Exploring group-threat and police-involved homicide: a spatial analysis of police involved homicide in US counties

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EXPLORING GROUP-THREAT AND POLICE-INVOLVED HOMICIDE: A SPATIAL ANALYSIS OF POLICE INVOLVED HOMICIDE IN US COUNTIES

By

Kyle Maksuta

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ABSTRACT

The recent advent of the Black Lives Matter movement has reinvigorated criminological inquiry into police violence. Recent advances in spatial analysis have opened new opportunities for understanding the spatial relationship between social structure and police violence. Spatial analysis is both statistically and substantively important to our understanding of police-involved-homicide (PIH), yet few studies have attempted to marry recent advances in spatial econometrics to this topic. The current study introduces spatial Durbin modeling (SDM) as a particularly useful approach to studying the spatial relationships between variables associated with group threat theory and PIH. Previous research has demonstrated the connections between group threat and PIH, however, the relationship has been tenuous. The incorporation of spatial factors into the equation allows for greater precision in our understanding of not only why these tragic events occur, but also where. To answer these questions, I build on previous research incorporating crowdsourced data on PIH from 2013-2019, with data from the 2012 American Community Survey, and the 2012 Uniform Crime Report. Findings from this study suggest that racial threat is not a significant predictor of police-involved homicide. Additionally, I find that economic threat, specifically the Gini coefficient and concentrated disadvantage exhibit significant direct effects on police-involved homicide, but the Gini coefficient also exhibits a significant positive indirect effect on police-involved homicide. Violent crime also exhibits a significant positive indirect effect. Overall, the present study sheds light on the effects of neighboring counties on focal county police-involved homicide and extends the application of group-threat into the spatial realm.
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CHAPTER 1: INTRODUCTION

“She had wanted her son to stand for what he believed and to be respectful. And he had died for believing his friends had a right to play their music loud, to be American teenagers.”
---Ta-Nehisi Coates, *Between the World and Me*

August 9, 2014, 18-year-old Michael Brown is shot and killed by a police officer in Ferguson Missouri after what police describe as a struggle. November 22, 2014, Tamir Rice, a 12-year-old Black kid, was shot and killed by 26-year-old White Cleveland Police Officer Timothy Loehmann because Tamir was holding a replica toy gun. On May 25, 2020, George Floyd was murdered by Minneapolis police after a White officer knelt on his neck for 9 minutes and 29 seconds. The incident was caught on cellphone video and has since spread to nearly every part of the world, revived the Black Lives Matter movement to front pages and televisions across the United States, and spurred on police reform within the same department in which the killing took place and across the country. On that same day, Amy Cooper, a White woman walking through New York City’s Central Park, called the police to report that a Black man, Christian Cooper who was an avid birdwatcher, was threatening her after he asked her to put her dog on a leash (Booker 2020). In each of these cases, an individual who was Black was identified as a threat, and action was taken against them. In three of the cases, the Black individual was killed.

Research has shown that people of color are, and have been historically, more likely to experience police-involved harm than Whites (Edwards, Esposito, and Lee 2018). This unfortunate reality has been largely driven by police shootings of young Black men. According to a recent study of police homicides between 2012 and 2018, Black men were killed at a rate of 2.1 per 100,000 compared to 0.6 per 100,000 for White men (Edwards et al. 2018: 1243). Using crowdsourced data, the authors estimated mortality risk from police homicide and found that Black
men had an estimated risk between 1.9 and 2.4 per 100,000 compared to 0.8 to 1.2 for Latino men, and 0.6 to 0.7 for White men (Edwards et al. 2018: 1243). Edwards, Lee, and Esposito (2019: 16793) find that the lifetime risk of being shot and killed by police for a Black male is 1 in 1,000. The extent to which police play a role in homicide has often been downplayed, with official estimates purporting around 4 percent of homicides each year are the result of police intervention. However, recent data has estimated that this number may be closer to 8 percent. Overall, police-involved homicide accounts for 0.05 percent of all male deaths in the US, but ratios of police-involved homicide are strongly correlated with both race and sex (Edwards et al. 2019). Official data from the Centers for Disease Control and Prevention (CDC) indicate that from at least, 1999 through 2017, homicide has been the leading cause of death among Black men between the ages of 15 to 34. The reality is that a Black man is more likely to die at the hands of another person, and more often at the hands of a police officer, than their White counterparts who are more likely to die from an accident or suicide (Edwards et al. 2018; Edwards et al. 2019).

