MINORITY REPRESENTATION IN POLICING: INTEGRATING REPRESENTATIVE BUREAUCRACY AND STRUCTURAL CONTINGENCY THEORIES

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MINORITY REPRESENTATION IN POLICING: INTEGRATING

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THEORIES

by

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ABSTRACT

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Scholars, police leaders, lawmakers, and the media have long suggested that a simple way to improve the effectiveness of the police is to increase departmental diversity. This idea is rooted in representative bureaucracy theory, which suggests that organizations that are more representative of their constituents have better outcomes. Relatedly, structural contingency theorists propose that organizational environments influence organizational structure, which in turn influences organizational performance.

The current study combines these theories to create a structural contingency model of representative bureaucracy and tests the model within a policing context. Specifically, it is proposed that disparities between women and men, Latinx and White, non-Latinx individuals; and Black and White, non-Latinx individuals within communities impact the percentage of women, Latinx, and Black officers employed by large municipal police departments, and the representation of these groups positively impacts index offense reporting and clearance rates. These propositions are tested using mixed-effects regression models for the analysis of longitudinal data with the population of large municipal police departments in the US from 1987 to 2017.

Results provide some support for the structural contingency model of representative bureaucracy. Minority representation in police departments has been increasing over time and is strongly related to the carrying capacity of the environment, but there is little evidence for the individual impact of various measures of disparity. Social disorganization is not an adequate instrumental variable for isolating the reporting rate of crimes using the Uniform Crime Reports. Measures of relative representation perform better than measures of absolute representation for representative bureaucracy theory. The Black relative representation rate was related to significant increases in clearance rates of several index offenses while the Latinx relative representation rate had the opposite effect. The difference is likely due to lower rates of Latinx relative representation in US police departments.

There are compelling reasons for increasing the diversity of police departments aside from gains in effectiveness, including increasing citizen trust in the police and preventing the concentration of power in a single demographic group. Police leaders looking to increase the diversity of their departments should implement proactive programs for the recruitment of minority officers.

KEY WORDS: Representative bureaucracy theory, Structural contingency theory, Policing, Organizations, Minority employment, Crime clearance, Index offenses, Mixed-effects regression models, Longitudinal research, Gender, race, and justice

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PREFACE

The democratic state cannot afford to exclude any considerable body of its citizens from full participation in its affairs. It requires at every point that superior insight and wisdom which is the peculiar product of the pooling of diverse streams of experience. In this lies the strength of representative government. Upon it depends the superiority of the democratic Civil Service over its totalitarian rivals. In a democracy competence alone is not enough. The public service must also be representative if the State is to liberate rather than to enslave. J. Donald Kingsley, 1944, p. 185.

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CHAPTER I

Introduction

The 1960s saw an unprecedented number of riots in the United States. From 1964 to 1971, there were upwards of 750 of these events (Postrel, 2004). Early in 1967, riots broke out in 23 cities, prompting President Lyndon B. Johnson to establish the National Advisory Commission on Civil Disorders (also known as the Kerner Commission) to investigate the causes of the civil unrest (The National Advisory Commission on Civil Disorders, 1968). The Kerner Commission (1968) concluded that “the most fundamental [factors influencing the riots was] the racial attitude and behavior of white Americans toward black Americans.” (The National Advisory Commission on Civil Disorders, 1968, p. 5). Symptomatic of these racial attitudes was “[*p*]*ervasive discrimination and segregation* in employment, education, and housing” which served to keep Black Americans from economic progress (The National Advisory Commission on Civil Disorders, 1968, p. 5, emphasis in original). The police, among other institutions, were implicated as supporting White racial attitudes and thus catalyzing the riots (The National Advisory Commission on Civil Disorders, 1968). The Commission recommended police forces hire more Black officers, review promotion requirements to allow more Black officers to move into supervisory positions, and to assign Black officers “to ensure that the police department is fully and visibly integrated” (The National Advisory Commission on Civil Disorders, 1968, p. 166). The report of the Kerner Commission was among the first national calls for the diversification of police forces, but it was not the last.

In the wake of protests following the shooting of Michael Brown in Ferguson, Missouri in 2014, then-President Barack Obama convened a similar commission tasked with identifying ways to improve police-community relations and reduce crime in the United States. Again, one of the recommendations of the report was to increase the diversity of the nation's police in order to improve citizen trust in and perceptions of legitimacy of the police (President's Task Force on 21st Century Policing, 2015). The President's Commission made explicit that diversity should not just include race, but should also include gender, language, life experiences, and cultural backgrounds. More recently, national news outlets have cited better representation of women as a simple way to improve the effectiveness and perceptions of legitimacy of the police (Asquith, 2016; Fantz & Tolan, 2020; Newton-Small, 2016; Wallace, 2017) and some empirical literature has supported the notion that increases in women police decrease use of force incidents (Lonsway et al., 2002; Porter & Prenzler, 2017; c.f. Schuck & Rabe-Hemp, 2014; Smith, 2003).

The reports by the national commissions and news outlets touch on two different mechanisms through which it is thought that diversity leads to better policing. The first is that people with a diverse range of backgrounds and experiences police differently. The Kerner Commission, for example, reasoned that Black officers could provide information about urban neighborhoods and be more effective at responding in riot situations (The National Advisory Commission on Civil Disorders, 1968). Similarly, calls for more women in policing have argued that women are less violent and more likely to take reports of violence against women seriously than are men (Asquith, 2016; Fantz & Toln, 2020; Newton-Small, 2016; Wallace, 2017). The second concerns the way in which civilians respond to diversity. Police departments that are more representative of their citizens are expected to elicit trust in and a feeling of legitimacy of the department (President's Task Force on 21st Century Policing, 2015). This may lead to less racial tension between police and citizens (The National Advisory Commission on Civil Disorders, 1968) and more women reporting instances of violent crime (Newton-Small, 2016).

Each of these reports implicitly references representative bureaucracy, an organizational theory that proposes that greater representation of social groups in organizations leads to better policies, procedures, and outcomes for the represented social groups (Kingsley, 1944; Krislov, 1974; Mosher, 1968). While research on policing has long included measures of the percentage of minority officers in departments for a variety of outcomes, the theory has just recently been cited in the policing literature (see Andrews & Miller, 2013; Hong, 2016; Meier & Nicholson-Crotty, 2006; Morabito et al., 2017; Shjarback, et al., 2017). The findings from some studies are tentatively hopeful. Greater representation of women in police departments has been associated with less gender disparity in speeding citations (Farrell, 2015) and an increase in arrests for intimate partner violence (Andrews & Miller, 2013) and sexual assault (Meier & Nicholson-Crotty, 2006). The findings regarding increased representation of officers of color, however, has been more mixed.

Despite calls for greater diversity as well as the theoretical and empirical backing of the idea, women and people of color have continued to be underrepresented in United States police departments. According to the most recently available data from the Law Enforcement Management and Administrative Statistics (LEMAS) survey, there were more than 12,000 local police departments employing approximately 477,000 police officers in the United States in 2013 (Reaves, 2015). Though women comprised just over half of the US population, police departments across the nation reported an average of 9.11% of their officers being women (U.S. Census Bureau, 2013; Bureau of Justice Statistics (BJS), 2013). Latinx individuals represented 16.6% of the population, but on average only 6.17% of officers. Similarly, approximately 12% of the U.S. population was Black, but the average police department employed Black officers at a rate of 6.09% (U.S. Census Bureau, 2013; BJS, 2013). Of the 2,826 departments surveyed by the Bureau of Justice Statistics, nearly one-quarter (23.54%) of departments employed no women officers, and nearly half (48.18% and 46.12%, respectively) employed no Latinx or Black officers (BJS, 2013).

As low as the rates of representation were in 2013, they represent an increase over time. Since the beginning of the collection of the LEMAS survey data in 1987, there has been a four percentage-point increase in women in local police departments and ethnic and racial minority representation has nearly doubled (Reaves, 2015). The underrepresentation of women, ethnic, and racial minorities in US police departments, however, is echoed (though magnified) as compared to other components of the criminal justice system in the US. The Bureau of Labor Statistics (2020) reports that in 2019, women made up 36.4% of lawyers, 52.5% of judges, magistrates, and other judicial workers; 44.6% of probation officers and correctional treatment specialists; and 30.1% of bailiffs, correctional officers, and jailers. Latinx individuals comprised 5.8% of lawyers, 8.6% of judges, magistrates, and other judicial workers; 15.8% of probation officers and correctional treatment specialists; and 12.3% of bailiffs, correctional officers, and jailers.

For Black individuals, those numbers were 5.9%, 13.4%, 26.7%, and 34.2%, respectively. It is interesting that women have broken into and increased their numerical representation in these traditionally male-dominated fields (Batton & Wright, 2019), but have remained particularly underrepresented in policing.

The estimates presented on representation in US policing mask important differences in representation by level of government and police department size. Federal police agencies employed greater percentages of women than did departments at lower levels of government (Hyland, 2018), and larger departments were more diverse overall than smaller departments (Reaves, 2015). In 2013, approximately 12% of municipal police officers were women; departments serving less than 25,000 residents had an average of 7% women officers while those serving more than 250,000 had more than double that amount (17%). Likewise, 27% of local officers in 2013 were non-White, with larger jurisdictions (those serving over 500,000 residents) employing an average of more than 40% people of color and smaller jurisdictions (those serving less than 50,000 residents) employing less than 20% of their officers from these populations (Reaves, 2015). Unfortunately, the LEMAS data collection no longer allows for the disaggregation of officers by both race and gender, so current information on the representation of women of color is unknown.

Research evidence has begun to accumulate about the effects of representation of women and people of color in police departments, but no clear pattern of findings has emerged. This may be due to a number of factors, including the variety of dependent variables examined (outcomes have included traffic stops and citations; intimate partner violence arrests; sexual assault reports, arrests, and clearances; simple assaults;

aggravated assaults; racist crime incidents; and clearance and arrest rates for property, violent, and drug crimes), the operationalization of representation (including measures of percent representation, diversity indices, and diversity ratios), and the lack of longitudinal research. Research has also begun to identify some of the factors related to representation, but most of this research has been done on organizational-level (rather than community-level) factors.

The purpose of the current study is to advance the understanding of the predictors and effects of gender, ethnic, and racial minority representation in policing while furthering representative bureaucracy theory. In support of these goals, a survey of prior research on representative bureaucracy theory is presented, followed by a comprehensive review of English-language literature on the impact of the representation of women and people of color in policing on organizational level indicators of performance. Next, a review of the structural contingency theory literature and studies using measures of the organizational environment to examine representation are presented. A theoretical integration of representative bureaucracy and structural contingency theories is delivered, wherein representation is treated as an element of police department structure that is affected by the organizational environment and, in turn, affects organizational functioning. Finally, it tests the propositions longitudinally by examining the effects of community-level factors (especially inequality) on representation and the effects of gender, ethnic, and racial minority representation on index crime reporting and clearance rates with a sample of large municipal police departments. Specifically, data from the population of large municipal police departments in the United States from 1987 – 2013 are used to test the theory.

CHAPTER II

Literature Review

The idea that civil servants should be representative of the populations they serve is as old as the idea of democracy, but it was not until 1944 that the term “representative bureaucracy” was coined (Krislov, 1967). Since that time, representative bureaucracy theory has evolved through the political, public administration, and diversity management literatures (Groeneveld & Van de Walle, 2010) and has been translated from a purely organizational theory to one which incorporates individual-level concepts. Representative bureaucracy theory makes propositions similar to both institutional organizational theory (that a more representative organization is more legitimate in the eyes of its stakeholders) and structural contingency theory (that more representative organizations perform better than less representative organizations), yet it has never been formally linked to either. In brief, the current study tests representative bureaucracy theory in policing and integrates representative bureaucracy and structural contingency theories to understand the environmental correlates of representation of women and people of color in policing. Prior to a more in-depth description of the current study, I provide a brief history and theoretical exposition of representative bureaucracy theory, comprehensively review its application in the policing literature, introduce structural contingency theory, and present the extant literature relating environmental factors to police representation.

Representative Bureaucracy Theory

The concept of representative bureaucracy was first described in 1944 by J. Donald Kingsley in his work examining the British civil service. Though he did not precisely define the concept of representativeness nor expound a formal theory, Kingsley’s (1944) central argument was that the civil service needed to better reflect the class structure of society (Groeneveld & Van de Walle, 2010; Kim, 1994). His concern was that hierarchical educational requirements for the civil service system virtually ensured that bureaucrats would predominantly come from the middle- and upper-classes, since they were the group privileged enough to pay for the type of education required (Kingsley, 1944). The danger in this, he held, was that privileged bureaucrats would not necessarily understand or empathize with lower-class constituents, and thus create a less effective bureaucracy. Kingsley (1944) also identified another problem: a bureaucracy unrepresentative of the people it serves breeds distrust in the underrepresented groups. While the main focus of the work was on social class representation, Kingsley (1944) also argued in favor of an increase in the number of women accepted into the civil service, saying, “For it is precisely because the female administrator is so exceptional and because women do not enjoy equality of opportunity inside, or outside, the service” that it is important they be allowed to participate (p. 185).

Similar to Kingsley’s (1944) work, the first comprehensive discussion of representative bureaucracy in the US regarded it as vital for preventing the consolidation of power in the higher social classes. Long (1952) argued that election to the U.S. Congress or office of the President all but required economic power, which served to make US politics more oligarchic than democratic. The role of bureaucracy under constitutionalism, he argued, was not to be subservient to Congress, but rather to serve as an intermediary between the government and the people through its role in the creation and administration of public policy. That bureaucrats were more representative of US society as a whole was desirable:

> Lacking a caste system to wall them off from their fellows, the members of [the civil service] are likely to be more responsive to the desires and needs of the broad public than a highly selected slice whose responsiveness is enforced by a mechanism of elections that frequently places more power in the hands of the campaign-backers than voters…Given the seemingly inevitable growth in the power of the bureaucracy through administrative discretion and administrative law, it is of critical importance that the bureaucracy be both representative and democratic in its composition and ethos (Long, 1952, p. 812-813).

The following decades saw academic interest in representative bureaucracy move out of an exclusively political arena and into the field of public administration, with a subsequent focus not on power, but on equal opportunity (Groeneveld & Van de Walle, 2010). Under this tradition, Krislov identified four meanings of representative bureaucracy, with the first exemplifying the equal opportunity ideal: "that all social groups have a right to political participation and to influence" (1967, p. 64), with bureaucratic representation one way to achieve this. His other three meanings of representative bureaucracy included a "functional" argument that more diverse bureaucracies would be better able to achieve their mandates, and he maintained that bureaucracies reflect values and power realities and create the possibility of societal change (Krislov, 1967, p. 64). Krislov (1974) later added to the theory a symbolic component: that bureaucracies should be representative of the whole of society in order to be considered legitimate (Groeneveld & Van de Walle, 2010).

Up until this point, representative bureaucracy focused on organizations, with theoretical arguments centering the representation of various social groups in bureaucracies. Mosher (1968) added an individual-level component to the theory when he made a distinction between two types of representation. First was passive representation, and in line with earlier conceptualizations, it was the extent to which organizations were descriptively representative of the demography of the populations they served. Like Long (1952), Mosher (1968) maintained that bureaucracies were essential to a well-functioning democracy and that passively representative bureaucracies played an important symbolic role in this (Kim, 1994; Lim, 2006; Riccucci & Van Ryzin, 2017). Mosher's (1968) addition to the theory was the concept of active representation, or the extent to which bureaucrats actively advocated on behalf of the groups they represented. He disapproved of this individual-level type of representation on the basis that it constituted a form of bias and was antithetical to achieving goals in the common interest (Mosher, 1968).

Though Mosher (1968) disapproved of active representation, the bulk of empirical research from the publication of his book forward focused on establishing a link between passive and active representation (Lim, 2006). The link between the two was hypothesized to be dependent on a number of things, including whether the policy or outcome was meaningful to the social group and whether the bureaucrat had discretion (Thompson, 1976). Little attention, however, was given to the mechanisms through which representation was expected to produce outcomes (Lim, 2006). Lim (2006) corrected this. Exemplifying Mosher's (1968) ideals of active representation, minority bureaucrats may show preference for minority citizens, or they may share values and beliefs with people sharing their background, empathy for those values and beliefs (even if they no longer share them), a sense of group identification, or maintain better communication with in-group members that lead the bureaucrats to make positive changes on behalf of their group (Lim, 2006).

Lim (2006) claimed that active representation, however, was unnecessary for representative bureaucracy to produce substantive benefits for minority groups. Minority bureaucrats may denounce or intervene in discriminatory behavior by other bureaucrats, non-minority bureaucrats may censure their own behavior in response to the presence of minority colleagues, and a combination of these may lead to a cultural shift over time (Lim, 2006). Minority bureaucrats may also indirectly affect the relationship between clients and the bureaucracy. An increase in minority representation in organizations may encourage minority citizens to interact with the organization more (i.e., demand inducement) or make some type of behavioral change that improves an organizational program’s chances of success (i.e., coproduction inducement) (Lim, 2006). Without controlling for the indirect effects that bureaucrats could have on minority clients, researchers were unable to establish a true link between passive and active representation but could still explore whether represented groups benefitted when people sharing their characteristics worked in organizations (Lim, 2006).

The diversity management field eventually took up the mantle of representative bureaucracy theory, with a shift in focus from affording equal opportunities to social groups through representative bureaucracy to the best ways to manage organizational diversity (Groeneveld & Van de Walle, 2010). This newest iteration of representative bureaucracy theory was a return to Krislov’s (1967) second concept: that diversity in organizations serves to increase performance and improve efficiency (Groeneveld & Van de Walle, 2010).

Thus, proponents of representative bureaucracy made two claims about the value of representation in organizations. First was a contingency argument: that bureaucracies more representative of their constituents would be more effective and have better outcomes for the represented groups (e.g., Kingsley, 1944; Krislov, 1967; Meier, 2019). The second was more symbolic (i.e., institutional) in nature: that representation increases trust in and confers legitimacy on the organization (e.g., Kingsley, 1944; Krislov, 1967; Mosher, 1968; Riccucci & Saidel, 1997). The three theoretical traditions of representative bureaucracy share two other commonalities (Groeneveld & Van de Walle, 2010). First, they assume that civil servants are not neutral automatons enacting existing policy; rather, bureaucrats act and interact in their jobs (i.e., have discretion) in ways that may make their social characteristics important. Second, they assume that the policy issue or outcome in question must have some meaning to the social group for bureaucrats of that group to affect it (this concept has been referred to both as salience and value congruence) (Groeneveld & Van de Walle, 2010).

The empirical literature is broadly supportive of the claims of representative bureaucracy theory. First, there is evidence that bureaucrats' values are at least partially shaped by social characteristics. For instance, female heads of state agencies reported being significantly more liberal politically, economically, socially, and morally than their male counterparts (Bowling et al., 2006) and women serving as child support enforcement supervisors reported significantly different organizational priorities than men in the same position (Wilkins, 2006). Bureaucrats of color were more likely to view improving conditions for minorities as part of their jobs (Bradbury & Kellough, 2007; Meier & Nigro, 1976; Selden et al., 1998) and stress the value of efficiency, effectiveness, and social equity in organizations than were White bureaucrats (Stazyk et al., 2017). Additionally, Black bureaucrats were more likely to share similar attitudes and values with their Black constituents than were White bureaucrats. White bureaucrats displayed little value congruence with their White constituents either. White constituents had more values in common with Black bureaucrats (Bradbury & Kellough, 2007).

Second, there is evidence that minority bureaucrats may behave differently than non-minority bureaucrats and that bureaucrats' minority status may change the client-bureaucrat relationship. While neither gender nor race of county supervisors of the Farmer's Home Administration directly affected the percentage of housing loans granted to minorities, acceptance of a minority representative role did, and minority bureaucrats were more likely to claim that role than were White bureaucrats (Selden et al., 1998; Sowa & Selden, 2003). Women reported being more likely to engage in a recycling and composting program when there were more women in the organization (Riccucci et al., 2016), and job seekers were both more likely to take steps to- and actually enroll in- an educational program within six months when they worked with a bureaucrat of their same gender (Guul, 2018).

Finally, representative bureaucracy at an organizational level enjoys support in multiple contexts. In public education, greater percentages of female and racial and ethnic minority teachers have been linked to greater passing rates of minority students (Favero & Molina, 2018; Keiser et al., 2002; Meier, 1993; Meier et al., 1999), greater odds of racial and ethnic minority students being placed in gifted and talented programs (Capers, 2018; Grissom & Nicholson-Crotty, 2009; Meier, 1993), and fewer students of color receiving corporal punishment and out-of-school suspensions (Grissom & Nicholson-

Crotty, 2009; Meier, 1993). Municipal governments employed greater percentages of Black full-time employees when they had a Black personnel director (Goode & Baldwin, 2005). At the federal level, Black representation of Equal Employment Opportunity Commission investigators was associated with a significant increase in the number of discrimination suits filed on behalf of Black employees (Hindera, 1993). Additionally, Presidential request budgets increased the number of line items for women and bilingual and immigrant education with greater representation of minorities in the senior executive service (Kim, 2003), and the goal achievement rate in federal agencies with a social justice orientation was greater in agencies with greater minority representation (Lee, 2019).

Representative Bureaucracy in Policing

The term "representative bureaucracy" is relatively new to the policing literature (it first appeared in Meier and Nicholson-Crotty's 2006 article), but researchers have long considered the effects of diversity in police organizations. While some researchers have found significant differences between women and men and non-White and White police officers in behaviors involving service (e.g., Brown et al., 2009; Schulenburg, 2015), detection (e.g., Rydberg & Terrill, 2010), arrest (e.g., Mastrofski et al., 1995; Novak et al., 2011; Robinson & Chandek, 2000; Schulenburg, 2015), and use of force (Donner et al., 2017; Ingram et al., 2018; Porter & Prenzler, 2017), others reported no differences (e.g., Alpert et al., 2005; Dixon et al., 2008; Fridell & Lim, 2016; Mastrofski et al., 1996; Rossler & Terrill, 2017; Tillyer & Engel, 2013; Worden, 1994; Worrall et al., 2018).

The focus of the current project, however, is on the substantive effects of representation at the organizational level rather than the question of active representation at the individual level. The literature on crime outcomes is summarized in Table 1, in which study information including the citation, sample, dependent variable, and independent variables of interest (i.e., measures of gender, ethnic, or racial minority representation or diversity) and their relationships with the dependent variables are presented. A quick view of the table reveals some patterns. There are more consistently significant relationships between the representation of women officers and police outcomes than between the representation of officers of color and outcomes. Furthermore, the relationships observed for the effects of women are more likely to be in line with the predictions of representative bureaucracy theory than are the relationships observed for officers of color.

In the following sections, I review the findings regarding the substantive effects of minority representation on all indicators of police performance in the literature: policy creation, traffic violations, sexual assault, intimate partner violence, other crimes, and police misconduct and use of force as well as on citizen perceptions of performance, trustworthiness, and fairness. I then summarize and contextualize these findings, providing potential explanations for mixed and unexpected findings. I have structured the literature review in this way in order to clearly distinguish the results reported in the prior literature from my interpretations of the causes of convergent and divergent results.

Table 1

Summary of Studies Incorporating Measures of Representation for Crime Outcomes

Study	Sample	DV	Key IVs (relationship)
		Traffic Violations	
Farrell (2015)	37 local PDs: Rhode Island; 2005	Speeding citation gender disparity:	% sworn female (-) Female * % sworn female (+) % female employees (+)
		Non-speeding citation gender disparity:	% sworn female (NS) Female * % sworn female (+) % female employees (NS)
Hong (2016)*	42 PDs: England & Wales; 2000-2001	Racial disparity in stop & search:	% sworn minorities (+)
Shjarback et al. (2017*	150 local PDs: Illinois & Missouri; 2007	White disparity index for traffic stops:	% White officers/% White population (NS)
		Black disparity index for traffic stops:	% Black officers/% Black population (+)
		Hispanic disparity index for traffic stops:	% Hispanic officers/% Hispanic population (NS)
Wilkins & Williams (2008)	8 police divisions: San Diego; 2000	Black disparity in vehicle stops:	% Black officers (+)
Wilkins & Williams (2009)	8 police divisions: San Diego; 2000	% vehicle stops involving a Latino driver:	% Latino officers (+)
		Sexual Assault	
Johnston & Houston (2018)*	43 PDs: England & Wales; 2002-2011	Number gender-based violence arrests (includes IPV; same year):	N senior female officers (-) Female/male officer ratio (-)
		Number gender-based violence arrests (includes IPV; one year lag):	N senior female officers (NS) Female/male officer ratio (-)

(continued)

Study	Sample	DV	Key IVs (relationship)
Meier & Nicholson-Crotty (2006)*	60 large metro counties: US; 1990-1997	Sexual assault report rate:	% sworn female (+)
		Sexual assault arrest rate:	% sworn female (+)
		Sexual assault arrest rate, controlling for reports:	% sworn female (+)
Morabito et al. (2017)*	152 PDs: US; 2007-2008	Sexual assault case open (vs. arrest):	% sworn female (NS) ≥12% sworn female (NS)
		Sexual assault case cleared exceptionally (vs. arrest):	% sworn female (NS) ≥12% sworn female (NS)
Schuck (2018)*	Municipal PDs: US; 1997-2013	Number sexual assaults reported (cross-sectional):	% female officers (+ 5 years)
		Number sexual assaults cleared (cross-sectional):	% female officers (+ 4 years)
		Number SA reported (longitudinal):	% female officers (-) % female officers*time (+)
		Number SA cleared (longitudinal):	% female officers (-) % female officers*time (+)
		Number SA reported (growth curve):	% female officers (-) % female officers*time (+) % Black officers (NS) % Black officers*time (-)
		Number SA cleared (growth curve):	% female officers (-) % female officers*time (+) % Black officers (NS) % Black officers*time (-)
Walfield (2016)	238 large PDs: US; 2007	Arrest (vs. exceptional clearance) for SA:	% sworn female (+)
		Domestic Violence	
Andrews & Miller (2013)*	38 PDs: England; 2004-2007	Average DV arrest rate:	Female chief constable (+) % sworn females (-) Police discretion (-) Female police*discretion (+)

(continued)

Study	Sample	DV	Key IVs (relationship)
Dichter et al. (2011)	PDs: US; 2000, 2003	Overall IPV arrest rate:	% sworn female (-)
		Female only IPV arrest rate:	% sworn female (-)
		Male only IPV arrest rate:	% sworn female (-)
		Dual IPV arrest rate:	% sworn female (-)
Eitle (2005)	115 PDs: US; 2000	Probability of arrest for IPV (includes SA):	% sworn female (NS)
Miller & Segal (2018)*	255 large counties: US; 1977-1991	Intimate partner homicide rate (female vics):	% female officers (-)
		Intimate partner homicide rate (male vics):	% female officers (-)
		Number non-fatal IPV assaults in previous 6 months:	% female officers (-)
		<u>Other Crimes</u>	
Donohue & Levitt (2001)	122 large PDs: US; 1977-1993	Total arrest rate (White):	% non-White police (+)
		Total arrest rate (non-White):	% White police (NS)
		Property arrest rate (White):	% non-White police (NS)
		Property arrest rate (non-White):	% White police (+)
		Violent arrest rate (White):	% non-White police (+)
		Violent arrest rate (non-White):	% White police (NS)
		Drug arrest rate (White):	% non-White police (+)
		Drug arrest rate (non-White):	% White police (NS)
		Arrest probability for simple assault:	% sworn Black (+)
		Arrest probability for agg. assault:	% sworn Black (NS)
Eitle et al. (2005)	105 PDs: US; 2000	Arrest probability for simple assault:	% sworn Black (+)
		Arrest probability for agg. assault:	% sworn Black (NS)

(continued)

Study	Sample	DV	Key IVs (relationship)
Hong (2016)*	42 PDs: England & Wales; 2000-2010	Number of total crime incidents:	% sworn minorities (-) % minority * size (NS)
		Number of racist crime incidents:	% sworn minorities (-) % minority * size (NS)
Hur (2013)*	464 PDs: US; 2003	Clearance rates of violent crimes:	Police racial diversity (-)
		Clearance rates of property crimes:	Police racial diversity (-)
		Clearance rates of index crimes:	Police racial diversity (-)
Miller & Segal (2018)*	40 largest MSAs: US; 1979-1991	Violent crime reporting by female victims:	Female officer share (+) DV*female officer share (+)
Sharp (2014)*	Cities 100,000+ population; 2003	Order maintenance arrest rate for Black citizens (Mayoral cities):	Black mayor (NS) Black city councilpersons (-)
		Order maintenance arrest rate for Black citizens (Council-manager cities):	Black mayor (NS) Black city councilpersons (NS)

*Denotes studies using representative bureaucracy framework

Policy Creation

The creation of policies is one mechanism through which increased representation might affect outcomes for citizens and has been studied in the context of hate crimes, racial profiling, and intimate partner violence (Farris & Holman, 2015; Jenness & Grattet, 2005; Miller, 2013). Jenness & Grattet (2005) created a measure of “perviousness,” or susceptibility to environmental influence, in their study of the adoption of hate crime policies by municipal and county police in California. The perviousness measure included workplace diversity as well as commitment to principles of community-oriented policing and was found to significantly increase the likelihood that a police department had adopted a hate crime policy. Because this was an aggregate measure, however, it is unclear whether representation had an independent effect on policy adoption.

In his study of the adoption of anti-profiling policies, Miller (2013) examined the effect of police diversity by including a Gini-Simpson index of gender and racial diversity. He found no relationship between this measure of diversity and adoption of anti-racial profiling policies, and a significant negative relationship between diversity and participation in the Stop Data Collection Program (Miller, 2013). Similarly, Farris and Holman (2015) reported no relationship between domestic violence policies and either the percentage of sheriffs' deputies who were women or the percentage of women in supervisory positions in sheriffs' departments.

Traffic Violations

Traffic violations provide an ideal context in which to examine the effects of representative bureaucracy in policing, particularly for people of color. Stop and citation decisions are highly discretionary and concerns about racial profiling may make them salient for Black and Latinx police officers (Shjarback et al., 2017; Wilkins & Williams, 2008, 2009). The results of these studies, however, have been contrary to the hypotheses of representative bureaucracy. Wilkins and Williams (2008, 2009), for example, examined the effects of the percentage of Black and Latinx officers in San Diego Police Department's eight police districts on the disparity between the percentage of stops of Black drivers compared to the Black driving population and the percentage of vehicle stops involving a Latinx driver, respectively. The percentage of Black and Latinx officers were related to significant increases in vehicle stops for each of these groups (Wilkins & Williams, 2008, 2009). Likewise, the percentage of sworn racial minority officers in English and Welsh police departments was also associated with significant increases in racial disparities in stop and search practices (Hong, 2016). Shjarback and colleagues

(2017) reported that the more closely a police department's percentage of Black officers mirrored their percentage in the city's population, the more the disparity in vehicle stops for Black drivers relative to the driving population increased. The same effect was not observed for Latinx and White officer representation on stop disparities for their respective groups (Shjarback et al., 2017). Potential explanations for these unexpected results and others are presented in the Summary section on page 31.

While there has been less public concern about gender disparities in moving violations than racial disparities, research has reported a fairly consistent pattern of lenient treatment of women by the police (though this effect has varied by community; Farrell, 2015). Farrell (2015) reported that controlling for incident characteristics, increasing the percentage of female police officers in local police departments decreased the likelihood that men would be cited for speeding (but not non-speeding) violations. In both the speeding and non-speeding models, a significant interaction was observed between female drivers and the percentage of female officers employed by the police agency such that women stopped in police departments employing a greater percentage of sworn women were more likely to be cited than in departments with fewer women police officers. The combined effects resulted in less disparities between women and men in traffic citations (Farrell, 2015).

Gender-Based Violence

Sexual assault and domestic violence are also ideal crimes to study the effects of representative bureaucracy. Though police officers may have less discretion in dealing with these crimes (due to the increase in offense seriousness and preferred arrest policies for domestic incidents), they have been defined as a women's issue through the political process (see Keiser et al., 2002) and so theoretically have a high degree of salience to women police officers. In the first introduction of representative bureaucracy theory to policing, Meier and Nicholson-Crotty (2006), for example, explored the effects of female representation on sexual assault reporting and clearance rates in 60 large US police departments using pooled data from 1990 to 1997. They reported that departments employing greater percentages of women experienced significantly greater numbers of sexual assault reports and arrests (Meier & Nicholson-Crotty, 2006). Later, Walfield (2016) reported a similar effect in 238 large US municipal and sheriff's offices. Controlling for incident-level characteristics, each percentage point increase in female officers employed by the department was associated with a significant 22% increase in the log-odds of a sexual assault case being cleared by arrest rather than exceptional means (Walfield, 2016).

The most comprehensive study to date combined data from the 1997, 2000, 2003, 2007, and 2013 Law Enforcement Management and Administrative Statistics (LEMAS) surveys with data from the US Census Bureau and the Uniform Crime Reporting program to assess the effects of female representation in police departments over time. Schuck (2018) found that in each of the five sexual assault reporting and four of the five sexual assault clearance cross-sectional models that the percentage of female officers was positively associated with the outcomes. Likewise, in the longitudinal models, police departments overall experienced a significant increase in rape reports over time and the departments with greater female representation experienced a greater increase in reports. Clearance rates, on the other hand, decreased over time but the decrease was not as severe in departments with greater percentages of female officers (Schuck, 2018). In sum, greater female representation was associated with an increase in sexual assault reporting and clearance rates over time.

Similar effects, however, have not been observed across all studies. Morabito, Pattavina, and Williams (2017) used data from 152 US police departments of varying sizes to examine the effects of representative bureaucracy on the relative odds of sexual assault cases being left open or cleared by exceptional means rather than being cleared by arrest. Besides including the percentage of female officers employed by departments, the authors also used an original measure to attempt to capture a “tipping point,” or whether representation must reach a certain critical mass before substantive effects are observed. Morabito and colleagues (2017) used the national average for female representation in police departments (approximately 12%) to create a dummy variable indicating whether the department had reached or exceeded the national average or not. The authors found no evidence that either the percentage of female officers employed by the department nor the tipping point measure exerted any influence on the likelihood of a case being left open or cleared by exceptional means rather than cleared by arrest (Morabito et al., 2017). Johnston and Houston (2018) took a different approach by exploring the impact of the number of senior (rather than line-level or the overall percentage) female officers on the number of gender-based violence arrests (most of which were sexual offenses, but also included intimate partner violence) in England and Wales from 2002 to 2011. They also included the ratio of female to male officers, finding that the officer ratio measure was negatively related to arrests in both the same-year and year-lag models and the number of senior female officers displayed a negative relationship in the same-year (but not the year-lag) model (Johnston & Houston, 2018).

The research on the impact of representative bureaucracy on domestic violence has reached the closest to unanimity of any of the dependent variables analyzed. The earliest study did not find a significant effect of the percentage of women police officers on the probability of arrest for intimate partner violence (Eitle, 2005), but the rest of research to date has reported negative relationships between the two. For example, Dichter, Marcus, Morabito, and Rhodes (2011) reported negative associations between the overall, female-only, male-only, and dual arrest rates for intimate partner violence. They also reported that incident-level characteristics (such as offense seriousness) had a greater impact than agency (such as the gender composition of the department) and community characteristics (such as the poverty level) on arrest rates (Dichter et al., 2011). This finding is difficult to interpret. On one hand, decreased arrest rates are generally considered indicative of decreased performance. Victims of intimate partner violence, however, frequently prefer the police do something other than arrest the perpetrator (Buzawa & Austin, 1993; Hirschel & Hutchinson, 2003), so decreased arrest rates may suggest a greater willingness to respect victim preferences.

Andrews and Miller (2013) added to the literature by including measures of not just the overall percentage of women in UK police departments, but also whether the department was headed by a female Chief Constable and how much discretionary time line-level officers had. The domestic violence arrest rate increased an average of six percentage points when police departments had female rather than male chief executives. Additionally, while the main effect of female representation on arrests was negative, a greater percentage of female officers with more discretionary time was associated with a significant increase in the domestic violence arrest rate (Andrews & Miller, 2013). This finding highlights the role of discretion in decision-making for representative bureaucracy. Finally, Miller and Segal (2018) reported significant decreases in the intimate partner homicide rate for both female and male victims as well as non-fatal intimate partner violence incidents with an increase in female police officers in large US metropolitan counties.

Other Crimes

The majority of research on the impact of minority representation in police departments on non-gendered offenses focus on the effects of non-White police on arrest rates for violent and property crimes, though reporting rates have also been examined. Hong (2016), for instance, explored the impact of racial minority officers on reporting of all crimes as well as racist crime incidents in England and Wales from 2000 to 2010. Contrary to expectations, the percentage of minority officers employed by police departments was related to a significant decrease in both types of crime reports (Hong, 2016). Miller and Segal (2018), on the other hand, found that violent crime reporting by female citizens increased with an increase in female representation in US police departments from 1979 to 1991. They also reported that women were more likely to report violence perpetrated by their male partners when there was greater representation of female police (Miller & Segal, 2018).

The effects of ethnic and racial minority representation on crime arrest and clearance rates are unclear. Donohue and Levitt (2001), for example, pooled data for total, violent, and drug arrest rates by race from 1977 to 1993. They found that police representation was generally related to racial patterns of arrest, such that the percentage of White police officers was related to significant increases in the arrest rates for non-

White citizens for property crimes and the percentage of non-White police officers was associated with significant increases in arrest rates for White citizens for total, violent, and drug crimes (Donohue & Levitt, 2001).

Eitle, Stolzenburg, and D'Alessio (2005) examined the arrest probability for both simple and aggravated assault. Controlling for incident and community characteristics, the percentage of Black officers exerted a positive influence on arrests for simple, but not aggravated, assault (Eitle et al., 2005). This work may underscore the importance of discretion, since it is likely that police officers had less discretion as offense seriousness increases. Finally, Hur (2013) reported that police racial diversity significantly decreased clearance rates for violent crimes, property crimes, and index crimes in US police departments.

Sharp (2014) took a unique approach to the study of representative bureaucracy by examining the impact of Black political incorporation on both representation in the police department and order maintenance arrests for Black citizens in the city. While the presence of a Black mayor was significantly related to an increase in the percentage of Black officers employed on the police force in US mayoral cities serving populations of 100,000 or more, the same effect was not observed in council-manager cities. Interestingly, it was the presence of Black councilmembers in mayoral cities (but not council-manager cities) that reduced the order maintenance arrest rate of the city's Black citizenry (Sharp, 2014).

Police Misconduct and Use of Force

Finally, the impact of minority representation on police outcomes has been studied for police misconduct and use of force, including use of force complaints, civil rights complaints, and use of deadly force by police officers. Though descriptive studies have suggested that women police engage in force less often than men (Lonsway et al., 2002; Porter & Prenzler, 2017), the majority of multivariate research on the topic has focused on the impact of the representation of racial and ethnic minority officers. Results have been mixed.

Most of the research on rates of complaints against police have reported either negative or non-significant effects of minority representation (Hickman & Piquero, 2009; Hong, 2017; Trochmann & Gover, 2016). Trochmann & Gover (2016), for example, reported a decrease in the number of uses of force complaints in large US cities as Black and Asian officers were increasingly represented in proportion to their share of the city population. The Hispanic representation ratio, on the other hand, was insignificant (Trochmann & Gover, 2016), as was the minority representation ratio for the use of force complaint and substantiation rates investigated by Hickman and Piquero (2009). Hong (2017) reported negative associations between the percentage of non-White officers employed by English and Welsh police departments and the number of substantiated uses of force complaints per officer, the percentage of use of force complaints sustained, and the percentage of Black complainants. A significant positive relationship between the percentage of non-White officers receiving complaints in relation to the percentage of non-White officers suggested that as police departments increased in size, they had a corresponding increase in use of force complaints, regardless of the demographic makeup of the force (Hong, 2017). It is important to note, however, that citizen trust in the police is a significant predictor of willingness to report use of force incidents (Messing et al., 2015), so these results should be interpreted with caution.

The sole exception to the complaint trend was Smith and Holmes (2003), who examined the impact of Black, Hispanic, and female representation on the average number of civil rights criminal complaints 114 large U.S. cities received from 1985 to 1990. The authors found that the Hispanic representation ratio (a measure comparing the percentage of Hispanic police officers to the percentage of Hispanic citizens in the population) was related to a significant increase in complaints, while the Black representation ratio and percentage of female officers was unrelated to civil rights complaints (Smith & Holmes, 2003).

A similar trend of negative or no relationships between minority representation and deadly force incidents was suggested by research using data from the turn of the century. Smith (2003) reported no significant relationships between the number of police killings of felons in the nations' largest cities and the Black or Hispanic representation ratios in 1998. He did find a significant positive relationship between the percentage of female officers in cities with over 100,000 citizens, but a similar effect was not observed in cities with over 250,000 citizens (Smith, 2003). Using data from two years later, Willits and Nowacki (2014) reported a negative relationship between the minority representation ratio and the number of deadly force incidents in cities with 25,000 or more residents.

Two innovative studies suggest that the relationship between minority representation and use of force may not be entirely straightforward. Ochs (2011), for instance, explored the effects of representative bureaucracy and the number of justified homicides by the police in 30 large cities from 1994 to 2004. She included measures of Black political incorporation (whether the city had a Black mayor and any Black city councilmembers), the percentage of Black police officers employed by the department, whether the department had a Black chief, and incident-level characteristics. While no significant relationships were reported at the organizational level, Black officers were found to have greater numbers of justified homicides against Black citizens, and White officers were found to have greater numbers of justified homicides against both White and Black citizens (Ochs, 2011). This may suggest either a geospatial component to police deadly force incidents (if Black officers were more likely to be assigned to predominantly Black neighborhoods and White officers were more likely to be assigned to predominantly White neighborhoods) and/or systematic bias against Black citizens.

More recently, Nicholson-Crotty, Nicholson-Crotty, and Fernandez (2017) used data from both the Mapping Police Violence study and the Washington Post police homicide data from 2014 to 2015 to explore the effects of Black officer representation on police-involved homicides of Black citizens. Because the two datasets capture two different definitions of police-involved homicides (the Mapping Police Violence data includes both on- and off-duty homicides, while the Washington Post data only includes on-duty), they were analyzed separately. There was no significant association observed between representation and police-involved homicides in the Mapping Police Violence data, but both the percentage of Black officers and the squared term of the same were found to be significantly associated with the outcome in the Washington Post data. This suggests that there is a non-linear association between Black police representation and on-duty police homicides of Black citizens, such that the percentage of Black officers in police departments increased homicides of Black citizens until Black officers comprised approximately 26% of officers. At that point, police homicides of Black citizens leveled off, and then were expected to decrease as the percentage of Black police officers reached 46%. Few departments, however, employed more than 30% Black police officers (Nicholson-Crotty et al., 2017).

Perceptions of Performance and Legitimacy

In addition to actual citizen outcomes, research has explored the effects of representative bureaucracy on citizen perceptions of police performance, trustworthiness, and fairness. To do this, Riccucci and colleagues (2014, 2018) used factorial vignettes in which they manipulated representativeness and outcomes in hypothetical departments. In the first study, Riccucci and colleagues (2014) studied the effects of gender representation on perceptions of performance, fairness, and trustworthiness in a hypothetical domestic violence unit. The experimental conditions were the gender makeup of the unit (nine male and one female officers versus four male and six female officers) and the arrest rate (30% versus 70%). Greater representation of women officers and a higher arrest rate were each associated with significant increases in citizen perceptions of performance, fairness, and trustworthiness (Riccucci et al., 2014).

Using the same methodological framework, the authors explored the impact of race on identical outcomes. The experimental conditions in the second study were a 15/85% split between Black and White and White and Black officers and a 22% increase or decrease in the number of citizen complaints received in the previous year. Greater representation of Black officers significantly increased Black citizens' perceptions of performance, trustworthiness, and fairness, and significantly decreased White citizens' perceptions of performance and trustworthiness (but not fairness). A decrease in complaints had a significant positive relationship with all outcomes for both Black and White citizens (Riccucci et al., 2018).

Summary

Some patterns emerge from the existing literature on police representativeness. Broadly speaking, there are more consistent results for gender than for race. An increase in the percentage of female officers in police departments decreases gender disparities in traffic violations (Farrell, 2015), increases sexual assault reporting and clearance (Meier & Nicholson-Crotty, 2006; Schuck, 2018; Walfield, 2016; but see Morabito et al., 2017), decreases rates of intimate partner homicide (Miller & Segal, 2018) and domestic violence arrest rates (Andrews & Miller, 2013; Dichter et al., 2011), and increases citizen perceptions of performance, trustworthiness, and fairness (Riccucci et al., 2014). Increases in representation of people of color in police departments, on the other hand, have increased disparities in traffic stops (Shjarback et al., 2017; Wilkins & Williams, 2008, 2009), have had mixed effects on crime clearance (Donohue & Levitt, 2001; Eitle et al., 2005; Hong, 2016; Hur, 2013) and police misconduct and use of force (Hickman & Piquero, 2009; Hong, 2017; Nicholson-Crotty et al., 2017; Ochs, 2011; Smith, 2003; Smith & Holmes, 2003; Trochmann & Gover, 2016; Willits & Nowacki, 2014), and have increased perceptions of performance, trustworthiness, and fairness for Black, but not White, citizens (Riccucci et al., 2018). This pattern of more consistent findings for gender than race in policing is opposite of that observed in the general organizational literature (Keiser et al., 2002), and deserves further attention.

There are two basic explanations for the differences observed between gender and race. First, there may be more substantive benefits of the addition of women to police departments than the addition of people of color. Shjarback and colleagues (2017) and Wilkins and Williams (2008, 2009) have suggested that organizational culture and socialization may serve to discourage active representation on the part of racial and ethnic minorities by making them more “Blue” (i.e., representatives of the police) than Black or Brown (i.e., representatives of their racial or ethnic groups). On the other hand, women in police departments with less than 10% female officers described being viewed first as women and then as police (Belknap & Shelley, 1993), which may allow for a type of “if you can’t join them, beat them” mentality. Indeed, women police officers have described doing their work differently than men and especially emphasized the helping aspects of police work, such as responding to victims and caring for women and children (Belknap & Shelley, 1993; Rabe-Hemp, 2009). This may make women more likely to engage in active representation that leads to substantive benefits for women citizens. Citizens may also be more likely to engage in coproduction with police departments when more women are represented on the force if they feel more comfortable reporting their victimization to women, for instance, or are more likely to cooperate with women police officers (Martin, 1999).

The second explanation is that observed differences may be attributable to issues with measurement of both the independent and dependent variables. Gender has been measured in a fairly consistent way across studies- Andrews and Miller (2013), Dichter et al. (2011), Eitle (2005), Farrell (2015), Meier and Nicholson-Crotty (2006), Miller and Segal (2018), Morabito et al. (2017), Schuck (2018), Smith (2003), Smith and Holmes (2003), and Walfield (2016) each included the percentage of female officers- and findings were most consistent regarding the impact of the percentage of women police officers on outcomes. Andrews and Miller (2013) also included whether an agency had a female chief constable, Johnston & Houston (2018) used the number of senior female officers as well as a female to male officer ratio, Morabito and colleagues (2017) created the "tipping point" measure, and Farrell (2015) also used the percentage of female employees (in addition to officers). With a single exception (female chief constable used by Andrews and Miller (2013)), these alternative measures of representation were unrelated to the dependent variables under study.

Racial and ethnic minority representation has been measured numerous ways. Some researchers have used the percentage of Black (Nicholson-Crotty et al., 2017; Ochs, 2011; Wilkins & Williams 2008), Latinx (Wilkins & Williams, 2009), or non-White or minority officers (Donohue & Levitt, 2001; Hong 2016, 2017). Others have used racial diversity (Hur, 2013) or gender and racial diversity (Miller, 2013) indices or minority representation ratios (Hickman & Piquero, 2009; Willits & Nowacki, 2014). Smith and Holmes (2003) created a measure of the percentage of minority officers employed by the department relative to the percentage of the corresponding minority group in the population served which was also used by Smith (2003), Shjarback and colleagues (2017), and Trochmann & Gover (2016). Ochs (2011) included measures of citizen/officer racial dyads and whether departments had a Black chief of police, and both Ochs (2011) and Sharp (2014) used measures of Black political incorporation in the mayor and city council offices. The diversity of measures used has hindered theoretical development and may have affected the findings of the studies using different measures.

In addition to the measurement of the independent variables, researchers have also studied a wider range of dependent variables for racial and ethnic minority representation than for female representation. The study of the substantive effects of gender representation in police departments has been limited to gender disparities in traffic violations (Farrell, 2015), sexual assault reporting and clearance (Meier & Nicholson-Crotty, 2006; Morabito et al., 2017; Schuck, 2018; Walfield, 2016), domestic violence arrests (Andrews & Miller, 2013); Dichter et al., 2011; Eitle, 2005), gender-based violence arrests (Johnston & Houston, 2018), reporting of violent crimes by female citizens (Miller & Segal, 2018), and two studies of police misconduct (Smith, 2003; Smith & Holmes, 2003). Measures of racial and ethnic minority representation, on the other hand, have been included in studies of disparities in traffic stops (Shjarback et al., 2017; Wilkins & Williams, 2008, 2009), arrests for total, property, violent, and drug crimes (Donohue & Levitt, 2011), simple and aggravated assaults (Eitle, 2005), total crime and racist crime incidents (Hong, 2016), clearance rates of violent, property, and index crimes (Hur, 2013), order maintenance arrest rates (Sharp, 2014), civil rights complaints (Smith & Holmes, 2003), use of force complaints and substantiated complaints (Hickman & Piquero, 2009; Hong, 2017; Trochmann & Gover, 2016), and police-involved homicides and use of deadly force (Nicholson-Crotty et al., 2017; Ochs, 2011; Smith, 2003; Willits & Nowacki, 2014).

Additionally, a variety of samples and time frames have been used. Samples have included San Diego police divisions (Wilkins & Williams, 2008, 2009), Rhode Island police departments (Farrell, 2015), Illinois and Missouri police departments (Shjarback et al., 2017), police departments elsewhere in the US (e.g., Dichter et al., 2011; Eitle et al., 2005; Hickman & Piquero, 2009; Walfield, 2016), and police departments in England and Wales (Andrews & Miller, 2013; Johnston & Houston, 2018; Hong, 2016, 2017).

Within the US, departments have been sampled from both municipal and county police and sampling frames have been limited by differing city and police department sizes. Additionally, time periods covered by research has ranged from 1977 (Miller & Segal, 2018) to 2015 (Nicholson-Crotty et al., 2017).

Though a variety of time points have been used, a crucial element missing from all but one study of the effects of police representation is time. Changes in organizational structure likely takes years to manifest in changes in organizational outcomes (Donaldson, 1987), and King (2009) has stressed the importance of understanding changes across the life course of police organizations. Additionally, some of the substantive effects of representative bureaucracy are hypothesized to come about as a result of cultural change in departments (Lim, 2006)- again, taking time. The majority of the research on police representation, however, has been cross-sectional. Some researchers have pooled data across time and controlled for the year (e.g., Andrews & Miller, 2013; Hong, 2016; Meier & Nicholson-Crotty, 2006), but only one longitudinal study has been published (i.e., Schuck, 2018).

The current study adds to the literature on representative bureaucracy in policing by exploring the effects of the representation of women and racial and ethnic minorities on index crime reporting (as a proxy for citizen trust in and perceptions of legitimacy of the police) and clearance (as a measure of police effectiveness) rates in the population of US large municipal police departments from 1987 to 2013. It also integrates representative bureaucracy and structural contingency theories to explore the effects of the environment, particularly inequality, on representation of women and people of color in US police departments. Structural contingency theory is well-suited to explain both the contributing factors and effects of representation because it proposes that organizational environments influence organizational structure (e.g., representation), which in turn impacts organizational performance. Structural contingency theory is also frequently invoked in the policing literature (Maguire & Uchida, 2000). Prior to an in-depth explanation of the current study, I describe structural contingency theory and the relevant literature on police employment of minority groups.

Structural Contingency Theory

Scholars began thinking about how to improve organizational performance in the early 20th century. Taylor's (1911) scientific management, Gulick and Urwick's (1937) administrative management, and Weber's (1947) bureaucracy studies epitomized what later came to be known as closed-system perspectives on organizations, which highlighted processes internal to organizations (Scott, 2008; Thompson, 1967). In the mid-1950s, scholars such as Parsons (1956) and Thompson (1956) began calling for the creation of a program of research to include theoretical development on the comparative study of organizations.

The development of structural contingency theory (SCT) began in the early 1960s (Ellis et al., 2002), and the following decade brought the introduction of neo-institutionalism, resource dependence, and population ecology theories (Aldrich, 2008). In contrast to the earlier closed-system perspectives (and in line with the introduction of general-systems theory), the open-systems theories considered organizations to be complex systems interdependent with their environments (Scott, 2008; Thompson, 1967; Van de Ven, 1976). Broadly, each of these theories hypothesized that changes in organizations were linked to changes in their environments. The exact nature of the environments and their effects, however, differed by theory. Resource dependence theory (Pfeffer & Salancik, 1978), for instance, focused on the sources of organizational funding and competition on organizational behavior, while institutional organizational theory (Meyer & Rowan, 1977) centered the symbolic environment and its effects on organizational legitimacy.

Structural contingency theory is a functionalist theory of organizations in that it predicts that organizations make rational changes to their structures when changes largely outside of their control (i.e., contingencies) affect organizational performance (Donaldson, 1995, 2006). Briefly, contingencies under consideration in the literature have included environment (Burns & Stalker, 1961; Pennings, 1975, 1987), size (Child & Mansfield, 1972; Weber, 1968), and strategy (Chandler, 1962; Galbraith, 1973); structural elements have included organizational complexity, formalization, centralization, and administrative intensity (Ford & Slocum, 1977); and performance has included efficiency, effectiveness, and "softer" features such as supervisor evaluations and self-perceptions and morale of organizational members (Dalton et al., 1980; Van de Ven, 1976). As SCT has developed over time, scholars have proposed links between various contingencies and structural components. While some have questioned whether there is a unified theory because of the number of proposed relationships between various contingency and structural elements, Donaldson (2001) identified three common elements of the structural contingency theories. First, there is a relationship between contingencies and organizational structure. Second, changes in contingencies lead to changes in organizational structure. Finally, the fit between the contingency and structure affects organizational performance (Donaldson, 2001).

Even with these commonalities, there have been different propositions as to how contingencies affect fit. Donaldson (1987) tested three models of structural contingency theory: contingency determinism (change in contingencies cause change in structure), strategic choice (organizational managers have the ability to choose between adjusting their structure and adjusting the contingency), and the "structural adaptation to regain fit" (SARFIT) model, finding the most support for the latter formulation.

The SARFIT model is a disequilibrium theory of organizational change in that it proposes that organizations are continually moving in and out of fit with their contingencies and must thus continuously adjust their structures (Donaldson 1987, 2001, 2006). A change in contingency (i.e., environment, size, strategy) leads to misfit between the contingency and the organizational structure, which leads to decreased performance (e.g., effectiveness or efficiency). The organization must make some type of structural adjustment in order to decrease the misfit with the environment and thus increase the performance of the organization (Donaldson, 1987, 1995, 2006). Importantly, these changes, though continuous, play out over years or even decades (Donaldson, 1987).

Organizational Environment

As the open-systems perspectives of organizations developed, so too did the conceptualization of organizational environments. Van de Ven (1976) defined the organizational environment as "the organizations and parties in the factor markets that supply an organization with its input resources, and the organizations and parties in the product markets that obtain the output products or services from an organization" (p. 65). The earliest studies were concerned mostly with the effects of environmental stability or instability on the organization (Dill, 1958; Burns & Stalker, 1961), while later work hypothesized that the uncertainty arising from instability was key to organizational change (Lawrence & Lorsch, 1967; Thompson, 1964).

Drawing on this and other literature, Aldrich (1979) identified six dimensions of organizational environments: capacity, homogeneity/heterogeneity, stability/instability, concentration/dispersion, domain consensus/dissensus, and turbulence. These were later reduced to three dimensions through factor analytic techniques by Dess and Beard (1984). Munificence (i.e., capacity) is the degree to which the environment can support organizational growth. Environmental complexity includes Aldrich's (1979) concepts of homogeneity/heterogeneity (or the range of diversity between elements of the environment, including other organizations, individuals, and social forces) and the amount of concentration or dispersion of resources. Finally, environmental dynamism refers to the volume of turnover in environmental elements (i.e., stability/instability) and the extent of change in degree of interconnectedness of those environmental elements (i.e., turbulence) (Dess & Beard, 1984).

Organizational Structure

Organizational structure can be thought of as the anatomy of an organization. Like the organizational environment, scholars have used a variety of measures of organizational structure. Ford and Slocum (1977) identified four dimensions of organizational structure based on prior literature: complexity, formalization, centralization, and administrative intensity. Organizational complexity refers to the degree of differentiation in an organization, and includes vertical differentiation (i.e., hierarchy), horizontal differentiation (i.e., number of work units or jobs), spatial differentiation (i.e., geographic dispersion), and personal differentiation (i.e., expertise).

Formalization refers to the control mechanisms used by organizations and can include both formal and informal policies, procedures, etc. Centralization is the degree to which decision-making power is concentrated or dispersed throughout the organization and is a second method of control. Finally, administrative intensity is the number of support personnel an organization employs (Ford & Slocum, 1977).

Organizational Performance

Ultimately, the goal of SCT is organizational design; that is, it seeks to provide recommendations for maximizing organizational performance (Donaldson, 2008). Performance, however, is necessarily a value judgement as different stakeholders (e.g., owners, managers, clients) may value different goals (Van de Ven, 1976). Van de Ven (1976) recommended three broad indicators of performance. Organizational efficiency is concerned with the ratio of input resources to output. Effectiveness, on the other hand, refers to meeting organizational goals. Finally, employee morale includes “softer” measures of intra-organizational performance, such as job satisfaction or absenteeism (Dalton et al., 1980; Van de Ven, 1976).

Structural Contingency Theory in Policing

Similar to representative bureaucracy, scholars had touched on the idea that police organizational environments may impact their structure and therefore functioning long before structural contingency theory was introduced to the policing literature (e.g., Henderson, 1975; Wilson, 1968). Langworthy (1986) was the first, however, to draw on organizational theory to explore the structure of US police departments, and Maguire (2003) later operationalized and tested the links between contingencies and police organizational structure.

