionate minority confinement to a “core requirement” for Formula Grant funding (OJJDP, 2009a). Under this amendment, states that received Federal Formula Grants were required, among other things, to determine the extent of DMC in their jurisdiction, identify its causes, and implement strategies to reduce its presence. States failing to achieve these goals—or at least show sustained effort toward them—risk losing one-fourth of their Formula Grant funds (Leiber, 2002).

Finally, in 2002, the third amendment to the JJDPA expanded the definition of DMC from disproportionate minority confinement to disproportionate minority contact (Kempf-Leonard, 2007; OJJDP, 2009a). Historically, attention to disproportionality in the juvenile justice system tended to focus on confinement (i.e., pre-adjudication detention and post-adjudication placement in a secure correctional facility) (NCCD, 2007). However, research suggests that much of the overrepresentation found at the post-adjudication confinement stage can be attributed to actions that occur earlier in the juvenile justice system, such as the initial arrest, pre-adjudication detention, and diversion decisions (NCCD, 2007; OJJDP, 2009a; Piquero, 2008). As such, the expanded definition of DMC to encompass all contact with the juvenile justice system requires states to address disproportionality not just in secure confinement, but in all stages of the juvenile justice system, from arrest to disposition.
The 2002 reauthorization of the JJDPA also allowed OJJDP to continue administering Formula Grants to states (Hsia, 2004). To be eligible for a Formula Grant under the amended version of the JJDPA, states must maintain compliance with four core requirements of the Act. First, deinstitutionalization of status offenders (DSO) requires that states cannot hold status offenders (i.e., a juvenile who commits an act that would not be a crime had it been committed by an adult) in a secure detention or correctional facility. Second, juveniles cannot be detained or confined in an adult correctional facility. Third, if lack of resources or facilities requires juveniles to be detained or confined in an adult facility, said juveniles must be separated by both sight and sound from adult offenders. Finally, as discussed above, states must address disproportionate minority contact via prevention and diversion programs and system improvements (Hsia, 2004; Public Law 114-22, 42 U.S.C. § 5601 et seq.). According to OJJDP (2009a), the purpose of requiring states to address these four core requirements is “to ensure equal and fair treatment for every youth in the juvenile justice system, regardless of race and ethnicity” (p. 1).

The JJDPA and its amendments (especially the first two) have required states to make identifying and addressing disproportionate minority contact a primary policy concern. Indeed, every state in the U.S. now participates in and receives funding from OJJDP’s Formula Grants program (OJJDP, n.d.), which has led to “considerable research and development of programs and policies aimed at understanding and reducing overrepresentation of minority youth in juvenile justice systems” (Kempf-Leonard, 2007, p. 72). This dissertation attempts to fill gaps in this body of research by using multiple statistical techniques to examine the relationship between youths’ race and five decision-points in the juvenile court process. If juvenile justice stakeholders are more informed and better able to understand a specific problem (which is the
impetus of this study in regards to DMC), they will have more accurate information on which to build appropriate remedial programs and policies.

THE CURRENT STUDY

Despite numerous efforts by Congress, OJJDP, and the states to reduce DMC, it can still be found in every state (Leiber, 2002). Both practitioners and researchers over the past 30 years have discovered that identifying and addressing DMC is not as straight-forward an endeavor as they initially believed it would be (Kempf-Leonard, 2007). In part, this is the result of two general limitations often found in prior DMC research: 1) a focus on only one stage of the juvenile court process and 2) methodological problems in comparing youth of different races who are otherwise similarly-situated.

Limitations of Single-Stage Studies

Most prior studies have focused on the effect of youths’ race at only one or two stages of the juvenile court process (e.g., detention, disposition, or adjudication) (Barton, 1976; Engen et al., 2002; Kempf-Leonard, 2007) or in a single juvenile court (Cauffman, Piquero, Kimonis, Steinberg, Chassin, & Fagan, 2007). For example, Kempf-Leonard (2007) argued that most DMC studies have focused on adjudication or disposition because they are the end stages of the court process and thus are arguably the most important stages in terms of intrusion into youths’ lives. While this narrow focus on only one decision point may not seem like much of a problem, it is in fact a major limitation for a few reasons. First, juvenile justice decision-making must be viewed as a process that includes all stages from intake to disposition (Leiber, 2013). Studies that examine the effect of race on only one stage cannot posit that there is (or is not) DMC in the juvenile justice system as a whole since research shows that there is an interdependence among
the decisions made at various stages (e.g., see Rodriguez, 2010). While these single-stage studies are important in that they add to the literature on DMC, more research is needed that examines the interconnectedness of decisions made across all stages of the juvenile court process. Similarly, findings based on the examination of a single juvenile court cannot be generalized to courts in other regions of the country—nor possibly even other regions of the same state. For example, Bray, Sample, and Kempf-Leonard (2005) concluded that the odds of placement in a secure confinement facility in Missouri significantly varied among counties based on whether the court was in an urban or rural location, caseload size, and percent of all cases that were felonies. Kempf-Leonard (2007) and Pope and Feyerherm (1995) argued that interpretations of research findings based on examination of a single court or a single stage of the juvenile court process that have been generalized to the system as a whole must be considered suspect or, at the very least, incomplete.

Another limitation inherent in single-stage studies is that they are more likely to under- or overestimate any possible effects of race on decision-making (Peck, Leiber, & Brubaker, 2014). In fact, Guevara, Herz, and Spohn (2006) posit that the mixed findings in prior research regarding the presence of DMC “are largely attributable to the examination of one stage of decision making and the comparison of findings from different stages of decision making” (p. 258). Similarly, studies that examine single, late-stage decision points such as disposition may underestimate race effects due to the relationships between early-stage decisions and race, which often predict late-stage decisions. For example, studies have shown that whether a juvenile is detained prior to an adjudication hearing can have an effect on adjudication and disposition decisions (Benekos, Merlo, & Puzzanchera, 2011; Bishop, 2005; Rodriguez, 2010).
Based on the limitations found in single-stage DMC studies, the most promising avenue to gaining a complete understanding of racial influences on juvenile court decision-making is research that examines multiple decision points in the court process (Benekos et al., 2011; Bishop, 2005; Guevara et al., 2006; Kempf-Leonard, 2007; Leiber, 2013; Peck et al., 2014; Pope & Feyerherm, 1995; Rodriguez, 2010). Doing so will allow researchers to identify the relative prevalence of DMC at different stages, as well as how it fluctuates as one moves throughout the juvenile court process. Unfortunately, few studies have conducted systematic examinations of the effects of juveniles’ race on decision-making across multiple decision points and in multiple juvenile court jurisdictions (Cauffman et al., 2007; Rodriguez, 2010). This study attempts to address this shortcoming by examining the relationship between race and five juvenile court outcomes—pre-adjudication detention, dismissal, adjudication, secure confinement, and waiver to criminal court—in seven juvenile courts in Ohio.

**Methodological Limitations of Addressing Similarly-Situated Youth**

The second limitation common in many DMC studies involves a potential methodological flaw. To identify potential causes of DMC, researchers must examine White and Non-White youth who are otherwise the same vis-à-vis legally-relevant and extralegal factors. “If they are not the same—or at least ‘similarly-situated’—then DMC may really occur as a result of the other ways in which they differ” (Kempf-Leonard, 2007, p. 75). The problem then revolves around how we define “similarly-situated.” Kempf-Leonard argued that this involves more than simply classifying youth by race; instead, research must examine youth who are identical—or as close to identical as possible—regarding all of the factors included in the data with the exception of race. Unfortunately, most DMC research does not do this (Owen & Takahashi, 2014).
The majority of studies that have examined the effects of race on juvenile court decision-making have used multivariate logistic regression (Higgins, Ricketts, Griffith, & Jirard, 2012; Peck et al., 2014; Rodriguez, Smith, & Zatz, 2009) or hierarchical generalized linear modeling (Armstrong & Rodriguez, 2005; Leiber, Peck, & Rodriguez, 2010, 2016). However, Jordan and Myers (2011) argued that, in the context of juvenile justice, these studies may be insufficient because the groups (i.e., White/Non-White) oftentimes differ among the independent variables, leading to nonequivalent treatment and control groups. Similarly, if any of the covariates included in the regression model are correlated with the error term, or if the functional form of a regression model is unknown or incorrectly defined, the resulting regression estimate may be biased. In addition, some studies have used blatantly incorrect statistical techniques, such as when Feld (1989) used ordinary least squares (OLS) regression with a dichotomous dependent variable (whether or not an attorney was appointed).

Despite these potential methodological flaws, however, studies that use counterfactual statistical methods—such as the treatment effect estimators used in the current study—to combat these limitations are seldom employed in this body of research. Different statistical techniques can be used to create a matched set of similarly-situated youth. For example, nearest neighbor matching creates a set of similarly-situated youth by matching White and Non-White youth with the smallest distance among the included covariates (Abadie et al., 2004; Abadie & Imbens, 2006; Rubin, 1973; Morgan & Harding, 2006), while inverse-probability weighting uses the inverse of the probability of receiving the treatment to match similarly-situated White and Non-White youth (StataCorp, 2013). Each of these techniques, however, can produce different treatment effect estimates depending on (1) how the matching is performed and (2) the manner in which the treatment effect is estimated. As such, this dissertation compares the relative strengths
and weaknesses of five different analytic techniques used to estimate the relationship between race and juvenile court outcomes. The five methods used here are nearest neighbor matching, regression adjustment, inverse-probability weighting, inverse-probability-weighted regression adjustment, and logistic regression. Logistic regression is included among the analytic techniques to serve as a baseline against which to compare the results obtained from the treatment effect estimators. While the focus of this study is on the relative usefulness of the four counterfactual approaches, these techniques are used here in an attempt to address the shortcomings of much prior DMC research and provide a more methodologically sound examination of the relationship between race and juvenile court outcomes.

Research Questions

Using official record data collected for 50,163 cases within seven Ohio juvenile courts, this dissertation seeks to address the following research questions:

1. After matching youth on legally-relevant and extralegal variables, what is the relationship between race and decision-making across five juvenile court outcomes: preadjudication detention, dismissal, adjudication, secure confinement, and waiver to criminal court?

2. Are there any differences among the results obtained from the four counterfactual analytic techniques relative to logistic regression?

3. If so, what are the relative strengths and weaknesses of each analytic technique as pertains to estimating the relationship between race and juvenile court outcomes?
SUMMARY

This dissertation seeks to add to the literature on disproportionate minority contact, race, and juvenile court outcomes by addressing two major limitations characteristic of many prior studies: 1) the use of a single court outcome or jurisdiction and 2) the use of inadequate analytic techniques to examine “similarly-situated” youth. Analyzing five decision points across seven juvenile courts allows for a more complete and accurate investigation of the relationship between race and court outcomes than found in most prior studies. Similarly, research has suggested that the multivariate regression statistical techniques common to most DMC research (e.g., logistic regression) may be methodologically inadequate because, for example, youth of different races may also differ on other independent variables included in the analysis (Jordan & Myers, 2011; Kempf-Leonard, 2007). The counterfactual approaches (e.g., treatment effect estimators) used in this dissertation employ different methods to closely match youth on all exogenous factors except race. This, in turn, results in a treatment effect estimate based on comparisons of similarly-situated youth—at least amongst the included covariates.

The balance of this dissertation is divided into four chapters. Chapter 2 presents a review of the literature regarding juvenile court decision-making, disproportionate minority contact, and the potential causes of and factors contributing to DMC. Prior research that examines the relationship between race and each of the five court outcomes is also presented in Chapter 2. Chapter 3 describes the study’s research design and methodology, including a discussion of the research questions, data, measures, and analytic plan. The results from the statistical analyses are provided in Chapter 4. Finally, Chapter 5 provides a substantive discussion of the results as they relate to the research questions, as well as the limitations of the study and suggestions for future research.
CHAPTER 2

JUVENILE COURT DECISION-MAKING AND DISPROPORTIONATE MINORITY CONTACT

As discussed in Chapter 1, the focus of this dissertation is on addressing the methodological issues surrounding past DMC research (i.e., Research Questions 2 and 3). However, the various counterfactual techniques are used here to address the substantive issue regarding the relationship between race and decision-making in the juvenile court (Research Question 1). As such, although the impetus of this study is methodological, it is important to provide a detailed background of the substantive issue addressed herein. The statistical techniques used in this study are presented in detail in Chapter 3.

This chapter begins with an overview of decision-making in the juvenile court, including a discussion of the factors identified by research as those most relied upon by court actors when making decisions. Next, a discussion of the extent of disproportionality and DMC in the juvenile justice system is presented. This is followed by a discussion of the two major competing perspectives on the cause of DMC—differential offending and differential treatment—as well as a few other potential explanations of DMC that have been presented in the literature. Finally, this chapter concludes with an overview of the extant literature regarding the relationship between race and each of the five court outcomes included in this study.

JUVENILE COURT DECISION-MAKING AND RACE

Since its inception in 1899 in Cook County, Illinois, the purpose of the juvenile court has been to make decisions that are in the best interests of the youth who come before it. Until the
late 20th century, this was typically accomplished with a rehabilitative ideal guiding all court actors’ actions and decisions. Delinquents in early juvenile courts were seen as “blameless but misguided children who were simply in need of redirection with the guidance of the court” (Scott & Steinberg, 2008, p. 7) and that court-administered rehabilitation could “cure” these misguided youth of their criminal propensities. This rehabilitative philosophy guided juvenile courts until the 1980s when it gave way to the “get tough” movement (i.e., a combination of retributive, deterrence, and incapacitation philosophies) that invaded both the criminal and juvenile justice systems.¹

No matter the underlying philosophy of the court during any given period, juvenile court actors have relied on different types of information to assist them in making decisions that can potentially affect a youth’s entire life (Albonetti, 1991; Bridges & Steen, 1998; Feld, 1999; Jordan & Myers, 2011; Kakar, 2006; Leiber & Fox, 2005; Leiber & Mack, 2003; Leiber et al., 2016; Rodriguez et al. 2009; Sampson & Laub, 1993; Tittle & Curran, 1988). This information typically falls into one of two categories: legal and extralegal factors. Legal factors are facts pertaining to the current offense and the offender’s prior delinquent record, such as offense seriousness, risk assessment scores, weapon use, victim injury, number of prior adjudications, number of prior arrests, and prior/current placement on probation. Conversely, extralegal factors have nothing to do with current or prior offenses, but instead are typically measures of sociodemographic, school, peer, or familial information. Examples of extralegal factors

¹ See discussion of juvenile waiver to criminal court beginning on page 45 for more details on this philosophical shift.
commonly used in juvenile justice research include youths’ race, age, sex, family structure, socioeconomic status, and educational status.

Most people would agree that decision-making should be guided solely by legal factors and that extralegal factors should have no influence on juvenile court outcomes. Studies show, however, that a number of both legal and extralegal factors affect juvenile court decision-making (Armstrong & Rodriguez, 2005; Bishop & Frazier, 1988; Piquero & Brame, 2009; Pope & Leiber, 2005; Rodriguez, 2010). For example, Armstrong & Rodriguez (2005) examined legal and extralegal variables, as well as county-level contextual factors, to determine their relationship with pre-adjudication detention. The authors found that youths’ race, gender, age, number of prior referrals, offense type, and county-level ethnic heterogeneity were the strongest predictors of the decision to detain youth.

The need to focus solely on legal factors during decision-making is not necessarily supported by the underlying philosophy of early juvenile courts, however. The original juvenile court was based on a social welfare model and the parens patriae philosophy (Armstrong & Rodriguez, 2005; Bishop & Leiber, 2011). As such, decision-making was based less on the instant offense and more on the individualized needs of each youth coming before the court (i.e., extralegal factors); dispositions for adjudicated youth were chosen based on what was in the best rehabilitative interest of the youth. However, the level of informality of the juvenile court, coupled with the large amount of discretion given to juvenile court judges, created an atmosphere that seemed to invite the possibility of racial discrimination (Armstrong & Rodriguez, 2005). For example, if court actors—specifically juvenile judges and probation officers—assess minority juveniles as being higher risk based on both legal and extralegal
factors, some level of racial disparity (and discrimination) at various decision-making points in
the system is inevitable (Bridges & Steen, 1998). Bishop and Leiber (2011) summarized,

The potential for race and class to influence processing decisions was great given
the enormous discretionary authority granted to justice officials, the lack of criteria
to guide decision-making, the informality and secrecy of court proceedings, the
confidentiality of case records, and—laudatory though the goal might have
seemed—the sheer arrogance embodied in the presumption that a cadre of
predominantly white, middle-class court personnel could diagnose impartially and
treat effectively the problems of “other people’s children” (p. 462).

Platt (1969) made a similar argument that the Child Savers of the late 19th century lobbied for the
creation of the first juvenile court not as a means of helping despondent children, but rather as a
method to maintain the middle-class status quo in an era of prolific immigration to large
Midwestern and Northeastern cities. Although rehabilitation remains—at least on paper—the
primary purpose of most juvenile courts, multiple societal and legal changes in the 1960s and
1970s led to the modification of juvenile court philosophy and policy to include punishment and
public safety as primary objectives. Although some have argued that this shift from rehabilitative
to punitive ideals could have the side-effect of reducing racial disparity in juvenile processing
(for example, via the use of sentencing guidelines), most recent studies show that DMC still
exists—to varying degrees—in all states and at a variety of stages of the process (Davis &
Sorensen, 2013; Leiber, 2002; Owen & Takahashi, 2014; Sullivan et al., 2016).

Overall, research provides considerable evidence that legal factors are the strongest—or
at least the most consistent—predictors of juvenile court actors’ decision-making (Brown &
Sorensen, 2013; Cauffman et al., 2007; Guevara et al., 2006; Kurtz et al., 2008; Thomas &
Sieverdes, 1975). However, many studies also provide strong evidence that extralegal factors
such as youths’ race still exert a significant influence on decision-making even after controlling
for legal factors (Armstrong & Rodriguez, 2005; Barton, 1976; Guevara et al., 2006; Leiber,
2013). For example, Barton (1976, p. 478) reviewed the literature on juvenile justice decision-making and concluded that “factors other than the present offense take on increasing importance in determining the fate of a youth” as he or she penetrates further into the system.

Despite the disagreement over the relative contribution of legal and extralegal factors to juvenile court decision-making, research over the past few decades has established three general findings regarding race and decision-making: 1) race has both a direct and indirect effect on decision-making; 2) race disparities tend to be found more often at the front-end of the court process relative to the back-end; and 3) racial biases tend to cumulate as youth move throughout the system (Engen et al., 2002; Leiber & Johnson, 2008; Rodriguez, 2010). The next sections of this chapter discuss these general findings in more detail.

**THE EXTENT OF DISPROPORTIONALITY AND DMC**

As mentioned in Chapter 1, research has noted the overrepresentation of minorities throughout the juvenile court process since the 1930s (Kempf-Leonard, 2007). In fact, this overrepresentation has become one of the most common findings in juvenile justice research (Bishop, 2005). However, despite half a century worth of research and policies focused on identifying the causes of overrepresentation, as well as a congressional mandate (via the first and second amendments to the JJDPA of 1974) to reduce DMC, it is still a significant national problem (Krisberg et al., 1987; Leiber et al., 2011; Owen & Takahashi, 2014). In fact, “get tough” policies that were implemented starting in the Reagan administration have actually exacerbated minority overrepresentation (McCarter, 2011). For example, although the number of minority youth arrested between 1977 and 1982 decreased, the number of minority youth placed in secure confinement facilities increased by 26% during the same period (Krisberg et al., 1987).
Similarly, Hindelang (1978) found that among both adults and juveniles, Black youth were significantly overrepresented in arrests for rape, robbery, and assault when compared to their proportion in the general population. This finding held true when examining both official reports (i.e., the Uniform Crime Reports) and victimization surveys (i.e., the National Crime Panel, precursor to the National Crime Victimization Survey).

Pope and Feyerherm (1995) examined 46 studies published between 1969 and 1989 and concluded that, in most studies, race effects were found at some (but not all) stages in the juvenile justice system. When all studies were examined as a whole, however, race effects could be found at every stage in at least one of the studies. Similarly, Davis and Sorensen (2013) reviewed assessments from 13 states and found that DMC was present in most states at various stages, but in no state were race effects present at every stage in the court process.

In 2002, approximately 4,100 youth were sentenced to adult correctional facilities (NCCD, 2007). Of these, minority youth comprised roughly 75% of the new admissions, and Black youth alone accounted for 58%. In 2003, the national referral rate to juvenile courts for Black youth (9,633 per 100,000) was over double the rate for White youth (4,431). Also in 2003, White youth were 62% of the general population, but comprised only 39% of the youth confined in secure facilities, while Black youth were 16% of the general population but 38% of the youth securely confined (NCCD, 2007).

The greatest racial disparities in the juvenile justice system tend to occur with youth charged with drug offenses. A report published by the National Council on Crime and Delinquency (NCCD, 2007) found that 75% of Black youth charged with a drug crime were formally processed in the juvenile court compared to only 50% of similarly-situated White drug offenders. Similarly, in 2003, White youth accounted for 69% of petitioned drug offense cases
but only 58% of cases waived to criminal court. Conversely, Black youth comprised 29% of cases petitioned for drug offenses but 41% of cases waived to criminal court.

These statistics demonstrate that despite its recognition as a national problem for decades, DMC is still a common characteristic of juvenile justice in the United States. For example, in his review of DMC studies that analyzed the effects of race on decision-making in 43 states, Leiber (2002) found that DMC was present in every state studied. Furthermore, in 32 of the 43 states (74%), race differences could not be completely explained by differential offending rates between White and Non-White youth. Engen and colleagues (2002) conducted a meta-analysis of DMC studies published between 1969 and 1999 (n=125) and concluded that direct race effects were found in 43% of the studies and indirect race effects—for example, via family structure and preadjudication detention—were found in 13% of the studies. Similarly, in her more recent review of the DMC literature, Bishop (2005) concluded that racial disparities that could not be explained by race differences in offending were found at every stage of the juvenile justice process. Despite copious evidence that DMC is prevalent across the U.S., however, research to date has not agreed on the underlying cause(s) of the overrepresentation.

CAUSES AND CORRELATES OF DISPROPORTIONATE MINORITY CONTACT

Primarily as a result of efforts by OJJDP and federal lawmakers, an abundance of research has examined the presence and extent of disproportionate minority contact in the juvenile justice system. According to Piquero (2008, p. 63), “[m]inority overrepresentation has come to be considered an established fact of crime; what remains in question is why minorities are overrepresented.” Furthermore, due to the requirements outlined by the Juvenile Justice and Delinquency Prevention Act, the focus of contemporary DMC research has shifted from mere
description of disproportionality to examinations of its causes and possible remedies. Similarly, Bishop (2005) argued that the issue is no longer whether there are racial differences in juvenile court processing, but rather how these differences manifest. Understanding the underlying causal mechanism(s) is a necessary component in developing and implementing policies and programs intended to successfully combat disproportionate minority contact (Bishop & Leiber, 2011).

Despite this abundance of recent DMC research, however, there is little agreement among researchers as to the principal cause(s) of disproportionate minority contact, nor is there consensus as to why minority youth penetrate deeper into the juvenile justice system at higher rates than their White counterparts (Bishop, 2005; Bishop & Leiber, 2011; Krisberg et al., 1987; NCCD, 2007; Piquero, 2008). One possible reason for this lack of consensus is that many prior DMC studies that use multivariate regression may be methodologically flawed (see Chapter 1 and below). For example, if there is little overlap among the covariates between White and Non-White youth, or if any of the included covariates are correlated with the error term in the regression equation, simple regression estimates of the effect of race may be biased, leading to inaccurate conclusions. The counterfactual techniques employed in this study ensure that unbiased treatment effect estimates are based on comparisons of similarly-situated youth, which will allow for a more complete and methodologically sound examination of DMC in the juvenile court. This, in turn, can better inform juvenile justice stakeholders of the potential cause(s) of DMC and the type of policies/programs that may reduce it.

Furthermore, there is a significant lack of research regarding the theoretical underpinnings of DMC (Davis & Sorensen, 2012). Specifically, although numerous studies conclude that racial disparity exists in the juvenile justice system and that this disparity may be caused by racial discrimination or bias, few studies expound upon the theoretical and causal
mechanism(s) by which race influences decision-making (Bridges & Steen, 1998; Davis & Sorensen, 2012; Moak, Thomas, Walker, & Gann, 2012; Tittle & Curran, 1988). Most contemporary explanations of overrepresentation and DMC have tended to focus on two competing perspectives: differential offending and differential treatment (Bishop & Leiber, 2011; Davis & Sorensen, 2013; Engen et al., 2002; Kurtz et al., 2008; Leiber & Fox, 2005; Piquero, 2008; Sullivan et al., 2016).

**Differential Offending**

The differential offending (or differential involvement) hypothesis posits that disproportionality in the juvenile justice system stems from minority youth committing more offenses relative to White youth and/or committing more of the types of offenses that come to the attention of the juvenile justice system and receive harsher punishments (Engen et al., 2002; Piquero, 2008). As such, according to the differential offending perspective, one would actually expect to see disproportionality in arrests and in the juvenile justice system (Kakar, 2006).

Research regarding the differential offending perspective is mixed. A number of studies have concluded that Black youth commit more serious violent crimes than White youth (Bishop, 2006; Sampson, Morenoff, & Raudenbush, 2005; Wolfgang, Figlio, & Sellin, 1972). For example, in their meta-analysis of DMC research, Engen and colleagues (2002) found that controlling for prior offending significantly reduced the odds of a direct race effect, but controlling for offense seriousness did not. Thus, they found partial support for the differential offending perspective. Similarly, in their more recent review of the DMC literature, Bishop and Leiber (2011, p. 454) concluded that “self-report and victimization data suggest that African American youth are considerably more likely to commit violent crimes than whites… For property and drug crimes, self-reports indicate minimal race differences in offending.” After
reviewing over 150 DMC studies, Bishop (2005) concluded that differences in offending behaviors between White and minority youth accounted for a portion of racial disparities in court processing. She stressed, however, that the evidence shows differential offending alone does not explain minority overrepresentation.

Some past research has posited that Non-White youth may be exposed to more risk factors than their White counterparts, thus providing a potential explanation for higher offending rates. For example, minority youth tend to populate socially disorganized neighborhoods more often than White youth (Shaw & McKay, 1942). Furthermore, the social norms in these neighborhoods often call for the use of violence against others in order to gain and maintain respect (Anderson, 1999). Thus, because racial minorities are more likely to live in inner-city, socially disorganized neighborhoods, one might expect them to differentially participate in violent behavior. Similarly, other macro-level factors may contribute to differential offending, such as socioeconomic factors (i.e., poverty and neighborhood disadvantage), as well as reduced opportunities for treatment and prevention programs in minority neighborhoods (Davis & Sorensen, 2012). In addition, Kakar (2006) argued that poor educational systems in many minority neighborhoods lead to excessive numbers of school failures and dropouts; this, in turn, may increase the number of minorities who commit crime for economic purposes.

Most studies, however, have found little or no significant racial differences in offending levels. For example, examining data from the Pathways to Desistance Study of serious juvenile offenders, Piquero and Brame (2008) concluded that there were no significant racial differences
in self-reported or official (based on arrests) offending. Similarly, Bishop & Leiber (2011) concluded that differences in offending levels account, in part, for racial disparities in decision-making, yet these differences by themselves are “insufficient to account for minority overrepresentation in the juvenile justice system” (p. 446). Overall, although some research provides limited support for the differential offending perspective, the overwhelming majority of DMC research has examined the differential treatment hypothesis (Kurtz, 2008).