The costs of police homicide are multiplicative, and range from the financial costs to families, communities, and municipalities where the homicides take place; the mental and physical costs to repair the harm caused; and as has historically been demonstrated, the civil unrest which may occur especially when the homicide is understood by the community to be unjustified. Recent shootings, including those identified above, have captured the nation’s attention, with much of the debate centered on the role of police in these shootings. Within the media sphere, narratives surrounding police-involved homicides reduce these encounters down to what Edwards et al. (2018: 1246) call "moments of crisis." These narratives have the effect of individualizing these occurrences to situations where the victim is shot because law enforcement personnel either feared for their life or the lives of others. However, the individualizing of these narratives masks the "broader social
forces that lead to distinct geographic and racial inequalities in police homicide (Edwards et al. 2018: 1246)."

While there is a long history of social science research exploring the causes and consequences of police-involved homicide, only recently has research begun to explore the significance of space and place. A recent study by Ross (2015) examines racial bias in police shooting incidents, using county-level data across the United States. Results from the analysis indicate a higher probability of unarmed Black Americans being shot compared to unarmed White Americans. Furthermore, and important as it related to the spatial relationships of police shootings, data demonstrate a high level of heterogeneity across counties, with some exhibiting relative risk ratios of 20 to 1 or more. While data indicate the presence of racial bias, the data also indicates no relationship between county-level crime and county-level racial bias in police shootings. This finding is at odds with previous studies and may be a result of the level of analysis used in the study. Another study by Klinger et al. (2016) tested the extent to which neighborhood characteristics influence an officer’s decision to shoot a suspect using data from 2003 through 2012 from St. Louis. Of the 230 officer-involved shooting incidents in their study, across 355 census blocks, Klinger et al. (2016) found that the majority of incidents involved White male officers and young Black male suspects. According to the descriptive data, most incidents involved suspicious behavior on the part of the suspect. However, shifting back to the aggregate level, Klinger et al. (2016) found that shootings were more likely to take place in socioeconomically disadvantaged neighborhoods, with larger Black populations, with high levels of firearm violence. Spatially, the study indicates that violence across spatial units only matters insofar as it relates to firearm violence in the focal neighborhood. In other words, firearm violence exhibits spatial dependence. However, there are concerns
regarding the interpretation of spatially lagged dependent variables in OLS models, as I will discuss later.

Lastly, a study by Edwards et al. (2018) estimates the risk of mortality from police homicide using a novel crowdsourced dataset capturing police-involved homicides from 2012 through 2018. The authors estimate Bayesian multilevel negative binomial regression models of police homicide with adult male victims at the county level. While they do not examine mortality spatially, they do explore regional variation in homicides. Some notable findings, in addition to those already discussed above, were that there were large regional and spatial variations in police homicides. For example, counties in the Middle Atlantic region had a median predicted risk ratio of 8.2 Black adult male police homicide victims for every White adult male, while similarly sized large central metro areas in the East South Central regions had among the lowest estimated Black relative adult mortality risk ratio at around 3. Overall, the Black male predicted risk ratio for metropolitan groups was at least 4.3 times greater than the White risk (Edwards et al. 2018: 1244).