Drawing on Blau's (1970) proposals about organizational size, Perrow's (1967) proposals regarding technology, and Wilson's (1968) work on political culture, Langworthy (1986) tested their relationships with police agency spatial differentiation, hierarchical differentiation, occupational differentiation, functional differentiation, and administrative overhead. He found that larger agencies were more structurally differentiated and had larger administrative components than did smaller agencies, that there were certain best fits between technology and structure, and that with the exception of population size, the other measures of environment (i.e., complexity and political culture) were not significantly related to organizational structure. Population size was highly correlated with organizational size (Langworthy, 1986).

Also drawing on the wider structural contingency literature, Maguire (2003) formalized the theoretical links between contingencies and police organizational structure. He proposed that police organizational context (i.e., contingencies), comprised of agency size, organizational age, technology, and environment would be predictive of structural complexity (i.e., vertical, functional, and spatial differentiation), which would in turn affect structural coordination and control mechanisms (i.e., centralization, formalization, and administrative intensity). As expected, organizational size explained most of the variance in organizational complexity such that larger agencies were more differentiated than smaller agencies. Organizational age also had a significant positive impact on vertical differentiation, and environmental dispersion had a significant positive effect and environmental instability a significant negative effect on spatial differentiation. Technology and environmental capacity and complexity were not predictive of organizational structure (Maguire, 2003).

It would be difficult to overstate the impact structural contingency theory has had on the police literature. Indeed, though most studies do not explicitly invoke the theory, it is the underlying premise of nearly all police research (Maguire & Uchida, 2000). Scholars have explored the linkages between contingencies and organizational structure (e.g., Hassell et al., 2003; Jurek & King, 2019; Jurek et al., 2017; Katz et al., 2002; King, 1999; Maguire, 1997, 2003, 2009), organizational structure and police performance (e.g., Chappell et al., 2006; Roberts et al., 2012), contingency and performance (e.g., Choi, 2011; Miller, 2013; Smith, 2004), and some combination of contingency and structure on performance (e.g., Dichter et al., 2011; Eitle, 2005; Eitle et al., 2014; Eitle & Monahan, 2009; Eitle et al., 2005; Farrell, 2014; Hickman & Piquero, 2009; Randol, 2012; Willits, 2014; Willits & Nowacki, 2014, 2016). Some have also investigated the link between contingencies and representation.

Organizational Environment and Police Representation

Researchers who have studied the representation of women and people of color in US police departments have included both organizational and environmental correlates. Organizational factors have included measures of incentives and benefits offered by police departments (e.g., Jordan et al., 2009; Kim & Mengistu, 1994; Schuck, 2014), requirements for recruits such as physical fitness and education (e.g., Jordan et al., 2009; Kim & Mengistu, 1994; Morabito & Shelley, 2015; Schuck, 2014), budget and hiring tactics (e.g., Jordan et al., 2009; Warner et al., 1989), and affirmative action policies and consent decrees. Of these, only the affirmative action policies and consent decrees had a consistent effect on minority representation in police departments, such that these policies increased representation (Lewis, 1989; Martin, 1991; Miller & Segal, 2012; Sass &

Troyer, 1999; Warner et al., 1989; Zhao et al., 2001; Zhao et al., 2006). The current review focuses, however, on the impact of factors external to the police department, including population, political representation, economy, and other social characteristics on police representation. See Table 2 for summary information, including the relationships between various measures of police organizational environments and the representation of women, Latinx, Black, and Asian officers. Common predictor variables include population size, the size of the minority population in the community, educational attainment, unemployment, labor force participation, income, residential stability, measures of political representation such as the presence of minority mayors and city council members, and region of the United States. Findings are summarized on page 50.

Table 2

Summary of Studies Incorporating Measures of Environment for Police Representation

Study	Sample	DV	Key IVs (relationship)
Alozie & Ramirez (1999)	182 cities 50,000+ population; 1990	% Hispanic male police:	% Hispanic population (+) Hispanic pop. growth rate (NS) Hisp. male edu. attain. (+) Hispanic mayor (NS) % Hispanic city council (NS) Population size (NS) % city budget/LE (-) Region (NS)
		% Hispanic female police:	% Hispanic population (+) Hispanic pop. growth rate (NS) Hisp. female edu. attain. (NS) Hispanic mayor (NS) % Hispanic city council (NS) Population size (NS) % city budget/LE (NS) Region (NS)

(continued)

Study	Sample	DV	Key IVs (relationship)
Chamlin & Sanders (2010)	All cities with PDs with 100+ FTE: US; 2000	% Black sworn:	% Black population (NS) Black mayor (+) Residential segregation (NS) Population size (NS) Police rate (+) Crime rate (NS) Region (NS)
Jordan et al. (2009)	Stratified random sample of 985 PDs: US; 2002	Female hires:	Unemployment rate (NS) Median family income (NS) % pop. with Bachelor's (NS)
		Minority hires:	Unemployment rate (NS) Median family income (NS) % pop. with Bachelor's (NS)
Kim & Mengistu (1994)	134 large municipal PDs: US; 1987	% female sworn:	Unemployment rate (+) Population change (NS) Region (varied) Population size (NS) Minority population size (NS) Education of pop (NS) Per capita income (+)
		% Black sworn:	Unemployment rate (NS) Population change (-) Region (varied) Population size (NS) Minority population size (+) Education of pop (NS) Per capita income (+)
		% Hispanic sworn:	Unemployment rate (NS) Population change (NS) Region (varied) Population size (NS) Hispanic population size (+) Education of pop (NS) Per capita income (NS)
		% Asian sworn:	Unemployment rate (NS) Population change (+) Region (NS) Population size (NS) Asian population size (+) Education of pop (NS) Per capita income (NS)

(continued)

Study	Sample	DV	Key IVs (relationship)
Lewis (1989)	72 PDs serving 100,000+ population: US; 1975 & 1985	% Black sworn:	% Black LFP (NS) % Blacks on city legislature (NS) N years of previous 5 there was a Black mayor (+) N years of previous 5 there was a Black chief (+) % Black in protective service (NS) South region (NS) Population size (NS)
Morabito & Shelley (2015)	1,655 PDs: US; 2003	Proportion female:	Proportion pop non-White (+) Region (varied) Structural disadvantage (NS) Residential stability (+) Robbery rate (+)
		Proportion non-White:	Proportion pop non-White (NS) Region (varied) Structural disadvantage (+) Residential stability (-) Robbery rate (NS)
		Proportion African American:	Proportion pop non-White (NS) Region (varied) Structural disadvantage (+) Residential stability (NS) Robbery rate (NS)
Sass & Troyer (1999)	508 PDs: US; 1981, 1987, 1991	% female new hires:	Female LFP (+ 1987) Private sector occupational segregation (NS) Council-manager city (- 1987) % female councilors (NS) Female mayor (NS)
Schuck (2014)	4,241 PDs & SDs: US; 2003 & 2007	% female officers:	Population size (+) Racial/ethnic diversity (+) % females college educated (NS) % married women (NS) Fertility rate (NS) Female LFP (NS) Egalitarian climate (NS)

(continued)

Study	Sample	DV	Key IVs (relationship)
Sharp (2014)	All PDs serving 100,000+ population: US; 2003	% Black sworn (mayoral cities):	Black mayor (+) Black city council rep. (NS) Violent crime rate (NS) Police rate (NS) % pop 18-24 years old (NS) Economy type (NS) % Black pop (+)
		% Black sworn (council-manager cities):	Black mayor (NS) Black city council rep. (NS) Violent crime rate (NS) Police rate (NS) % pop 18-24 years old (NS) Economy type (NS) % Black pop. (+)
Warner et al. (1989)	281 cities serving 25,000+ population: US; 1987	% female sworn 1987:	% sworn females 1984 (+) Female mayor (-) % female city councilors (+) Region (yes) Population size (NS)
Zhao et al. (2001)	281 PDs serving 25,000+ population: US; 1993, 1996	% female	Population size (+) % Black population (+) Female mayor (+) % female city councilors (NS) Region (NS)
		% White female	Population size (NS) % Black population (NS) Female mayor (NS) % female city councilors (NS) Region (NS)
		% Black female	Population size (+) % Black population (+) Female mayor (+) % female city councilors (NS) Region (NS)
		% Hispanic female	Population size (+) % Hispanic population (+) Female mayor (NS) % female city councilors (NS) Region (NS)

(continued)

Study	Sample	DV	Key IVs (relationship)
Zhao et al. (2006)	281 PDs serving 25,000+ population: US; 1993, 1996, 2000	% female	Population size (+) % Black pop (+) Region (varied) Govt. structure (NS) Female mayor (NS) % female city councilors (NS)
		% White female	Population size (NS) % Black pop (NS) Region (varied) Govt. structure (NS) Female mayor (NS) % female city councilors (NS)
		% Black female	Population size (NS) % Black pop (+) Region (varied) Govt. structure (NS) Female mayor (NS) % female city councilors (NS)
		% Hispanic female	Population size (NS) % Hispanic pop (+) Region (NS) Govt. structure (NS) Female mayor (NS) % female city councilors (NS)

The majority of research using representation of police minorities as a dependent variable have included measures of the size of the population served (Lewis, 1989; Schuck, 2014; Warner et al., 1989), size of the ethnic or racial minority population served (Chamlin & Sanders, 2010; Morabito & Shelley, 2015; Sharp, 2014), or both (Alozie & Ramirez, 1999; Kim & Mengistu, 1994; Zhao et al., 2001; Zhao et al., 2005, 2006). Generally, the literature shows no connection between population size and the percentage of Latinx males and females (Alozie & Ramirez, 1999; Kim & Mengistu, 1994), the percentage of Black officers (Chamlin & Sanders, 2010; Kim & Mengistu, 1994; Lewis, 1989), the percentage Asian officers (Kim & Mengistu, 1994), or the percentage of women officers (Kim & Mengistu, 1994; Warner et al., 1989) employed by police departments (a few exceptions notwithstanding (Schuck, 2014, Zhao et al., 2001, Zhao et al. 2005, Zhao et al., 2006)).

Findings regarding the impact of ethnic and racial minority population size on minority representation have been more consistent. Patterns of ethnic and racial minority representation have usually been predictive of their associated representation in police departments, such that greater percentages of Latinx, Black, and Asian citizens in the population have been associated with greater percentages of Latinx, Black, and Asian police officers, respectively (Alozie & Ramirez, 1999; Kim & Mengistu, 1994; Sharp, 2014; Zhao et al., 2001; Zhao et al., 2005, 2006; c.f. Chamlin & Sanders, 2010; Morabito & Shelley, 2015). Interestingly, greater racial and ethnic diversity among citizens have been associated with greater total female representation in police departments as well (Morabito & Shelley, 2015; Schuck, 2014; Zhao et al., 2001; Zhao et al., 2006; c.f. Kim & Mengistu, 1994).

Findings regarding the impact of political representation on police representation have been mixed. Alozie and Ramirez (1999) reported no significant effect of having either a Latinx mayor or the percentage of Latinx city councilors on the percentage of Latinx males or females employed by departments, while Zhao and colleagues (2005) found a positive effect of both Latinx mayors and police chiefs on Latinx officers. Chamlin and Sanders (2010), Lewis (1989), and Sharp (2014) reported a positive association between the presence of Black mayors and the percentage of Black full-time sworn officers (c.f. Zhao et al., 2005), Lewis (1989) and Zhao et al. (2005) reported a similar association between the presence of Black police chiefs and Black officers, and there have been no significant relationships reported between the percentage of Black individuals on the city council and Black officers in the police department (Lewis, 1989; Sharp, 2014). The relationships between female political representation and police representation are unclear, with some studies finding no effects of mayors or city councilors (Sass & Troyer, 1999; Zhao et al., 2006), some reporting negative (Warner et al., 1989) or positive (Zhao et al., 2001) effects of female mayors, and some reporting positive (Warner et al., 1989) or no (Zhao et al., 2001) associations between the percentage of women serving as city councilors on the percentage of women serving in police departments.

Economic factors under consideration have included the educational attainment (Alozie & Ramirez, 1999; Jordan et al., 2009; Kim & Mengistu, 1994; Schuck, 2014), unemployment rate (Jordan et al., 2009; Kim & Mengistu, 1994), median family income (Jordan et al., 2009; Kim & Mengistu, 1994), and labor force participation of citizens (Lewis, 1989; Sass & Troyer, 1999; Schuck, 2014), occupational segregation (Sass & Troyer, 1999; Schuck, 2014), economy type (Sharp, 2014), and the proportion of the city budget dedicated to law enforcement (Alozie & Ramirez, 1999). Most of these have had no significant impact on the employment of women or people of color by police departments, but there have been some exceptions. Alozie and Ramirez (1999) found that the educational attainment of Latinx women and men was positively associated with their representation in US police departments. Kim and Mengistu (1994) reported no such relationship between educational attainment and representation, but the income per capita was related to an increase in the percentage of sworn women and Black (though not Latinx or Asian) officers. Sass and Troyer (1999) reported that an increase in women's participation in the labor force significantly increased the percentage of new female hires in police departments.

Finally, scholars have explored the effects of the social environment on police representation. These have included region of the US (Alozie & Ramirez, 1999; Chamlin & Sanders, 2010; Kim & Mengistu, 1994; Lewis, 1989; Morabito & Shelley, 2015; Warner et al., 1989, Zhao et al, 2001; Zhao et al., 2006), crime rate (Chamlin & Sanders, 2010; Morabito & Shelley, 2015; Sharp, 2014), residential segregation (Chamlin & Sanders, 2010), population change (Kim & Mengistu, 1994), structural disadvantage and residential stability (Morabito & Shelley, 2015), fertility and marriage rates (Schuck, 2014), and the percentage of the population aged 18 to 24 (Sharp, 2014). With few exceptions (Kim & Mengistu, 1994; Morabito & Shelley, 2015; Zhao et al., 2006), these measures have not significantly impacted the representation of women and people of color in US police departments.

Summary

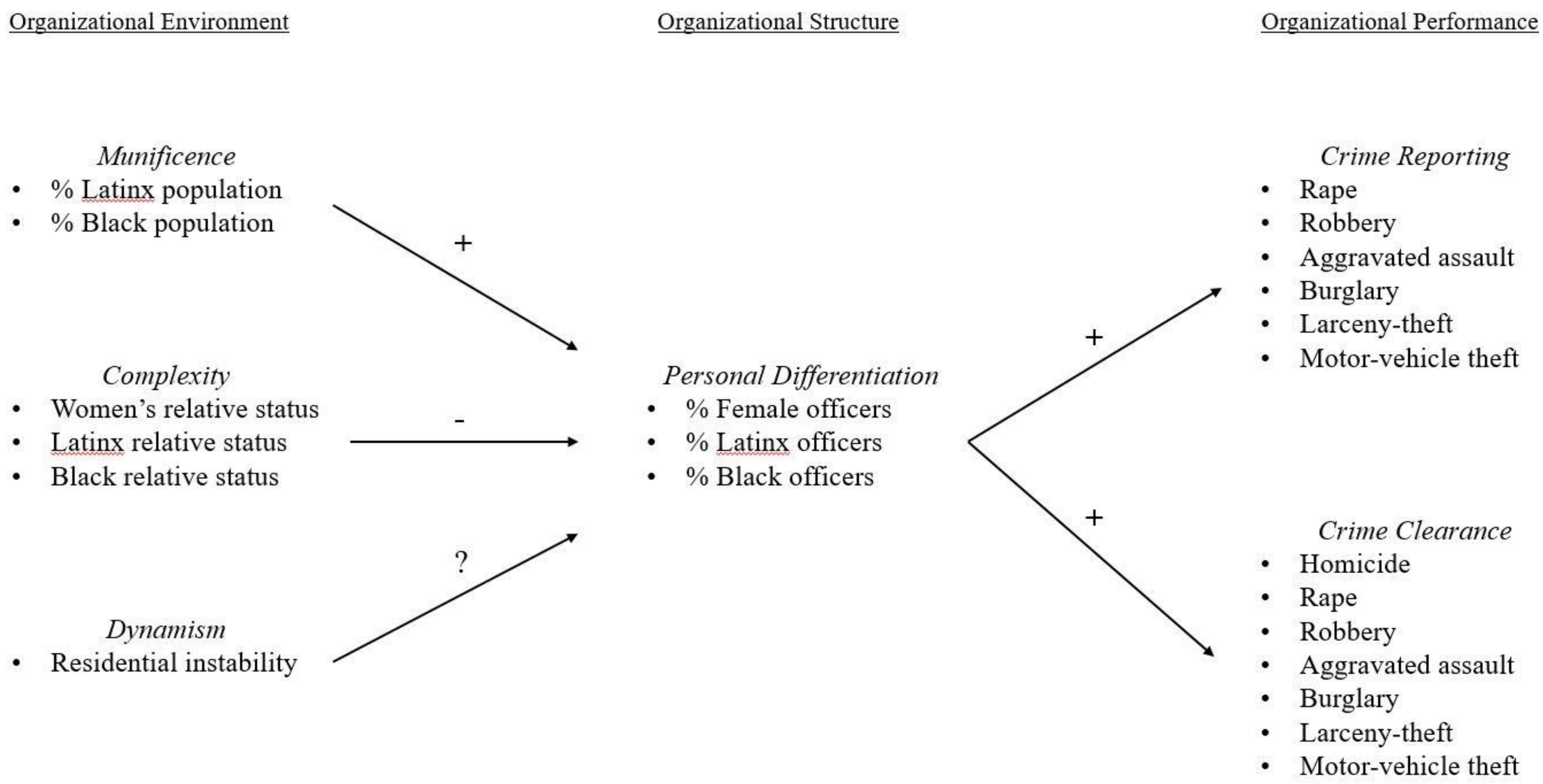
Scholars studying the employment of gender, ethnic, and racial minority officers in US police departments have drawn on a number of theoretical traditions, and thus have used a variety of measures of organizations and environments. While size of the population has not generally had a significant relationship with representation, racial diversity of the population has. The effects of political representation have been mixed, while measures of the economy and social characteristics seem to have little, if any, impact on representation. Similar to research on representative bureaucracy, however, most of this research has been cross-sectional. The current study adds to this literature by proposing theoretical links between structural contingency theory and representative bureaucracy and testing these propositions in a longitudinal study.

Current Study

The current study explores both the precursors and effects of representative bureaucracy in large US police departments over time. It proposes an integration of structural contingency and representative bureaucracy theories: specifically, that the environmental contingencies of munificence, complexity, and dynamism (Dess & Beard, 1984) influence representation of women and people of color in police departments (personal differentiation (Perrow, 1967)), which in turn influences police outcomes. Specific propositions follow; see Figure 1 for an illustration of the proposed relationships and measures.

Figure 1

A Structural Contingency Model of Representative Bureaucracy in Policing: Proposed Relationships



Police Organizational Environment

The current study proposes several measures of the organizational environments of police may have an impact on the percentage of gender, racial, and ethnic minorities employed by departments. First, the size of the minority population may impose limitations on the percentage of that population employed by organizations, so the percentage of Latinx and Black citizens living in the departments' jurisdictions is used as a measure of *munificence* (i.e., capacity (Dess & Beard, 1984)). It is hypothesized that:

> Hypothesis 1: As the percentage of Latinx and Black citizens in a departments' jurisdiction increases, there will be a corresponding increase in the percentage of women officers employed by the department.
>
> Hypothesis 2: As the percentage of Latinx citizens in a departments' jurisdiction increases, there will be a corresponding increase in the percentage of Latinx officers employed by the department.
>
> Hypothesis 3: As the percentage of Black citizens in a departments' jurisdiction increases, there will be a corresponding increase in the percentage of Black officers employed by the department.

Second, environmental complexity (Dess & Beard, 1984) may have an impact on police representation. *Relative status* (Jurek & King, 2019) is a measure of the extent of concentration or dispersion of resources in groups within a community, and is in following with Heimer's (2019) contention that inequality should be a focus of the criminological literature. It is expected that:

Hypothesis 4: As the status of women in the community becomes more equal to that of men, there will be a corresponding increase in women's representation in police departments.

Hypothesis 5: As the status of Latinx individuals in the community becomes more equal to that of White, non-Latinx individuals, there will be a corresponding increase in the representation of Latinx officers in police departments.

Hypothesis 6: As the status of Black individuals in the community becomes more equal to that of White, non-Latinx individuals, there will be a corresponding increase in the representation of Black officers in police departments.

Finally, dynamism (Dess & Beard, 1984) may impact representation. *Residential stability* is used as a measure of environmental stability/instability, though no directional hypotheses are proposed for how this may affect police representation.

Police Structure

Following Perrow (1967), the current study proposes that representation is a type of structural arrangement; specifically, representation is one type of personal differentiation, and therefore is a measure of organizational complexity. The current study uses measures of *representation of women officers*, *representation of Latinx officers*, and *representation of Black officers* in US police departments.

Police Performance

Two indicators of police performance are included in the current study. First, *reporting rates* of index offenses are used as an indicator of the extent to which citizens trust the police and view them as a legitimate organization. Second, *clearance rates* of index offenses are used as an indicator of police effectiveness.

Drawing on representative bureaucracy theory, it is expected that the representation of women, Latinx, and Black officers in police departments will have a general positive impact on reporting rates of index offenses (except homicide). That is, increased representation will increase demand inducement (the extent to which minority constituents interact with organizations (Lim, 2006)) among minority populations, which will have the substantive effect of increasing crime reporting rates.

Hypothesis 7: As the percentage of women police officers employed by departments increases, there will be a corresponding increase in reporting rates of index offenses (except murder).

Hypothesis 8: As the percentage of Latinx police officers employed by departments increases, there will be a corresponding increase in reporting rates of index offenses (except murder).

Hypothesis 8a: This will be especially pronounced in cities with larger Latinx populations.

Hypothesis 9: As the percentage of Black police officers employed by departments increases, there will be a corresponding increase in reporting rates of index offenses (except murder).

Hypothesis 9a: This will be especially pronounced in cities with larger Black populations.

Similarly, it is expected that increases in women, Latinx, and Black officers will have positive impacts on clearance rates of index offenses. This may work through a number of mechanisms (Lim, 2006): minority officers may actively advocate for training, policies or procedures that might affect clearance rates of certain crimes (e.g., sexual violence) and/or intervene in discriminatory behaviors that hinder criminal investigations; non-minority officers may be less likely to engage in discriminatory behaviors due to the presence of increased minority officers in their departments; or minority citizens (e.g., as witnesses) may be more likely to engage with minority officers (i.e., coproduction inducement) which would have the substantive effect of increasing the likelihood of crime clearance.

Hypothesis 10: As the percentage of women police officers employed by departments increases, there will be a corresponding increase in clearance rates of index offenses.

Hypothesis 11: As the percentage of Latinx police officers employed by departments increases, there will be a corresponding increase in clearance rates of index offenses.

Hypothesis 11a: This will be especially pronounced in cities with larger Latinx populations.

Hypothesis 12: As the percentage of Black police officers employed by departments increases, there will be a corresponding increase in clearance rates of index offenses.

Hypothesis 12a: This will be especially pronounced in cities with larger Black populations.

In both reporting and clearance, the effects for Latinx and Black officers are expected to be stronger in cities with greater Latinx and Black populations, respectively, because prior literature has indicated that citizens' perceptions of organizational trustworthiness, legitimacy, and fairness are impacted by the relationship between citizen and officer race (Riccucci et al., 2018). Additionally, hypotheses 8, 9, 11, and 12 are all tested using both absolute (i.e., percent representation) and relative (i.e., percent of officers relative to the percent of citizens of the ethnic or racial group in the community) measures of representation.

CHAPTER III

Methodology

To test the hypotheses presented in Chapter II, data from three sources are used. In this chapter I describe the three data sources, the measures derived from each, and the procedures for combining and analyzing the data.

Data

Law Enforcement Management and Administrative Statistics

The first data source is the Law Enforcement Management and Administrative Statistics (LEMAS) survey. LEMAS is a multiwave, single point of contact establishment survey of police organizations in the US (Langworthy, 2002; Maguire, 2002; Matusiak et al., 2014). It is one of only three ongoing national data collection programs that gather information on police organizations and was selected because it is the only such survey to collect information on police employee gender, ethnicity, and race (Banks et al., 2016).

The Bureau of Justice Statistics (BJS) has conducted the LEMAS survey periodically since 1987 in conjunction with its Census of State and Local Law Enforcement Agencies (CSLLEA) program. The CSLLEA universe is identified through an extensive cross reference of previous survey administrations with lists of police organizations maintained by the FBI, police membership organizations, the State Peace Officer Standards and Training offices, and other state agencies; thus, it is likely the most complete list of state and local police agencies in the US (Banks et al., 2016). The BJS uses the CSLLEA as the sampling frame for LEMAS and sampling is conducted in two parts: a census of large police agencies (defined as having 100 or more full-time equivalent officers[1]) and a stratified random sample of smaller police agencies (Langworthy, 2002). Response rates for the LEMAS survey are consistently high (ranging from a low of 86% in 2013 to a high of 97.4% in 2000 overall (1997 response rate not reported) and higher response rates for the census of large agencies than for the overall population) and item nonresponse is generally low (Langworthy, 2002). The BJS imputes missing data before archival (Banks et al., 2016; Langworthy, 2002).

While the reliability of certain items captured by LEMAS has been questioned (e.g., the existence of specialized bias crime units (Walker & Katz, 1995)), it is likely that questions which are unambiguous, objective, and value-neutral (such as counts of police employees) yield valid responses (Maguire, 2002). Indeed, comparisons of police employee counts using the FBI Police Employees data, the International City/County Management Association's Municipal Yearbooks data, and the LEMAS data reveal that with few exceptions, these types of data are highly reliable (King, 1997; King et al., 2011; Uchida & King, 2002).

Data on police employees from the 1987 (BJS, 1987), 1990 (BJS, 1990), 1993 (BJS, 1993), 1997 (BJS, 1997), 2000 (BJS, 2000), 2003 (BJS, 2003), 2007 (BJS, 2007), and 2013 (BJS, 2013) surveys are used for the current project. Data are limited to the large (i.e., 135 or more full time employees in 1987 and 100 or more full time officers thereafter) municipal police departments because these agencies serve a defined population that can be enumerated by the US Census. Accordingly, the current project is a comparative analysis of the population of large municipal police departments in the US

[1] The 1987 data collection defined large agencies as having 135 or more full-time equivalent employees.

from 1987 to 2013. The number of organizations meeting this criteria per year is presented in Table 3.

Table 3

Number of Large Municipal Police Departments Reporting to LEMAS 1987 – 2013

Year	n
1987	255
1990	380
1993	413
1997	452
2000	472
2003	493
2007	519
2013	497

Uniform Crime Reports

The FBI's Uniform Crime Reports (UCR) are a collection of police agency administrative data which have served as the nation's premier source of information about crimes reported to the police since 1930 (Maltz, 1977; Uchida & King, 2002). Police agencies submit monthly data either directly to the FBI or through an intermediary state agency. Reporting to UCR is voluntary. Overall response rates for municipalities is about 70%, with less missing data in larger cities than small cities and suburbs (Lynch & Jarvis, 2008).

The FBI has an extensive quality assurance review process for the UCR data program. Both software and human reviews ensure the data are logically consistent, that outliers are detected both cross-sectionally (i.e., compared to similar agencies during the same timeframe) and longitudinally (i.e., compared to the agency's previously reported data), and that the balance of various variables (e.g., simple and aggravated assaults) is proportional. Any data points flagged as logically inconsistent, outliers, or nonproportional are manually checked by staff (Akiyama & Propheter, 2005). Missing data (though uncommon in large cities) is imputed by the FBI prior to data release (Lynch & Jarvis, 2008).

The UCR consists of seven separate data collections: Offenses Known to the Police, Arrests (ASR), Law Enforcement Officers Killed and Assaulted (LEOKA), Police Employees, Arson Reports, Supplementary Homicide Reports (SHR), and the Hate Crime Supplement (Lynch & Jarvis, 2008). For the current project, data from the Offenses Known to the Police and Arrests collections are used. The longitudinal data were combined and made available through the Inter-university Consortium for Political and Social Research by Kaplan (2019). The UCR data serve as dependent variables in the second and third sets of analyses.

United States Census

The United States Census Bureau collects information on population characteristics every ten years as part of the federally mandated decennial census; smaller-scale data collections are conducted in intermediate years as part of the American Community Survey. Data for places associated with the local police departments included in the current project are used. Data from the 1980 (United States Census Bureau, 1983), 1990 (United States Census Bureau, 1992), 2000 (United States Census Bureau, 2000), and 2010 (United States Census Bureau, 2010) census’ are combined with data from the 2017 American Community Survey (United States Census Bureau, 2017). See Analytic Procedure for information on the calculation of intercensal estimates.

Measures

Police Environment

The current study proposes that gendered and racialized inequality in the environments of police departments may influence the percentages of women, Latinx, and Black officers employed by departments. Specifically, it is expected that the percentage of the population who are Latinx and Black affects the percentage of women, and Latinx and Black officers, respectively, employed by police departments, and that the relative status of women to men and people of color to White individuals and residential stability also impact the employment of these groups. Additionally, the second and third set of models controls for social disorganization and all models control for region of the US.

Munificence: Latinx population. The percentage of the population that is Latinx in each year is estimated from information from the US Census. This measure serves as a time-varying covariate in the first, second, and fourth set of analyses.

Munificence: Black population. The percentage of the population that is Black in each year is estimated from information from the US Census. This measure serves as a time-varying covariate in the first, second, and fourth set of analyses.

Complexity: Women's relative status. Women's status relative to men is designed to capture gender inequality in the community in income, labor force participation, employment, and education (Jurek & King, 2019). Four measures are included.[2] Income refers to the amount of money individuals regularly receive (including wages, salary, tips, social security payments, welfare payments, disability benefits, etc.)

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[2] Originally, this was intended to be a summated scale. Factor analyses, however, revealed the scale was not a good fit for the data. See Results section and Appendix A for detailed information.

(US Census, n.d.). Gender inequality in income is calculated by subtracting the female median income from the male median income in each year for each city. Labor force participation (LFP) refers to the percentage of people participating in the labor force. The measure of LFP inequality is calculated by subtracting the percentage of women aged 16 years or older participating in the civilian labor force from the percentage of men aged 16 years or older participating in the civilian labor force in each year. Employment inequality is calculated by subtracting the percentage of women aged 16 years or older who were employed in the civilian labor force from the percentage of men aged 16 years or older who were employed in the civilian labor force in each year. Education inequality is calculated by subtracting the percentage of women 25 years or older who had a Bachelor's degree or higher from the percentage of men 25 years or older who had a Bachelor's degree or higher in each year. For each measure negative values are indicative of the minority group outperforming the majority group, a zero value is indicative of perfect equality between the minority and majority group, and increasing positive values indicate greater inequality in favor of the majority group. These measures serve as time-varying covariates in the first set of analyses.

Complexity: Latinx relative status. The measures of Latinx status are created similarly to that of women's relative status, except that the measures of income, labor force participation, employment, and education are created by comparing each measure for Latinx individuals in the community to that of White, non-Latinx individuals in the community. Additionally, the income measure used is the average (i.e., per capita), rather than the median.

Complexity: Black relative status. Similarly, the measures of Black relative status are created by comparing the measures of per capita income, labor force participation, employment, and education for Black individuals in the community to that of White, non-Latinx individuals in the community. These measures serves as time-varying covariates in the first set of analyses.

Dynamism: Residential instability. Residential instability (or dynamism) is a measure of population churn. The 1980 – 2000 decennial census gathered migration information on the number of individuals five years of age or older who lived in the same house five years prior to the census. Thereafter a similar measure is captured- the number of individuals one year of age or older who lived in the same house one year prior. Comparisons of county-level migration flows from the 2000 Census to the 2005 – 2009 ACS indicate the measures are similar in magnitude and the census data, as expected, are predictive of the ACS data (Benetsky & Koerber, 2012). Descriptive statistics, however, indicate a dramatic change in residential instability at the time of the different operationalization (see Results for more information). While this measure was intended to serve as a time-varying covariate in the first set of analyses, it will not be used due to its questionable validity.

Social disorganization. The current study uses a measure of social disorganization to attempt to isolate reporting behaviors from the crime rate. Four[3] measures identified by Osgood and Chambers (2000) as social disorganization variables

[3] Osgood and Chambers (2000) also used a measure of residential instability, defined as above. Factor analyses revealed this measure was not a good fit with the other four measures, so was removed. See section on factor analysis and Results for more information.

impacting crime at the county level[4] are used to create a summated social disorganization index. Ethnic heterogeneity is calculated as

$$1 - (\textit{percent White households}^2 + \textit{percent non-White households}^2)$$

with scores closer to zero representing less population diversity and scores closer to .5 indicative of more population diversity. The percentage of female-headed households is used as a measure of family disruption. Poverty is defined as the percentage of individuals below the poverty line in the year prior to the year under study. Finally, the unemployment rate is the percentage of individuals 16 years of age or older in the civilian labor force who are unemployed. Each of these measures are standardized by converting it to a *z*-score and summed so that greater numbers are indicative of higher levels of social disorganization. This measure serves as a time-varying covariate in the second set of analyses.

Region. The final measure is region of the US, defined by the US Census Bureau. Region is a time-invariant control used in all models. The Midwest region serves as the reference category.

Police Structure.

The current study proposes that representation of minorities in police departments is a structural arrangement indicative of organizational complexity and referred to as personal differentiation. Women and Latinx and Black individuals are the minority groups under study in the current project.

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[4] Previous research on social disorganization focused on communities within urban areas. Osgood and Chambers (2000) demonstrated that these measures are applicable to larger communities as well as those outside traditional urban settings.

While the operationalization of female representation has been consistent across previous studies (i.e., the percentage of women officers employed), three distinct measures of racial and ethnic minority representation have been used in the prior literature. The simplest is the same measure used for female representation: the percentage of Latinx or Black individuals employed by police organizations (used by Eitle et al., 2005; Nicholson-Crotty et al., 2017; Ochs, 2011; Schuck, 2018; Wilkins & Williams, 2008, 2009). Researchers such as Hur (2012) and Miller (2013) have used measures of heterogeneity (such as a Blau index of diversity or a Gini coefficient), but these measures fail to capture the independent influence of specific groups, instead capturing the overall effect of diversity. A third option used by Smith (2003), Smith and Holmes (2003), and Shjarback and colleagues (2017) is to use a ratio of the percentage of officers of color employed by departments to their group's representation in the population served. This operationalization aligns with the wording of Mosher's (1968) conceptualization of passive representative bureaucracy ("…the source of origin of individuals and the degree to which, collectively, they mirror the total society." (p. 12)). Because there is theoretical disagreement about the appropriate measurement of representation, I create one measure of female representation and two measures each of ethnic and racial representation using data from the 1987, 1990, 1993, 1997, 2000, 2003, 2007, and 2013 LEMAS surveys.

First, I calculate the percentage of women, Latinx, and Black officers employed by each large municipal police department. The wording of the LEMAS surveys changed across the data collection years but it is still possible to create meaningful longitudinal measures from these data. From 1987 to 2000, the survey instrument used a data collection grid that asked for the numbers of officers by sex in columns and race and ethnicity in rows. Specifically, respondents were asked to report the number of male and female officers in the following racial/ethnic categories: White, not of Hispanic origin; Black or African American, not of Hispanic origin; Hispanic or Latino; American Indian or Alaska native; Asian; Native Hawaiian or Other Pacific Islander; and Some other race. The 2007 and 2013 data collection instruments separated the questions, asking about the total number of full- and part-time sworn personnel by sex and the number of full-time sworn personnel by race and ethnicity in a different question.

Absolute female representation. The percentage of female police officers employed by departments was calculated by dividing the total number of full-time female officers reported on the LEMAS survey by the total number of full-time officers employed by the departments in each year and multiplying that by 100.

Absolute Latinx representation. The percentage of Latinx police officers employed by departments was calculated by dividing the total number of full-time Hispanic or Latino officers reported on the LEMAS survey by the total number of full-time officers employed by the departments in each year and multiplying that by 100.

Absolute Black representation. The percentage of Black police officers employed by departments was calculated by dividing the total number of full-time Black or African-American, not of Hispanic origin officers reported on the LEMAS survey by the total number of full-time officers employed by the departments in each year and multiplying that by 100.

Second, I create measures of ethnic and racial representation relative to the number of individuals in each group in the community. Following Shjarback and colleagues (2017), a constant of 0.01 was added to both the numerator and denominator. This "functional zero" does not substantively change the measure but serves to prevent mathematical issues with zeros in division (as would happen in cases where either no Black or Latinx officers were employed by the department and/or lived in the community). A similar measure for female representation was not created due to the lack of variation in the denominator (i.e., most cities have approximately equal representation of men and women in the community).

Relative Latinx representation. The measure of Latinx police officer representation relative to Latinx community representation was calculated with the following formula:

$$\frac{\%\, Latinx\ police\ officers +\ .01}{\%\, Latinx\ community\ members +\ .01}$$

Relative Black representation. The measure of relative representation was calculated in the same way for race as it was for ethnicity:

$$\frac{\%\, Black\ police\ officers +\ .01}{\%\, Black\ community\ members + .01}$$

Values of one are indicative of perfect representation of officers of color proportional to people of color in the community. Communities in which officers of color are underrepresented are characterized by values less than one and those that have values greater than one are indicative of overrepresentation of officers of color (Shjarback et al., 2017).

The absolute measures of representation (i.e., the percentage measures) serve as the dependent variables for the first set of analyses. Both sets of representation measures serve as time-varying covariates/independent variables of interest for the second, third, fourth, and fifth set of analyses; results are compared and theoretical implications are discussed.

Organizational size. Organizational size refers to the number of full-time employees of each department (Maguire, 2003). In the current study, organizational size serves as a time-varying covariate for all analyses.

Police Performance

The current study proposes that a) index crime reporting and b) index crime clearance rates may be affected by minority representation in large US municipal police departments. Data from the FBI's UCR program were used to create the 14 crime measures.

The **homicide, rape, robbery, aggravated assault, burglary, larceny-theft, and motor-vehicle theft reporting rates** were calculated by dividing the total number of each crime type reported to the police each year by the population[5] and multiplying that by 100,000. This calculation yields the index crime rate per 100,000 population for each crime type for large US cities. In order to isolate the effect of crime reporting from crimes committed, analyses control for social disorganization (related to crime in urban areas (Blau & Blau, 1982)) but unrelated to crime reporting behaviors (Baumer, 2002), see community measures, above, for details). The measures of crime reporting serve as the dependent variables in the second and third set of analyses.

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[5] I use the intercensal population estimates calculated from the 1980 – 2010 US decennial censuses and the 2017 ACS for the denominator (rather than the population reported by the FBI) in order to maintain consistency in population estimates. The FBI uses the state growth rate (rather than the growth rate of the city) to calculate its reported population estimates (Lynch & Jarvis, 2008), so my population measure is likely more accurate as well.

Clearance rates for **homicide, rape, robbery, aggravated assault, burglary, larceny-theft, and motor-vehicle theft** were calculated by dividing the total number of crimes cleared[6] by the total number of crimes reported for each year and multiplying that by 100. This yields the percentage of crimes reported that were cleared by the police in a given year. The crime clearance measures serve as the dependent variables in the fourth and fifth set of analyses.

Analytic Procedures

Data Linkage

The current study requires the merging of 14 datasets. Since police departments serve as the unit of analysis, each wave of LEMAS data were limited to large (employing 135 or more sworn individuals in 1987 and 100 or more sworn employees thereafter) municipal agencies. In order to link LEMAS data sets, police departments were assigned an identification number with a manual check of the name and Originating Agency Identification (ORI) number. Police data were merged with UCR data using the ORI code and with the Census Place data using the name and location of the agency.

Linear Interpolation

Intercensal estimates were obtained through the use of linear interpolation. Linear interpolation is commonly used to estimate community data between censuses for longitudinal analyses, though the validity of this method was not examined prior to 2015 (Weden et al., 2015). In order to assess the validity of the method, Weden and colleagues (2015) compared interpolated demographic and socioeconomic data from the 2000 and 2010 censuses for counties and census tracts to data from the Census Bureau's Population

[6] Observations of subjects that reported zero offenses were marked as missing to avoid the problem of dividing by zero.

Estimates Program and the Small Area Income and Poverty Estimates. The authors found that interpolated demographic estimates were highly reliable: less than 10% of estimates were outside of a one percentage point range. Interpolated socioeconomic measures were less reliable, though 90% of the estimates were within a seven percentage point range. Estimates for larger population sizes were more reliable, both when comparing county estimates to census tract estimates and larger counties to smaller counties (Weden et al., 2015). Because the population of large municipalities in the sample are comparable to the size of the counties defined as large in the analysis, linear interpolation was used.

For each Census measure a difference score was calculated by subtracting the 2010 measure from the 2017 measure, the 2000 measure from the 2010 measure, the 1990 measure from the 2000 measure, and the 1980 measure from the 1990 measure. This was divided by seven for the 2010 – 2017 estimate and by ten for all other estimates (to estimate the average annual change); the resulting value was multiplied by the number of years from the decennial census estimate and added to the starting value of the decennial census estimate.

Factor Analysis

Exploratory factor analyses were performed for all indices (i.e., women's relative status, Latinx relative status, Black relative status, social disorganization) to check for internal consistency prior to multivariate analyses. Appropriate adjustments (e.g., dropping variables that were not consistent with other measures) were made. See Results for detailed information.

Data Screening

Data were screened for normality, univariate outliers, and multicollinearity. Appropriate adjustments (e.g., transformation of non-normal data) were made using R package “robumeta” (Fisher et al., 2017). Details are presented in the Results section.

Plan of Analysis

There are a number of issues that must be considered when selecting an analytic method for longitudinal research. These include the structure of the outcome variable, the number of research subjects, the number of observations per subject, the number and type of covariates, and the variance-covariance structure of the data (Hedeker & Gibbons, 2006). Because the outcome variables in the current project are continuous and have an approximately normal distribution, the number of subjects is large, the number of observations vary between subjects, and both categorical and continuous covariates are included, data were analyzed using mixed-effects regression models for longitudinal analyses. Mixed-effects regression models, also known as hierarchical linear models (HLMs), are more robust than traditional methods of longitudinal data analysis (such as univariate and multivariate analyses of variance and time-series analysis) because they are forgiving of missing data (missing data are considered ignorable if the pattern of missingness can be explained by covariates) and do not have restrictive assumptions about variance-covariance structures or the number and spacing of time points under study. They also allow for the estimation of subject effects over time (rather than being limited to group trends) by including a random-subject term (Hedeker & Gibbons, 2006; Gibbons et al., 2010).

Hierarchical linear models for longitudinal data treat observations at different time points as being nested within subjects (in the current study, police departments). As such, level-1 of the equation estimates the growth trajectory of each individual subject (within-subjects model) and the level-2 equation uses the growth parameters as outcome variables (between-subjects model (Raudenbush & Bryk, 2002). Time is treated as a continuous measure and in the current study is coded as years. The intercept is interpreted as the value of the dependent variable at the zero-coded time-point; in the current study, the most recent time point for each model is coded zero. Slope parameters are interpreted as the amount of both group and subject change over time. Level-1 predictor variables are referred to as time-varying covariates because they change over time, while level-2 predictor variables are time-invariant (Hedeker & Gibbons, 2006).

A process of model-building is recommended for mixed-effects regression models wherein additional parameters are added one-by-one into models with the new specifications tested against the old to determine whether the new term(s) improve model fit (Field, 2013; Hedeker & Gibbons, 2006; Raudenbush & Bryk, 2002). For each of the 34 dependent variables in the current study, the same model-building process is used.

First, a baseline model (also referred to as an unconditional or one-way analysis of variance (ANOVA)) is specified by regressing time on the outcome variable. No level-2 predictors are specified in this model. Formally,

$$\text{Level-1:} \quad y_{ij} = \beta_0 + \beta_1 t_{ij} + \varepsilon_{ij}$$

where the outcome (y) for subject i at observation j (both denoted by subscripts) is a function of the population level of the outcome (β_0) at time 0 plus the population average slope (β_1) multiplied by the level of time (t) plus the error for subject i at observation j

(ε_{ij}). In other words, this model estimates the mean intercept (i.e., the average value of the outcome variable at time 0) and mean rate of change per unit of time. A significant effect of time on the outcome variable is indicative that the population mean of the outcome changes over time and thus that it is appropriate to proceed with a mixed-effects regression model. Additionally, the results provide a log-likelihood statistic by which to evaluate the model fit of the subsequent model.

Next, a random-intercept model adds a term for the random effect of the subject on the outcome:

$$\text{Level-1:} \quad y_{ij} = b_{0i} + b_{1i}t_{ij} + \varepsilon_{ij}$$

$$\text{Level-2:} \quad \begin{aligned} b_{0i} &= \beta_0 + v_{0i} \\ b_{1i} &= \beta_1 \end{aligned}$$

In this model, the outcome (*y*) for subject *i* at observation *j* is estimated by its level at time 0 (b_{0i}) plus its slope. Subject i's initial level is influenced by both the population initial level (β_0) and the unique contribution of the subject (v_{0i}). Here the individual slopes (b_{1i}) are held at the population mean (β_1), so it only tests whether the outcomes differ between subjects. The random intercept model assumes variances and covariances across time are the same (i.e., have compound symmetry), so at this stage the intraclass correlation (ICC) is calculated. The ICC is the ratio of subject-level variance to total variance, calculated as

$$ICC = \sigma_v^2 \,/\, \sigma^2 + \sigma_v^2$$

and is indicative of the proportion of variance due to subjects (Hedeker & Gibbons, 2006).

Third, a random-intercept and trend model also allows the slopes to vary randomly between subjects with the following modification to the level-2 model:

$$\text{Level-2:}\quad \begin{aligned} b_{0i} &= \beta_0 + v_{0i} \\ b_{1i} &= \beta_1 + v_{1i} \end{aligned}$$

This allows the slopes (as well as the intercepts) of the outcomes for individual subjects to vary randomly.

Fourth is the quadratic model. The previous models treated the effect of time on the outcome as being linear. The addition of a squared term of time tests whether there is a curvilinear effect of time. The model becomes:

$$\text{Level-1:}\quad y_{ij} = b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^2 + \varepsilon_{ij}$$

$$\text{Level-2:}\quad \begin{aligned} b_{0i} &= \beta_0 + v_{0i} \\ b_{1i} &= \beta_1 + v_{1i} \\ b_{2i} &= \beta_2 + v_{2i} \end{aligned}$$

Here, each subject's outcome varies as a function of their intercept as well as time. The population average intercept and each subject's deviation from that are given by β_0 and v_{0i}, the average linear trend and each subject's deviation are given by β_1 and v_{1i}, and the average quadratic trend and each subject's deviation are given by β_2 and v_{2i}.

The fifth model I refer to as the contextual model. The contextual variable (i.e., region of the US) is added to the level-2 model because it varies by subject but not time. The augmentation takes the form:

$$\text{Level-2:}\quad \begin{aligned} b_{0i} &= \beta_0 + \beta_2 R_i + \beta_3 R_i + \beta_4 R_i + v_{0i} \\ b_{1i} &= \beta_1 + \beta_5 R_i + \beta_6 R_i + \beta_7 R_i + v_{1i} \end{aligned}$$

where β_0 and β_1 represent the average time 0 outcome and slope (respectively) for the population. The time 0 population outcome (β_0) is added to the average difference in the outcome for subjects in the Northeast region (as compared to the Midwest) at time 0 (β_2), the average difference for subjects in the South region (compared to the Midwest) at time 0 (β_3), the average difference for subjects in the West region (compared to the Midwest) at time 0 (β_4), and the individual subject's deviation from their group intercept (v_{0i}). The term for the slope (b_{1i}) of each subject is constructed in the same way.

The next model introduces the independent variables of interest in the form of time-varying covariates. Each of these covariates is grand-mean centered ($x_{ij} - \bar{x}$) so that the model intercept is interpretable as the outcome at time 0 for subjects with the average value(s) of the time-varying covariate(s). The time-varying covariates are entered into the model at level-1 and the level-2 model is supplemented so that each subject's level of the covariate is multiplied by the average difference in the outcome for a unit change in the covariate (see *Model Summaries*, next, for complete formulas).

Finally, a model is estimated that tests whether there is an interaction between time and the time-varying covariates. Significant results indicate that the time-varying covariate has a differential impact over time. As each new model in the sequence is estimated, it is evaluated against the previous model to test whether it represents an improvement. To do this, the model deviance statistics (i.e., the log-likelihoods) are compared to one another. In cases where the most recent model represents an improvement over the previous model (as indicated by a lower absolute value of the log-likelihood), the parameters are carried forth into the next model. In cases where there was not an improvement, the parameters from the most recent model are dropped for the next model. For example, if the quadratic time model (model 4) was found to not be a significant improvement over the random intercept and trend model (model 3), the contextual model would be estimated without the polynomial for time.

Model Summaries

Models 1 – 3. The first set of analyses test hypotheses one through six regarding the impact of the organizational environment on representation. The three dependent variables are the percentage of women officers, the percentage of Latinx officers, and the percentage of Black officers employed by large US municipal police departments. Because we do not expect environmental variables to have an immediate impact on police organizations (e.g., we do not expect that a change in environmental complexity would alter the personal differentiation in police departments in the same year), time-varying covariates for these models are lagged three[7] years (i.e., personal differentiation in 2013 is predicted by environmental complexity in 2010). Level-1 (time-varying) predictors included are munificence (i.e., percent Latinx citizens, percent Black citizens), complexity (i.e., disparities in income, labor force participation, employment, and education), and organizational size. The level-2 (time-invariant) predictor is region of the US. A complete model (one in which each of the additional parameters identified above contributed significantly to the model) would be calculated by:

$$
\begin{aligned}
\text{Level-1:}\quad y_{ij} =\ & b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^{2} + b_{3i}Muni_{ij} + b_{4i}ID_{ij} + b_{5i}LFPD_{ij} + \\
& b_{6i}EmD_{ij} + b_{7i}EdD_{ij} + b_{8j}S_{ij} + b_{9j}(Muni_{ij} * t_{ij}) + \\
& b_{10j}(ID_{ij} * t_{ij}) + b_{11j}(LFPD_{ij} * t_{ij}) + b_{11j}(EmD_{ij} * t_{ij}) + \\
& b_{12j}(EdD_{ij} * t_{ij}) + b_{13j}(S_{ij} * t_{ij}) + \varepsilon_{ij}
\end{aligned}
$$

$$
\begin{aligned}
\text{Level-2:}\quad b_{0i} &= \beta_0 + \beta_{14}R_i + \beta_{15}R_i + \beta_{16}R_i + v_{0i} \\
b_{1i} &= \beta_1 + \beta_{17}R_i + \beta_{18}R_i + \beta_{19}R_i + v_{1i} \\
b_{2i} &= \beta_2 + v_{2i} \\
b_{3i} &= \beta_3 \\
b_{4i} &= \beta_4 \\
b_{5i} &= \beta_5 \\
b_{6i} &= \beta_6
\end{aligned}
$$

[7] I attempted to arrive at the number of years to lag the data empirically. Preliminary models were run with all time-varying, time-invariant, and quadratic terms included for each of the dependent variables for no lag and for lags one to ten years. It was clear from the results, however, that the model fit improved with a reduction in time points. I chose to use the three-year lag for all models as a balance between loss of information and model fit. See Table B2.1 in Appendix A for details.

$$\begin{aligned} b_{7i} &= \beta_7 \\ b_{8i} &= \beta_8 \\ b_{9i} &= \beta_9 \\ b_{10i} &= \beta_{10} \\ b_{11i} &= \beta_{11} \\ b_{12i} &= \beta_{12} \\ b_{13i} &= \beta_{13} \end{aligned}$$

where y_{ij} represents the percentage of female, Latinx, or Black officers employed by department *i* at time *j*. This is calculated at level-1 by the summation of department *i*'s percent representation at time 0 (b_{0i}), department *i*'s average slope (b_{1i}) multiplied by the level of time (t_{ij}), department *i*'s average slope (b_{2i}) multiplied by the level of time squared (t_{ij}^2), department *i*'s change in slope due to munificence (b_{3i}), department *i*'s change in slope due to income disparity (b_{4i}), department *i*'s change in slope due to LFP disparity (b_{5i}), department *i*'s change in slope due to employment disparity (b_{6i}), department *i*'s change in slope due to education disparity (b_{7i}), department *i*'s change in slope due to organizational size (b_{8i}), and department *i*'s error at time *j* (ε_{ij}). The level-2 model estimates the intercept (b_{0i}) as a function of region of the US (β_{14}, β_{15}, and β_{16}) and the slope (*beta*s 1 – 13) based on the contributions of region of the US and individual departures from the group mean, the quadratic time trend and the subject departure from the population mean, and the population average slopes of munificence, income disparity, LFP disparity, employment disparity, education disparity, organizational size, munificence by time, income disparity by time, LFP disparity by time, employment disparity by time, education disparity by time, and organizational size by time.

Models 4 – 10. The next set of analyses test hypotheses seven through nine (that female, Latinx, and Black representation are related to index crime reporting rates) by regressing measures of representation, social disorganization, a multiplicative interaction effect of representation by population (for hypotheses 8a and 9a), organizational size, and region of the US on index crime reporting rates. Specifically, the seven dependent variables include the homicide, rape, robbery, aggravated assault, burglary, larceny-theft, and motor-vehicle theft reporting rates which are each lead three years from the predictor variables. Time-varying covariates (level-1 measures) include the percentage of women officers, percentage of Latinx officers, percentage of Black officers, social disorganization, organizational size, the percentage of Latinx officers * percentage Latinx population, and the percentage of Black officers * percentage Black population. Specifically,

$$\text{Level-1: } y_{ij} = b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^2 + b_{3i}AR_{ij} + b_{4i}SD_{ij} + b_{5i}S_{ij} + b_{6j}(AR_{ij} * Muni_{ij}) + b_{7j}(AR_{ij} * t_{ij}) + b_{8j}(SD_{ij} * t_{ij}) + b_{9j}(S_{ij} * t_{ij}) + \varepsilon_{ij}$$

$$\begin{aligned} \text{Level-2: } b_{0i} &= \beta_0 + \beta_{10}R_i + \beta_{11}R_i + \beta_{12}R_i + v_{0i} \\ b_{1i} &= \beta_1 + \beta_{13}R_i + \beta_{14}R_i + \beta_{15}R_i + v_{1i} \\ b_{2i} &= \beta_2 + v_{2i} \\ b_{3i} &= \beta_3 \\ b_{4i} &= \beta_4 \\ b_{5i} &= \beta_5 \\ b_{6i} &= \beta_6 \\ b_{7i} &= \beta_7 \\ b_{8i} &= \beta_8 \\ b_{9i} &= \beta_9 \end{aligned}$$

Models 11 – 17. Models 11 through 17 also test hypotheses seven through nine, though with the relative measure of representation. Because relative representation is already a measure of association between the employment of officers of color and the size of communities of color, the multiplicative interaction term is not included. The formula is thus

$$\text{Level-1: } y_{ij} = b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^2 + b_{3i}RR_{ij} + b_{4i}SD_{ij} + b_{5i}S_{ij} + b_{6j}(RR_{ij} * t_{ij}) + b_{8j}(SD_{ij} * t_{ij}) + b_{9j}(S_{ij} * t_{ij}) + \varepsilon_{ij}$$

$$\text{Level-2: } b_{0i} = \beta_0 + \beta_{10}R_i + \beta_{11}R_i + \beta_{12}R_i + v_{0i}$$

$$
\begin{aligned}
b_{1i} &= \beta_1 + \beta_{13}R_i + \beta_{14}R_i + \beta_{15}R_i + v_{1i}\\
b_{2i} &= \beta_2 + v_{2i}\\
b_{3i} &= \beta_3\\
b_{4i} &= \beta_4\\
b_{5i} &= \beta_5\\
b_{6i} &= \beta_6\\
b_{7i} &= \beta_7\\
b_{8i} &= \beta_8\\
b_{9i} &= \beta_9
\end{aligned}
$$

with each of the seven dependent variables for index crime reporting rates.

Models 18 – 24. The next set of analyses test hypotheses ten through twelve (that female, Latinx, and Black representation are related to index crime clearance rates) by regressing measures of representation, organizational size, and region of the US on index crime clearance rates. Dependent variables include the homicide, rape, robbery, aggravated assault, burglary, larceny-theft, and motor-vehicle theft clearance rates and are lead three years from the independent variables. For each of these models, the complete formula is given by:

Level-1: $y_{ij} = b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^2 + b_{3i}AR_{ij} + b_{4i}S_{ij} + b_{5j}(AR_{ij} * Muni_{ij}) + b_{6j}(AR_{ij} * t_{ij}) + b_{7j}(S_{ij} * t_{ij}) + \varepsilon_{ij}$

Level-2:

$$
\begin{aligned}
b_{0i} &= \beta_0 + \beta_8R_i + \beta_9R_i + \beta_{10}R_i + v_{0i}\\
b_{1i} &= \beta_1 + \beta_{11}R_i + \beta_{12}R_i + \beta_{13}R_i + v_{1i}\\
b_{2i} &= \beta_2 + v_{2i}\\
b_{3i} &= \beta_3\\
b_{4i} &= \beta_4\\
b_{5i} &= \beta_5\\
b_{6i} &= \beta_6\\
b_{7i} &= \beta_7
\end{aligned}
$$

Models 25 – 31. Similarly, the final set of models test hypotheses ten through twelve again with the independent variable of interest the measure of relative representation. For these,

Level-1: $y_{ij} = b_{0i} + b_{1i}t_{ij} + b_{2i}t_{ij}^2 + b_{3i}RR_{ij} + b_{4i}S_{ij} + b_{5j}(RR_{ij} * t_{ij}) + b_{6j}(S_{ij} * t_{ij}) + \varepsilon_{ij}$

$$
\begin{aligned}
\text{Level-2:}\quad b_{0i} &= \beta_0 + \beta_7 R_i + \beta_8 R_i + \beta_9 R_i + v_{0i} \\
b_{1i} &= \beta_1 + \beta_{10} R_i + \beta_{11} R_i + \beta_{12} R_i + v_{1i} \\
b_{2i} &= \beta_2 + v_{2i} \\
b_{3i} &= \beta_3 \\
b_{4i} &= \beta_4 \\
b_{5i} &= \beta_5 \\
b_{6i} &= \beta_6
\end{aligned}
$$

See Table 4 for a summary of the models.