**Differential Treatment**

The differential treatment perspective posits that minority youth are subjected to more formal social control (i.e., are treated harsher)—based solely or in part on their race—than their White counterparts at all stages of the system, from initial police contact to court disposition (Bishop, 2005; Engen et al., 2002; Sullivan et al., 2016; Kakar, 2006; Piquero, 2008; Rodriguez, 2010). In other words, typically due to discriminatory/stereotypical factors or “historically rooted patterns of racial inequality” (Piquero, 2008, p. 60), criminal justice actors (i.e., police, court, and correctional officials) treat minority youth differently—and often harsher—than White youth, which leads to the minority overrepresentation found in the juvenile justice system. These stereotypes depict minorities as undisciplined, coming from dysfunctional families, sexually deviant, more likely to use drugs, and less amenable to treatment (see discussion of focal concerns theory below) (Feld, 1999; Leiber, 2013; Leiber & Fox, 2005). According to proponents of the differential treatment perspective, this discriminatory treatment remains present even when minority and White youth commit the same offense. For example, Piquero

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2 For a discussion of the differences and similarities between official and self-reported delinquency, see Elliott & Ageton, 1980; Hindelang, Hirshi, & Weis (1979); and Pollock, Menard, Elliott, & Huizinga (2015).
(2008) found Black youth were more likely than their White counterparts to be adjudicated and sentenced to a secure confinement facility, even when they committed the same offense.

One prevalent theory that attempts to explain judicial decision-making and falls within the differential treatment paradigm is the uncertainty avoidance/focal concerns perspective (Albonetti, 1991; Bridges & Steen, 1998; Steffensmeier, Ulmer, & Kramer, 1998). This paradigm posits that, in the absence of complete information regarding the offense and offender, court actors—primarily judges—base their sentencing decisions on three focal concerns: the perceived blameworthiness of the defendant; community protection (i.e., likelihood of recidivism); and practical constraints such as limited resources and costs to the juvenile justice system (Steffensmeier et al., 1998). Race and ethnicity enter the equation because judges rarely have adequate information or time to effectively assess these focal concerns in order to reach their sentencing decisions. In these situations, their decisions are oftentimes based on attributes perceived to be characteristic of certain groups (Albonetti, 1991; Brown & Sorensen, 2013; Harris, 2009; Steffensmeier et al., 1998). For example, racial minorities and males are seen by many juvenile court personnel as more dangerous and blameworthy than their White and female counterparts, respectively (Brown & Sorensen, 2013). “The result is decision making made on the basis of past experience, stereotypes, [and] prejudices” (Albonetti, 1991, p. 249).

While the immediate negative consequences of decisions based on these factors are apparent (e.g., more severe official sanctions for minority youth), the ancillary consequences of these decisions are often overlooked. For example, if attributions of dangerousness are based on stereotypes and serve to disadvantage minority youth, this can result in their having less access to potentially life-altering services and rehabilitative programs such as mental health and substance abuse treatment (Rodriguez, Smith, & Zatz, 2009).
Although focal concerns is one of the dominant perspectives used to explain disparate treatment based on race, age, and gender in adult sentencing, it has rarely been applied to juvenile courts. In one of the few studies applying focal concerns to juvenile court processing, Bishop, Leiber, and Johnson (2010; Leiber, 2015) attempted to combine focal concerns with organizational theory and apply it to the various stages of juvenile court processing:

“An integration of the organizational coupling framework—with its emphasis on the action sets involved in decision making—and focal concerns theory—with its insights into the goals of decision making and the application of stereotypes in the service of those goals—offers a promising framework for understanding connections between the organizational context in which processing decisions are made and the influence of legal, sociodemographic, and contextual factors in decision processes” (Bishop et al., 2010, p. 217).

After applying their theory to over 5,000 juveniles processed through a juvenile court in a Midwestern state, the authors found strong support for their perspective at both the intake and disposition stages of the juvenile court process.

Conflict theories have also been used to explain DMC via the differential treatment hypothesis. Conflict theorists would suggest that minority youth are likely to be treated harsher than White youth because they are powerless (e.g., they exert no control over institutions of social control) and/or they present a threat to the majority group (Higgins, Ricketts, Griffith, & Jirard, 2012; Sampson & Laub, 1993). For example, Hawkins (1987) argued that as minority populations grow in both population and political power, the political power of the majority is threatened.3 This, in turn, leads to a greater use of formal social control mechanisms (i.e., arrest and conviction) to diffuse the perceived threat. An offshoot of conflict theory that attempts to

3 Conflict theories are more applicable to racial disparities among adults rather than juveniles since the latter have no political power and do not compete for jobs. However, it is plausible that the increased use of formal social control against adult racial minorities can trickle down to the juvenile justice system.
explain racial disparities in juvenile justice processing is the racial threat thesis (Blalock, 1967; Tittle & Curran, 1988). This perspective posits that as the presence of racial minorities in a community increases, the White majority views this as a threat to the status quo—the one in which they possess the most power. This perceived threat leads to the increased use of punitive social control (e.g., arrest, adjudication) against racial minorities as a means of dispelling the threat (Leiber, Peck, & Rodriguez, 2016).

Davis & Sorensen (2012) used state-level data from 38 states to determine if the racial threat hypothesis could explain disproportionality in secure confinement. Of the two racial threat measures included in the study (percentage Black and Black-White unemployed ratio), only percentage Black was a statistically significant predictor of secure confinement. This finding provided partial support for the racial threat hypothesis in that as the Black population of a state grows, the White majority feels threatened and triggers the use of more formal social control (in this case, secure confinement). Conversely, Leiber and colleagues (2016) used the racial threat hypothesis to guide their study of 37 juvenile courts located in three geographically diverse states. The authors found that the percentage of Black population in the county had no direct effect on any of the three court outcomes (i.e., intake, adjudication, and disposition). Similar results were found for percentage of Hispanic population. It should be noted, however, that juveniles’ race did have a statistically significant individual-level effect on the intake decision. Specifically, both Black and Hispanic juveniles were significantly more likely to be formally processed—as opposed to diverted—compared to their White counterparts.

Moak and colleagues (2012) used a similar theory, symbolic threat (Sampson & Laub, 1993; Tittle & Curran, 1988), to examine the effect of race on pre-adjudication detention in a Southern state. Through the use of multilevel modeling including both contextual and individual-
level measures, the authors concluded that the symbolic threat measures (concentrated
disadvantage, residential stability, and urbanization) did not significantly predict length of
detention. These findings were similar to those found in Sampson and Laub’s (1993) seminal
work on the symbolic threat hypothesis.

Bridges and Steen (1998) argued that the manner in which probation officers assess the
risk level of adjudicated juveniles prior to disposition can have an effect on DMC via differential
treatment. Similar to the use of presentence investigations (PSIs) in criminal courts, juvenile
court judges often depend on probation officers’ recommendations found in predisposition
reports when making disposition decisions. Probation officers typically attempt to assess whether
juveniles’ actions resulted from internal factors (e.g., personality, attitude) or external factors
(e.g., environment, delinquent peers). This distinction is important because juveniles whose
actions are deemed to result from external characteristics are held, on average, less culpable than
those whose actions result from internal characteristics (Bridges & Steen, 1998; Tittle & Curran,
1988). Therefore, if probation officers consistently assess minority juveniles’ actions as being the
result of internal factors more often than for White juveniles (or assess White juveniles’ actions
as the result of external factors more often than minority juveniles), one would expect that
minority juveniles would receive harsher dispositions than their similarly-situated White
counterparts, lending support to the differential treatment perspective. Situations such as this are
the focus of Research Question 1 in this study. If a significant relationship between race and
court outcomes remains even after youth are matched on legal and extralegal variables, we could
infer that there is some degree of differential treatment occurring in the seven juvenile courts
included in this study.
Bridges and Steen (1998) examined juvenile probation officers’ narrative reports, as well as court records, to determine the relationship (if any) between race, officers’ perceptions of offenders, and sentence recommendations. The authors found that probation officers were significantly more likely to attribute Black youths’ delinquency to internal factors and White youths’ delinquency to external factors, even after controlling for offense severity and prior delinquency. Furthermore, officers assigned higher risk and suggested harsher sentences for those youth whose behavior was attributed to internal characteristics. Although race had no significant direct effect on recommended sentences, the authors found a significant indirect effect via officers’ perceptions of offenders. Specifically, Black youths’ delinquency was more often perceived as being caused by internal characteristics, and youth with faulty internal characteristics were given harsher sentence recommendations. The authors concluded, “[i]nsofar as officials judge black youth to be more dangerous than white youth, they do so because they attribute crime by blacks to negative personalities or their attitudinal traits” (Bridges & Steen, 1998, p. 567).

Some research has posited that differential treatment of juvenile offenders based on race is due in part to “race-neutral” police practices and policies that tend to disproportionately affect minority youth (Kempf-Leonard, 2007; Piquero, 2008). For example, hot-spot policing targets high-crime neighborhoods for increased police presence and surveillance, and these neighborhoods tend to be those in which minorities reside. Although this police strategy—used by police departments across the U.S.—seems race-neutral, Bishop (2005, p. 63) argued that “[s]ubjecting poor, minority neighborhoods to differential surveillance and more police-initiated investigative stops may provoke antagonism among minority youth who perceive that they are being harassed, which in turn increases their likelihood of arrest, detention, and court
processing,” as well as harsher sanctions (Piquero, 2008). Other research opines that factors contributing to differential treatment may include “institutional racism, selective enforcement, biased risk assessment instruments, differential administrative practices, unequal access to effective legal counsel, and legislative policies that disparately affect youth of color” (Davis & Sorensen, 2012, p. 297).

Another possible contributing factor to DMC that falls within the differential treatment perspective is the large amount of discretion given to juvenile court decision-makers. Unbridled judicial discretion can result in a dependence on biases, stereotypes, and anecdotal evidence in the determination of juvenile offenders’ culpability and amenability to treatment (Bishop & Leiber, 2011; Bridges & Steen, 1998; Davis & Sorensen, 2013; Peck, Leiber, & Brubaker, 2014; Piquero, 2008; Tittle & Curran, 1988). For example, Piquero (2008) concluded that racial disproportionality in judicial decision-making was found more often in cases involving less serious offenses that provided more discretion to the juvenile court judge. Similarly, Davis and Sorensen (2013) argued that the highest level of disparity not explained by legal factors in their study was found in cases that allow for the greatest amount of discretion (i.e., drug, status, and public order offenses). As such, case characteristics (i.e., offense type and offense seriousness) are included in this study to control for the varying amount of discretion judges have in a given case depending on these characteristics.

Although much research shows that there are racial disparities in the juvenile justice system that cannot be completely explained by differential offending or other legally-relevant factors (Engen et al., 2002), some studies have found little to no significant differences in the way White and Non-White youth are treated. For example, Tracy (2005) examined four decision points (detention, referral to DA, referral to court, and secure confinement) in three Texas
counties and found that minority youth were treated differently than White youth in only five out of 36 possible scenarios (four decision points, three counties, three offender groups), providing little evidence of widespread differential treatment. In addition, Tracy’s (2005) assertion that “prior research has provided neither methodologically nor statistically adequate documentation” that DMC is due to either differential treatment differential offending was one of the driving forces behind this study, which attempts to provide some of this methodologically and statistically adequate documentation (p. 306; emphasis added).

Other Possible Explanations of DMC

As shown above, much research has addressed the possible cause(s) of disproportionate minority contact. Despite its abundance, however, the DMC research to date has failed to produce consistent evidence to support one explanation over the others (Engen et al., 2002). Research has supported and contradicted both the differential offending and differential treatment hypotheses. This conflicting evidence led Piquero (2008) to posit that “some sort of mixed model [that combines differential offending and differential treatment] offers the most promise for understanding the issue” (p. 67). Furthermore, other researchers have posited alternative explanations of overrepresentation and DMC that do not necessarily conform strictly to differential offending or differential treatment.

For example, in their report published by OJJDP, Hsia, Bridges, and McHale (2004, p. 12) outlined several factors within the juvenile justice system that contribute to DMC: racial stereotyping (both intentional and unintentional) and cultural insensitivity; lack of alternatives to detention and incarceration; misuse of discretionary authority in implementing laws and policies; and lack of culturally and linguistically appropriate services. In addition to these factors residing within the juvenile justice system, the authors found that educational systems (e.g., lack of
resources in schools in minority neighborhoods, inability to prevent dropouts), socioeconomic conditions (e.g., poverty, lack of job opportunities, and high crime rates in predominately minority neighborhoods), and family factors (e.g., low-income, single-parent households) each contribute to the increased disproportionality of minority youth in the juvenile justice system.

Kakar (2006, p. 378) conducted focus groups with 60 juvenile justice stakeholders (e.g., law enforcement, juvenile court personnel, school representatives, community organizations) and concluded that factors contributing to DMC could be broken down into six categories: system factors (e.g., bias, lack of alternatives, inadequate resources); social factors (e.g., distressed neighborhoods, lack of role models, low collective efficacy); family factors (e.g., family conflict, poor parenting skills, lack of concern); education factors (e.g., poor academic performance, dropout, school discipline problems); individual factors (e.g., mental development, antisocial friends, lack of motivation); and economic factors (e.g., extreme poverty, lack of employment opportunities).

One type of policy that has had a substantial impact on minority youth is drug policies introduced in the 1980s as part of the “war on drugs.” These policies have been shown to affect minority communities more severely than White communities (Bishop, 2005; Chin, 2002; Sullivan et al., 2016; Piquero, 2008; Tonry, 1994). For example, throughout the 1970s, White youth were arrested at a higher rate than Black youth. However, by the 1990s (after the war on drugs began), Black youth were arrested for drug crimes at rates almost five times higher than those for White youth. The primary source of this disparity is that drug enforcement strategies often focus on inner-city, low-level drug dealers who tend to operate primarily in minority neighborhoods (Bishop & Leiber, 2011).
The effect of race regarding drug crimes, however, goes further than police contact and arrest. For example, Sullivan and colleagues (2016) examined the effect of race on case processing for youth charged with weapon- and drug-related offenses. Among their findings, the authors concluded that for drug-related offenses, Non-White juveniles were 55% more likely to be detained and over five times more likely to be waived to criminal court compared to similarly-situated White youth. It should be noted, however, that Non-White youth were also significantly more likely to have their case dismissed relative to White drug offenders, while there were no race effects for adjudication or post-adjudication placement in a secure confinement facility.

As evidenced by the preceding discussion, research from the past half century has posited numerous potential explanations of overrepresentation and disproportionate minority contact in the juvenile justice system. A consensus has yet to form, however, regarding the principle cause(s) of DMC. In part, this study attempts to address this lack of consensus. Specifically, if it is found that race maintains a statistically significant effect on the various court outcomes after controlling/matching on legal and extralegal factors, then that would provide some evidence that differential treatment may be occurring. Furthermore, the causes and correlates of disproportionality may be different as juveniles move throughout the juvenile justice process. As such, the following section presents an overview of the literature regarding the relationship between race and five juvenile court outcomes.

PRIOR RESEARCH ON RACE AND JUVENILE COURT OUTCOMES

Since the 1994 amendment to the JJDPA that required states participating in the federal Formula Grants Program to examine the presence, causes, and possible corrective strategies regarding DMC, an “explosion” in DMC research has occurred (Davis & Sorensen, 2012, 2013;
Guevara et al., 2006; McCoy, Walker, & Rodney, 2012; OJJDP, 2009). Furthermore, this “explosion” has led to a significant increase in theory-focused and methodologically sound studies of juvenile court decision-making at various decision-making points in the juvenile court process. The results of this research, however, have been mixed at best (Engen et al., 2002; McCoy et al., 2012).

One possible factor contributing to the mixed results found in DMC research is that these studies tend to differ in their research methodology and statistical techniques (Engen et al., 2002), which may lead to biased conclusions regarding the effect of race on juvenile justice decision-making (see Chapter 3). Despite the potential limitations in the extant literature, DMC research has produced three common ways in which race can affect decision-making in the juvenile court (Guevara et al., 2006). First, some studies indicate that race has a direct effect on decision-making (Bishop, 2005; Engen et al., 2002; Leiber, 2015), which suggests racial discrimination by juvenile court actors. Second, some studies claim the relationship of race on decision-making is indirect (Bridges & Steen, 1998; Engen et al., 2002; Leiber & Stairs, 1999). These studies suggest that race-neutral factors such as family structure and neighborhood of residence, which are actually highly correlated with race, have the strongest effect on decision-making. Third, some studies have found cumulative race effects as youth move through the decision-making process (Davis & Sorensen, 2013; Guevara et al., 2006; Rodriguez, 2010; Sickmund & Puzzanchera, 2014).

As discussed in Chapter 1, most research that analyzed the effect of race on juvenile court decision-making examined only one, or sometimes two, stages of the process. There have been, however, a few systematic examinations of DMC across multiple stages of the court process. In addition, with few exceptions, most prior DMC research has focused on the White/Black or
White/Non-White dichotomy; other races and ethnicities have not received as much empirical attention.

Rodriguez (2010) conducted one of the few studies of how race affects decision making across all decision-points in the juvenile court. Specifically, she studied a sample of 23,156 delinquents and status offenders in Arizona to examine the effect of race/ethnicity and contextual (i.e., community-level) factors on decisions involving diversion, detention, petition, adjudication, and disposition. Using hierarchical generalized linear modeling, Rodriguez found that both Black (Odds Ratio [OR]=0.60) and American Indian youth (OR=0.73) were significantly less likely to be diverted from official court processing relative to their White counterparts. Similarly, Black, Latino, and American Indian youth were all significantly more likely to be detained prior to adjudication compared to Whites, while race played no significant role in the decision to file a formal petition with the juvenile court. For both adjudication and disposition, only Black youth were treated significantly different compared to White youth. Specifically, Black youth were 37% more likely to have their charges dismissed (versus being adjudicated delinquent) compared to Whites, but were 70% more likely to receive an out-of-home placement compared adjudicated White youth.

A recent study by Duran and Posadas (2013) provides an interesting examination of DMC in a state (New Mexico) in which White youth are the minority population. During the study period, Hispanic youth comprised 50% of the state’s juvenile population, 34% were White, 13% Native American, and 2% African American. The authors analyzed official data for nine decision points over a seven-year period. They found that White youth were underrepresented at each decision point except for diversion, where they were overrepresented. Similarly, minority youth were significantly overrepresented at each decision point except for diversion, where they
were underrepresented. For example, 69% of cases resulting in secure confinement and 72% of cases waived to criminal court involved Hispanic youth, despite the fact that they made up only 50% of the juvenile population. Similarly, African American youth were found to be arrested at a rate nearly double that of White youth.

Similarly, Owen and Takahashi (2014) examined DMC in Fresno County (California), where Hispanic youth comprise approximately 57% of the juvenile population. The authors found that Black youth were significantly more likely to be referred to juvenile court, detained, placed in secure confinement, and waived to criminal court and less likely to be diverted when compared to White youth. Interestingly, however, the rate of contact with the juvenile court was not significantly different between White and Hispanic youth. Taken together, the studies by Duran and Posadas (2013) and Owen and Takahashi (2014) provide evidence that DMC exists even in jurisdictions in which Whites are the actual minority group, although to varying degrees based on which racial groups are compared. As mentioned previously, however, studies such as these that examine DMC at multiple decision-points are rare in the literature. Instead, most DMC studies examine only one or two stages of the court process. This research is presented in following sections. In addition, Table 2.1 at the end of this section provides a summary of the literature on the various decision-points, the key findings for each, and the analytic methods typically used.

Case Dismissal/Diversion

After police take a juvenile into custody and decide to send the case to the juvenile court, the first step in the court process is intake. At this stage, intake officers or juvenile probation officers screen cases to determine whether a formal delinquency petition should be filed. This decision is typically based on a review of the arrest record, the youth’s prior court record (if
any), and interviews with the youth and his/her parents (Bishop, 2005). If the intake agent
determines that the case does not warrant an official petition, other available options include
dropping the charges or handling the case informally without further court intervention (i.e.,
placing the juvenile in a diversion program). Across the U.S., roughly half of all juvenile court
referrals are disposed of at this stage via dismissal of charges or diversion (Bishop, 2005).
Despite the obvious importance of this stage in the juvenile court process—as well as the
significant discretionary authority afforded to intake officials—the relative lack of empirical
attention paid to the correlates of the intake decision (compared to other decision-points) is
surprising (Thomas & Sieverdes, 1975).

Thomas and Sieverdes (1975) conducted one of the first in-depth examinations of the
juvenile court intake process to determine the legal and extralegal correlates of the decision to
file a formal petition with the court. The authors examined nine possible predictors of the intake
decision and concluded that both legal and extralegal factors played a role in the decision.
Specifically, seriousness of the instant offense (gamma [\(\gamma\)] = .527) was the strongest predictor,
followed by onset age (\(\gamma = .389\)), current age (\(\gamma = .323\)), number of co-defendants (\(\gamma = -.299\)),
race (\(\gamma = .288\)), family stability (\(\gamma = .219\)), and sex (\(\gamma = .113\)). Indeed, legal variables—offense
seriousness and prior history—tend to be the strongest predictors at this stage (Bishop, 2005).
Cohen and Kluegel (1979a) examined predictors of intake decisions in the Denver and Memphis
juvenile courts and concluded that juveniles’ race had no significant effect—direct or indirect—
on the decisions made by intake personnel. Instead, the strongest predictors of intake decisions
were youths’ sex, offense type, and prior record. However, despite this finding, most studies also
conclude that legal factors alone cannot explain all racial disparities found in case dismissal
(Bishop, 2005).
In their study of race, social contexts, and diversion from juvenile court among multiple jurisdictions in Iowa, Leiber and Stairs (1999) found that race had both a direct effect on diversion and an indirect effect via family status (i.e., one- vs. two-parent household) where Black youth were significantly less likely to be diverted relative to White youth. In a similar study in 2003, Leiber and Mack found that Black youth were significantly more likely to be formally petitioned at intake compared to White youth. It should be noted, however, that Black youth were also more likely to receive leniency at intake: White youth were less likely to have their charges dropped than participate in a diversion program compared to African American youth. In a more recent study, Leiber and colleagues (2011) examined the extent to which race (along with other legal and extralegal factors) influenced intake decisions before and after the implementation of DMC reduction initiatives in a single jurisdiction. They found that Black youth were 53% more likely to be referred to juvenile court than White youth in the decade after the DMC initiatives were enacted. While this finding is significant, it should be noted that in the decade prior to the DMC initiatives, Black youth had an even higher chance of referral (61%) relative to White youth, which suggests a slight reduction in disproportionality in this jurisdiction.

**Preadjudication Detention**

The next step in the juvenile court process is the determination by a juvenile court judge of whether a youth warrants pre-adjudication detention. Following arrest and petition to juvenile court, an estimated 600,000 youth are placed in pre-adjudication detention facilities each year while awaiting further court hearings (Kurtz, Linnemann, & Spohn, 2008). Juvenile courts use detention to prevent pre-adjudication offenders from committing further offenses or to ensure their presence at further court proceedings. Under certain circumstances, courts may also detain a
youth for his or her own well-being and/or protection (Rodriguez, 2007; Schall v. Martin, 467 U.S. 253 [1984]).

Detention is the most often studied decision-point in DMC research, as well as one of the decision-points where disproportionality is most often found (e.g., Bishop & Leiber, 2011; Moak et al., 2012). The decision to detain a youth is a critical juncture in the juvenile justice system, not just because it inflicts loss of freedom and liberty on youth, but also because research has found that the detention decision can influence later decisions in the court process (see below; Bishop, 2005; Cohen & Kluegel, 1979b; Kurtz et al., 2008; Leiber, 2003).

Kurtz and colleagues (2008) examined the detention decision in a sample of youth from a single county in Kansas. Their primary aim was to determine the relative impact of race and lack of informal social control (e.g., family history of arrest, single-parent household) on the decision to detain. Overall, the authors found that while Black youth comprised only 8% of the county’s juvenile population, they accounted for nearly 25% of detained youth. The authors next conducted separate analyses for the decision to detain based on race. As hypothesized, offense type and offense seriousness were two of the strongest predictors of detention for both White and Non-White youth. However, regarding informal social control, family arrest history, school enrollment, and single-parent household were significant predictors of detention for Non-White youth, but non-significant for White youth. The authors argue that this “may largely be due to a pervasive negative stereotype of the stability and effectiveness of minority families” (p. 151).

Leiber and Fox (2005) examined juvenile court referrals to one county in Iowa over 21 years to determine if race had an influence on pre-adjudication detention. The authors found that, net of other legally-relevant and extralegal factors, Black youth were 5% more likely to be detained relative to White youth. Furthermore, although race was not a statistically significant
predictor of the intake decision, detention was significant in that youth who were detained were more likely to have their case formally processed and less likely to be diverted or have their case dismissed. Thus, because Black youth were more likely to be detained compared to White youth, they were also more likely to have their case formally processed.

Guevara and colleagues (2006) examined the effect of race on pre-adjudication detention in two large Midwestern counties and found that White youth were 41% less likely to be detained relative to their Non-White counterparts. When they further disaggregated the sample based on race, however, the effect of race was only present when comparing White and Non-White males; there was no significant difference in the odds of detention for White and Non-White females.

Rodriguez (2007) examined the effect of contextual and individual-level factors (including race) on the decision to detain youth prior to adjudication among 3,000 juvenile court referrals in a single jurisdiction in a southwest state. Among the most notable findings was that Black youth were significantly less likely than White youth to be detained, while there was no statistically significant difference in the odds of detention between Latino and White youth. The author explained this finding by suggesting that because Black youth were disproportionately arrested compared to White youth (at least in this jurisdiction), juvenile court judges were using their discretion to not detain minority youth as a means of a “correction process.”

Another method of analyzing the relationship between race and detention is to look not at the yes/no decision to detain, but rather the actual length of detention. For example, Moak and

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4 Interestingly, neither of the contextual variables included in this study—unemployment rate and poverty level—were significant predictors of detention, a finding that fails to support the racial threat hypothesis discussed above.
colleagues (2012) conducted a multilevel analysis of race and detention in a Southern state. Individual-level factors included in the study were race, gender, age, offense seriousness, and drug use, while contextual-level (i.e., county) factors addressed the degree of urbanization, violent crime rate, residential stability, and concentrated disadvantage. They found that, net of these controls, race played an important role in predicting the length of detention. Specifically, Non-White youth, on average, were detained for significantly greater lengths of time than their White counterparts.

One possible explanation in detention disparity is that intake officers and juvenile court judges tend to believe that juveniles living in two-parent homes will receive increased parental surveillance relative to those living with only one parent, thus preventing future delinquency. According to this reasoning, youth living with only one parent need to be detained in order to offset their increased likelihood of future delinquency (McCoy et al., 2012). The problem, however, is that minority juveniles are disproportionately represented in single-parent households; this, in turn, leads more minority youth to be detained relative to their White counterparts. For example, in their study of race, family status, and detention among over 16,000 juveniles in a southwestern state, McCoy and colleagues (2012) found that (1) Black youth were over twice as likely to come from single-parent homes compared to White youth and (2) youth from single-parent homes were significantly more likely to be detained relative to youth from two-parent homes.

Another possible reason for the racial disproportionality in detention is that the decision in some jurisdictions does not involve judicial review (although detained youth must go before a judge within 48 hours to determine if further detention is warranted) (Kurtz et al., 2008). Instead, the decision is in these jurisdictions left to police officers or juvenile intake personnel who often
have less education, experience, and/or training regarding juveniles, which can potentially lead to subjective decisions based, in part, on racial stereotypes.

Whatever the explanation of the often-observed racial disparity in pre-adjudication detention, judges’ decisions at this stage of the process play a vital role in future decision-making points via a cumulative, or “snowball,” effect (Davis & Sorensen, 2013; Kempf-Leonard, 2007; Sickmund & Puzzanchera, 2014). According to this view, the interrelatedness of decisions throughout the juvenile justice system can have a cumulative impact on minority overrepresentation as youth move through the system. In other words, decisions made at earlier stages can affect (and lead to greater racial overrepresentation in) decisions made at later stages (Leiber & Fox, 2005; NCCD, 2007; Piquero, 2008; Rodriguez, 2010). For example, Guevara et al. (2006) found that pre-adjudication detention—which affected Non-White youth at a higher rate in their study—significantly increased the odds of an out-of-home placement after adjudication, thus providing evidence for the cumulative effect of race on juvenile court decision-making. This cumulative disadvantage demonstrates why it is important to examine multiple decision points in any study aiming to determine the effect of race on juvenile justice decision-making (Engen et al., 2002).