The findings in these studies are important for multiple reasons. First, while police-involved homicides are often depicted as the result of individual-level behaviors and choices, data point toward a more systemic issue that is both spatially and socially dependent. Second, in order to address the issues endemic with police-involved homicide, it is necessary to understand where these issues are occurring and the factors influencing them. Third, sociological and criminological research has consistently shown that place matters, and that it is a key input to the well-being of communities and the individuals living in them. By focusing on these places, we may be able to better allocate finite resources to help these communities and the law enforcement agencies tasked with their protection. However, they have still left large gaps in the research yet to be explored.
Critiques of current police-involved homicide research can be grouped into two distinct areas. First, many studies exploring police shootings are largely descriptive, and focus on situational factors, instead of the macro landscape of police shootings. Research findings within this area are largely mixed, with studies purporting racial bias in some cases, in some places, during specific time periods, and other studies finding racial bias or at least, disproportionality in minority police contact and homicide (Liska and Yu 1992; Legewie and Fagan 2016; Klinger et al. 2016; Jacobs and O’Brien 1998; Lautenschlager and Omori 2019; Gray and Parker 2020; Helms and Constanza 2020; Holmes et al. 2019). However, studies that do approach the topic from a more macro-oriented perspective, often approach the topic from an atheoretical perspective. Furthermore, even fewer studies exploring police shootings attempt to do so by understanding and examining the way place and space interact with one another to influence where police shootings take place. Those that do, do so without help from social theory, and thus are limited in their explanatory power (Ross 2015, Klinger et al. 2016). My study aims to address this concern by directly incorporating and testing the relevance of group threat theory to police-involved homicides. This is not to say that studies focusing on the individual level are wrong, or unwarranted. On the contrary, they simply approach the question of what factors influence police-involved homicide from a different perspective, often time focusing on characteristics of the suspect, encounter, or law enforcement officer. Often these studies provide insight into the tragic events that play out across the United States, while also framing events at the micro-level. However, the stunning regularity of these events begs for the exploration of how these individual-level encounters are structured by larger social forces. Group-threat theory provides an initial theoretical framework through which to understand how these events are structured at the macro-level, and previous work has indicated that group-threat is an important predictor in social control outcomes.
Building on previous work within group-threat theory, my study will attempt to understand and incorporate spatial econometrics into the theory. To date, only one study has spatially analyzed police-involved homicide from a theoretical perspective (Klinger et al. 2016), by incorporating spatial lag variables into OLS regression models, and spatially isolated to one state. While I will discuss this at length, I plan to introduce the spatial Durbin model (SDM) as a potentially useful approach to exploring the spatial relationship between group threat and PIH. The importance of studying PIH from a spatial perspective cannot be understated, as previous studies on PIH may be misleading because of modeling issues associated with spatial dependence, ignoring the potentially important relationships between spatial neighbors. Again, I will explore this later when I discuss spatial spillover and social relativity.

The second major issue within the literature relates to the numerous data and methodological limitations which have plagued this field for nearly seven decades. The significance of data limitations cannot be overstated, as a recent study by Gray and Parker (2019) found. In their study, they compare the official Federal Bureau of Investigation’s (FBI) Supplemental Homicide Report (SHR) to the new Mapping Police Violence (MPV) unofficial database. I will discuss the MPV dataset later as it is the basis for the analysis of my study. That said, the results from their study highlight the important differences between official and unofficial data. First, criticism of official data on police homicides is well documented (Fyfe 2002), but the stark contrasts between official and unofficial data become more visible when the data on police shootings is disaggregated by race. Specifically, the SHR underreports police shootings and represents a "lower level of racial disparities in rates than what is found in the MPV data” (Gray and Parker 2019: 41). They go on to note that analyses using the SHR may produce inconsistencies concerning the structural features influencing police shootings of Blacks and Whites. For example, when examining Black victims
of police homicide, the measures of percent Hispanic and unemployment rate are statistically significant in SHR models, but not in MPV models. It is important to note that Gray and Parker (2019) examine this data at the state level, which may also mask some of the structural differences at smaller units of analysis. However, differences in effect sizes and significance across models are still readily apparent. This issue has been largely resolved in recent times, as many researchers have begun to turn to crowd-sourced based data. In line with this shift, I plan to utilize the MPV dataset.

Building on concerns with data and methodology, some recent studies have sparked debate on how to conceptualize, operationalize, and properly incorporate police-involved homicide into statistical analysis. Notably, the works of Fryer (2016; 2018), Cesario, Johnson, and Terrill (2019), Knox and Mummolo (2019), Knox, Lowe, and Mummolo (2020), Ross, Winterhalder, and McElreath (2018), and Feldman (2016), have tackled the question of adopting the proper risk set when analyzing police-involved homicide data. The idea is that when a researcher does not control for the proper risk set, results may lead the researcher to misrepresent their findings. While the debate on this topic is far from concluded, preliminary findings indicate that when calculating rates for inclusion in statistical models, the denominator used in the calculation can drastically alter findings. Fryer (2016; 2018) finds that when calculating rates based on arrest instead of population, the differences in police shootings between Black and Whites disappears. However, others have argued that this approach makes illogical assumptions and ignores and delegitimizes arguments that the criminal justice system treats some groups favorably and others less so (Feldman 2016; Knox and Mummolo 2019; Knox, Lowe, and Mummolo 2020; Ross, Winterhalder, and McElreath 2018). I tend to agree with the work of the latter authors and believe that the assumptions
underlying Fryer's work are important in stimulating debate around proper model specification and variable operationalization.