Table 4

Model Summaries

	Models 1 – 3	Models 4 – 10	Models 11 – 17	Models 18 – 24	Models 25 – 31
DV	Representation	Reporting rate	Reporting rate	Clearance rate	Clearance rate
Time	-2013 = 0 -1993 = -20	-2017 = 0[1] -1987 = -30	-2017 = 0[1] -1987 = -30	-2017 = 0[1] -1987 = -30	-2017 = 0[1] -1987 = -30
Level-1	-Munificence -Complexity -Dynamism	-Absolute rep. -Absolute rep.*Munificence -Social disorg.	-Relative rep. -Social disorg.	-Absolute rep. -Absolute rep.*Munificence	-Relative rep.
Level-2	-Org. size -Region	-Org. size -Region	-Org. size -Region	-Org. size -Region	-Org. size -Region

[1]The UCR definition of rape changed in 2011; legacy rape and revised rape definitions are incomparable. For these models, 2010 = 0, 1987 = -23

CHAPTER IV

Results

Results of the factor analyses, data screening and management, descriptive statistics, and multivariate analyses are presented below. All analyses were conducted in R (R Core Team, 2020). Packages used for specific analyses are noted below; others used include “car” (Fox & Weisburg, (2019) and “tidyverse” (Wickham et al., 2019).

Factor Analyses

Factor analyses were used to assess whether the proposed scales demonstrated sufficient internal reliability. The R packages used for these analyses were “GPArotation” (Bernaards & Jennrich, 2005) and “psych” (Revelle, 2019); all results are presented in Appendix A. To conduct the initial factor analyses, data from each of the census years (i.e., 1980, 1990, 2000, 2010, and 2017) were pooled. Intercensal estimates were removed due to concerns with autocorrelation. The first factor analysis included 16 measures of gender, ethnic, and racial disparities in income (i.e., median income for gender and family, household, and per capita income for ethnicity and race), labor force participation, employment rate, and education rate as well as five measures of social disorganization (i.e., residential instability, ethnic heterogeneity, percent female-headed households, poverty rate, and unemployment rate). Because it was assumed there would be four underlying factors (i.e., women’s relative status, Latinx relative status, Black relative status, and social disorganization) which would be associated with one another, a direct oblimin rotation was used (Field, 2013) and a four-factor solution was requested. The four-factor solution was deemed sufficient (chi^2 = 4,845.50, df = 132, p = 0.000), a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy indicated that the variance in the data was likely due to an underlying factor structure (overall MSA = 0.81) (Kaiser & Rice, 1974), and Bartlett's test of sphericity indicated that the variables were related and therefore amenable to factor analysis (chi^2 = 45,016.54, df = 210, p = 0.000). See Table A1.1 in Appendix A for results. One variable (i.e., female employment disparity) had an individual MSA value of less than .50, so was removed for the next analysis (results presented in Table A1.2). This improved the overall MSA to 0.82. With the exception of factors two and four, the other factors were not highly correlated (see Table A1.3) so a third factor analysis was run using a varimax rotation.

Results of the third factor analysis (presented in Table A1.4) were congruent with the first two. The four-factor solution was sufficient (chi^2 = 4,562.80, df = 116, p = 0.000) and both the KMO (overall MSA = 0.82) and Bartlett's test (chi^2 = 44,364.99, df = 190, p = 0.000) indicated that the data were appropriate for factor analysis. The factor solution arrived at, however, bore only a slight resemblance to what was expected. The three measures of income disparity and educational disparities between Latinx and White, non-Latinx individuals within communities were highly related to one another (factor loadings ranged from 0.728 – 0.923), while LFP and employment disparities by ethnicity were more related (albeit weakly; loadings = 0.332, 0.442 respectively) to residential instability (0.958) and gendered education disparity (0.391). Each of the six measures of racial disparities loaded on a single factor, though the loadings were relatively low (ranging from 0.357 to 0.769). Four of the measures of social disorganization loaded acceptably together (i.e., ethnic heterogeneity = 0.408, percent female-headed households = 0.818, poverty rate = 0.858, and unemployment rate = 0.691), while none of the measures of gender disparities loaded acceptably together.

An analysis of the reliabilities highlighted the above identified issues with most of the proposed scales. First, the data were separated by census year to check that scales demonstrated appropriate reliability over time. Then, Cronbach's alpha was calculated for each scale in each census year. Results are presented in Table A1.5. The four-item gender disparity scale demonstrated poor to acceptable reliability. Removal of employment disparity between women and men increased the reliability, though the alpha values still are indicative of poor to acceptable reliability ($\alpha = 0.54 – 0.74$). For the measures of Latinx relative status, the family income disparity measure was used (rather than household or per capita) because it had the highest loading with the rest of the scale items in the previous analyses. Again, Cronbach's alpha values ranging from 0.43 to 0.59 showed poor reliability of the proposed scale. Household income performed better than the other measures of income for racial disparities. The proposed racial disparity scale demonstrated questionable to acceptable Cronbach's alpha scores ($\alpha = 0.65 – 0.72$). Finally, the four-item social disorganization scale (with residential instability removed) demonstrated the highest internal consistency, with alpha values ranging from 0.75 to 0.86. The four-item social disorganization scale was thus the only scale that was retained; all indicators of relative status are entered into the respective models separately.

Data Screening and Management

Mixed-effects regression models are extensions of linear regression models, so data are screened in a similar fashion. This includes assessing for outliers, linearity, normality, and homoscedasticity (Field, 2013). The assumption of normality references both the sampling distribution and the residuals. Because I have a large sample size (ranging from 253 to 516 observations per year), the central limit theorem indicates the sampling distribution will approximate a normal curve and thus is not a concern. The residuals are assumed to be normally distributed for the same reason.

Data were assessed for univariate outliers using a series of boxplots, presented in Appendix B. As demonstrated in the Appendix B figures, univariate outliers were common in the study variables. In many cases (i.e., percent Latinx citizens, percent Black citizens, income disparity by gender, ethnicity, and race; percent Latinx officers, percent Black officers, relative representation of both Latinx and Black officers, organizational size, the actual crime rates for all index offenses, and the clearance rates for robbery, burglary, and motor-vehicle theft) the outliers contributed to an extreme right skew in the data for one or more years (see tables in APPENDIX B for skewness and kurtosis statistics). Common methods of dealing with univariate outliers include deletion and alteration, usually by transforming the variable with the natural logarithm (Tabachnick & Fidell, 2013; Warner, 2013). The natural log can only be computed for values greater than zero, however, and multiple variables in the current study include negative values. Because this common data transformation was not viable for many of the variables, I elected to remove observations[8] that were outside of three standard deviations ($-3 > z > 3$) of the mean of each variable. This was done for all continuous variables with the exception of organizational size, which was calculated with the natural log first. The remaining outliers of the log of organizational size were removed.

[8] Note: I removed observations, not cases, in order to retain as many cases as possible. Outliers accounted for between 0% and 5.85% ($\bar{x}$ = 1.28%) of the environmental observations per measure, per year; between 0% and 3.63% ($\bar{x}$ = 1.44%) of the organizational observations per measure, per year; between 0% and 9.09% ($\bar{x}$ = 1.53%) of the crime rate observations per measure, per year; and between 0% and 1.94% ($\bar{x}$ = 0.56%) of the crime clearance observations per measure, per year.

The linearity and homoscedasticity assumptions are assessed post-hoc through examinations of plots of residuals (Field, 2013; Tabachnick & Fidell, 2013). Specifically, model equations, homoscedasticity, outliers, and symmetry are assessed with a Tukey-Anscombe plot of the residuals against the fitted values; the variance of the residuals is assessed with a scale-location plot of the square-root of the absolute values of the residuals; normality is assessed with a quantile-quantile (QQ) plot; and the residuals are plotted against each of the predictor variables (Tanadini, n.d.). Examinations of these plots revealed no issues with the model equations, heteroscedasticity, outliers, symmetry, variance, or normality for the models predicting female and Black representation. For the model predicting Latinx representation, there was some evidence of heteroscedasticity and increasing variance of the residuals with increased fitted values. Additionally, the model showed some evidence of a non-normal distribution of errors, though not so much as to be of concern. Heteroscedasticity and non-normal distribution of errors was observed in all of the crime models. Plotting the residuals against the independent variables showed there was greater variance in errors as ethnic and racial representation of both citizens and officers increased. A similar effect was observed for organizational size. Finally, the normal OLS assumption of independence of errors is violated because subjects are measured at multiple points in time. Mixed-effects regression models are Zcv designed, however, to account for the dependence of observations.

Descriptive Statistics

Below I present variable descriptive statistics obtained using packages "Rapport" (Blagotić & Daróczi, 2015), "SummaryTools" (Comtois, 2020), and "FSA" (Ogle, Wheeler, & Dinno, 2020). All figures were created using ggplot2, included in the "tidyverse" package (Wickham et al., 2019).

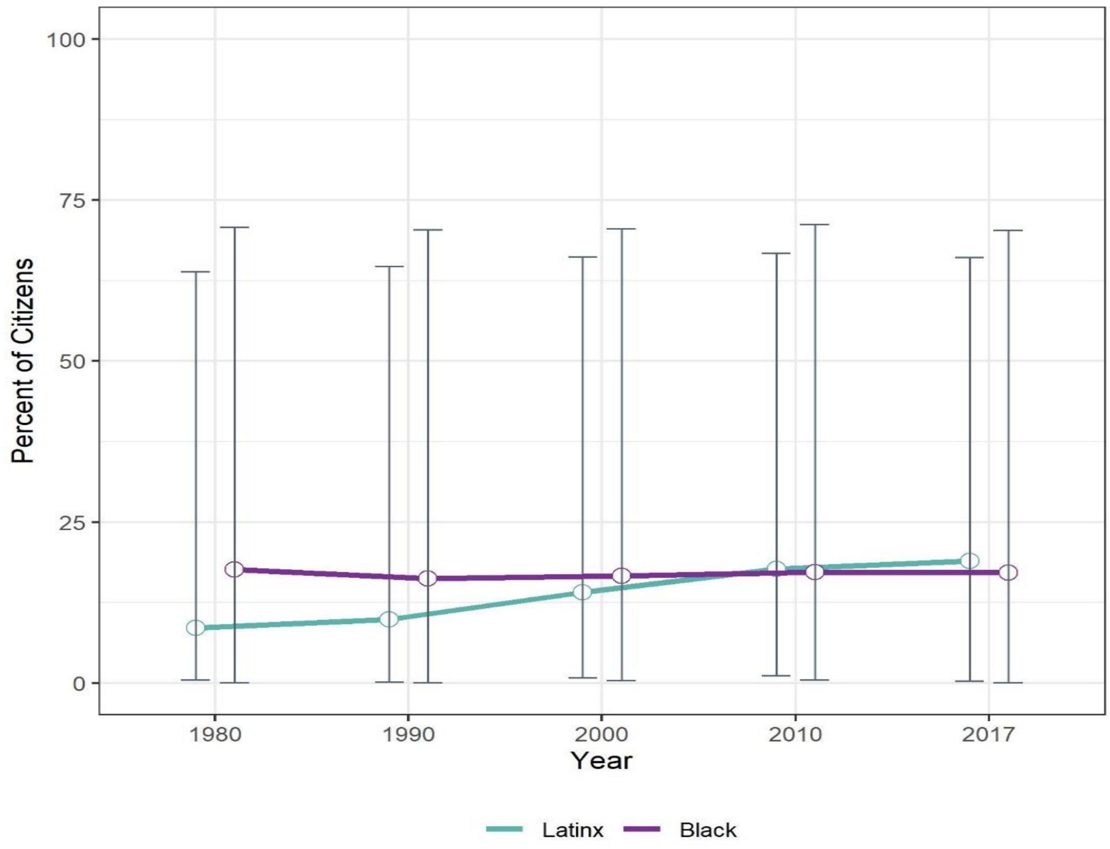
Organizational Environment

Measures of the organizational environment included in the current study are munificence, several indicators of complexity, and residential instability. Environmental control variables include social disorganization and region of the US. Descriptive statistics are presented in Table 5 for the five census-reporting years; intercensal values were estimated using the linear trend between reporting years.

Munificence. The percentage of Latinx citizens in the nation's largest cities has been increasing over time, while the percentage of Black citizens has remained fairly stable from 1980 to 2017. In 2017, the mean percentage of Latinx citizens in large US cities was 18.92 and the mean percentage of Black citizens was 17.13. See Figure 2 for summary information.

Figure 2

Organizational Environment: Munificence

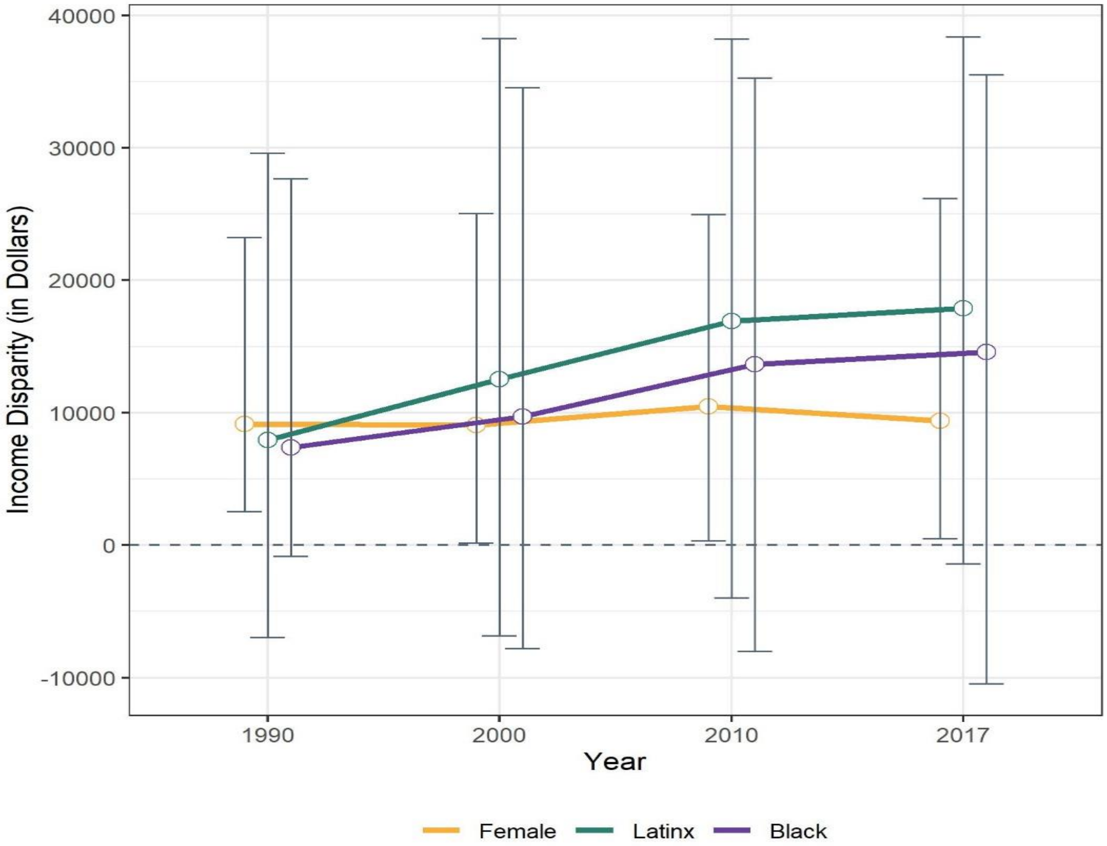


Note: Teal and purple lines indicative of the mean. Vertical lines indicative of the range.

Complexity. The complexity of police organizational environments are captured with disparities in income, labor force participation rates, employment rates, and education rates. As can be seen in Figure 3, the average disparity in income between citizens of color and White, non- Latinx citizens has approximately doubled since 1990. In 2017, Latinx citizens earned on average $17,886.92 less than White, non-Latinx citizens and Black citizens earned on average $14,580.92 less than White, non-Latinx

Figure 3

Organizational Environment: Complexity (Income Disparity)

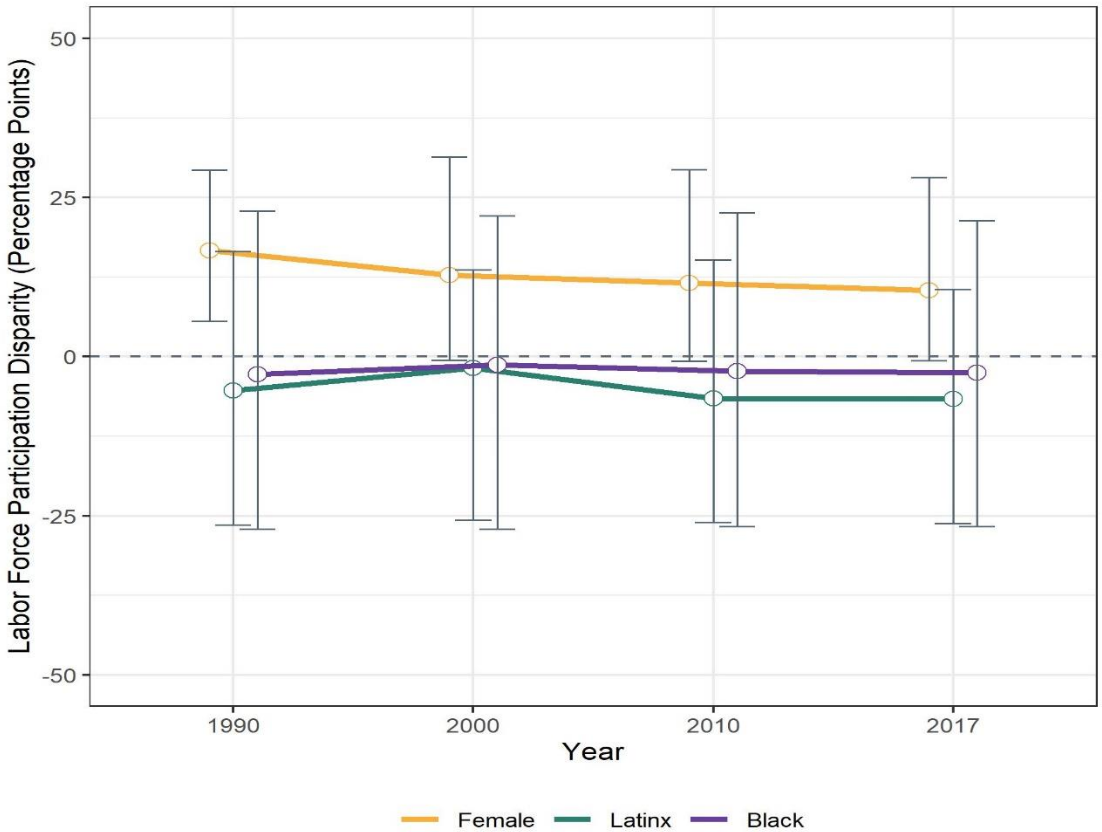


Note: Yellow, teal, and purple lines are indicative of the mean; grey vertical lines are indicative of the range, dashed grey horizontal line indicates no income disparity between represented groups.

citizens. The median income disparity between women and men has hovered around $10,000 since 1990, with men earning more than women in all large cities. Both labor force participation and employment rates have remained fairly stable since 1990 (see Figure 4 and Figure 5), though the LFP rate has varied more between cities than the employment rate. There has generally been greater LFP for men compared to women and people of color compared to White individuals. Since 1990 there has been virtually no difference in employment rates between men and women, White, non-Latinx individuals

Figure 4

Organizational Environment: Complexity (LFP Disparity)

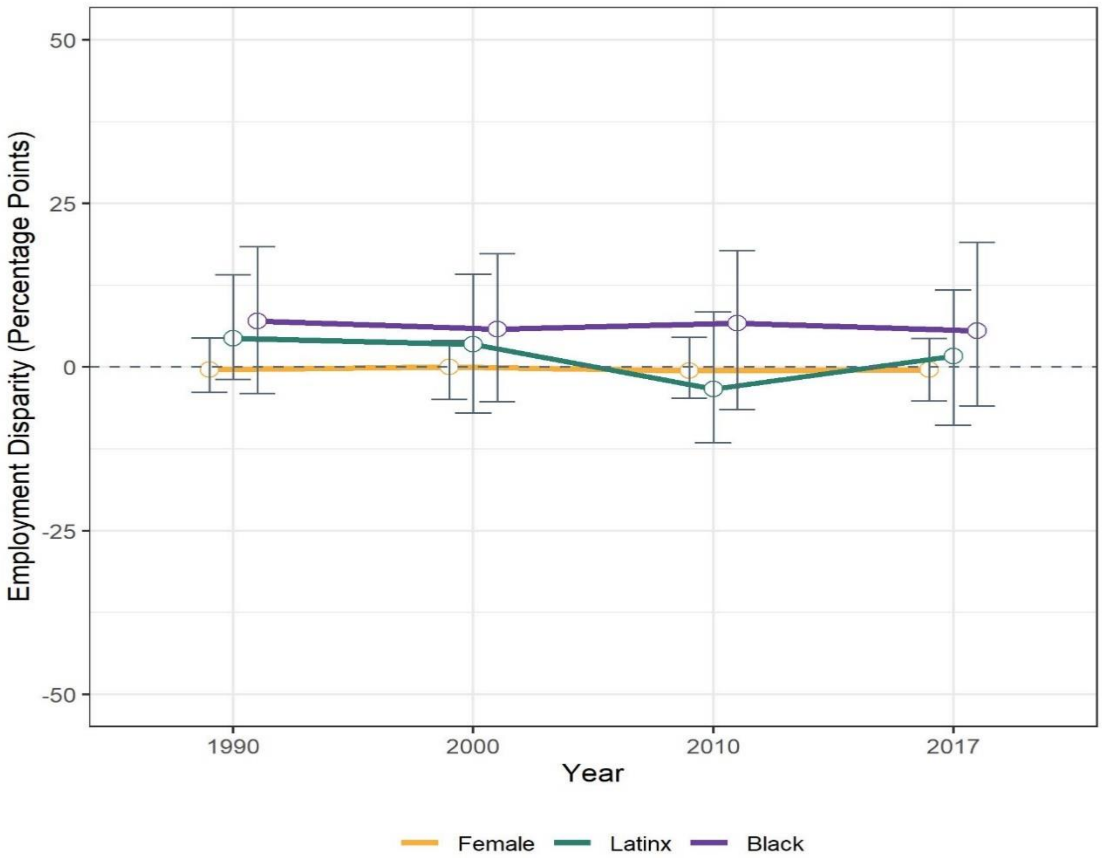


Note: Yellow, teal, and purple lines are indicative of the mean; grey vertical lines are indicative of the range, dashed grey horizontal line indicates no LFP disparity between represented groups.

have generally been employed at greater rates than Latinx individuals (though the average employment rate of Latinx individuals exceeded that of White, non-Latinx individuals in 2010). Disparities in educational attainment have been dynamic. While people of color had similar levels of educational attainment in 1990 (though lower than that of White, non-Latinx people), that worsened over time such that Latinx individuals had the lowest educational attainment in 2013, followed by Black individuals, then

Figure 5

Organizational Environment: Complexity (Employment Disparity)

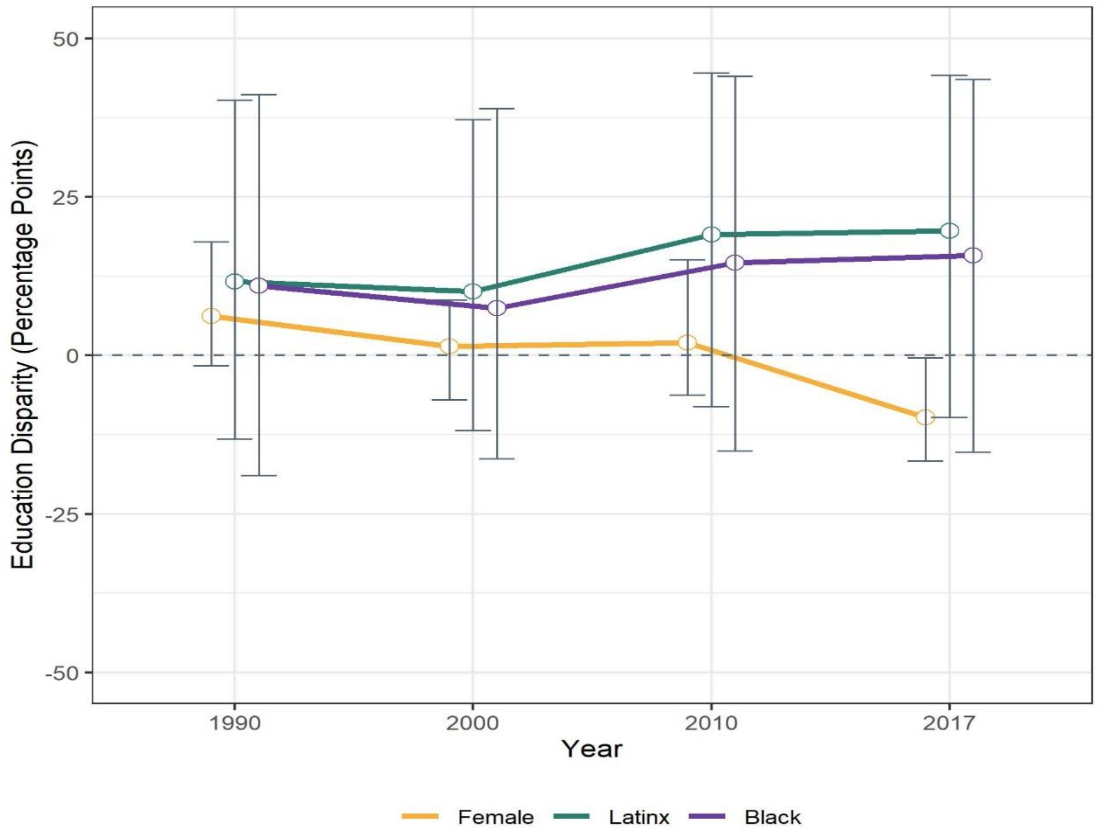


Note: Yellow, teal, and purple lines are indicative of the mean; grey vertical lines are indicative of the range, dashed grey horizontal line indicates no employment disparity between represented groups.

White, non-Latinx individuals. Disparities between women and men lowered between 1990 and 2000, then reversed course so that women's educational attainment outpaced men's in 2013. See Figure 6.

Figure 6

Organizational Environment: Complexity (Educational Disparity)

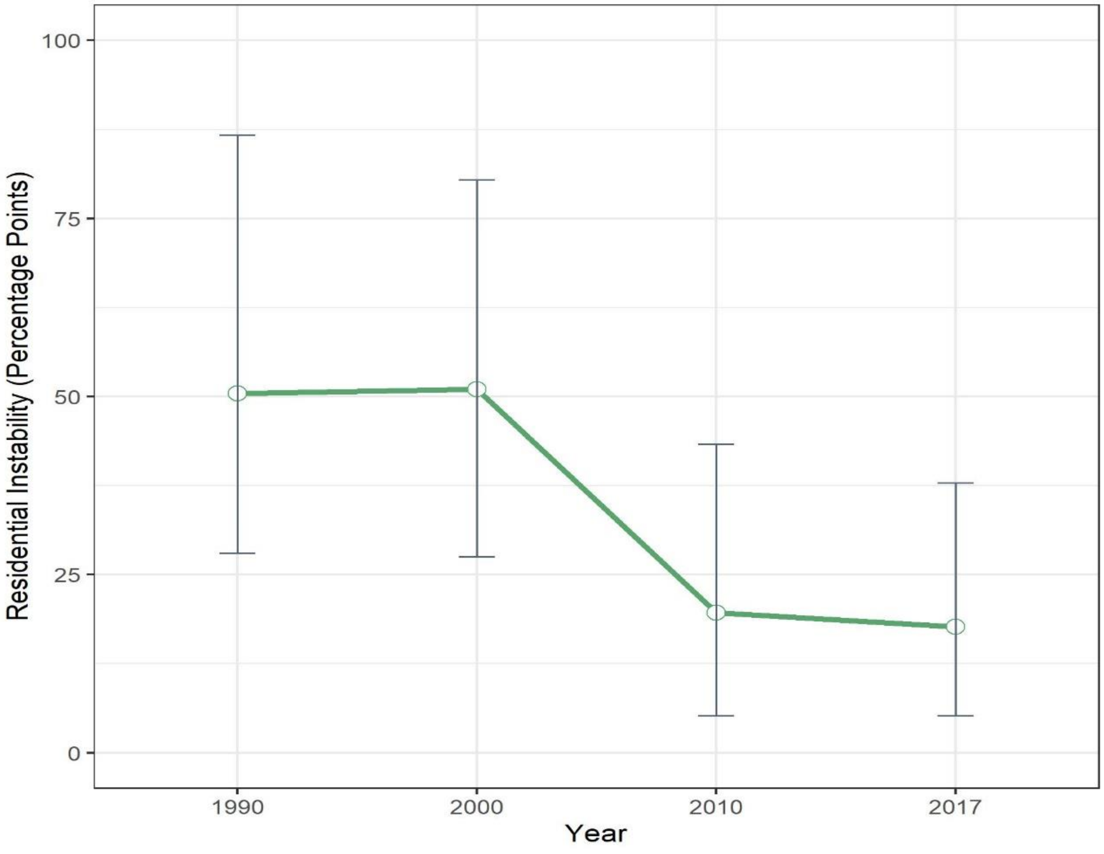


Note: Yellow, teal, and purple lines are indicative of the mean; grey vertical lines are indicative of the range, dashed grey horizontal line indicates no educational disparity between represented groups.

Dynamism. Residential instability was measured by the US Census as the number of individuals aged five years or older who lived in a different house five years prior in 1990 and 2000; this was changed for 2010 and subsequent years to the number of individuals aged one year or older who lived in a different house one year prior. Though Benetsky and Koerber (2012) estimated that the change reflected estimates that were similar in magnitude, Figure 7 showed a dramatic change in the estimates between 2000 and 2010 and thus will not be used in the analyses.

Figure 7

Organizational Environment: Dynamism

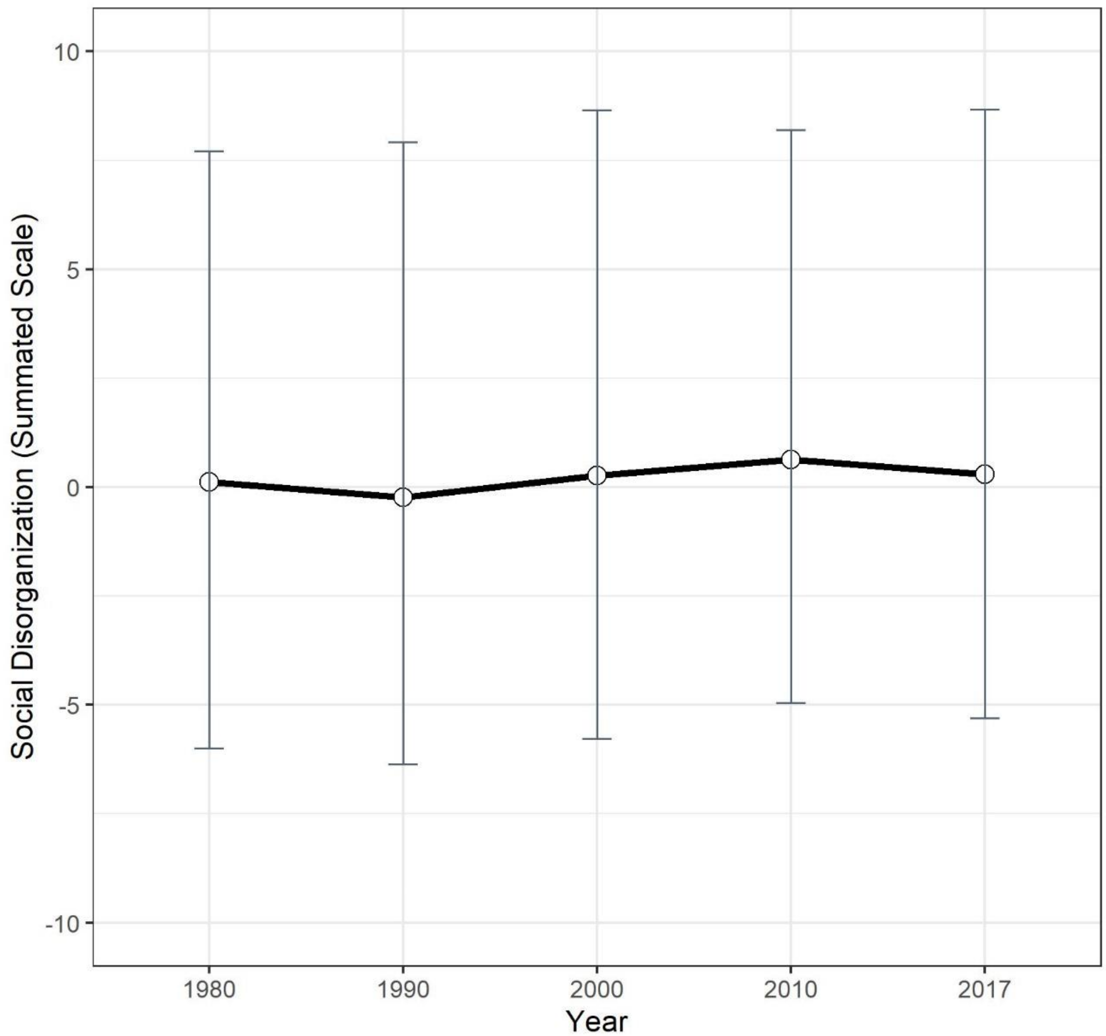


Note: Green line is indicative of the mean; grey vertical lines are indicative of the range.

Controls. The social disorganization scale was constructed by summating the standardized values of ethnic heterogeneity, the percentage of female-headed households, the poverty rate, and the unemployment rate. Social disorganization in the cities in the sample decreased from 1980 to 1990, increased until 2010, and then dropped again in 2017. See Figure 8.

Figure 8

Social Disorganization

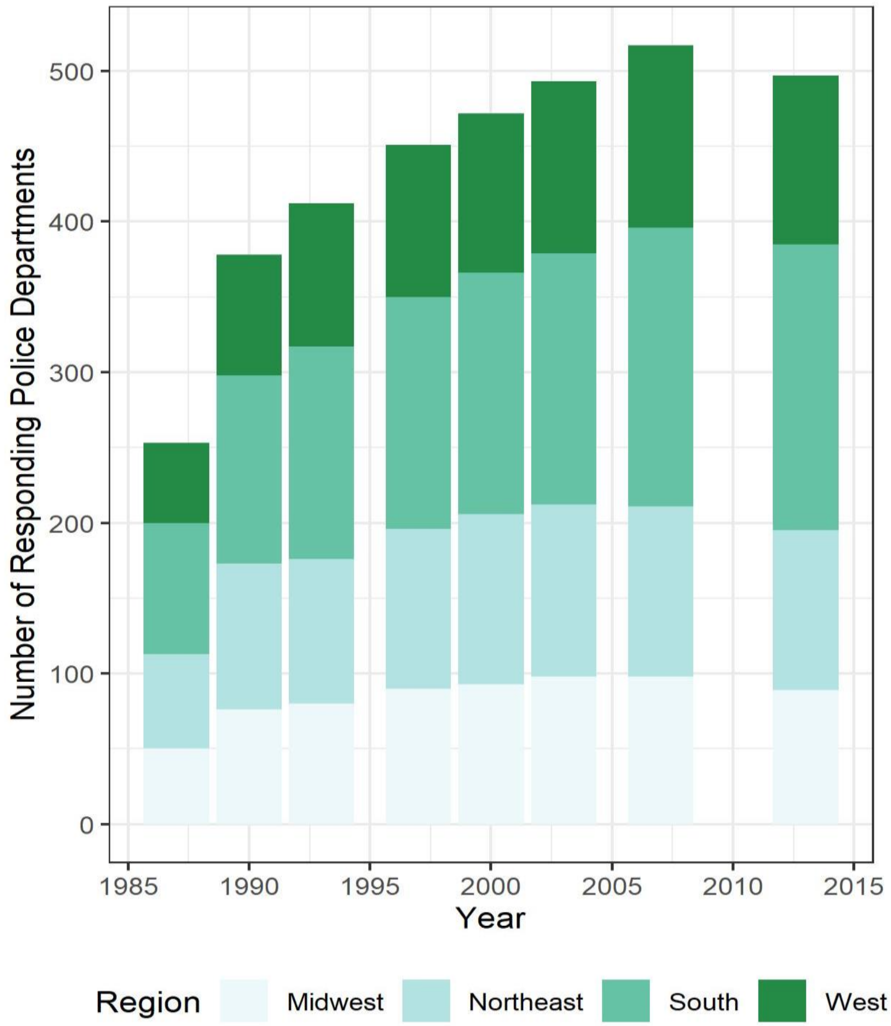


Note: Black line is indicative of the mean; grey vertical lines are indicative of the range.

Response rates from the four regions of the US have remained fairly stable over time (see Figure 9 and Table 6). Approximately 20% of the large municipal police departments are in the Midwest, 25% in the Northeast, 35% in the South, and 20% in the West.

Figure 9

Region of the United States



,l.

Table 5

Descriptive Statistics: Organizational Environment

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Munificence					
Percent Latinx citizens	(225)[1]	(465)	(530)	(456)	(454)
Mean	8.52	9.87	14.05	17.73	18.92
SD	11.13	12.07	14.24	14.74	15.24
Min	0.50	0.13	0.80	1.10	0.30
Median	3.90	4.45	8.60	13.35	14.35
Max	63.90	64.67	66.20	66.80	66.10
Percent zero	0.00	0.00	0.00	0.00	0.00
Percent Black citizens	(227)	(469)	(534)	(466)	(466)
Mean	17.60	16.19	16.66	17.17	17.13
SD	16.85	16.46	16.69	16.12	15.94
Min	0.10	0.08	0.40	0.50	0.10
Median	12.00	9.43	10.70	11.40	11.50
Max	70.80	70.43	70.60	71.20	70.30
Percent zero	0.00	0.00	0.00	0.00	0.00
Complexity					
Median income disparity (gender)	---	(470)	(540)	(461)	(456)
Mean	---	$9,157.14	$9,050.71	$10,487.26	$9,374.16
SD	---	$3,513.99	$4,121.88	$4,571.05	$4,485.88
Min	---	$2,544.00	$184.00	$315.00	$478.00
Median	---	$8,585.50	$8,297.00	$9,405.00	$8,548.50
Max	---	$23,237.00	$25,051.00	$24,971.00	$26,171.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Percent zero	---	0.00	0.00	0.00	0.00
Per capita income disparity (ethnicity)	---	(389)	(542)	(458)	(443)
Mean	---	$7,927.34	$12,541.47	$16,922.57	$17,886.92
SD	---	$4,149.81	$6,104.13	$6,520.40	$6,991.12
Min	---	-$6,950.00	-$6,834.00	-$3,955.00	-$1,412.00
Median	---	$7,508.00	$11,292.00	$15,973.00	$16,867.00
Max	---	$29,587.00	$38,255.00	$38,191.00	$38,373.00
Percent zero	---	0.00	0.00	0.00	0.00
Per capita income disparity (race)	---	(426)	(536)	(459)	(445)
Mean	---	$7,367.09	$9,693.68	$13,654.35	$14,580.92
SD	---	$3,988.30	$5,845.61	$7,131.90	$7,477.77
Min	---	-$851.00	-$7,786.00	-$8,004.00	-$10,445.00
Median	---	$6,685.50	$8,983.50	$12,839.00	$13,743.00
Max	---	$27,656.00	$34,536.00	$35,255.00	$3,5510.00
Percent zero	---	0.00	0.00	0.00	0.00
LFP disparity (gender)	---	(472)	(541)	(476)	(471)
Mean	---	16.65	12.82	11.54	10.39
SD	---	3.82	3.84	4.46	4.39
Min	---	5.57	-0.57	-0.72	-0.64
Median	---	16.65	12.74	11.48	10.20
Max	---	29.32	31.37	29.37	28.18
Percent zero	---	0.00	0.00	0.00	0.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
LFP disparity (ethnicity)	---	(383)	(537)	(472)	(468)
Mean	---	-5.29	-1.76	-6.53	-6.66
SD	---	6.81	6.52	6.78	5.99
Min	---	-26.40	-25.66	-26.00	-26.20
Median	---	-5.10	-1.27	-5.90	-6.50
Max	---	16.50	13.65	15.20	10.60
Percent zero	---	0.52	0.00	0.85	0.43
LFP disparity (race)	---	(420)	(537)	(470)	(472)
Mean	---	-2.74	-1.27	-2.27	-2.50
SD	---	7.68	7.74	7.74	7.71
Min	---	-27.10	-27.08	-26.70	-26.70
Median	---	-1.95	-0.78	-2.00	-2.60
Max	---	22.90	22.15	22.60	21.40
Percent zero	---	0.24	0.00	0.64	0.21
Employment disparity (gender)	---	(469)	(535)	(467)	(469)
Mean	---	-0.38	0.02	-0.55	-0.38
SD	---	1.45	1.32	1.61	1.47
Min	---	-3.88	-4.96	-4.75	-5.19
Median	---	0.50	0.04	-0.59	-0.35
Max	---	4.51	4.03	4.56	4.40
Percent zero	---	0.00	0.00	0.00	0.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Employment disparity (ethnicity)	---	(383)	(539)	(471)	(471)
Mean	---	4.42	3.47	-3.32	1.65
SD	---	3.16	3.28	2.94	2.92
Min	---	-1.90	-6.95	-11.50	-8.90
Median	---	4.20	3.14	-3.60	1.50
Max	---	14.10	14.18	8.40	11.80
Percent zero	---	0.00	0.00	0.42	2.12
Employment disparity (race)	---	(425)	(540)	(463)	(471)
Mean	---	7.06	5.76	6.69	5.54
SD	---	3.82	3.69	4.53	4.14
Min	---	-4.00	-5.22	-6.50	-5.90
Median	---	7.20	5.74	7.10	5.50
Max	---	18.40	17.32	17.80	19.10
Percent zero	---	0.00	0.00	0.00	1.06
Education disparity (gender)	---	(457)	(542)	(476)	(374)
Mean	---	6.25	1.44	2.00	-9.77
SD	---	3.38	1.85	3.29	3.15
Min	---	-1.60	-6.98	-6.22	-16.60
Median	---	6.00	1.46	1.65	-9.75
Max	---	17.90	8.74	15.16	-0.40
Percent zero	---	0.22	0.00	0.00	0.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Education disparity (ethnicity)	---	(386)	(541)	(461)	(455)
Mean	---	11.62	10.09	19.08	19.66
SD	---	9.20	6.61	10.05	10.40
Min	---	-13.20	-11.85	-8.02	-9.80
Median	---	11.10	9.86	17.99	19.70
Max	---	40.30	37.25	44.60	44.20
Percent zero	---	0.26	0.00	0.00	0.00
Education disparity (race)	---	(422)	(542)	(460)	(456)
Mean	---	10.98	7.49	14.59	15.77
SD	---	9.87	7.11	11.75	11.58
Min	---	-18.90	-16.31	-15.08	-15.20
Median	---	10.80	7.40	12.98	14.80
Max	---	41.20	38.93	44.10	43.60
Percent zero	---	0.00	0.00	0.00	0.22
Dynamism					
Residential instability	(230)	(474)	(542)	(476)	(475)
Mean	49.49	50.48	51.02	19.66	17.71
SD	8.94	8.96	7.64	5.63	5.47
Min	27.80	28.00	27.50	5.20	5.20
Median	49.40	50.60	50.70	19.45	17.40
Max	74.90	86.70	80.40	43.30	37.90
Percent zero	0.00	0.00	0.00	0.00	0.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Social disorganization					
Scale	(201)	(467)	(541)	(476)	(475)
Mean	0.12	-0.24	0.27	0.63	0.30
SD	3.09	3.14	3.01	2.47	2.51
Min	-5.99	-6.36	-5.78	-4.95	-5.31
Median	-0.20	-0.43	0.07	0.55	0.17
Max	8.35	7.92	8.66	8.20	8.67
Percent zero	---	---	---	---	---
Ethnic heterogeneity[2]	(222)	(474)	(542)	(476)	(475)
Mean	0.31	0.32	0.37	0.40	0.39
SD	0.15	0.14	0.12	0.10	0.10
Min	0.02	0.03	0.04	0.08	0.07
Median	0.31	0.34	0.41	0.43	0.42
Max	0.50	0.50	0.50	0.50	0.50
Percent zero	0.00	0.00	0.00	0.00	0.00
Percent female-headed households[2]	(227)	(472)	(542)	(476)	(475)
Mean	19.53	13.79	14.48	15.48	15.09
SD	6.54	4.68	4.99	5.08	5.09
Min	7.57	5.50	5.90	5.50	4.90
Median	18.53	12.75	13.55	14.90	14.70
Max	43.86	36.90	37.70	35.60	33.40
Percent zero	0.00	0.00	0.00	0.00	0.00

(continued)

	1980 n = 253	1990 n = 656	2000 n = 656	2010 n = 496	2017 n = 496
Poverty rate[2]	(230)	(474)	(542)	(476)	(475)
Mean	11.03	14.56	14.45	16.72	17.77
SD	5.16	7.62	6.84	7.16	7.40
Min	2.10	1.50	2.20	2.90	3.70
Median	10.20	14.25	14.30	16.70	17.50
Max	32.30	43.90	37.40	36.90	41.20
Percent zero	0.00	0.00	0.00	0.00	0.00
Unemployment rate[2]	(230)	(473)	(542)	(476)	(475)
Mean	7.91	7.02	6.72	5.66	4.63
SD	8.38	2.91	2.73	1.64	1.52
Min	2.00	2.38	2.20	2.60	1.90
Median	6.15	6.48	6.21	5.50	4.30
Max	62.10	31.35	16.73	13.50	11.40
Percent zero	0.00	0.00	0.00	0.00	0.00

[1]Valid ns reported in parentheses.
[2]Measures were standardized and included in the social disorganization scale.

Police Organizations

Descriptive statistics are presented for each of the eight LEMAS reporting years in Table 6. Measures of absolute representation serve as the dependent variables in the first set of analyses; measures of absolute and relative representation and organizational size serve as time-varying covariates in models four through 31.

Table 6

Descriptive Statistics: Police Organizations

	1987 n = 253	1990 n = 378	1993 n = 412	1997 n = 451	2000 n = 472	2003 n = 493	2007 n = 516	2013 n = 496
<u>Absolute representation</u>								
Percent female officers	(233)	(376)	(408)	(448)	(468)	(488)	(503)	(490)
Mean	7.00	7.34	8.26	8.90	9.33	9.94	10.51	10.96
SD	3.94	4.18	4.49	4.46	4.53	4.49	4.53	4.53
Min	0.00	0.00	0.00	0.00	0.00	0.51	1.35	0.86
Median	6.75	6.76	7.69	8.51	8.92	9.52	9.86	10.50
Max	19.13	22.81	22.85	24.09	24.09	23.87	23.98	23.47
Percent zero	1.29	0.80	1.23	0.89	0.64	0.00	0.00	0.00

(continued)

	1987 n = 253	1990 n = 378	1993 n = 412	1997 n = 451	2000 n = 472	2003 n = 493	2007 n = 516	2013 n = 496
Percent Latinx officers	(250)	(373)	(403)	(442)	(461)	(481)	(497)	(478)
Mean	4.46	4.47	5.43	5.95	6.57	7.06	7.92	8.35
SD	6.84	6.58	6.93	7.35	7.89	8.45	8.66	9.21
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	1.93	2.04	2.88	3.37	3.65	4.27	4.88	5.20
Max	42.97	44.50	43.27	45.28	42.86	44.46	44.17	45.30
Percent zero	18.80	22.79	16.13	13.80	13.88	12.06	8.25	9.21
Percent Black officers	(234)	(371)	(401)	(441)	(461)	(478)	(497)	(479)
Mean	9.52	8.57	9.12	9.04	9.09	8.74	8.37	8.18
SD	8.90	8.86	9.28	9.22	9.32	8.93	8.69	8.45
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	6.41	5.08	5.66	5.68	5.73	5.22	5.38	5.00
Max	44.91	39.37	44.52	42.32	45.75	43.98	44.40	42.23
Percent zero	6.41	8.36	7.98	6.58	5.42	4.39	4.43	6.47

(continued)

	1987 n = 253	1990 n = 378	1993 n = 412	1997 n = 451	2000 n = 472	2003 n = 493	2007 n = 516	2013 n = 496
<u>Relative representation</u>								
Latinx officers	(227)	(374)	(386)	(423)	(451)	(462)	(476)	(470)
Mean	0.44	0.43	0.45	0.45	0.45	0.45	0.45	0.45
SD	0.36	0.38	0.35	0.34	0.33	0.32	0.31	0.32
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.37	0.37	0.41	0.42	0.41	0.39	0.41	0.40
Max	1.69	1.65	1.64	1.72	1.72	1.69	1.73	1.70
Percent zero	---	---	---	---	---	---	---	---
Black officers	(213)	(375)	(390)	(430)	(455)	(466)	(480)	(473)
Mean	0.58	0.60	0.69	0.69	0.69	0.71	0.65	0.63
SD	0.45	0.50	0.61	0.58	0.61	0.60	0.49	0.55
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.49	0.51	0.57	0.56	0.55	0.56	0.53	0.49
Max	4.01	4.39	4.33	4.41	4.22	4.34	2.77	4.16
Percent zero	---	---	---	---	---	---	---	---

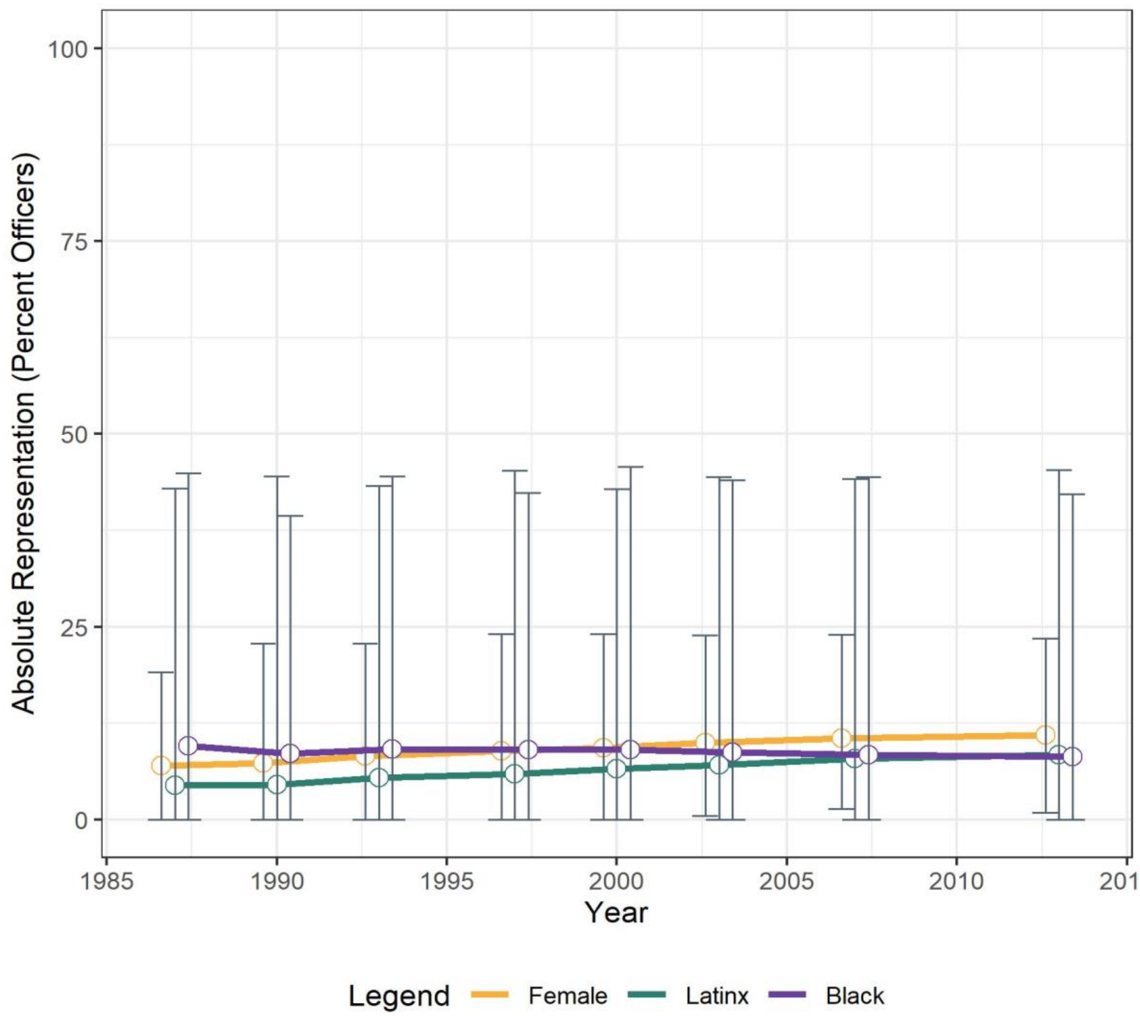
(continued)

	1987 n = 253	1990 n = 378	1993 n = 412	1997 n = 451	2000 n = 472	2003 n = 493	2007 n = 516	2013 n = 496
Organizational size								
Full-time employees	(246)	(372)	(405)	(444)	(465)	(486)	(509)	(490)
Mean	515.87	417.33	406.29	409.88	417.05	407.89	405.71	402.35
SD	531.28	499.32	488.01	501.46	514.82	513.39	499.16	519.65
Min	145.00	104.00	105.00	106.00	106.00	103.00	108.00	108.00
Median	303.50	228.50	222.00	221.00	228.00	223.50	225.00	219.00
Max	3,448.00	3,487.00	3,535.00	3,710.00	3,649.00	3,790.00	3,739.00	4,022.00
Region of the US								
Region	(253)	(378)	(412)	(451)	(472)	(493)	(516)	(496)
Midwest	19.76%	20.11%	19.42%	19.96%	19.70%	19.88%	18.99%	17.94%
Northeast	24.90%	25.66%	23.30%	23.50%	23.94%	23.12%	21.90%	21.37%
South	34.39%	33.07%	34.22%	34.15%	33.90%	33.87%	35.85%	38.31%
West	20.95%	21.16%	23.06%	22.39%	22.46%	23.12%	23.26%	22.38%

Absolute representation. The average percentage of women and Latinx officers in large municipal police departments in the US have been increasing steadily since 1987, from 7.00% and 4.46% to 10.96% and 8.35% in 2013, respectively (see Figure 10). At the same time, the trend has been decreasing for Black officers, with an average of 9.52% in 1987 and 8.18% in 2013. Women have always comprised less than one-quarter of the officers in these large cities;

Figure 10

Police Organizations: Absolute Representation

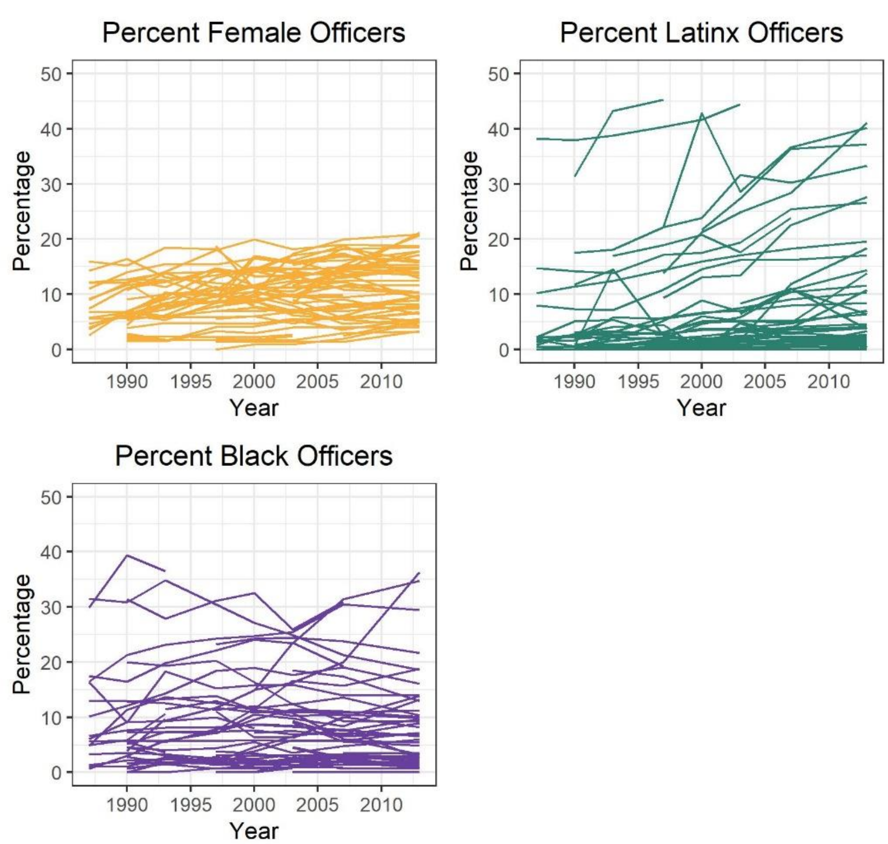


Note: Yellow, teal, and purple lines are indicative of the mean; grey vertical lines are indicative of the range.

similarly, people of color have comprised less than half of police officers in even the most diverse agencies. The summary information presented in Figure 10 provides an incomplete picture of the differences between departments, however. Figure 11 plots the trend in absolute representation for a random sample of 65 agencies. While it appears that the summary information presented above for the representation of women in police departments (i.e., a slow linear trend upwards) mirrors the individual trends, there is much more variation in the trends for representation of officers of color. It appears that the percentage of Latinx and Black officers has remained low and steady for a large proportion of agencies while a smaller proportion have seen significant increases or decreases over time.