**Adjudication**

The adjudication stage of the juvenile court process—in which juvenile court judges decide whether the evidence warrants a finding of delinquency—is the juvenile court equivalent of a trial in criminal courts. In the juvenile justice system, judges are given wide discretion at this stage. This, combined with the fact that youth are often not represented by legal counsel during adjudication and that many juvenile offenses are vague (e.g., status offenses), can lead to possible biased and/or discriminatory decision-making by court personnel at this stage of the
juvenile justice process (Tittle & Curran, 1988). However, contrary to the findings at every other stage in the juvenile court process, the most common finding regarding the adjudication decision is that there is little to no racial disproportionality at this stage. This may be due to the fact that adjudication tends to be the stage where the most emphasis is placed on the facts of the case (e.g., offense seriousness and number of prior offenses) and legal rules of procedure (Bishop et al., 2010). Furthermore, some studies show that White youth are actually more likely than Non-White youth to be adjudicated delinquent (Bishop, 2005; Johnson & Secret, 1990). For example, in their study of the effects of race on juvenile court decision-making in Nebraska, Johnson and Secret (1990) found that White youth were significantly more likely than Black youth to be adjudicated delinquent. Specifically, the odds of delinquent adjudication for White youth were two to three times higher than for their Black counterparts. Leiber (2013) argued that Black youth often receive less harsh outcomes at this stage due to a “correction factor” in which juvenile court judges “correct” the more severe outcomes Black youth experience at the front end of the juvenile justice process. In other words, judges use this correction process to remedy the minority overrepresentation found at the front-end of the juvenile court by treating minority youth less severely at the back-end of the process (Rodríguez, 2010).

Not all research indicates that there is no racial disproportionality at this stage, however. For example, Leiber (2015) examined the effects of race and prior offending on multiple juvenile court outcomes among a sample of youth petitioned to a Midwestern juvenile court. Among the findings, Leiber concluded that Black youth were significantly more likely to be adjudicated

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5 It should be noted that in each of the other decision points examined in this study (detention, petition, and disposition), the authors found a significant race effect that negatively affected Black youth.
delinquent compared to their White counterparts. Prior record was the strongest predictor of case outcomes, however. This is not surprising since many juvenile court judges view number of prior referrals as a proxy of both culpability and future offending potential (Leiber, 2015; Steffensmeier et al., 1998).

Secure Confinement

For youth who are adjudicated delinquent, the next stage of the court process is the disposition hearing, which is the equivalent of the sentencing hearing in the adult system. During this stage, judges must decide what sanction(s) to place on the offender. Similar to criminal courts, two of the most common sanctions at this stage are probation and placement in an out-of-home secure confinement facility (i.e., correctional institution). Furthermore, contrary to the rehabilitative priorities of early juvenile courts in which dispositions were based solely on what was in the best interest of the juvenile, today’s juvenile courts focus more on the factors that tend to predict adult punishments, such as community safety, deterrence, and retribution (Cauffman et al., 2007).

Most research conducted on this stage of the juvenile court process has concluded that youths’ prior offense and disposition histories are the strongest predictors of secure confinement, but that race often has a significant direct effect, even after controlling for legal variables (Bishop, 2005). Furthermore, although prior record and previous dispositions may seem race-neutral as predictors of case dispositions, research has suggested that Non-White youth more often accrue longer offense histories and dispositions than their White counterparts, leading to more severe dispositions in later cases (Bishop & Leiber, 2011). Similarly, Barton (1976) argued that race tends to be correlated with extralegal variables shown to influence disposition
decisions, such as SES, family structure, and educational achievement, to the point where Black youth are more often placed in secure confinement.

Using data from the Uniform Crime Reports and the Census of Juveniles in Residential placement, Davis and Sorensen (2013) sought to examine the extent to which juvenile justice systems across the U.S. were successful in reducing disproportionality in minority placement (i.e., secure confinement) after the introduction of the amendments to the Juvenile Justice and Delinquency Prevention Act (see Chapter 1). After controlling for rates of arrest, they found that the Black:White ratio of juvenile placement decreased by 20% from 1997 to 2006. However, Black youth were still placed in secure facilities at a rate 70% higher than their White counterparts. Similarly, in their study of case outcomes for adjudicated juveniles (out-of-home placement vs. probation), Rodriguez et al. (2009) found that Black youth were 2.5 times more likely to be placed in a secure correctional facility relative to White youth, all other things being equal. There was no statistically significant difference in secure confinement between White and Latino youth, however. Higgins et al. (2012) used propensity score matching to examine the effect of race on juvenile incarceration among a sample of youth petitioned to juvenile courts in Pennsylvania (N=41,561). After matching White and Black youth on numerous legally-relevant and extralegal/sociodemographic variables, the authors found that Black youth were 1.28 times more likely to be placed in secure, out-of-home facilities than their White counterparts.

Not all prior analyses have produced a significant race effect on the decision to place youth in secure confinement, however. Cauffman and colleagues (2007) used data from the Pathways to Desistance study, a longitudinal study of serious juvenile offenders in Phoenix and Philadelphia, to examine the effects of demographic, psychological, contextual, and legal variables on juvenile court dispositions (probation vs. secure confinement). Using logistic
regression, the authors concluded that race (White/Black/Hispanic) was not a significant predictor of case disposition. Indeed, of the demographic variables included in the analysis, only site, sex, and age were significantly related to disposition. Specifically, youth adjudicated in Philadelphia, males, and younger youth were more likely to be placed in secure confinement than receive probation. The authors concluded, however, that legal factors were more important predictors of case disposition than individual or environmental factors. Furthermore, Leiber et al. (2011) found that White youth were significantly more likely than Black youth to be placed in secure confinement in the decade after the JJDPA’s DMC mandate. In responding to this surprising finding, the authors suggested that judges may be overcompensating in response to the mandate to reduce minority confinement (see discussion of “correction effect” in previous section). Despite these mixed findings, in addition to the fact that legally-relevant factors tend to be the strongest predictors of secure confinement, most studies provide empirical evidence that youths’ race remains a significant predictor of secure confinement, all other things being equal.

**Waiver to Criminal Court**

Arguably the most important decision made by juvenile court personnel in cases involving serious juvenile offenders is whether the juvenile court should waive its jurisdiction and send the youth to be tried in criminal court. The juvenile justice system was founded on the belief that youth are not as culpable for their actions as are adults and that juvenile offenders should be treated rather than punished (Brown & Sorensen, 2012; Harris, 2009; Males & Macallair, 2000). However, the rate of violent crimes committed by juveniles steadily increased in the 1980s and 1990s (Sickmund, Snyder, & Poe-Yamagata, 1997), which led the public to contend that the juvenile justice system was ineffective in addressing serious, violent delinquency (Brown & Sorensen, 2013). As a result, juvenile justice policies in many
jurisdictions have shifted from a treatment and rehabilitation focus to one of incapacitation and punishment, at least for serious offenders (Harris, 2009). This shift is evidenced by the fact that, over the past 20 years, almost every state legislature enacted new laws (or revised old ones) that made it easier to remove youth from juvenile court jurisdiction and place them within the purview of criminal courts due to the belief that criminal courts were more able to inflict harsher punishment and, subsequently, reduce recidivism among youthful offenders (Brown & Sorensen, 2013 Males & Macallair, 2000). The primary purpose of juvenile waiver is to serve as a “safety valve” to remove from the juvenile justice system those juveniles deemed incapable—by virtue of their current and/or prior delinquent behavior—of benefiting from juvenile court sanctions (Olsen, 2005). Today, every state in the U.S. has laws allowing juveniles to be transferred to adult criminal courts under certain circumstances or if certain conditions are met.

It seems, however, that lawmakers were blind to the myriad negative consequences that can result from youth being incarcerated with adult offenders, including learning new criminal behavior and attitudes, stigmatization, lack of treatment programs, loss of self-respect, and loss of future life opportunities (Brown & Sorensen, 2012, 2013). Furthermore, some recent research has shown that minority youth are disproportionately waived to criminal court and tried as adults (Brown & Sorensen, 2013; Males & Macallair, 2000).

Brown and Sorensen (2013) examined the effect of legal (i.e., offense type and severity, number of previous petitions, and age) and extralegal factors (i.e., race, ethnicity, and gender) on the decision to waive juveniles to criminal court in Texas’ largest county. Their bivariate analysis revealed that a significantly larger proportion of Blacks (57%), Hispanics (54%), and males (53%) were transferred to criminal court than were Whites (23%) and females (15%). In addition, those charged with a violent crime (76%) were more likely to be transferred than youth
charged with a drug or property offense (8.7%), while youth with two or more prior petitions (96%) were more likely to be transferred than those with zero or one prior petition (49%). When all of the variables were combined in the multivariate analysis, every variable was found to be a significant predictor of the transfer decision. Among the strongest findings were that Black youth were over three times more likely to be transferred than White youth, and males were almost seven times more likely than females to be transferred. The strongest predictor, however, was prior record; youth with two or more prior petitions were over 20 times more likely to be transferred than youth with zero or one prior petition.

Males and Macallair (2000) examined judicial waiver to criminal court in Los Angeles County between 1996 and 1999. Among their conclusions, the authors found that minority youth (Hispanic, Black, and Asian) were 2.8 times more likely to be arrested for a violent crime, 6.2 times more likely to be waived to criminal court, and seven times more likely to be incarcerated after criminal court conviction compared to similarly-situated White youth.

As mentioned above, however, a few studies have concluded that race is not a significant predictor of the decision to waive youth to criminal court. For example, in their study using the Pathways to Desistance data discussed in the previous section, Cauffman and colleagues (2007) found that race was not a significant predictor of the decision to waive a case to criminal court in Phoenix. Instead, the decision to waive juvenile court jurisdiction was associated more with age (older), sex (male), offense type (violent), and alcohol dependence. Furthermore, Leiber and Johnson (2008) found an unexpected result in that Black youth were significantly less likely to be waived to criminal court or sentenced to secure confinement relative to similarly-situated White youth; instead, Black youth were more likely to receive the less-severe outcome of
community-based punishment (i.e., probation). This finding, however, was conditioned on youths’ age.
Table 2.1. Research Summary of Juvenile Court Decision-Points

<table>
<thead>
<tr>
<th>Court Outcome</th>
<th>Key Findings</th>
<th>Typical Analytic Methods Used</th>
</tr>
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| **Case Dismissal**    | • Legal variables tend to be the strongest predictor, but race also plays a role  
                         • Non-White youth significantly more likely to be petitioned compared to White youth  
                         • Common indirect effect of race via family status                                                                                           | • Logistic regression  
                         • HGLM  
                         • Log-linear analysis                                                                                                                        |
| **Preadjudication Detention** | • One of the decision-points where disproportionality is most often found  
                             • Legal variables tend to be strongest predictors  
                             • But most studies find that Non-White youth are more likely to be detained  
                             • Detention status can affect later decisions                                                                                          | • Logistic regression  
                             • HLM/HGLM                                                                                                                                   |
| **Adjudication**      | • Most studies find little to no DMC at this stage  
                             • Some studies find that White youth are more likely to be adjudicated  
                             • Legal variables are strongest predictor  
                             • Race may have indirect effect via detention status                                                                                   | • Logistic regression  
                             • HGLM                                                                                                                                        |
| **Secure Confinement** | • Legal variables are strongest predictor; though they may not be race-neutral, as Non-White youth often accrue longer offense histories  
                             • Non-White youth still significantly more likely to be placed in a secure facility                                                        | • Logistic regression  
                             • PSM                                                                                                                                          |
| **Waiver**            | • Legal variables are strongest predictor  
                             • Still, Non-White youth are significantly more likely to be waived  
                             • Youths waived to criminal court often receive harsher dispositions than those who remain in juvenile court                                  | • Logistic regression                                                                                                                          |

Note: HLM = hierarchical linear modeling; HGLM: hierarchical generalized linear modeling; PSM: propensity score matching
SUMMARY

The research discussed above provides significant evidence that disproportionate minority contact is present—to varying degrees—at every stage of the juvenile court process and in every state. However, much of the extant literature falls victim to one (or both) of two potentially major limitations. First, most of the studies discussed above focus on the effect of youths’ race at only one or sometimes two stages of the juvenile court process. This is problematic because juvenile justice is a process; examinations of a single stage of the process are, at best, suspect and more likely miss potential race effects. For example, suppose a study examined only the secure confinement decision and found no race effect. The authors could claim that race does not play a role in the decision to send youth to a secure correctional facility. However, if race was a significant predictor of an earlier decision point, say detention, there would in fact be an indirect effect of race on the secure confinement decision via detention status.

Second, as shown in Table 2.1, most DMC studies employ multivariate logistic regression in an attempt to examine youth who are “similarly-situated” on all factors except race. However, this analytic technique may be insufficient because, for example, the use of regression can make it “easy for an analyst to overlook fundamental mismatches between treatment and control cases” (Morgan & Harding, 2006, p. 46). For example, if the youth in a sample significantly differed on the exogenous variables included in the analysis, the resulting regression estimate would be based on a comparison of nonequivalent treatment and control groups. Similarly, when simple regression is used and one of the independent variables in the model is correlated with a variable in the error term, then the calculated regression estimate will be biased (Morgan & Winship, 2015). As such, because most prior DMC studies employ these
statistical methods, there may be reason to question the accuracy of their results in light of these limitations. The limitations of regression analysis are discussed in more detail in the next chapter.

This dissertation attempts to address these limitations and, subsequently, add to the knowledge base on race, DMC, and juvenile court outcomes. Specifically, using official record data collected on 50,163 cases in seven juvenile courts in Ohio, this study examines the relationship between race and five juvenile court outcomes representing decisions made from the beginning of the court process to the end. In addition, five separate analytic techniques—four treatment effect estimators and logistic regression as a baseline—are used to closely match youth on all exogenous factors except race, thus estimating the effect of race on court outcomes using a matched sample of similarly-situated youth. Chapter 3 provides a more in-depth discussion of the statistical challenges found in analyzing DMC issues, as well as a presentation of the research design, methodology, and analytic plan used in this study.
CHAPTER 3

RESEARCH METHODS

This chapter presents the research methodology used in this dissertation. First, the three research questions guiding the study are presented and discussed. Next, a description of the data used to test the research questions, the operationalization of the independent and dependent variables, and descriptive statistics of the sample are provided. Finally, this chapter concludes with a detailed overview of the analytic plan for this study, including discussion of the five statistical techniques used to address the research questions.

RESEARCH QUESTIONS

As mentioned in Chapter 1, this dissertation is guided by three research questions—one substantive and two methodological. Research Question 1 asks: After matching youth on legally-relevant and extralegal variables, what is the relationship between race and decision-making across five juvenile court outcomes? Based on the prior research discussed in Chapter 2, it is expected that Non-White youth will be treated harsher (e.g., less likely to have case dismissed, more likely to be placed in secure confinement following adjudication) compared to their White counterparts at most stages of the juvenile court process (Bishop, 2005; Davis & Sorensen, 2013; Guevara et al., 2006; Higgins et al., 2012; Leiber, 2015; Leiber & Stairs, 1999; Lieber et al., 2011; Males & Macallair, 2000; Thomas & Sieverdes, 1975).

Research Question 2 states: Are there any differences among the results obtained from the four counterfactual analytic techniques relative to logistic regression? A large portion of prior DMC research has examined the topic using multivariate logistic regression (Higgins et al., 2012; Peck et al., 2014; Rodriguez et al., 2009). It is possible, however, that this technique may
not be best suited to examine DMC. For example, the two groups (i.e., White/Non-White) oftentimes differ among the included independent variables, leading to results based on the comparison of nonequivalent groups. This is referred to as a lack of common support, or a situation in which the distribution of the covariate matrices between treatment and control groups is not identical (Morgan & Harding, 2006; Nichols, 2007; Rosenbaum & Rubin, 1983; Stuart, 2010). While this limitation is not taken in to account in logistic regression, it is considered in matching methods in that the results obtained via matching are conditional on the area of common support (see discussion of nearest neighbor matching below).

Similarly, suppose that a researcher wants to estimate the effect of a dichotomous independent variable (X) on a specific outcome (Y). The simple regression equation would be

\[ Y = a + bX + e. \]

However, if X is correlated with any of the variables included in the error term (e)—which is common in social science research that includes race as a primary variable of interest—then the calculated regression estimate will be biased (Morgan & Winship, 2015). Furthermore, matching estimators may be superior to regression when the true functional form of a model is unknown. In these situations, matching estimators are more suitable because they nonparametrically balance the covariates during the matching process, thus precluding the need to define a functional form (Abadie & Imbens, 2006; Morgan & Harding, 2006). Similarly, Mathison (1988) argued that using multiple methods to examine the same phenomenon—termed methodological triangulation—can also reduce bias and improve the validity of research findings because the flaws of one statistical method may be a strength of another. As such, this

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6 Unfortunately, this is rarely reported in published research.
study uses four counterfactual techniques that are designed to calculate an average treatment effect based solely on comparing outcomes among sets of youth who are identical—or at least similarly-situated—except for their race. Doing so will allow for a more methodologically sound examination of race effects on juvenile court outcomes relative to correlational techniques. Because there is no common metric between logistic regression and the counterfactual approaches, the methods will be compared primarily using the direction, significance, and relative strength of the regression coefficient for race (logistic regression) and the average treatment effect estimates (counterfactual methods).  

Finally, Research Question 3 asks: What are the relative strengths and weaknesses of each analytic technique as pertains to estimating the relationship between race and juvenile court outcomes? Although there are a number of counterfactual approaches available to researchers, there is little guidance in the literature to assist in choosing among them or which works best (Morgan & Harding, 2006; Stuart, 2010). As such, this study attempts to fill in the gaps in the literature and provide an overview and comparison of four counterfactual approaches to estimating treatment effects using juvenile DMC as a focal point. In part, answering this research question will include discussion of loss of cases, covariate balance, post-matching diagnostics, and covariate overlap between White and Non-White youth (see Chapter 4).

As discussed above, the only way to produce accurate conclusions regarding the effect of race on juvenile justice decision-making is to compare youth of different races who are otherwise the same. “If they are not the same—or at least ‘similarly-situated’—then DMC may really occur.

Relative comparisons among the four counterfactual approaches will be much more straightforward as they share a common metric (i.e., ATE) and use similar methods for calculating other parameters.
as a result of the other ways in which they differ” (Kempf-Leonard, 2007, p. 75). As such, while the focus of this dissertation may be more methodological in nature (Research Questions 2 and 3), the various methods are used to address the substantive issue of the relationship between race and juvenile court outcomes (Research Question 1). If counterfactual techniques are indeed a more suitable approach to examining DMC in the juvenile justice system, it follows that results obtained from these techniques would hold more weight compared to prior DMC research and provide stakeholders with research upon which they can more confidently base policy.

DATA

The data used in this dissertation were originally collected for the Ohio Disproportionate Minority Contact Assessment, a project conducted by the University of Cincinnati’s Center for Criminal Justice Research (CCJR; Sullivan et al., 2016). This project used both quantitative and qualitative methods to examine the presence and potential causes of DMC in 13 counties in Ohio. The CCJR research team collected multiple types of data from each county. The quantitative data included official arrest data for juveniles from 20 law enforcement agencies across 10 counties (N=20,334), juvenile court case data from each of the 13 counties (N=75,946), and individual-level data for a sample of youth confined in secure Ohio Department of Youth Services facilities (N=1,514). All of these data were collected for juveniles aged 10-17 who were arrested, petitioned, or confined between January 1, 2010 and December 31, 2011. The qualitative data included information from 131 interviews with juvenile justice personnel, 32 days of juvenile court observation, and 17 focus groups with police personnel. This study focuses on the quantitative case data collected from the juvenile courts.
Juvenile court data collection began in summer 2012 and continued until late 2015. At the beginning of the study, the CCJR research team provided each court with a list of requested data/measures. Data were then collected using one of two methods. Some courts submitted electronic data directly to the research team. For other courts, CCJR-trained data collectors retrieved and coded court files onto data collection forms that were later entered into an electronic database maintained by the CCJR. These data were then checked for accuracy and cleaned. Each case contained demographic information on the petitioned youth (e.g., age, race, sex), their criminal history (e.g., number of prior charges, history of probation), the current offense(s) (e.g., offense seriousness, offense type, number of charges), and dichotomous measures of five court outcomes (see Dependent Variables section below).

The data used here are a subsample of the juvenile court record data collected from the 13 juvenile courts. Specifically, case-level data from seven of the 13 counties are used. These seven counties were selected due to their in-depth coverage on both independent and dependent variables; in other words, each of these seven counties contained relatively little missing information amongst the relevant variables. For example, one of the courts not included in the current study was missing information on pre-adjudication detention for 32% of its cases, while a different court had missing offense seriousness information for 21% of its cases. Conversely, there was less than 4% missing data on each variable among the seven counties included in this study, except for the adjudication outcome variable (see discussion in Dependent Variables section below). Furthermore, the selected counties are geographically and racially diverse and represent both rural and urban areas of the state, thus providing a useful sample on which to examine DMC. This selection criteria resulted in a preliminary sample of 50,626 cases. To ensure consistency across analytic techniques and outcomes (see below), 463 cases were
removed from the sample due to missing data on one or more of the independent variables. This resulted in a final sample of 50,163 cases. Table 3.1 provides a breakdown of the final sample by county.

<table>
<thead>
<tr>
<th>County</th>
<th>N</th>
<th>% of Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>County A</td>
<td>5,062</td>
<td>10.1</td>
</tr>
<tr>
<td>County B</td>
<td>424</td>
<td>0.8</td>
</tr>
<tr>
<td>County C</td>
<td>16,431</td>
<td>32.7</td>
</tr>
<tr>
<td>County D</td>
<td>865</td>
<td>1.7</td>
</tr>
<tr>
<td>County E</td>
<td>16,014</td>
<td>31.9</td>
</tr>
<tr>
<td>County F</td>
<td>10,969</td>
<td>21.9</td>
</tr>
<tr>
<td>County G</td>
<td>398</td>
<td>0.8</td>
</tr>
<tr>
<td>Total</td>
<td>50,163</td>
<td>100</td>
</tr>
</tbody>
</table>

Dependent Variables

The primary dependent variables in this study are dichotomous measures of case outcomes at five key decision points in the juvenile court process: case dismissal, preadjudication detention, adjudication, secure confinement, and waiver to criminal court. Each outcome variable was coded as 0=No, 1=Yes. This section discusses the operationalization of these variables and the inclusion criteria used for the analysis of each outcome. The descriptive statistics for each of the five outcome measures are presented in Table 3.2.

Case Dismissal.

This variable indicates whether petitioned youth had their case officially dismissed, for any reason, prior to an adjudication hearing. This decision is typically made by intake unit personnel, a juvenile probation officer, or a juvenile court judge/magistrate, depending on how

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8 Analyses revealed no significant differences in youths’ race or other pertinent variables between the deleted and retained cases.
the court is structured (Bishop, 2005). Approximately 22% of the cases included in this study were dismissed prior to an adjudication hearing (see Table 3.2).\(^9\)

<table>
<thead>
<tr>
<th>Measure</th>
<th>Analytic Sample N</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Dismissal</td>
<td>48,369</td>
<td>0.215</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
<td>50,054</td>
<td>0.193</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Adjudication(^1)</td>
<td>31,232</td>
<td>0.910</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Secure Confinement(^2)</td>
<td>28,421</td>
<td>0.068</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Waiver(^3)</td>
<td>9,181</td>
<td>0.037</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

\(^1\) Analytic sample includes only non-dismissed cases  
\(^2\) Analytic sample includes only adjudicated youth  
\(^3\) Analytic sample includes only cases involving a felony offense

**Preadjudication Detention**

The next step in the juvenile court process is the judicial decision of whether youth should be detained prior to their adjudication hearing. As such, the detention variable indicates whether a youth was placed in a secure detention facility while awaiting adjudication. Slightly more than 19% of the cases in this sample involved youth who were detained prior to adjudication.

In addition, research routinely finds that youth who are detained often receive harsher outcomes at later stages of the juvenile court process (Bishop, 2005; Cohen & Kluegal, 1979b; Kurtz et al., 2008; Leiber, 2003). Therefore, as discussed in the next section, detention is also included as an independent variable in the analyses of the adjudication, secure confinement, and waiver outcomes in this study.

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\(^9\) Some counties included cases that were diverted from formal prosecution in their measure of dismissed cases. Therefore, it is possible that a portion of dismissed cases were actually diverted (as opposed to straight dismissal of charges).
**Adjudication**

The adjudication variable indicates whether a youth was formally found delinquent following an adjudicatory hearing. The models examining the adjudication outcome include only the 37,960 cases that were not dismissed at the front end of the court process (i.e., for obvious reasons, cases that were dismissed prior to an adjudication hearing are not included in the adjudication analysis). Of the non-dismissed cases included in this study, the various counties did not provide adjudication information for 6,728 cases, leaving a final analytic sample of 31,232 cases for the adjudication analyses. Of these cases, 91% were formally adjudicated delinquent at this stage.

**Secure Confinement**

For youth who are adjudicated delinquent, the most severe sanction they can receive is confinement in a secure correctional facility—the juvenile equivalent of adult prisons. As such, this variable indicates whether adjudicated youth were placed in an out-of-home secure correctional facility. Of the 28,421 adjudicated youth in the sample, 6.8% were placed in secure confinement. Conversely, most adjudicated youth received less severe sanctions, such as probation, substance abuse treatment (residential or nonresidential), drug court, restitution, or community service.

**Waiver to Criminal Court**

The final outcome measure included in this study is the waiver decision. This variable indicates whether youth had their case waived to criminal (i.e., adult) court. Because no youth

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10 Analyses of the analytic sample with and without the dropped cases revealed no significant differences between the two on any of the included covariates.

11 In *Roper v. Simmons*, 543 U.S. 551 (2005), the U.S. Supreme Court deemed the death penalty unconstitutional for those persons who commit a capital offense under the age of 18.
charged with a misdemeanor or status offense in this data had their case waived, the sample for this outcome includes only youth charged with a felony offense (N=9,266). Of these cases, the various counties did not provide waiver information for 85 cases, leaving a final analytic sample of 9,181 cases for the waiver analyses.

As discussed in Chapter 2, waiver is arguably the most important decision made by juvenile court personnel because youth tried and subsequently convicted in criminal courts are more likely to be housed in secure facilities with adult offenders, which has been shown to increase the odds of learning new criminal behaviors and attitudes, stigmatization, and victimization (Brown & Sorensen, 2012, 2013). In this sample, 3.7% of the cases involving a felony charge were waived to criminal court.

**Independent Variables**

Based on the frequent finding that both legal and extralegal factors play a role in juvenile court decision-making (Armstrong & Rodriguez, 2005; Barton, 1976; Bishop, 2005; Guevara et al., 2006; Leiber, 2013; Cohen & Kluegel, 1979a), this study includes measures of both types. This section discusses each of the independent/matching variables included in the models, including the primary independent variable, race. Table 3.3 presents the descriptive statistics for each of the independent variables.

**Primary Independent (“Treatment”) Variable**

The primary variable of interest in this study is youths’ race. In the original data, race was recorded as: White (36.8%), African American (58.5%), Asian (0.1%), Other (3.1%), and Bi-Racial (1.5%). Because less than 5% of the sample included youth who were not White or African American, youths’ race was recoded as $0=White, 1=Non-White$ for the final analyses. In addition, youths’ race was also dichotomized to comport with the requirements of the
counterfactual statistical techniques used in this study, which call for binary “treatment” variables. The final sample was 36.8% White and 63.2% Non-White youth.