Overall, the literature on police-involved homicide is dominated by discussions surrounding individual events, situational characteristics, and largely descriptive analyses of who is most likely to be a victim. However, thanks to the work of Liska and Yu (1992), the application of group threat to PIH is more systematic than it was in the past. However, recent advancements in both data quality and methodological techniques now allow researchers to explore the structural determinants of PIH, building on previous research. Studies such as Ross (2015), Klinger et al. (2016), and Edwards et al. (2018) have together, identified a few key insights which require exploration. First, the findings from Ross (2015) indicate that the spatial relationship between police shootings and their local environment is significant. Klinger et al. (2016) build on this by identifying how race interacts with other environmental factors such as violence, and that this relationship is spatially dependent on both the focal neighborhoods and neighboring communities. Lastly, the work of Edwards et al. (2018) provides a bird’s eye view of police-involved homicide across the United States. Their work points to the need for additional research examining unofficial datasets and exploring the determinants of spatial inequalities across the United States. The current study seeks to fill these gaps by utilizing spatial econometric models to examine the determinants of police shootings across US counties from 2013 through 2019. I expect substantive theoretical contributions can be made through the incorporation of spatial econometrics.

**Research Objectives**

The current study builds on previous work in two important ways. First, the current study aims to elucidate the implications for group threat theory of the spatial relationships that are characteristic of police-involved-homicide. The importance of incorporating spatial econometrics
is significant for two specific reasons. The first reason is that previous nonspatial research that has applied the group threat perspective may be misleading because nonspatial statistical modeling does not account for spatial dependence, including omitted variable bias, such as the influence of neighbors on focal communities. To overcome this potential oversight, my study will test if spatial models outperform nonspatial models of group threat. The second substantive contribution of incorporating spatial econometrics is the potential to uncover theoretical linkages undetected by nonspatial models. Specifically, my study will test whether racial threat has spillover effects into neighboring counties, and the impact of threat on neighboring county PIH.

The second major contribution of this study is through my use of the novel spatial Durbin model (SDM). Previous spatial studies of PIH (Klinger et al. 2016; Ross 2015) have been limited in their methodological approach to studying spatial spillover. Notably, the work of Klinger et al. (2016) only includes a spatially lagged dependent variable in their OLS models. The issue with this approach is that it can be difficult to disentangle direct and indirect effects of independent variables. LeSage and Pace (2014) note that in research two model specifications are worth considering, the spatial Durbin error model (SDEM) or the spatial Durbin model (SDM). The SDM approach overcomes this methodological shortcoming by allowing me to tease out the direct and indirect effects of the independent variables on the dependent variable. This approach has not been attempted in the literature yet and may prove to be a superior method in both model fit and usefulness of interpretation of the findings. I will discuss this further in chapter 3.

Overview of Dissertation

My dissertation is comprised of four additional chapters. Chapter 2 is devoted to the theoretical foundations of group threat theory and a literature review of prior studies using group threat theory. Specifically, I will review the work of Hubert Blalock, who is the theorist most often associated
with the roots of group threat theory. In my review of group threat, I will also highlight important research topics that have been explored and neglected in the literature to date. I will conclude the chapter with how my study will build on this literature, while also filling gaps in previous theoretical development on group threat and social control, and finish with my main theoretical hypotheses.

Chapter 3 describes the data and methods used in the study of group threat and police-involved homicide. The beginning of the chapter will cover recent advancements in data of PIH, and the key advantages and drawbacks of using crowdsourced data. Next, I will describe how group threat is operationalized across multiple key studies, and how my data and variables are uniquely suited to answer my research questions. Third, I will examine how spatial analysis has been used to examine questions of group threat, and the usefulness of including spatial models in multivariate analysis, and why SDM is a useful tool for rectifying some of the spatial inconsistencies in other studies. Lastly, I will describe the analytical models I will use to examine and test my research questions and hypotheses.

Chapter 4 describes the results and main findings from the analysis. Specifically, this chapter begins with a descriptive analysis of key dependent and independent variables, including the extent of police-involved homicide in the current dataset. Following this, I examine initial nonspatial associations, and then begin my initial spatial exploration by testing for spatial autocorrelation, and mapping key independent variables to assess the extent of potential spatial relationships. Building on this, I turn to the spatial Durbin model for my last analysis and break down the findings into direct and indirect effects of group-threat on police-involved homicide.