Figure 11

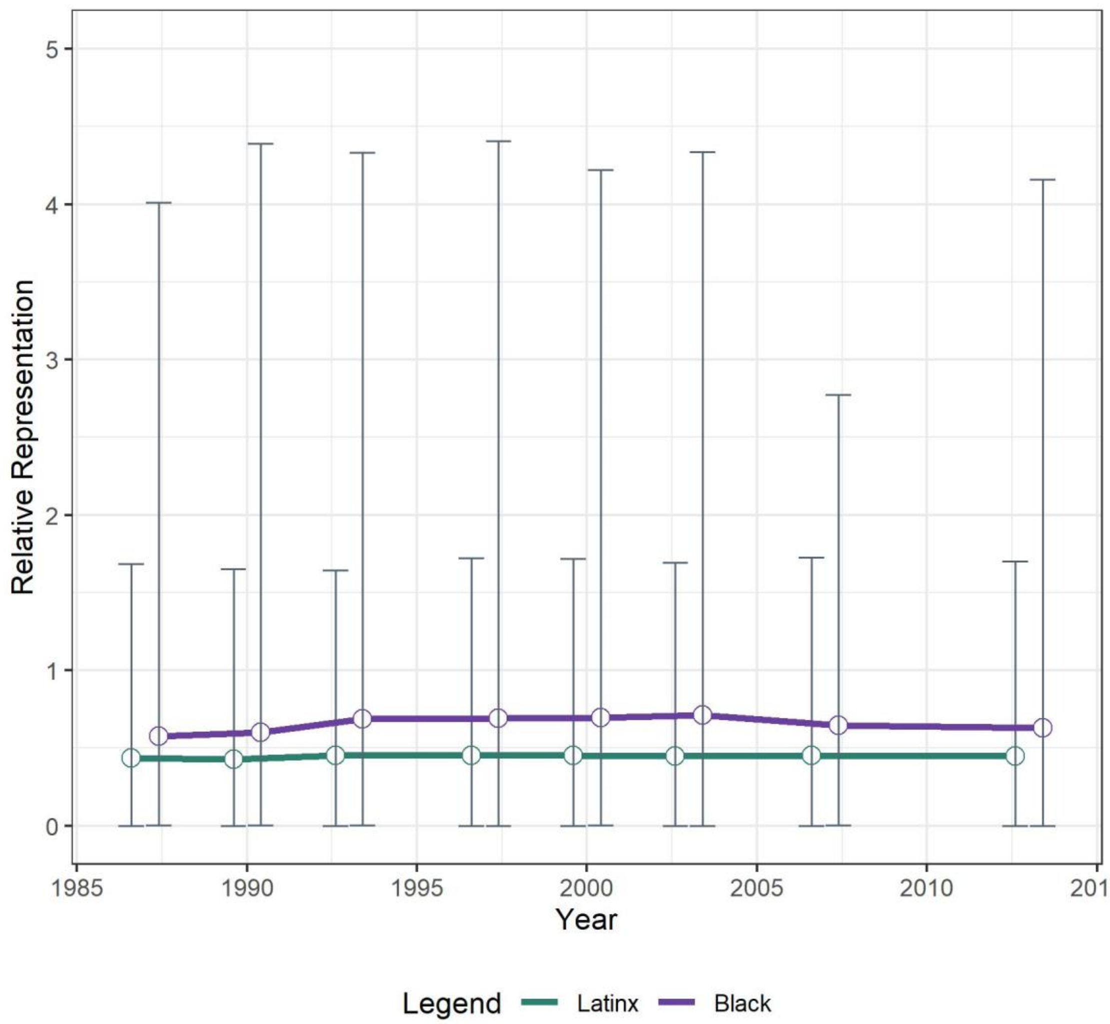
Spaghetti Plots: Absolute Representation



Relative Representation. In contrast to measures of absolute representation, the relative representation of Latinx and Black officers to Latinx and Black citizens within their communities has remained fairly stable since 1987 (see Figure 12). The average relative representation of Latinx officers has remained at 0.45 since 1993, while for Black officers relative representation started at 0.58 in 1987, rose to a peak of 0.71 in 2003, and fell back to 0.63 in 2013. The averages that are less than 1.00 reveal that in most places

Figure 12

Police Organizations: Relative Representation



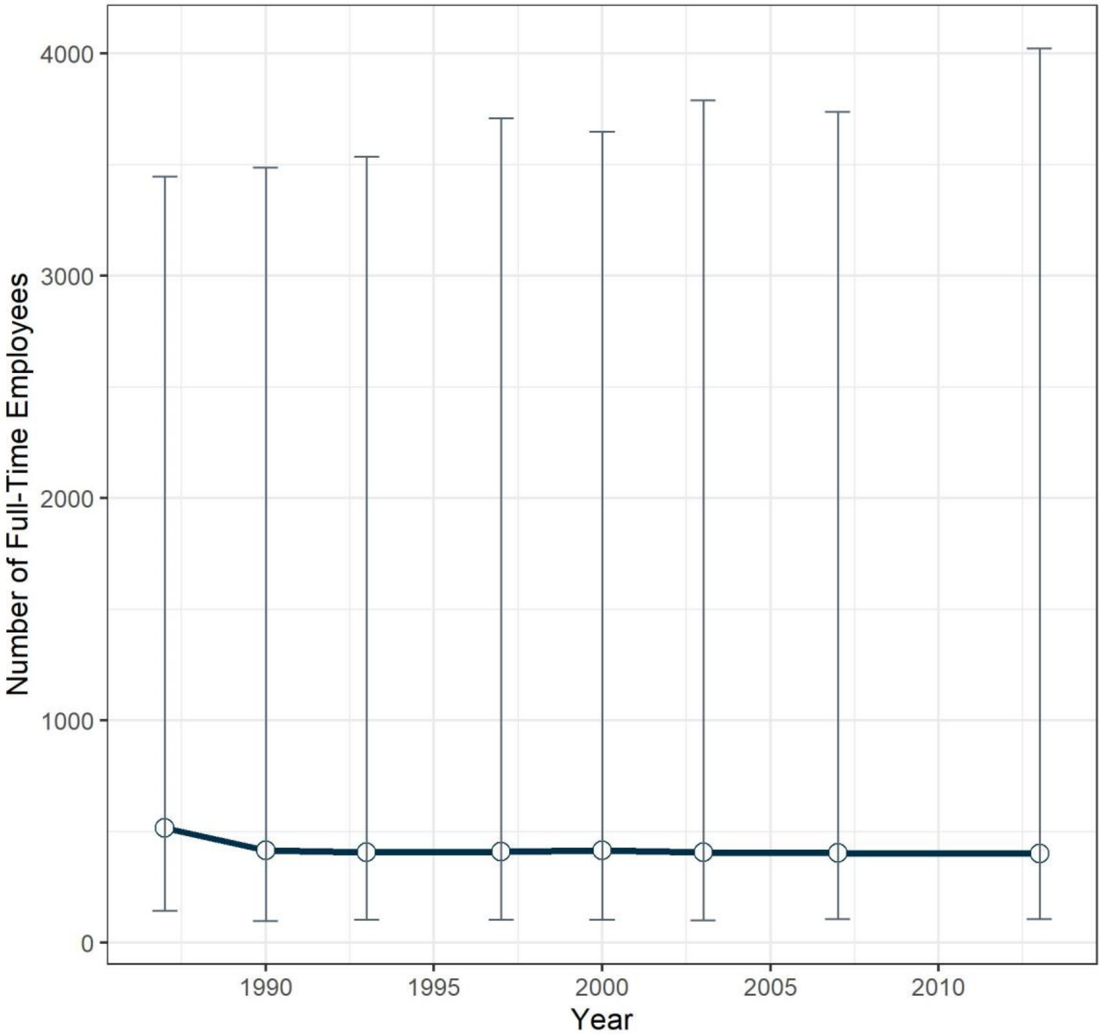
Note: Teal and purple lines are indicative of the mean; grey vertical lines are indicative of the range.

officers of color are underrepresented in comparison to their demographic makeup in the community. Maximum values over 1.00, however, indicate that in some places ethnic and racial minority officers are overrepresented relative to their size in the community.

Organizational Size. With the exception of 1987 (when the inclusion criteria for participation in the long-form version of LEMAS was different), the number of full-time employees large municipal police departments in the US have had on their pay-roll has remained stable. In 1990 the mean organizational size was 417.33 full-time employees, in 2013 that number was 402.35. The upper limit, however, has been increasing, with a maximum reported size of 3,448 employees in 1987 and 4,022 in 2013 (see Figure 13). Due to a significant positive skew, the natural log of organizational size is used for all analyses.

Figure 13

Police Organization: Size



Note: Blue line are indicative of the mean; grey vertical lines are indicative of the range.

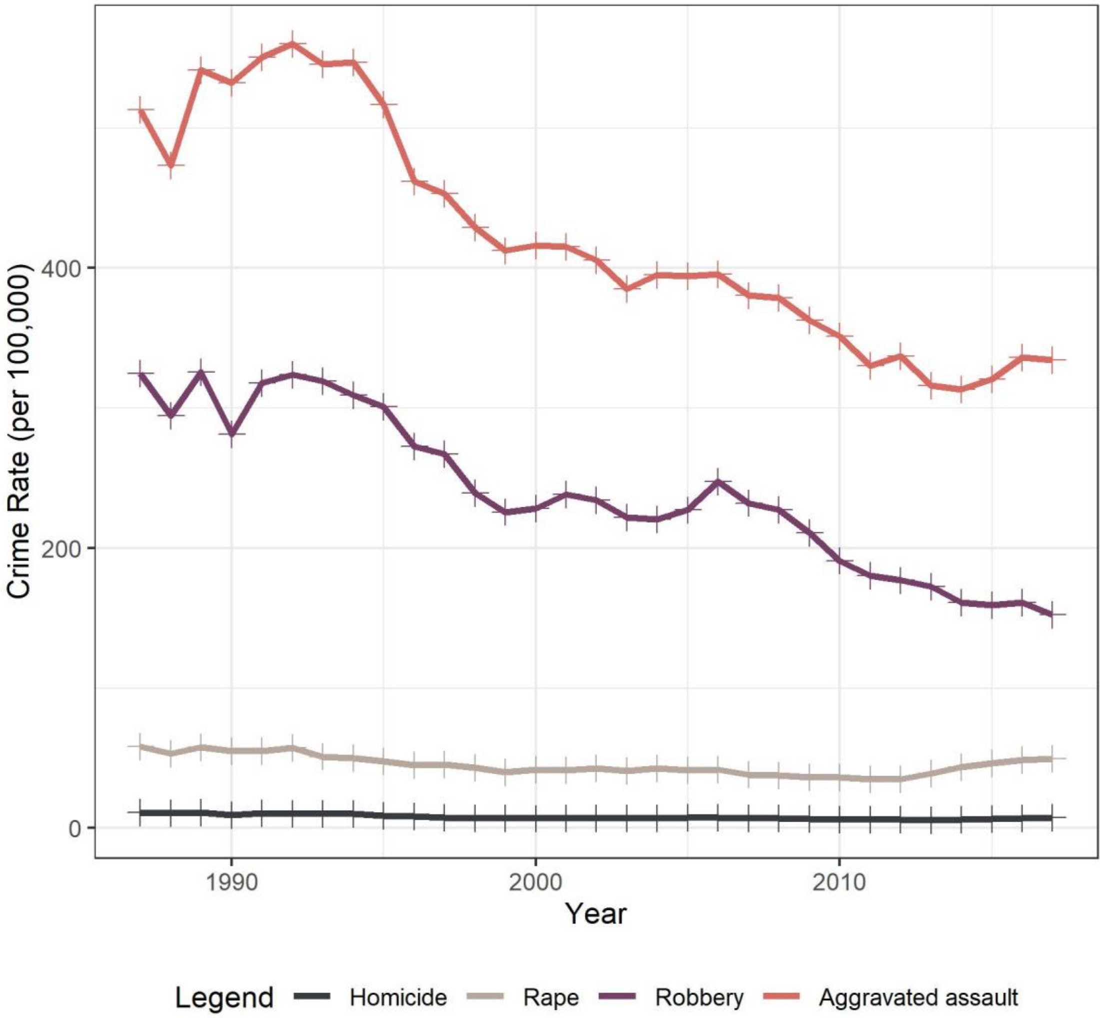
Police Performance

Descriptive statistics for the number of crimes reported to the police and the clearance rates for index offenses from 1987 to 2017 are presented in Table 7.

Crime Rates. The number of crimes reported to the police per 100,000 population peaked in the early 1990s and has enjoyed a downward trend overall since then (see Figure 14).

Figure 14

Violent Crime Rate

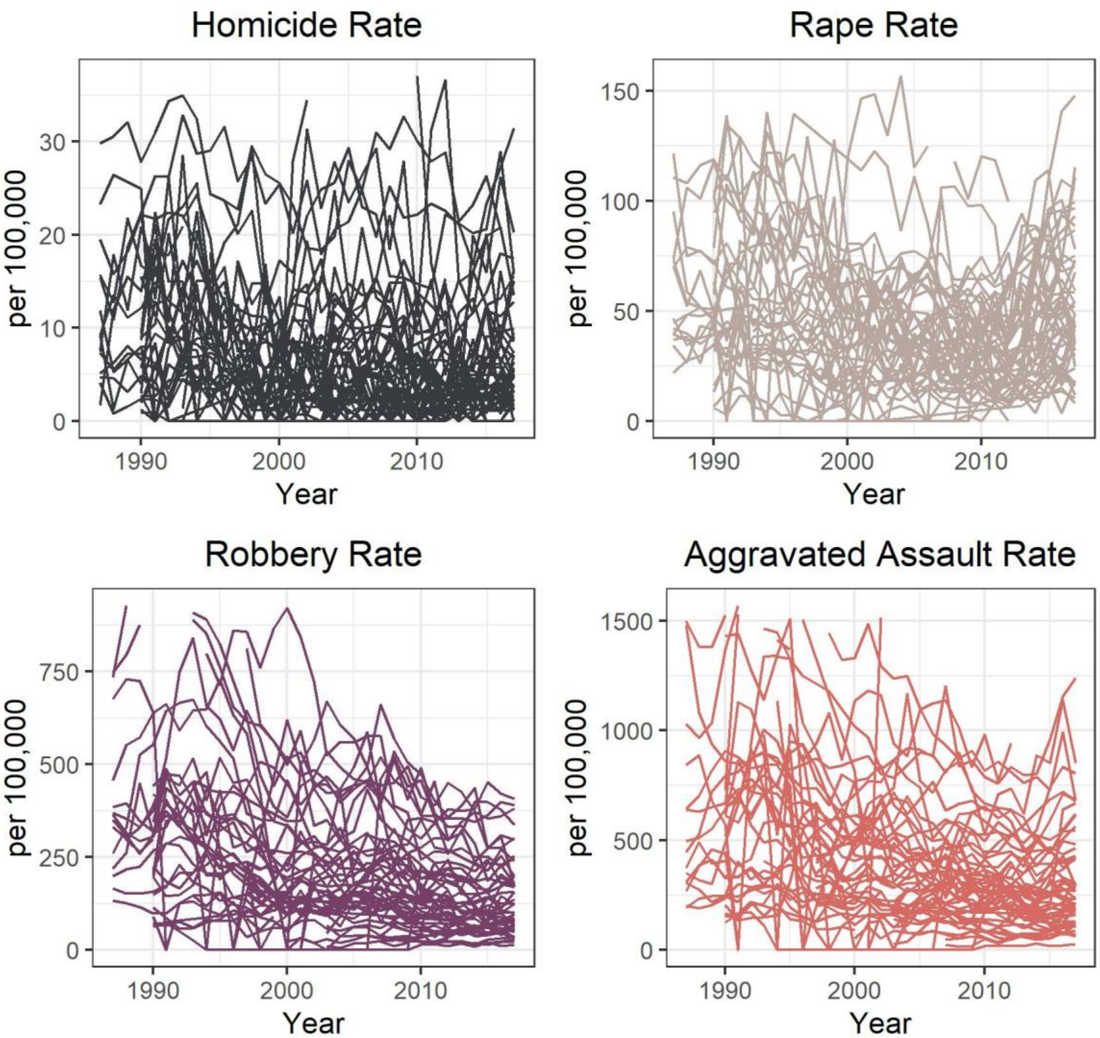


Similar to the summary information for absolute representation, the trends mask differences between subjects. Figure 15 (presenting a random sample of 65 cities' crime rates) shows that despite the average downward trend, there is significant variation in crime trends between cities. Nevertheless, the average homicide rate in 2017 was 7.45 per

100,000 (range = 0.00 – 37.83), the average rape rate in 2010 was 36.28 per 100,000 (range = 0.00 – 143.86), the average robbery rate in 2017 was 152.26 per 100,000 (range = 0.00 – 693.65), and the average aggravated assault rate in 2017 was 335.08 per 100,000 (range = 0.00 – 1,499.27).

Figure 15

Spaghetti Plots: Violent Crime Rates



Note: Y-axis scales differ due to significant differences in violent crime rates.

The property crime rate has likewise been declining since the early 1990s, with an average 2017 burglary rate of 578.08 per 100,000 (range = 0.00 – 2,441.68), larceny-theft rate of 2,412.67 per 100,000 (range = 0.00 – 8,931.60), and motor-vehicle theft rate of 335.96 per 100,000 (range = 0.00 – 1,393.44). Overall trends are depicted in Figure 16, trends for a random sample of 65 cities are presented in Figure 17.

Figure 16

Property Crime Rates

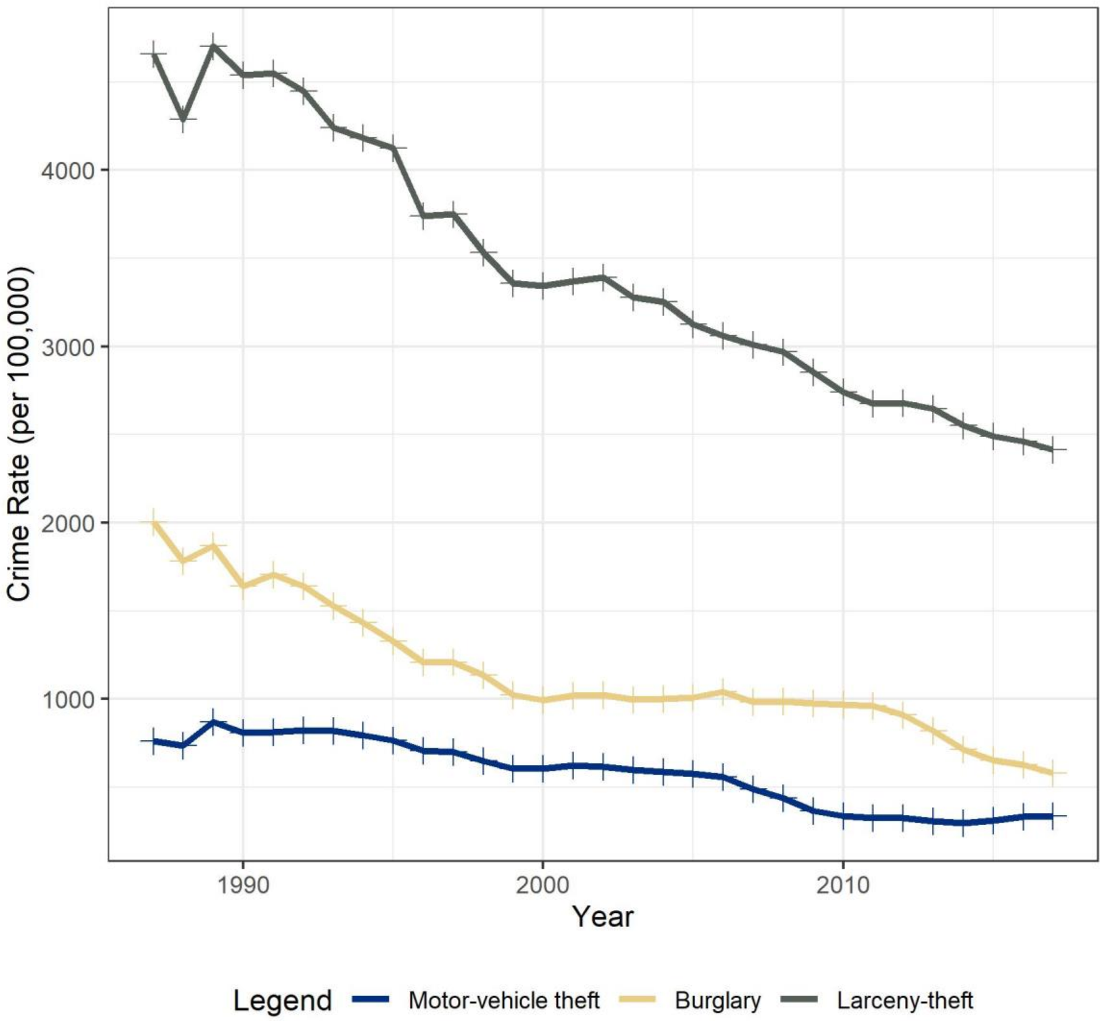
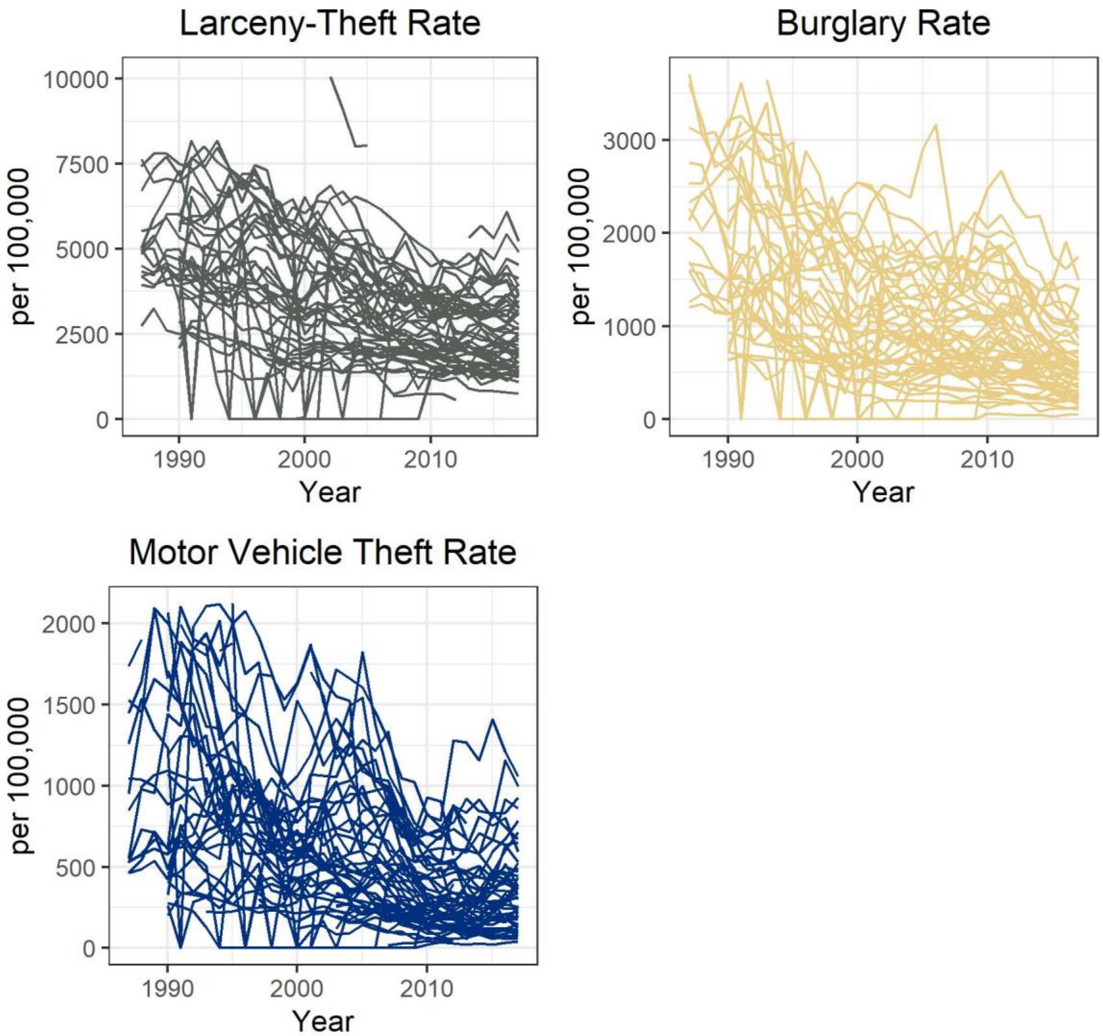


Figure 17

Spaghetti Plots: Property Crime Rates

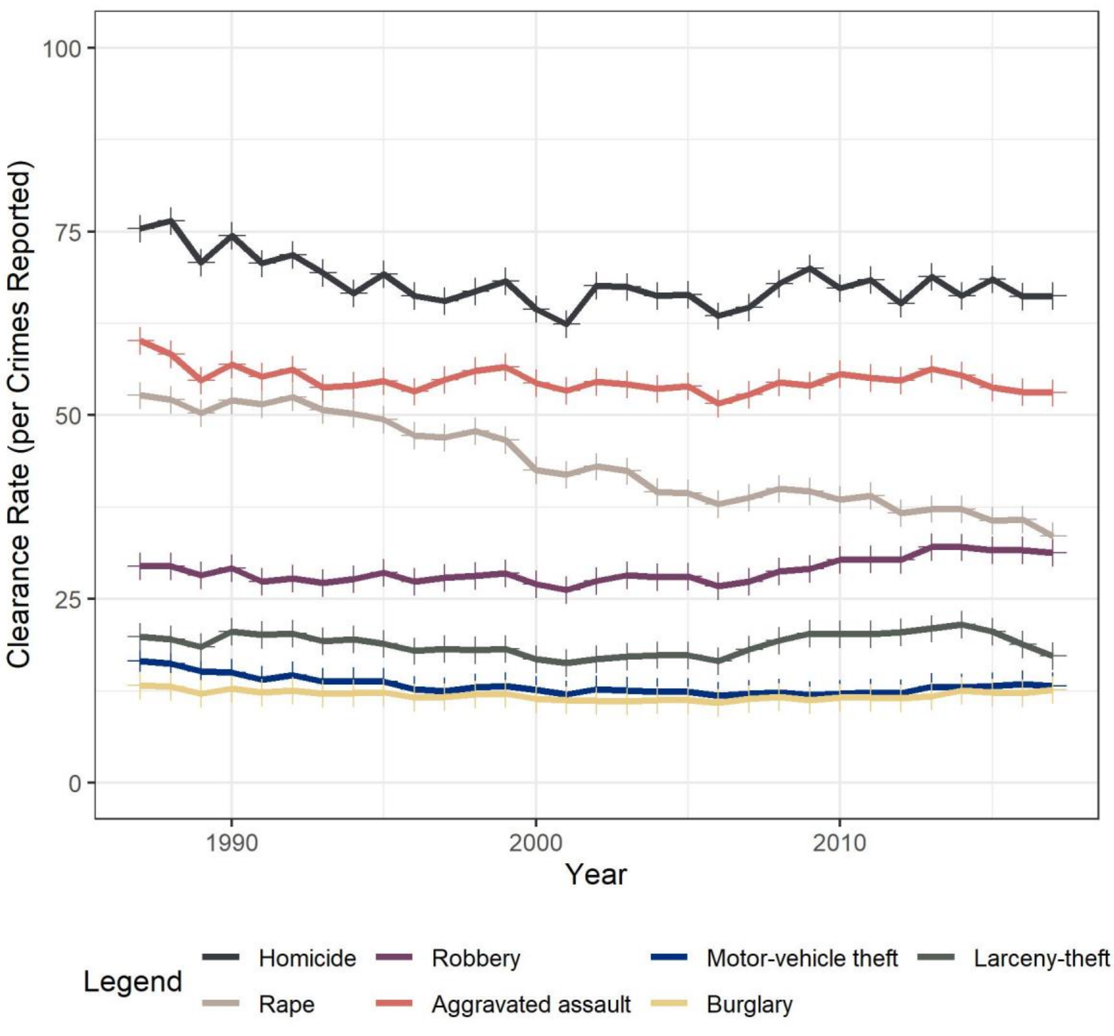


Note: Y-axis scales differ due to significant differences in property crime rates.

Clearance Rates. Index offense clearance rates have changed little since 1987, though there appears in Figure 18 to be a slight downward trend in clearances of homicides and rapes and a slight upward trend in robbery clearance rates. The same pattern has persisted across the timeframe, such that homicides clearance rates are the highest ($\bar{x}$ = 66.16%, min. = 0.00%, max. = 200.00% in 2017), followed by aggravated assault ($\bar{x}$ = 53.09%, min. = 0.00%, max. = 119.90% in 2017), rape ($\bar{x}$ = 38.59%, min. = 0.00%, max. = 120.00% in 2010), robbery ($\bar{x}$ = 31.36%, min. = 0.00%, max. = 75.00% in

Figure 18

Index Crime Clearance Rates



2017), larceny-theft ($\bar{x}$ = 17.28%, min. = 0.00%, max. = 49.73% in 2017), motor-vehicle theft ($\bar{x}$ = 13.20%, min. = 0.00%, max. = 53.18% in 2017), and burglary ($\bar{x}$ = 12.67%, min. = 0.00%, max. = 35.96% in 2017). Trends for a random sample of 65 cities are presented in Figure 19 and Figure 20.

Figure 19

Spaghetti Plots: Violent Crime Clearance Rates

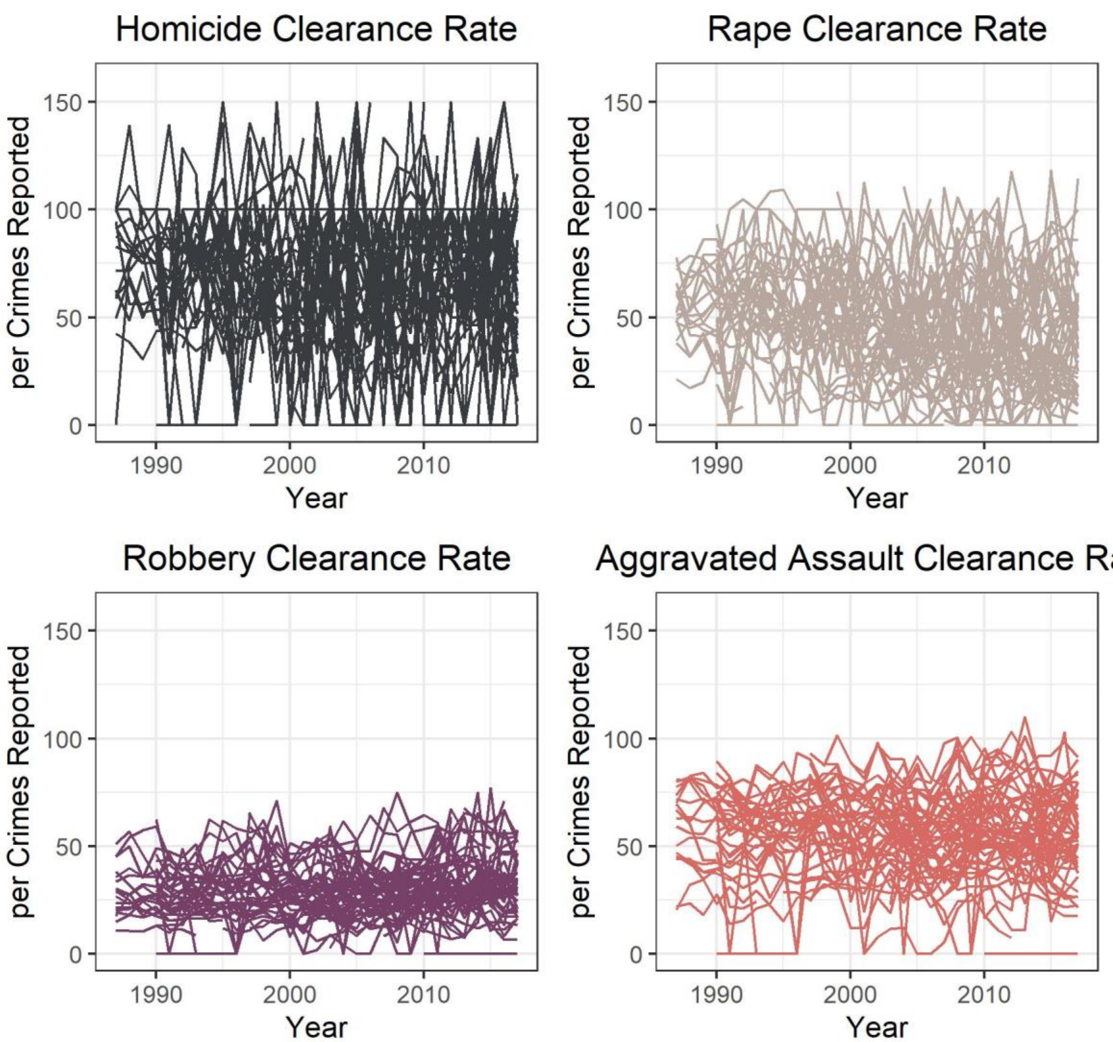


Figure 20

Spaghetti Plots: Property Crime Clearance Rates

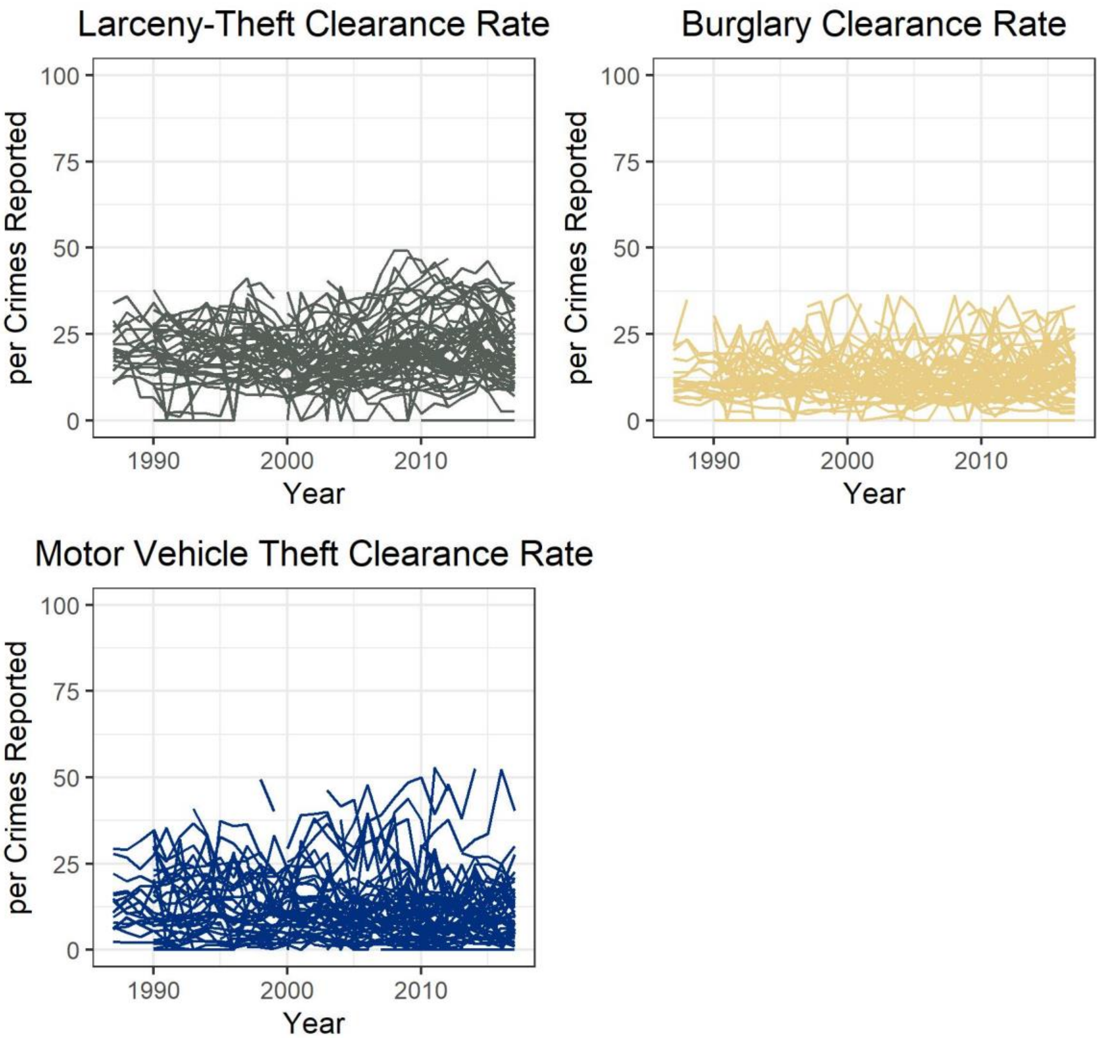


Table 7

Descriptive Statistics: Organizational Performance, Panel A (Index Offenses 1987 – 1996)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Actual Crime (per 100,000)										
Homicide	(236)	(235)	(229)	(354)	(342)	(344)	(372)	(374)	(377)	(383)
Mean	11.25	10.48	11.04	9.21	10.50	10.12	10.35	10.19	9.00	8.27
SD	8.70	8.61	8.82	8.10	9.01	9.00	8.74	8.55	7.91	7.98
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	9.21	8.60	8.29	7.29	8.37	8.04	8.79	8.24	7.35	6.64
Max	37.52	37.09	37.44	38.05	37.88	37.79	36.43	36.54	37.17	35.98
Percent zero	2.54	9.79	4.37	7.63	9.94	8.72	8.06	9.63	11.14	15.93

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Rape	(237)	(233)	(233)	(369)	(353)	(352)	(392)	(390)	(393)	(390)
Mean	58.39	53.03	57.63	54.88	55.10	57.52	51.12	50.14	47.93	44.86
SD	35.09	35.93	35.29	36.84	37.06	36.67	36.01	34.33	33.65	32.90
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	54.08	49.19	52.82	49.93	50.94	53.70	47.67	45.51	43.93	40.49
Max	157.69	158.57	158.18	157.73	157.91	157.34	154.70	154.51	155.06	150.25
Percent zero	2.53	9.87	3.00	5.69	7.65	5.97	10.97	7.95	7.12	11.79
Robbery	(226)	(226)	(218)	(340)	(328)	(329)	(368)	(369)	(376)	(380)
Mean	324.61	294.39	325.75	281.23	317.69	323.75	319.84	309.72	301.48	273.35
SD	222.66	225.73	227.70	213.83	231.03	227.36	239.14	225.80	225.33	215.34
Min	13.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	260.93	239.10	269.33	222.54	267.58	276.78	264.68	265.48	248.39	227.12
Max	930.59	928.98	937.67	937.09	928.20	933.87	925.60	920.67	916.98	932.09
Percent zero	0.00	7.08	1.38	2.65	3.96	2.13	3.53	4.88	6.12	10.26

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Agg. Assault	(235)	(234)	(233)	(361)	(345)	(338)	(371)	(377)	(376)	(380)
Mean	513.06	473.06	541.51	533.00	551.10	561.01	545.96	547.58	517.19	462.66
SD	339.94	335.04	346.86	377.12	382.69	365.30	374.27	377.96	362.93	350.33
Min	36.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	411.75	404.77	457.79	443.51	488.76	495.17	453.29	482.54	453.80	393.74
Max	1,565.34	1,520.98	1,568.16	1,539.00	1,570.97	1,556.44	1,509.44	1,550.40	1,550.46	1,557.53
Percent zero	0.00	6.84	1.29	2.22	3.77	2.07	3.50	4.77	6.12	10.26
Burglary	(229)	(231)	(225)	(361)	(352)	(354)	(393)	(392)	(391)	(394)
Mean	2,002.04	1,780.30	1,867.68	1,639.85	1,707.19	1,641.55	1,527.31	1,433.58	1,327.51	1,210.17
SD	773.74	862.97	769.46	750.23	821.30	750.35	767.51	727.03	698.41	717.32
Min	364.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	1,947.57	1,785.90	1,796.12	1,553.60	1,636.59	1,547.81	1,452.38	1,368.26	1,274.79	1,156.49
Max	3,708.67	3,645.81	3,661.10	3,575.56	3,698.67	3,514.21	3,665.77	3,521.87	3,171.85	3,353.06
Percent zero	0.00	6.93	1.33	2.22	3.69	1.98	3.31	4.59	5.88	9.90

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Larceny-theft	(239)	(239)	(238)	(374)	(360)	(360)	(393)	(392)	(392)	(391)
Mean	4,658.18	4,288.95	4,702.55	4,540.40	4,552.79	4,450.76	4,240.09	4,179.88	4,120.95	3,744.65
SD	1,723.96	2,010.42	1,815.90	1,822.89	1,922.61	1,776.96	1,867.08	1,897.76	1,968.46	2,026.43
Min	1229.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	4,391.90	4,273.64	4,633.90	4,338.06	4,335.50	4,245.30	4,066.76	4,029.36	4,006.87	3,717.23
Max	9,471.40	10,091.22	10,081.19	9,722.62	10,154.73	10,520.56	10,212.96	10,327.62	10,504.61	9,400.35
Percent zero	0.00	6.69	1.26	2.14	3.61	1.94	3.31	4.59	5.87	9.97
M.V. Theft	(229)	(224)	(221)	(349)	(327)	(332)	(379)	(377)	(383)	(385)
Mean	761.14	735.28	868.99	806.23	812.34	820.06	821.24	794.66	766.65	709.10
SD	469.09	493.28	516.02	512.37	505.26	500.47	531.80	496.30	489.78	482.16
Min	163.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	590.61	593.40	754.67	627.17	688.51	696.23	700.08	691.73	662.84	617.35
Max	2,050.20	2,036.60	2,110.72	2,123.09	2,114.36	2,120.66	2,135.58	2,127.05	2,129.97	2,131.61
Percent zero	0.00	7.14	1.36	2.29	3.98	2.11	3.43	4.77	6.01	10.13

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Clearance rates (per crimes reported)[1]										
Homicide	(245)	(227)	(240)	(347)	(332)	(342)	(376)	(365)	(357)	(339)
Mean	75.42	76.45	71.06	74.49	70.81	72.01	69.31	66.57	68.82	66.56
SD	29.79	29.21	33.62	33.76	30.99	33.83	36.54	32.84	38.52	40.16
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	76.47	76.74	76.88	76.00	71.98	75.00	71.69	69.77	71.43	70.00
Max	200.00	200.00	166.67	200.00	200.00	200.00	200.00	200.00	200.00	200.00
Percent zero	2.86	1.76	10.42	5.76	6.33	7.02	9.84	9.86	11.48	15.63
Rape	(244)	(227)	(243)	(352)	(347)	(351)	(365)	(376)	(376)	(359)
Mean	52.69	52.10	50.47	51.97	51.41	52.44	50.66	50.08	49.28	47.16
SD	17.75	20.11	24.30	21.98	22.88	21.83	24.51	25.27	25.88	28.22
Min	9.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	53.38	53.51	51.67	53.03	52.82	52.00	52.54	52.19	50.00	48.72
Max	117.95	122.22	103.45	107.41	120.00	120.72	120.00	108.33	121.43	126.67
Percent zero	0.00	0.88	7.00	3.41	4.32	1.14	5.21	5.85	6.65	10.86

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Robbery	(249)	(233)	(246)	(366)	(361)	(366)	(396)	(388)	(383)	(366)
Mean	29.49	29.45	28.33	29.21	27.32	27.85	27.12	27.64	28.54	27.40
SD	11.35	12.55	14.30	12.58	11.90	11.11	12.58	12.60	14.07	15.26
Min	3.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	28.83	27.93	27.62	28.11	26.84	26.93	25.14	26.17	27.23	26.57
Max	69.70	76.76	76.09	73.03	67.15	65.79	69.23	71.75	77.51	71.88
Percent zero	0.00	1.29	6.91	2.73	3.88	1.37	4.29	4.12	5.74	10.38
Agg. Assault	(250)	(233)	(246)	(365)	(361)	(367)	(396)	(389)	(383)	(367)
Mean	60.14	58.32	54.96	56.90	55.21	56.27	53.69	53.85	54.40	53.21
SD	16.97	18.82	22.88	19.22	20.39	18.50	20.32	19.91	22.39	25.20
Min	9.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	60.68	59.41	58.56	59.16	58.98	58.40	56.21	56.12	57.24	58.27
Max	105.71	106.67	100.00	100.00	97.57	100.00	100.00	120.00	104.60	121.32
Percent zero	0.00	1.29	6.91	2.74	3.88	1.36	4.29	4.37	6.01	10.63

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
Burglary	(249)	(233)	(243)	(363)	(358)	(365)	(394)	(384)	(381)	(363)
Mean	13.25	13.06	12.13	12.75	12.20	12.55	12.10	12.15	12.29	11.59
SD	5.92	6.55	6.76	6.03	6.30	6.42	6.56	6.54	6.85	7.40
Min	1.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	11.81	11.77	11.15	12.02	11.43	11.14	11.19	10.72	11.25	10.99
Max	33.93	35.13	34.71	35.86	35.11	36.43	36.09	34.42	34.70	33.57
Percent zero	0.00	1.29	7.00	2.75	3.63	1.37	4.31	4.17	5.51	10.74
Larceny-theft	(251)	(234)	(247)	(367)	(361)	(366)	(394)	(387)	(382)	(365)
Mean	19.87	19.54	18.56	20.57	20.13	20.31	19.25	19.50	18.90	17.93
SD	6.68	7.27	8.68	7.65	8.08	7.58	8.44	8.65	8.98	9.78
Min	3.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	19.04	19.47	18.27	21.01	20.10	20.06	18.90	18.63	19.03	18.25
Max	46.65	47.60	44.19	42.66	48.93	47.25	42.76	48.08	44.80	43.81
Percent zero	0.00	1.28	6.88	2.72	3.60	1.09	4.06	4.13	5.50	10.68

(continued)

	1987 n = 253	1988 n = 253	1989 n = 253	1990 n = 378	1991 n = 378	1992 n = 378	1993 n = 412	1994 n = 412	1995 n = 412	1996 n = 412
M.V. Theft	(250)	(232)	(244)	(357)	(355)	(363)	(389)	(380)	(376)	(363)
Mean	16.57	16.18	15.25	15.03	14.05	14.59	13.72	13.85	13.68	12.65
SD	10.43	10.43	11.16	10.55	10.39	10.86	10.76	10.90	10.70	10.74
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	14.89	14.21	13.84	13.32	11.68	11.84	11.29	11.36	11.0	10.18
Max	52.33	46.09	50.52	48.62	52.00	53.11	51.24	50.39	50.28	50.63
Percent zero	0.40	1.72	7.38	3.36	3.66	1.38	4.37	5.53	6.38	11.02

[1]Excluded cases with zero reported crimes to avoid dividing by zero

Descriptive Statistics: Organizational Performance, Panel B (Index Offenses 1997 – 2006)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
<u>Actual Crime (per 100,000)</u>										
Homicide	(419)	(423)	(428)	(447)	(437)	(435)	(456)	(456)	(452)	(450)
Mean	7.50	7.19	6.93	6.81	7.01	7.10	6.93	6.85	7.33	7.35
SD	7.10	7.15	7.19	7.09	7.02	6.96	7.07	6.67	7.18	7.34
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	5.62	5.22	4.81	4.80	4.86	5.25	4.96	5.25	5.17	4.90
Max	36.61	38.07	36.82	36.91	36.28	36.44	37.79	34.67	36.40	38.08
Percent zero	14.56	15.13	15.65	15.88	13.73	11.49	14.04	13.38	12.17	8.67
Rape	(431)	(430)	(431)	(454)	(443)	(442)	(463)	(463)	(464)	(463)
Mean	45.42	43.31	40.04	41.79	41.42	42.69	40.99	42.48	41.33	41.81
SD	32.45	31.04	27.57	29.16	28.72	28.65	28.27	28.51	27.07	27.74
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	42.49	40.22	36.59	38.18	38.57	39.63	37.57	37.38	36.83	37.58
Max	153.43	159.44	56.71	155.21	159.23	149.89	147.14	158.72	136.40	142.02
Percent zero	8.12	8.84	7.66	6.61	7.00	7.01	7.34	5.18	5.17	5.62

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
Robbery	(423)	(423)	(429)	(450)	(442)	(442)	(463)	(464)	(463)	(461)
Mean	267.24	239.07	225.73	227.95	237.70	234.05	221.41	220.19	226.97	246.97
SD	219.00	192.84	190.33	189.43	189.28	179.54	179.90	170.38	182.12	186.72
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	216.50	187.92	168.89	165.24	189.68	186.50	174.49	174.71	170.86	194.49
Max	918.15	910.23	924.84	925.93	909.36	827.62	886.40	831.33	934.12	935.15
Percent zero	6.15	7.09	6.06	5.11	5.20	4.75	5.40	3.66	3.67	0.87
Agg. Assault	(418)	(421)	(427)	(452)	(441)	(440)	(462)	(461)	(458)	(456)
Mean	453.00	428.78	412.25	415.48	413.55	404.14	385.18	395.12	394.48	395.34
SD	340.19	323.04	318.10	319.66	311.61	300.52	295.56	298.35	289.07	272.26
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	392.97	351.55	332.96	354.09	356.59	336.72	306.07	324.10	321.97	323.57
Max	1,555.12	1,515.68	1,523.82	1,490.42	1,485.38	1,570.20	1,525.40	1,467.13	1,492.76	1,508.83
Percent zero	6.22	7.13	6.09	4.87	5.22	4.77	5.41	3.69	3.71	0.88

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
Burglary	(431)	(431)	(432)	(453)	(444)	(444)	(465)	(464)	(465)	(464)
Mean	1,209.64	1,134.23	1,021.67	993.81	1,020.76	1,023.52	993.69	998.24	1,008.59	1,038.53
SD	697.14	670.61	626.04	597.79	597.14	602.84	606.71	564.22	591.69	608.40
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	1,124.51	1,030.75	921.84	884.18	914.65	945.72	915.59	891.60	893.29	912.10
Max	3,486.98	3,290.64	3,350.53	3,015.93	2,803.56	3,654.03	3,599.46	3,040.28	3,421.03	3,412.16
Percent zero	6.03	6.96	6.02	4.64	5.18	4.73	5.16	3.66	3.66	0.86
Larceny-theft	(428)	(428)	(429)	(450)	(440)	(442)	(463)	(463)	(463)	(462)
Mean	3,748.92	3,534.31	3,358.26	3,350.44	3,374.67	3,398.87	3,274.85	3,251.78	3,124.94	3,059.04
SD	1,971.07	1,908.85	1,799.91	1,763.13	1,658.48	1,665.85	1,675.34	1,568.32	1,511.66	1,329.92
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	3,655.10	3,395.79	3,271.82	3,151.62	3,286.43	3,304.47	3,232.97	3,054.92	3,020.71	2,887.97
Max	9,981.81	10,558.63	10,569.86	10,133.05	8,108.90	10,059.51	10,176.66	9,645.33	9,586.01	7,825.73
Percent zero	6.07	7.01	6.06	4.67	5.23	4.75	4.97	3.67	3.67	1.08

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
M.V. Theft	(424)	(429)	(428)	(449)	(439)	(437)	(459)	(460)	(460)	(459)
Mean	699.62	648.26	603.43	603.72	621.43	614.06	599.08	586.57	476.25	558.41
SD	466.59	438.66	410.56	422.61	432.23	424.54	426.07	406.88	405.00	378.04
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	615.35	570.27	524.00	521.67	536.40	510.94	481.26	483.06	454.85	461.93
Max	2,125.97	2,029.50	2,089.09	2,097.33	2,135.82	2,069.68	2,005.83	2,104.85	2,066.51	2,089.16
Percent zero	6.13	6.99	6.07	5.12	5.24	4.81	5.23	3.70	3.70	0.87
Clearance rates (per crimes reported)[1]										
Homicide	(380)	(373)	(372)	(390)	(394)	(402)	(420)	(415)	(425)	(443)
Mean	65.54	66.95	68.33	64.33	62.68	67.70	67.40	66.19	66.38	63.53
SD	36.45	37.90	38.06	38.11	36.69	39.59	37.31	37.30	37.02	36.65
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	66.67	70.08	66.67	65.54	66.67	70.42	66.67	66.67	66.67	66.67
Max	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
Percent zero	12.63	12.60	11.02	12.05	12.44	10.45	10.24	8.92	9.18	11.96

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
Rape	(411)	(406)	(412)	(436)	(433)	(434)	(454)	(462)	(463)	(458)
Mean	47.01	47.86	46.58	42.53	41.76	42.74	42.34	39.60	39.36	37.80
SD	26.73	25.42	25.00	24.52	25.34	24.67	25.14	24.54	24.75	24.01
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	50.00	50.00	47.21	42.36	40.27	41.94	39.77	37.98	36.36	35.15
Max	125.00	125.00	114.29	103.45	114.29	120.00	114.29	110.71	116.67	125.00
Percent zero	9.00	6.40	5.58	7.11	8.78	5.53	5.95	6.28	5.40	6.33
Robbery	(421)	(415)	(419)	(444)	(444)	(446)	(464)	(471)	(473)	(485)
Mean	27.90	28.11	28.43	26.99	26.24	27.39	28.27	28.00	28.03	26.71
SD	14.81	13.86	13.77	14.04	13.62	13.62	14.10	14.25	13.62	13.94
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	26.96	27.22	27.41	25.84	25.26	25.49	27.41	27.79	27.33	25.81
Max	76.27	70.00	71.05	74.51	64.76	71.15	71.88	75.00	75.00	74.19
Percent zero	7.60	5.78	5.25	6.76	6.53	3.81	4.74	5.31	3.81	6.60

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
Agg. Assault	(419)	(416)	(420)	(448)	(444)	(447)	(466)	(473)	(475)	(486)
Mean	54.85	55.98	56.51	54.43	53.30	54.48	54.22	53.57	53.89	51.54
SD	23.11	21.55	20.68	21.52	22.09	20.95	20.88	20.85	19.82	21.54
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	58.99	58.80	58.35	56.97	56.89	55.79	55.78	54.57	55.48	54.61
Max	117.63	122.22	119.82	103.23	100.00	108.93	100.00	108.41	103.37	121.60
Percent zero	7.88	5.05	5.00	6.03	6.53	4.03	4.72	5.07	3.58	6.58
Burglary	(417)	(415)	(415)	(446)	(443)	(443)	(459)	(470)	(469)	(482)
Mean	11.71	12.07	12.07	11.43	11.22	11.12	11.02	11.24	11.23	10.85
SD	6.92	6.78	6.73	6.54	6.72	6.02	5.99	6.44	5.98	5.94
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	11.11	11.67	11.11	10.70	10.08	10.32	10.39	10.10	10.31	10.16
Max	36.29	35.56	35.65	36.49	36.47	33.25	36.29	35.98	35.71	32.57
Percent zero	7.67	5.54	5.06	6.50	6.55	3.84	5.01	5.11	3.84	6.64

(continued)

	1997 n = 451	1998 n = 451	1999 n = 451	2000 n = 472	2001 n = 472	2002 n = 472	2003 n = 493	2004 n = 493	2005 n = 493	2006 n = 493
Larceny-theft	(418)	(415)	(417)	(447)	(443)	(443)	(465)	(471)	(471)	(483)
Mean	18.19	18.01	18.18	16.77	16.28	16.74	17.14	17.39	17.38	16.58
SD	9.36	8.91	8.86	8.76	8.57	8.18	8.74	8.81	8.43	8.61
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	18.25	17.63	17.62	16.52	16.14	16.15	16.48	16.96	16.77	16.20
Max	48.65	46.22	47.30	47.06	44.69	47.79	49.30	45.31	48.22	49.67
Percent zero	7.66	5.06	5.04	6.26	6.55	3.61	4.95	5.10	3.61	6.63
M.V. Theft	(414)	(411)	(416)	(445)	(441)	(442)	(463)	(469)	(471)	(480)
Mean	12.50	12.92	13.13	12.63	12.06	12.68	12.50	12.35	12.37	11.88
SD	10.08	9.97	10.87	10.79	10.29	10.59	9.97	10.38	10.27	10.03
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	10.42	10.58	10.88	10.18	9.82	9.86	10.07	9.77	9.68	9.16
Max	47.40	49.45	50.53	52.55	50.50	51.28	53.28	51.48	50.37	50.00
Percent zero	8.45	5.60	6.25	7.42	7.48	4.98	5.40	5.33	4.46	6.88

[1]Excluded cases with zero reported crimes to avoid dividing by zero

Descriptive Statistics: Organizational Performance Panel C (Index Offenses 2007 – 2017)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Actual Crime (per 100,000)											
Homicide	(474)	(478)	(476)	(480)	(482)	(481)	(466)	(467)	(466)	(466)	(465)
Mean	7.04	7.06	6.49	6.18	6.14	6.28	5.79	6.11	6.67	7.00	7.45
SD	6.90	6.83	4.49	6.22	6.63	7.05	6.09	6.71	6.93	7.62	7.70
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	4.91	4.99	4.09	4.20	4.02	4.06	3.86	3.97	4.45	4.45	5.01
Max	37.67	37.55	34.39	37.32	37.55	36.61	37.81	37.70	37.95	38.03	37.83
Percent zero	11.60	10.25	7.77	10.83	11.00	12.68	13.52	12.42	10.94	14.81	10.32
Rape	(482)	(483)	(483)	(488)	(486)	(482)	(471)	(472)	(469)	(472)	(469)
Mean	38.32	37.51	36.16	36.28	35.07	34.93	39.21	43.58	46.41	48.72	49.42
SD	25.41	25.45	23.60	23.53	23.36	22.32	27.28	29.17	28.42	29.06	29.47
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	33.93	33.86	32.19	32.21	30.19	30.61	32.26	37.60	44.22	45.26	45.01
Max	142.64	144.82	147.49	143.86	159.13	142.62	150.45	156.60	154.71	157.23	149.13
Percent zero	5.19	5.18	4.55	1.23	1.03	0.62	0.85	0.85	1.71	1.27	1.07

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Robbery	(483)	(484)	(484)	(488)	(485)	(484)	(472)	(473)	(473)	(473)	(473)
Mean	232.14	227.43	210.98	190.60	180.33	176.85	173.17	161.24	159.44	161.45	152.26
SD	174.16	172.03	160.90	151.39	143.96	139.93	149.52	138.31	134.86	131.88	117.96
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	184.58	175.80	170.80	146.78	140.59	143.048	131.89	119.54	124.01	129.67	122.77
Max	927.24	921.01	877.83	920.56	852.89	825.54	932.63	857.41	907.86	844.57	693.65
Percent zero	0.41	0.83	0.41	0.20	0.41	0.21	0.21	0.63	0.85	1.06	1.06
Agg. Assault	(480)	(484)	(483)	(488)	(485)	(485)	(472)	(472)	(471)	(471)	(471)
Mean	380.25	378.82	362.45	350.94	330.12	336.86	317.20	313.81	321.09	336.75	335.08
SD	264.27	272.22	260.38	255.08	240.86	250.24	241.53	240.25	249.24	260.88	260.20
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	319.80	305.97	298.05	284.97	269.10	273.08	259.01	257.61	263.41	274.71	279.28
Max	1,528.66	1,520.31	1,544.35	1,559.05	1,533.32	1,427.80	1,317.39	1,400.06	1,467.86	1,446.13	1,499.27
Percent zero	0.42	0.83	0.41	0.20	0.62	0.21	0.21	0.64	0.85	1.27	1.06