**Table 3.3. Descriptive Statistics for Independent/Matching Variables**

<table>
<thead>
<tr>
<th>Measure</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race (1=Non-White)</td>
<td>50,163</td>
<td>0.632</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td># Prior Charges</td>
<td>50,163</td>
<td>2.77</td>
<td>4.63</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td># Current Charges</td>
<td>50,163</td>
<td>2.07</td>
<td>2.35</td>
<td>1</td>
<td>65</td>
</tr>
<tr>
<td>Age</td>
<td>50,163</td>
<td>15.85</td>
<td>1.62</td>
<td>10.00</td>
<td>17.99</td>
</tr>
<tr>
<td>Sex (1=Female)</td>
<td>50,163</td>
<td>0.33</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Detention</td>
<td>50,054</td>
<td>0.19</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Offense Type1</td>
<td>50,163</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Violent/Sex Offense</td>
<td>11,305</td>
<td>(22.5%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property</td>
<td>12,490</td>
<td>(24.9%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drug/Alcohol</td>
<td>3,151</td>
<td>(6.3%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Status</td>
<td>14,139</td>
<td>(28.2%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>9,078</td>
<td>(18.1%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offense Level2</td>
<td>50,163</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Felony</td>
<td>9,266</td>
<td>(18.5%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Misdemeanor</td>
<td>25,682</td>
<td>(51.2%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>15,215</td>
<td>(30.3%)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Legal Variables**

*Prior Charges Filed.* This variable is a continuous measure of the number of official charges brought against a youth in all cases prior to the current one. Based on previous research, it is expected that youth with more prior charges will receive harsher treatment throughout their current interaction with the juvenile court (e.g., less likely to have case dismissed, more likely to be sent to a secure correctional facility), independent of youths’ race (Bishop, 2005; Bishop & Leiber, 2010; Bishop & Sorensen, 2013; Cohen & Kluegel, 1979a). This measure ranges from

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12 Each of the counterfactual techniques used in the present study can be considered a “treatment effect estimator;” in this dissertation, race is considered the treatment. In other words, instead of using these techniques to examine an outcome for “treated” and “untreated” cases, this study uses them to examine outcomes for similarly-situated White and Non-White youths.

13 Although not discussed in this dissertation, more recent developments in treatment effect estimators do allow multi-categorical treatments.
zero to 50 and has a mean of 2.77 and standard deviation of 4.63, although approximately 43% of the cases involved youth with zero prior charges. As discussed below, this variable exemplifies a measure with limited overlap between White and Non-White youth, which can potentially result in biased regression estimates.

Number of Charges in the Current Case. This is a continuous variable that indicates the number of separate charges—or counts—against a youth in the current court case. Youth petitioned on numerous charges may be perceived as more serious delinquents and thus in need of more severe treatment from the juvenile court (Engen et al., 2002). Number of charges ranges from one to 65 with a mean of 2.07 and a standard deviation of 2.35.

Most Serious Offense Type. As discussed in Chapter 2, offense type is often found to be one of the best predictors of case outcomes (Bishop, 2005; Brown & Sorensen, 2013; Kurtz et al., 2008; Thomas & Sieverdes, 1975). If a youth is charged with more than one offense in a given case, this categorical variable indicates the most serious offense type among the charges. For youth charged with a single offense, however, this variable indicates the category of that offense. The offense categories include: violent/sex offenses, property offenses, drug/alcohol offenses, status offenses, and other offenses.14 As shown in Table 3.3, the most common offense type among the cases included in the sample is status offenses (28.2%), followed by property offenses (24.9%), violent/sex offenses (22.5%), other offenses (18.1%), and drug/alcohol offenses (6.3%). In the logistic regression analysis, violent/sex offenses are used as the reference category.

14 The “other” category for most serious offense category includes offenses such as public order crimes, court order violations, and probation violations.
Most Serious Offense Level. Similar to offense type, offense level/seriousness is often considered to be one of the strongest predictors of juvenile court outcomes (Armstrong & Rodriguez, 2005; Cauffman et al., 2007; Guevara et al., 2006). In this study, most serious offense level is a categorical variable that identifies the level (i.e., seriousness) of the charge(s) against a youth. Similar to the previous variable, for youth charged with more than one offense in the current case, most serious offense level indicates the level of the most serious offense among the charges. For youth charged with a single offense, this measure indicates the seriousness of that offense. The offense level categories include felony (18.5%), misdemeanor (51.2%), and other (30.3%). In the logistic regression analysis, felony offenses are used as the reference category.

Extralegal Variables

When examining juvenile court processing, models that control only for legal variables may be underspecified (Bishop, 2005). Because extralegal factors are sometimes legitimate considerations in juvenile courts (with the possible exception of a youth’s sex), researchers should also include these factors in their statistical models, as these models do a better job at explaining possible disproportionality more effectively than models limited to legal factors (Bishop, 2005). The four extralegal factors included in this study are discussed below.

Sex. Because most delinquent acts are committed by males (Furdella & Puzzanchera, 2015), it is important to include youths’ sex in any matching/regression models. Youths’ sex is a dichotomous measure that indicates whether a youth is male or female. Males constitute 67.1% of the sample, while females make up the remaining 32.9%. These proportions are consistent

15 The “other” category for most serious offense level includes offenses such as failure to appear and status offenses.
with the latest figures of the proportions of male and female juveniles coming into contact with
the juvenile justice system (Furdella & Puzzanchera, 2015).

**Age.** Age is a continuous measure that indicates youths’ age at the time a formal petition
was filed in the juvenile court. Youths’ age is a commonly used extralegal factor in juvenile
delinquency studies because many law enforcement and juvenile court actors equate a juvenile’s
age with his or her degree of culpability (Armstrong & Rodriguez, 2005; Bishop et al., 2010;
Leiber, 2015). For this study, as well as the larger DMC assessment from which the data
originate, “juvenile” was defined as a youth between the ages of 10 and 17. The average age at
case initiation among the youth in the sample was 15.85 years old with a standard deviation of
1.62.

**County.** This variable indicates the original county in which the juvenile court petition
was filed. Because the seven counties included in this study vary in population, location, and
demographic characteristics, it is important to control for—or match youth on—the county of
origin in order to address these differences in the analyses. As shown in Table 3.1, the number of
cases in the sample from each county varies dramatically: from 398 cases in County G to 16,431
in County C.

**Preadjudication Detention.** The final independent/matching variable indicates whether
youth were detained in a secure facility between the time of their arrest and any further juvenile
court proceedings. As discussed above, detention also serves as a dependent variable since it is
one of the first decisions juvenile court personnel must make after a petition is filed. However,
due to the often-observed cumulative effect of preadjudication detention on future court
outcomes (see Bishop, 2005; Cohen & Kluegal, 1979b; Kurtz et al., 2008; Leiber, 2003; Leiber
& Fox, 2005; Rodriguez, 2010), detention is used as an independent variable in the analysis of
the adjudication, secure confinement, and waiver to criminal court outcomes. Indeed, Rodriguez (2010) argued that any detailed examination of DMC in the juvenile justice system “must take into account the critical role of preadjudication detention and the possible cumulative effects of race … in court outcomes” (p. 397). In this study, youth were detained in approximately 20% of the cases.

**ANALYTIC PLAN**

The analytic process for this study is divided into two parts. First, the Relative Rate Index (RRI) will be calculated for each of the five court outcomes. The RRI is a descriptive statistic that calculates the ratio of the difference in proportions of White and Non-White youth who experience a specific outcome in the court process (see full description below; Benekos, Merlo, & Puzzanchera, 2011; Leiber et al., 2011; Sickmund & Puzzanchera, 2014). This figure allows researchers to determine whether any initial disproportionality exists at the various stages of the juvenile court—albeit without the influence of any other variables.

Next, the primary goal of this dissertation is to address Kempf-Leonard’s (2007) assertion that youth must be as “similarly-situated” as possible in order to draw accurate conclusions regarding the effect of race on juvenile court decision-making. As such, the impetus of this study is to compare the relative strengths and weaknesses of four different counterfactual analytic techniques used to address Research Question 1. Unfortunately, although studies that use counterfactual techniques may be better able to address the court outcomes of similarly-situated youth, this type of methodology is rare in juvenile justice research (Higgins et al., 2012).

The four counterfactual approaches used in this study are nearest neighbor matching, regression adjustment, inverse-probability weighting, and inverse-probability-weighted
regression adjustment. In addition, logistic regression is included in the analyses to serve as a baseline against which to compare the results from the four counterfactual methods. Both the counterfactual techniques and logistic regression are implemented using Stata® 14. Each of these statistical techniques is discussed in more detail below.

**Relative Rate Index (RRI)**

The first step in assessing potential DMC is to calculate a preliminary measure of whether and at which stages it exists, as well as its extent (Sickmund & Puzzanchera, 2014). Fortunately, the 2002 amendment to the Juvenile Justice and Delinquency Prevention Act introduced the Relative Rate Index (RRI) as a measure for assessing DMC at different decision points (Benekos, Merlo, & Puzzanchera, 2011; Leiber et al., 2011; Sickmund & Puzzanchera, 2014). The RRI provides a single statistic (i.e., a ratio) that measures the relative rate of activity at different stages of the juvenile court (e.g., dismissal, adjudication, and waiver) for Non-White youth relative to the rate for White youth (OJJDP, 2009c). In other words, the RRI is the rate of minority youth who experience a given outcome divided by the rate of White youth who experience the same outcome.

The RRI is calculated as follows: First, the proportion of youth experiencing a certain court outcome is calculated for both White and Non-White youth by dividing the number of youth who experience said outcome by the total number of youth who could have possibly experienced the outcome. For example, to calculate the proportion of pre-adjudication detention for Non-White youth, one would divide the number of detained Non-White youth by the total number of Non-White youth referred to the juvenile court. Second, after calculating this proportion for both White and Non-White youth, the RRI is calculated by dividing the proportion of Non-White youth who experienced the outcome by the proportion of White youth who
experienced the outcome. An RRI value of 1.00 indicates equal rates of a given outcome between White and Non-White youth. OJJDP (2009c) suggests that an RRI value greater than 1.20—or less than 0.95 for the case dismissal outcome—indicates significant disproportionality that disadvantages Non-White youth. In this study, RRIs are calculated for each of the five juvenile court outcomes and are used as a preliminary measure of racial disproportionality (see Chapter 4).

The RRI is intended only to be a diagnostic tool to determine whether racial disproportionality exists and its relative extent at various stages of the juvenile court process (Benekos, Merlo, & Puzzanchera, 2011). As such, it cannot address the potential causes of this disproportionality, specifically whether it resulted from differential offending or differential treatment of Non-White youth in the system (Davis & Sorensen, 2012; Leiber et al. 2011).

Once the RRIs are calculated for each decision-point, the next step is to examine the effect of race on decision-making after matching youth on—or controlling for—legal and extralegal variables. In this study, this task is accomplished by using four counterfactual approaches, as well as logistic regression. The balance of this chapter provides an overview of these techniques.

Logistic Regression

Although most studies in the field of juvenile justice that examine dichotomous outcomes use logistic regression (e.g., Bishop et al., 2010; Cauffman et al., 2007; Guevara et al., 2006; Johnson & Secret, 1990; Leiber & Fox, 2005; Leiber & Mack, 2003; Peck et al., 2014), there are multiple attributes of counterfactual techniques that may make them better suited to inquiries of this nature. As such, logistic regression is used in this study as a point of comparison for the four counterfactual approaches.
Logistic regression is a maximum-likelihood method that predicts the probability of an outcome given a set of continuous and/or categorical independent variables. Maximum-likelihood methods generate regression coefficients for each variable that maximize the probability of obtaining the observed outcome. Like other forms of regression, logistic regression allows researchers to fit a model to the data in order to predict an outcome. Unlike other forms of regression, however, logistic regression predicts the odds of an outcome occurring—conditional on a set of covariates. The formula for logistic regression is

$$\ln \frac{P}{1-P} = a + b_1X_1 + b_2X_2 + \cdots + b_kX_k$$

where $P$ is the probability of experiencing a given outcome (e.g., case dismissal, waiver to criminal court). During the implementation of logistic regression, a regression coefficient is calculated for each independent variable included in the model, as well as an indicator ($p$) of each coefficient’s statistical significance. As the value of a statistically significant predictor changes, so too do the odds of experiencing a given outcome.

After estimating a logistic regression model, several statistics can inform the analyst of the strength of the covariates and the model as a whole. First, the log likelihood chi-square (\(-2LL\)) statistic provides a measure of the overall fit of the model on the data. A significant \(-2LL\) indicates a minimal probability that the results of the model happened by chance. Second, the area under the receiver operating characteristic (ROC) curve provides a measure of the predictive power of a model. More precisely, it is a measure of how well a model correctly predicts positive and negative outcomes. An area under the ROC curve of 0.5 means that a model has no predictive power, while a model with an area of 1 has perfect predictive power. In other words, the closer the area under the ROC curve is to 1, the more predictive power of the model. Third,
as mentioned above, \( p < .05 \) for a predictor variable indicates that the variable is a statistically significant predictor of the outcome. Finally, odds ratios (OR) for each predictor can be easily calculated by applying exponentiation: \( \text{OR} = e^\beta \). Odds ratios indicate the change in the odds of the outcome associated with a one-unit change in the predictor. For example, if the logistic regression of adjudication on youths’ race (0=White, 1=Non-White) produced an \( \text{OR} = 1.25 \), this would indicate that the odds of being adjudicated delinquent for Non-White youth are 25% higher compared to White youth or, stated differently, that Non-White youth are 1.25 times more likely to be adjudicated delinquent relative to White youth. Each of these statistics will be presented and discussed in Chapter 4.

Despite its widespread use in juvenile justice research (Bishop et al., 2010; Cauffman et al., 2007; Guevara et al., 2006; Higgins et al., 2012; Leiber & Fox, 2005; Leiber & Mack, 2003; Owen & Takahashi, 2014; Peck et al., 2014; Rodriguez et al., 2009), there are certain aspects of logistic regression that may make it a less effective approach for estimating treatment effects relative to certain counterfactual techniques. These regression limitations are discussed in the following sections. This dissertation posits that counterfactual techniques’ ability to address these limitations make them a more appropriate approach to examining DMC in the juvenile justice system.

**Counterfactual Techniques**

In the context of treatment effects, causality refers to the “net gain or loss observed in the outcome of the treatment group that can be attributed to malleable variables in the intervention” (Guo & Fraser, 2015, p. 22). When estimating causal effects, researchers are essentially attempting to compare the difference between an individual’s (or case’s) potential outcomes: the
outcome if individual \( i \) receives the treatment, denoted as \( Y(1) \), and the outcome if individual \( i \) receives the control, \( Y(0) \) (Stuart, 2010). The difference between these two outcomes,

\[
Y_i(1) - Y_i(0),
\]

is the individual-level treatment effect. The average of all of the treatment effects among the matched pairs in a sample is the average treatment effect (ATE; Morgan & Harding, 2006; Qi, Racine, & Wooldridge, 2008; Rosenbaum & Rubin, 1983):

\[
\tau_{ate} = E [Y_i(1) - Y_i(0)].
\]

It is impossible, however, to calculate the individual-level treatment effect. In non-experimental designs such as the current study, researchers can observe only one of the potential outcomes; it is impossible to observe both \( Y(0) \) and \( Y(1) \). Although only one of the potential outcomes can be observed in experimental studies as well, due to the random assignment of subjects in experimental studies, researchers can assume balance among relevant covariates between treatment and control subjects. This is not the case in non-experimental designs. The outcome that is not observed is called the counterfactual outcome (Guo & Fraser, 2015; Todd, 2010). As such, counterfactual statistical approaches can be used to address this “missing data problem” (Guo & Fraser, 2015; Rosenbaum & Rubin, 1983; Rubin, 1976; StataCorp, 2013) by creating a set of treatment and control group subjects that are matched on a number of covariates so that they are as similarly-situated as possible, with the exception of treatment status (Rubin, 1973; Nichols, 2007; Rosenbaum & Rubin, 1983; Stuart, 2010). The outcome of the matched control case serves as the counterfactual for the treatment case, and vice-versa. The specific method of determining a “good” or “close” match among the covariate matrices of treated and control cases varies among the different counterfactual techniques (see below; Morgan & Harding, 2006; Rosenbaum & Rubin, 1983).
Each of the counterfactual methods used in this study can be considered matching approaches (either implicitly or explicitly) in that they all “aim to equate or balance the distribution of covariates in the treated and control groups” (Stuart, 2010, p. 2). In addition, each counterfactual approach relies on three primary assumptions (Abadie & Imbens, 2006; Guo & Fraser, 2015; Morgan & Harding, 2006; Nichols, 2007; Rosenbaum & Rubin, 1983, 1985; Rubin, 1980; StataCorp, 2013; Stuart, 2010). First is the strongly ignorable treatment assignment assumption—sometimes called the conditionally independent assumption (StataCorp, 2013)—which holds that treatment assignment must be independent of potential outcomes after any independent variables are considered (i.e., controlled) (Rosenbaum & Rubin, 1983). In other words, “after conditioning on [all relevant] covariates, when no unobservable variable affects both treatment assignment and the potential outcomes, the potential outcomes are conditionally independent of the treatment” (StataCorp, 2013, p. 50). When youths’ race is used as the treatment variable—as is the case in this study—this assumption is met \textit{a priori}. The second assumption is the stable unit treatment value assumption (SUTVA), which requires that one case’s outcome is not affected by the treatment status of any other cases in the sample. This could arise in studies where, for example, there is limited space in a treatment program that causes individual \(a\) to be placed in the control group because individual \(b\) took the last available slot in the treatment group (Rosenbaum & Rubin, 1983). Finally, there must be sufficient overlap—or common support—among the matching covariates between treatment and control cases. This simply means that the data must allow for adequate matches based on the covariates between treatment and control subjects. Data in which there is little overlap in the matching variables may produce biased estimates of the treatment effect due to the poor quality of matched pairs or the lack of an available match for a given case, which can lead to the analyses relying on
extrapolation. Researchers must ensure that their data meet these necessary assumptions before they can proceed to the next stage in the analytic process, which is applying the various techniques to their data. If it is determined that the data does not meet all of the assumptions (e.g., little or no covariate overlap between treated and control subjects), the researcher may need to consider alternate methodological techniques to analyze the data.

There are four steps in any counterfactual/matching method: (1) determine the distance measure used to define a good match; (2) employ a matching method; (3) assess the quality of the matched sample; and (4) estimate the treatment effect (Stuart, 2010). Among these steps, Stuart (2010) and Nichols (2007) opine that gauging the quality of the matched pairs is arguably the most important step when using counterfactual approaches. If a matching estimator produces poor matches between treatment and control cases, the resulting estimate of the treatment effect will be biased. As such, the post-estimation diagnostics for each estimator will be presented in Chapter 4.

As mentioned previously, counterfactual methods tend to have a few advantages over multivariate regression and other maximum-likelihood techniques. First, matching methods include post-match diagnostics that are able to identify the quality of the matches and variables in which there is not sufficient overlap between the treated and control groups—which, can lead to biased estimates of the treatment effect (Stuart, 2010). If the diagnostics indicate poor overlap, the researcher can then attempt to address this by, for example, adjusting the parameters of the matching procedure. Regression model diagnostics do not address this potential lack of overlap.

Second, Morgan and Harding (2006) argue that using regression often makes it “easy for an analyst to overlook fundamental mismatches between treatment and control cases” (p. 46), such as those instances in which there is insufficient overlap or balance between the groups. For
example, in the data used here, the average number of prior charges is significantly higher for Non-White youth (3.08, s.d. = 4.89) compared to White youth (2.24, s.d. = 4.10), indicating some degree of a lack of overlap between the two groups ($t = -20.46, p < .05$). Furthermore, Figure 3.1 provides a more detailed illustration of the distribution of priors between White and Non-White youth in the sample. As can be seen in the overlaid histograms, there are some disparities among the two distributions. Similarly, the Kolmogorov-Smirnov (K-S) test for equality of distributions allows researchers to test whether the distribution of a variable (e.g., priors) is the same across two values of another variable (e.g., race: White/Non-White; Morgan & Harding, 2006). The K-S test conducted on the distributions of priors for White and Non-White youth indicated that there are significant differences in the distributions ($D = .081, p = .000$). This lack of overlap means that logistic regression may rely on some level of extrapolation when calculating the regression coefficient, potentially leading to a biased treatment effect estimate (Black, 2015). A more detailed discussion of covariate overlap is presented in Chapter 4.
Figure 3.1. Distribution of Priors by Youths’ Race

Third, matching estimators generally are easier to implement, interpret, and present to an audience compared to regression models that use multiple control variables (Guo & Fraser, 2015; Rosenbaum & Rubin, 1983). “While the use of simple OLS models [over matching] may have been justified when computing was both expensive and relatively primitive” (Black, 2015, p. 9), most matching estimators can now be conducted on the average personal computer using readily-available statistical software.

Finally, as mentioned above, matching methods do not require the researcher to define the functional form of the treatment model; instead, these methods nonparametrically balance the covariates during the matching process (Abadie & Imbens, 2006; Morgan & Harding, 2006; Todd, 2010). “Thus, matching may significantly outperform regression when the true functional form of a regression is nonlinear but a simple linear specification is used” (Morgan & Harding,
2006, p. 51). It should be noted, however, that counterfactual methods—like regression—still rely on researchers’ ability to account for all relevant control variables.

Using simulated data, Morgan and Harding (2006) showed that different counterfactual estimators—and even the same counterfactual estimator calculated using different statistical software—can produce different treatment effect estimates. Indeed, although a number of counterfactual techniques have been established, there is little guidance in the literature to assist researchers in choosing among them or which works best (Stuart, 2010). Therefore, in addition to addressing the substantive research question regarding the relationship between race and juvenile court outcomes, this dissertation also attempts to address this gap in the literature by examining the relative strengths and weaknesses of four counterfactual approaches. In addition, the use of multiple statistical techniques (i.e., methodological triangulation) can result in a higher degree of confidence in conclusions about DMC (Sullivan, McGloin, Ray, & Caudy, 2009). In other words, if all five statistical techniques used in this study provide similar results regarding DMC at the various decision points, we can be more confident that the results are accurate relative to the results obtained from any single method. Conversely, if the five techniques produce contradictory results, the researcher should first attempt to determine the cause of the inconsistent findings. In this situation, no matter the results, the researcher should focus on the findings for the method(s) in which the research methodology and data best meet the assumptions and underlying logic of the analytic method. The following sections provide an overview of the counterfactual approaches used in this study. Table 3.4 at the end of this section summarizes the counterfactual methods.
Nearest Neighbor Matching

Basic (i.e., “simple” or 1:1) nearest neighbor matching (NNM) randomly orders the treatment cases and matches each treatment case to the single control case with the smallest “distance” among the included covariates (Abadie, Drukker, Herr, & Imbens, 2004; Abadie & Imbens, 2006; Morgan & Harding, 2006; Nichols, 2007; Rubin, 1973; StataCorp, 2013; Stuart, 2010). To determine the distance between control and treatment cases, this study uses the Mahalanobis metric, which calculates the distance between potential matches using the inverse of the variance-covariance matrix of the covariates (Guo & Fraser, 2015):

\[ d_{Mahalanobis} = (x_t - x_c)^T T^{-1} (x_t - x_c) \]

where \(x_t\) and \(x_c\) are the matrix of covariates for treated and control groups, respectively, and \(T\) is the sample variance-covariance matrix. According to Rubin (1979), the Mahalanobis distance measure is best suited for situations in which there are relatively few covariates (eight or fewer, such as the present case).

In most applications, NNM calculates an average treatment effect for a sample of treated and control cases. For example, Abadie and colleagues (2004) used NNM to examine the effect of a job readiness program on future earnings. In this study, however, the “treatment” examined is youths’ race. In this sense, NNM matches White (control) and Non-White (treatment) youth based on a series of matching covariates in order to impute the counterfactual for each treatment case and then estimates the average treatment effect by averaging within-match differences in the outcome variables between the treatment and control cases (Abadie & Imbens, 2006; Morgan & Harding, 2006).

As opposed to 1:1 NNM, multiple nearest neighbor matches can be used for each treatment case as well. In this instance, matched control cases are given the weight of \(1/k\), where
$k$ equals the number of control cases matched to a treatment case (Morgan & Harding, 2006; Stuart, 2010). This results in a lower expected variance of the treatment effect, but can also potentially increase bias due to the higher probability of making poor matches (Caliendo & Kopeinig, 2005). However, Rosenbaum and Rubin (1985) argue for the use of multiple nearest neighbor matches so that each treatment case is matched with a control case (termed “inexact matching”) and thus used in the analysis, as opposed to “incomplete matching” in which the cases with no matches are dropped from the analysis. The use of inexact matching with multiple nearest neighbors produces a relatively small residual bias compared to incomplete matching. This study follows the recommendation of Abadie and colleagues (2004, p. 298) of using four matches for each case “because it offers the benefit of not relying on too little information without incorporating observations that are not sufficiently similar.”

A major advantage of NNM is that it is nonparametric in that no assumptions are made about the functional form of either the treatment or outcome models. Conversely, average treatment effects derived from logistic regression are highly unstable if the model specification is inaccurate (Kreif, Grieve, Radice, & Sekhon, 2013). The nonparametric nature of NNM does come at a cost, however, as it requires a large sample size in order to approach the true value of the treatment effect estimate relative to estimators that specify a functional form (Drukker, 2014). The analytic sample for each of the five juvenile court outcomes examined in this study exceed this requirement. Furthermore, this study uses matching with replacement, which allows each observation to be used as a match multiple times and lowers the potential bias associated with the matching process by increasing the number of high-quality matches (Abadie & Imbens, 2002, 2006; Abadie et al., 2004; Stuart, 2010; Todd, 2010). There is a caveat, however. If an observation is used as a match more than once, the expected variance of the estimated treatment
effect is reduced, but the bias in the estimated treatment effect can potentially increase due to the possibility of multiple poor matches. Fortunately, this bias can be minimized by including a caliper restriction in the matching process (see below). Furthermore, matching with replacement is preferred over matching without replacement because in the latter the estimated treatment effect is dependent on the initial ordering of the treatment cases (Caliendo & Kopeinig, 2005; Rubin, 1973; Todd, 2010), potentially resulting in different estimates each time the matching process is performed if the data is ordered differently.

For the county, sex, offense type, and offense seriousness variables in this study, exact matching is used. Exact matching requires that potential matches have identical values for each variable included in the exact match list (Morgan & Harding, 2006; Rosenbaum & Rubin, 1983, 1985). With exact matching, treatment and control cases are first matched using the exact match variables, then the “closest” match based on the continuous variables is chosen. Using exact matching for these variables ensures that the matched pairs in the final sample are identical—at least on these variables—and thus suitable for comparison. One potential downside to exact matching, however, is that cases with no exact match are left out of the analysis, potentially limiting the generalizability of the results if a large number of cases are omitted (Stuart, 2010). In addition, because this study includes more than one continuous variable in the matching process (age, number of priors, and number of current charges), the treatment effect estimate may be somewhat biased due to the small discrepancies in the covariate matrix between matched treatment and control cases (Guo & Fraser, 2015). As such, this study includes a bias-corrected estimator—which uses regression to adjust for the difference in the matches for the continuous covariates—in the NNM analysis to minimize any potential bias.
To avoid “bad” matches (Todd, 2010), a caliper restriction is imposed in the NNM analysis. Including a caliper value in the matching process implements a maximum distance allowed between matched treatment and control cases, thus ensuring that matched pairs are sufficiently “close” to each other in terms of the covariates included in the models. Based on the suggestion of Morgan and Winship (2015), a caliper = 0.25 standard deviations of the Mahalanobis metric is used in this study. One potential drawback of including a caliper requirement, however, is that cases with no matches within the caliper will be dropped from the analysis (Caliendo & Kopeinig, 2005; Stuart, 2010; Todd, 2010). This will require the estimated treatment effect to be interpreted conditionally on the region of common support (i.e., the matched cases actually included in the analysis; Todd, 2010). According to Morgan and Harding (2006), however,

Even if imposing the common support condition results in throwing away some of the treatment cases, this can be considered an important substantive finding, especially for interpreting the treatment effect estimate. In this case, the resulting estimate is the treatment effect for a subset of the [cases] only and, in particular, a treatment effect estimate that is informative only about those in the treatment and control groups who are equivalent with respect to observed treatment selection variables (pp. 47-48).