Lastly, Chapter 5 discusses and ties together the main findings of the current study with the main research goals. Specifically, I outline key findings, and discuss how the findings contribute
and build on previous research in the field. Following that, I outline limitations of the current study, and potential avenues for future research.
CHAPTER 2. THEORETICAL FOUNDATIONS AND PRIOR RESEARCH:
SOCIAL CONTROL, GROUP THREAT, AND NEW DIRECTIONS

As frontline responders to crime and deviance, police are often thrust into situations that may result in loss of life and liberty, and while police use of deadly force is relatively rare, they are significant events, often drawing attention from mass media and other outlets. It is without a doubt that during times of political, economic, and social upheaval, these events take on even more significance as explicit signifiers of conflict between groups. The past few years have seen the emergence of more than a few notable deaths of Black individuals across the United States, such as Tamir Rice, George Floyd, and Breonna Taylor. Many of these recent tragedies were caught on tape, and they have since blown up across social media outlets and have even given rise to mass protests across the nation. As social scientists, it is our job to make sense of these tragic and more often senseless displays of violence perpetrated by members of the state. The study of police killings is not new, but that does not mean the literature on it is close to conclusive on why people of color are more likely to experience police harm than Whites, or why young Black men are more likely to die at the hands of police than in a car accident; or why young Black men are more than two times as likely to die from police homicide than their White counterparts. The emergence of the Black Lives Matter (BLM) movement, while only recently formed in 2013, represents a movement to end systematic racism and oppression, and to intervene in violence inflicted on Black communities. As social scientists, we may understand BLM as part of the larger social fabric, and a new rising force in the fight for equality, a fight that began long before 1960, but one which finds its roots in social perspectives of that time.
Since the 1960s, the conflict perspective has emerged as the dominant theoretical perspective when exploring topics related to minority group relations (Liska 1992). Pivotal to this perspective is the view that contemporary social relations are unequal and exploitative (Jacobs and Britt 1979). Furthermore, it is assumed that these unequal relations are maintained by force. As such, conflict theorists believe that violence is a "crucial element that sustains the unequal relationships” (Jacobs and Britt 1979: 403). This perspective assumes that some law violations are more threatening than others and that some people are more threatening than others. In turn, these threats are posited to produce greater levels of social control to counteract the threats. Conflict theory further posits that the state is an instrument of the ascendant classes (Jacobs and Britt 1979), and that law formulation and enforcement reflect the interests of the powerful (Liska and Yu 1992: 53).

Research exploring the factors associated with police-involved homicide (PIH) is as varied as the theories used to explain them. At the macro-level, group threat theory has emerged as the de facto explanatory model for PIH, with many studies applying the main tenets of the theory since the early 1960s. Some social scientists were critical of early studies within this area and described that literature as nothing more than an ill-defined and disorganized bank of knowledge that is poorly conceptualized and operationalized (Liska 1987). However, recent studies have begun to resolve these issues. Given the focus of this study is on spatially testing group threat theory and its applicability to PIH, I believe it is important to return to the roots of the theory and chart the theoretical development of group threat. Furthermore, it is imperative to elucidate the spatial component of group threat theory, an area that has been largely ignored within the literature. Specifically, I will review the work of Hubert Blalock, who is the theorist most often associated with the roots of group threat theory. In my review of group threat, I will also highlight important research topics that have been explored and neglected in the literature to date. I will then explore
potential spatial relationships between group threat and PIH. I will conclude this chapter with how my study will build on this literature, while also filling gaps in previous theoretical development on group threat and social control.

The Emergence of Group Threat Theory

During the 1960s questions on how to respond to and control crime were emerging (Liska and Yu 1992). Self-report surveys from the time identified that many Americans were concerned about crime and victimization (Liska 1992). Uniform Crime Report data indicated that crime rates had increased from 160 per 100,000 in 1960 to 364 per 100,000 in 1970, an increase of 227 percent. Also, during this period, and potentially as a direct response to concerns with crime and victimization, crime control activities and expenditures also increased. Data from 1950 to 1965 show that there were 1.9 police officers per 1,000 residents, but by 1975 there were 2.5. At the height of the civil rights movement during the 1960s, and rising racial tensions in the United States, scholars began to turn their eyes toward social theories exploring racial discrimination and conflict between groups.

Hubert Blalock’s (1967) work made a “concerted effort to lay the theoretical foundation for systematic empirical investigation of social processes involving unequal groups (Jackson 1992: 89).” Blalock’s essential argument was that unequal groups continually struggle for dominance and maintenance of their dominance with assistance from the resources they have or have access to. These resources may be financial or political, and both may be invoked to help protect themselves from those who might threaten their power.