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Burglary	(483)	(484)	(484)	(488)	(486)	(486)	(473)	(473)	(473)	(473)	(474)
Mean	983.29	985.09	976.47	968.01	959.88	908.17	821.33	714.84	651.15	627.21	578.08
SD	548.01	569.62	585.37	610.47	614.37	539.63	499.95	444.08	397.76	389.11	364.85
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	863.97	867.45	845.58	823.73	797.81	782.98	729.03	632.44	565.69	569.75	516.67
Max	3,562.16	3,174.01	3,490.77	3,642.62	3,619.38	3,449.83	3,237.50	2,713.93	2,314.96	2,351.51	2,441.68
Percent zero	0.41	0.83	0.41	0.20	0.41	0.21	0.21	0.63	0.85	1.06	1.05
Larceny-theft	(484)	(484)	(483)	(487)	(485)	(485)	(472)	(472)	(472)	(472)	(473)
Mean	3,010.74	2,967.86	2,853.27	2,739.48	2,675.56	2,677.98	2,657.44	2,553.08	2,492.14	2,461.44	2,412.67
SD	1,310.43	1,310.69	1,225.13	1,196.79	1,198.33	1,167.39	1,264.11	1,230.47	1,210.48	1,207.06	1,224.91
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	2,851.75	2,780.73	2,705.48	2,610.98	2,536.87	2,556.29	2,472.24	2,358.80	2,322.97	2,279.61	2,192.68
Max	10,057.22	10,237.64	8,788.01	9,994.76	9,686.65	9,491.41	9,395.76	9,054.48	8,446.28	7,919.63	8,931.60
Percent zero	0.62	1.03	0.62	0.62	0.82	0.62	0.21	0.85	0.85	1.06	1.06

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
M.V. Theft	(482)	(485)	(485)	(488)	(486)	(485)	(472)	(473)	(473)	(473)	(474)
Mean	488.44	436.79	363.97	336.18	325.02	324.47	306.15	297.36	309.26	333.07	335.96
SD	337.06	318.58	264.68	254.23	256.40	263.34	253.23	250.85	253.71	263.23	252.82
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	383.89	338.65	292.93	263.95	240.55	245.55	234.10	230.32	237.97	265.69	275.50
Max	1,915.46	2,114.35	1,997.05	1,765.82	1,693.65	1,774.22	1,699.01	1,866.74	1,908.12	1,667.94	1,393.44
Percent zero	0.41	0.82	0.41	0.20	0.41	0.21	0.21	0.63	0.85	1.06	1.05
Clearance rates (per crimes reported)[1]											
Homicide	(446)	(444)	(461)	(444)	(448)	(435)	(423)	(422)	(432)	(410)	(429)
Mean	64.66	67.97	69.97	67.22	68.44	65.14	68.91	66.29	68.46	66.20	66.16
SD	33.98	35.92	40.87	38.04	44.42	38.07	42.15	37.33	40.96	38.84	39.51
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	66.67	72.38	72.73	68.44	66.67	66.67	66.67	68.59	66.67	66.67	66.67
Max	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
Percent zero	9.64	9.68	11.93	11.71	13.84	11.49	10.17	11.85	10.19	9.02	9.79

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Rape	(486)	(487)	(487)	(507)	(505)	(505)	(485)	(486)	(486)	(485)	(488)
Mean	38.87	40.04	39.70	38.59	39.08	36.71	37.29	37.23	35.69	35.83	33.64
SD	24.98	25.01	25.10	26.31	26.47	25.13	25.26	25.30	25.03	24.74	23.46
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	34.89	36.67	37.58	35.00	36.00	33.33	33.33	33.33	32.45	32.65	30.77
Max	126.09	123.81	125.00	120.00	125.00	118.60	106.67	108.70	122.22	11.76	114.29
Percent zero	5.56	5.34	6.98	8.28	8.51	8.32	7.42	7.61	7.41	7.42	7.79
Robbery	(509)	(508)	(510)	(510)	(510)	(510)	(493)	(483)	(487)	(483)	(481)
Mean	27.41	28.83	29.10	30.32	30.41	30.36	32.08	32.05	31.62	31.74	31.36
SD	13.46	13.88	14.52	14.78	14.88	14.76	15.62	14.94	15.79	15.70	15.16
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	26.78	28.57	28.98	30.00	30.31	29.52	30.67	31.34	30.58	30.40	30.54
Max	67.86	75.00	72.73	76.92	75.00	75.00	72.73	76.67	76.92	75.00	75.00
Percent zero	5.50	4.92	7.25	5.49	5.88	5.29	4.06	4.14	4.72	4.14	3.95

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Agg. Assault	(514)	(511)	(513)	(513)	(512)	(514)	(494)	(491)	(490)	(487)	(489)
Mean	52.82	54.49	54.03	55.66	55.12	54.79	56.29	55.48	53.82	53.22	53.09
SD	20.87	21.04	21.86	20.93	21.45	21.13	20.40	19.93	20.86	20.80	20.85
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	54.67	56.25	57.21	58.65	57.87	57.64	58.31	57.76	55.79	53.69	53.05
Max	121.43	100.45	112.68	105.56	109.09	103.03	120.59	103.88	114.13	118.00	119.90
Percent zero	5.25	4.70	7.02	5.07	5.66	5.25	4.05	4.07	4.29	4.11	3.89
Burglary	(511)	(508)	(511)	(513)	(511)	(508)	(489)	(487)	(490)	(486)	(484)
Mean	11.47	11.66	11.24	11.63	11.56	11.47	11.77	12.55	12.34	12.21	12.67
SD	6.24	6.09	6.48	6.61	6.51	6.28	6.26	6.67	7.01	6.70	6.93
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	10.84	11.35	10.51	10.72	10.96	10.85	11.08	11.92	11.28	11.60	11.82
Max	36.54	36.25	34.74	35.83	33.54	36.16	30.94	33.63	35.66	35.72	35.96
Percent zero	5.28	4.72	7.05	5.07	5.68	5.31	4.09	4.11	4.29	4.12	3.93

(continued)

	2007 n = 516	2008 n = 516	2009 n = 516	2010 n = 516	2011 n = 516	2012 n = 516	2013 n = 496	2014 n = 496	2015 n = 496	2016 n = 496	2017 n = 496
Larceny-theft	(512)	(505)	(510)	(508)	(507)	(507)	(491)	(487)	(488)	(486)	(484)
Mean	18.17	19.38	20.30	20.23	20.27	20.48	20.98	21.61	20.60	18.85	17.28
SD	9.23	9.62	10.64	10.15	10.29	10.55	10.57	10.73	10.58	9.94	9.38
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	17.69	19.24	20.56	20.49	20.47	20.88	21.07	21.86	19.95	18.18	16.33
Max	48.13	49.76	49.07	47.02	46.95	49.33	48.94	48.71	48.49	49.47	49.73
Percent zero	5.27	4.75	7.06	4.92	5.72	5.13	4.07	4.11	4.10	4.12	3.93
M.V. Theft	(508)	(506)	(511)	(508)	(511)	(510)	(491)	(484)	(485)	(485)	(483)
Mean	12.15	12.31	11.95	12.14	12.29	12.26	13.06	13.05	13.17	13.45	13.20
SD	9.53	9.87	10.01	9.90	10.20	10.05	10.25	9.49	9.74	10.02	9.42
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	9.87	10.16	9.17	9.49	9.58	10.10	10.66	11.29	11.42	11.25	11.16
Max	50.60	52.27	52.85	51.35	52.76	49.43	53.07	52.53	53.25	52.29	53.18
Percent zero	6.10	6.13	8.81	6.30	6.65	6.27	5.50	4.96	5.57	4.54	4.76

[1]Excluded cases with zero reported crimes to avoid dividing by zero

Analytic Considerations: Missing Data & Test Statistics

Some considerations for analysis of mixed-effects regression models are missing data and test statistics. Missing data, depending on the amount and pattern of missingness, can affect the generalizability of results (Tabachnick & Fidell, 2013; Warner, 2013). Fortunately, the analytic procedures used in mixed-effects regression models for longitudinal data analysis are robust to missing data (Hedeker & Gibbons, 2006). This is largely due to the measurement of time as a continuous variable, which allows for subjects to be measured at different timepoints and to have varying measurement occasions. Subjects that are missing data on one or more occasions are not removed from the analysis. In the case that a subject only responds at one timepoint, their score on the outcome variable is used to calculate the average at that timepoint but does not affect the calculation of the slope. If a subject misses one or more measurement occasions between two responses, the missing timepoints are filled in with the linear estimate between the two occasions. Attrition (i.e., subjects dropping out of a study and not returning) is a concern for mixed-effects regression models in longitudinal studies, but is not often observed in these data. What happens more frequently is “intermittent missing data,” or subjects that do not respond to one or more LEMAS surveys (and relatedly, those who select into the study at later measurement occasions). In these data this is largely due to organizational size: organizations that have fewer than 100 employees are not included in the long-form data collection. Because this pattern of missingness can be explained by one of the covariates (i.e., organizational size), it is considered a special form of missing completely at random (MCAR) and is thus ignorable (Hedeker & Gibbons, 2006).

Under the framework of null-hypothesis significance testing, the *p*-value is frequently used to calculate the probability that the observed results would be true under the conditions of the null hypothesis. The *p*-value is based on the confidence interval using a predefined asymptotic distribution (usually a *z*-, *t*-, or *F*-distribution) and the degrees of freedom included in a model. Models that include random parameters, however, cannot be assumed to have null distributions of these types. Additionally, the degrees of freedom are difficult to estimate with the use of random parameters, so the *p*-value is not included in estimates of mixed-effects regression models in R (Bolker, 2020; Social Science Computing Cooperative (SSCC), 2016). An alternative to the conventional method of creation of confidence intervals is the profile-likelihood confidence interval, which is based on a chi-square distribution (Venzon & Moolgavkar, 1988). It provides confidence interval estimates after holding the effects of all other model parameters constant and is among the more reliable methods of testing the significance of effects (Bolker, 2020; SSCC, 2016). The profiled confidence interval will be used to determine the statistical significance of the multivariate models.

Multivariate Models

Multivariate mixed-effects regression models are run using the lme4 package (Bates et al., 2020), profiled confidence intervals are obtained using the MASS package (Ripley et al., 2020), and r-squared values are obtained with the r2glmm package (Jaeger, 2017).

Models 1 – 3: Personal Differentiation

The first dependent variable under consideration is the percentage of female officers employed by the nation’s largest police departments. This is estimated in a series of seven models as explained in the plan of analysis, with a total of 2,398 observations from 551 subjects. The unconditional model regresses only time on the dependent variable. The effect of time on the outcome variable is positive and significant (profiled 95% CI = 0.1169/0.1701), indicating that the percentage of female officers has been increasing significantly over time, with an average of 11.27 percent for the population in 2013. The addition of the random subject term improves on the model fit (from a log-Likelihood of -7,221 to -6,153), indicating that departments differ significantly in the percentage of female officers employed in 2013. Here, the intraclass correlation (ICC) is calculated as a ratio of the subject variance to the total variance. The ICC value of 0.7692 indicates that approximately 77% of the variance in the employment of women is attributable to the difference between police departments (rather than within departments across time).

The addition of the random trend component (and the significant positive random effect of time) indicates that the slope (i.e., rate of change) differs significantly between departments. The quadratic model added a measure of time-squared to estimate whether there was any curvature observed in the data. A decrease in the log-likelihood as well as a profile confidence interval not inclusive of zero indicates that the relationship between time and the percentage of female officers employed by departments is nonlinear. Because the interpretation of polynomials is not straightforward, Figure 21 shows the predicted time trends for each of the quadratic models predicting minority officer representation. The contextual model added region of the US as a control variable, which was observed to have a significant effect on the outcome. Next, the main-effects model added the variables indicative of organizational size and environmental munificence and complexity. This model provides evidence that the rate of change in the percentage of female officers employed by police departments is significantly affected by organizational size, both measures of munificence, and income and LFP disparities between women and men.

Finally, time interactions were included in the model to test whether the relationships between the time-varying covariates and the dependent variable changed over time. Because the time-varying covariates are grand-mean centered, the model intercept of 10.49 indicates that organizations of average size, munificence, and complexity and a value of zero on each of the interaction terms had an average of 10.49% female officers in 2013. The estimated population standard deviation from this mean is 3.78 percentage points (= $\sqrt{14.28}$, the variance associated with departments). The average rate of change is 0.04 (or a gain of approximately 4 percentage points per year) with a standard deviation of 2.00 percentage points. Departments in the Northeast region employed an average of 2.13 percentage points fewer female officers in 2013 than those in the Midwest and those in the South and West regions employed an average of 1.11 and 1.22 percentage points (respectively) more than those in the Midwest region in female employment. Controlling for each of the other covariates (i.e., holding the other main effects at mean levels and the interaction terms at zero), organizational size had a significant positive effect on female employment, such that for each unit change in the natural logarithm of organizational size there was a corresponding 1.53 percentage point increase in the percentage of female officers employed by large municipal police departments in the US. An increase in Black munificence in communities was associated with a significant increase in female employment. Additionally, both of these effects were magnified over time (as indicated by the significant coefficients for the corresponding interaction terms). While there was a significant (though negligible) main effect of income disparity observed in the previous model, this was not observed in the final model; there was, however a significant (though again, negligible) positive interaction effect for income by time. For each percentage point increase in LFP disparity between women and men (i.e., in communities where women were less equal to men), there was a significant 0.15 percentage point decrease in the dependent variable. No other significant effects of environmental complexity were observed. In total, approximately 33% of the variance in the dependent variable was explained by the final model. See Table 8 for results.

Figure 21

Predicted Probabilities: Time, Time-Squared, and Percent Representation

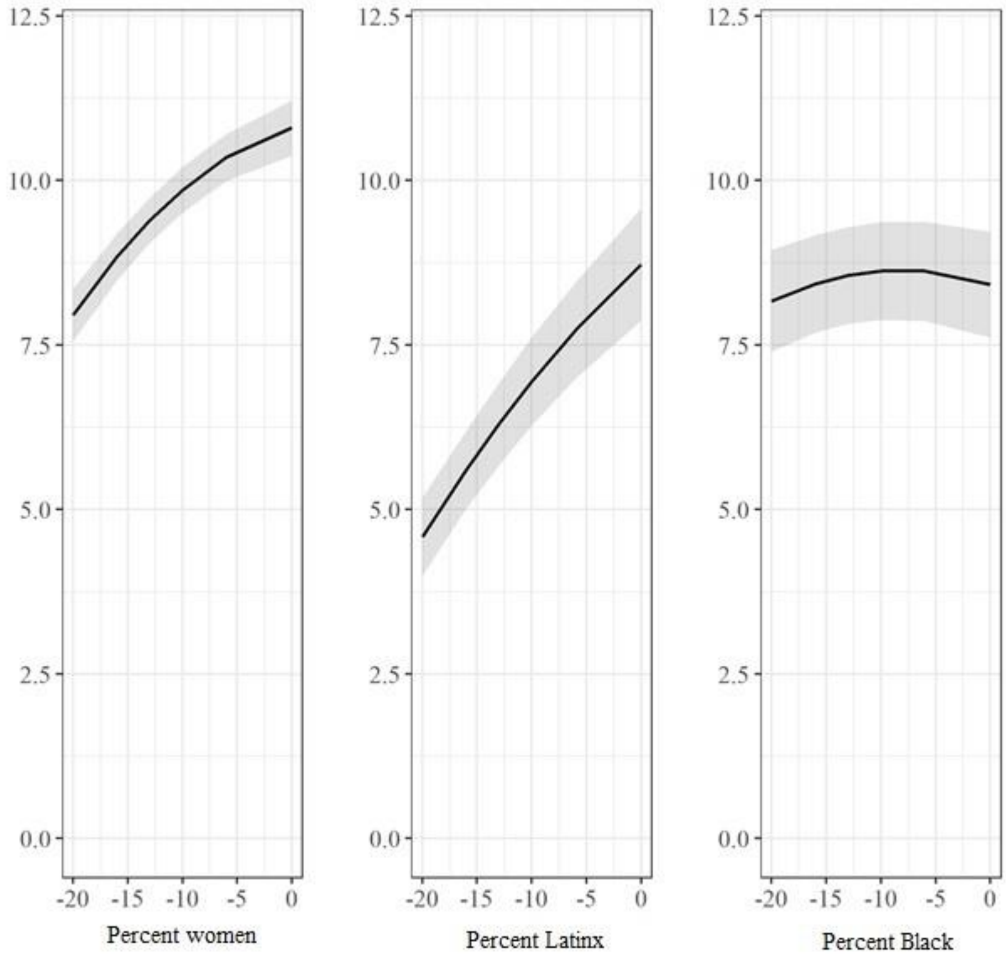


Table 8

Mixed-Effects Regression Models: Percent Female Officers

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	11.27† (0.17)	11.07† (0.19)		11.08† (0.21)		10.80† (0.21)		10.54† (0.39)		10.59† (0.35)		10.49† (0.35)	
Time	0.14† (0.01)	0.14† (0.01)	0.041	0.14† (0.01)	0.040	0.05† (0.02)	0.000	0.04† (0.02)	0.000	0.05† (0.02)	0.001	0.04† (0.02)	0.001
Time^2						-0.00† (0.00)	0.002	-0.00† (0.00)	0.002	-0.00† (0.00)	0.002	-0.00† (0.00)	0.002
Region													
Northeast								-2.46† (0.50)	0.034	-2.16† (0.44)	0.032	-2.13† (0.44)	0.031
South								1.80† (0.45)	0.024	1.13† (0.41)	0.009	1.11† (0.42	0.008
West								0.44 (0.49)	0.001	1.15† (0.45)	0.009	1.22† (0.45)	0.010
Size (log)										1.68† (0.19)	0.086	1.53† (0.25)	0.022

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Percent Latinx										-0.03† (0.01)	0.007	-0.00 (0.01)	0.000
Percent Black										0.05† (0.01)	0.022	0.07† (0.01)	0.018
Income dis.										-0.00† (0.00)	0.000	0.00 (0.00)	0.001
LFP dis.										-0.11† (0.03)	0.005	-0.15† (0.05)	0.003
Employment dis.										0.04 (0.06)	0.000	0.08 (0.09)	0.000
Education dis.										-0.03 (0.03)	0.000	-0.04 (0.06)	0.000
Size*Time												-0.01 (0.02)	0.000
Percent Latinx*Time												0.00† (0.00)	0.003
Percent Black*Time												0.00† (0.00)	0.003

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Income dis. *Time												0.00† (0.00)	0.001
LFP dis. *Time												-0.00 (0.00)	0.000
Employment dis. *Time												0.00 (0.01)	0.000
Education dis. *Time												-0.00 (0.00)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		14.92†		20.15†		20.13†		18.09†		14.28†		14.28†	
Time				0.04†		0.04†		0.04†		0.04†		0.04†	
Residual		2.12†		2.91†		2.86†		2.86†		2.85†		2.84†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-7221	-6153	-6034	-5989	-5945	-5863	-5854
R^2	0.043	0.041	0.040	0.042	0.163	0.321	0.326

Notes:
† = profile confidence interval does not include 0
ICC = 0.7692
n observations = 2,498, n subjects=551

The second dependent variable is the percentage of Latinx officers employed by large US police departments. Results are based on 2,318 observations from 554 departments. The unconditional model indicates that the percentage of Latinx officers employed by police departments differs significantly and has been increasing over time. The random-intercept model shows there is significant variation between subjects in the dependent variable; in fact, 89% of the variation is between departments. The change in percentage also differs significantly over time and is non-linear (see Figure 21). Both the contextual and main-effects models provide evidence that the employment of Latinx officers is effected by the organizational environments of the departments. Specifically, the average police department in 2013 had about 8% Latinx officers (population SD = 5.67 percentage points) and gained an average of 0.09 percent officers per year. There was no evidence that, controlling for other factors, region of the US influenced the employment of Latinx officers. Organizational size and the percentage of Latinx citizens in the community, however, each exerted a statistically significant effect on the outcome, such that each unit increase in the log of organizational size increased the percent of Latinx officers by 1.30% and each percent increase in Latinx population increased the percent of Latinx officers by 0.45%. The effect of the size of the Latinx population increased over time. There was no evidence of a main effect of environmental complexity on the employment of Latinx officers, but a statistically significant (but negligible) interaction was observed between time and income disparity, LFP disparity, and education disparity. The model explained approximately 61.5% of the variation in the percentage of Latinx officers employed by large municipal police departments in the US. Results are presented in Table 9.

Table 9

Mixed-Effects Regression Models: Percent Latinx Officers

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	7.88† (0.30)	8.84† (0.34)		8.88† (0.43)		8.73† (0.44)		6.88† (0.70)		8.05† (0.44)		7.99† (0.44)	
Time	0.07† (0.03)	0.22† (0.01)	0.030	0.20† (0.02)	0.025	0.15† (0.03)	0.001	0.15† (0.03)	0.001	0.08† (0.03)	0.001	0.09† (0.03)	0.001
$Time^2$						-0.00† (0.00)	0.00	-0.00† (0.00)	0.000	-0.00† (0.00)	0.001	-0.00† (0.00)	0.001
Region													
Northeast								0.82 (0.85)	0.001	-0.91 (0.54)	0.003	-0.81 (0.54)	0.003
South								0.62 (0.78)	0.001	0.06 (0.49)	0.000	0.12 (0.49)	0.000
West								6.03† (0.83)	0.063	0.96 (0.56)	0.004	1.06 (0.57)	0.004
Size (log)										1.08† (0.22)	0.025	1.30† (0.35)	0.010

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Percent Latinx										0.41† (0.01)	0.528	0.45† (0.02)	0.284
Income dis.										-0.00 (0.00)	0.000	0.00 (0.00)	0.001
LFP dis.										0.03 (0.02)	0.001	-0.02 (0.03)	0.000
Employment dis.										-0.01 (0.03)	0.000	0.08 (0.05)	0.001
Education dis.										0.00 (0.02)	0.000	-0.05 (0.03)	0.001
Size*Time												0.02 (0.02)	0.000
Percent Latinx*Time												0.00† (0.00)	0.004
Income dis. *Time												0.00† (0.00)	0.001
LFP dis. *Time												-0.00† (0.00)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Employment dis. *Time												0.01 (0.00)	0.001
Education dis. *Time												-0.00† (0.00)	0.002
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		59.08†		98.92†		98.15†		87.95†		33.09†		32.10†	
Time				0.08†		0.08†		0.08†		0.07†		0.06†	
Residual		7.13†		3.70†		3.68†		3.67†		3.79†		3.77†	
Log Likelihood	-8065	-6521		-6202		-6198		-6163		-5890		-5877	
R^2	0.003	0.030		0.025		0.025		0.109		0.609		0.615	

Notes:
† = profile confidence interval does not include 0
ICC = .8923
n observations = 2,318, n subjects = 554

The third dependent variable was the percentage of Black officers employed by US police departments, investigated with 2,416 observations from 556 police departments. The employment of Black police officers has declined non-linearly (see Figure 21) over time, with significant variation (94%) between departments. The average department in 2013 saw the employment of 8.79% Black officers with a population standard deviation of 4.76%. Departments lost an average of 0.09% Black officers per year. Departments in the Northeast region employed an average of 1.3% fewer Black officers than those in the Midwest. No significant differences were observed between the South or West and Midwest regions. Larger police departments and those located in cities with greater Black populations were both significantly more likely to employ greater percentages of Black officers than smaller departments and those in cities with fewer Black citizens. Income disparity exhibited a small but statistically significant positive effect on the dependent variable, and a small but statistically significant interaction effect between time and LFP disparity was observed. The model explained 73.6% of the variance in the percentage of Black officers employed by large municipal police departments in the US. See Table 10 for results and Figure 22 for model comparisons.

Table 10

Mixed-Effects Regression Models: Percent Black Officers

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	7.95† (0.34)	8.61† (0.38)		8.60† (0.41)		8.42† (0.41)		7.79† (0.81)		8.77† (0.42)		8.79† (0.42)	
Time	-0.10† (0.03)	0.01† (0.01)	0.000	0.01 (0.01)	0.000	-0.05† (0.02)	0.000	-0.06† (0.02)	0.000	-0.08† (0.02)	0.001	-0.09† (0.02)	0.001
$Time^2$						-0.00 (0.00)†	0.000	-0.00† (0.00)	0.000	-0.00† (0.00)	0.001	-0.00† (0.00)	0.001
Region													
Northeast								-0.95 (1.10)	0.001	-1.29† (0.55)	0.008	-1.30† (0.55)	0.008
South								4.60† (0.99)	0.037	-0.90 (0.51)	0.004	-0.94 (0.51)	0.005
West								-3.60† (1.08)	0.019	-0.36 (0.54)	0.001	-0.40 (0.54)	0.001
Size (log)										1.46 (0.22)	0.045	1.66† (0.30)	0.016

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Percent Black										0.45† (0.01)	0.626	0.45† (0.01)	0.349
Income dis.										0.00† (0.00)	0.009	0.00† (0.00)	0.004
LFP dis.										-0.00 (0.02)	0.000	-0.04 (0.02)	0.001
Employment dis.										-0.02 (0.02)	0.000	-0.01 (0.03)	0.000
Education dis.										0.00 (0.01)	0.000	-0.00 (0.02)	0.000
Size*Time												0.02 (0.02)	0.000
Percent Black*Time												0.00 (0.00)	0.000
Income dis. *Time												-0.00 (0.00)	0.000
LFP dis. *Time												-0.00† (0.00)	0.001

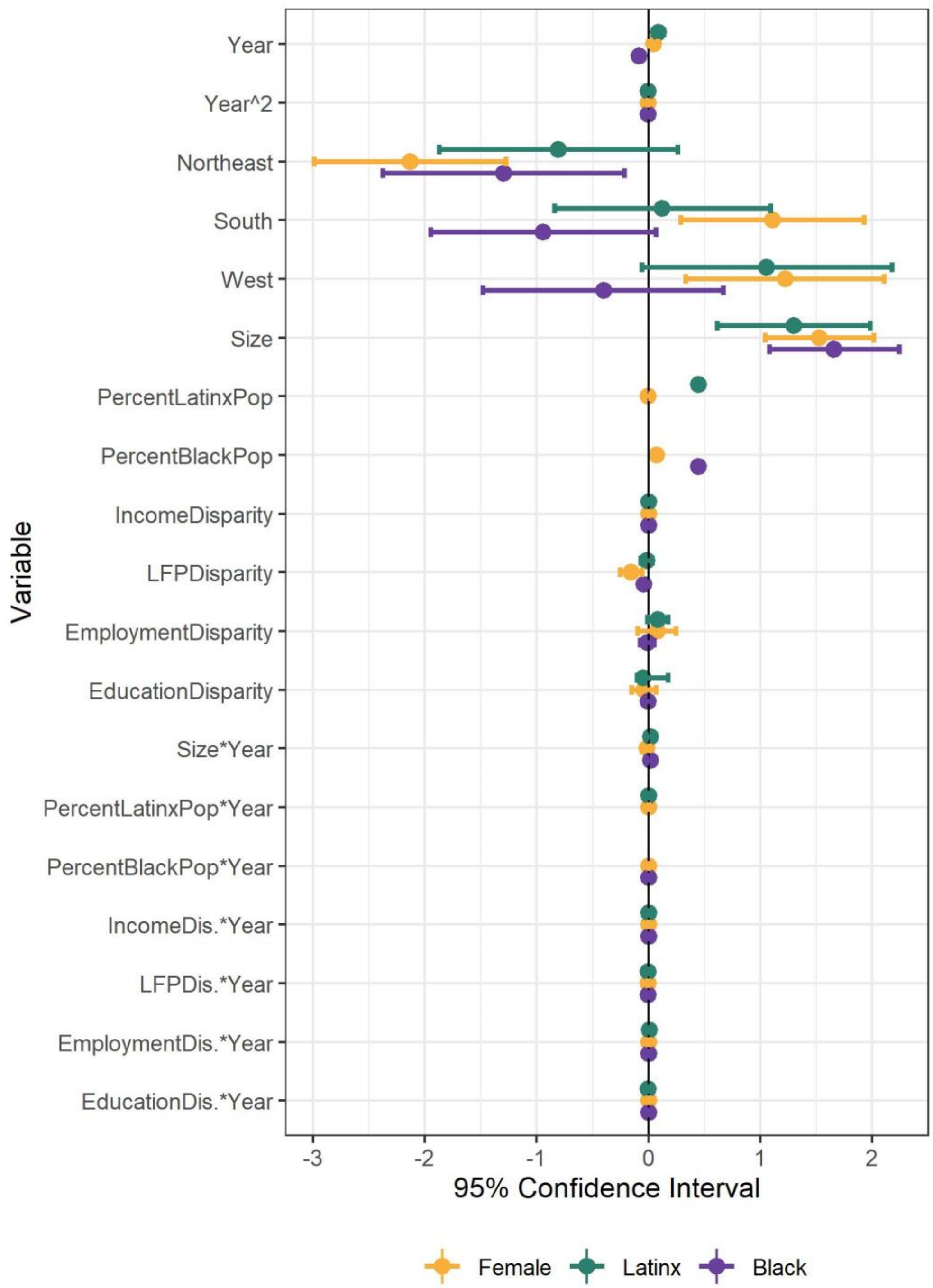
(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model	
Employment dis. *Time							0.00 (0.00)	0.000
Education dis. *Time							-0.00 (0.00)	0.000
Random effects	Est.	Est.	Est.	Est.	Est.	Est.	Est.	
Department		76.77†	88.52†	88.00†	75.43†	22.61†	22.64†	
Time			0.06†	0.06†	0.06†	0.05†	0.04†	
Residual		4.88†	2.55†	2.53†	2.53†	2.56†	2.56†	
Log Likelihood	-8677	-6483	-6228	-6221	-6181	-5759	-5755	
R^2	0.006	0.000	0.000	0.000	0.155	0.736	0.736	

Notes:
† = profile confidence interval does not include 0
ICC= .9403
n observations = 2,416, n subjects = 556

Figure 22

Forest Plot: Representation Model Comparison



Models 4 – 10: Reporting Rates and Absolute Representation

Models four through ten consider the crime reporting rates predicted by absolute representation of minority officers. There is a challenge inherent in examining crime reporting with official agency data because official data tend to represent changes in *crimes committed* rather than changes in reporting practices. One method of dealing with this challenge is to control for a variable related to actual crime but not reporting behaviors. The idea is to take up as much of the variance in actual crime as possible so the remaining variance is attributable to reporting behaviors. I use social disorganization for this purpose because it is correlated with actual crime in metropolitan areas (Blau & Blau, 1982) but not with reporting behaviors (Baumer, 2002). We know that actual crime has been decreasing over time while crime reporting for nonlethal violent crime and property crime has been increasing (Baumer & Lauritsen, 2010). A negative coefficient for time after the inclusion of social disorganization would thus indicate that the variable is not working as intended. Because the interpretation of coefficients with polynomials included is not straightforward, a model is added before the quadratic model to test the effect of controlling for social disorganization on the linear time coefficient.

Unfortunately, social disorganization did not control for enough of the variance in actual crime to effectively examine crime reporting. Social disorganization explained between less than one percent and 29% of the variance in the models. The coefficients for time continued to be negative for all seven dependent variables after the addition of the control (see tables in APPENDIX E), so I did not proceed with the analyses.

Models 11 – 17: Reporting Rate and Relative Representation

The analytic plan for these models was to proceed as in the models above, with the difference being the use of the measure of relative representation rather than absolute representation. Since social disorganization did not adequately control for the number of crimes committed, these analyses were not completed.

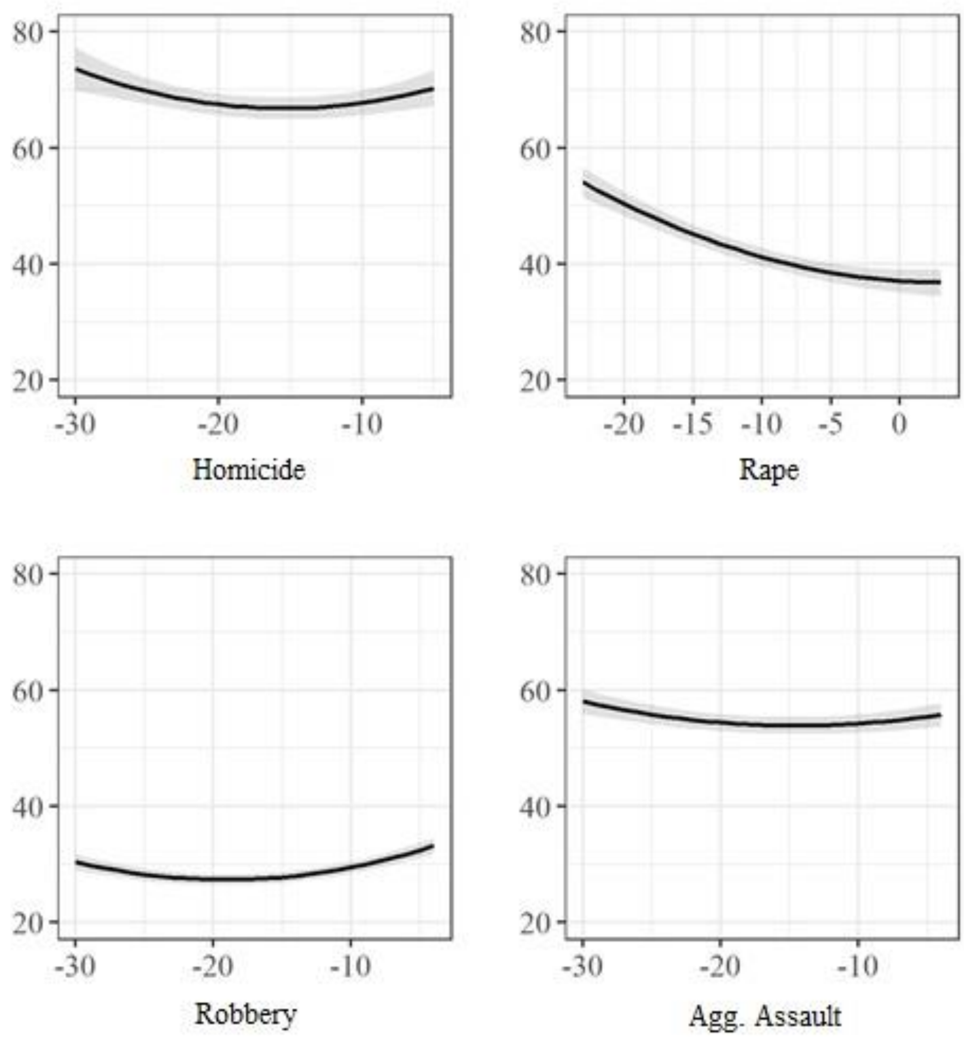
Models 18 – 24: Clearance Rate and Absolute Representation

The next set of models uses the index offense clearance rates (operationalized as the percentage of crimes cleared out of the total number reported each year) as dependent variables and the measures of absolute representation (i.e., percent female officers, percent Latinx officers, percent Black officers) as the independent variables of interest. These test hypotheses 10 through 12, that increases in absolute representation lead to greater clearance rates.

The first dependent variable examined is the homicide clearance rate. The linear term for time is insignificant in the first three models but the addition of the quadratic term is significant. This indicates that the effect of time on the homicide clearance rate is non-linear (see Figure 23). Additionally, the ICC indicates that the majority (78.53%) of difference in the dependent variable is within (rather than between) departments. The contextual model shows significant differences in clearance rates by region of the US, and the main-effects model shows a slight increase in the clearance rate with the addition of female officers and a slight decrease with the addition of officers of color. Controlling for the Latinx and Black population, organizational size, and the interaction effects, however, washes out some of these effects. The final model indicates that police departments in the Midwest region of average size with average percentages of minority officers and no interactions between variables solved an average of 60.08% of homicides in 2013.

Figure 23

Predicted Probabilities: Time, Time-Squared, and Violent Crime Clearance



Departments in the Northeast cleared on average 16.93% more homicides than those in the Midwest. Similarly, organizations in the South and West regions cleared 18.97% and 14.17% more homicides respectively than those in the Midwest.

Organizations with greater percentages of Black officers cleared significantly fewer homicides (approximately 1% fewer with each 1% increase), but this effect has been declining over time. Organizations in cities with greater percentages of Latinx citizens also cleared significantly fewer homicides. The percentage of female and Latinx officers, organizational size, interactions between officers of color and citizens of color, and interactions between time and size and time and female and Latinx representation did not exert a statistically significant effect on the homicide clearance rate. The interaction model explained 5.3% of the variance in the dependent variable. The results of these models are based on 8,243 observations from 525 subjects and are presented in Table 11.

Table 11

Mixed-effects Regression Models: Homicide Clearance & Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	67.23† (0.97)	66.86† (1.20)		67.58† (1.60)		73.95† (2.22)		62.17† (2.78)		61.45† (2.72)		60.08† (2.86)	
Time	-0.05 (0.06)	-0.08 (0.05)	0.001	1.19 (1.09)	0.001	0.94† (0.25)	0.002	0.83† (0.26)	0.001	0.91† (0.26)	0.001	0.95† (0.26)	0.002
$Time^2$						0.03† (0.01)	0.002	0.03† (0.01)	0.001	0.03† (0.01)	0.002	0.03† (0.01)	0.002
Region													
Northeast								13.89† (2.63)	0.013	15.50† (2.55)	0.015	16.93† (2.59)	0.017
South								14.85† (2.33)	0.020	17.36† (2.23)	0.027	18.97† (2.27)	0.030
West								13.22† (2.51)	0.013	13.66† (2.54)	0.012	14.17† (2.68)	0.012
Crime rate (log)								-2.22 (1.29)	0.001	-0.43 (1.31)	0.000	-0.21 (1.33)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-0.96 (1.19)	0.000	2.41 (2.32)	0.000
Percent female ofc.										0.44† (0.18)	0.002	0.14 (0.38)	0.000
Percent Latinx ofc.										-0.28† (0.10)	0.003	-0.04 (0.23)	0.000
Percent Black ofc.										-0.63† (0.10)	0.014	-1.06† (0.25)	0.005
Percent Latinx pop.												-0.22† (0.09)	0.002
Percent Black pop.												-0.12 (0.09)	0.001
Percent Latinx ofc. * Percent Latinx pop.												-0.00 (0.00)	0.000
Percent Black ofc. * Percent Black pop.												0.01 (0.00)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												0.19 (0.12)	0.001
Percent female ofc. * Time												-0.02 (0.02)	0.005
Percent Latinx ofc. * Time												-0.00 (0.00)	0.000
Percent Black ofc. * Time												-0.02† (0.01)	0.001
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		300.00†		780.82†		731.40†		709.44†		645.79†		617.20†	
Time				1.19†		1.10†		1.17†		1.22†		1.20†	
Residual		1096.00†		1042.01†		1042.30†		1039.45†		1039.24†		1039.50†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-41463	-40945	-40879	-40871	-40847	-40822	-40813
R^2	0.001	0.001	0.001	0.002	0.025	0.046	0.053

Notes:
† = profile confidence interval does not include 0
ICC = .2147
n observations = 8,243 , n subjects = 525

The second dependent variable under consideration is the sexual assault clearance rate. The significant negative coefficient for time in the first three models indicates that the sexual assault clearance rate has been declining over time (approximately 0.68% per year in the linear models) and this effect is not linear (see Figure 23). The contextual model indicates that there are significant differences in clearance rates by region and crime rate. The main effects model suggests that the sexual assault clearance rates are affected positively by female representation and negatively by Black representation. Controlling for the minority population and interactions, however, rendered the impact of absolute representation insignificant. Based on 7,706 observations from 512 large municipal police departments, the average police department in the Midwest cleared 30.51% of the sexual assaults reported in 2011. The population standard deviation from this mean, however, was 22.33, indicating a wide range of clearance rates. Departments in the Northeast, South, and West regions cleared an average of 10.59%, 14.49%, and 6.31% more cases respectively than did those in the Midwest. Absolute representation of women, Latinx, and Black officers did not significantly affect the clearance rates of sexual assault, nor did organizational size, crime rate, size of ethnic and racial minority populations, interactions between officers of color and citizens of color, or interactions of time and size or time and representation. Approximately eight percent of the variance in the sexual assault clearance rate was explained by the variables in the model (See Table 12).

Table 12

Mixed-Effects Regression Models: Rape Clearance and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	35.54† (0.52)	35.10† (0.86)		35.43† (1.15)		37.74† (1.22)		28.78† (1.93)		29.23† (1.95)		30.51† (2.13)	
Time	-0.74† (0.04)	-0.74† (0.04)	0.035	-0.68† (0.08)	0.031	-0.03 (0.14)	0.000	0.12 (0.15)	0.000	0.15 (0.15)	0.000	0.16 (0.17)	0.000
$Time^2$						0.03† (0.01)	0.002	0.03† (0.01)	0.003	0.04† (0.01)	0.003	0.04† (0.01)	0.003
Region													
Northeast								10.43† (2.37)	0.016	10.78† (2.41)	0.016	10.59† (2.49)	0.014
South								13.78† (2.14)	0.035	13.99† (2.17)	0.035	14.49† (2.25)	0.035
West								9.13† (2.30)	0.013	7.03† (2.43)	0.007	6.31† (2.61)	0.004
Crime rate (log)								1.70† (0.84)	0.001	1.86† (0.86)	0.001	1.99† (0.87)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										0.47 (1.08)	0.000	0.42 (1.67)	0.000
Percent female ofc.										0.30† (0.14)	0.002	0.02 (0.24)	0.000
Percent Latinx ofc.										0.16 (0.09)	0.002	0.11 (0.17)	0.000
Percent Black ofc.										-0.21† (0.09)	0.003	0.16 (0.18)	0.000
Percent Latinx pop.												0.03 (0.08)	0.000
Percent Black pop.												-0.12 (0.08)	0.001
Percent Latinx ofc. * Percent Latinx pop.												-0.01 (0.00)	0.001
Percent Black ofc. * Percent Black pop.												-0.00 (0.00)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												0.00 (0.11)	0.000
Percent female ofc. * Time												-0.02 (0.02)	0.000
Percent Latinx ofc. * Time												-0.01 (0.01)	0.001
Percent Black ofc. * Time												0.01 (0.01)	0.001
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		279.00†		542.98†		542.76†		502.38†		500.26†		498.70†	
Time				1.99†		1.97†		1.93†		1.91†		1.92†	
Residual		363.00†		296.51†		295.28†		295.06†		294.81†		294.25†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-35610	-34252	-33831	-33815	-33792	-33786	-33781
R^2	0.038	0.035	0.031	0.034	0.071	0.077	0.083

Notes:
† = profile confidence interval does not include 0
ICC = .4342
n observations = 7,706, n subjects = 512

The next dependent variable, the robbery clearance rate, was investigated with 9,013 observations from 541 subjects. Significant positive coefficients for time in the first three models are indicative that the robbery clearance rate has been increasing over time. The addition of the significant coefficient for time squared indicates this has not been linear (see Figure 23). Significant positive coefficients for region and crime rate in the contextual model suggest that the clearance rate differs by both, and the main effects model suggests that organizational size, the percentage of female officers, and the percentage of Black officers may exert significant effects on the robbery clearance rate. The final model shows that large municipal police departments in the US clear approximately 29% of robberies reported each year and that the percentage of robberies cleared per year has increased non-linearly over time. Departments in the Northeast, South, and West regions clear, on average, 9%, 11%, and 8% more robberies respectively than those in the Midwest. Organizational size, the percentage of female officers, and the percentage of Latinx officers do not significantly impact the robbery clearance rate. Each point increase in the percentage of Black officers is related to a 0.20% reduction in robbery clearance, as are each point increase in the percentage of Latinx and Black citizens in the community. This model explains 14.9% of the variance in this dependent variable. Results are presented in Table 13.

Table 13

Mixed-Effects Regression Models: Robbery Clearance and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	31.21† (0.34)	30.34† (0.53)		31.30† (0.78)		36.68† (0.87)		30.38† (1.23)		29.98† (1.19)		28.94† (1.24)	
Time	0.16† (0.02)	0.07† (0.01)	0.001	0.16† (0.04)	0.007	0.98† (0.07)	0.011	0.92† (0.07)	0.010	0.92† (0.07)	0.011	0.97† (0.08)	0.012
Time^2						0.03† (0.00)	0.009	0.02† (0.00)	0.009	0.02† (0.00)	0.008	0.03† (0.00)	0.010
Region													
Northeast								6.82† (1.40)	0.023	7.08† (1.33)	0.025	8.66† (1.33)	0.036
South								7.80† (1.25)	0.039	9.04† (1.19)	0.052	11.13† (1.20)	0.074
West								7.62† (1.35)	0.032	7.75† (1.32)	0.027	8.17† (1.39)	0.030
Crime rate (log)								-1.24† (0.39)	0.002	-0.83† (0.40)	0.001	-0.71 (0.40)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-1.48† (0.58)	0.005	-1.21 (1.03)	0.001
Percent female ofc.										0.14† (0.07)	0.001	0.10 (0.14)	0.000
Percent Latinx ofc.										-0.07 (0.04)	0.001	0.05 (0.09)	0.000
Percent Black ofc.										-0.27† (0.05)	0.018	-0.22† (0.10)	0.002
Percent Latinx pop.												-0.20† (0.04)	0.012
Percent Black pop.												-0.19† (0.04)	0.011
Percent Latinx ofc. * Percent Latinx pop.												-0.00 (0.00)	0.000
Percent Black ofc. * Percent Black pop.												0.00 (0.00)	0.002

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												-0.01 (0.05)	0.000
Percent female ofc. * Time												-0.00 (0.01)	0.000
Percent Latinx ofc. * Time												-0.00 (0.00)	0.000
Percent Black ofc. * Time												-0.00 (0.00)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		112.20†		272.99†		264.38†		239.00†		222.50†		206.85†	
Time				0.78†		0.46†		0.45†		0.45†		0.44†	
Residual		91.90†		71.84†		70.37†		70.40†		70.50†		70.36†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-36391	-33924	-33257	-33170	-33144	-33117	-33091
R^2	0.007	0.001	0.007	0.014	0.060	0.102	0.149

Notes:
† = profile confidence interval does not include 0
ICC = .5499
n observations = 9,013, n subjects = 541

The final violent crime model under examination is aggravated assault. Though time was not significantly associated with the aggravated assault clearance rate in the unconditional model, the random-intercept model suggests that the rate has been decreasing over time. Indeed, significant coefficients for both time and time-squared in the final four models indicate that the aggravated assault clearance rate has changed over time. See Figure 23 for the effect of time on this dependent variable. The results of the contextual and main-effects models for aggravated assault are similar to those for robbery in that they suggest significant differences by region, crime rate, organizational size, and absolute representation of female, Latinx, and Black officers. The final model indicates, however, no effects related to gender or ethnicity. The average police department cleared 44.99% of aggravated assaults per year, with departments in the Northeast clearing 18.75% more, those in the South clearing 16.24% more, and those in the West clearing 13.94% more than those in the Midwest. Departments in cities with larger populations of Latinx and Black citizens cleared significantly fewer robberies. These results were based on 9,044 observations from 541 departments and explained 14% of the variance in the aggravated assault clearance rate. See Table 14 for results of the aggravated assault models and Figure 24 for comparison of the violent crime models.

Table 14

Mixed-Effects Regression Models: Aggravated Assault Clearance and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	54.11† (0.51)	52.98† (0.81)		53.93† (1.14)		57.51† (1.27)		46.24† (1.85)		45.46† (1.78)		44.99† (1.88)	
Time	-0.03 (0.03)	-0.14† (0.02)	0.002	-0.05 (0.05)	0.001	0.50† (0.10	0.001	0.42† (0.11)	0.001	0.42† (0.11)	0.001	0.50† (0.11)	0.001
Time^2						0.02† (0.00)	0.002	0.02† (0.00)	0.002	0.01† (0.00)	0.001	0.02† (0.00)	0.002
Region													
Northeast								16.61† (2.14)	0.060	17.30† (2.05)	0.063	18.75† (2.09)	0.071
South								12.02† (1.91)	0.041	14.05† (1.83)	0.056	16.24† (1.87)	0.070
West								13.63† (2.06)	0.045	13.81† (2.04)	0.041	13.94† (2.17)	0.038
Crime rate (log)								-1.70† (0.57)	0.002	-1.17† (0.57)	0.001	-1.11 (0.58)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-1.96† (0.89)	0.004	-2.42 (1.51)	0.001
Percent female ofc.										0.22† (0.10)	0.001	0.27 (0.20)	0.000
Percent Latinx ofc.										-0.15† (0.07)	0.003	-0.14 (0.13)	0.000
Percent Black ofc.										-0.39† (0.07)	0.017	-0.67† (0.15)	0.002
Percent Latinx pop.												-0.17† (0.06)	0.004
Percent Black pop.												-0.21† (0.06)	0.006
Percent Latinx ofc. * Percent Latinx pop.												-0.00 (0.00)	0.001
Percent Black ofc. * Percent Black pop.												0.00 (0.00)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												-0.05 (0.07)	0.000
Percent female ofc. * Time												-0.01 (0.05)	0.000
Percent Latinx ofc. * Time												-0.01† (0.01)	0.001
Percent Black ofc. * Time												-0.01 (0.01)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		270.00†		582.44†		573.00†		516.68†		473.46†		455.49†	
Time				1.02†		1.00†		0.99†		0.99†		0.97†	
Residual		192.00†		147.78†		147.00†		147.18†		147.36†		147.14†	

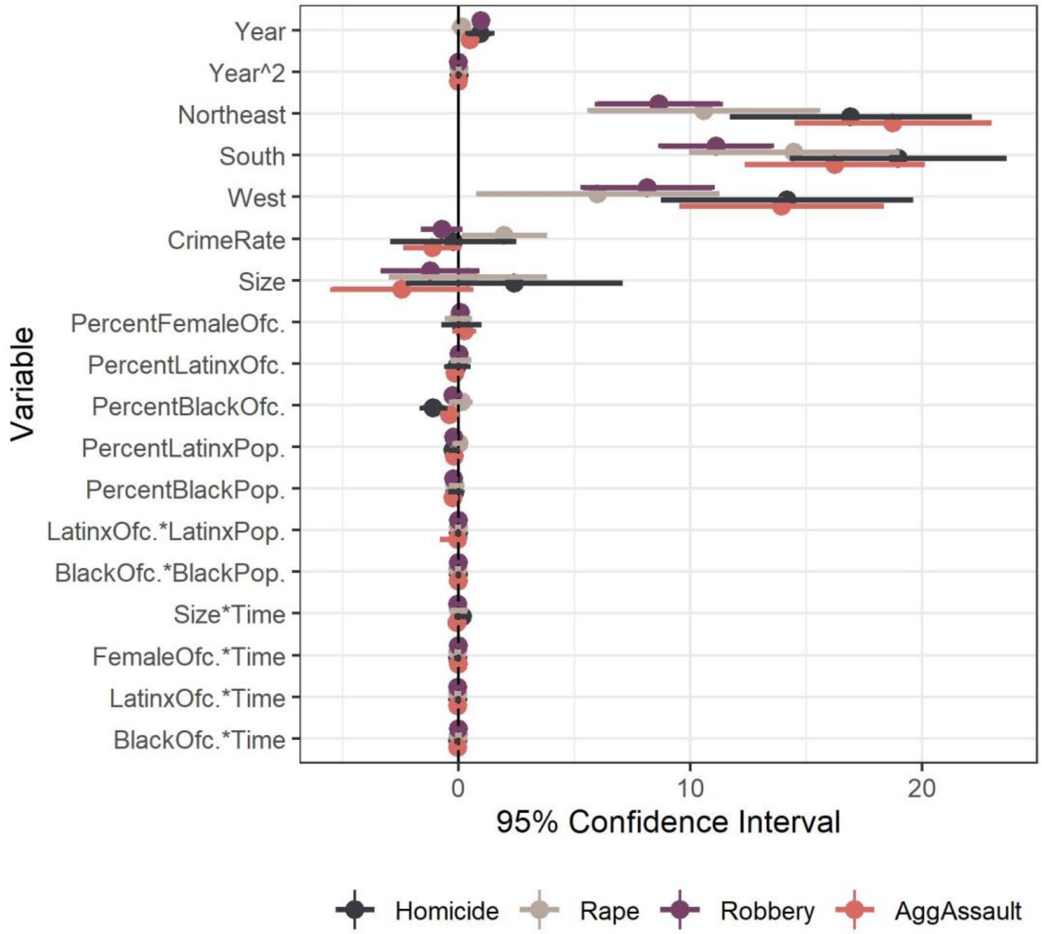
(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-40174	-37412	-36686	-36667	-36630	-36605	-36590
R^2	0.001	0.002	0.001	0.002	0.076	0.112	0.140

Notes:
† = profile confidence interval does not include 0
ICC = .5842
n observations = 9,044, n subjects = 541

Figure 24

Forest Plot: Violent Crime and Absolute Representation Model Comparisons



The first property crime under investigation is burglary. The random-intercept model suggests that the clearance rate for this crime may be decreasing over time and the quadratic model (as well as the remaining models) confirm the non-linear impact of time on the burglary clearance rate (see Figure 25). The contextual model suggests there may be significant difference in clearance by region of the US and crime rate. The main-effects model suggests an impact of organizational size and representation of women, Latinx, and Black officers. The interaction model shows that on average, police departments cleared approximately 10% of the burglaries reported in 2013. Departments in the Northeast, South, and West cleared between four and five percent more burglaries that year than did those in the Midwest. Each percentage point increase in employment of Latinx officers was associated with a 0.13% decrease in the number of burglaries cleared. Additionally, departments located in cities with larger Latinx populations cleared significantly fewer burglaries. This model, based on 8,993observations from 541 subjects explained 10.4% of the variance in the burglary clearance rate. See Table 15 for results.

Figure 25

Predicted Probabilities: Time, Time-Squared, and Property Crime Clearance

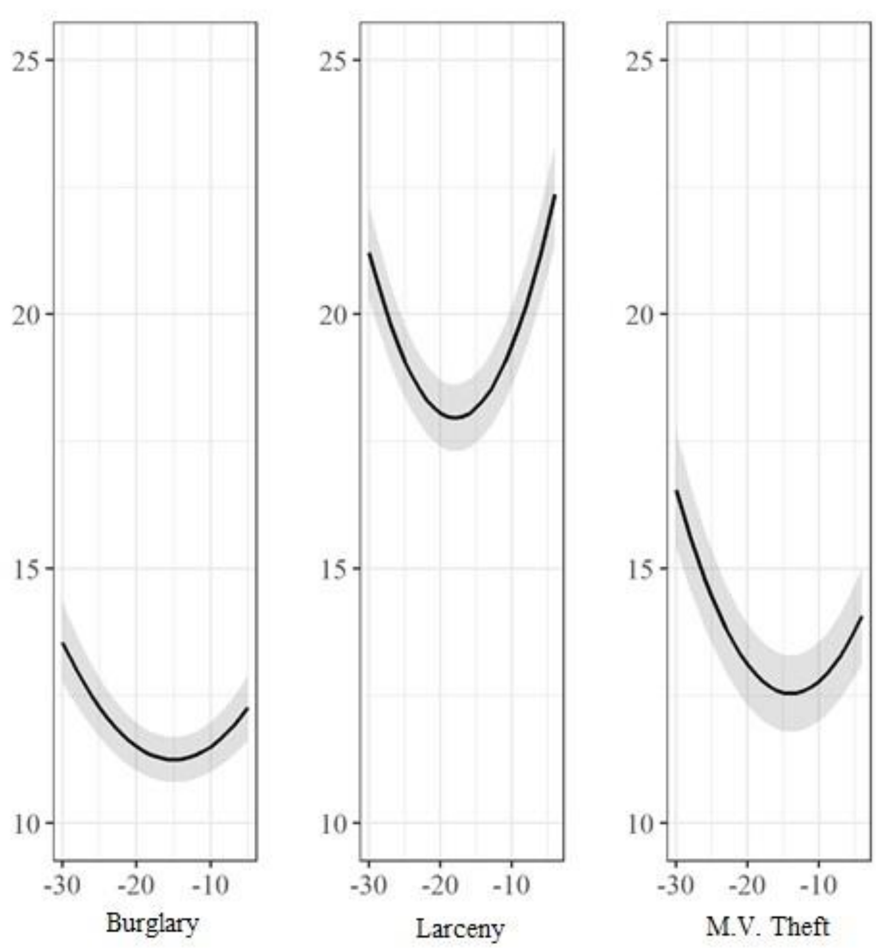


Table 15

Mixed-Effects Regression Models: Burglary and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	$SP\ R^2$	Est. (SE)	$SP\ R^2$	Est. (SE)	$SP\ R^2$	Est. (SE)	$SP\ R^2$	Est. (SE)	$SP\ R^2$	Est. (SE)	$SP\ R^2$
Intercept	11.50† (0.16)	11.20† (0.25)		53.96† (7.35)		13.56† (0.39)		10.23† (0.57)		9.90† (0.56)		9.60† (0.59)	
Time	-0.01 (0.01)	-0.04† (0.01)	0.002	0.12 (0.35)	0.002	0.31† (0.03)	0.005	0.28† (0.03)	0.004	0.28† (0.03)	0.004	0.28† (0.04)	0.004
$Time^2$						0.01† (0.00)	0.006	0.01† (0.00)	0.006	0.01† (0.00)	0.006	0.01† (0.00)	0.006
Region													
Northeast								4.00† (0.66)	0.036	4.43† (0.65)	0.041	4.90† (0.67)	0.048
South								4.68† (0.58)	0.061	5.04† (0.58)	0.069	5.44† (0.60)	0.075
West								2.98† (0.63)	0.022	3.50† (0.64)	0.026	3.90† (0.69)	0.029
Crime rate (log)								-0.60† (0.17)	0.002	-0.52† (0.17)	0.001	-0.50† (0.18)	0.001

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-0.57† (0.28)	0.003	-0.24 (0.47)	0.000
Percent female ofc.										0.08† (0.03)	0.002	0.00 (0.06)	0.000
Percent Latinx ofc.										-0.07† (0.02)	0.006	-0.13† (0.04)	0.003
Percent Black ofc.										-0.05† (0.02)	0.003	-0.00 (0.05)	0.000
Percent Latinx pop.												-0.05† (0.02)	0.003
Percent Black pop.												-0.03 (0.02)	0.001
Percent Latinx ofc. * Percent Latinx pop.												0.00 (0.00)	0.000
Percent Black ofc. * Percent Black pop.												-0.00 (0.00)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												0.02 (0.02)	0.000
Percent female ofc. * Time												-0.00 (0.00)	0.000
Percent Latinx ofc. * Time												-0.01† (0.00)	0.003
Percent Black ofc. * Time												0.00 (0.00)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		24.20†		53.96†		52.52†		47.45†		44.63†		43.54†	
Time				0.12†		0.12†		0.12†		0.12†		0.12†	
Residual		20.10*		14.98*		14.75*		14.74*		14.75*		14.72†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-29498	-27017	-26198	-26132	-26096	-26082	-26071
R^2	0.001	0.002	0.002	0.007	0.073	0.091	0.104

Notes:
† = profile confidence interval does not include 0
ICC = .5458
n observations = 8,993, n subjects = 541

The larceny clearance rate is examined with 8,993 observations from 541 organizations. The random-intercept model indicates that organizations have been increasing their larceny clearance rates by approximately 0.05% per year. The quadratic model shows that this effect has been curvilinear (see Figure 25). The interaction model shows that in 2013, the average large municipal police department in the US cleared 20.45% of the reported larcenies. Again, departments in the Northeast, South, and West cleared significantly more (range = 3.51 – 6.10) larcenies than did those in the Midwest. Additionally, the crime rate exerted a significant negative effect on the clearance rate of larceny. Organizational size, percent female officers, and percent Black officers did not significantly impact the clearance rate. Organizations with greater employment of Latinx and Black officers cleared significantly fewer larcenies and this effect has been increasing significantly (though negligibly) for Latinx representation over time. Organizations located in cities with larger Latinx and Black populations also experienced a significant reduction in the number of larcenies cleared. This model (reported in Table 16) explained 12.4% of the variance in the larceny clearance rate.