In other words, although all cases may not be included in the estimation of the treatment effect, said effect may actually be more accurate because few poor matches are included in the analysis. As mentioned above, however, the use of matching with replacement should prevent the loss of a large number of cases being excluded from the analysis.

Unlike NNM, in which the exclusion of unmatched cases from the analysis can hinder the estimate of an accurate treatment effect, the following “weighting” counterfactual methods address this potential limitation by including all cases in the analysis. Treatment and control cases are weighted instead of matched, thus reducing the likelihood that any cases will be
excluded from the analysis. Conversely, the following counterfactual methods are quite similar to NNM in that each is used to calculate predicted counterfactual outcomes and use the differences in those outcomes to estimate average treatment effects. The primary difference between NNM and the following methods is the manner in which the counterfactual outcomes are calculated (Morgan & Harding, 2006; StataCorp, 2013).

Regression Adjustment

Regression adjustment (RA) uses a regression model—in this case, logistic—to predict the counterfactual outcomes adjusted for the covariates included in the treatment effect estimation process (StataCorp, 2013). This is accomplished using a two-stage process. First, separate regression models of the outcome—conditioned on the covariates—are fit to treatment and control cases. Next, the averages of the predicted outcomes for each case and treatment level are calculated. The average difference of these predicted outcomes is the average treatment effect. According to Kreif and colleagues (2013, p. 180), regression adjustment “can decrease the sensitivity of the estimated ATEs to the chosen specification of the [outcome] model and can reduce finite sample bias and increase efficiency compared to matching alone.” In addition, an advantage of RA—as implemented in Stata® 14—is that both of these steps are implemented at the same time. This eliminates the need to adjust the standard errors in the second step if there were any uncertainty regarding the regression fit from the first step (StataCorp, 2013).

Inverse-Probability Weighting

Inverse probability weighting (IPW) uses the inverse of the probability of receiving the treatment to correct for the missing data problem inherent in observational data: that for each case, we can observe only one of the potential outcomes (StataCorp, 2013). Like regression adjustment, IPW uses a two-stage process to calculate the average treatment effect (Freedman &
Berk, 2008). First, a model of treatment status is fitted on the covariates and then the inverse of the probability of receiving the treatment is calculated. The formula for the inverse-probability weights is

\[ w_i = \frac{Z_i}{e_i} + \frac{(1 - Z_i)}{1 - e_i} \]

where \( Z_i \) is an indicator representing whether subject \( i \) received the treatment and \( e_i \) is the propensity score for subject \( i \) (Austin, 2011). Second, the inverse-probability weights calculated in the first step are used to compute weighted averages of the outcome (e.g., detention, adjudication) for each case and treatment level (i.e., White/Non-White). The difference in the weighted averages is the average treatment effect for the sample.

As long as there is sufficient overlap among the covariates included in the analysis and the treatment model is correctly specified, the inverse-probability weights will not be too large. Limiting the size of the inverse-probability weights is important because as the weights increase, so too does the variance (Freedman & Berk, 2008; Kreif et al., 2013; Stuart, 2010). In addition, like RA, both of these steps are implemented at the same time, thus precluding the need to adjust the standard errors in the second step (StataCorp, 2013). Another advantage of IPW is that, like nearest neighbor matching, IPW is nonparametric in that it does not make any assumptions about the functional form of the outcome model (Drukker, 2014).

**Inverse-Probability-Weighted Regression Adjustment**

As the name implies, inverse-probability-weighted regression adjustment (IPWRA) is a combination of IPW and RA in that separate models are used to predict treatment status and outcomes, respectively (StataCorp, 2013). Unlike IPW and RA, however, IPWRA uses a three-stage process to calculate treatment effects. First, a treatment status model is fitted on the
covariates and inverse-probability of treatment weights are calculated using the formula
described above. Second, the inverse-probability weights are used to compute a regression model
for the outcome for both control and treatment cases, which results in predicted outcomes for
each case. Finally, the difference of the means of the predicted outcomes is the average treatment
effect.

An advantage of IPWRA is that it is a doubly robust (DR) estimator (Bang & Robins,
2005; Freedman & Berk, 2008; StataCorp, 2013). This means that the treatment effect estimate
“remains consistent [as long as] either a model for the treatment assignment or a model for
counterfactual data is correctly specified” (Bang & Robins, 2005, p. 962). In other words, since
we cannot be certain that the models used to predict both the treatment status and counterfactual
outcomes are correct, DR estimators give researchers two chances to produce a consistent
treatment effect estimate. As long as one of the models is correctly specified, the resulting
treatment effect estimate will be accurate, even if the other model is misspecified (StataCorp,
2013). Furthermore, in instances where both models are correctly specified, the use of the
inverse probability weights causes the accuracy of the estimated ATE to be unaffected
(Freedman & Berk, 2008). This property is not shared by maximum-likelihood estimators such
as logistic regression. If both models are misspecified, however, some studies have shown that
the resulting treatment effect estimate may be less efficient than using regression alone
(Freedman & Berk, 2008; Kreif et al., 2013). Table 3.4 presents a brief summary of the four
counterfactual methods.
Table 3.4. Summary of Counterfactual Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor</td>
<td>Matches txt and control case(s) with the smallest distance based on covariates; imputes counterfactual for each txt case and then estimates ATE; nonparametric estimator; conditional on region of common support</td>
</tr>
<tr>
<td>Matching</td>
<td></td>
</tr>
<tr>
<td>Regression Adjustment</td>
<td>First fits separate regression models of outcome for each treatment level, then computes averages of POs for each subject and treatment level; contrast of these averages is the ATE</td>
</tr>
<tr>
<td>Inverse-Probability</td>
<td>A model of txt status is fitted on covariates and IP weights are calculated; next, these weights are used to compute averages of the outcome for each case and txt level; contrast of averages is the ATE</td>
</tr>
<tr>
<td>Weighting</td>
<td></td>
</tr>
<tr>
<td>IPW Regression</td>
<td>Txt model fitted on covariates and inverse-probability weights are calculated; IP weights used to compute outcome models for both control and treatment cases; difference in POs is the ATE; “doubly robust”</td>
</tr>
<tr>
<td>Adjustment</td>
<td></td>
</tr>
</tbody>
</table>

**SUMMARY**

This chapter presented a discussion of the study’s research design and methodology, including an overview of the research questions, data, variables, and analytic plan. The purpose of the use of five different analytic techniques in this study is twofold. First, the various techniques are used to examine the relationship between youths’ race and juvenile court outcomes. Based on prior research (see Chapter 2), it is expected that Non-White youth will be treated harsher than White youth, independent of other factors. Second, although counterfactual approaches are plentiful in number, there is little guidance in the extant literature on how to choose among them or which works best. Four counterfactual methods are used here in hopes of providing a detailed summary of their relative strengths and weaknesses as pertains to examining the relationship between race and juvenile court outcomes. The following chapter discusses the results of the analyses presented above.
CHAPTER 4
RESULTS

This chapter presents the results from the analyses used to address the three research questions discussed in the previous chapter. First, the Relative Rate Index for each of the five court outcomes is presented to provide a baseline measure of disproportionality. Next, results from the multivariate analyses (logistic regression and the four counterfactual estimation techniques) are presented for each court outcome (Research Question 1). Next, Research Question 2 is addressed by determining whether there are any substantive differences in the results obtained from the various analytic methods. Finally, the chapter concludes with a discussion of the relative strengths and weaknesses of each analytic technique as they pertain to the current study, including loss of cases, covariate balance, post-matching diagnostics, and overlap (Research Question 3). Chapter 5 provides a detailed discussion of the results and their relevance for understanding DMC, as well as limitations of the study and suggestions for future research.

RESEARCH QUESTION 1

The first research question asks: After matching youth on legally-relevant and extralegal variables, what is the relationship between race and decision-making across five juvenile court outcomes? Before addressing this question, it is important to discuss the existence and magnitude of any baseline (i.e., unconditional) disproportionality between White and Non-White youth in the data. To determine baseline disproportionality, the Relative Rate Index (RRI) is presented for each of the five court outcomes. Next, logistic regression models are estimated for each court
outcome to serve as a multivariate baseline and point of comparison. Finally, the results from the four counterfactual techniques are presented. The results from the multivariate models (logistic regression and counterfactual techniques) are presented separately for each court outcome and serve as the primary method in which Research Question 1 is answered.

**Relative Rate Index (RRI)**

The RRI provides a single statistic that measures the relative rate of experiencing a given outcome at different stages of the juvenile court for Non-White youth relative to the rate for White youth. It is important to note that RRIs do not consider any control variables, so their usefulness is limited to providing an unconditional view of disproportionality in the raw data.\(^\text{16}\) An RRI value of 1.00 indicates equal prevalence of a given outcome between White and Non-White youth. An RRI value greater than 1.20—or less than 0.95 for the case dismissal outcome—indicates significant disproportionality that disadvantages Non-White youth (OJJDP, 2009c).

Table 4.1 presents the breakdown of each court outcome by youths’ race found in the raw data. This data was used to calculate the RRIs. As shown in the table, the percentage of White and Non-White youth in the analytic samples was very similar across the outcomes. The noticeable differences were seen when looking at the percentages of White and Non-White youth who experienced each of the outcomes (e.g., youth who were detained or who were adjudicated delinquent). In the raw data, Non-White youth were more likely to have their case dismissed, be detained prior to an adjudication hearing, be placed in secure confinement after adjudication, and

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\(^{16}\) This is similar to the use of chi-square analysis for two nominal-level variables (e.g., race and a dichotomous outcome).
be waived to criminal court. Conversely, White youth were more likely to be adjudicated delinquent.

Table 4.1. Breakdown of Court Outcomes by Race

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Analytic Sample N</th>
<th>% W Youth in Sample</th>
<th>% W Youth w/ Outcome=1</th>
<th>% NW Youth in Sample</th>
<th>% NW Youth w/ Outcome=1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Dismissal</td>
<td>48,369</td>
<td>36.17%</td>
<td>19.45%</td>
<td>63.83%</td>
<td>22.69%</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
<td>50,054</td>
<td>36.76%</td>
<td>14.28%</td>
<td>63.24%</td>
<td>22.24%</td>
</tr>
<tr>
<td>Adjudication</td>
<td>31,232</td>
<td>37.93%</td>
<td>70.65%</td>
<td>62.07%</td>
<td>66.79%</td>
</tr>
<tr>
<td>Secure Confinement</td>
<td>28,421</td>
<td>36.24%</td>
<td>3.00%</td>
<td>63.76%</td>
<td>4.53%</td>
</tr>
<tr>
<td>Waiver</td>
<td>9,181</td>
<td>36.17%</td>
<td>0.23%</td>
<td>63.83%</td>
<td>0.97%</td>
</tr>
</tbody>
</table>

Table 4.2 presents the probability of experiencing a given outcome for both White and Non-White youth, as well as the RRI for said outcome based on the data available here. In addition, the raw differences in the probabilities are presented. These differences can be loosely compared to the ATEs for each outcome (see below). The probability of having their case dismissed was 0.194 for White youth and 0.227 for Non-White youth, with a corresponding RRI value of 1.167. This indicated that there was no significant baseline disproportionality in the probability of case dismissal between White and Non-White youth—although the RRI value does approach significance. The probability of being detained prior to an adjudication hearing was significantly lower for White youth (0.143) than for Non-White youth (0.222; RRI=1.557).

Table 4.2. Relative Rate Indices

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Probability White</th>
<th>Probability Non-White</th>
<th>Difference</th>
<th>RRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Dismissal</td>
<td>0.194</td>
<td>0.227</td>
<td>0.033</td>
<td>1.167</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
<td>0.143</td>
<td>0.222</td>
<td>0.079</td>
<td>1.557*</td>
</tr>
<tr>
<td>Adjudication</td>
<td>0.901</td>
<td>0.916</td>
<td>0.015</td>
<td>1.017</td>
</tr>
<tr>
<td>Secure Confinement</td>
<td>0.047</td>
<td>0.081</td>
<td>0.034</td>
<td>1.713*</td>
</tr>
<tr>
<td>Waiver</td>
<td>0.019</td>
<td>0.042</td>
<td>0.023</td>
<td>2.265*</td>
</tr>
</tbody>
</table>

Note: OJJDP (2009c) suggests that an RRI value greater than 1.20—or less than 0.95 for the case dismissal outcome—indicates significant disproportionality that disadvantages Non-White youth.
The probabilities of being adjudicated delinquent for White (0.901) and Non-White (0.916) youth were very similar, indicating little to no unconditional disproportionality at that stage of the court process (RRI=1.017). The final two court outcomes included in this study were the two outcomes where initial disproportionality was most prevalent. Non-White youth were significantly more likely to be placed in a secure confinement facility post-adjudication relative to their White counterparts (RRI=1.713). Similarly, the probability of waiver to criminal court for Non-White youth (0.042) was over twice as high as that for White youth (0.019; RRI=2.265). Overall, there was evidence of initial disproportionality for three of the five court outcomes examined in this study, in addition to another outcome that approached significance. The following sections present the results for the multivariate analyses for each of the five court outcomes.

**Case Dismissal**

The first decision-point examined in this study was whether a youth had his or her case dismissed at the front end of the court process. Recall from Chapter 3 that this outcome also included youth who were diverted from formal processing.

**Logistic Regression**

Table 4.3 presents the logistic regression results for case dismissal. The significant log likelihood chi-square (-2LL) indicated that the model fit the data quite well ($\chi^2 = 3990.78; df=17; p<.05$). In addition, the area under the receiver operating characteristic (ROC) curve was 0.695,

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17 Probabilities and the RRI for the adjudication outcome were calculated using only non-dismissed cases.
18 Probabilities and the RRI for the secure confinement outcome were calculated using only youth who were adjudicated delinquent.
19 Because no youth charged solely with a misdemeanor or status offense was waived to criminal court, probabilities and the RRI for the waiver outcome were calculated using only cases involving at least one felony charge.
indicating the model had a moderate level of predictive power. Of primary interest, Non-White youth were 6% more likely to have their case dismissed relative to White youth (Odds Ratio [OR]=1.06). This result was noteworthy because it indicated White youth had worse outcomes at this decision point relative to Non-White youth. While this is not unprecedented, it is rare in the DMC literature (see Chapter 2). In addition, while this difference was statistically significant, it was not substantively large. This result may be an artifact of the variables included in the model (e.g., a suppression effect).

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<thead>
<tr>
<th></th>
<th>B</th>
<th>Odds Ratio</th>
<th>SE</th>
<th>p</th>
<th>95% CI</th>
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<td>-.031 -.019</td>
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<tr>
<td>Offense Category&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>.000</td>
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</tr>
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<tr>
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<td>-.092 .400</td>
</tr>
</tbody>
</table>

Table 4.3. Logistic Regression – Case Dismissal

<sup>a</sup> Reference category is County E
<sup>b</sup> Reference category is violent/sex offenses.
<sup>c</sup> Reference category is felony.
Relative to the reference category\textsuperscript{20} (County E), the odds of case dismissal differed substantially among the counties, evidenced by odds ratios varying from 0.15 to 4.50. Females were 12% more likely to have their case dismissed compared to males (OR=1.12), while age was not a significant predictor of dismissal. Each of the legally relevant variables was significant. A one-unit increase in number of priors and number of current charges decreased the odds of case dismissal by 2% and 47%, respectively. Interestingly, youth charged with a property offense (OR=0.68), drug/alcohol offense (OR=0.67), status offense (OR=0.60, or other offense (OR=0.77) were significantly less likely to have their case dismissed relative to those charged with a violent or sex offense. The fact that over 62% of the violent/sex offenses included in the data were misdemeanors (e.g., school fights) may contribute to this finding. Finally, compared to youth charged with a felony, those charged with a misdemeanor were 23% less likely to have their case dismissed.

Counterfactual Techniques

The average treatment effects (ATE)\textsuperscript{21} for the four counterfactual techniques for case dismissal are presented in Table 4.4. Recall from Chapter 3 that the nearest neighbor matching (NNM) analyses in this study used exact matching for each of the categorical variables.\textsuperscript{22} This means that Non-White youth were first matched with White youth who had identical values for each of the categorical variables. Then, using the Mahalanobis distance metric, the closest match

\textsuperscript{20} County E was chosen as the reference because it is the largest county in terms of the number of cases included in the analysis.

\textsuperscript{21} The average treatment effect for the treated (ATT) for each counterfactual method and court outcome was calculated as well. The results were very similar to the corresponding ATEs and are presented in Appendix A. For a more detailed discussion of ATTs, see Guo & Fraser (2015; Chapter 2); Morgan & Harding (2006); Morgan & Winship (2015; Chapter 2).

\textsuperscript{22} As well as preadjudication detention in the models where it was included as an independent/matching variable (i.e., adjudication, secure confinement, and waiver).
based on the continuous variable matrix was chosen as the final match. In addition, this study required a minimum of four nearest neighbor matches for each treatment case and imposed a 0.25 caliper restriction on potential matched pairs. These restrictions ensured that there was enough information on which to base treatment effect estimates and that there were no poor matches used in the analyses (Abadie et al., 2004). Cases that did not have four matches and/or had no matches within the 0.25 caliper were dropped from the analysis.

For NNM, the ATE reflects the change in the proportion of Non-White youth who have their case dismissed relative to White youth—conditioned on all of the independent variables included in the analysis. While conducting the NNM analysis, 216 cases were identified that did not have four exact matches. As a result, Stata dropped these cases from the analysis; thus, the NNM results are based on the 48,153 cases with at least four matches (see Chapter 3). As seen in Table 4.4, the counterfactual methods also calculate a potential outcome mean (PO Mean) in addition to the ATE. The PO Mean is the average predicted proportion of an outcome for the control group (i.e., White youth) after the matching/adjustment process. For example, the PO Mean for NNM (.205) indicated that, after the counterfactuals were estimated, 20.5% of White youth in the matched sample had their case dismissed. Combined with the statistically significant ATE (.014), the NNM results indicated that, after the matching process, 21.9% of Non-White youth

23 Ancillary analyses were conducted that removed the four nearest neighbor (4NN) match constraint. In this analysis, the number of required nearest neighbor matches was reduced to one (1NN). These results are presented in Appendix B. The 1NN and 4NN analyses produced very similar results regarding the predicted ATE, PO Mean, and statistical significance for all five court outcomes. The most noticeable difference between the 1NN and 4NN analyses was that the former resulted in fewer cases being dropped from the analyses. Among the five court outcomes, the 1NN analyses reduced the number of cases dropped by approximately 21-37%. Although more cases were included in the 1NN analyses, their inclusion had little effect on the substantive results. The largest difference in ATEs between the 1NN and 4NN analyses for any of the court outcomes was .002. The largest difference in predicted PO Means was .002 as well. In addition, the statistical significance and direction of the relationships between race and the court outcomes remained unchanged.
youth had their case dismissed. In other words, Non-White youth were 6.8% more likely to have their case dismissed compared to White youth (ATE/PO Mean*100 = .014/.205*100 = 6.8%).

Table 4.4. Average Treatment Effects – Case Dismissal

<table>
<thead>
<tr>
<th>Method</th>
<th>ATE</th>
<th>Robust SE</th>
<th>p</th>
<th>95% CI</th>
<th>PO Mean (White)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor Matching</td>
<td>.014</td>
<td>.004</td>
<td>.001</td>
<td>.006 .023</td>
<td>.205</td>
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<tr>
<td>Regression Adjustment</td>
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<td>.004</td>
<td>.317</td>
<td>-.004 .012</td>
<td>.215</td>
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<tr>
<td>Inverse Probability Weighting</td>
<td>.004</td>
<td>.004</td>
<td>.337</td>
<td>-.004 .012</td>
<td>.213</td>
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<tr>
<td>IPW Regression Adjustment</td>
<td>.005</td>
<td>.004</td>
<td>.252</td>
<td>-.003 .013</td>
<td>.214</td>
</tr>
</tbody>
</table>

Similar to NNM, the ATE for regression adjustment (RA) estimates the difference in the probability of an outcome for White and Non-White youth. RA calculates an ATE and PO Mean by first fitting separate regression models of an outcome on White and Non-White youth. The averages of the predicted outcomes (i.e., PO Means) are then calculated, and the difference of these averages is the ATE. In this study, the PO Mean for RA (.215) indicated that, after the counterfactuals were estimated, 21.5% of White youth in the sample had their case dismissed. However, the ATE for RA (.004) indicated that there was no statistically significant difference in case dismissal between White and Non-White youth.

Inverse probability weighting (IPW) calculates ATEs and PO Means by first fitting a model of treatment status on the covariates and calculating the inverse of the probability of receiving the treatment. These inverse-probability weights are then used to calculate the weighted averages of an outcome for both White and Non-White youth. The difference in the weighted averages is the ATE. The information provided by the ATE and PO Mean for IPW is identical to that of RA: they represent the difference in the proportion of White/Non-White youth experiencing an outcome and the average proportion of White youth experiencing an outcome after the weighting process, respectively. Here, the IPW results indicated that, on average, 21.3%
of cases involving White youth were dismissed, while 21.7% of cases involving Non-White youth were dismissed. This difference (ATE=.004) was not statistically significant.

The final counterfactual technique used in this study is inverse-probability-weighted regression adjustment (IPWRA). As the name implies this method is a combination of RA and IPW. To calculate the ATE and PO Mean, the inverse-probability weights calculated in IPW are used in the regression models in RA. Recall from the previous chapter that IPWRA is a doubly robust method, meaning that only one of the two models (treatment or outcome) has to be correctly specified to produce an accurate estimate of the ATE. Though calculated differently, the ATE and PO Mean for IPWRA provide the same information as the previous two analytic techniques. As shown in Table 4.4, the IPWRA results indicated no significant difference in the probability of case dismissal between matched White and Non-White youth (ATE=.005).

In summary, the results from the five statistical analyses provided mixed results regarding the relationship between race and case dismissal. The logistic regression and NNM results indicated a significant (albeit relatively weak) relationship that disadvantaged White youth. Conversely, results from the RA, IPW, and IPWRA analyses were not statistically significant. The potential explanations and substantive implications of these mixed results are discussed in the next chapter.

**Preadjudication Detention**

The next court outcome examined in this study was preadjudication detention. At this stage, juvenile court personnel must determine whether the circumstances in a petitioned case warrant the detention of the youth prior to an adjudication hearing. As discussed previously, this decision-point is especially important due to the finding in previous studies of a link between preadjudication detention and subsequent court outcomes.
Logistic Regression

The results of the logistic regression analysis of preadjudication detention are presented in Table 4.5. The -2LL chi-square ($\chi^2 = 9696.34; df=17; p<.05$) suggested that the model fit the data well, and the area under the ROC curve (0.807) indicated that the model has a moderately high level of predictive power. Results indicated that Non-White youth were 44% more likely to be detained relative to White youth (OR=1.44), after controlling for all other variables. This finding is consistent with most of the prior research discussed in Chapter 2. The odds of being detained varied greatly depending on the county of origin; odds ratios relative to the reference county ranged from 0.92 to 8.58. Females (OR=0.84) were significantly less likely to be detained compared to males, while a one-year increase in age equated to a 2% decrease in the odds of being detained (OR=0.98).
Table 4.5. Logistic Regression – Preadjudication Detention

<table>
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<tr>
<th></th>
<th>B</th>
<th>Odds Ratio</th>
<th>SE</th>
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<td></td>
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<td>.423</td>
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</tbody>
</table>

^1 Reference category is County E

^2 Reference category is violent/sex offenses.

^3 Reference category is felony.

Each of the legally relevant variables was significant in the hypothesized direction. One-unit increases in number of priors and number of current charges increased the odds of detention by 9% and 13%, respectively. Youth charged with a property offense (OR=0.37), drug/alcohol offense (OR=0.28), status offense (OR=0.19), or other offense (OR=0.60) were significantly less likely to be detained compared to youth charged with a violent or sex offense. Relative to youth charged with a felony, those charged with a misdemeanor were 71% less likely to be detained and those charged with other offense levels were 84% less likely to be detained.
Counterfactual Techniques

The ATEs and PO Means for preadjudication detention are presented in Table 4.6. The results from each of the four counterfactual methods were quite similar. For the NNM analysis, 196 cases were dropped due to fewer than four exact matches. Using the remaining 49,858 cases, NNM estimated a significant ATE (.040; p<.05), indicating that 16.8% of White youth and 20.8% of Non-White youth were detained. In other words, Non-White youth were 23.8% more likely to be detained relative to White youth after matching on the included legal and extralegal covariates.

<table>
<thead>
<tr>
<th>Method</th>
<th>ATE</th>
<th>Robust SE</th>
<th>p</th>
<th>95% CI</th>
<th>PO Mean (White)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor Matching</td>
<td>.040</td>
<td>.004</td>
<td>.000</td>
<td>.032 .047</td>
<td>.168</td>
</tr>
<tr>
<td>Regression Adjustment</td>
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<td>.000</td>
<td>.036 .051</td>
<td>.164</td>
</tr>
<tr>
<td>Inverse Probability Weighting</td>
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<td>.000</td>
<td>.031 .046</td>
<td>.167</td>
</tr>
<tr>
<td>IPW Regression Adjustment</td>
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<td>.004</td>
<td>.000</td>
<td>.036 .050</td>
<td>.164</td>
</tr>
</tbody>
</table>

The ATE (.043) and PO Mean (.164) obtained from the RA analysis indicated that, after the adjustment process, 16.4% of White youth were detained, while 20.7% of Non-White youth were detained. This difference of 26.2% was statistically significant. Compared to RA, IPW produced a slightly higher PO Mean (.167) and a slightly lower ATE (.030), though the latter did maintain its statistical significance. Combining these values, the IPW analysis indicated that Non-White youth were 23.4% more likely to be detained compared to White youth. Finally, results from the IPWRA analysis were identical to those of RA (PO Mean=.164; ATE=.043; p<.05).

In summary, results from all five analytic techniques reached the same general conclusion regarding the relationship between race and preadjudication detention. Taken as a
whole, these analyses suggested that race plays a significant role in the decision to detain youth prior to an adjudication hearing, even after conditioning the relationship on the included covariates.

**Adjudication**

The third court outcome examined in this study was adjudication. At this stage, the juvenile court judge must determine whether the evidence in a case warrants a finding of delinquent—the juvenile court equivalent of a guilty verdict in criminal court. As discussed above, prior research has concluded that whether a youth was detained prior to an adjudication hearing often has an impact on this decision-point. As such, detention is included in the adjudication analysis as an independent/matching variable. The adjudication analysis includes only those cases that were not dismissed at the front end of the court process (N=31,230).

**Logistic Regression**

Table 4.7 presents the logistic regression results for the adjudication outcome. Results indicated that the model fit the data well ($\chi^2 =3660.77; df=18; p<.05$) and that it had a moderately high level of predictive power (area under ROC curve = 0.807). As shown in Table 4.7, Non-White youth were slightly less likely to be adjudicated compared to White youth, although this finding was not statistically significant. Youth in every county were significantly less likely to be adjudicated delinquent relative to youth in the reference county (ORs ranged from 0.05 to 0.55). Females were significantly less likely to be adjudicated compared to males (OR=0.85), while a one-year increase in age decreased the odds of adjudication by 3% (OR=0.97). As hypothesized, youth who were detained prior to an adjudication hearing were over twice as likely to be adjudicated delinquent compared to youth who were not detained.
Number of priors was not a significant predictor of adjudication, but a one-unit increase in the number of current charges increased the odds of adjudication by 57% (OR=1.57). Youth charged with a property offense (OR=1.23), status offense (OR=1.35), or other offense (OR=5.15) were significantly more likely to be adjudicated relative to those charged with a violent or sex offense. Interestingly, youth charged with a misdemeanor were significantly more likely to be adjudicated delinquent compared to those charged with a felony.
Counterfactual Techniques

The results of the counterfactual methods for the adjudication outcome are presented in Table 4.8. The NNM analysis dropped 759 cases that had fewer than four exact matches. Another 73 cases were excluded from the analysis because they did not have matches within the 0.25 caliper restriction. This left a final analytic sample of 30,400 for the NNM analysis. Results indicated that there was not a significant difference in adjudication between White and Non-White youth after the matching process (ATE = -.004; PO Mean = .916). The RA analysis produced similar nonsignificant findings regarding the relationship between race and adjudication (ATE = -.006; PO Mean = .912).