Within Blalock's work is the idea that the majority will continually operationalize resources to maintain their power over a threatening minority. The threat derived from a particular minority group varies by place, time, and the specific characteristics of that minority group whether real or
perceived. Scholars who have elaborated on and tested the main facets of Blalock’s theory have done so by investigating the extent to which agents of social control such as the police, act to maintain power relationships. The impetus behind these studies is that fear of crime or victimization and loss of dominance plays an important role in majority groups mobilizing agents of social control as a means of maintaining power relationships. Often these fears, according to the empirical literature, emerge in similar situations and similar contexts. That is to say, as minority populations increase combined with high levels of inequality and poverty, dominant groups are more likely to perceive these disadvantaged groups as threatening to their way of life. More specifically, research within the area of minority group threat has outlined that the minority group presence, inequality, and poverty contribute to higher crime rates through processes described in social disorganization theory, structural theories, and conflict theory (Jackson 1992: 90). Taken together, the above processes give rise to fear of crime, and thus dominant groups act to maintain the current power relationship through the mobilization of resources, such as agents of social control like the police.

For example, research by Jackson (1989; 1992) examined how minority group visibility (measured as percent Black) influenced police force size and capital expenditures on policing. Using a national dataset of U.S. cities (n=288), the results indicated a positive relationship between Black visibility and crime rate, and police force size and capital expenditures on policing. However, the relationship was curvilinear and demonstrated that as the Black population reached fifty percent and greater, police force size and spending dropped significantly. This finding is reflected in Blalock’s initial work and is known as the nonlinearity hypothesis. The idea is that as the proportion of a minority population increases up to a certain point, the dominant group will see this as an increasing threat to them and will mobilize resources to combat the threat. However,
once the minority group reaches a threshold point, resource mobilization will drop off, as relationships between the groups become normalized. Jackson’s research is likely how Blalock would have envisioned his theory being applied, notably because of his apprehension with having his work misinterpreted. While Jackson’s work understands there to be a conflict between two groups, the conflict is one derived from a structural-functionalist perspective. The structural-functionalist perspective views resource allocation as a result of societal pressures to quell deviant and criminal segments of society. In the case of Jackson's work, capital expenditures on policing were positively associated with crime, but also with the increase in proportion Black population. While crime may be amenable to a straightforward interpretation (i.e. as crime increases, so does spending on crime to resolve it), the interpretation for increased capital appropriation to policing and increase in the Black population is not.

**Misinterpretations of Blalock**

While many descriptions of Blalock’s minority threat theory portray it as a conflict theory, an alternative framework may be put forth. Certainly, while there are elements of conflict theory in Blalock's work, including an entire chapter devoted to power and discrimination, his writing also borrows from the work of anomie and strain theorists, such as Merton directly, and Cloward indirectly. In fact, from the outset of Blalock’s chapter on power and discrimination, he argues against the use of Marxist conceptions of power, opting for a view of power as one situated in a "power contest" rather than a "power struggle." Specifically, Blalock states that he wants to "avoid a Marxian type of interpretation, namely, that discrimination results from a conscious, rational attempt on the part of elites to subordinate the minority to their interests. The processes involved are certainly more complex than this, and usually much more subtle” (Blalock 1967: 109). Given this realization, it is interesting that most researchers applying his theory have ignored this. Below
I will attempt to summarize Blalock’s theory of minority group relations, while also highlighting the more important elements of his theory which have been obfuscated by recent group threat literature.

At the base level of Blalock's theory is a discussion of economic and social theories, and their various assumptions for behavior. On the one hand, Blalock recognizes the importance of economic theory and the pleasure principle, that individuals will seek to satisfy their pleasures and minimize their pains; but additionally, Blalock contends that economic theory may be enriched with what he calls "status theories." Status theories refer to theories that identify that motivation is derived from cultural and social edicts which predispose us to act in ways in line with them. In other words, status theories understand behavior to be the result of the relationship between culturally prescribed goals, and the institutionalized means available to an individual in achieving those goals. For Merton, the imbalance between culturally prescribed goals and the institutionalized means of obtaining said goals results in anomie. For Merton, cultural goals and social structure may exist independently but work together to produce two main types of states: malintegrated states where there is a disjunction between the two; and integrated states where there exists a balance between the two. Anomie results from the malintegrated state, where generally there is an emphasis on a goal, but relatively little emphasis on legitimate means of obtaining said goal. According to Merton, crime and deviance are most likely to occur when an individual lacks access to legitimate means and must turn to illegitimate means of obtaining their goals. Cloward (1959) on the other hand, argues that Merton does not account for differential access to means. For instance, Cloward claims that even if certain groups of people have differential access to legitimate means of success, that does not mean that they automatically have access to illegitimate means. Drawing on Sutherland, Cloward (1959: 167-8) remarks that the genesis of a professional thief
does not reside simply in the inclination to steal. For Cloward, the thief becomes the thief when he is accepted by other thieves. According to Cloward and Ohlin (1960), the availability of illegitimate means is controlled by the availability of alternative opportunities, and the position of a person within the social structure. This is an important distinction between Cloward and Merton and provides a convenient segue into Blalock’s work.