Table 16

Mixed-Effects Regression Models: Larceny Clearance and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	20.92† (0.23)	20.19† (0.37)		20.52† (0.59)		25.23† (0.62)		21.79† (0.90)		21.26† (0.86)		20.45† (0.91)	
Time	0.12† (0.01)	0.05† (0.01)	0.001	0.09† (0.03)	0.005	0.81† (0.04)	0.016	0.74† (0.05)	0.014	0.74† (0.05)	0.015	0.74† (0.05)	0.015
Time^2						0.02† (0.00)	0.014	0.02† (0.00)	0.013	0.02† (0.00)	0.013	0.02† (0.00)	0.014
Region													
Northeast								2.53† (1.01)	0.007	2.77† (0.96)	0.008	3.51† (0.99)	0.012
South								4.35† (0.91)	0.025	5.33† (0.86)	0.039	6.10† (0.90)	0.047
West								4.23† (0.98)	0.021	4.88† (0.96)	0.025	5.26† (1.04)	0.025
Crime rate (log)								-1.39† (0.22)	0.005	-1.20† (0.22)	0.004	-1.14† (0.22)	0.003

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-1.10† (0.41)		0.57 (0.75)	0.000
Percent female ofc.										0.05 (0.04)	0.005	0.04 (0.09)	0.000
Percent Latinx ofc.										-0.14† (0.03)	0.010	-0.42† (0.06)	0.014
Percent Black ofc.										-0.13† (0.03)	0.009	-0.13† (0.07)	0.001
Percent Latinx pop.												-0.07† (0.03)	0.003
Percent Black pop.												-0.06† (0.03)	0.002
Percent Latinx ofc. * Percent Latinx pop.												0.00† (0.00)	0.002
Percent Black ofc. * Percent Black pop.												-0.00 (0.00)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												0.09† (0.03)	0.002
Percent female ofc. * Time												-0.00 (0.00)	0.000
Percent Latinx ofc. * Time												-0.02† (0.00)	0.009
Percent Black ofc. * Time												-0.00 (0.00)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		59.30†		162.78†		155.46†		150.07†		136.34†		132.79†	
Time				0.27†		0.25†		0.25†		0.25†		0.25†	
Residual		36.70†		25.11†		24.00†		23.90†		23.91†		23.74†	

(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-32816	-29796	-28646	-28456	-28424	-28394	-28369
R^2	0.008	0.001	0.005	0.017	0.051	0.097	0.124

Notes:
† = profile confidence interval does not include 0
ICC = .6176
n observations = 8,993, n subjects = 541

Finally, the impact of absolute representation on the motor-vehicle theft clearance rate is examined with 8,950 observations from 540 large municipal police departments. The motor-vehicle theft clearance rate has been decreasing significantly over time, and this effect is non-linear (see Figure 25). Police departments cleared, on average, 12.26% of the crimes reported in 2013, with departments in the South clearing an average of 7.18% greater crimes than those in the Midwest. Each percentage point increase in Latinx officers was associated with a 0.19% reduction in the number of crimes cleared. Similarly, each percentage point increase in the Latinx population of the cities was associated with 0.08% decrease in the motor-vehicle theft clearance rate. The model explains 13.4% of the variation in the dependent variable. See Table 17 for results and Figure 26 for property crime model comparisons.

Table 17

Mixed-Effects Regression Models: Motor-Vehicle Theft Clearance and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	12.61† (0.26)	11.89† (0.40)		12.35† (0.54)		15.54† (0.59)		13.91† (0.91)		13.38† (0.90)		12.26† (0.94)	
Time	-0.04† (0.01)	-0.10† (0.01)	0.005	-0.06† (0.03)	0.002	0.43† (0.05)	0.004	0.41† (0.05)	0.004	0.41† (0.05)	0.004	0.42† (0.05)	0.004
$Time^2$						0.02† (0.00)	0.006	0.02† (0.00)	0.006	0.01† (0.00)	0.006	0.02† (0.00)	0.006
Region													
Northeast								-1.55 (1.11)	0.002	-0.78 (1.09)	0.001	0.27 (1.11)	0.000
South								5.71† (0.99)	0.038	6.43† (0.97)	0.047	7.18† (0.99)	0.055
West								-0.85 (1.07)	0.001	-0.12 (1.07)	0.000	0.92 (1.14)	0.001
Crime rate (log)								-0.33 (0.26)	0.000	-0.19 (0.26)	0.000	-0.20 (0.26)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size (log)										-1.04† (0.45)	0.004	-0.47 (0.72)	0.000
Percent female ofc.										0.17† (0.04)	0.003	-0.02 (0.09)	0.000
Percent Latinx ofc.										-0.12† (0.03)	0.006	-0.19† (0.06)	0.002
Percent Black ofc.										-0.12† (0.03)	0.006	-0.11 (0.07)	0.001
Percent Latinx pop.												-0.08† (0.03)	0.004
Percent Black pop.												-0.05 (0.03)	0.001
Percent Latinx ofc. * Percent Latinx pop.												0.01† (0.00)	0.004
Percent Black ofc. * Percent Black pop.												-0.00 (0.00)	0.000

(continued)

	Unconditional model	Random-intercept model		Random-intercept & trend model		Quadratic model		Contextual model		Main-effects model		Interaction model	
	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time												0.02 (0.04)	0.000
Percent female ofc. * Time												-0.01† (0.00)	0.001
Percent Latinx ofc. * Time												-0.00 (0.00)	0.000
Percent Black ofc. * Time												-0.00 (0.00)	0.000
Random effects	Est.	Est.		Est.		Est.		Est.		Est.		Est.	
Department		70.50†		128.43†		125.90†		116.44†		110.17†		105.49†	
Time				0.25†		0.25†		0.25†		0.25†		0.25†	
Residual		40.40†		30.12†		29.58†		29.60†		29.57†		29.53†	

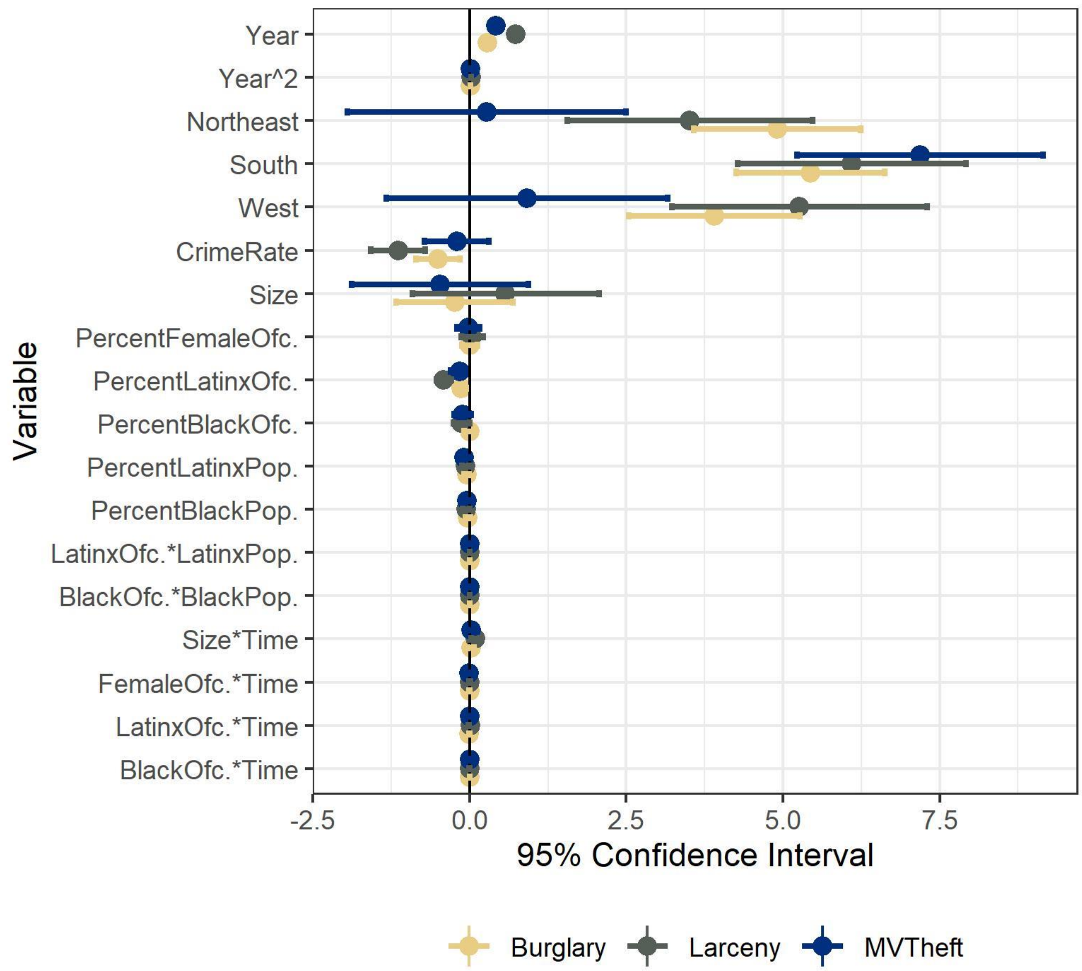
(continued)

	Unconditional model	Random-intercept model	Random-intercept & trend model	Quadratic model	Contextual model	Main-effects model	Interaction model
Log Likelihood	-33525	-30098	-29302	-29229	-29192	-29170	-29158
R^2	0.001	0.005	0.002	0.008	0.092	0.117	0.134

Notes:
† = profile confidence interval does not include 0
ICC = .6359
n observations = 8,950, n subjects = 540

Figure 26

Forest Plot: Property Crime Clearance and Absolute Representation Model Comparisons



Models 25 – 31: Clearance Rate and Relative Representation

The final set of models explore the same set of dependent variables as the previous section (i.e., violent crime clearance rates). The independent variable of interest for these models are the measures of Latinx and Black officers relative to Latinx and Black citizen populations in the communities served by the organization. Because the first four models in the analytic procedure are equivalent (i.e., they include the same sample and predictors), I present only the results of the main-effects and interaction models.

Results of the final homicide clearance rate models when relative representation is used are substantively similar in many ways to the results when the measure of absolute representation is used. The intercept (representing the percentage of homicide cases cleared in 2013) only differs by two percentage points (62.70 in this model, compared to 60.08 in the absolute representation model), the effects of time and time-squared are similar, and the Northeast, South, and West regions all clear significantly more of these cases than do departments in the Midwest (exact estimates vary by a few percentage points). Crime rate, organizational size, and the percentage of female officers do not impact the homicide clearance rate. The relative representation of Latinx and Black officers to citizens, on the other hand, does. For each unit increase in Latinx relative representation, there is a corresponding 10.70% decrease I the homicide clearance rate. On the other hand, as Black relative representation increases, there is a corresponding 9.76% increase in the number of homicides cleared. Furthermore, this effect has been increasing significantly over time. This model explains 3% of the variance in the homicide clearance rate. See Table 18 for results.

Table 18

Mixed-Effects Regression Models: Homicide Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	62.35† (2.77)		62.70† (2.79)	
Time	0.84† (0.26)	0.001	0.86† (0.26)	0.001
$Time^2$	0.03† (0.01)	0.001	0.03† (0.01)	0.001
Region				
Northeast	13.65† (2.64)	0.012	13.77† (2.65)	0.012
South	14.71† (2.31)	0.020	14.58† (2.32)	0.019
West	13.36† (2.53)	0.013	13.20† (2.54)	0.012
Crime rate (log)	-1.40 (1.32)	0.000	-1.49 (1.33)	0.000
Size (log)	-3.12† (1.19)	0.003	-1.68 (2.27)	0.000
Percent female ofc.	0.12 (0.18)	0.000	-0.27 (0.37)	0.000
Latinx relative rep.	-2.47 (2.03)	0.000	-10.70† (4.88)	0.001
Black relative rep.	1.51 (1.35)	0.000	9.76† (3.26)	0.002
Size * Time			0.09 (0.11)	0.000
Percent female ofc. * Time			-0.03 (0.02)	0.000

(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Latinx relative rep. * Time			-0.44 (0.24)	0.001
Black relative rep. * Time			0.46† (0.16)	0.002
Random effects	Est.		Est.	
Department	696.91†		679.79†	
Time	1.18†		1.12†	
Residual	1039.65†		1039.04†	
Log Likelihood	-40843		-40837	
R^2	0.029		0.032	

Notes:
† = profile confidence interval does not include 0
n observations = 8,243, n subjects = 525

For the 2011 sexual assault clearance rate, the intercept in the final model is 29.15 (slightly less than the previous estimate of 30.51). Again, time functions similarly in these models as compared to the absolute representation models as does region of the US. While there were no significant effects for any of the measures of representation in the previous section, the Black relative representation measure here exerts a statistically significant positive effect on the sexual assault clearance rate. This model (presented in Table 19) explains 7.3% of the variance in the dependent variable.

Table 19

Mixed-Effects Regression Models: Sexual Assault Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	28.97† (1.94)		29.15† (1.94)	
Time	0.13 (0.15)	0.000	0.14 (0.16)	0.000
Time^2	0.03† (0.01)	0.003	0.04† (0.01)	0.003
Region				
Northeast	11.04† (2.40)	0.017	11.01† (2.41)	0.017
South	13.64† (2.14)	0.034	13.54† (2.15)	0.033
West	8.41† (2.33)	0.011	8.30† (2.34)	0.010
Crime rate (log)	1.70† (0.86)	0.001	1.70† (0.86)	0.001
Size (log)	0.13 (1.04)	0.000	0.08 (1.60)	0.000
Percent female ofc.	0.17 (0.14)	0.001	0.00 (0.23)	0.000
Latinx relative rep.	0.16 (1.41)	0.000	-0.15 (2.81)	0.000
Black relative rep.	1.73 (0.90)	0.001	3.84† (1.78)	0.001
Size * Time			-0.00 (0.11)	0.000
Percent female ofc. * Time			-0.02 (0.02)	0.000

(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Latinx relative rep. * Time			-0.03 (0.19)	0.000
Black relative rep. * Time			0.18 (0.13)	0.000
Random effects	Est.		Est.	
Department	500.07†		501.89	
Time	1.91†		1.94	
Residual	294.89†		294.59	
Log Likelihood	-33789		-33787	
R^2	0.073		0.073	

Notes:
† = profile confidence interval does not include 0
n observations = 7,706, n subjects = 512

The relative representation model of the robbery clearance rate estimates that the average police department cleared 30.36% of these crimes in 2013 (in comparison to the absolute representation model estimate of 28.94). The clearance rate has been increasing non-linearly over time, and organizations in the Northeast, South, and West regions cleared significantly more robberies than organizations in the Midwest. In contrast to the equivalent absolute representation model (which showed no effect for organizational size), this model indicates that larger organizations cleared fewer robberies than did smaller organizations as did organizations in cities with grater crime rates. No significant effect of officer representation were observed. Approximately 8% of the variance was explained by this model, presented in Table 20.

Table 20

Mixed-Effects Regression Models: Robbery Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	30.19† (1.22)		30.36† (1.22)	
Time	0.89† (0.07)	0.010	0.91† (0.07)	0.010
$Time^2$	0.02† (0.00)	0.008	0.02† (0.00)	0.008
Region				
Northeast	6.60† (1.37)	0.021	6.56† (1.38)	0.021
South	7.89† (1.22)	0.040	7.82† (1.23)	0.039
West	7.74† (1.33)	0.031	7.68† (1.33)	0.031
Crime rate (log)	-0.98† (0.40)	0.001	-1.00† (0.40)	0.001
Size (log)	-2.40† (0.58)	0.012	-3.14† (1.02)	0.004
Percent female ofc.	0.03 (0.06)	0.000	0.02 (0.14)	0.000
Latinx relative rep.	-0.94 (0.66)	0.000	0.65 (1.59)	0.000
Black relative rep.	0.82 (0.43)	0.001	1.94 (1.07)	0.001

(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time			-0.04 (0.05)	0.000
Percent female ofc. * Time			-0.00 (0.01)	0.000
Latinx relative rep. * Time			0.09 (0.08)	0.000
Black relative rep. * Time			0.06 (0.05)	0.000
Random effects	Est.		Est.	
Department	231.86†		230.69†	
Time	0.45†		0.44†	
Residual	70.42†		70.71†	
Log Likelihood	-33132		-33131	
R^2	0.079		0.081	

Notes:
† = profile confidence interval does not include 0
n observations = 9,013, n subjects = 541

The final aggravated assault clearance rate model shows that on average, large municipal police departments cleared 45.99% of the aggravated assaults reported in 2013. This compares favorably with the estimate of 44.99 in the absolute representation model. Similarly, the estimates of a 16.44% increase in the Northeast, 12.24% increase in the South, and 13.94% increase in the West as compared to the Midwest compare favorably to the estimates of 18.75%, 16.24%, and 13.94% increase in respective regions from the absolute representation model. Increases in the crime rate in the community and organizational size were both associated with significant reductions in aggravated assault clearances. The absolute representation model indicated that greater percentages of Black officers were associated with a significant decrease in the clearance rate, but the models that use the measures of relative representation show no significant change based on these measures. This model explained 9.4% of the variance in the aggravated assault clearance rate. See Table 21 for results and Figure 27 for model comparisons.

Table 21

Mixed-Effects Regression Models: Aggravated Assault Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	45.92† (1.82)		45.99† (1.83)	
Time	0.39† (0.11)	0.001	0.41† (0.11)	0.001
Time^2	0.01† (0.00)	0.001	0.01† (0.00)	0.001
Region				
Northeast	16.39† (2.12)	0.057	16.44† (2.12)	0.057
South	12.20† (1.88)	0.042	12.24† (1.88)	0.042
West	13.90† (2.04)	0.044	13.94† (2.05)	0.044
Crime rate (log)	-1.36† (0.57)	0.001	-1.46† (0.58)	0.001
Size (log)	-3.35† (0.88)	0.011	-5.25† (1.49)	0.005
Percent female ofc.	0.06 (0.09)	0.000	0.13 (0.20)	0.000
Latinx relative rep.	-1.35 (0.96)	0.000	-0.35 (2.30)	0.000
Black relative rep.	0.96 (0.63)	0.000	0.07 (1.55)	0.000
Size * Time			-0.11 (0.07)	0.001

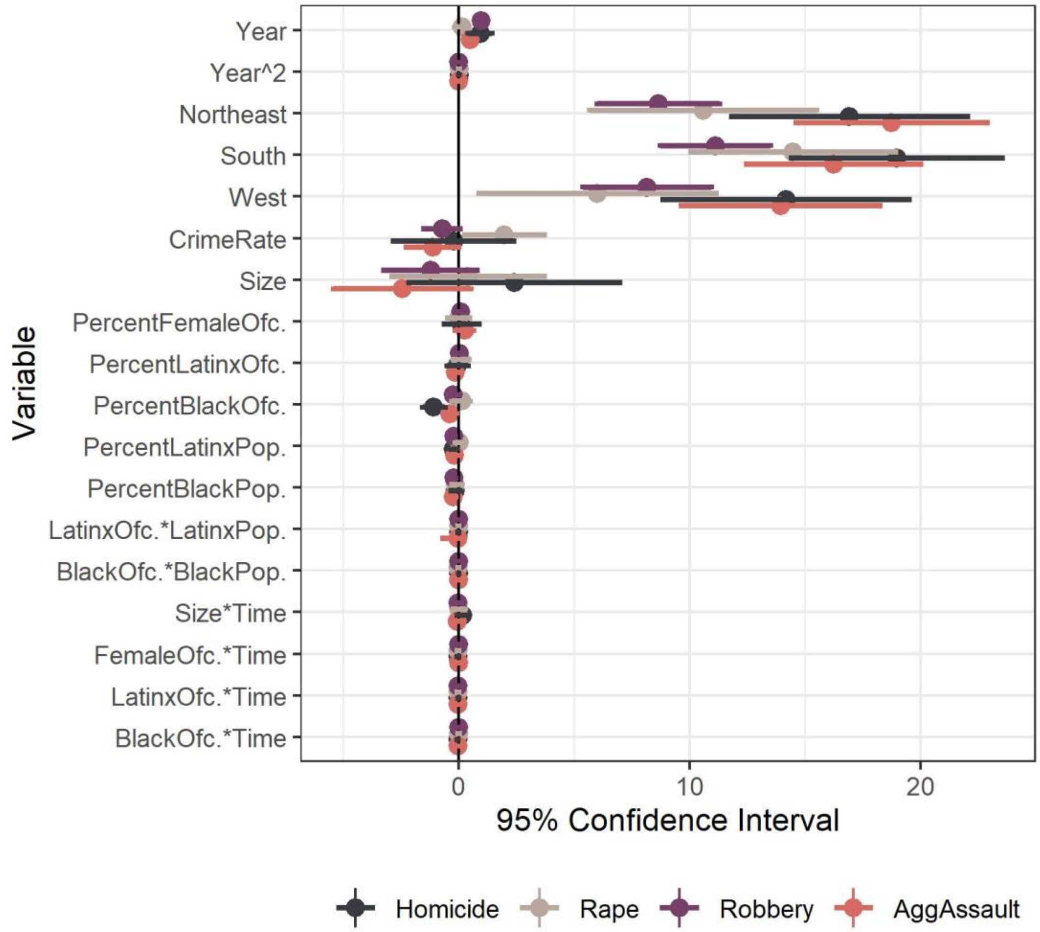
(continued)

	Main-effects model		Interaction model	
Percent female ofc. * Time			0.00 (0.01)	0.000
Latinx relative rep. * Time			0.06 (0.11)	0.000
Black relative rep. * Time			-0.05 (0.08)	0.000
Random effects	Est.		Est.	
Department	499.75†		497.82†	
Time	1.00†		0.99†	
Residual	147.18†		147.17†	
Log Likelihood	-36621		-36619	
R^2	0.092		0.094	

Notes:
† = profile confidence interval does not include 0
n observations = 9,044, n subjects = 541

Figure 27

Forest Plot: Violent Crime Clearance and Relative Representation Model Comparisons



The estimates for the intercept, time, time-squared, and region of the US were similar for the absolute and relative representation models for the burglary clearance rate. The final model estimated an average of 10.08% of burglaries cleared in 2013, with an increase of 4.07% in the Northeast, 4.70% in the South, and 3.12% in the West as compared to the Midwest. Neither crime rate, organizational size, percent female officers, nor Black relative representation exerted a statistically significant effect on the burglary clearance rate. Departments with greater proportional representation of Latinx officers to citizens, however, experienced a significant reduction in the percentage of burglaries cleared. The final model (see Table 22) explained 8.3% of the variance in the dependent variable.

Table 22

Mixed-Effects Regression Models: Burglary Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	10.16† (0.56)		10.08† (0.56)	
Time	0.27† (0.03)	0.004	0.27† (0.04)	0.004
Time^2	0.01† (0.00)	0.005	0.01† (0.00)	0.005
Region				
Northeast	4.04† (0.65)	0.036	4.07† (0.65)	0.036
South	4.65† (0.58)	0.061	4.70† (0.58)	0.062
West	3.05† (0.63)	0.022	3.12† (0.63)	0.023
Crime rate (log)	-0.53† (0.17)	0.001	-0.54 (0.18)	0.001
Size (log)	-0.83† (0.27)	0.007	-0.73 (0.46)	0.001
Percent female ofc.	0.06† (0.03)	0.001	0.02 (0.06)	0.000
Latinx relative rep.	-0.73† (0.31)	0.001	-1.91† (0.73)	0.001
Black relative rep.	0.26 (0.20)	0.000	-0.38 (0.49)	0.000
Size * Time			0.01 (0.02)	0.000

(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Percent female ofc. * Time			-0.00 (0.00)	0.000
Latinx relative rep. * Time			-0.07 (0.04)	0.000
Black relative rep. * Time			-0.04 (0.03)	0.000
Random effects	Est.		Est.	
Department	46.14†		46.14†	
Time	0.12†		0.12†	
Residual	14.74†		14.73†	
Log Likelihood	-26087		-26083	
R^2	0.082		0.083	

Notes:
† = profile confidence interval does not include 0
n observations = 8,993, n subjects = 541

For the larceny clearance rate, the absolute and relative representation models provided similar estimates for the intercept, time, time-squared, and region of the US. Organizational size did not significantly affect the clearance rate in either model, though the crime rate had a negative impact on both. The absolute representation model showed statistically significant negative effects for the percentage of Latinx and Black officers employed by departments and the percentage of Latinx and Black citizens in the population served. The relative representation model indicated a significant negative effect of Latinx and Black representation on the larceny clearance rate. Approximately 8% of the variance was explained by the variables in the model (see Table 23).

Table 23

Mixed-Effects Regression Models: Larceny Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	21.62† (0.88)		21.35† (0.87)	
Time	0.72† (0.05)	0.014	0.70† (0.05)	0.013
Time^2	0.02† (0.00)	0.012	0.02† (0.00)	0.012
Region				
Northeast	2.18† (0.98)	0.005	2.26† (0.98)	0.005
South	4.39† (0.88)	0.027	4.56† (0.88)	0.029
West	4.45† (0.95)	0.022	4.49† (0.95)	0.023
Crime rate (log)	-1.25† (0.22)	0.004	-1.24† (0.22)	0.004
Size (log)	-1.64† (0.40)	0.012	-0.68 (0.74)	0.000
Percent female ofc.	0.01 (0.04)	0.000	0.05 (0.09)	0.000
Latinx relative rep.	-1.57† (0.40)	0.002	-6.05† (0.99)	0.005
Black relative rep.	0.13 (0.26)	0.000	-1.51† (0.68)	0.001

(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Size * Time			0.05 (0.03)	0.001
Percent female ofc. * Time			0.00 (0.00)	0.000
Latinx relative rep. * Time			-0.24† (0.05)	0.003
Black relative rep. * Time			-0.09† (0.03)	0.001
Random effects	Est.		Est.	
Department	144.56†		141.59†	
Time	0.26†		0.26†	
Residual	23.89†		23.79†	
Log Likelihood	-28407		-28388	
R^2	-0.074		0.078	

Notes:
† = profile confidence interval does not include 0
n observations = 8,993, n subjects = 541

Finally, estimates for the intercept, time, time-squared, and region of the US were similar for the absolute and relative representation models explaining the motor-vehicle theft clearance rate. When using the measures of relative representation, increasing organizational size was associated with a decrease in the motor-vehicle theft clearance rate (in comparison to the absolute representation model, which showed no effect of organizational size on this dependent variable). Both the absolute and relative representation models estimated significant negative effects of the representation of Latinx officers on the motor-vehicle clearance rate. This model explained 10.5% of the variance in the dependent variable. See Table 24 for results and Figure 28 for model comparison.

Table 24

Mixed-Effects Regression Models: Motor-Vehicle Theft Clearance and Relative Representation

	Main-effects model		Interaction model	
Fixed effects	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	13.80† (0.91)		13.68† (0.91)	
Time	0.40† (0.05)	0.004	0.40† (0.05)	0.004
Time^2	0.01† (0.00)	0.005	0.01† (0.00)	0.005
Region				
Northeast	-1.45 (1.10)	0.002	-1.40 (1.10)	0.002
South	5.64† (0.98)	0.037	5.73† (0.98)	0.038
West	-0.70 (1.06)	0.000	-0.59 (1.06)	0.00
Crime rate (log)	-0.21 (0.26)	0.000	-0.25 (0.26)	0.000
Size (log)	-1.55† (0.44)	0.010	-1.47† (0.70)	0.002
Percent female ofc.	0.13† (0.04)	0.002	-0.04 (0.09)	0.000

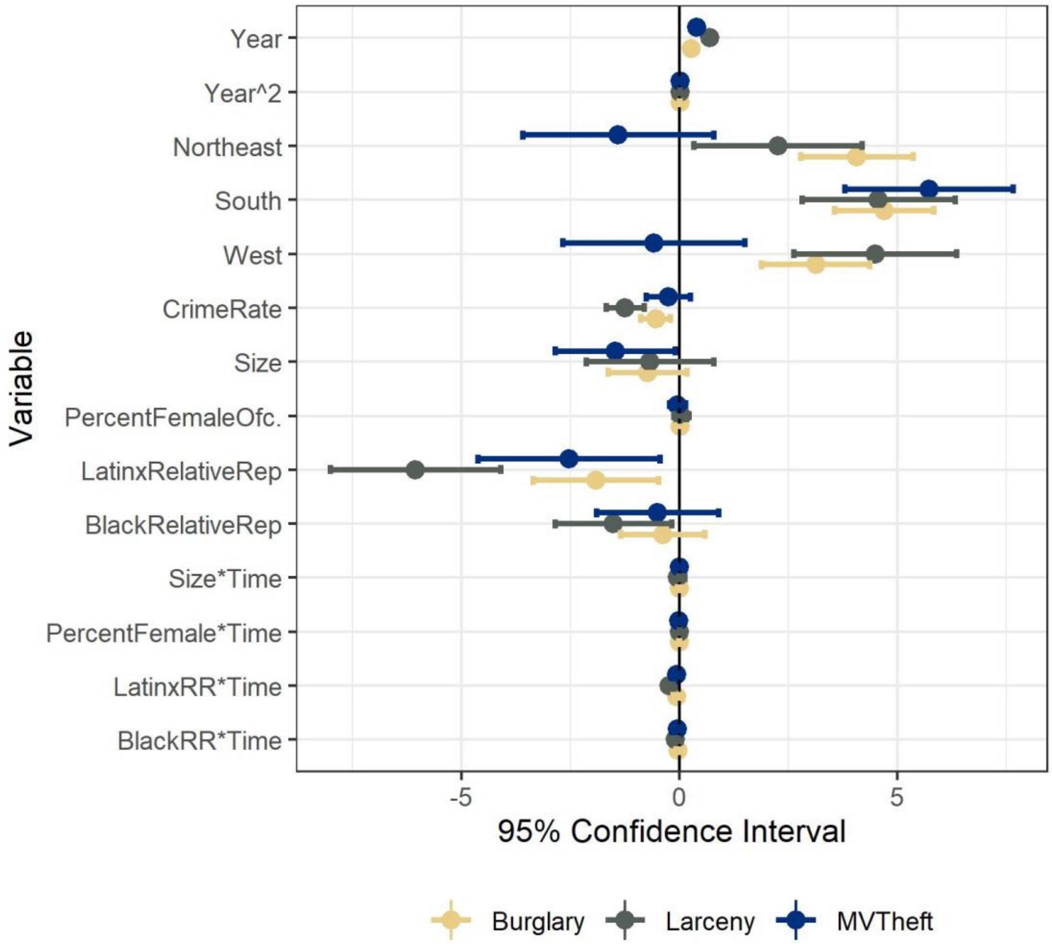
(continued)

	Main-effects model		Interaction model	
	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Latinx relative rep.	-1.38† (0.44)	0.001	-2.54† (1.06)	0.001
Black relative rep.	0.43 (0.29)	0.000	-0.50 (0.72)	0.000
Size * Time			0.00 (0.03)	0.000
Percent female ofc. * Time			-0.01† (0.00)	0.001
Latinx relative rep. * Time			-0.07 (0.05)	0.000
Black relative rep. * Time			-0.05 (0.04)	0.000
Random effects	Est.		Est.	
Department	114.35†		113.48†	
Time	0.25†		0.25†	
Residual	29.55†		29.52†	
Log Likelihood	-29178		-29172	
R^2	0.103		0.105	

Notes:
† = profile confidence interval does not include 0
n observations = 8,950, n subjects = 540

Figure 28

Forest Plot: Property Crime and Relative Representation Model Comparisons



CHAPTER V

Discussion

Increasing the representativeness of police departments has been touted as a method to improve riot response (The National Advisory Commission on Civil Disorders, 1968), mend police-community relations and reduce crime (The National Advisory Commission on Civil Disorders, 1968), improve the effectiveness and perceptions of legitimacy of the police (Asquith, 2016; Fantz & Tolan, 2020; Newton-Small, 2016; Wallace, 2017), and decrease the number of police use-of-force incidents (Lonsway et al., 2002; Porter & Prenzler, 2017; c.f. Schuck & Rabe-Hemp, 2014; Smith, 2003). These ideas are rooted in representative bureaucracy theory, which posits that increased representation of social groups in organizations leads to better policies, procedures, and outcomes for the represented groups (Kingsley, 1944; Krislov, 1974; Mosher, 1968). The current project advanced representative bureaucracy theory by supplementing it with structural contingency theory and tested its application to policing in the US.

Representative bureaucracy and structural contingency theories come from different philosophical traditions. The first conceptualization of representative bureaucracy was from the field of politics, where it later moved into the academic sphere of public administration and then the business world in the form of diversity management (Groenevel & Van de Walle, 2010). Structural contingency theory, on the other hand, is from and has remained a tradition of organizational design (i.e., how best to shape organizations to maximize performance) (Donaldson, 2008). Despite their differing backgrounds, the two theories are compatible. Structural contingency theory posits that contingencies in the organizational environment affect organizational structure, which in turn affects organizational performance (Donaldson, 2001). I proposed that gender, ethnic, and racial inequalities in the environments of organizations affect personal differentiation (also known as representation, which is a part of organizational structure), which in turn affects organizational outcomes.

I tested these propositions using the population of large municipal police departments in the US from 1987 to 2017. Specifically, I tested first whether gendered and racialized inequalities in the jurisdictions police serve were related to the percentage of women, Latinx, and Black officers employed by police departments and second whether this representation affected crime reporting or clearance rates. Below I discuss findings relating to personal differentiation within US police departments followed by a discussion of findings regarding police performance. I then present the limitations and directions for future research.

Police Structure

My first hypothesis, that the percentage of Latinx and Black citizens in police departments' jurisdictions would positively affect the representation of women officers in those police departments, was based on previous literature that found the same. Specifically, Morabito and Shelley (2015), Schuck (2014), Zhao et al. (2001), and Zhao et al. (2006) found that as the percentage of people of color in communities increased, so did the percentage of females represented in police departments (c.f., Kim & Mengistu, 1994). I found partial support for this hypothesis. Each percentage-point increase in the share of the population that was Black increased the representation of women officers by an average of 0.07 percentage points. Latinx population share had no effect on female representation. Hypotheses two and three, that increases in the share of Latinx and Black citizens in communities would increase the percentage of Latinx and Black officers respectively employed by police departments was based in structural contingency theory. Specifically, Aldrich (1979) and Dess and Beard (1984) proposed that munificence (or capacity) allows organizations to grow. Both hypotheses were supported, with each percentage point increase in the share of the population that was Latinx and Black corresponding to a 0.45% increase in the share of Latinx and Black officers in large municipal police departments. Furthermore, this effect was amplified over time for Latinx officers.

The findings regarding the impact of munificence on ethnic and racial minority representation in US police departments are straightforward. Aldrich (2008) explained that organizations are situated within environments that affect their growth, change, and survivability through methods similar to ecology, such as diversity, distribution, and competition and cooperation. Under this model, all of the organizations in a given environment compete for resources, both monetary and people. The carrying capacity (i.e., munificence) of a population is an important component of the competition for resources. Once a budget has been set for a city, for example, a certain percentage of that budget is dedicated for public safety. It takes extraordinary measures on behalf of public safety organizations (such as applying for federal grants) to gain additional monetary resources because there are other organizational types competing for the budget the city has set. The competition for people-resources works in much the same way. There are many types of organizations in cities that are competing for employees, and it is expected that without extraordinary measures undertaken by police organizations (such as targeted recruitment programs) only a certain percentage of the population will select into the policing profession. Without extraordinary circumstances, it is expected that a certain percentage of the people resources available in a community will be effectively "budgeted" for different sectors. Evidence for this theoretical proposition was observed in these data. The average representation of Latinx officers proportional to Latinx citizens in each community was 0.44 in 1987, 0.43 in 1990, and 0.45 in 1993, 1997, 2000, 2003, 2007, and 2013. The average Black officer-to-citizen ratio varied between 0.58 and 0.71 in that timeframe. The fact that the proportional representation of officers of color was fairly stable over time lends credence to the idea that the community has a certain carrying capacity for the number of people it can contribute to given professions and that this is a contingency that affects the structure of police organizations.

Does the same mechanism explain representation of women on police forces? Perhaps to a certain extent. It is logical to expect that there is also a certain percentage of women who are interested and available to apply for positions in police organizations. The percentage of women (and men) citizens is stable across US cities, and there is likely a corresponding stability in the number of women and men interested and available for policing across communities (though differing between groups). Why are these differences between groups (i.e., women and men, people of color and White, non-Latinx citizens) observed? To find the answer to this question we must understand the motivations that drive individuals to apply for policing jobs (Clinkenbeard, Solomon, & Rief, 2020). I will return to this (and other issues regarding the multi-level nature of organizations) in the Limitations section.

Hypotheses four through six concerned the impact of environmental complexity on personal differentiation. Aldrich (1979) and Dess and Beard (1984) proposed that the extent of concentration or dispersion of resources within organizational environments may affect the structure of organizations. More recently, Heimer (2019) argued that inequality should be a focus of criminological literature. Combining these ideas (and drawing on previous research related to economic status within communities such as Whaley (2001) and Jurek and King (2019)), I hypothesized that as the status of women compared to men, Latinx individuals compared to White, non-Latinx individuals; and Black individuals compared to White, non-Latinx individuals increased, there would be a corresponding increase in the representation of women, Latinx, and Black officers respectively. The measures of status included disparities in income, labor force participation, employment, and education.

These hypotheses, as tested, were mostly not supported. The only statistically significant finding in the hypothesized direction was that as the disparity in the labor force participation rate between women and men decreased, so too did the percentage of women officers employed by police departments. This may indicate that as women and men become more equal in labor force participation, women are more able to enter into traditionally male-oriented jobs such as policing. The other statistically significant result observed in this set of hypotheses was opposite that of what was expected: that as the disparity in income between Black individuals and White, non-Latinx individuals in the community increased, so too did the share of Black officers in the police department. This may be attributable to occupational segregation and prestige. Historically, policing has been considered a low-to-middling prestige occupation (Swanton & Wilson, 1974) and it is possible that in communities with greater occupational segregation (as indicated by White, non-Latinx individuals earning more per capita than Black individuals) Black individuals are blocked from higher-prestige occupations. Other differences in income, labor force participation, employment, and education between women and men, Latinx and White, non-Latinx; and Black and White, non-Latinx populations did not affect representation of these groups on police forces.

Measuring the environments of police organizations is notoriously difficult, as there are a virtually infinite number of factors that might matter (Langworthy, 1986). Structural contingency theory points toward concepts such as the diversity between elements in the environment, concentration of resources, and environmental instability (Aldrich, 1979; Dess & Beard, 1984), but these are all broad concepts that again can be operationalized in a number of ways. I originally planned to use an index of diversity that would capture the combined impact of multiple indicators of inequality, including income, labor force participation, employment, and education (Jurek & King, 2019). Unfortunately, factor analytic techniques did not support this methodology, which shows that these four variables are not reflective of one or more latent variables. Inequality in income, labor force participation, employment, and education are not summative and there is little evidence for the impact of any of these factors individually on the employment of gender, ethnic, and racial minority officers in US police departments. We know, however, that inequality is intersectional, not additive (Crenshaw, 1991; Kabeer, 2016), so it is still possible that there is a combined effect of these or other indicators of inequality that could not be captured in the current project.

Despite these challenges, the results of this study are supportive of the proposition that there is a structural contingency model of representative bureaucracy. Findings show that though personal differentiation has been changing significantly over time, these changes are not driven by time (i.e., very little of the variation in representation was explained by time). Furthermore, between 33% and 74% of the variation in the representation of women, Latinx, and Black officers in police departments was explained by the environmental measures included in the study. As predicted by theory and in line with previous research, munificence was a significant proportion of this. Future work on the representation of social groups within organizations should take a structural contingency approach and include measures of the organizational environment.

Police Performance

Police performance was conceptualized in two different ways for the current study. The first was the index crime reporting rate, operationalized as the number of crimes reported per 100,000 population per year. The second was the index crime clearance rate, operationalized as the percentage of crimes cleared each year as a function of the total number of crimes reported. I drew on representative bureaucracy theory for hypotheses seven through 12. These hypotheses were tested with measures of both absolute and relative representation.

Hypotheses seven through nine concerned the effect of gender, ethnic, and racial minority officer representation on index crime reporting rates. Specifically, I hypothesized that as the representation of women, Latinx, and Black officers increased there would be a corresponding increase in the number of crimes reported to the police due to increased demand inducement (Lim, 2006). The Uniform Crime Reports are considered to be the premier source of information about actual crime trends in the US. I planned to use the instrumental variable (IV) approach to isolate the effect of crime reporting from crimes committed. The IV approach uses a variable correlated with the outcome but not the predictor variables to control for the variation in the dependent variable attributable to the independent variable and thus allow the estimate of the impact of the predictor variables (Angrist & Pischke, 2015). I used an index of social disorganization, previously shown to be correlated with crime commission but unrelated to crime reporting (Baumer, 2002; Blau & Blau, 1982). Social disorganization, however, did not control for enough of the variance in crime commission in this study. Previous research has shown that crime rates have been decreasing over time but that crime reporting rates have been increasing for nonlethal violent crime and property crime (Baumer & Lauritsen, 2010). Social disorganization only explained between zero and 30% of the variance in the crime rate in this study and was not enough to change the negative coefficient for time (indicative of the declining crime rate) to a positive coefficient (which would be indicative that the variable had adequately controlled for trends in actual crime and that the reporting rate has been increasing). I was not able, therefore, to test hypotheses seven through nine.

The final set of hypotheses concerned the impact of representation on index offense clearance rates. Table 24 shows the direction of statistically significant results observed in these models to summarize this information.

Table 24

Summary of Relationships between Officer Representation and Crime Clearance

	Female	Latinx		Black	
	Absolute	Absolute	Relative	Absolute	Relative
Homicide			-	-	+
Rape					+
Robbery				-	
Aggravated assault				-	
Burglary		-	-		
Larceny		-	-	-	-
Motor-vehicle theft		-	-		

Note: The direction of statistically significant results between the independent variable (representation) and the dependent variable (crime clearance rate) are marked.

Hypothesis 10 was that as the percentage of women police officers employed by departments increases, there would be a corresponding increase in the clearance rates of index offenses. This hypothesis was not supported in any of the final models. In the models estimating the effects of absolute representation of officers of color, the percentage of female officers had a positive impact on the homicide, rape, robbery, aggravated assault, burglary, and motor-vehicle theft rates in the main effects models. A similar effect was observed for the main-effects models using the relative measure of representation for burglary and motor-vehicle theft, but in all cases this effect was washed out in the interaction model. I suspect this is due not to the addition of the interaction effects (which were mostly insignificant and explained little of the variation as indicated by low semi-partial R^2 values), but to the addition of measures of population diversity (i.e., percent Latinx and Black citizens in the absolute representation models and the same as part of the relative representation models).

Hypothesis 11 stated that as the percentage of Latinx police officers employed by departments increases, there will be a corresponding increase in clearance rates of index offenses. Its corollary, hypothesis 11a, predicted that this effect would be especially pronounced in cities with greater shares of Latinx citizens. These hypotheses were not supported and in fact, the opposite effect was observed for property crimes using the measure of absolute representation and for homicide and each of the property crimes using the measure of relative representation.

Hypotheses 12 and 12a predicted the same effects of the previous two hypotheses for the effect of Black officer representation. Partial support for these hypotheses were observed. While the percentage of Black officers employed by police departments had a negative impact on clearance rates of homicide, robbery, aggravated assault, and larceny, the relative representation of Black officers to citizens had a positive effect on the homicide and rape clearance rates (though still a negative impact on the larceny clearance rate).

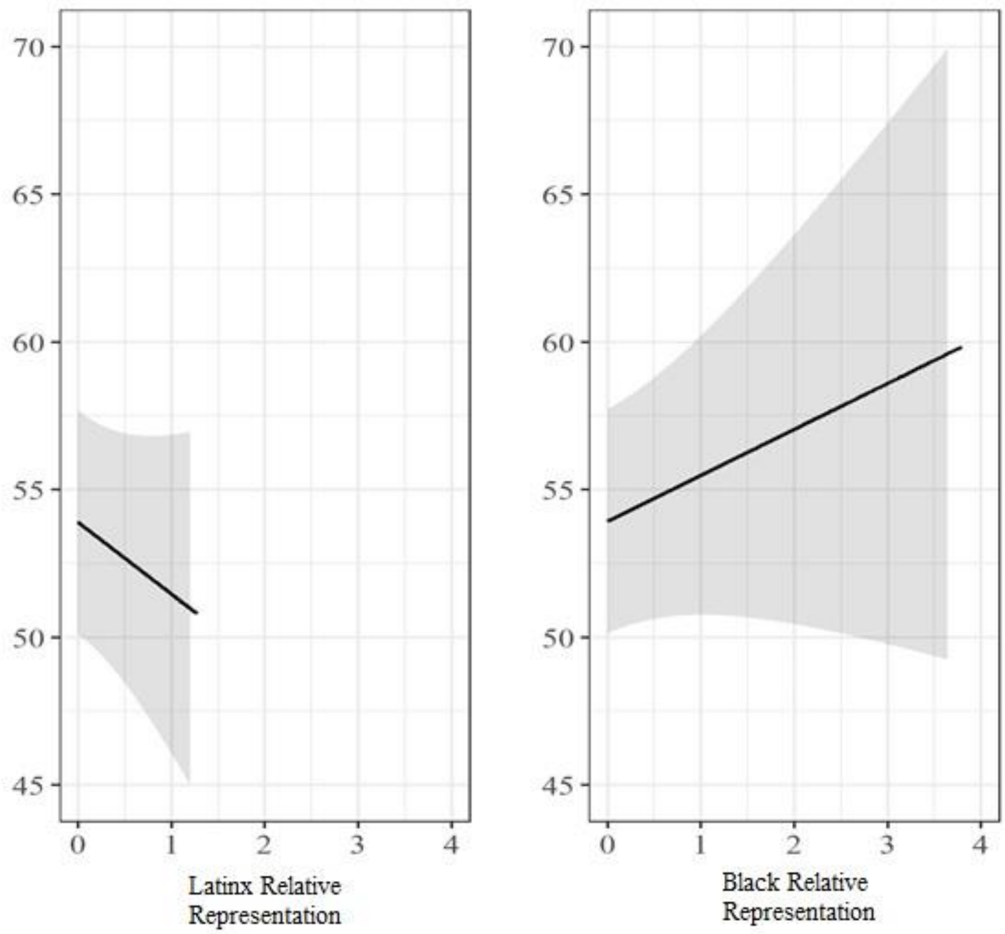
Overall, the observed effects for representation were small. The statistically significant effects of the impact of officers of color on the index crime clearance rates (measured both ways) explained only between 0% and 1.4% of the variation in the models. Furthermore, the final models explained between 3.2% and 14.9% of the total variation in the dependent variables. In other words, personal differentiation had little impact on index offense clearance rates and most of the variation in these rates was left unexplained. This finding was not surprising. The crime clearance rate is affected by a number of factors both internal and external to organizations that were not measured in the current study. Other important elements of organizational structure that may impact crime clearance rates include functional differentiation in the form of specialized investigatory units, centralization of decision-making, scope of tasks investigators are responsible for, and the extent of formalization of rules and procedures. Factors external to the organization that likely affect clearance rates are the number of non-crime calls for service the department receives, the department's relationship with the crime lab, the crime lab's workload, and the extent of collective efficacy in the city.

With everything else that could have an effect on crime clearance rates, it is interesting that the global measure used (i.e., percentage of minority officers in the entire department) did have a statistically significant effect for Latinx and Black officers (see Limitations for a more information). What is clear from the results is that simply increasing the percentage of officers of color in all police departments does not improve the clearance rate. It is important to consider the representation of officers proportional to the population demographics of the community. Why, though, does proportional representation of Latinx officers lead to decreasing clearance rates and proportional representation of Black officers lead to increasing clearance rates? Figure 29 provides one possible explanation.

The average relative representation of Latinx officers has ranged between 0.43 and 0.45 from 1987 to 2013, with a minimum value of zero and a maximum of 1.73. The relative representation of Black officers has ranged from 0.58 to 0.71, with a minimum value of zero and a maximum value of 4.41 (refer to Figure 12). Keeping in mind that a value of zero is indicative of no representation, a value of one is indicative of perfect representation of officers to citizens, and values over one are indicative of overrepresentation of officers to citizens, police departments, on average, have fewer racial and ethnic minority officers than their respective shares in the community. Black officers are overrepresented to a greater extent than Latinx citizens, however, and the models were not able to provide a predicted probability so far out of the range of the observed data for Latinx relative representation. It is entirely possible that the overrepresentation of Black officers observed in many cities is driving the result, and that as Latinx officers become closer to proportional representation and exceed it in some cities that the effect might change from a negative to a positive direction.

Figure 29

Predicted Probability of the Homicide Clearance Rate by the Relative Representation of Latinx and Black Officers



Note: Vertical axis is the percentage of crimes cleared, horizontal axis is the measure of relative representation (0 = no representation, 1 = perfect representation, x>1 = overrepresentation of Latinx officers to citizens (left) and Black officers to citizens (right)).

This may be due to a “tipping point” effect. Theorists working on representative bureaucracy have previously posited that a certain critical mass of traditionally underrepresented groups must be met before the passive representation of a social group is translated to substantive effects for the organization (Henderson, 1979; Kanter, 1977a, 1977b; Keiser et al., 2002; Meier, 1993; Nicholson-Crotty et al., 2011; Nicholson-Crotty et al., 2017; Thompson, 1976). Policing researchers have suggested that police organizational culture in particular exerts a powerful socialization effect such that police officers feel the need to be "Blue" rather than Black, Brown, or female (Shjarback et al., 2017; Wilkins & Williams, 2008, 2009).

A related idea that may impact the substantive effects of minority representation on organizations is the racialized and gendered nature of organizations. According to Ray (2019), bureaucracies have traditionally been viewed as race-neutral structures that racialized bodies participate in. Ray (2019) argues that organizations are not race-neutral, which has a number of implications for organizational functioning. These implications include the ability of the racialized organization to affect the agency of the racialized bodies acting within them; the legitimation of the "unequal distribution of resources," the use of Whiteness as a powerful form of currency, and differential enforcement of organizational rules along racial lines (Ray, 2019, p. 26). Drawing on Stinchcombe's (1965) work on founding effects and the trajectory of organizations, Ray (2019, p. 38) argues that racial hierarchies become institutionalized in organizations and are thus reproduced in "facially-neutral bureaucratic processes." It is not a stretch to imagine that if organizations are racialized that they can also be gendered in similar ways. Batton and Wright (2019) find that patriarchal structures do in fact permeate the criminal justice system, including policing. Indeed, patriarchy and white supremacy interact and often enhance one another (Bjork-James, 2020; Combahee River Collective, 1977; Crenshaw, 1991; Steinberg & Kincheloe, 2001).

Policing in the US is traditionally a White and male institution (Batton & Wright, 2019; Franklin, 2005; Morash & Haarr, 2012). As such, organizational hierarchies and processes likely diminish the agency of people that do not fit into these social categories (Ray, 2019). It is very possible that a critical mass of traditionally underrepresented groups must be met before those groups have the agency required to make substantive changes in the organization.

The underrepresentation of women, Latinx, and Black officers as a percentage of the entire organization is also likely to be magnified at higher levels in the organizational hierarchy. Ray (2019) predicts that in racialized organizations, Whiteness is a credential that conveys greater legitimacy on White individuals and allows them to pass more easily into positions of power. A natural extension of that logic is that maleness is also a credential conferring the same benefits. What this means is that groups that are underrepresented in the organization are less likely to be promoted than individuals from majority groups. Indeed, research has found that people of color and women hold fewer supervisory positions in police organizations than their White male counterparts (BLS, 2020; Gustafson, 2013; Shjarback & Todak, 2019). This lower representation of women and ethnic and racial minority officers in investigatory and decision-making positions may hinder the ability of these groups to have substantive effects on crime clearance rates.

Overall, the findings of this study are in line with previous research on the effects of representation of traditionally underrepresented groups on police performance in that the findings are mixed and not always in alignment with the most basic predictions of representative bureaucracy theory. A more nuanced read of the theory is required for understanding the mixed results observed. Representative bureaucracy theory predicts, for example, the existence of a tipping point below which representation is not expected to have substantive effects, so the fact that much of the policing literature (including this study) finds no effects of certain types of representation on various outcomes is likely due to continued low representation of these groups in police organizations.

Another of the challenges facing the representative bureaucracy literature has been the inconsistency with the measurement of representation. The results of this study demonstrate that Mosher's (1968) conceptualization of proportional representation has more substantive effects on organizations than does the measurement of representation as a percentage of organizational employment. This finding also aligns with the structural contingency model of representative bureaucracy in that it considers the effects of the environment organizations are situated within as well as the organizations themselves.

In addition to examining the linkages between representation and outcomes, future research in this area should also explore the mechanisms through which representation is expected to affect outcomes. Are the values of minority officers regarding justice, law, and order reflective of the values of minority citizens? How are these values affected by police academy and field training? Do citizens view more diverse police agencies as more trustworthy or legitimate? Are crime victims more comfortable reporting and/or more cooperative with police investigators that share their demographic characteristics? The answers to these and other related questions have important implications for theory and practice.

Limitations & Directions for Future Research

The current study had a number of limitations. Here I discuss some of the constraints and directions for future research when studying personal differentiation and police performance as outcomes as well as the conceptual basis of the study.

Under the structural contingency model of representative bureaucracy, I predicted that three elements of the organizational environment would impact personal differentiation: munificence, complexity, and dynamism. Munificence was captured exactly as intended with the percentage of Latinx and Black citizens in the communities that police departments served. The measure(s) of environmental complexity were less than ideal, however. Dess and Beard (1984) identified environmental complexity as including both the range of diversity between elements of the environment (such as other organizations, individuals, and social forces) and the degree of concentration of resources. I identified four measures previously used as indicators of inequality (i.e., income, labor force participation, employment, education) (Whaley, 2001) that had loaded together using factor analytic techniques (Jurek & King, 2019), but these measures did not come together as expected in the current research. In addition, I was unable to test the impact of dynamism because the US Census Bureau changed the way it captured residential instability in the middle of the study period. The structural contingency model of representative bureaucracy should be further developed and refine the types of inequality that are likely to matter in labor markets and test these conceptualizations. Future research should also either validate a mathematical correction to account for the different operationalizations of residential instability or test the impact of dynamism using data pre- and post-change.

There were several shortcomings with conceptualization and measurement of the police performance section of this project. First and foremost, clearance rates of index offenses are not the best indicators of police performance. Among other things, crime control is only one of many police mandates, index offenses are a small portion of the crimes police respond to, a focus on crime reduction does not take into account the strategies used to achieve lower numbers, and crime levels can only fall so far (Sparrow, 2015). The rates at which citizens report crimes to the police is a better indicator of police performance (Sparrow, 2015), but unfortunately I was not able to measure the crime reporting rate using the Uniform Crime Reports. Future research should measure the impact of a representative police force on a number of metrics that are closely tied to the police mandate, including aiding victims of crime, protecting the rights of citizens, serving the community, and creating a sense of safety in the communities they serve (Goldstein, 1977) as well as other variables that may impact outcomes such as citizen trust in the police and perceptions of procedural justice, communication and working relationships with external stakeholders, and police organizational culture. Additionally, in order to facilitate the study of the role of the police in citizen decisions to report crimes, the National Crime Victimization Survey should be linked directly to cities (rather than metropolitan statistical areas or counties).

Though crime clearance (especially of index offenses) is not the best conceptualization of police performance, it does fall under the police mandate and deserves further study. The complete transition from the Uniform Crime Reporting System to the National Incident-Based Reporting System (NIBRS) will allow for much better tests of representative bureaucracy theory for a number of reasons. First, NIBRS collects information on crimes other than index offenses. This is important because as offense severity increases, police discretion in how to proceed with the case decreases. Additionally, different crime types may hold more or less significance for different social groups. Discretion and salience are important theoretical concepts in the representative bureaucracy tradition that I was unable to examine in the current study. NIBRS also collects information on incidents. This means that research using these data can control for relevant incident-level characteristics (such as whether a suspect was identified by the victim) and examine dyads to answer questions about active representation (e.g., are women officers more likely to solve crimes committed against women than men officers?).

Finally, my measures of representation were not ideal for the study of the clearance rates of index offenses. While there is good reason to suspect that an increase in department-wide representation of officers with different social characteristics may positively impact crime reporting (due to the visibility of line-level officers and demand inducement), there are likely better measures for crime clearance. Most of the work done in the process of clearing crimes is done by investigatory units, not by line-level officers or supervisors. Future research should examine the impact of the demographic makeup of detectives in police departments to more precisely examine whether the representativeness of the police doing the investigative work have an impact on investigative outcomes. The representativeness of the command staff may also be a fruitful area for future representative bureaucracy work since they are the individuals responsible for making and enforcing policies that impact lower-ranking officers and potentially the people they serve.