Table 4.8. Average Treatment Effects – Adjudication

<table>
<thead>
<tr>
<th>Method</th>
<th>ATE</th>
<th>Robust SE</th>
<th>p</th>
<th>95% CI</th>
<th>PO Mean (White)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor Matching</td>
<td>-.004</td>
<td>.003</td>
<td>.167</td>
<td>-.011 .002</td>
<td>.916</td>
</tr>
<tr>
<td>Regression Adjustment</td>
<td>-.006</td>
<td>.003</td>
<td>.074</td>
<td>-.012 .001</td>
<td>.912</td>
</tr>
<tr>
<td>Inverse Probability Weighting</td>
<td>-.008</td>
<td>.003</td>
<td>.014</td>
<td>-.015 -.002</td>
<td>.913</td>
</tr>
<tr>
<td>IPW Regression Adjustment</td>
<td>-.007</td>
<td>.003</td>
<td>.043</td>
<td>-.013 -.001</td>
<td>.912</td>
</tr>
</tbody>
</table>

Unlike the previous analyses, IPW and IPWRA produced significant treatment effect estimates. The PO Mean for IPW was .913 and the ATE was -.008, which when combined indicated that Non-White youth were 0.9% less likely to be adjudicated delinquent relative to White youth. Similarly, the PO Mean (.912) and ATE (-.007) for the IPWRA analysis indicated that, after the adjustment process, 91.2% of White youth were adjudicated delinquent compared to 90.5% of Non-White youth, a difference of 0.8%. Although statistically significant, these differences (0.9% and 0.8%) were very small substantively. This finding is discussed in more detail in the following chapter.
Overall, there were mixed findings regarding the relationship between race and adjudication among the four counterfactual approaches. Both NNM and RA concluded that there was no significant relationship. Conversely, the ATEs for both IPW and IPWRA indicated a statistically significant relationship between race and adjudication, although the differences between White and Non-White youth were very small substantively.

**Secure Confinement**

The next stage of the juvenile court process is the disposition stage. Of primary interest in this study was whether a youth was removed from his or her home and placed in a secure correctional facility, relative to less severe dispositions such as probation, restitution, or mediation. The secure confinement analyses used the subsample of youth who were adjudicated delinquent (N=28,421). It is worth noting that placement in a secure facility was a relatively infrequent event. In the raw data, only 6.78% of adjudicated youth were placed in a secure confinement facility, although the percentage of White youth placed in secure confinement (4.73%) was considerably lower than for Non-White youth (8.10%). The possible methodological implications of estimating such relationships with infrequent outcomes are discussed in more detail in Chapter 5.

**Logistic Regression**

The logistic regression results for secure confinement are presented in Table 4.9. The likelihood ratio chi-square test indicated that the model fit the data well ($-2LL \chi^2 =5051.45; df =18; p<.05$). In addition, the area under the ROC curve (.909) indicated that the model had a high level of predictive power. Results of the analysis indicated a significant difference in the odds of secure confinement between White and Non-White youth. Specifically, Non-White youth were 30% more likely to be placed in a secure confinement facility than White youth (OR=1.30).
Adjudicated youth in every county were significantly more likely to be placed in secure confinement relative to reference county (County E), although there was a large amount of variation amongst the counties (OR range: 4.43 – 37.98). Females were significantly less likely to be placed in secure confinement (OR=0.57) compared to males, while a one-year increase in age increased the odds of placement by 9% (OR=1.09).

Table 4.9. Logistic Regression – Secure Confinement

<table>
<thead>
<tr>
<th></th>
<th>Odds Ratio</th>
<th>SE</th>
<th>P</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race (1=Non-White)</td>
<td>.262</td>
<td>1.30</td>
<td>.066</td>
<td>.000</td>
</tr>
<tr>
<td>County¹</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County A</td>
<td>1.678</td>
<td>5.35</td>
<td>.172</td>
<td>.000</td>
</tr>
<tr>
<td>County B</td>
<td>3.126</td>
<td>22.78</td>
<td>.285</td>
<td>.000</td>
</tr>
<tr>
<td>County C</td>
<td>3.140</td>
<td>23.10</td>
<td>.144</td>
<td>.000</td>
</tr>
<tr>
<td>County D</td>
<td>2.856</td>
<td>17.39</td>
<td>.244</td>
<td>.000</td>
</tr>
<tr>
<td>County F</td>
<td>3.637</td>
<td>37.98</td>
<td>.141</td>
<td>.000</td>
</tr>
<tr>
<td>County G</td>
<td>1.488</td>
<td>4.43</td>
<td>.483</td>
<td>.02</td>
</tr>
<tr>
<td>Sex (1=Female)</td>
<td>-.569</td>
<td>0.57</td>
<td>.075</td>
<td>.000</td>
</tr>
<tr>
<td>Age</td>
<td>.086</td>
<td>1.09</td>
<td>.019</td>
<td>.000</td>
</tr>
<tr>
<td>Number of Priors</td>
<td>.107</td>
<td>1.11</td>
<td>.006</td>
<td>.000</td>
</tr>
<tr>
<td>Number of Current Charges</td>
<td>.115</td>
<td>1.12</td>
<td>.010</td>
<td>.000</td>
</tr>
<tr>
<td>Offense Category²</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property</td>
<td>-.119</td>
<td>0.89</td>
<td>.063</td>
<td>.059</td>
</tr>
<tr>
<td>Drug/Alcohol</td>
<td>-.381</td>
<td>0.68</td>
<td>.128</td>
<td>.003</td>
</tr>
<tr>
<td>Status Offense</td>
<td>-.403</td>
<td>0.67</td>
<td>.148</td>
<td>.007</td>
</tr>
<tr>
<td>Other</td>
<td>-.299</td>
<td>0.74</td>
<td>.103</td>
<td>.004</td>
</tr>
<tr>
<td>Offense Level³</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Misdemeanor</td>
<td>-1.572</td>
<td>0.21</td>
<td>.068</td>
<td>.000</td>
</tr>
<tr>
<td>Other</td>
<td>-3.146</td>
<td>0.04</td>
<td>.262</td>
<td>.000</td>
</tr>
<tr>
<td>Detention</td>
<td>1.053</td>
<td>2.87</td>
<td>.059</td>
<td>.000</td>
</tr>
<tr>
<td>Constant</td>
<td>-6.671</td>
<td>3.36</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.359</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-2LL Chi-Square</td>
<td>5051.45*</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹Reference category is County E  
²Reference category is violent/sex offenses.  
³Reference category is felony.

Similar to the adjudication analysis above, youth who were detained prior to adjudication were almost three times more likely to be placed in secure confinement after adjudication.
(OR=2.87). A one-unit increase in number of priors and number of current charges significantly increased the odds of placement in a secure facility by 11% and 12%, respectively. Compared to youth charged with a violent or sex offense, those charged with a drug/alcohol offense (OR=0.68), status offense (OR=0.67), or other offense (OR=0.74) were significantly less likely to be placed in secure confinement. The difference between property offenders and violent/sex offenders was not significant. Finally, youth charged with a misdemeanor (OR=0.21) or other offense (OR=0.04) were significantly less likely to be placed in secure confinement relative to those charged with a felony.

**Counterfactual Techniques**

Results from the counterfactual methods for secure confinement are shown in Table 4.10. Findings were quite similar among the four methods. A total of 785 cases were dropped during the NNM analysis: 724 were excluded due to fewer than four exact matches and 61 were excluded due to no matches within the 0.25 caliper restriction. As seen in Table 4.10, the statistically significant ATE and PO Mean from the NNM analysis indicated that, after the matching process, adjudicated Non-White youth were 21.4% more likely to be placed in secure confinement relative to their White counterparts (ATE=.012; PO Mean=.056).

<table>
<thead>
<tr>
<th>Method</th>
<th>ATE</th>
<th>Robust SE</th>
<th>p</th>
<th>95% CI</th>
<th>PO Mean (White)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor Matching</td>
<td>.012</td>
<td>.003</td>
<td>.000</td>
<td>.006 - .018</td>
<td>.056</td>
</tr>
<tr>
<td>Regression Adjustment</td>
<td>.015</td>
<td>.003</td>
<td>.000</td>
<td>.008 - .021</td>
<td>.056</td>
</tr>
<tr>
<td>Inverse Probability Weighting</td>
<td>.016</td>
<td>.003</td>
<td>.000</td>
<td>.010 - .023</td>
<td>.055</td>
</tr>
<tr>
<td>IPW Regression Adjustment</td>
<td>.015</td>
<td>.003</td>
<td>.000</td>
<td>.009 - .021</td>
<td>.057</td>
</tr>
</tbody>
</table>

The PO Mean (.056) and ATE (.015) for the RA analysis indicated that, after the adjustment process, 5.6% of adjudicated White youth were placed in a secure facility compared
to 6.8% of Non-White youth. This difference, 26.8%, was statistically significant. The results for IPW (ATE=.016; PO Mean=.055; difference=29.1%) and IPWRA (ATE=.015; PO Mean=.057; difference=26.3%) were similar, and both indicated that Non-White youth were significantly more likely to be placed in a secure confinement facility compared to White youth. Overall, each of the counterfactual methods produced statistically significant treatment effect estimates that disadvantaged Non-White youth at this stage of the court process.

**Waiver to Criminal Court**

The final stage of the juvenile court process examined in this study was waiver to criminal court. This stage is of critical importance because youth waived to and subsequently convicted in criminal courts can receive substantially more severe sentences than those available in juvenile court, including the possibility of life in prison without the possibility of parole. Because no youth in the current data charged with a misdemeanor or lower offense was waived to criminal court, the waiver analysis was limited to youth charged with at least one felony offense (N=9,181). In the raw data, waiver to criminal court was an extremely rare event (3.68% of cases involving a felony), but there was a large difference between the percentage of White (1.86%) and Non-White youth (4.22%) who were waived.

**Logistic Regression**

Table 4.11 presents the logistic regression results for the waiver outcome. The model fit the data well (-2LL $\chi^2 = 781.76; df = 14; p < .05$) and, like the previous model, the area under the ROC curve (0.898) indicated a high level of predictive power. As expected, the relationship between race and the court outcomes appeared strongest at this stage of the process. Specifically, Non-White youth (OR=2.76) were almost three times more likely than White youth to be waived to criminal court. Relative to the reference, only youth in County B (OR=15.94) had significantly
different odds of being waived. Females were 96% less likely to be waived compared to males (OR=0.04), while age was not a significant predictor of waiver. Youth who were detained after being taken into custody were 73% more likely to be waived relative to those not detained. A one-unit increase in the number of prior charges significantly increased the odds of being waived by 8% (OR=1.08). Finally, youth charged with a property offense (OR=0.16), drug/alcohol offense (OR=0.10), or other offense (OR=0.27) were significantly less likely to be waived relative to those charged with a violent or sex offense.

**Table 4.11. Logistic Regression – Waiver**

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>Odds Ratio</th>
<th>SE</th>
<th>p</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race (1=Non-White)</td>
<td>1.015</td>
<td>2.76</td>
<td>.211</td>
<td>.000</td>
<td>.601 - 1.429</td>
</tr>
<tr>
<td>County 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County A</td>
<td>.526</td>
<td>1.69</td>
<td>.305</td>
<td>.085</td>
<td>-.073 - 1.124</td>
</tr>
<tr>
<td>County B</td>
<td>2.769</td>
<td>15.94</td>
<td>.393</td>
<td>.000</td>
<td>1.999 - 3.539</td>
</tr>
<tr>
<td>County C</td>
<td>-.194</td>
<td>0.82</td>
<td>.167</td>
<td>.245</td>
<td>-.522 - .133</td>
</tr>
<tr>
<td>County D</td>
<td>.528</td>
<td>1.70</td>
<td>.511</td>
<td>.301</td>
<td>-.473 - 1.530</td>
</tr>
<tr>
<td>County F</td>
<td>-.255</td>
<td>0.77</td>
<td>.229</td>
<td>.265</td>
<td>-.704 - .194</td>
</tr>
<tr>
<td>County G 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (1=Female)</td>
<td>-3.180</td>
<td>0.04</td>
<td>.584</td>
<td>.000</td>
<td>-4.325 - 2.034</td>
</tr>
<tr>
<td>Age</td>
<td>1.016</td>
<td>2.76</td>
<td>.079</td>
<td>.000</td>
<td>0.861 - 1.171</td>
</tr>
<tr>
<td>Number of Priors</td>
<td>.078</td>
<td>1.08</td>
<td>.010</td>
<td>.000</td>
<td>0.059 - 0.097</td>
</tr>
<tr>
<td>Number of Current Charges</td>
<td>-.016</td>
<td>0.98</td>
<td>.026</td>
<td>.545</td>
<td>-.067 - 0.035</td>
</tr>
<tr>
<td>Offense Category 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property</td>
<td>-1.813</td>
<td>0.16</td>
<td>.172</td>
<td>.000</td>
<td>-2.150 - 1.477</td>
</tr>
<tr>
<td>Drug/Alcohol</td>
<td>-2.290</td>
<td>0.10</td>
<td>.401</td>
<td>.000</td>
<td>-3.076 - 1.505</td>
</tr>
<tr>
<td>Status Offense 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>-1.328</td>
<td>0.27</td>
<td>.249</td>
<td>.000</td>
<td>-1.816 - .840</td>
</tr>
<tr>
<td>Detention</td>
<td>.550</td>
<td>1.73</td>
<td>.134</td>
<td>.000</td>
<td>0.288 - 0.811</td>
</tr>
<tr>
<td>Constant</td>
<td>-20.932</td>
<td>1.378</td>
<td>.000</td>
<td></td>
<td>-23.633 - 18.231</td>
</tr>
</tbody>
</table>

Pseudo R² | 0.274 |
-2LL Chi-Square | 781.76* |

1 Reference category is County E.
2 No youths from County G were waived to criminal court.
3 Reference category is violent/sex offenses.
4 No youths charged with a status offense were waived to criminal court.
Counterfactual Techniques

Table 4.12 presents the results of the counterfactual techniques for the waiver outcome. The matching process dropped 399 cases due to fewer than four exact matches and 26 cases due to no matches within the 0.25 caliper restriction. This resulted in a final analytic sample of 8,756 cases for the NNM analysis. Results indicated that, after the matching process, 1.3% of White youth and 3.9% of Non-White youth were waived to criminal court, a statistically significant difference of 200% (ATE=.026; PO Mean=.013). Although the raw difference in the percentage of White and Non-White youth waived to criminal court was relatively small (2.6 percentage points), it was substantively important when considering that only 3.7% of the analytic sample was waived to criminal court. In other words, the NNM results indicated that Non-White youth were three times as likely to be waived compared to similarly-situated White youth.

The ATEs (.027) and PO Means (.014) for RA and IPWRA were identical and statistically significant, indicating that Non-White youth were 192% more likely to be waived than White youth. The ATE (.024) and PO Mean (.016) for the IPW analysis indicated that 1.6% of White youth were waived and 4.0% of Non-White youth were waived. This difference—150%—was statistically significant. Overall, the ATEs and PO Means for all of the methodologies were similar and all were statistically significant. These results suggested that even after weighting/matching, Non-White youth were considerably more likely than White youth to be waived to criminal court.

<table>
<thead>
<tr>
<th>Methodology</th>
<th>ATE</th>
<th>Robust SE</th>
<th>p</th>
<th>95% CI</th>
<th>PO Mean (White)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor Matching</td>
<td>.026</td>
<td>.004</td>
<td>.000</td>
<td>.018 .033</td>
<td>.013</td>
</tr>
<tr>
<td>Regression Adjustment</td>
<td>.027</td>
<td>.004</td>
<td>.000</td>
<td>.019 .034</td>
<td>.014</td>
</tr>
<tr>
<td>Inverse Probability Weighting</td>
<td>.024</td>
<td>.004</td>
<td>.000</td>
<td>.016 .032</td>
<td>.016</td>
</tr>
<tr>
<td>IPW Regression Adjustment</td>
<td>.027</td>
<td>.004</td>
<td>.000</td>
<td>.020 .034</td>
<td>.014</td>
</tr>
</tbody>
</table>
Summary

The focus of Research Question 1 centered on the relationship between race and juvenile court outcomes. The preceding analyses provided evidence that DMC exists—to varying degrees—in the seven county courts examined herein. For the preadjudication detention, secure confinement, and waiver outcomes, there was consensus among the five analytic methods that Non-White youth received harsher outcomes at these stages relative to White youth. Conversely, there was little evidence of DMC at the case dismissal and adjudication stages. For each of those outcomes, three of the analytic methods indicated no statistically significant relationship with race. Furthermore, the remaining two methods for each outcome—regression and NNM for case dismissal, and IPW and IPWRA for adjudication—produced significant estimates that favored Non-White youth.

RESEARCH QUESTION 2

This section discusses the results as they pertain to Research Question 2, which asks: Are there any differences among the results obtained from the four counterfactual analytic techniques relative to logistic regression? Because there is no common metric between logistic regression and the counterfactual approaches, the methods are compared primarily using the direction, significance, and relative strength of the regression coefficient for race (logistic regression) and the ATE estimates (counterfactual approaches). However, because each outcome used in this study is dichotomous, the ATEs and PO Means produced by the counterfactual methods can be interpreted in terms of a change in the percentage or proportion between White and Non-White youth (StataCorp, 2013). As such, the percent differences produced by the ATEs and PO Means can be loosely compared to the odds ratios estimated via logistic regression.
Table 4.13 provides a summary of the statistical results for each outcome and analytic method. Specifically, the table indicates whether there was a significant relationship between race and court outcomes for each of the five analytic methods, along with the appropriate effect estimate (OR or ATE).

<table>
<thead>
<tr>
<th>Table 4.13. Significant Relationship between Race and Court Outcomes?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Case Dismissal</strong></td>
</tr>
<tr>
<td>Regression (OR)</td>
</tr>
<tr>
<td>Yes (1.06)</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
</tr>
<tr>
<td>Yes (1.44)</td>
</tr>
<tr>
<td>Adjudication</td>
</tr>
<tr>
<td>No (0.92)</td>
</tr>
<tr>
<td>Secure Confinement</td>
</tr>
<tr>
<td>Yes (1.30)</td>
</tr>
<tr>
<td>Waiver</td>
</tr>
<tr>
<td>Yes (2.76)</td>
</tr>
</tbody>
</table>

For the case dismissal outcome, both regression and NNM produced relatively small yet statistically significant estimates. The odds ratio for regression indicated that Non-White youth were 6% more likely to have their case dismissed, after controlling for all other variables. Similarly, the NNM analysis indicated that, after the matching process, the number of Non-White youth who had their case dismissed was 6.8% higher than White youth. Though results for the three remaining counterfactual methods were not statistically significant, they were similar to logistic regression and NNM in terms of the direction of the relationship between race and case dismissal.

As shown in Table 4.13, all five analytic techniques produced a statistically significant relationship between race and preadjudication detention. In addition, the direction of said relationship was the same amongst the techniques, indicating that Non-White youth were more
likely to be detained relative to their White counterparts. The primary difference between the regression and counterfactual results was the strength of the relationship. The regression analysis indicated that Non-White youth were 44% more likely to be detained compared to White youth, all else being equal. The predicted differences between White and Non-White youth for each of the counterfactual methods was noticeably smaller. According to the counterfactual results, Non-White youth were 23% to 26% more likely than White youth to be detained, depending on which of the analytic techniques was used.

There was disagreement among the five analytic techniques regarding the relationship between race and adjudication, though all five did produce a negative relationship. The logistic regression, NNM, and RA analyses produced estimates that were not statistically significant. The remaining two methods (IPW and IPWRA) produced significant ATEs, though they were only marginally larger than the ATEs for NNM and RA. Specifically, the IPW and IPWRA estimates indicated that, after the weighting process, Non-White youth were 0.88% and 0.77% less likely to be adjudicated than similarly-situated White youth, respectively.\textsuperscript{24}

The results for the secure confinement outcome were very similar to those of preadjudication detention. Specifically, all five analytic techniques indicated that there was a statistically significant relationship between race and placement in a secure correctional facility that disadvantaged Non-White youth. In addition, the techniques produced relatively similar results regarding the strength of the relationship. For logistic regression, the odds ratio indicated that, after controlling for all other covariates, adjudicated Non-White youth were 30% more

\textsuperscript{24} Although the logistic regression odds ratio for adjudication (0.92) was not statistically significant, it indicated a much larger difference in adjudication between White and Non-White youth (8\%) than did IPW and IPWRA.
likely to be placed in secure confinement than White youth. Values for the ATEs and PO Means for the counterfactual methods reflected slightly smaller differences. The NNM analysis indicated that Non-White youth were 21.4% more likely than White youth to be placed in a secure confinement facility post-adjudication, while the RA analysis indicated Non-White youth were 26.8% more likely. The IPW and IPWRA analyses produced similar results: 29.1% and 26.3% higher, respectively.

The strongest relationship between race and the court outcomes was found in the waiver decision. Each analytic technique indicated that Non-White youth were significantly more likely to be waived to criminal court compared to White youth. The odds ratio for regression indicated that Non-White youth were almost three times more likely to be waived (OR=2.76). Three of the counterfactual methods produced differences in the waiver outcome between White and Non-White youth that were larger than that found in logistic regression, while the remaining counterfactual method produced a slightly smaller difference. Specifically, the NNM analysis indicated that Non-White youth were 200% more likely to be waived than White youth. Similarly, the RA and IPWRA analyses both concluded that Non-White youth were almost twice as likely to be waived (193%), even after the adjustment process, while the IPW analysis indicated Non-White youth were 150% more likely to be waived.

Summary

Research Question 2 addressed the differences among the results found using each of the analytic techniques. For the case dismissal and adjudication outcomes, the five methods produced mixed results: two methods produced a significant race relationship and three methods did not. For the remaining court outcomes, all five analytic methods produced a significant relationship between race and the outcome. The primary difference between the logistic
regression and counterfactual results was that, with few exceptions, the regression analyses indicated stronger relationships between race and the court outcomes than any of the counterfactual methods.

**RESEARCH QUESTION 3**

One of the primary goals of this dissertation was to provide a more thorough understanding of DMC in juvenile courts, particularly as it relates to the differential offending and differential treatment hypotheses. As mentioned in Chapter 2, doing so requires that researchers use the best-equipped statistical technique(s) to ensure that the youth who are compared are as similarly-situated as possible. The most common technique used in prior research to examine DMC has been logistic regression; however, it is possible that some of the limitations inherent in regression estimators may limit their usefulness in examining DMC.²⁵ If this is the case, results obtained from those studies may be flawed, making it difficult to draw meaningful conclusions regarding the extent of DMC. This, in turn, could affect policy at those agencies that rely on empirical research to determine their response(s) to DMC.

The results discussed above provided strong evidence of disproportionate minority contact in three of the five outcomes included in this study. For the other two outcomes—case dismissal and adjudication—results obtained from the five analytic methods produced mixed results regarding their relationship with race. Thus, it is important to determine if one or more of the analytic methods is “better” than the others. In other words, out of the five analytic methods

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²⁵ See Chapter 3 for a complete discussion of the limitations of multivariate regression.
used in this study, should we put more confidence in the results obtained from one technique over the others?²⁶

This section addresses Research Question 3 and attempts to provide a thorough comparison of regression and the four counterfactual statistical methods to determine their relative usefulness in addressing important research questions related to DMC. Research Question 3 asks: *What are the relative strengths and weaknesses of each analytic technique as pertains to estimating the relationship between race and juvenile court outcomes?* Answering this question entails discussion of loss of cases, covariate balance, post-matching diagnostics, and covariate distribution overlap between White and Non-White youth.

**Loss of Cases**

One of the most important aspects of statistical analyses that must be addressed is the potential loss of cases in the estimation process. Cases may be dropped from the analysis for different reasons, such as missing data for any of the independent or dependent variables, perfect prediction of an outcome, or multicollinearity. As discussed in Chapter 3, however, cases with missing data on any of the independent/matching variables were excluded from the dataset. This means that for the logistic regression, RA, IPW, and IPWRA analyses, no cases were dropped from their respective analytic samples during the estimation process.

Due to the nature of the matching process, however, a limited number of cases were dropped in the NNM analysis for each outcome. Table 4.14 displays the number of cases dropped and the reason for exclusion for each outcome. Cases were dropped because either (1) there were fewer than the required four exact matches for a case or (2) there were no matches

²⁶The answer to this question is discussed in detail in Chapter 5.
within the required 0.25 caliper (measured in the number of standard deviations of the Mahalanobis metric). As seen in the table, the number of cases dropped from the analyses varied from 0.39% for case dismissal to 4.63% for waiver.

<table>
<thead>
<tr>
<th></th>
<th>Fewer Than 4 Exact Matches</th>
<th>No Matches Within 0.25 Caliper</th>
<th>Total Cases Dropped</th>
<th>% of Analytic Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Dismissal</td>
<td>216</td>
<td>0</td>
<td>216</td>
<td>0.45</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
<td>196</td>
<td>0</td>
<td>196</td>
<td>0.39</td>
</tr>
<tr>
<td>Adjudication</td>
<td>759</td>
<td>73</td>
<td>832</td>
<td>2.66</td>
</tr>
<tr>
<td>Secure Confinement</td>
<td>724</td>
<td>61</td>
<td>785</td>
<td>2.76</td>
</tr>
<tr>
<td>Waiver</td>
<td>399</td>
<td>26</td>
<td>425</td>
<td>4.63</td>
</tr>
</tbody>
</table>

The cases dropped from the NNM analysis can be considered outliers in that they were dissimilar to all of the other cases included in the analysis. Most of the dropped cases had extremely high values for either number of prior charges or number of current charges, meaning that for these cases there were no good matches between White and Non-White youth on these variables. Thus, although excluding these cases from the analyses required the ATEs to be interpreted conditionally on the region of common support, said ATEs may actually be more accurate because no poor or inadequate matches were included in the analysis. When there are outliers such as this—or a lack of overlap—regression analysis will rely on some level of extrapolation when estimating the regression coefficient, potentially leading to a biased estimate. However, because the number of cases dropped from the NNM analyses was quite small relative

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27 Analyses were re-ran using two different caliper values (0.15 and 0.35) to determine how sensitive the findings were to the caliper restriction. There were no significant differences in any of the results obtained from the 0.15, 0.25, and 0.35 caliper settings. For more detail, see the discussion of distance below.
to the analytic sample sizes, it is probable that they had little effect on the treatment effect estimate to begin with. This finding is discussed in more detail in the next chapter.

**Covariate Balance**

Another important indicator regarding the counterfactual methods is how well they balance the covariates between the treatment and control groups before estimating the treatment effect estimate (i.e., ATE). In this dissertation, balance refers to how well each analytic method creates groups of “similarly-situated” White and Non-White youth prior to estimating the corresponding ATE. Covariates are completely balanced when their distributions do not vary between the treatment and control groups (StataCorp, 2013). It follows that the better an analytic technique balances the covariates, the more accurate its corresponding ATE due to the fact that it is less subject to endogeneity or selection problems—at least on observable variables (Morgan & Harding, 2006). This section discusses the balance check for three of the counterfactual methods: NNM, IPW, and IPWRA. Unfortunately, there is no balance check for RA as it does not predict a treatment status model nor use a matching method (StataCorp, 2013).