Blalock, picking up on Merton’s work, contends that the imbalance between goals and means is dependent on competition between groups, which may manifest in various ways, such as direct discrimination and oppression against a minority group. Like Cloward, Blalock accepts the assumption that the availability of alternatives plays an important role in motivating people to act and rests much of his theoretical work on this assumption. As noted above, one of the key issues plaguing the group threat literature is the inadequate attention paid to theoretical constructs and the motivational impetus behind theoretical models. In tying this back to Merton and Cloward, both theorists seek to answer why people and groups act in a deviant way. For Merton, it is the result of an imbalance between goals and means, while Cloward understands it to be more complicated, and elaborates on a theoretical model which views access to means as an important motivating factor. Blalock, in building on this work attempts to explore Cloward's main contention that some groups lack access to means, by claiming that differential access to resources is dependent on a complex relationship between dominant and minority groups who compete against one another. Thus, the main question for Blalock is similar to Merton’s and Cloward’s in that he is attempting to answer why some groups may discriminate against others, while some do not. This is ultimately the most important question to answer when studying group threat and is at the heart of the issues within the current state of the literature.
What factors influence why certain groups discriminate against some groups but not others? At the heart of Blalock’s theory of minority group relations is the flexibility hypothesis. The flexibility hypothesis plays an important role throughout his theoretical discussion and is the main motivational force behind discriminatory actions. The flexibility principle seeks to integrate economic and status/cultural theories into a theory of minority discrimination. The thread which connects the rational aspects of economic theories and the non-rational parts of cultural theories is found in strain theory. For Blalock, individuals exist in a society that prescribes specific cultural goals and means of obtaining them. Strain emerges when the means of obtaining a goal are not available or limited, and thus to overcome this strain or imbalance between goals and means, an individual may act in a deviant manner. Blalock contends that as individuals and members of society we often have many goals, but that some of these goals are more important than others, and that some goals, by their inherent quality, can only be satisfied by a limited number of alternative means. He notes further that cultural goals can often only be satisfied by a limited number of alternative means. In other words, while the generalized economic theory views decisions as a balancing act between the benefits and drawbacks of actions, strain theory introduce wrinkles into the equation by limiting decisions to those which are culturally valued and achievable. Bringing the two together, Blalock suggests that people are likely to choose means of obtaining goals that are most efficient or produce the least amount of strain. However, this becomes more complicated when multiple goals are introduced, and the means of obtaining these goals are dependent on one another. For example, one may prefer specific means if those means are aligned with a goal that is more important to them than another goal. Blalock understands people to be consistently engaging in mental balancing between goals and means, assigning importance to some and not to others. In the end, Blalock resolves that individuals are more likely to take the easy way
out. That is to say, people will likely choose means which are the least resource-intensive, and still allow them to achieve their goal.

The question of importance is how do individuals determine which goals are more important, and which means to choose? The hypothetical scenario drawn by Blalock is instructive for the answer. Suppose we have an individual with two goals, each with equal importance, but one goal has three distinct means of achieving it with one specific mean being superior. On the other hand, the second goal has many different means but all of them are not obvious as to whether they will succeed. In this situation, some of the latter means may be compatible with the first goal, and some of them may not. Given this reality, it is more likely that someone would choose means which are most efficient in achieving the first goal, even if those means come from the second goal. In this way, we might find that the first goal may have a much more important effect in determining the means of the second goal because the means of the second goal are not as obvious. In defining the flexibility principle, Blalock (1967: 40) states that "those goals permitting the least flexibility as to choice among means may be expected to have the greatest influence in determining the direction of behavior, though not necessarily its intensity or persistence.”