A limitation for both the police structure and police performance sections of this research is the narrow range of types of representation used. I focused on the representation of women, Latinx, and Black officers because of the availability of data and numerical representation of these groups, but representative bureaucracy theory encompasses a range of different social attributes, including sexual orientation, gender identity, social class, religion, and nationality. At a minimum, the Federal Bureau of Investigation should add ethnicity to its counts of police employees and the Bureau of Justice Statistics should bring back the use of the data collection grid that separated police employee demographic data by gender, ethnicity, and race. These large-scale data collection projects are unlikely to adopt questions about other relevant demographics, but researchers collecting data to test representative bureaucracy theory should consider going beyond the study of gender, ethnicity, and race.

Finally, there are two conceptual issues with the current study that I would like to acknowledge. The first I have alluded to before. Organizations (and thus organizational processes) are inherently multi-level (Kozlowski & Klein, 2000). Individuals may work in small, formal or informal working groups that are subsumed by the organization which exists in a population of organizations that are all affected by meso- and macro-level processes. I have chosen to focus on organizational-level processes because they have a large potential for change. It is important to remember, however, that the study of any issue affecting an organization at a single level will not provide the complete picture of the process. For example, to answer the question of how to increase the representation of minorities in police departments, we need to think about individual, organizational, and societal factors. What are the motivations of individuals who want to enter policing?

What drives people away from policing? What can organizations do to increase recruitment based on these factors? Do organizations have policies in place that serve as barriers to minority recruitment and retention and how can these be changed? Can these organizational barriers be addressed at a societal level through legislation that reduces barriers to employment? The answers to these questions all have important implications for minority employment and studying any one level in isolation will not provide a complete solution.

Lastly, in keeping with the organizational design mandate of structural contingency theory, I have centered the potential benefits of increasing diversity for police organizations. Berrey (2015) refers to this as the "business case for diversity," or the idea that diversity is a goal because it is good for the organization. There are, however, other important reasons that organizations should be representative of the people they serve. Organizations that are unrepresentative of their constituents are likely to be distrusted by those that do not see themselves reflected in the organization (Kingsley, 1944). This may be particularly salient for police organizations because they have state-sanctioned authority to use force (Bittner, 1970) and thus wield power that most citizens do not have. It is important that this power is not concentrated in a single group (gender, ethnicity, race, social class) of people because of the potential for abuse of that power and the role of bureaucracy under constitutionalism to serve as an intermediary between the government and the people (Long, 1952). As a final point, the representativeness of bureaucracies reflects the values and power realities of societies (Krislov, 1967) and the continued underrepresentation of women and people of color in the police and other bureaucracies is indicative of continued inequality in the US.

Conclusion

If the number of riots in the US in the late 1960s were unprecedented (750 recorded from 1964 to 1971 (Postrel, 2004)), the protests around the country during the summer this project was completed were truly extraordinary. After George Floyd was killed by a police officer on May 25, 2020, over 10,600 protests were recorded in the US between that date and August 22, 2020 (The Armed Conflict Location and Event Data Project (ACLED), 2020). Protests were logged in close to 550 locations with half a million people participating at the height of the protests on June 6, 2020 (Buchanan, Bui, & Patel, 2020). The vast majority (close to 95%) of these protests were peaceful and most were linked to the Black Lives Matter movement (ACLED, 2020). Some of the calls for police reform were familiar, such as limiting uses of force and promoting de-escalation tactics, and calls to defund and abolish the police entered the mainstream (Ciaramella, 2020; Cineas, 2020).

While defunding and abolition involve deep philosophical questions about the nature of justice, many of the questions surrounding the effectiveness of various types of reformation can be answered empirically. That is not to say, however, that theory and philosophy should be left out of considerations of reformation. On the contrary, theory and philosophy point us towards the questions we should be asking about reformation as well as providing likely answers. For instance, representative bureaucracy theory predicts there should be positive effects of minority representation on organizational outcomes. The current study demonstrated that Black relative representation in large police organizations increased the clearance rates of homicide and rape, though it decreased larceny clearance rates. Likewise, the Latinx relative representation rate had a negative impact on clearance rates of several index offenses. This should not be taken to mean that organizations with greater ethnic and racial minority representation are better or worse than organizations with less representation; it shows only that clearance rates were impacted in a particular way. There is good reason (theoretically and empirically) to believe that with greater proportional representation of Latinx officers would come greater clearance rates. There is also good reason to believe that increasing representation would positively impact citizens' trust in and perceptions of legitimacy of the police, and that an unrepresentative police force is both reflective of existing inequalities in society and antithetical to democratic ideals (Kingsley, 1944; Krislov, 1967, 1974; Long, 1952; Mosher, 1968).Criminal justice system stakeholders wishing to increase the representativeness of police organizations must actively work to do so. Representation does not increase of its own accord over time, and the environment exerts some constraints on the demographic makeup of organizations (in particular, size of the minority population). These constraints are not insurmountable, however. Research has consistently demonstrated that affirmative action programs and consent decrees lead to greater representation of gender, ethnic, and racial minorities in police departments (Lewis, 1989; Martin, 1991; Miller & Segal, 2012; Sass & Troyer, 1999; Warner et al., 1989; Zhao et al., 2001; Zhao et al., 2006). Police leaders can adopt affirmative action programs, create targeted recruitment strategies, and examine barriers within their organizations to the hiring, retention, and promotion of traditionally underrepresented minorities to correct them. Interest groups such as the International Association of Chiefs of Police can promote the benefits of more representative organizations and develop model policies for hiring, retention, and promotion. Legislative bodies can impose consent decrees on organizations that have consistently low levels of diversity. Criminal justice researchers can support these efforts by partnering with agencies to evaluate changes and making the results of their research accessible and available to stakeholders. The representativeness of the police and other bureaucratic institutions in the US is a multilevel problem that will require cooperation between multiple stakeholders to solve. It is work well worth doing to reduce inequality and in so doing uphold democratic ideals.

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APPENDIX A

Table A1.1

Initial Factor Analysis: Direct Oblimin

Variable	Factor 1	Factor 2	Factor 3	Factor 4
Median income disparity (gender)			-0.650	-0.175
LFP disparity (gender)	0.103	-0.226	-0.427	0.272
Employment disparity (gender)	0.174		-0.121	0.209
Education disparity (gender)	-0.180	-0.133		0.378
Family income disparity (ethnicity)	0.923			
Household income disparity (ethnicity)	0.862			
Per capita income disparity (ethnicity)	0.835			
LFP disparity (ethnicity)	0.200			0.360
Employment disparity (ethnicity)				0.469
Education disparity (ethnicity)	0.712			
Family income disparity (race)	0.112	0.837		
Household income disparity (race)		0.914	-0.115	
Per capita income disparity (race)	0.270	0.675		
LFP disparity (race)	-0.180	0.545		0.158
Employment disparity (race)	-0.200	0.444	0.302	
Education disparity (race)	0.137	0.652	0.153	
Residential instability				0.984
Ethnic heterogeneity	0.250		0.429	
Percent female-headed households		-0.127	0.821	-0.184
Poverty rate		0.106	0.862	
Unemployment rate		-0.123	0.696	0.271

Note: Data for 1980, 1990, 2000, 2010, and 2017 were pooled, and a four-factor solution was requested. The greatest factor loading in each row was highlighted in grey.

Table A1.2

Second Factor Analysis: Direct Oblimin with One Low-Performing Item Removed

Variable	Factor 1	Factor 2	Factor 3	Factor 4
Median income disparity (gender)			-0.649	-0.175
LFP disparity (gender)		-0.221	-0.425	0.271
~~Employment disparity (gender)~~	---	---	---	---
Education disparity (gender)	-0.179	-0.133		0.379
Family income disparity (ethnicity)	0.928			
Household income disparity (ethnicity)	0.867			
Per capita income disparity (ethnicity)	0.830			
LFP disparity (ethnicity)	0.207			0.362
Employment disparity (ethnicity)				0.470
Education disparity (ethnicity)	0.707			
Family income disparity (race)	0.111	0.838		
Household income disparity (race)		0.915	-0.114	
Per capita income disparity (race)	0.263	0.680		
LFP disparity (race)	-0.178	0.543		0.159
Employment disparity (race)	-0.200	0.444	0.302	
Education disparity (race)	0.133	0.655	0.152	
Residential instability				0.984
Ethnic heterogeneity	0.253		0.430	
Percent female-headed households		-0.127	0.822	-0.185
Poverty rate		0.106	0.862	
Unemployment rate		-0.123	0.696	0.271

Note: Data for 1980, 1990, 2000, 2010, and 2017 were pooled, and a four-factor solution was requested. The greatest factor loading in each row was highlighted in grey.

Table A1.3

Correlation Matrix: Relationships between Factors

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1.000	0.350	-0.022	-0.219
Factor 2	0.348	1.000	0.140	-0.677
Factor 3	-0.022	0.140	1.000	0.019
Factor 4	-0.219	-0.680	0.019	1.000

Table A1.4

Second Factor Analysis: Varimax with One Low-Performing Item Removed

Variable	Factor 1	Factor 2	Factor 3	Factor 4
Median income disparity (gender)	0.186	-0.651		-0.151
LFP disparity (gender)		-0.433	-0.194	0.285
~~Employment disparity (gender)~~	---	---	---	---
Education disparity (gender)	-0.343		-0.154	0.391
Family income disparity (ethnicity)	0.923		0.222	
Household income disparity (ethnicity)	0.819	-0.118	0.141	
Per capita income disparity (ethnicity)	0.870	-0.115	0.218	-0.147
LFP disparity (ethnicity)	0.109			0.332
Employment disparity (ethnicity)				0.442
Education disparity (ethnicity)	0.728		0.203	
Family income disparity (race)	0.552		0.734	
Household income disparity (race)	0.479	-0.108	0.769	-0.114
Per capita income disparity (race)	0.614		0.631	
LFP disparity (race)		0.107	0.433	0.122
Employment disparity (race)		0.318	0.357	
Education disparity (race)	0.444	0.143	0.593	
Residential instability	-0.309			0.958
Ethnic heterogeneity	0.241	0.408	0.120	
Percent female-headed households		0.818		-0.199
Poverty rate		0.858	0.141	
Unemployment rate	-0.199	0.691		0.244

Note: Data for 1980, 1990, 2000, 2010, and 2017 were pooled, and a four-factor solution was requested. The greatest factor loading in each row was highlighted in grey.

Table A1.5

Proposed Scale Factor Loadings and Reliability

Variable	1980	1990	2000	2010	2017
Female relative status α^1 =	---	0.67	0.69	0.74	0.54
Median income disparity	---	0.997	0.579	0.796	0.997
LFP disparity	---	0.427	0.980	0.606	0.402
Employment disparity	---	0.121	0.268	0.342	0.101
Education disparity	---	0.601	0.403	0.709	-0.443
Latinx relative status α =	---	0.59	0.59	0.43	0.57
Family income disparity	---	0.983	0.871	0.997	0.997
LFP disparity	---	0.253	0.371	0.208	0.247
Employment disparity	---	0.270	0.168	---	0.149
Education disparity	---	0.596	0.712	0.687	0.717
Black relative status α =	---	0.69	0.70	0.65	0.72T
Household income disparity	---	0.890	0.718	0.740	0.769
LFP disparity	---	0.471	0.618	0.527	0.625
Employment disparity	---	0.366	0.422	0.339	0.424
Education disparity	---	0.662	0.708	0.768	0.832
Social disorganization α^2 =	0.75	0.86	0.84	0.75	0.77
Ethnic heterogeneity	0.700	0.564	0.405	0.280	0.282
Percent female-headed households	0.917	0.921	0.830	0.931	0.895
Poverty rate	0.864	0.754	0.892	0.721	0.769
Unemployment rate	0.260	0.878	0.911	0.757	0.842
Residential instability	-0.262	-0.204	---	---	---

Note: Standardized Cronbach's alphas (α) are presented.
[1]Standardized alpha if employment disparity is dropped
[2]Standardized alpha if residential instability is dropped

APPENDIX B

Table B2.1

Preliminary Model Comparisons

	Log-Likelihood										
	0 year lag	1 year lag	2 year lag	3 year lag	4 year lag	5 year lag	6 year lag	7 year lag	8 year lag	9 year lag	10 year lag
Percent female officers	-6564.7	-5780.0	-5787.1	-5827.8	-4915.6	-4907.6	-4932.5	-4995.9	-4062.1	-4065.9	-4104.2
Percent Latinx officers	-6773.0	-6059.2	-5854.4	-6012.9	-4888.8	-4933.7	-4924.7	-5025.3	-3947.1	-3927.6	-3959.4
Percent Black officers	-6689.6	-5691.1	-5786.2	-5990.6	-4750.1	-4772.5	-4811.9	-4898.6	-3915.1	-3935.6	-3967.2
Homicide reports	-8795.7	-8940.2	-8676.4	-8763.0	-8683.0	-7312.8	-7449.7	-7326.4	-7191.5	-7384.0	-7176.5
Rape reports	-13528.8	-13419.6	-13282.6	-13368.2	-13183.0	-11081.7	-11203.5	-11136.4	-11171.5	-11189.7	-11199.4
Robbery reports	-17995.4	-17997.0	-17821.0	-17934.3	-17474.0	-14945.8	-15071.5	-14978.1	-14823.4	-14740.7	-14750.7
Agg. assault reports	-19970.9	-19906.7	-19801.4	-19785.6	-19554.3	-16659.6	-16640.5	-16488.1	-16386.0	-16509.4	-16437.8
Burglary reports	-22394.7	-22235.2	-22146.9	-22412.0	-21994.1	-18718.3	-18849.0	-18498.3	-18440.3	-18366.1	-18354.9
Larceny reports	-25378.0	-25278.7	-25103.6	-25314.5	-24833.0	-21167.5	-21221.2	-20862.9	-20834.6	-20778.6	-20697.3
MV theft reports	-20870.8	-20515.2	-20603.2	-20709.2	-20342.9	-17419.7	-17541.6	-17279.5	-17193.3	-17201.4	-17167.2
Homicide clearance	-14138.5	-13865.0	-14265.9	-14068.5	-14000.6	-12069.0	-12034.1	-12006.4	-12131.8	-12206.8	-12177.1

(continued)

	Log-Likelihood										
	0 year lag	1 year lag	2 year lag	3 year lag	4 year lag	5 year lag	6 year lag	7 year lag	8 year lag	9 year lag	10 year lag
Rape clearance	-13579.8	-13623.7	-13703.7	-13631.5	-13789.4	-11701.2	-11713.8	-12035.1	-11790.6	-11886.7	-11803.0
Robbery clearance	-12188.7	-12011.3	-11956.4	-12105.2	-11937.6	-10223.3	-10390.5	-10324.1	-10198.1	-10398.9	-10327.2
Agg. assault clearance	-13341.3	-13165.4	-13259.2	-13218.6	-13320.3	-11193.0	-11351.0	-11361.2	-11241.2	-11442.1	-11230.8
Burglary clearance	-11230.8	-9713.6	-9764.3	-9578.6	-9733.8	-8161.6	-8151.4	-8372.3	-8267.6	-8262.6	-8276.7
Larceny clearance	-10611.1	-10385.4	-10616.9	-10534.9	-10403.9	-8802.3	-9272.2	-9041.5	-9122.5	-9192.7	-9182.0
MV theft clearance	-10933.7	-10678.2	-10804.1	-10764.1	-10674.9	-9091.6	-8681.2	-9360.3	-9144.6	-9370.4	-9137.2

APPENDIX C

Figure C3.1

Boxplot: Percent Latinx Citizens, 1990 – 2018[9]

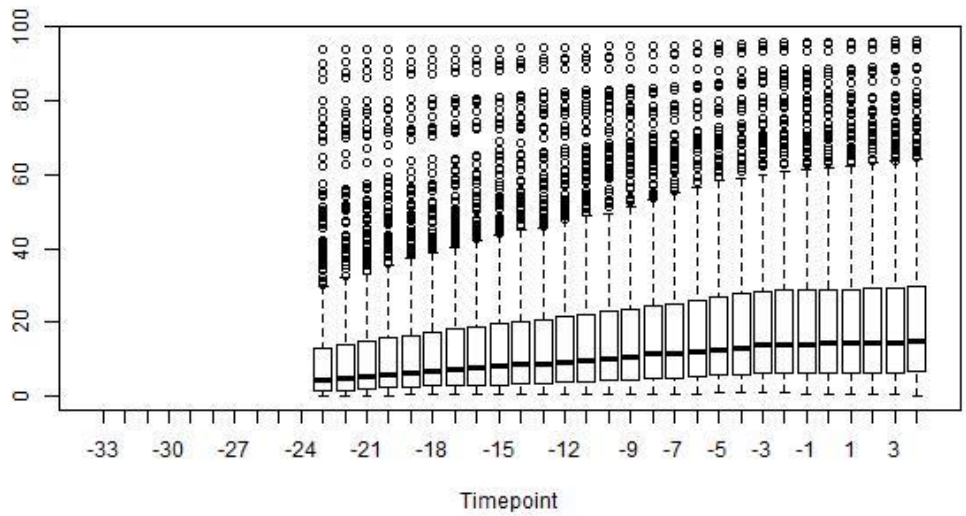
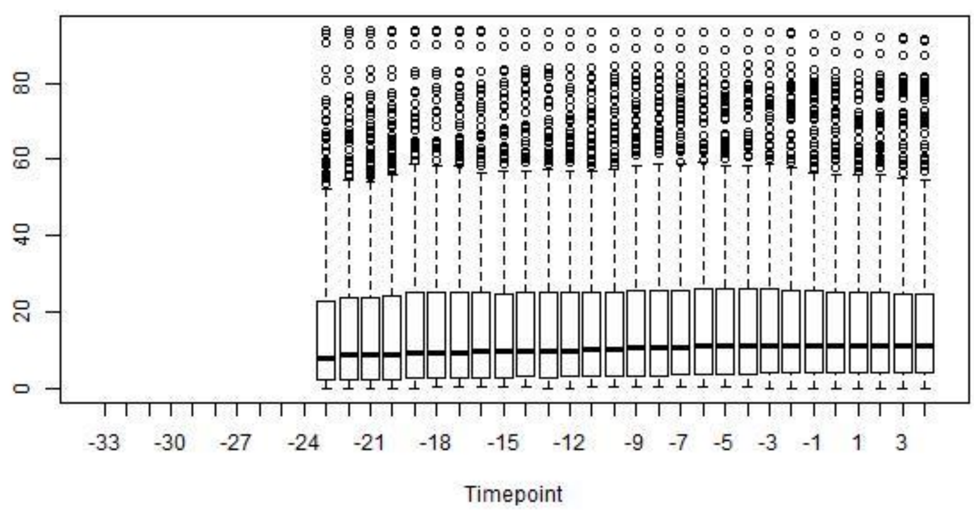


Figure C3.2

Boxplot: Percent Black Citizens, 1990 – 2018



[9] Timepoint 0 = 2013

Figure C3.3
Boxplot: Income Disparity (Gender), 1990 – 2018

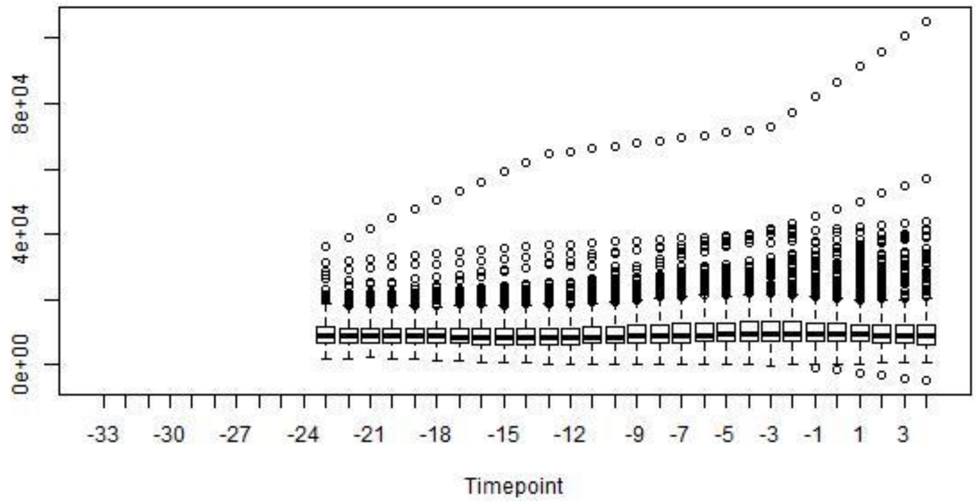


Figure C3.4
Boxplot: Income Disparity (Ethnicity), 1990 – 2018

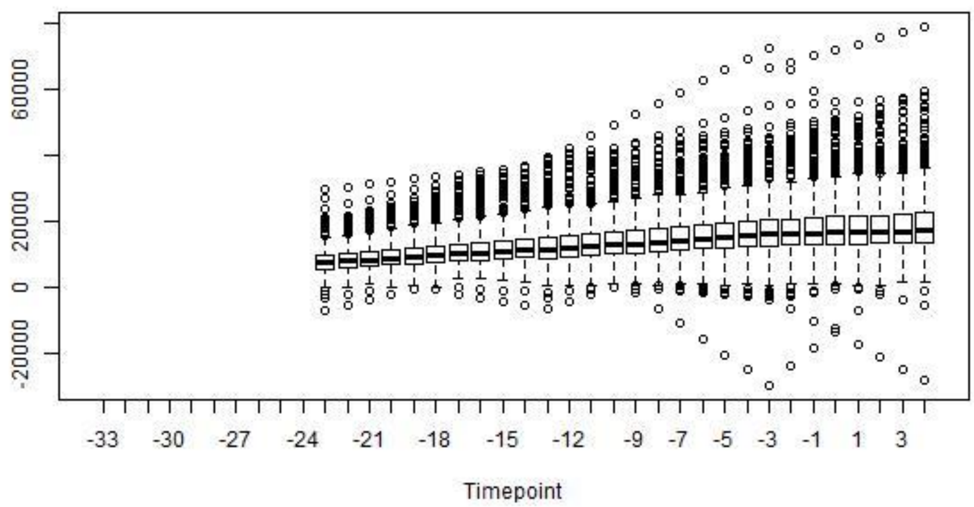


Figure C3.5
Boxplot: Income Disparity (Race), 1990 – 2018

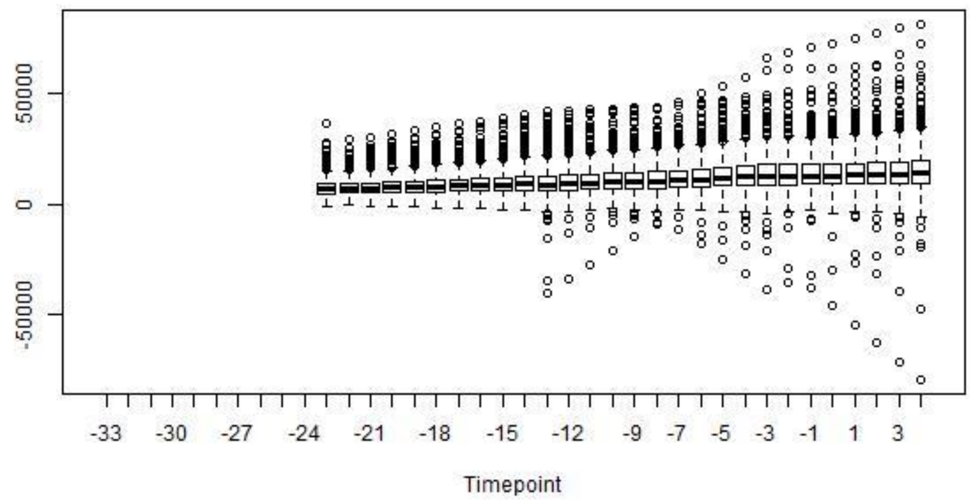


Figure C3.6
Boxplot: LFP Disparity (Gender), 1990 – 2018

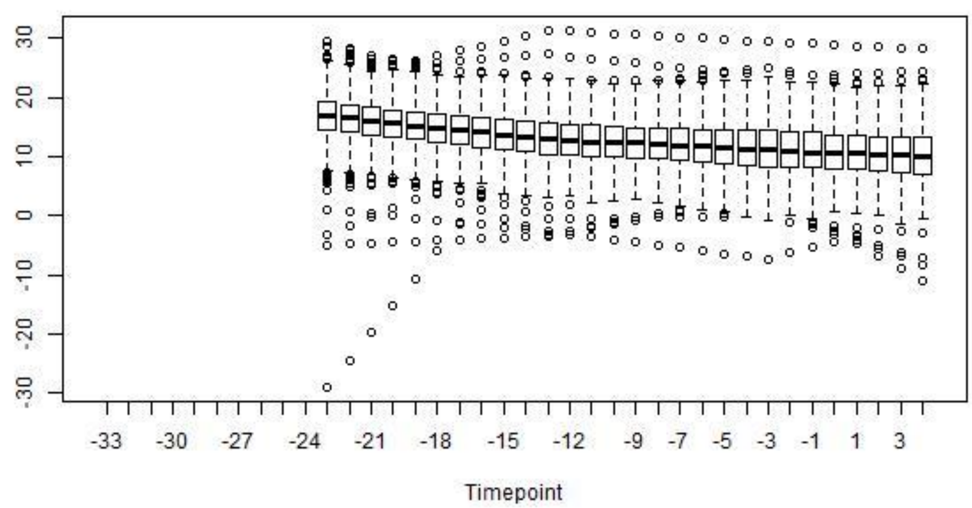


Figure C3.7
Boxplot: LFP Disparity (Ethnicity), 1990 – 2018

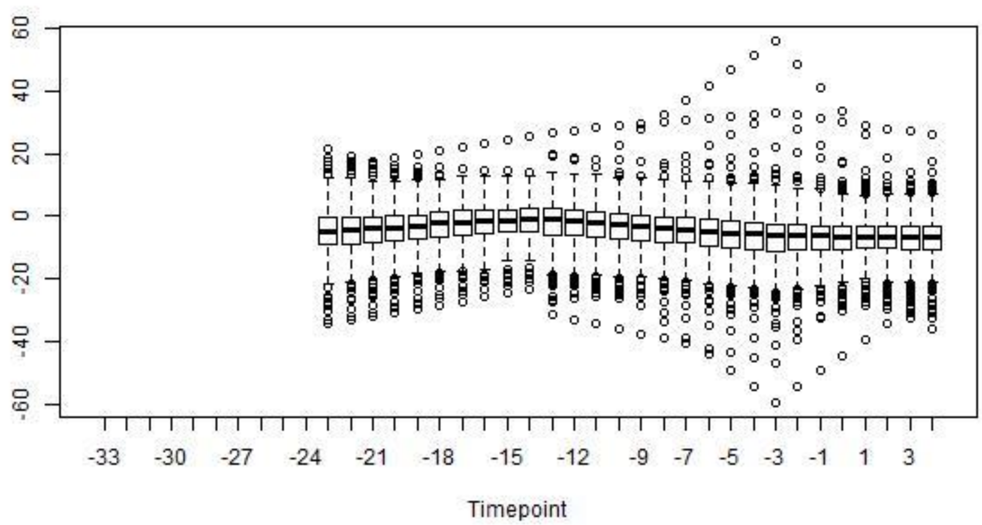


Figure C3.8
Boxplot: LFP Disparity (Race), 1990 – 2018

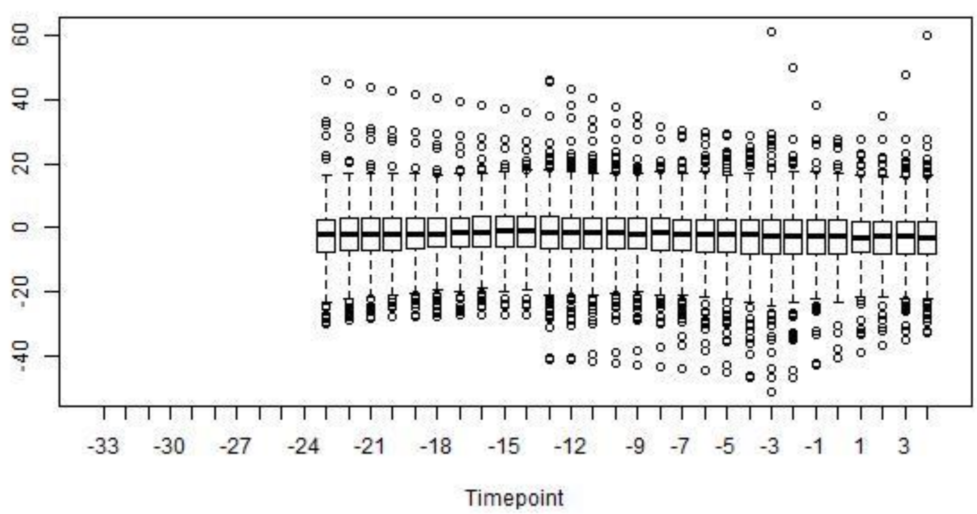


Figure C3.9
Boxplot: Employment Disparity (Gender), 1990 – 2018

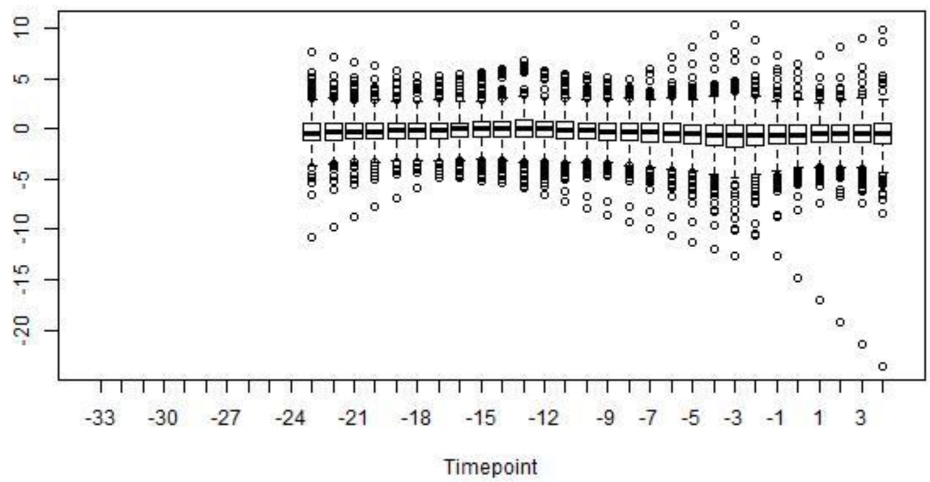


Figure C3.10
Boxplot: Employment Disparity (Ethnicity), 1990 – 2018

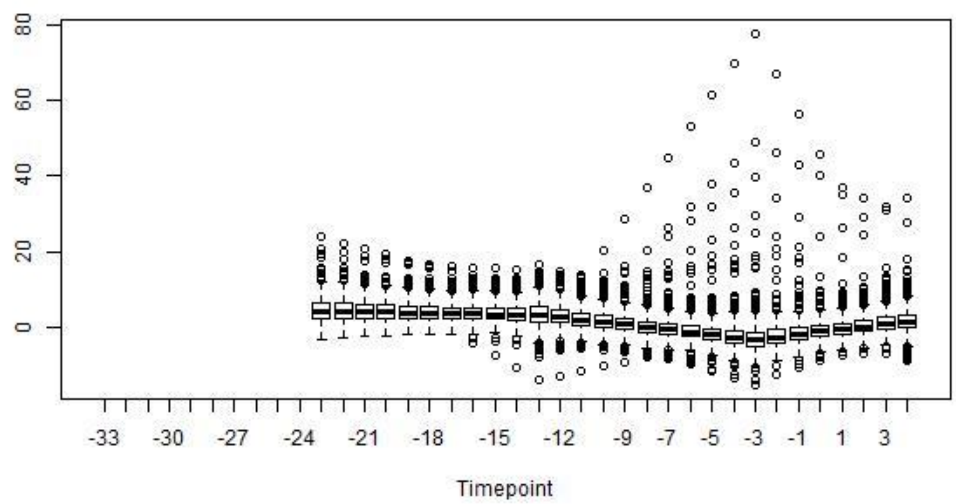


Figure C3.11

Boxplot: Employment Disparity (Race), 1990 – 2018

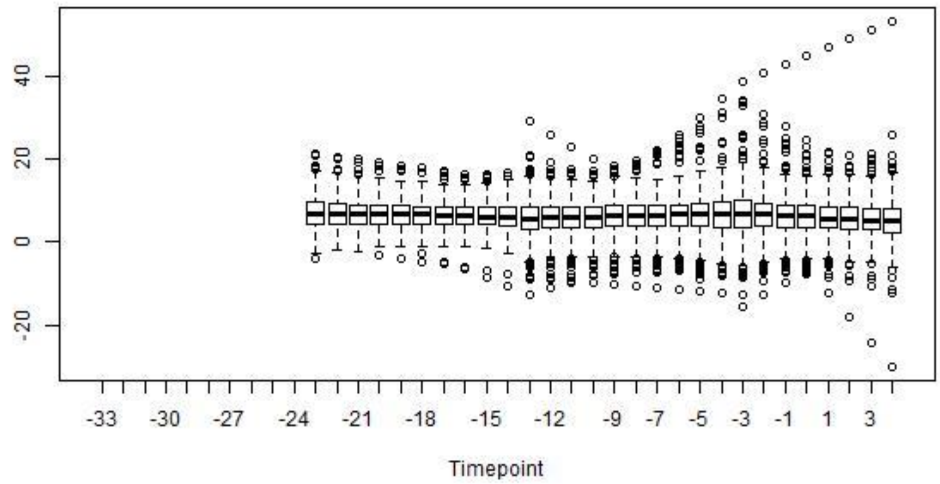


Figure C3.12

Boxplot: Education Disparity (Gender), 1990 – 2018

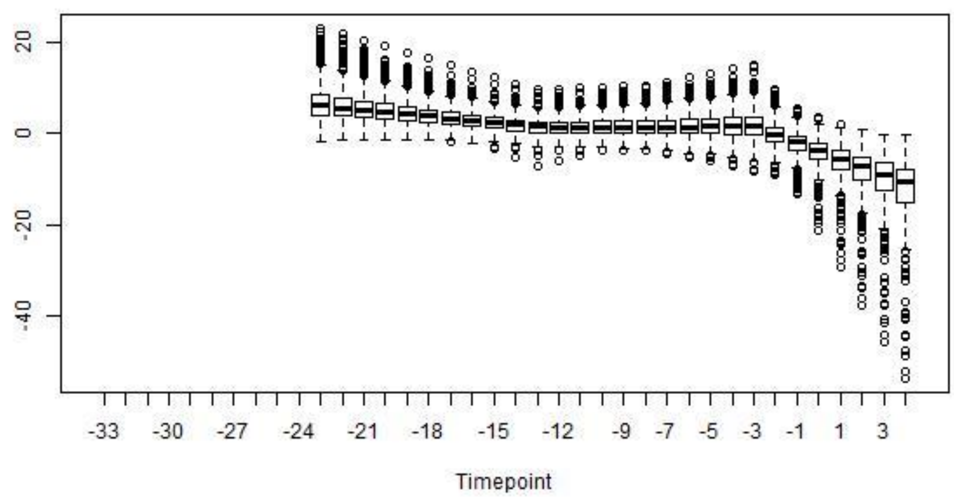


Figure C3.13
Boxplot: Education Disparity (Ethnicity), 1990 – 2018

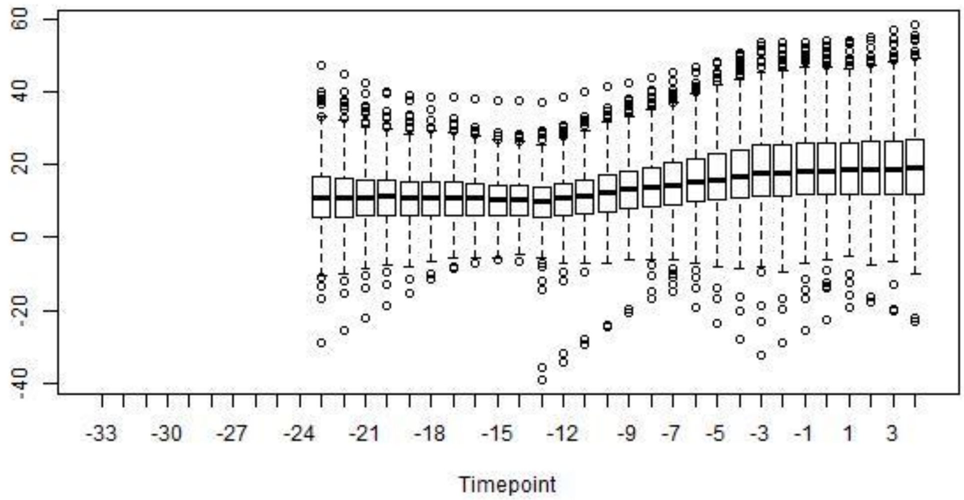


Figure C3.14
Boxplot: Education Disparity (Race), 1990 – 2018

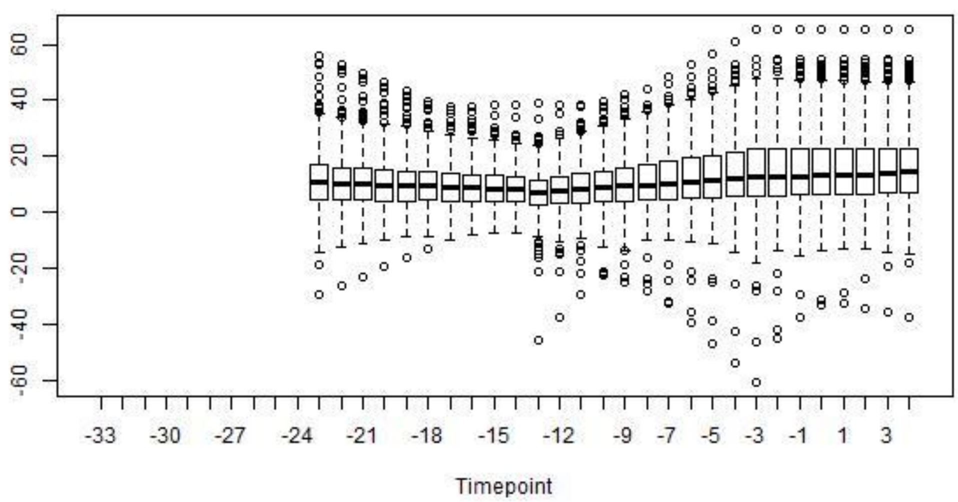


Figure C3.15

Boxplot: Social Disorganization, 1990 – 2018

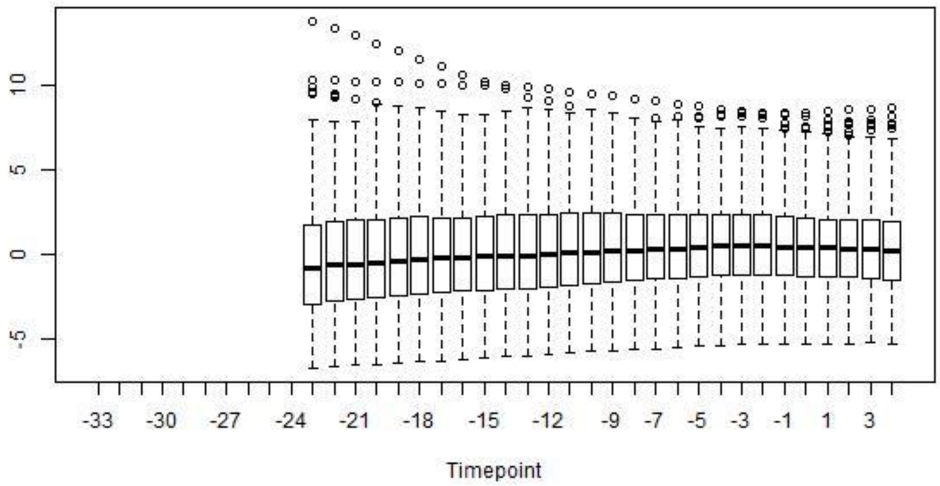
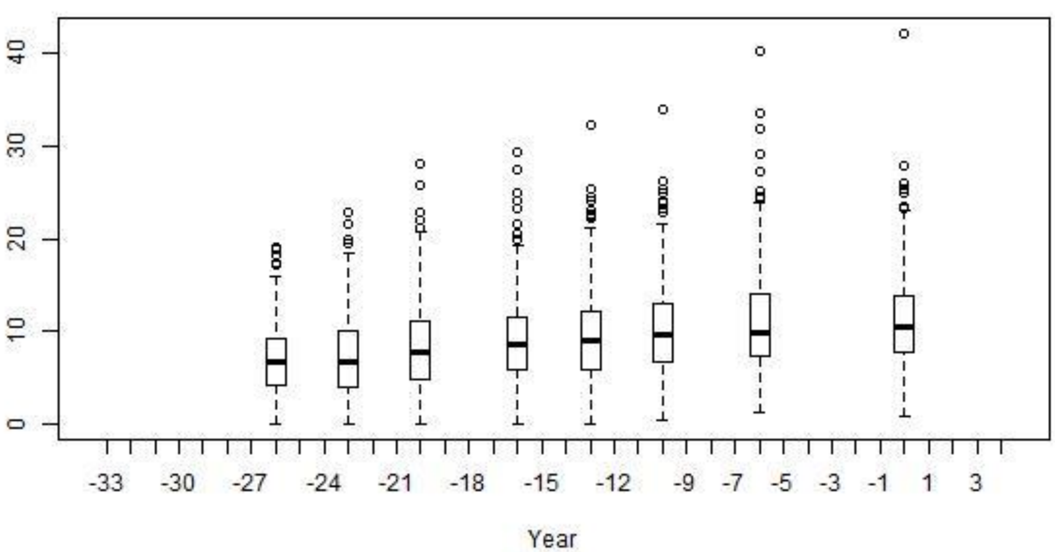


Figure C3.16

Boxplot: Female Absolute Representation (Percent Female Officers), 1987 – 2013[10]



[10] Timepoint 0 = 2013

Figure C3.17
Boxplot: Latinx Absolute Representation (Percent Latinx Officers), 1987 – 2013

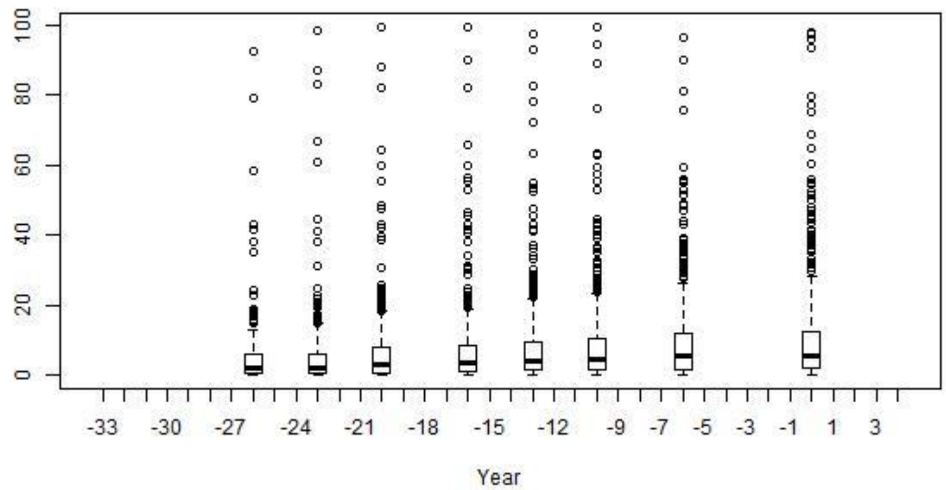


Figure C3.18
Boxplot: Black Absolute Representation (Percent Black Officers), 1987 – 2013

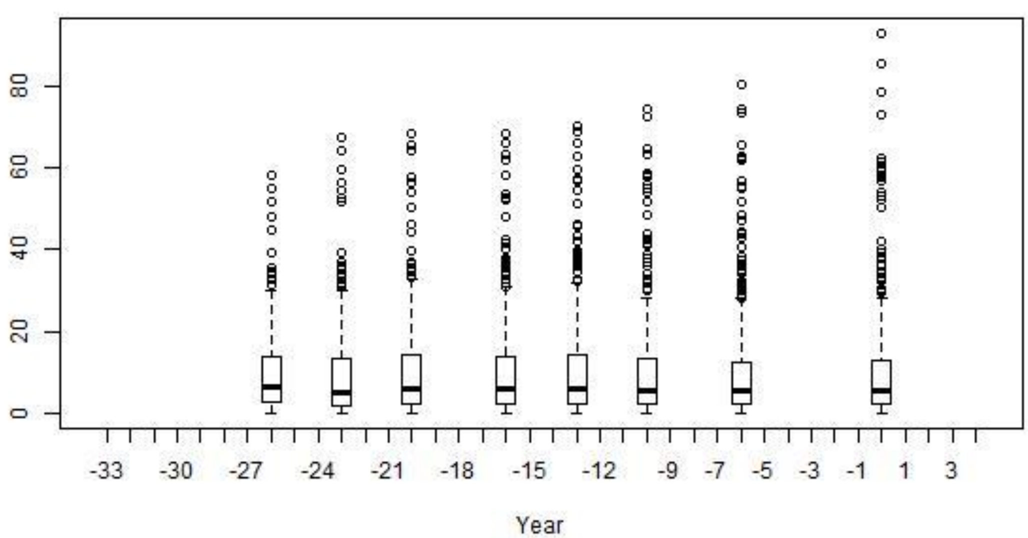


Figure C3.19
Boxplot: Latinx Relative Representation, 1987 – 2013

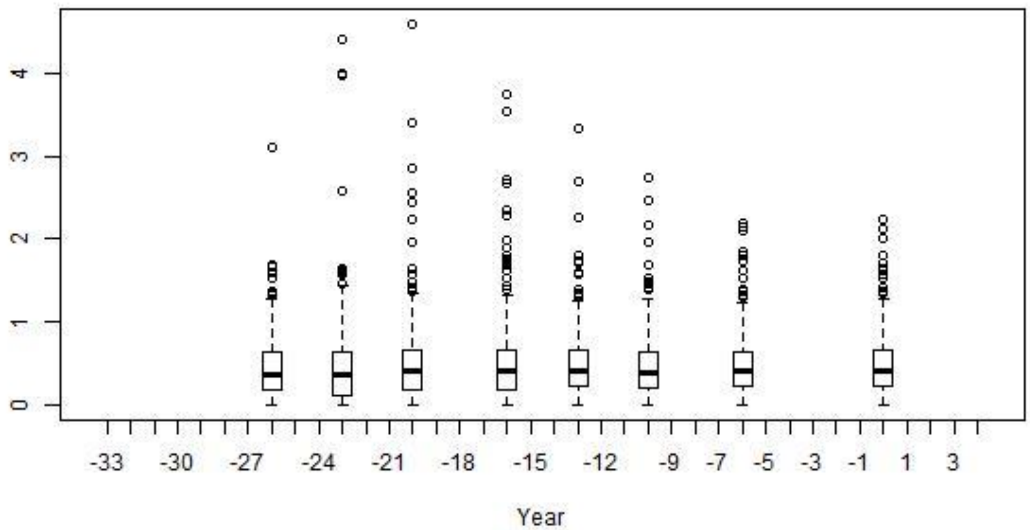


Figure C3.20
Boxplot: Black Relative Representation, 1987 – 2013

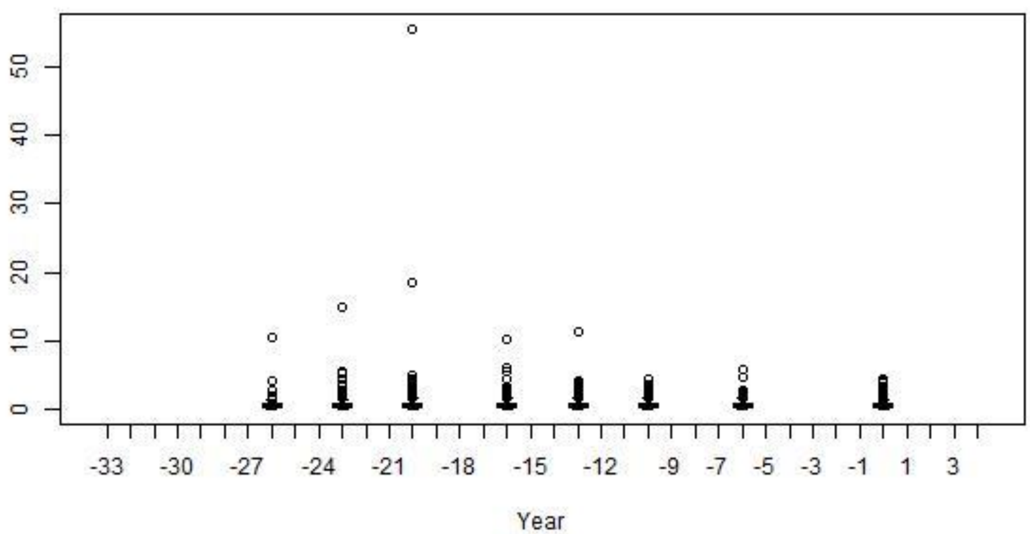


Figure C3.21
Boxplot: Organizational Size, 1987 – 2013

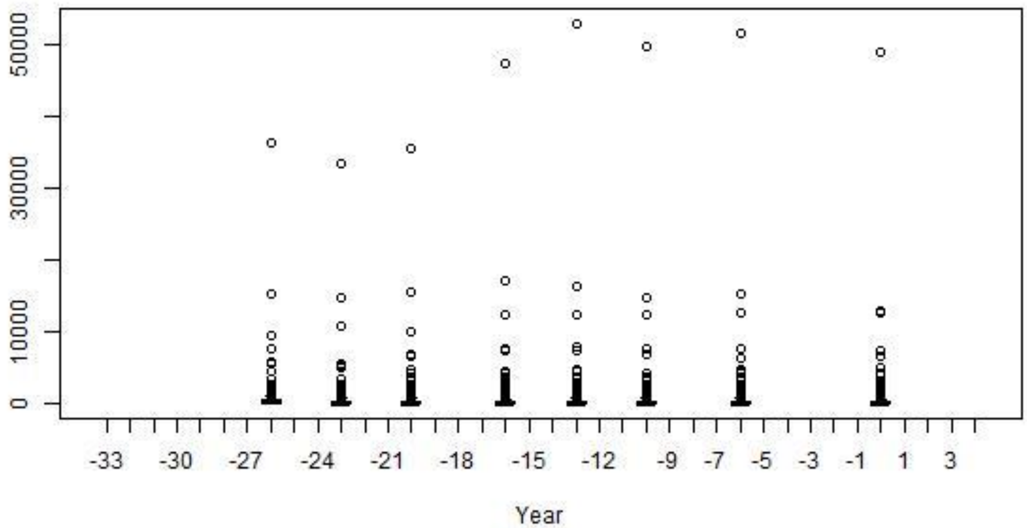
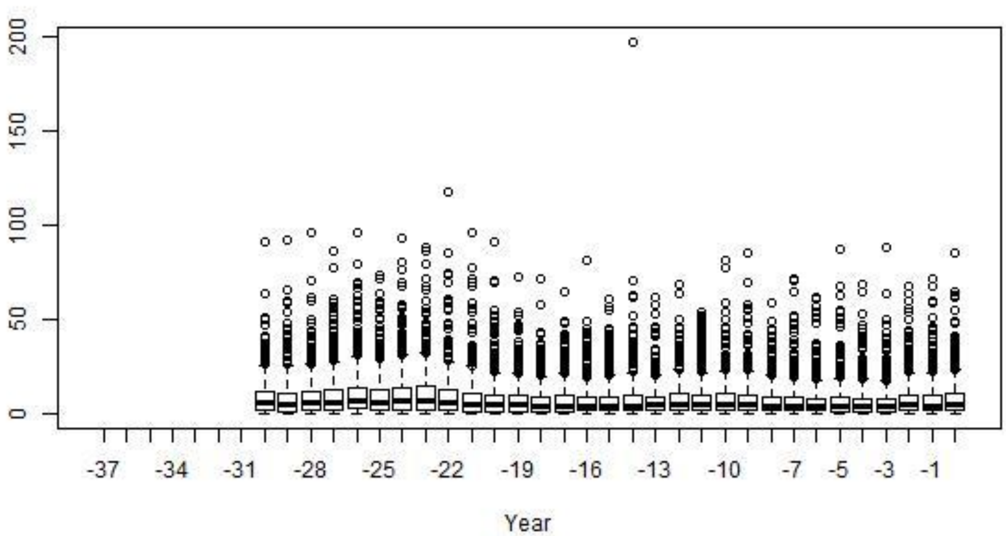


Figure C3.22
Boxplot: Actual Homicide Rate, 1987 – 2017[11]