For each court outcome, the balance check compares the average standardized differences between White and Non-White youth for each covariate. Measured using pooled standard deviation units, standardized difference tests compare the differences in means between treatment and control groups for each variable included in the analysis (Austin, 2009).\(^{28}\) The

\[d = \frac{(\bar{x}_{\text{treatment}} - \bar{x}_{\text{control}})}{\sqrt{\text{s}_{\text{treatment}}^2 + \text{s}_{\text{control}}^2}}\]

and the equation for dichotomous variables is

\[d = \frac{(\bar{x}_{\text{treatment}} - \bar{x}_{\text{control}})}{\sqrt{\text{s}_{\text{treatment}}(1-\bar{x}_{\text{treatment}}) \times \text{s}_{\text{control}}(1-\bar{x}_{\text{control}})}}\]

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\(^{28}\) The standardized difference equation for continuous variables is
standardized difference is measured both before the matching/weighting process (i.e., in the raw data) and after. Covariates that are perfectly balanced will have a standardized difference of zero (0.00). The balance checks also calculate the variance ratio between White and Non-White youth for each variable (i.e., variance for White youth divided by the variance for Non-White youth) both before and after the matching/weighting process. Covariates that are perfectly balanced will have a variance ratio of one (1.00). Appendices C-G display the results of the balance checks in tabular form.

An initial observation from the balance checks was that the standardized differences and variance ratios were identical for IPW and IPWRA. This occurred because the first step in the ATE calculation for these methods is identical: a treatment status model was fitted on the covariates and the inverse-probability of treatment weights were calculated. Thus, because the weighting process is the same for IPW and IPWRA, it follows that the standardized differences and variance ratios would be the same.

The most noticeable attribute of the balance checks was that NNM produced standardized differences of 0 and variance ratios of 1 for each variable except the three continuous covariates (age, number of priors, and number of current charges). This occurred because exact matching was used for sex, county, offense category, and offense level in the NNM analysis, meaning that these covariates were perfectly balanced between White and Non-White youth. This was also true for the preadjudication detention variable in the three models where it was included as a covariate (see Appendices E, F, and G). IPW and IPWRA reduced the absolute value of the

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standardized differences and variance ratio for almost every categorical variable in each of the five outcomes. Although none of them equaled the desired 0 or 1, most were very close. The maximum absolute value for the standardized differences among the categorical variables was 0.0288 (County F in the waiver analysis), and the maximum distance from 1 for the variance ratios was .0737 (County A in the waiver analysis). Faraone (2008) suggests that standardized differences within ±0.2 can be considered adequate balance. Taken together, these figures indicated that IPW, IPWRA, and especially NNM did a very good job of balancing the categorical variables.

The effectiveness of the counterfactual methods in balancing the three continuous variables differed among the outcomes. Each counterfactual method produced relatively low standardized differences for each outcome, with differences ranging from .0006 (number of current charges in the NNM analysis) to .0910 (number of priors in the NNM analysis). When attention was shifted to the variance ratios for the continuous variables, however, some of the results suggested that number of priors and number of current charges were poorly balanced, even after the matching/weighting process.\(^\text{29}\) Specifically, IPW and IPWRA did a poor job of balancing number of priors for each of the outcomes; each variance ratio was noticeably less than 1, ranging from .5973 to .7251. Results were better—though far from perfect—for number of charges in the NNM analysis. Here, the variance ratios ranged from .8596 to .8964.

Overall, the counterfactual methods were able to adequately balance all of the variables when measured in terms of the standardized differences between White and Non-White youth.

\(^{29}\) Though not specifically discussed in terms of variance ratios, results from Faraone (2008) suggest that ratios between 0.8 and 1.2 can be considered adequately balanced.
When degree of balance was based on the variance ratio, however, results varied among the covariates as to which method (NNM or IPW/IPWRA) was more effective at balancing the covariates. NNM outperformed IPW and IPWRA in balancing the categorical variables due to the exact match requirement which resulted in perfect balance for those variables. For the three continuous variables, however, there were no consistent findings regarding which method(s) best balanced the covariates.

**Post-Matching Diagnostic – Distance**

An aspect of matching estimators that is closely related to covariate balance is the average “distance” among the nearest neighbor matches for each matched pair. Distance is measured in the number of standard deviations of the Mahalanobis metric and quantifies how similar matches are in terms of their values for the included covariates. If all treatment and control cases were perfectly matched on each covariate (i.e., perfect balance), the average distance would be 0. However, because this study uses three continuous variables, perfect matching is not an attainable achievement. Instead, we want average distances that are as close to zero as possible. Table 4.15 displays the average distance between matches for each court outcome.

<table>
<thead>
<tr>
<th>Court Outcome</th>
<th>Mean Distance between Matches</th>
<th>Standard Error</th>
<th>SD</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Dismissal</td>
<td>.002</td>
<td>.001</td>
<td>.004</td>
<td>0 - .231</td>
</tr>
<tr>
<td>Preadjudication Detention</td>
<td>.002</td>
<td>.002</td>
<td>.004</td>
<td>0 - .232</td>
</tr>
<tr>
<td>Adjudication</td>
<td>.003</td>
<td>.002</td>
<td>.005</td>
<td>0 - .231</td>
</tr>
<tr>
<td>Secure Confinement</td>
<td>.003</td>
<td>.003</td>
<td>.005</td>
<td>0 - .227</td>
</tr>
<tr>
<td>Waiver</td>
<td>.004</td>
<td>.005</td>
<td>.006</td>
<td>0 - .172</td>
</tr>
</tbody>
</table>

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30 Because the other analytic techniques are not formal matching estimators, there is no post-analysis distance diagnostic for those techniques.
The average distance between matches was very small for all of the outcomes, ranging from 0.002 to 0.004 standard deviation units. This indicated that (1) there was a sufficient amount of overlap among the covariates, and (2) there were almost no poor matches used in the calculation of the NNM treatment effect estimates. It is important to note, however, that the distances shown in Table 4.15 were calculated on the final matched sample for each outcome. As such, the cases that were dropped from the NNM analyses due to fewer than four exact matches or no matches within the 0.25 caliper restriction\textsuperscript{31} were not included in the mean distance calculations. Had they been included, the average distances would have been higher for each outcome.

**Covariate Overlap**

Recall from Chapter 3 that there must be sufficient overlap—or common support—among the covariates between the treatment and control cases. If there is little overlap among the covariates, both regression and counterfactual methods may produce biased treatment effect estimates due to comparisons of dissimilar treatment and control cases. Chapter 3 presented an example of potential lack of overlap with the *number of priors* variable. The cumulative probability graph and Kolmogorov-Smirnov test for equality of distributions both indicated that there was a low to moderate level of overlap between White and Non-White youth for number of priors. This means that logistic regression will rely on some degree of extrapolation when estimating the regression coefficient and/or that some observations may exert an outsized influence.

\textsuperscript{31} Measured using the same scale of Mahalanobis standard deviation units.
A low level of overlap for a single variable, however, does not make the prediction of an unbiased treatment effect estimate impossible. Rather than focusing on a single variable, the overlap assumption pertains more to the overall distribution of all covariates for the treatment and control groups. A potential lack of overlap can be addressed in NNM analysis via the use of a caliper restriction, such as the 0.25 standard deviations restriction used in this study. In this instance, cases in the area of the covariate distribution where there is little overlap (i.e., cases that do not have matches within the specified caliper restriction) will be dropped from the analysis. As mentioned above, if a large number of cases are excluded from the analysis, the findings must be interpreted conditionally on the region of common support. Recall from Table 4.14 that few cases were dropped in the NNM analysis for each court outcome, from 0.45% for case dismissal to 4.63% for waiver. The relatively small number of cases dropped from each analysis indicated that there was an adequate level of overlap between White and Non-White youth.32

One advantage of IPW and IPWRA—as conducted in Stata® 14—is the availability of a direct method to check the overlap assumption. These overlap plots graph the estimated densities of the probability of being placed in each treatment level (hence the reason they are only available after IPW and IPWRA). “The overlap assumption is satisfied when there is a chance of seeing observations in both the control and the treatment groups at each combination of covariates” (StataCorp, 2013, p. 282). If the estimated density for either the treatment or control group has a large mass near 0 or 1, this indicates a violation of the overlap assumption. Figures 4.1, 4.2, 4.3, 4.4, and 4.5 display the overlap plots for the five court outcomes.

32 Unfortunately, there is no guidance in the literature regarding what is considered an acceptable amount of case loss in nearest neighbor matching (i.e., there is no formal test or “rule of thumb”).
Figure 4.1. Overlap Plot – Case Dismissal

Figure 4.2. Overlap Plot – Preadjudication Detention
Figure 4.3. Overlap Plot – Adjudication

Figure 4.4. Overlap Plot – Secure Confinement
As shown in the figures, none of the densities of the predicted probabilities had a large mass at 0 or 1. In addition, the estimated densities for both White and Non-White youth tended to increase and decrease at the same values of the propensity score scale. For example, Figure 4.1 (case dismissal) shows that the estimated densities for both White and Non-White youth peaked at propensity scores of approximately 0.30, 0.55, and 0.75. Taken together, these figures indicated that the overlap assumption was met within the analytic sample for each outcome.33

SUMMARY

This chapter presented the analytic results used to address the three research questions included in this dissertation. First, after matching/controlling for legal and extralegal variables,

33 Notice in Figure 4.5 that there is a mass around 0.10 for Non-White youth, with no corresponding mass for White youth. This indicates a relatively low level of overlap at this propensity score. This is the reason that 425 cases (4.63% of the analytic sample) was dropped from the NNM analysis for the waiver outcome. This finding is discussed further in Chapter 5.
analyses indicated that there were varying degrees of disproportionality found throughout the five juvenile court outcomes. Specifically, results suggested that Non-White youth were significantly more likely than White youth to be detained prior to adjudication, placed in a secure confinement facility post-adjudication, and waived to criminal court. For these three outcomes, the findings provided some evidence for the differential treatment perspective in that the included covariates—both legally relevant and extralegal—could not account for all of the disproportionality in the outcomes between White and Non-White youth. Conversely, results were mixed regarding case dismissal and adjudication, but it appeared that there was little to no DMC at these decision-points. Specifically, the two significant ATEs produced at each of these outcomes indicated that Non-White youth were more likely to have their case dismissed and less likely to be adjudicated delinquent.

Next, there were some differences among the results obtained from the five analytic techniques (Research Question 2). For the case dismissal and adjudication outcomes, two of the five methods indicated a significant race effect, while the remaining three did not. Similarly, for those outcomes where all five methods produced significant treatment effect estimates, the logistic regression analyses generally indicated stronger relationships between race and the outcomes compared to the counterfactual approaches. For example, in the preadjudication detention analyses, logistic regression indicated that Non-White youth were 44% more likely to be detained relative to similarly-situated White youth, while the various counterfactual methods indicated that Non-White youth were 23-26% more likely to be detained. Similar results were found for each court outcome.

Finally, the relative strengths and weaknesses of the statistical approaches were discussed in terms of their case loss, covariate balance, mean match distance, and overlap. Due to the four
nearest neighbor match and 0.25 caliper restrictions, a small number of cases were excluded from the NNM analyses (0.39% to 4.63% of the analytic samples). The remaining cases—those used to calculate the ATE—were quite similar among the included covariates between White and Non-White youth, as evidenced by the small mean distances between matches (.002 to .004). In addition, the post-analysis balance checks indicated that (1) NNM perfectly balanced the categorical covariates, (2) IPW and IPWRA balanced the categorical covariates quite well, and (3) the counterfactual methods varied in their ability to balance the continuous covariates. These results are discussed in further detail in Chapter 5, along with their implications and relevance for understanding DMC.
CHAPTER 5
DISCUSSION AND CONCLUSION

This chapter provides a detailed summary and discussion of the results presented in the previous chapter. First, the results are summarized and the relevance of the findings is discussed in the context of prior DMC research. The next section discusses this study’s contributions to the substantive DMC literature. The following section addresses the study’s contributions to the methodological literature, particularly as they pertain to understanding DMC. The chapter concludes with a discussion of the study’s limitations, as well as suggestions for future research.

SUMMARY AND RELEVANCE OF FINDINGS

The results presented in the previous chapter revealed that disproportionate minority contact exists to varying degrees across the five decision-points and seven courts examined in this study. The unconditional relative rate indices (RRIs) suggested that Non-White youth had worse outcomes at the preadjudication detention, secure confinement, and waiver to criminal court stages. In addition, although it was not statistically significant, the RRI for case dismissal did approach significance, but not in the expected direction (i.e., Non-White youth were slightly more likely to have their case dismissed). The RRI for the adjudication outcome was not significant. Recall from previous chapters, however, that the RRI’s usefulness in determining the true extent or potential cause(s) of DMC is limited because RRIs do not consider any control variables. Accordingly, it is impossible to rule out rival causes (e.g., differential offending) in any disproportionality found using the RRI. As such, this dissertation used logistic regression
and four counterfactual treatment effect estimators to more adequately assess the relationship between race and juvenile court outcomes.

The five multivariate analyses used in this dissertation produced mixed results at the case dismissal stage. Specifically, logistic regression and nearest neighbor matching (NNM) indicated that Non-White youth were significantly more likely to have their case dismissed relative to White youth, although the effect was relatively small (only a 6% difference between White and Non-White youth). Combined with the large analytic sample size (N=48,369), however, this 6% difference indicated that over 3,000 more Non-White youth had their case dismissed than did White youth—a somewhat large difference from a substantive viewpoint. The remaining analytic techniques—regression adjustment (RA), inverse-probability weighting (IPW), and inverse-probability-weighted regression adjustment (IPWRA)—indicated that there was not a statistically significant relationship between race and case dismissal.34

The case dismissal results were interesting because most prior research has found that Non-White youth receive worse outcomes than their White counterparts at this stage of the juvenile court process (Leiber & Mack, 2003; Leiber & Stairs, 1999; Leiber et al., 2011; Thomas & Sieverges, 1975). As such, the logistic regression and NNM analyses produced results that conflict with most previous DMC studies. Furthermore, although the RA, IPW, and IPWRA analyses produced nonsignificant findings, these too conflicted with most prior research in regards to the direction of the relationship. However, because juvenile courts’ administration, philosophy, and procedures can differ dramatically from county-to-county and state-to-state

34 Though nonsignificant, these analytic techniques too indicated that Non-White youth were more likely to have their case dismissed than White youth.
(Bray et al., 2005), the case dismissal results obtained in this study may be an artifact of those differences. In addition, these findings may be the result of a “correction effect” occurring at this stage of the court process (Leiber, 2013; Rodriguez, 2007, 2010). In other words, because Non-White youth were arrested more frequently than White youth, juvenile court personnel may have used their discretion at this stage to correct this disproportionality, thus resulting in more Non-White youth having their case dismissed relative to White youth. Based on the mixed findings from this study and how they conflict with most prior studies, additional research is needed at this stage to more accurately assess the role of race on the decision to dismiss juvenile court cases.

The results from all five analytic techniques provided evidence that DMC was present at the preadjudication detention stage. Specifically, even after conditioning the relationship on the included covariates, Non-White youth were significantly more likely to be detained prior to an adjudication hearing relative to similarly-situated White youth. The various statistical methods indicated that Non-White youth were 23-44% more likely to be detained. As discussed in Chapter 2, preadjudication detention is one of the most often studied stages in DMC research, as well as one of the stages where disproportionality is most often found (Bishop & Leiber, 2011; Leiber & Fox, 2011; Moak et al., 2012). The results obtained in this dissertation mirrored those found in most prior DMC studies that focused on the detention stage.

Similarly, this study provided further evidence that preadjudication detention plays a significant role in later stages via a “snowball” effect (Davis & Sorensen, 2013; Guevara et al.,

35 While most “correction effect” research tends to focus on the adjudication stage of the juvenile court process (Sullivan et al., 2016), it is entirely plausible that this correction could occur at the intake stage via intake officers’ large amount of discretion.
2006; Kempf-Leonard, 2007; Sickmund & Puzzanchera, 2014; Sullivan et al., 2016). Based on prior research, detention was included as an independent/matching variable in the adjudication, secure confinement, and waiver analyses. At these stages, preadjudication detention was a significant predictor of each outcome. In other words, youth who were detained prior to an adjudication hearing were significantly more likely to be adjudicated delinquent, placed in a secure confinement facility post-adjudication, and waived to criminal court compared to those who were not detained, indicating an indirect effect of race on these outcomes via detention status. This finding emphasizes the need to address—in all future DMC research—one of the primary limitations of prior DMC research upon which this dissertation is based: that juvenile court decision-making must be viewed as a process that includes all stages from intake to disposition. Because decisions made at the various stages of the court process are often interconnected, studies that include only a single stage may under- or overestimate any possible relationship between race and juvenile court outcomes.

The analytic results for the adjudication outcome were inconclusive. The logistic regression, NNM, and RA analyses indicated that the relationship between race and adjudication was not statistically significant. Conversely, the IPW and IPWRA analyses suggested that, after accounting for the covariates, Non-White youth were significantly less likely to be adjudicated delinquent compared to White youth. Although statistically significant, the relationship was quite weak substantively (less than 1% difference between White and Non-White youth).³⁶

³⁶ The ATEs for IPW (-.008; p = .014) and IPWRA (-.007; p = .043) were more than likely statistically significant only due to the large analytic sample size.
Overall, the adjudication results paralleled those found in prior research. First, like the regression, NNM, and RA analyses here, most prior research has found that there is little to no racial disproportionality at the adjudication stage (Bishop, 2005; Bishop & Leiber, 2011). Second, some studies have found that White youth are more likely than Non-White youth to be adjudicated delinquent (Johnson & Secret, 1990; Leiber, 2013). This result was duplicated in this study in the IPW and IPWRA analyses.

Results from each analytic method indicated that there was a significant relationship between race and post-adjudication placement in a secure confinement facility. Specifically, Non-White youth were significantly more likely to be placed in post-adjudication secure confinement relative to similarly-situated White youth. In addition, the estimated strength of this relationship was quite similar among the five methods. Results from the various methods indicated that Non-White youth were between 26% (NNM) to 30% (logistic regression) more likely to be placed in a secure facility relative to White youth after conditioning on the included covariates. These results mirrored those of most prior research, though the effect sizes estimated in this study were generally smaller than those found in the extant literature (Davis & Sorensen, 2013; Rodriguez et al., 2009).

The final court outcome examined in this dissertation was waiver to criminal court. Similar to the secure confinement analyses, each analytic technique concluded that Non-White youth were significantly more likely than White youth to have their case waived to criminal court, even after controlling for legally-relevant and extralegal factors. As expected based on prior studies (Brown & Sorensen, 2013; Males & Macallair, 2000), the relationship between race

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37 The results for the other three methods fell between these estimates.
and the five court outcomes was strongest at this stage. Specifically, results suggested that Non-White youth were between 150% (IPW) and 200% (NNM) more likely to be waived, depending on which of the five methodologies was used.

In summary, the five analytic techniques used here provided varying amounts of evidence that DMC exists in the seven juvenile courts included in this study. All five analytic techniques concluded that Non-White youth received worse outcomes at the preadjudication detention, secure confinement, and waiver stages of the juvenile court process. Specifically, the various analytic techniques indicated that Non-White youth were 23-44% more likely to be detained prior to an adjudication hearing, 21-30% more likely to be placed in a post-adjudication secure confinement facility, and 150-200% more likely to be waived to criminal court. The results for these three stages coincide with the bulk of prior DMC research. Conversely, three of the methodologies concluded that there was no significant relationship between race and case dismissal, while the remaining two methodologies found a significant relationship that disadvantaged White youth. Specifically, logistic regression and NNM indicated that Non-White youth were approximately 6% more likely than White youth to have their case dismissed. Similar results were found for adjudication: three analytic techniques found no significant relationship between race and adjudication, while the IPW and IPWRA analyses concluded that Non-White youth were significantly less likely to be adjudicated, although the difference was less than 1%. However, as mentioned above, all of these conclusions must be interpreted conditionally based on the characteristics specific to this study.
CONTRIBUTIONS TO THE DMC LITERATURE

This dissertation addressed two limitations often found in prior DMC research: (1) a focus on only one stage of the juvenile court and/or a single court and (2) potential methodological flaws of using multivariate logistic regression to compare youth of different races who are otherwise similarly-situated. The first limitation—and how this study addressed it—is discussed in this section. The subsequent section discusses the methodological limitations found in prior DMC research and how they were addressed in this dissertation.

Juvenile justice decision-making must be viewed as a process including all stages of the juvenile court (Leiber, 2013). Single-stage studies are more likely to under- or overestimate the effects of race on court outcomes (Guevara et al., 2006; Peck et al., 2014). Similarly, findings based on a single juvenile court cannot be generalized to courts in other regions. Although single-stage and single-site studies contribute to the literature on DMC, more research is needed that studies multiple juvenile courts as well as the interdependence of decisions made across all stages of the court process. This dissertation addressed this need by examining the relationship between race and five juvenile court outcomes across seven juvenile courts. In addition, the results of this study provided evidence that, at a minimum, preadjudication detention status needs to be included in any studies that examine later juvenile court outcomes (i.e., adjudication, disposition, and waiver). Furthermore, the use of multiple juvenile court outcomes showed that DMC was present at the three decision-points—detention, secure confinement, and waiver—where potential loss of liberty and freedom are both more severe and more likely to occur.  

38 This does not imply that the more severe outcomes at the case dismissal and adjudication stages lack any loss of freedoms or liberty, only that the more severe outcomes at the other three stages entail a much higher degree of restrictions on youths’ freedom and liberty. Furthermore, being waived to criminal court can have a profound effect on a youth’s future, especially in those jurisdictions that have “once an adult, always an adult” statutes.
As discussed in Chapter 2, most contemporary explanations of DMC tend to fall into one of two competing perspectives: differential offending and differential treatment (Bishop & Leiber, 2011; Davis & Sorensen, 2013; Engen et al., 2002; Kurtz et al., 2008; Piquero, 2008). The differential offending hypothesis opines that disproportionality in the juvenile justice system is caused primarily by Non-White youth committing more offenses and/or more serious offenses compared to White youth. According to this perspective, there is little to no discrimination by juvenile court personnel. Conversely, the differential treatment hypothesis posits that Non-White youth are treated harsher—based solely or in part on their race—than similarly-situated White youth. Under this perspective, juvenile court personnel may rely on discriminatory or stereotypical factors in their decision-making process, thus leading to racial disproportionality.

This dissertation provided some evidence for the differential treatment perspective—at least for three of the court outcomes included in the study. Even after matching on/controlling for legally-relevant (prior record, offense type, offense seriousness, number of charges) and extralegal factors (age, sex, and county), there was a significant relationship between race and preadjudication detention, secure confinement, and waiver to criminal court that disadvantaged Non-White youth. In other words, these covariates alone could not explain away the disproportionality found in the raw data at these three decision-points. Because there remained a significant relationship between race and these court outcomes after controlling for the covariates, one can infer that there was some degree of differential treatment occurring in the seven juvenile courts included in this study.39 This inference is bolstered by the fact that the counterfactual methods used in this study are some of the most methodologically rigorous

39 See below regarding the potential limitation of not including some relevant covariates.
analytic techniques for addressing selection bias within observational studies (Guo & Fraser, 2015; Morgan & Harding, 2006; Morgan & Winship, 2015).

The findings in this study for case dismissal and adjudication contribute to the extant literature in a somewhat unique manner. For case dismissal, the logistic regression and NNM analyses concluded that there was a significant relationship between race and dismissal, while the remaining analytic methods produced nonsignificant relationships. The two significant effects, however, indicated that White youth received worse outcomes at this decision-point.\(^\text{40}\) The findings from the five analytic methods provided mixed evidence regarding the relationship between race and case dismissal; this closely mirrored what has been found in prior research. For example, as discussed in Chapter 2, previous research has found that Non-White youth were significantly less likely to have their case dismissed (Leiber & Stairs, 1999; Thomas & Sieverdes, 1975), that there was no relationship between race and dismissal (Cohen & Kluegel, 1979a; Rodriguez, 2010), and that Non-White youth were significantly more likely to have their case dismissed (Leiber & Mack, 2003).

Similarly, only two of the five analytic methods (IPW and IPWRA) produced significant results for adjudication, and the direction of the relationship indicated that Non-White youth were adjudicated less often than similarly-situated White youth. As such, these results contribute to the DMC literature in that they provide an additional layer of evidence that racial disproportionality is rarely seen at this decision-point, likely due to a “correction effect” or heavy reliance on legally-relevant factors during the decision-making process (Bishop, 2005; Bishop &

\(^{40}\) Although the results for RA, IPW, and IPWRA were not statistically significant, they too indicated that White youth received worse outcomes at this decision-point.
Leiber, 2011; Johnson & Secret, 1990; Leiber, 2013). Even though results from two of the analyses were statistically significant, the substantive difference in adjudication rates between White and Non-White youth was very small (less than 1% for both analytic techniques).

Combining the results for case dismissal and adjudication from the current study and prior studies, it appears that the significance of race varies substantially from one court to the next, making it quite difficult (if not impossible) to give an accurate description of the relationships across the U.S. Indeed, there was significant variation in the raw percentages of youth who had their case dismissed and adjudicated delinquent across the seven courts used in this study. The percentage of cases dismissed at intake ranged from 5.9% (County G) to 37.9% (County E), while the percentage of youth adjudicated delinquent ranged from 56.8% (County G) to 96.7% (County A). These mixed and inconclusive results highlighted the importance of conducting county- or court-level DMC assessments to determine whether and to what extent DMC may be present at the various decision-points in a given juvenile court. Indeed, Hsia and colleagues (2004, p. 35) posit that if efforts to reduce DMC are to be successful, there must be consistent local implementation of intervention strategies designed to address a court’s unique characteristics and population served, as well as strong partnerships among researchers, legislators, and juvenile justice practitioners. In other words, there is no panacea for reducing DMC; instead, programs should be implemented based on the unique findings of localized assessment studies.

**Methodological Triangulation**

This study also contributed to the substantive literature via its methodological rigor. The use of five different analytic techniques (i.e., methodological triangulation) made this dissertation one of the most methodologically-intense studies of DMC to date. Using multiple
statistical methods to examine the same data and phenomenon reduces bias and can improve the validity of research because the flaws of one statistical method may be a strength of another (Mathison, 1988). Furthermore, if each of the methods produces similar results, methodological triangulation can result in a higher degree of confidence in the findings (Sullivan et al., 2009). In other words, when methodological triangulation is used and the statistical methods produce similar results, “the result will be a convergence upon the truth about some social phenomenon” (Mathison, 1988, p. 14). For example, for three of the five court outcomes in this study, all five statistical methods indicated that there was a significant relationship with race—although the effect sizes did differ somewhat among the analytic techniques. As such, we can be confident that the results were accurate and not an artifact of a single statistical technique.

Conversely, for case dismissal and adjudication, there was no consensus among the five methods regarding the statistical significance of the relationship between race and the outcomes. This finding illustrates the need for methodological triangulation. Had this study used only logistic regression or NNM for the case dismissal analysis, or IPW or IPWRA for the adjudication analysis, the results would have been completely different (i.e., statistically significant vs. nonsignificant) had any of the other methods been used for each outcome. In situations such as this, because most research uses a single multivariate analytic technique, it is essential that the researcher choose the method that best adheres to the assumptions and underlying logic of the analytic method. The following section builds on this aspect of this dissertation and discusses the study’s contributions to the methodological literature.
CONTRIBUTIONS TO THE METHODOLOGICAL LITERATURE

Although this dissertation addressed the substantive issue of the relationship between race and juvenile court outcomes, a primary focus was to examine the relative strengths and weaknesses of five statistical techniques in the context of analyzing DMC. This section first compares multivariate regression estimators and counterfactual methods in general. Next, the strengths and weaknesses of the individual counterfactual methods are presented. This is followed by a discussion of how to choose among the analytic methods, or which method “works best.”

Comparing Multivariate Regression and Counterfactual Estimators

As discussed previously, a large portion of prior DMC research used multivariate logistic regression to examine the effect of race on juvenile court outcomes. There are, however, a number of limitations inherent in regression estimators that may indicate they are insufficient for analyzing DMC. First, the simplicity of implementation of regression can lead researchers to overlook fundamental problems in the data, such as correlation between an independent variable and the error term. Second, White and Non-White youth oftentimes differ among legally-relevant and extralegal covariates, leading to nonequivalent treatment and control groups and resulting in heavy reliance on extrapolation to predict expected outcomes. Finally, if the true functional form of a model is unknown, regression estimates may be biased. Based on these limitations, results obtained from studies that use multivariate regression estimators may be flawed, making it difficult to draw meaningful conclusions regarding the presence and extent of DMC.41

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41 For the most part, the logistic regression results in this study were relatively similar to those from the counterfactual methods. As further discussed below, this was due primarily to the large sample size.
Consequently, this could have severe consequences for agencies that rely on empirical research to create policies and programs to address the DMC problem. As such, it is crucial that researchers use the best-equipped statistical analyses to compare similarly-situated youth in order to get the most accurate and dependable estimates of DMC. Unfortunately, there is no definitive rule as to when a given method can be considered “good enough” in regards to choosing among possible analytic techniques.42

The four counterfactual methods used in this study address the weaknesses of multivariate regression. First, depending on which one is used, counterfactual methods employ various techniques to balance the distribution of covariates between White and Non-White youth. In the context of this study, balance refers to how well a counterfactual method creates groups of similarly-situated White and Non-White youth prior to estimating a treatment effect. An advantage of NNM, IPW, and IPWRA is that post-estimation balance checks can easily be performed to see how well each method balances the covariates between the treatment and control groups. These balance checks allow researchers to see how well the methods reduce the standardized differences and variance ratios for each covariate included in the model. In perfectly balanced data, the post-analysis standardized differences would be 0 for each variable and the variance ratio would be 1 for each variable. As discussed in the previous chapter, NNM with exact matching produced perfect balance among the categorical covariates. While IPW and IPWRA achieved considerably better balance for the continuous variables than that found in the raw data, neither method produced the desired 0 for standardized difference or 1 for variance

42 Sensitivity analysis could potentially assist researchers in this aspect. See “Inclusion of Relevant Variables” section below for further discussion.
ratio—though they came very close on multiple occasions. The effectiveness of the three methods varied in their ability to balance the three continuous variables. Thus, based solely on the methods’ ability to balance the covariates, it appears that we can place more confidence in the NNM results than those from IPW or IPWRA.

Second, one of the counterfactual methods (nearest neighbor matching) can create a region of common support where only similarly-situated White and Non-White youth are included in the analysis. While this addresses the potential extrapolation problem found in logistic regression, if a large number of cases are excluded because they are outside the region of common support, the results must be interpreted conditionally on the area of common support (see below). A similar aspect of NNM is that post-match analysis can calculate the number of times each case is used as a match to determine whether the analysis relied too heavily on any single case when calculating the ATE. If a small number of cases are used excessively as matches (for example, 500 times in samples as large as the current study), this could bias the estimated ATE. In this dissertation, the number of times a single case was used as a match ranged from 1 to 58 for the five court outcomes, indicating that the analyses did not rely too heavily on any case(s).

Third, post-estimation diagnostics can identify the quality of matches and covariate balance to determine the amount of homogeneity between the groups and whether the analytic method is suitable based on the data. These diagnostics are not readily available in regression analyses. Finally, the counterfactual methods used in this study are nonparametric in that they do

43 Outlier analysis can be—and was—conducted to examine such possibilities.
44 There was one case in the waiver analysis that was used as a match 111 times. This was still a relatively small number considering the large analytic sample size.
not require defining the functional form of the treatment model. In fact, inverse-probability-weighted regression adjustment is a “doubly robust” estimator, meaning that the calculated treatment effect estimate (i.e., ATE) “remains consistent [as long as] either a model for the treatment assignment or a model for counterfactual data is correctly specified” (Bang & Robins, 2005, p. 962). In other words, IPWRA gives researchers two chances to produce a consistent treatment effect estimate. Taken together—and acknowledging the fact that the logistic regression and counterfactual results in this study were quite similar—this dissertation posits that counterfactual analytic methods are better-suited to studying DMC than are the more common maximum-likelihood estimators associated with multivariate logistic regression. The justifications for this assertion are discussed in detail in the following sections.

There is, however, a considerable weakness of counterfactual methods relative to logistic regression. Unlike regression, counterfactual methods cannot determine the relative strengths of included covariates other than the treatment variable (Morgan & Winship, 2015). For example, in the secure confinement analysis in this study, the logistic regression and counterfactual analyses indicated that Non-White youth were 21-30% more likely to be placed in a secure facility compared to similarly-situated White youth. Only the logistic regression analysis, however, was able to inform us that, for example, the odds of secure confinement varied significantly among the counties (ORs ranged from 4.43 to 37.98); that females were significantly less likely to be placed in secure confinement relative to males (OR=0.57); and that a one-unit increase in the number of prior charges was equated with an 11% increase in the odds of secure confinement. This information was not readily available when the counterfactual methods were used. If a researcher is interested solely in knowing the effect of a treatment on an outcome (i.e, localized understanding), this is not a problem. But if the knowledge sought is the
effect of a treatment on an outcome as well as the effects of other covariates (i.e., global understanding), logistic regression would be the better choice.

**Strengths and Weaknesses of the Counterfactual Methods**

In general, the four counterfactual methods used in this study produced similar results. For three of the outcomes, all of the counterfactual methods produced statistically significant ATEs in the same direction. In addition, the calculated ATEs were quite similar among the different methods (see Table 4.12). The difference between the highest and lowest ATEs was .004 for preadjudication detention, .004 for secure confinement, and .003 for waiver to criminal court. Even at the two court outcomes where the counterfactual methods produced mixed findings regarding the significance of race, the ATEs were very similar and the standard errors were identical. The difference in ATEs was .010 for case dismissal and .004 for adjudication. Due to these similarities, a discussion of the technical differences among the methods is required before a determination can be made regarding which method is best suited for studying DMC.

**Nearest Neighbor Matching**

A major strength of NNM is its nonparametric nature in that no assumption is made about the functional form of the treatment or outcome models. Conversely, regression coefficients can be highly unstable if the model specification is inaccurate (Kreif et al., 2013). There is a caveat, however, to the nonparametric nature of NNM. Because nonparametric estimators converge to the true value of the treatment effect estimate at a slower rate, NNM requires a large sample size relative to parametric estimators that specify a functional form (Drukker, 2014). Each of the

45 The similar ATEs and identical standard errors between the methods that produced significant results and those that did not accentuate how close each method was to the p = .05 cutoff for these outcomes.
analytic samples in this study was sufficiently large enough to meet this requirement, but this is not guaranteed in all studies of race and juvenile court outcomes.

Another advantage of NNM arises in situations where the outcome is a rare event, such as the secure confinement and waiver outcomes in this study. In these situations, there may not be enough positive outcomes (e.g., waived youth) at each combination of treatment level and value of the included covariates to be able to calculate a stable treatment effect estimate with logistic regression (Braitman & Rosenbaum, 2002). Indeed, according to King and Zeng (2001), logistic regression often underestimates regression coefficients when studying rare outcomes. NNM, however, can still produce accurate treatment effect estimates in these situations as long as there is a reasonable amount of variation in the outcome variable for each level of the treatment, or, in the context of the current study, as long as there are enough White and Non-White youth in the sample who were waived and enough White and Non-White youth who were not waived. This condition was met in this study.

One potential weakness of NNM is that some cases may be excluded from the analysis if they do not meet the requirements imposed to insure no poor matches are included. For example, in this study, match quality was restricted by two requirements. First, the number of nearest neighbor matches for each case was set to four because it ensured that enough data was used to produce an accurate estimate while at the same time limiting the likelihood of poor matches (Abadie et al., 2004). Second, a caliper restriction of 0.25 standard deviations of the Mahalanobis metric was used to ensure that matched cases were sufficiently similar in terms of their values for the three continuous variables (age, number of priors, and number of current charges). Any cases that did not meet these two requirements were dropped from the NNM analyses. As shown in Table 4.13, this resulted in excluding cases from the analyses ranging from 0.39% of the analytic
sample for preadjudication detention to 4.63% of the analytic sample for waiver to criminal court.

Upon further examination of the cases dropped from the NNM analyses, most had extreme values for either number of prior charges or number of current charges. For example, in the analytic sample for case dismissal, many of the dropped cases had more than 20 prior and/or current charges. The analytic sample means for prior charges and current charges were 2.77 and 2.07, respectively. Taken together, these values indicated that the excluded cases were extreme outliers and were dropped from the analysis because they had no “good” matches. The same characteristics of dropped cases were found for the remaining court outcomes as well. From a practical viewpoint, excluding these extreme outliers from the NNM analyses makes sense because they cannot be considered “normal” or “average” cases. For example, in the raw data, 43% of the cases in the sample had no prior charges, 84% had five or fewer prior charges, and 93% had 10 or fewer charges. Similar proportions were found for number of current charges: 59% had only one current charge, 94% had five or fewer, and 99% had 10 or fewer. Thus, the cases in this sample with 11-50 prior charges and/or 11-65 current charges were extreme outliers relative to the rest of the cases; most youth who interact with the juvenile justice system do not have 50 prior charges or 50 charges in the current case. Thus, although excluding these outliers requires the NNM results to be interpreted conditionally, said results will apply to the relatively “normal” or “average” youth who make up the vast majority of cases coming into contact with the juvenile court.46

46 To determine if the dropped cases may influence the logistic regression analyses, additional logistic regression models were calculated that excluded the cases dropped in the NNM analyses. For example, instead of using the 31,232 cases in the analytic sample for adjudication (as was the case with the primary logistic regression analyses discussed in the previous chapter), this supplementary analysis used the 30,400 cases that were included in the final
Due to the dropped cases, results from the NNM analyses must be interpreted conditionally on the region of common support, namely cases that did not have extreme values for any of the covariates. However, in the context of DMC research, even though a small number of cases were excluded from the analyses, the resulting treatment effect estimates can be even more informative than had the outliers remained in the analysis (Morgan & Harding, 2006). In this case, the ATEs represented the treatment effect only for the cases that were sufficiently similar in terms of the included covariates. This addressed one of the fundamental tenets upon which this dissertation was based: that to obtain a true understanding of disproportionality in the juvenile justice system, researchers must ensure that they are comparing youth of different races who are otherwise as similarly-situated as possible (Kempf-Leonard, 2007).

**Regression Adjustment**

Unlike NNM, the remaining counterfactual methods used in this study do not exclude cases from the analyses (except those cases with missing values for any of the included variables). Given the manner in which regression adjustment (RA) estimates treatment effects, however, there are situations in which the use of all cases can be problematic when using this technique. As discussed in Chapter 3, RA calculates treatment effect estimates by first fitting separate regression models of an outcome to treatment and control cases and then calculating the

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NNM analysis (i.e., it did not include the 832 cases dropped from the NNM analysis). Results from these ancillary regression analyses indicated that the exclusion of the non-matched cases had no effect on the race coefficient for case dismissal, preadjudication detention, or adjudication. The odds ratio for secure confinement (1.28) was two percentage points lower than that found in the primary regression analysis (1.30), while the OR for waiver (2.61) was 15 percentage points lower than the original regression analysis (2.76).

47 It is important to note that if cases are dropped during NNM, researchers must be aware of which cases are dropped and how their exclusion may affect the findings.
predicted outcomes for each group. The mean difference of the predicted outcomes is the ATE. Problems occur when, like in the current study, there are extreme outliers in the data (i.e., when there is a lack of overlap at some areas of the covariate matrix between White and Non-White youth). Like logistic regression, this may cause the RA regression models to rely on extrapolation when estimating the regression coefficients. Consequently, these imprecise coefficients can bias the treatment effect estimate. This did not appear to be a problem in this study due to the fact that all four counterfactual methods produced similar ATEs for each court outcome. As stated above, however, this may be due to the large sample size used in this study. Research that uses RA with smaller samples in which there are extreme outliers may experience the potential problems inherent in extrapolation.

**Inverse-Probability Weighting**

Inverse-probability weighting (IPW) addresses RA’s sole reliance on regression coefficients to calculate treatment effect estimates—and the potential problems it presents. IPW first fits a model of treatment status on the covariates. Next, the inverse of the probability of receiving treatment is calculated, and these inverse-probability weights are used to compute weighted means of an outcome for each case and treatment level. The average difference in this weighted means is the ATE. Although all cases are included in IPW analyses, the use of weighting ensures that extreme values found in the data do not appreciably bias the treatment effect estimate. A potential weakness of IPW is that the treatment model must be correctly specified; if it is not, the inverse-probability weights can be quite large, leading to biased ATEs

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48 The primary difference between RA and logistic regression is that the former predicts two separate models based on treatment level (i.e., treatment and control) whereas the latter produces a single model that applies to both treatment levels.
and increased variance. This did not appear to be a problem in any of the analyses in the current study.

**Inverse-Probability-Weighted Regression Adjustment**

Inverse-probability-weighted regression adjustment (IPWRA) combines aspects of RA and IPW. Like IPW, a model of treatment status is fitted on the covariates and inverse-probability weights are calculated. Next, the inverse-probability weights are used to fit separate regression models to treatment and control cases to obtain the predicted outcomes for each case. The average difference in the predicted outcomes between treatment and control groups is the ATE. In other words, IPWRA uses the inverse-probability weights produced by IPW in the regression models in RA (instead of the raw data typically used in RA to produce predicted outcomes).

The primary advantage of IPWRA is that it is a doubly robust (DR) estimator (Bang & Robins, 2005). DR estimators give researchers two chances to produce an accurate estimate of the treatment effect since only the treatment model or the outcome model has to be correctly specified. Even if only one of the models is incorrectly specified, DR estimators provide significant improvements in efficiency over multivariate regression methods (Bang & Robins, 2005). Since we can never be certain that both the treatment and outcome models are correctly specified, the doubly robust feature of IPWRA is highly desirable. Neither logistic regression nor any of the other counterfactual methods used in this study share this doubly-robust property. As long as either the treatment or outcome model is correctly specified, IPWRA can be considered

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49 The “doubly robust” property is not relevant to NNM since the latter is a matching estimator and thus does not require defining the functional form for either the outcome or treatment model.
superior to RA or IPW alone. However, if both models are misspecified, there is no consensus as to which method will work best (StataCorp, 2013).

Choosing among the Analytic Techniques

Multiple counterfactual estimators have been developed over the past few decades. This fact can be interpreted as both a positive and negative, however. On the positive side, having multiple counterfactual methods available means that researchers can choose the one that best fits their data and analytic goals. Similarly, relative to multivariate regression, the counterfactual framework in and of itself allows researchers to more easily identify situations in which there is insufficient overlap or balance between treatment and control cases (Morgan & Harding, 2006). Conversely, although multiple counterfactual estimators now exist, the relevant literature provides little guidance for choosing among them or which works best. As such, based on the strengths and weaknesses of the various techniques discussed above, this section provides two suggestions regarding which technique is best suited to research on disproportionate minority contact in the juvenile justice system.

Before presenting the suggestions, however, an important point regarding the effects of a study’s sample size must be discussed. As noted above, for the most part, logistic regression and each of the four counterfactual methods used in this study produced relatively similar results—although the regression analyses tended to indicate slightly stronger relationships between race and the court outcomes compared to the counterfactual methods. This was most likely due to the especially large analytic sample size for each court outcome. As sample size increases, the various methods have more data available to compare similarly-situated youth and, subsequently, estimate ATEs that are as close as possible to the true treatment effect (Caliendo & Kopeinig, 2005). Thus, as long as common support is achieved in the data, there may be little difference in
the estimated treatment effects among the analytic methods.\(^{50}\) As sample size decreases, however, the particular method each analytic technique uses to calculate the treatment effect—as well as their respective tradeoffs between bias and efficiency—become increasingly important (Caliendo & Kopeinig, 2005). Unlike the results found in this dissertation, studies that use smaller sample sizes will likely see larger differences in the estimated treatment effects among the analytic methods. Thus, the value added to the study of DMC in the juvenile justice system by using counterfactual methods is more likely to be found in studies that use smaller samples than those used in the current study. To test this assertion in the current study, the preadjudication detention analyses were re-run using only cases from County E (N=865).\(^{51}\) Based on this relatively small sample, the logistic regression results indicated a significant relationship between race and detention, while all four counterfactual methods produced nonsignificant results. In sum, it appears that counterfactual methods may be superior to regression when sample sizes are relatively small, but as sample sizes increase, regression and counterfactual methods tend to produce more comparable treatment effect estimates.

If all or most of the covariates included in the analysis are categorical, nearest neighbor matching with exact matching appears to be the method most appropriate to analyzing DMC.\(^{52}\) This would ensure that the analysis is comparing White and Non-White youth who are truly “similarly-situated” in terms of the included covariates. For categorical variables, NNM perfectly

\(^{50}\) If there is no common support between the treatment and control groups, the average treatment effect cannot be estimated, no matter the sample size.

\(^{51}\) County E was chosen because it contained a relatively small number of cases while also having a sufficient number of cases in which the youth was detained prior to adjudication.

\(^{52}\) If all covariates are categorical and the sample size is sufficiently large to allow exact matching, NNM would be by far the most appropriate method since it would guarantee perfect covariate balance between White and Non-White youth.
balances the covariates between White and Non-White youth (i.e., all post-estimation standardized differences are 0 and all variance ratios are 1). Furthermore, as discussed previously, although cases without exact matches may be dropped from the analysis, this could actually increase our understanding of DMC since only cases with perfect matches are included in the analysis. Again, this addresses Kempf-Leonard’s (2007, p. 75) assertion that “if [youth of different races] are not the same [in terms of included covariates]—or at least ‘similarly-situated’—then DMC may really occur as a result of the other ways in which they differ.”

If there are multiple continuous variables included in the analysis—like the three included in this study—a caliper restriction and the use of multiple nearest neighbor matches should be added to the NNM analysis. The caliper restriction ensures that matches based on the continuous variables are sufficiently “close,” thus limiting the possibility that treatment effect estimates are based on poor matches. Similarly, using multiple nearest neighbor matches per case (1) ensures that each case in the sample has a chance to be used in the ATE calculation and (2) can increase the precision of the estimated ATE due to a larger analytic sample size (Austin, 2010). As such, this study followed Abadie and colleagues’ (2004) suggestion of four nearest neighbor matches for each case “because it offers the benefit of not relying on too little information without incorporating observations that are not sufficiently similar” (p. 298). The combination of a caliper restriction and multiple matches produces the most accurate treatment effect estimates when exact matching on continuous variables is not viable and ensures that, for

53 Because the analytic samples in this study were very large, using four nearest neighbor matches was not a problem. For small samples, however, researchers might elect to choose fewer nearest neighbor matches.
example, an 11 year-old youth is not matched with a 17 year-old youth or that a youth with no prior charges is not matched with a youth with 10 priors.

As discussed previously, however, NNM—as well as the other counterfactual techniques—is limited to providing knowledge of the effect of a treatment on a given outcome (i.e., localized understanding). Conversely, logistic regression can provide the treatment effect as well as the effects of other included covariates on the outcome (i.e., global understanding). Thus, if DMC researchers are interested in gleaning the relative strength of both race and other covariates on court outcomes, logistic regression would be the better choice.

**LIMITATIONS AND FUTURE RESEARCH**

As discussed above, this dissertation attempted to provide more detailed insight into the substantive issue of disproportionate minority contact in the juvenile justice system by addressing two primary shortcomings found in much prior DMC research: a focus on a single stage of the juvenile court process and/or a single court and methodological problems in comparing similarly-situated youth. While the data and analytic methodologies used in this study adequately address these problems, a few limitations remained. This section discusses these limitations, as well as suggestions for how future research may build upon this study.

**Inclusion of Relevant Variables**

An important consideration when studying DMC across multiple stages centers on variable selection for each model/stage. In this regard, “only variables that influence simultaneously the [treatment] decision and the outcome variable should be included” at each subsequent stage (Caliendo and Kopeinig, 2005, p. 6). The inclusion of irrelevant (i.e., nonsignificant) variables will not bias the estimated treatment effect, but it can inflate the
standard error. Conversely, Rubin and Thomas (1996) argue that if there is any question regarding whether a specific variable should be included in the model—based on theory and/or prior research—it is best to include it in the model.

As discussed in Chapter 2, research over the past few decades has identified numerous variables found to be correlated with juvenile court outcomes and decision-making, such as demographic characteristics (Armstrong & Rodriguez, 2005; Barton, 1976; Guevara et al., 2006; Leiber, 2013), prior interaction with the juvenile court (Bishop, 2005; Cohen & Kluegel, 1979a; Leiber, 2015), and offense-related characteristics (Brown & Sorensen, 2013; Cauffman et al., 2007; Thomas & Sieverdes, 1975). While these variables were included in the current study, data was not available for some relevant variables identified by prior research that could better match youth as similarly-situated. For example, Thomas and Sieverdes (1975) concluded that onset age and number of co-defendants were both significant factors considered during the intake decision. Similarly, family structure (Kurtz et al., 2008; McCoy et al., 2012) and educational status (Barton, 1976) have been found to predict various juvenile court outcomes. It is possible that factors such as these can significantly differ, even among seemingly similarly-situated youth (Kempf-Leonard, 2007). While these types of factors may not necessarily be better predictors of the juvenile court outcomes included in this study than the covariates already present, including them in future research can increase confidence that the White and Non-White youth being compared are as similarly-situated as possible on as many legal and extralegal variables as possible.

Furthermore, one tactic to address DMC in juvenile courts that has recently gained popularity is standardized risk assessments for the intake, detention, and dispositions stages of the court process (Hsia et al., 2004; Kurtz et al., 2008). The purpose of these instruments is to
reduce the amount of potential racial bias and stereotyping among juvenile court decision-makers. “At a minimum, an assessment tool reduces some of the subjectivity still present in [decision-making] and helps to ensure that decisions are based on presenting behaviors rather than misconceptions” (Kurtz et al., 2008, p. 152). However, Mallett and Stadard-Dare (2010) examined the relationship between detention and race in a Midwestern county that uses the Youth Level of Service Inventory (YLSI), a standardized youth assessment tool that identifies risk and needs, and found that black youth were still over two times more likely to be detained than their white counterparts. This finding suggests that while use of a standardized risk assessment may reduce racial disproportionality in the detention decision, it does not eliminate it. Despite this finding, however, risk assessment scores are an increasingly vital part of decision-making in juvenile courts (Schwalbe, Fraser, & Day, 2006). As such, future research should strive to include as many evidence-based correlates of juvenile court decision-making as possible. This would ensure that future studies are indeed comparing White and Non-White youth who are as similar as possible and thus providing the most accurate picture of DMC. Similarly, this would also provide a closer facsimile of the factors that may play a role in juvenile court decision-making. Furthermore, after including all relevant variables included in the data, researchers can perform sensitivity tests to determine how sensitive their results are to omitted variables. Specifically, sensitivity analysis addresses the question of how strongly an unmeasured variable must influence the analysis for it to make a significant difference on the estimated treatment effect (Caliendo & Kopeinig, 2005).

**Lack of Police Contact Data**

This study examined the relationship between race and decision-making in the juvenile justice system. However, no data was available in the current study that measured relevant
aspects of youths’ interactions with police. Piquero (2008) argued that a sizable gap in the DMC literature is the lack of research examining the first stage of contact: interaction with police. Although the police are an important part of the juvenile justice system and maintain a high level of discretion regarding contact with juveniles, little research has studied this issue. To obtain a truly accurate understanding of DMC, future research should attempt to include measures of prior police-youth interactions and—if possible—indicators of “differing police presence, patrolling, and profiling in minority and non-minority neighborhoods” (Piquero, 2008, p. 65). Doing so would fill a large gap in the body of DMC literature and provide an even more thorough examination of the connections among the stages of the juvenile justice system. In addition, studies that combine both police and court data may be better able to address the underlying cause(s) of DMC, namely whether it results from differential treatment, differential offending, or some combination of the two.

**Disaggregating Data by Offense Type and Sex**

This study did not run separate analyses based on youths’ sex or offense type. Instead, both males and females and youth charged with any of the five offense categories were included in the models. While this is not necessarily a limitation of the study, it is something that future research should address. For example, recall from Chapter 2 that a large proportion of racial disproportionality in the juvenile justice system occurs with youth charged with drug offenses (NCCD, 2007). Bishop and Leiber (2011), however, found that there was little race difference in drug usage among youth. Taken together, these findings suggest that minority drug offenders may be receiving differential treatment compared to White drug offenders. Future research should examine this potential race-offense type interaction (see Sullivan et al., 2016).

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Similarly, some research has posited that the relationship between race and juvenile court decision-making may vary based on youths’ sex. In other words, the “effect” of race on court outcomes may differ among White males, Non-White males, White females, and Non-White females. For example, males—both White and Non-White—may be viewed by juvenile court personnel as more dangerous and/or culpable compared to females (Brown & Sorensen, 2013; Steffensmeier et al., 1998). Furthermore, in their study of race, sex, and preadjudication detention, Guevara et al. (2006) concluded that a significant race effect was present only when comparing White and Non-White males; there was no significant difference in the odds of detention for White and Non-White females. While this study touches on these issues by using exact matching for sex and offense type, future research may be better served by running separate analyses and comparing any potential interaction effects. In addition, future analyses could examine the differences among the race/sex combinations in terms of penetration into the juvenile justice system, as well as the degree of interdependence among the court outcomes.54

CONCLUSION

This dissertation addressed two limitations often found in prior disproportionate minority contact research. First, the majority of prior DMC studies have focused on a single juvenile court and/or a single stage of the court process. Due to the interconnectedness among court outcomes and the variation in decision-making processes across juvenile courts, these studies may

54 An alternative method of studying how race affects the degree of penetration into the juvenile justice system would be to use an ordinal-level outcome measure. For example: 0=case dismissed/diverted at intake; 1=case petitioned to court but not adjudicated delinquency; 2=adjudicated delinquent with minor disposition; 3=adjudicated delinquent with probation disposition; 4=adjudicated delinquent with secure confinement disposition; 5=waived to criminal court.
underestimate any possible effects of race on decision-making. As such, this dissertation used a sample of over 50,000 youth referred to seven juvenile courts in Ohio to examine the relationship between race and five juvenile court outcomes. Second, to obtain a true depiction of DMC, research must examine White and Non-White youth who are as similarly-situated as possible in all attributes except race. Unfortunately, the statistical analysis most often used to achieve this—multivariate logistic regression—may not be the most effective method to study DMC due to a number of potential weaknesses. As such, this dissertation examined the relationship between race and court outcomes using four counterfactual statistical methods and suggested that these methods are better equipped to study disproportionality than logistic regression—at least with finite samples.

The use of methodological triangulation made this one of the most methodologically-rigorous investigations of DMC to date. Findings from the various statistical analyses indicated that Non-White youth were significantly more likely than White youth to be detained prior to adjudication, placed in secure confinement after adjudication, and waived to criminal court, even after controlling for a number of legally-relevant and extralegal variables. There was no consensus among the analytic techniques for case dismissal or adjudication, and the techniques that did indicate a significant relationship found that White youth received worse outcomes at these decision-points.

The results of this study provided significant contributions to both the substantive and methodological literature. This study showed that although DMC was present at some stages of the juvenile courts included in the study, it was not present at every stage. In addition, the finding that similarly-situated White and Non-White youth received significantly different outcomes at the detention, secure confinement, and waiver stages provided a strong foundation for examining
the differential treatment hypothesis more extensively based on a methodologically rigorous study. From a methodological perspective, this dissertation contributed to the literature by demonstrating the strengths and weaknesses of five analytic techniques as they pertain to studying DMC. Based on the findings—as well as available post-analysis diagnostics, covariate balance, and the fit between the data and the various techniques—this study suggested that nearest neighbor matching with exact matching is the best-equipped statistical technique to produce accurate estimates of the presence and extent of DMC in the juvenile justice system. Future research might build on this dissertation by including additional evidence-based independent/matching variables, including police-juvenile contact data, and breaking down analyses based on youths’ sex and offense type.
References


# APPENDIX A

## Average Treatment Effects for the Treated – Case Dismissal

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**APPENDIX B**

### NNM Analyses with One Nearest Neighbor Match

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### Pre- and Post-Analysis Balance Summary – Case Dismissal

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**APPENDIX D**

Pre- and Post-Analysis Balance Summary – Preadjudication Detention

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## APPENDIX F

Pre- and Post-Analysis Balance Summary – Secure Confinement

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### APPENDIX G

Pre- and Post-Analysis Balance Summary – Waiver

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