[11] Timepoint 0 = 2017

Figure C3.23
Boxplot: Actual Rape Rate, 1987 – 2017

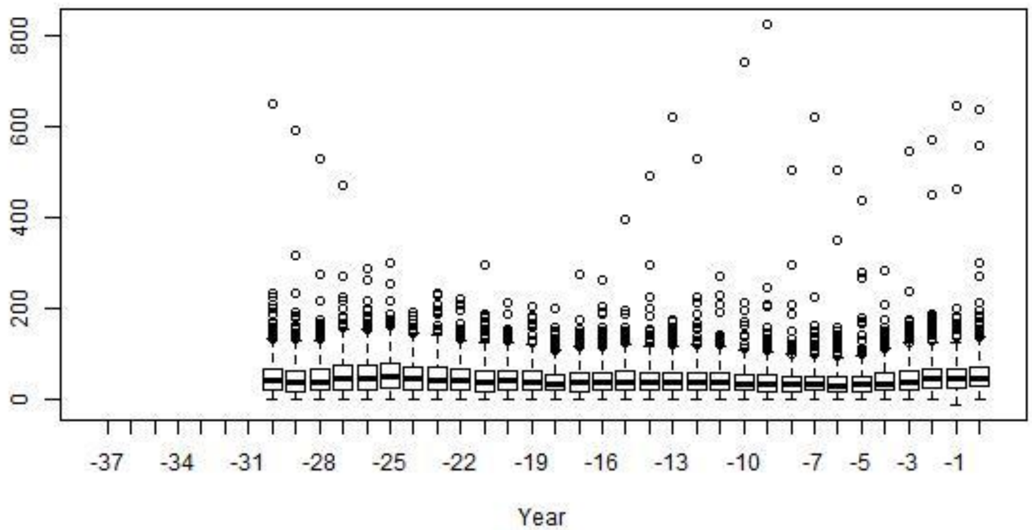


Figure C3.24
Boxplot: Actual Robbery Rate, 1987 – 2017

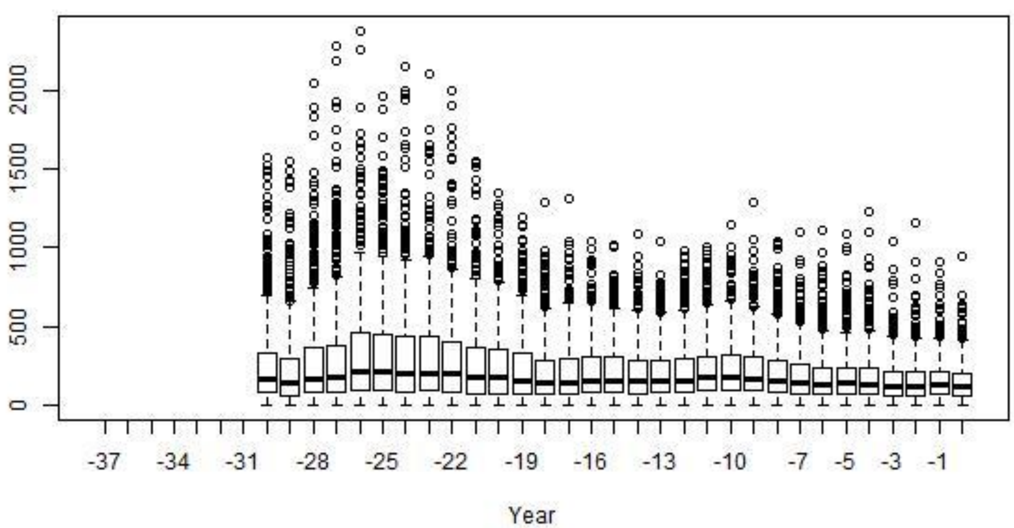


Figure C3.25
Boxplot: Actual Aggravated Assault Rate, 1987 – 2017

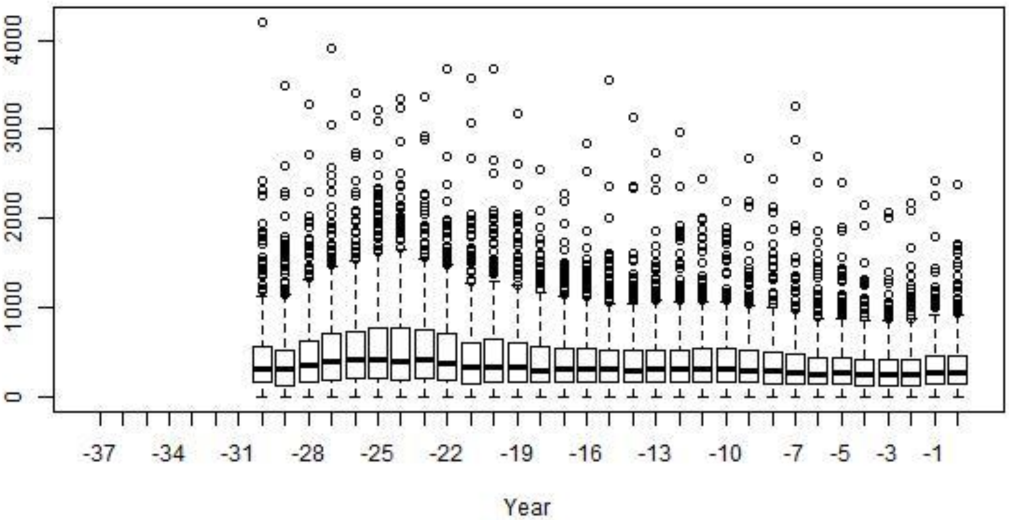


Figure C3.26
Boxplot: Actual Burglary Rate, 1987 – 2017

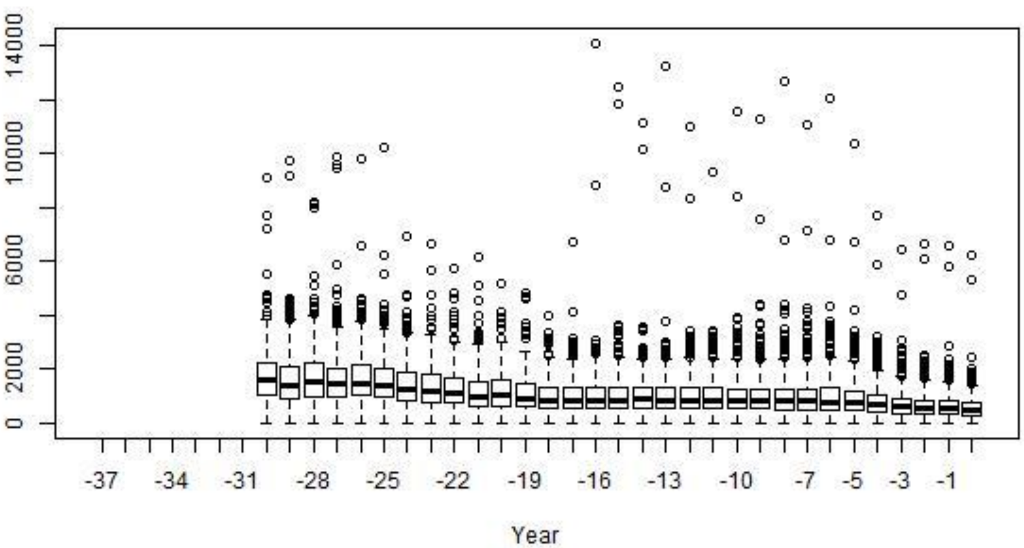


Figure C3.27
Boxplot: Actual Larceny Rate, 1987 – 2017

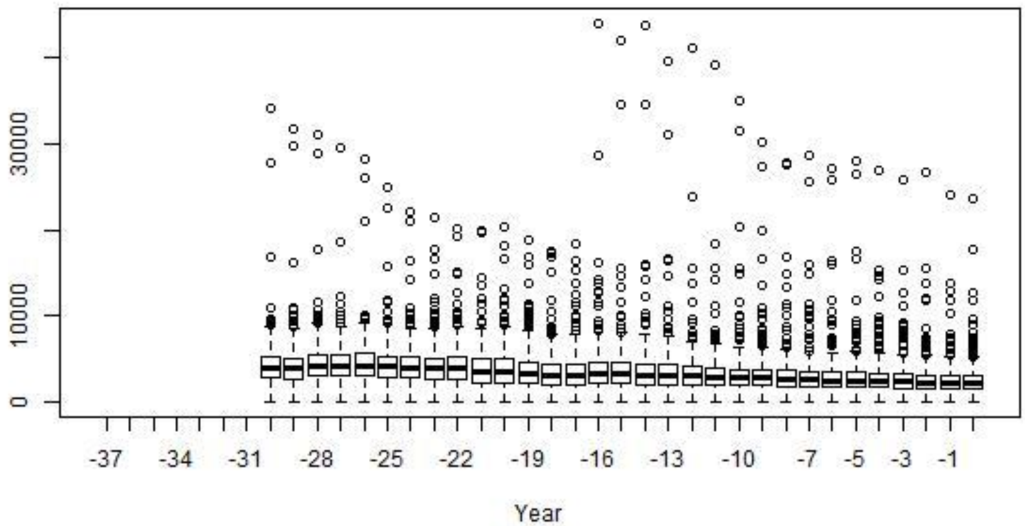


Figure C3.28
Boxplot: Actual Motor-Vehicle Theft Rate, 1987 – 2017

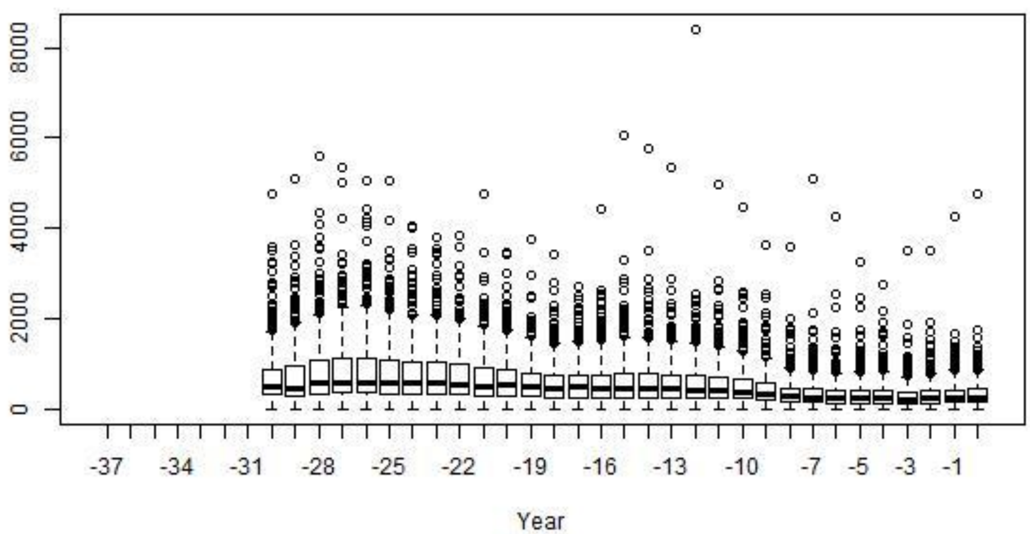


Figure C3.29
Boxplot: Homicide Clearance Rate, 1987 – 2017

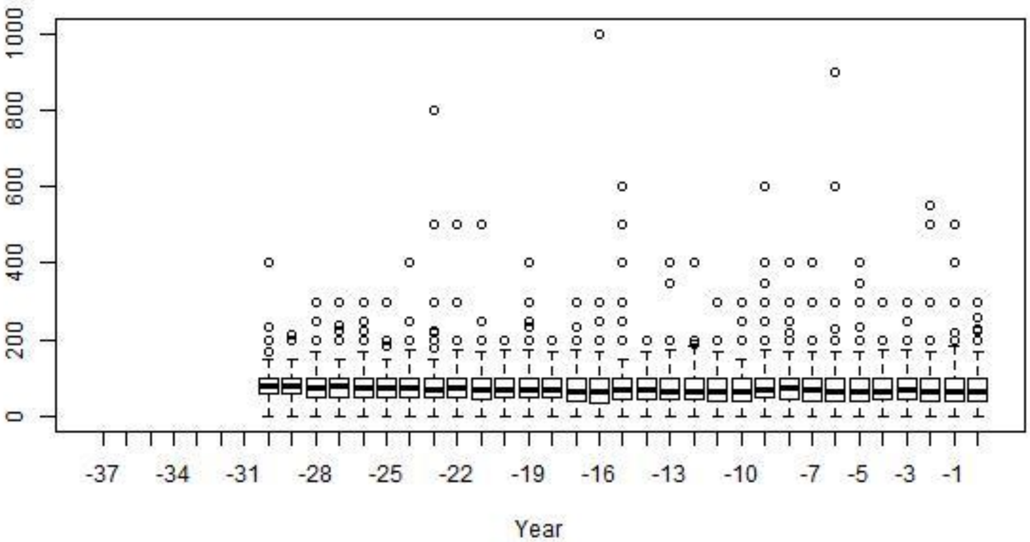


Figure C3.30
Boxplot: Rape Clearance Rate, 1987 – 2017

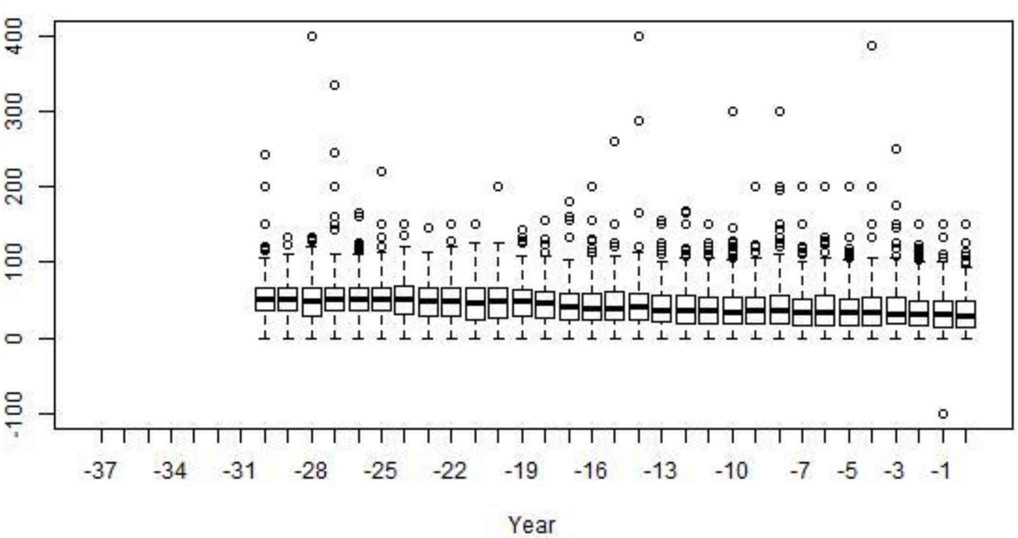


Figure C3.31
Boxplot: Robbery Clearance Rate, 1987 – 2017

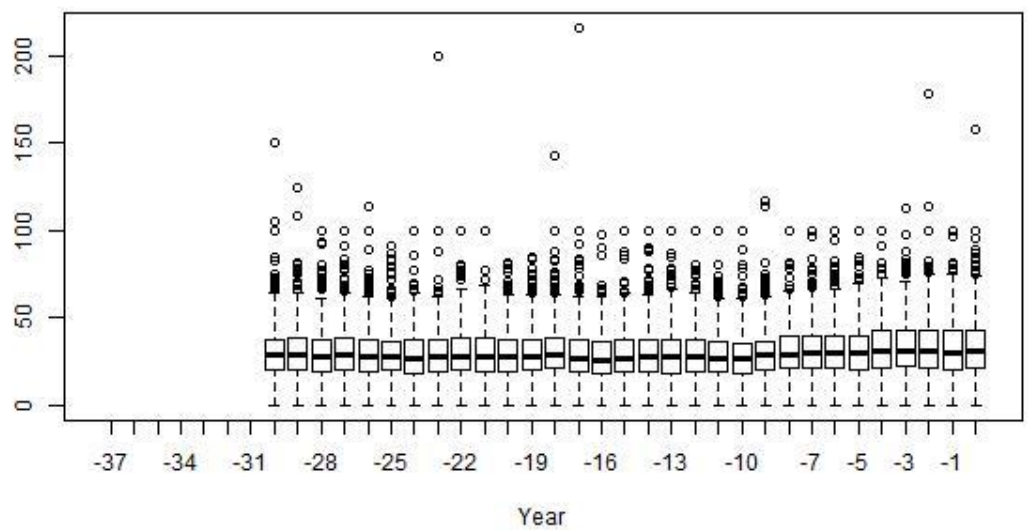


Figure C3.32
Boxplot: Aggravated Assault Clearance Rate, 1987 – 2017

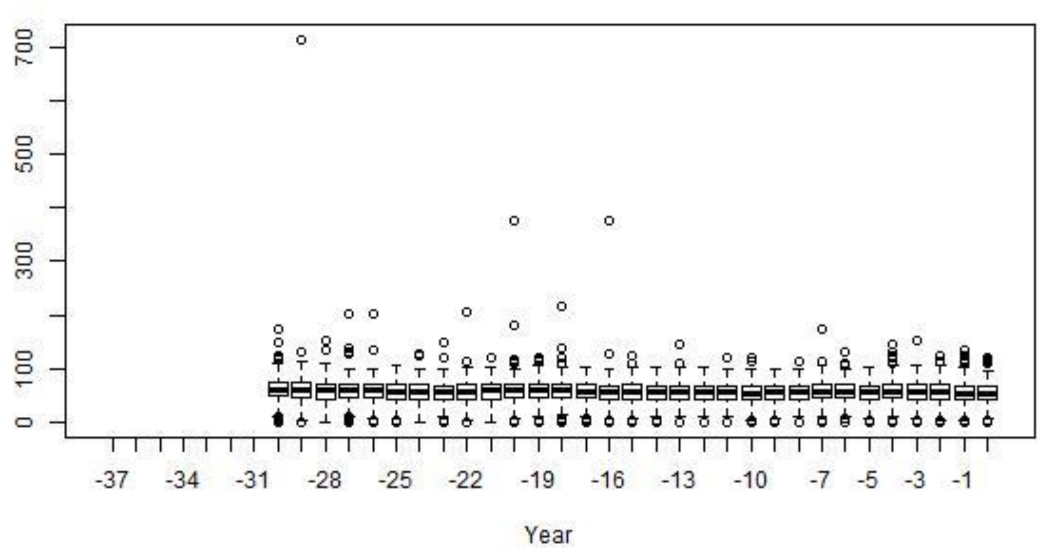


Figure C3.33

Boxplot: Burglary Clearance Rate, 1987 – 2017

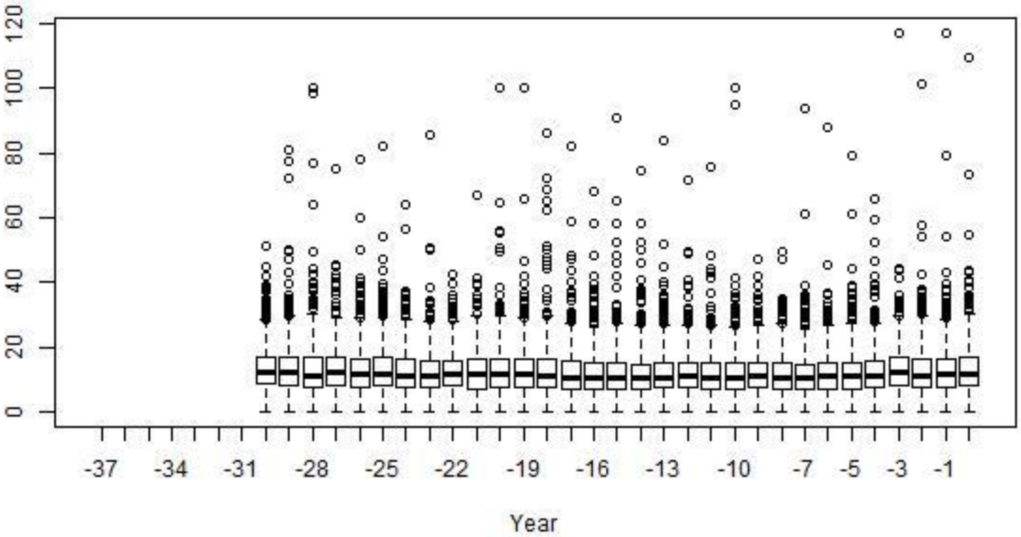


Figure C3.34

Boxplot: Larceny Clearance Rate, 1987 – 2017

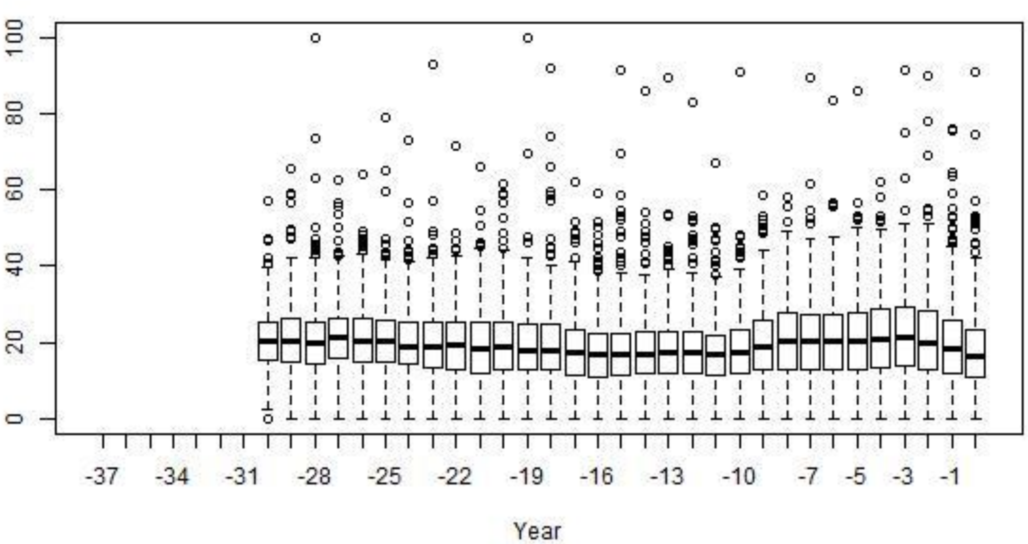
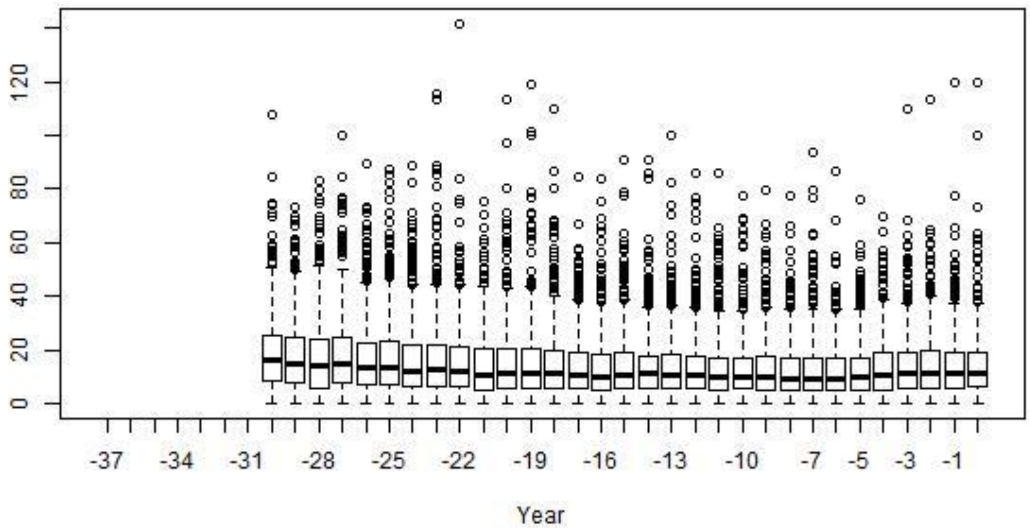


Figure C3.35

Boxplot: Motor-Vehicle Theft Clearance Rate, 1987 – 2017



APPENDIX D

Table D4.1

Environmental Measures: Data Check

Variable	1980	1990	2000	2010	2017
Munificence					
Percent Latinx citizens					
Skewness	3.00	2.49	1.91	1.57	1.47
Kurtosis	10.93	7.24	3.84	2.30	1.89
Percent Black citizens					
Skewness	1.11	1.40	1.38	1.42	1.44
Kurtosis	0.65	1.66	1.37	1.57	1.71
Complexity					
Median income disparity (gender)					
Skewness	-	1.59	1.56	1.90	2.26
Kurtosis	-	4.48	4.36	4.92	6.45
Per capita income disparity (ethnicity)					
Skewness	-	1.18	1.19	1.05	1.60
Kurtosis	-	3.79	2.68	5.54	4.29
Per capita income disparity (race)					
Skewness	-	1.95	1.22	1.08	0.06
Kurtosis	-	7.76	4.18	3.94	14.03
LFP disparity (gender)					
Mean	-	-0.28	0.02	0.15	-0.13
SD	-	1.50	1.06	0.11	1.23

(continued)

Variable	1980	1990	2000	2010	2017
LFP disparity (ethnicity)					
Skewness	-	-0.19	-0.34	0.14	-0.16
Kurtosis	-	1.41	1.31	2.50	2.32
LFP disparity (race)					
Skewness	-	-0.34	0.24	-0.28	0.20
Kurtosis	-	1.57	2.41	2.44	1.02
Employment disparity (gender)					
Skewness	-	-0.23	0.06	0.63	-0.27
Kurtosis	-	4.55	3.07	3.69	1.61
Employment disparity (ethnicity)					
Skewness	-	1.27	0.17	1.86	0.89
Kurtosis	-	3.22	1.93	12.25	3.04
Employment disparity (race)					
Skewness	-	0.23	-0.31	0.69	2.13
Kurtosis	-	0.38	1.19	4.58	19.55
Education disparity (gender)					
Skewness	-	1.27	0.25	0.82	-2.02
Kurtosis	-	2.44	1.26	1.13	6.11
Education disparity (ethnicity)					
Skewness	-	0.10	-0.24	0.21	0.32
Kurtosis	-	1.17	3.49	1.11	0.35
Education disparity (race)					
Skewness	-	0.55	0.17	0.21	0.45
Kurtosis	-	1.77	0.99	1.10	0.73

(continued)

Variable	1980	1990	2000	2010	2017
Dynamism					
Residential instability (percent)					
Skewness	0.18	0.10	0.12	0.65	0.71
Kurtosis	-0.16	0.05	0.56	1.16	1.12
Social disorganization					
Scale					
Skewness	1.69	0.55	0.26	0.18	0.32
Kurtosis	5.33	0.32	-0.47	-0.32	-0.07

Table D4.2

Organizational Measures: Data Check

	1987	1990	1993	1997	2000	2003	2007	2013
Absolute representation								
Percent female officers								
Skewness	0.56	0.68	0.73	0.79	0.80	0.74	1.10	1.02
Kurtosis	0.15	0.26	0.71	1.05	1.11	1.09	2.83	2.89
Percent Latinx officers								
Skewness	4.92	5.08	4.32	4.06	3.67	3.46	3.00	3.03
Kurtosis	30.75	32.43	24.73	21.83	17.75	15.38	12.20	11.49
Percent Black officers								
Skewness	1.79	2.15	2.08	2.14	2.20	2.35	2.62	2.84
Kurtosis	3.96	5.93	5.30	5.49	5.77	6.42	8.35	9.94
Relative representation								
Latinx officers								
Skewness	1.90	3.39	3.58	2.63	2.01	1.65	1.57	1.35
Kurtosis	7.79	19.97	21.14	12.01	9.11	5.66	4.32	3.33

(continued)

	1987	1990	1993	1997	2000	2003	2007	2013
Black officers								
Skewness	8.80	9.78	16.31	5.53	6.62	2.52	3.22	2.83
Kurtosis	99.71	132.48	289.57	49.20	74.04	8.45	19.10	12.14

Table D4.3

Crime Normality Check:. Panel A: 1987-1996

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Actual Crime										
Homicide										
Skewness	1.69	1.75	1.74	2.26	2.28	1.99	2.25	2.40	3.22	3.04
Kurtosis	3.59	4.00	3.68	6.61	7.26	4.67	6.94	7.73	15.56	13.40
Rape										
Skewness	1.17	1.57	1.27	0.99	1.05	0.85	0.60	0.95	0.70	0.97
Kurtosis	2.18	4.79	2.75	1.67	2.29	1.17	-0.09	1.45	0.22	1.17
Robbery										
Skewness	1.45	1.35	1.59	1.92	1.79	1.61	1.77	1.76	1.94	1.61
Kurtosis	1.99	1.66	2.95	4.49	4.45	2.94	4.11	4.25	5.49	3.46
Aggravated Assault										
Skewness	1.50	1.61	1.85	1.34	1.50	1.61	1.55	1.27	1.26	1.67
Kurtosis	2.59	3.77	5.87	1.83	3.17	3.58	3.18	2.04	1.78	4.32

(continued)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Burglary										
Skewness	1.95	1.38	1.35	0.72	0.38	0.511	0.51	0.43	0.58	0.30
Kurtosis	8.73	7.86	5.08	0.68	-0.06	0.06	0.37	0.22	1.03	-0.23
Larceny-theft										
Skewness	5.98	4.83	5.10	0.28	0.09	0.33	1.51	0.92	1.05	1.11
Kurtosis	51.78	38.81	41.21	0.46	0.31	0.42	10.61	4.67	5.97	6.16
Motor-Vehicle Theft										
Skewness	1.57	1.31	1.23	1.90	1.63	1.61	1.40	1.45	1.29	1.16
Kurtosis	2.46	1.58	1.25	5.68	3.79	4.04	2.68	2.98	2.34	2.10
Clearance rates										
Homicide										
Skewness	-0.34	-0.33	-0.61	-0.78	-0.47	-0.24	-0.40	-0.44	-0.19	-0.36
Kurtosis	0.92	1.05	0.21	0.42	0.36	0.84	0.23	0.12	-0.12	-0.43

(continued)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Rape										
Skewness	0.58	-0.21	-0.36	0.18	-0.19	0.25	-0.11	-0.15	0.16	0.10
Kurtosis	2.56	0.38	-0.44	1.54	0.13	0.53	-0.30	-0.61	-0.02	-0.57
Robbery										
Skewness	2.90	0.70	0.40	0.48	0.08	0.52	0.49	0.54	0.36	0.11
Kurtosis	20.41	1.14	1.08	1.02	0.31	1.11	1.14	1.35	0.47	-0.11
Aggravated Assault										
Skewness	0.55	-0.34	-0.55	-0.34	-0.80	-0.53	-0.58	-0.67	-0.66	-0.67
Kurtosis	5.02	0.77	1.15	1.46	0.47	0.18	0.61	0.84	0.38	0.01
Burglary										
Skewness	1.21	1.30	0.94	1.21	1.08	1.19	1.34	2.68	0.92	1.40
Kurtosis	1.66	2.70	1.72	3.05	2.39	2.04	4.21	17.52	1.44	5.26
Larceny-theft										
Skewness	0.58	0.29	-0.08	-0.12	-0.13	1.08	0.69	1.33	0.41	0.24
Kurtosis	0.52	0.79	0.32	1.00	0.70	6.78	3.23	8.42	2.11	0.93

(continued)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Motor-Vehicle Theft										
Skewness	0.88	0.95	1.25	1.69	1.61	1.78	1.80	2.37	3.07	1.53
Kurtosis	0.67	1.02	2.31	4.08	3.61	4.67	4.30	9.00	18.84	3.45

Crime Normality Check. Panel B: 1997-2006

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
<u>Actual Crime</u>										
Homicide										
Skewness	3.08	2.63	2.72	2.27	2.83	2.49	2.79	2.81	2.16	2.20
Kurtosis	13.85	9.62	11.83	7.40	13.63	8.45	11.02	10.61	5.72	5.27
Rape										
Skewness	0.91	0.93	1.13	0.79	1.07	1.18	1.96	1.19	1.16	1.55
Kurtosis	1.03	1.13	2.66	0.62	2.17	2.81	9.82	2.21	3.26	6.92
Robbery										
Skewness	1.45	1.48	1.50	1.52	1.25	1.21	1.40	1.30	1.38	1.33
Kurtosis	2.28	2.48	2.73	2.82	1.47	1.34	2.01	1.71	1.87	1.64
Aggravated Assault										
Skewness	1.65	1.73	1.48	1.34	1.61	1.45	1.60	1.63	1.84	2.08
Kurtosis	3.67	4.24	2.71	2.05	4.22	2.64	4.10	3.90	4.90	6.54

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
										(continued)
Burglary										
Skewness	0.55	0.70	0.68	1.95	0.59	0.88	1.02	0.89	0.87	1.17
Kurtosis	0.24	1.07	0.28	12.00	-0.02	1.40	2.07	1.34	0.96	1.44
Larceny-theft										
Skewness	1.52	1.28	1.92	1.35	1.07	0.83	1.17	1.45	1.44	1.61
Kurtosis	7.96	5.44	9.70	5.02	4.15	2.87	5.44	8.03	4.47	8.12
Motor-Vehicle Theft										
Skewness	1.23	1.10	1.37	1.38	1.32	1.63	1.59	1.43	1.36	1.70
Kurtosis	2.31	1.79	2.73	2.31	2.01	3.91	4.10	2.74	2.23	4.24
<u>Clearance rates</u>										
Homicide										
Skewness	-0.19	-0.37	-0.23	-0.02	-0.12	-0.27	-0.23	-0.29	-0.01	-0.09
Kurtosis	-0.14	-0.25	-0.19	-0.19	-0.49	-0.55	-0.39	-0.60	-0.32	-0.45

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Rape										
Skewness	-0.07	0.07	0.14	0.68	0.55	0.35	0.54	0.73	0.90	1.10
Kurtosis	-0.71	-0.26	-0.44	1.73	0.71	-0.38	0.43	0.95	1.65	2.19
Robbery										
Skewness	0.36	0.34	0.35	0.54	0.54	0.53	0.59	0.53	0.66	0.50
Kurtosis	0.36	0.57	0.77	0.97	1.48	0.73	1.18	0.85	1.62	0.83
Aggravated Assault										
Skewness	-0.43	-0.60	-0.72	-0.77	-0.65	-0.50	-0.56	-0.36	-0.55	-0.60
Kurtosis	1.96	0.89	1.27	0.63	0.47	0.42	0.50	1.01	0.49	0.42
Burglary										
Skewness	3.23	1.38	1.24	1.38	1.19	1.49	2.60	2.77	2.35	2.32
Kurtosis	23.08	6.85	3.38	5.36	2.80	5.03	13.25	17.93	12.30	15.34
Larceny-theft										
Skewness	0.50	0.45	0.70	0.47	0.61	1.08	1.56	1.56	1.21	0.75

(continued)

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Kurtosis	1.56	1.85	2.21	1.25	1.50	3.83	5.74	6.40	5.44	2.54
										(continued)
Motor-Vehicle Theft										
Skewness	2.63	2.92	1.63	1.42	1.74	1.70	2.17	2.02	1.96	1.77
Kurtosis	12.31	16.65	3.78	2.19	4.19	3.71	8.13	5.72	5.45	3.78

Crime normality check. Panel C: 2007-2017

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
<u>Actual Crime</u>											
Homicide											
Skewness	2.89	2.87	256	2.95	2.90	3.59	3.30	3.51	2.91	2.55	2.83
Kurtosis	12.26	11.77	8.45	11.99	12.00	19.53	16.02	20.65	12.09	8.78	12.04
Rape											
Skewness	1.35	1.98	1.64	1.08	1.27	2.59	1.28	0.94	1.11	0.84	1.73
Kurtosis	3.55	8.53	6.12	1.63	2.80	14.26	2.15	0.86	2.12	0.91	7.15
Robbery											
Skewness	1.68	1.37	1.44	1.63	1.82	2.01	2.15	1.74	1.74	1.69	1.79
Kurtosis	2.02	2.07	2.40	3.32	4.80	5.90	6.96	3.75	4.12	3.84	5.22
Aggravated Assault											
Skewness	1.68	1.42	1.55	1.38	1.53	1.67	1.96	1.84	1.94	2.29	2.14
Kurtosis	4.00	2.51	3.46	2.49	3.51	4.23	6.95	5.76	6.48	9.61	7.80

(continued)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Burglary											
Skewness	1.35	1.30	1.46	1.42	1.35	1.15	1.38	1.39	1.15	1.26	1.24
Kurtosis	2.94	2.85	3.39	2.88	2.32	1.66	2.81	2.85	1.68	2.38	2.32
Larceny-theft											
Skewness	2.07	1.71	1.89	1.61	1.62	1.70	1.94	1.88	1.74	1.67	1.85
Kurtosis	12.91	8.51	9.76	7.05	7.59	8.05	8.30	8.82	7.60	6.86	7.55
Motor-Vehicle Theft											
Skewness	1.78	1.74	1.93	1.76	1.93	2.38	2.43	2.23	1.99	1.72	1.42
Kurtosis	4.77	4.40	6.19	4.28	5.10	8.77	9.17	7.19	5.95	3.91	2.27
Clearance rates											
Homicide											
Skewness	-0.28	-0.32	-0.33	-0.25	-0.20	-0.15	-0.12	-0.36	-0.09	0.04	-0.15
Kurtosis	-0.45	-0.29	-0.61	-0.40	-0.61	-0.56	-0.34	-0.54	-0.46	-0.08	-0.53

(continued)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Rape											
Skewness	0.86	0.54	0.94	0.66	0.59	0.65	0.74	0.88	0.86	0.69	0.69
Kurtosis	0.86	-0.09	2.21	0.15	-0.04	0.10	0.40	1.23	0.83	0.27	0.12
Robbery											
Skewness	0.85	0.96	0.34	0.49	0.40	0.40	0.30	0.62	1.47	0.46	1.22
Kurtosis	2.60	3.96	0.97	1.22	1.08	0.86	-0.03	1.49	9.29	0.38	5.67
Aggravated Assault											
Skewness	-0.63	-0.64	-0.84	-0.39	-0.82	-0.74	-0.59	-0.71	-0.47	-0.32	-0.27
Kurtosis	0.67	0.55	0.55	2.21	0.60	0.55	1.05	0.66	0.50	0.80	0.74
Burglary											
Skewness	3.25	1.04	1.08	3.01	2.57	2.44	2.03	4.23	3.11	4.39	3.44
Kurtosis	29.89	3.05	3.13	26.54	21.37	15.00	9.45	45.62	28.91	48.25	31.54
Larceny-theft											
Skewness	1.00	0.37	0.10	0.56	0.46	0.55	0.59	0.57	0.61	0.66	0.86
Kurtosis	5.54	0.57	-0.11	2.63	1.73	1.71	0.08	2.32	2.28	1.50	2.10

(continued)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Motor-Vehicle Theft											
Skewness	1.86	1.61	1.62	2.12	1.58	1.57	1.47	2.36	2.37	2.52	2.65
Kurtosis	5.02	3.51	4.13	7.78	4.61	3.56	2.97	11.60	12.18	14.62	15.96

APPENDIX E

Table E5.1

Mixed-Effects Regression Models: Homicide Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	4.66† (0.17)	5.25† (0.28)		5.24† (0.30)		5.36† (0.25)	
Time	-0.16† (0.01)	-0.10† (0.01)	0.011	-0.10† (0.01)	0.010	-0.10† (0.01)	0.017
Social disorg.						1.33† (0.06)	0.294
Random effects	Est.	Est.		Est.		Est.	
Department		36.00†		40.14†		26.11†	
Time				0.06†		0.05†	
Residual		14.40†		11.97†		12.09†	
Log Likelihood	-31334	-26683		-26189		-26020	
R^2	0.026	0.011		0.010		0.311	

Notes:
† = profile confidence interval does not include 0
ICC = 0.7136
n observations = 9,343, n subjects = 538

Table E5.2

Mixed-Effects Regression Models: Rape Reports and Absolute Representation

	Uncon ditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	34.35† (0.60)	35.25† (1.14)		35.44† (1.21)		35.57† (1.19)	
Time	-0.81† (0.05)	-0.73† (0.03)	0.02 5	-0.68† (0.08)	0.021	-0.67† (0.08)	0.023
Social disorg.						3.25† (0.30)	0.092
Random effects	Est.	Est.		Est.		Est.	
Department		600.00†		660.66†		633.89†	
Time				2.52†		2.38†	
Residual		281.00†		196.00†		196.38†	
Log Likelihood		-35931		-34973		-34924	
R^2		0.025		0.021		0.119	

Notes:
† = profile confidence interval does not include 0
ICC = .6809
n observations = 8,271, n subjects = 520

Table E5.3

Mixed-Effects Regression Models: Robbery Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	114.79† (4.28)	130.64† (7.16)		129.37† (6.23)		130.76† (5.35)	
Time	-6.79† (0.25)	-5.34† (0.12)	0.046	-5.17† (0.36)	0.042	-5.33† (0.34)	0.067
Social disorg.						24.49† (1.42)	0.170
Random effects	Est.	Est.		Est.		Est.	
Department		24928.00†		17571.00†		12198.40†	
Time				52.00†		46.80†	
Residual		6427.00†		4096.00†		4158.90†	
Log Likelihood		-55388		-53843		-53750	
R^2		0.046		0.042			

Notes:
† = profile confidence interval does not include 0
ICC= 0.7950
n observations = 9,360, n subjects = 540

Table E5.4

Mixed-Effects Regression Models: Aggravated Assault Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	244.28† (7.21)	258.74† (11.71)		256.82† (13.31)		260.97† (12.30)	
Time	-9.82† (0.41)	-8.26† (0.25)	0.039	-8.24† (0.75)	0.036	-8.22† (0.72)	0.047
Social disorg.						37.62† (2.77)	0.119
Random effects	Est.	Est.		Est.		Est.	
Department		63546.00†		80479.00†		67071.00†	
Time				230.00†		211.00†	
Residual		25183.00†		16179.00†		16325.00†	
Log Likelihood	-66291	-61547		-60132		-60060	
R^2	0.057	0.039		0.036		0.166	

Notes:
† = profile confidence interval does not include 0
ICC= .7162
n observations = 9,341, n subjects = 542

Table E5.5

Mixed-Effects Regression Models: Burglary Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	524.34† (14.68)	563.21† (24.12)		557.34† (25.25)		562.26† (23.90)	
Time	-32.77† (0.84)	-28.80† (0.50)	0.105	-28.58† (1.41)	0.098	-28.68† (1.36)	0.120
Social disorg.						58.51† (5.81)	0.072
Random effects	Est.	Est.		Est.		Est.	
Department		268700†		282845†		247571†	
Time				777†		725†	
Residual		109209†		76881†		77750†	
Log Likelihood	-73862	-69225		-68117		-68080	
R^2	0.139	0.105		0.098		0.190	

Notes:
† = profile confidence interval does not include 0
ICC= .7110
n observations = 9,456 , n subjects = 541

Table E5.6

Mixed-Effects Regression Models: Larceny Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	1993.41† (37.75)	2025.00† (62.50)		2038.61† (59.15)		2042.20† (58.80)	
Time	-79.80† (2.16)	-75.30† (1.30)	0.107	-73.07† (3.62)	0.097	-73.20† (3.60)	0.099
Social disorg.						46.20† (15.70)	0.006
Random effects	Est.	Est.		Est.		Est.	
Department		1808369†		1506555†		1484056†	
Time				5198†		5108†	
Residual		723466†		496780†		497793†	
Log Likelihood	-82579	-77972		-76732		-76728	
R^2	0.127	0.107		0.097		0.109	

Notes:
† = profile confidence interval does not include 0
ICC = .7143
n observations = 9,432, n subjects = 541

Table E5.7

Mixed-Effects Regression Models: Motor-Vehicle Theft Reports and Absolute Representation

	Unconditional model	Random-intercept model		Random-intercept & trend model		Disorganization model	
Fixed effects	Est. (SE)	Est. (SE)	SP R^2	Est. (SE)	SP R^2	Est. (SE)	SP R^2
Intercept	148.29† (9.26)	185.92† (14.46)		185.25† (14.28)		186.96† (14.09)	
Time	-24.03† (0.53)	-20.81† (0.34)	0.141	-20.27† (0.97)	0.128	-20.40† (0.95)	0.145
Social disorg.						28.01† (3.54)	0.041
Random effects	Est.	Est.		Est.		Est.	
Department		93285†		86475†		83540†	
Time				385†		370†	
Residual		47189†		29394†		29548†	
Log Likelihood	-68735	-64519		-62897		-62871	
R^2	0.179	0.141		0.128		0.186	

Notes:
† = profile confidence interval does not include 0
ICC = .6641
n observations = 9,356, n subjects = 541

VITA

Alicia L. Jurek, Ph.D.

EDUCATION

2015- 2020 **Doctor of Philosophy, Criminal Justice and Criminology**
Sam Houston State University
Dissertation: Minority representation in policing: Integrating representative bureaucracy and structural contingency theories
Chair: Dr. William R. King
Graduation: December 2020

2013- 2015 **Master of Arts, Criminal Justice and Criminology**
Sam Houston State University
Thesis: Police agency responses to human trafficking as a function of gendered police agency & community attributes
Chair: Dr. William R. King

2010- 2013 **Bachelor of Science**
Sam Houston State University
Major: Criminal Justice, *Minor:* Psychology
Honors Thesis: International terrorism: Terrorist and extremist groups in Africa and the Middle East, risk assessment, and prevention and mitigation of terrorist threat
Chair: Dr. William R. King

RESEARCH INTERESTS

Police organizations; Organizational theory; Representative bureaucracy; Gender, race, and the criminal justice system; Criminal investigations

PEER-REVIEWED PUBLICATIONS

Henry, T. S., & **Jurek, A. L.** (2020). Identification, corroboration, and charging: Examining the use of DNA evidence by prosecutors in sexual assault cases. *Feminist Criminology, 15*(5), 634-658.

Jurek, A. L., & King, W. R. (2020). Structural responses to gendered social problems: Police agency adaptations to human trafficking. *Police Quarterly*, *23*(1), 25-54.

Matusiak, M. C., & **Jurek, A. L.** (2017). Does agency type matter? A comparison of chiefs' perceptions of the institutional environment across three agency types. *Policing & Society*, *29*(3), 349-364.

Jurek, A. L., Matusiak, M. C., & Matusiak, R. E. (2017). Structural elaboration in police organizations: An exploration. *Policing: An International Journal of Police Strategies & Management*, *40*(2), 351-365.

Franklin, C. A., Brady, P. Q., & **Jurek, A. L.** (2017). Responding to gendered violence among college students: The impact of participant characteristics on direct bystander intervention behavior. *Journal of School Violence, 16*(2), 189-206.

Under Review

Davis, R. C., **Jurek, A. L.**, Shadwick, J. T., & Wells, W. Investigative outcomes of CODIS matches in previously untested sexual assault kits.

In Preparation

Brady, P. Q., King, W. R., & **Jurek, A. L.** The job, the whole job, and nothing but the job: Examining the role of social support, work-family conflict, and burnout among a national sample of police chiefs. In preparation for a special issue in *Policing: An International Journal.*

Jurek, A. L. Toward a model of the microfoundations of organizational legitimacy: Measuring propriety and validity.

Jurek, A. L., Kelley, S., & Wells, W. Investigative effort in sexual assault cases.

Jurek, A. L., Matusiak, M. C., & King, W. R. Distal crises as local stimuli in police agencies: A pre- post analysis of institutional sector dynamics.

NON-REFEREED PUBLICATIONS

Jurek, A. L., Shadwick, J. T., & Wells, W. (2019). Policing major cities in Texas. Bill Blackwood Law Enforcement Management Institute of Texas. College of Criminal Justice. Sam Houston State University.

Jurek, A. L., Shadwick, J. T., & Wells, W. (2018). Employee care and work place incentives: Report on the Montgomery County Constables Office, Precinct 3 Employee Survey. Bill Blackwood Law Enforcement Management Institute of Texas. College of Criminal Justice. Sam Houston State University.

Jurek, A. L., & King, W. R. (2018). The Texas Chiefs of Police Panel Project: Wave II executive summary. Bill Blackwood Law Enforcement Management Institute of Texas. College of Criminal Justice. Sam Houston State University.

King, W. R., & **Jurek, A. L.** (2017). Out of business: The prevalence of disbanded police agencies and its consequences for sheriffs. *Sheriff & Deputy Magazine, 68*(2), 22-23.

Jurek, A. L., Matusiak, M. C., & King, W. R. (2017). Local police agency response to distal crises. Bill Blackwood Law Enforcement Management Institute of Texas. College of Criminal Justice. Sam Houston State University.

Jurek, A. L., & King, W. R. (2016). The Texas Chiefs of Police Panel Project: Research summary. Bill Blackwood Law Enforcement Management Institute of Texas. College of Criminal Justice. Sam Houston State University.

Jurek, A. L. (2016). Police responses to human trafficking. Crime Victims' Institute. College of Criminal Justice. Sam Houston State University.

Jurek, A. L., & Franklin, C. A. (2014). Human traffickers, buyers, and sex tourism. Crime Victims' Institute. College of Criminal Justice. Sam Houston State University.

King, W. R., Wells, W., & **Jurek, A. L.** (2014). Improving NIBIN: Responses from NIBIN partner sites: A short report prepared for the Bureau of Alcohol, Tobacco, Firearms, and Explosives, and Forensic Technology, Inc.

FUNDED RESEARCH

Research assistant (June 2019 – August 2020): "Kansas City Crime Gun Intelligence Center (CGIC) initiative." Board of Police Commissioners- Kansas City Police Department (Research partner: University of Missouri, Kansas City; Principal Investigator: Novak, K. J.). BJA award number 2017-DG-BX-0001. $131,934.

Independent consultant (July 2017 – September 2019): "A new approach to utilizing evidence from sexual assault kits in Texas: Benefits and costs of a universal testing statute." Police Foundation (Project director: Davis, R. C.). NIJ award number 2016-IJ-CX-0019. $235,794.

Research assistant (September 2013 – December 2013): "Opening the black box of NIBIN: A process and outcome evaluation of the use of NIBIN and its effects on criminal investigations." King, W. R., Wells, W., Katz, C., Maguire, E. R., & Frank, J. NIJ award number 2010-DN-BX-0001. $341,807.

Under Review

Grant Writer (August 2020 – September 2020): "Venspirator- A new paradigm in respiratory care for COVID-19. Dalton, J. Submitted September 8, 2020 to NIH under PHS 2020 Omnibus Solicitation of the NIH, CDC and FDA for Small Business Innovation Research Grants.

Unfunded applications

Jurek, A. L. "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of gender, racial, and ethnic minority representation on index offenses, 1987 – 2014." NIJ Graduate Research Fellowship Program, Solicitation NIJ-2019-15466.

Jurek, A. L. "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of gender, racial, and ethnic minority representation on index offenses, 1987 – 2014." BJS Graduate Research Fellowship Program, Solicitation BJS-2019-16229.

Jurek, A. L. (2019). "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of minority representation on index offenses." Harry Frank Guggenheim Foundation Dissertation Fellowship.

Jurek, A. L. (2018, 2019). "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of gender, racial, and ethnic minority representation on index offenses, 1987 – 2014." ASC DWC *Feminist Criminology* Graduate Research Scholarship.

Jurek, A. L. (2018, 2019). "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of gender, racial, and ethnic minority representation on index offenses, 1987 – 2014." ASC DWC Larry J. Siegel Graduate Fellowship for the Study of Gender and Crime.

Jurek, A. L. (2018). "Structural adaptation in police agencies and crime control: A longitudinal analysis of the causes and effects of gender, racial, and ethnic minority representation on index offenses, 1987 – 2014." NIJ Graduate Research Fellowship Program, Solicitation NIJ-2018-13640.

RESEARCH ASSISTANTSHIPS

Graduate Research Assistant Bill Blackwood Law Enforcement Management Institute of Texas (LEMIT) (June 2015- Present): Dr. William Wells

- Project Manager: Texas Chiefs of Police Panel Project
- Project Assistant: Montgomery County Constables Precinct 3 Employee Survey

Graduate Research Assistant (August 2013- May 2015): Dr. William R. King

- Project Assistant: Texas Chiefs of Police Panel Project
- Data archivist: "A process and outcome evaluation of the use of NIBIN and its effects on criminal investigations in the United States, 2006 – 2012." NIJ award 2010-DN-BX-0001

INVITED PRESENTATIONS

Jurek, A. L. (2019, April 10). Network analysis. Presentation to the Criminal Justice Graduate Student Organization, Sam Houston State University.

Jurek, A. L. (2019, April 4). Women in criminal justice organizations. Presentation to E. O'Neal's Gender and Crime class, Sam Houston State University.

Jurek, A. L. (2019, March 28). Sexual assault kits and the criminal justice system. Presentation to N. Niebuhr's Victimology class, Sam Houston State University.

Brady, P. Q., King, W. R., & **Jurek, A. L.** (2019, March 22). The job, the whole job, and nothing but the job: Findings from SACOP's national survey of police chief burnout. Preliminary findings presented at the International Association of Chiefs of Police's State Associations of Chiefs of Police's 2019 Division Midyear Conference in Austin, Texas.

Jurek, A. L. (2017, September 22). The Ph.D. decision brown bag. Presentation to the Criminal Justice Graduate Student Organization, Sam Houston State University.

Jurek, A. L. (2017, April 7). Network analysis. Presentation to the Criminal Justice Graduate Student Organization, Sam Houston State University.

Jurek, A. L., & Dittmann, W. L. (2015, September 11). Thesis workshop. Presentation to the Criminal Justice Graduate Student Organization, Sam Houston State University.

CONFERENCE PRESENTATIONS

Jurek, A. L. (2019, November). Structural adaptation in police agencies and crime control: A longitudinal analysis. Paper presented at the meeting of the American Society of Criminology, San Francisco, CA.

Kelley, S., **Jurek, A. L.**, & Wells, W. (2019, November). Investigative effort in sexual assault cases. Paper presented at the meeting of the American Society of Criminology, San Francisco, CA.

Bostaph, L. G., **Jurek, A. L.**, Krieg, A., & Matusiak, M. C. (2019, September). Academic careers: There are no bad questions. Roundtable presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L. (2019, September). Police representation and crime reporting: A longitudinal analysis. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L., & Henry, T. S. (2018, November). Identification, corroboration, and charging: Examining the use of DNA evidence by prosecutors in sexual assault cases. Paper presented at the meeting of the American Society of Criminology, Atlanta, GA.

Jurek, A. L., & King, W. R. (2018, September). Female representation in U.S. police departments, 1980 – 2010. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L., & King, W. R. (2017, November). The microfoundations of institutional theory in policing: A novel measurement proposal (using network analysis). Paper presented at the meeting of the American Society of Criminology, Philadelphia, PA.

Jurek, A. L. (2017, September). Court processing in the United States: Insights and future directions from organizational theories. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L., Matusiak, M. C., & King, W. R. (2017, March). Local police agency response to distal crises in policing. Paper presented at the meeting of the Academy of Criminal Justice Sciences, Kansas City, MO.

King, W. R., & **Jurek, A. L.** (2016, November). The population ecology of local police agencies in the United States: An empirical examination. Paper presented at the meeting of the American Society of Criminology, New Orleans, LA.

Matusiak, M. C., & **Jurek, A. L.** (2016, November). Does agency type matter? A comparison of chiefs' perceptions of the institutional environment across three agency types. Paper presented at the meeting of the American Society of Criminology, New Orleans, LA.

Jurek, A. L. (2016, September). Correctional institutions as organizations and their influence on inmate assaults. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L., & Matusiak, M. C. (2016, March). Structural elaboration in police organizations: An exploration. Paper presented at the meeting of the Academy of Criminal Justice Sciences, Denver, CO.

Jurek, A. L., & King, W. R. (2015, November). Police agency adaptation: The influence of gendered organizational and community factors on responses to human trafficking. Paper presented at the meeting of the American Society of Criminology, Washington, DC.

Jurek, A. L., & King, W. R. (2015, September). Police agency response to human trafficking. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

Jurek, A. L., & King, W. R. (2015, March). Gendered organizational environment as a determinant of police agency adaptation. Paper presented at the meeting of the Academy of Criminal Justice Sciences, Orlando, FL.

Ashworth, L., **Jurek, A. L.**, Brady, P. Q., & Franklin, C. A. (2015, March). Preventing sexual assault: Correlates of bystander intentions to intervene. Poster presented at the meeting of the Academy of Criminal Justice Sciences, Orlando, FL.

Jurek, A. L., & Gerber, J. (2014, November). "It wasn't rape:" Rapists' neutralizing techniques for sexual assault. Paper presented at the meeting of the American Society of Criminology, San Francisco, CA.

Jurek, A. L., (2012, September). Terrorist and extremist groups in Africa and the Middle East: An assessment in the era of Arab Spring. Paper presented at the meeting of the Midwestern Criminal Justice Association, Chicago, IL.

TEACHING EXPERIENCE

Instructor of Record

- Introduction to Methods of Research (CRIJ 3378): Sam Houston State University, Huntsville, TX
- Criminology (two-week course): Zhejiang Police College, Hangzhou, China

Teaching Assistant

- Victimology (CRIJ 3350): Sam Houston State University (Instructors of record: Cortney A. Franklin, Kelly E. Knight)

PROFESSIONAL DEVELOPMENT

"16th Annual Diversity Leadership Conference." (2020, February 21 – 22). Sponsored by the Sam Houston State University Center for Diversity and Intercultural Affairs. Huntsville, TX.

"Division on Women and Crime Professional Development Panel for Graduate Students and Early Career Feminist Scholars." (2019, November 14). American Society of Criminology Division on Women & Crime Professional Development panel, sponsored by ASC DWC. Presented by Mona Danner, Vera Lopez, and Nancy Wonders. San Francisco, CA.

"A Campus-Wide Response to Sexual Misconduct: Best Practices." (2019, August 7). Forensic Technology Center of Excellence, a program of the National Institute of Justice in collaboration with RTI International, webinar taught by Elizabeth Seney.

"Introduction to Data Analysis and Graphics Using R." (2019, May 28 – 31). University of Texas at Austin, Department of Statistics and Data Sciences Summer Statistics Institute, taught by Steven V. Hernandez. Austin, TX.

"Teacher Training Workshop." (2018, November 16). American Society of Criminology Division on Women & Crime Professional Development panel, sponsored by ASC DWC Committee on Teaching and Pedagogy and moderated by Allison Foley. Atlanta, GA.

"Longitudinal Data Analysis, Including Categorical Outcomes." (2018, August 6 – 10). ICPSR summer workshop, taught by Donald Hedeker. Ann Arbor, MI.

"FERPA." (2018, March 7). Teaching Assistant Certification Series. Sam Houston State University, taught by Rhonda Beassie. Huntsville, TX.

"Teaching and Learning with Technology." (2018, March 30). Teaching Assistant Certification Series. Sam Houston State University, taught by Drs. Kimberly Laprare and Marilyn Rice. Huntsville, TX.

"ACJS Doctoral Summit." (2018, February 15 – 17). 7.5-hour professional development workshop hosted by the Academy of Criminal Justice Sciences. Program facilitator: Dr. Heather Pfeifer. New Orleans, LA.

"Journal Manuscript Reviewer Training Workshop." (2016, November 17). Sponsored by the ASC Division on Women and Crime, taught by Drs. Rosemary Barberet and Francis Bernat. New Orleans, LA.

"Teaching Online: Strategies for Success." (2016, November 2 (completed)). 40-hour training on teaching online with Blackboard, taught by Jacob Spradlin.

"Introduction to Network Analysis: Study Design and Methods." (2016, July 25 – 29). ICPSR summer workshop, taught by Bernice A. Pescosolido and Ann McCranie. Bloomington, IN.

"Going Places with Spatial Development." (2016, June 22). Online course offered by Esri and Udemy, taught by Linda Beale and David DiBiase.

SERVICE

Field

- Host and driver (2019). Polish National Police Delegation to Sam Houston State University.
- Curriculum design assistant. (2016 – 2019). Texas Major Cities Police Chief Leadership Series.
- Project manager. (2015 – 2019). Texas Chiefs of Police Panel Project.
- Project assistant. (2017 – 2018). Montgomery County Constables Precinct 3 Employee Survey.
- Volunteer (2017). 27th Annual Problem-Oriented Policing Conference, Houston, TX.

Department

- Undergraduate mentor (2019). SHSU Criminal Justice Graduate Student Organization – Lambda Alpha Epsilon research partnership.
- Peer mentor (2014 – 2015, 2016 – 2019). SHSU Criminal Justice Graduate Student Organization.
- Committee chair (2017 – 2019). SHSU Criminal Justice Graduate Student Organization – Lambda Alpha Epsilon research partnership.
- Committee member (2017 – 2019). Walk a Mile in Her Shoes. Sam Houston State University.
- Peer tutor (2018). Advanced Statistics I.
- Student representative (2014 – 2018). SHSU Department of Criminal Justice and Criminology faculty search committee.
- Event organizer (2017 – 2018). SHSU Criminal Justice faculty-graduate student fundraising competition.

Professional

- Judge (2020). Student Paper Competition. Midwestern Criminal Justice Association Student Paper Competition Committee, Virtual event.

- Judge (2019). Undergraduate Student Poster Competition. Midwestern Criminal Justice Association Student Poster Competition Committee, Chicago, IL.
- Volunteer (2016 – 2017). Criminal Justice Career and Graduate School Fair, Midwestern Criminal Justice Association, Chicago, IL.
- Judge (2017). Undergraduate Student Paper Competition. Midwestern Criminal Justice Association Student Paper Competition Committee.
- Volunteer (2017). Employment Exchange. Academy of Criminal Justice Sciences, Kansas City, MO.

Community

- Letter Writer (2020). Vote Forward.

Journal Reviews

Journal of Family Violence, Journal of Crime & Justice, Journal of School Violence, Justice Quarterly

AWARDS AND SCHOLARSHIPS

2018 – 2020	John Lee McMaster Criminal Justice Scholarship
2013 – 2020	Sam Houston State University Graduate Fellowship
2019	Association of Doctoral Programs in Criminology and Criminal Justice Student Research Award
2019	Bertha Turner and Beulah East Scholarship. American Association of University Women, Huntsville, Texas Branch
2018	Graduate Student Poster Award. Division on Women & Crime, American Society of Criminology
2017, 2018	Honorable Mention Graduate Student Paper Award. Midwestern Criminal Justice Association
2017 - 2018	O.B. Ellis – J. Philip Gibbs Memorial Scholarship
2017, 2018	Sam Houston State University Graduate Studies Scholarship
2015, 2016, 2018	SHSU Criminal Justice Graduate Student Organization Travel Scholarship
2015 – 2017	Rolando, Josefa, & Jocelyn del Carmen Doctoral Criminal Justice Scholarship
2016	Outstanding Graduate Student Paper Award: Midwestern Criminal Justice Association

2016	Sam Houston State University Graduate Studies Scholarship
2016	Excellence in Writing Award, Sam Houston State University
2015	Outstanding Graduate Student Paper Award. Midwestern Criminal Justice Association
2014	Alternate: Joseph E. Pryor Graduate/Alumni Fellowship Alpha Chi National College Honor Scholarship Society
2013	Third alternate: H.Y. Benedict Fellowship Alpha Chi National College Honor Scholarship Society
2013	Magna Cum Laude, Highest Honors Sam Houston State University
2012 – 2013	Criminal Justice Undergraduate Research Fellowship
2010 – 2013	Elliot T. Bowers Honors College Scholarship
2011 – 2012	100 Club Criminal Justice Scholarship
2010 - 2012	Sam Houston State University Transfer Scholarship
2008 – 2012	Sunshine Ladies Foundation Scholarship

PROFESSIONAL AFFILIATIONS

Academy of Criminal Justice Sciences
- Minorities & Women Section
- Police Section

American Association of University Women

American Society of Criminology
- Division of Critical Criminology & Social Justice
- Division of People of Color & Crime
- Division of Policing
- Division on Women & Crime

International Association of Chiefs of Police

Midwestern Criminal Justice Association

INTERNSHIPS

2013	Naval Criminal Investigative Service, Corpus Christi, TX

2010	Feminist Majority Foundation: National Center for Women and Policing, Arlington, VA