The importance of the flexibility principle to Blalock’s work cannot be understated, as it sets the base assumptions for how discrimination against minority groups takes form. For this, Blalock provides two basic assumptions. The first is that for discrimination of minority groups to take place, (1) minorities must be directly relevant to at least some of the means to important goals, and (2) that these means are appropriate for large segments of the dominant group. In other words, for discrimination to take place, minority groups must be impeding the means of a dominant group, and that group must have limited alternatives to dealing with the issue other than through action such as discrimination.
Based on the flexibility principle, competition is the most salient factor contributing to discrimination. But an additional important distinction can be made for target selection. Blalock notes that it is assumed individuals will seek to minimize punishment for aggression against a target. In this way, minorities make for excellent scapegoats and are not as well protected as other potential targets. Borrowing from routine activities theory, a person or group is more likely to be victimized when they are available, there exists a likely offender, and a capable guardian is absent. In the case of minority group discrimination, Blalock assumes that minorities are more suitable targets in the sense that the social backlash for such actions against them is unlikely to result in serious punishment. At a macro-level, Blalock (1967: 43) states that minorities are "apt to be relatively unprotected by society at large." In moving toward a testable proposition, Blalock indicates that at the macro-level, as the level of frustration produced by strains increases, the greater the intensity of aggression there will be against a minority group.

**Power and Social Control**

The extent to which a specific group can resolve the conflict between themselves and another group is based on the level of resources each group has and the power each group must mobilize using their resources. Resources may take many forms, and the usefulness of a resource varies depending on the source of conflict between groups. According to Blalock, power originates from three sources: numbers, resources, and social organization. Numbers reflect the direct numerical population figures of a given group. Resources reflect the actual sources of power or those properties of the individual or group that provide the power potential or ability to exercise power. Resources include money, prestige, knowledge, competence, deceit, fraud, and/or natural/supernatural resources. Based on the flexibility hypothesis, the greater the level of resources, the greater the flexibility of choice, and thus the likelihood of discriminatory behavior
is reduced because goals have multiple avenues for satisfaction. In situations where a group does not have access to resources, it is more likely they will turn to illegitimate means if those means reinforce highly valued internalized societal goals. The last source of power is social organization. This concept is largely ambiguous in Blalock's work, and as such, will be put to the side for this study. But the concept is speaking to the idea that groups realize their vested interests in coming together and are thus able to pool resources in a way that is advantageous to all in the group. While ambiguous in Blalock’s work, theoretical development within the social disorganization literature over the past three decades has begun to shed light on how the social structure of communities influence their capacity for collective action. Notably Sampson, Raudenbush and Earls (1997) introduce the concept of collective efficacy, which is defined as the capacity and willingness of community to intervene on behalf of the common good. Sampson et al. (1997) identify key ecological concepts present in Bursik and Grasmick’s (1988) systemic model as key determinants, including residential stability, lack of concentrated disadvantage, and trust and solidarity among neighbors. Collective efficacy is important in that it provides a link between neighborhood characteristics, social control, and crime. In their article, Sampson et al. (1997) found that, collective efficacy mediated the relationship between neighborhood characteristics and crime. Another important point to make is that collective efficacy is not meant to be reducible to the individual level, this is to say that collective efficacy is an emergent property, fully realized at the neighborhood level. In practice, this is incredibly difficult to measure, especially at a macro-level given limitations in data.

**Summarizing Blalock**
Summarizing the work of Blalock is a monumental task, especially given the breadth of his theoretical writing on minority relations. In fact, by the end of his six-chapter book, there are 97 different theoretical propositions provided, covering a vast array of different social and racial topics. For example, at one point Blalock explores race and professional sports to understand the factors associated with competition and discrimination among minority athletes. In his example, he draws on the legacy of Jackie Robinson, the first Black athlete to break the color barrier in Major League Baseball. In many ways, each theoretical proposition is a hypothesis. Trying to break down all 97 propositions would be a herculean task and is beyond the scope of this work. However, some general summaries can be made about Blalock's work and its significance toward our understanding of racial discrimination and social control.

Blalock's theory is largely a strain theory that leans on general economic theory in explaining when and why people may engage in discriminatory behavior. At the heart of his theory is the idea that competition among different groups breeds strain, which leads to action. Action is largely determined by the power of different groups, which is measured as the level of resources a group has and the extent to which they can mobilize those resources to realize a specific goal. The mobilization of resources may take many forms, including the expansion of social control, such as higher per capita spending on police, the passing of laws that advantage themselves or using their resources to physically move away from a minority group. The option chosen is based on multiple factors including, perceived and real threat, the options available to the dominant group to realize their goals, and whether the options available are adequate to resolve the issue.

Ultimately, Blalock contends that researchers must attempt to measure and account for the flexibility in choice those in higher social classes enjoy. Blalock hypothesizes that the level of resources available to a dominant group does not alone mean they will engage in discriminatory
behavior. In actuality, he argues that higher resources must be combined with a real threat to the dominant group by a minority group that is both visible and is either engaged in behavior that might threaten the dominant group or contain the resources to potentially threaten the dominant group. Thus, it is important for any study exploring a given topic to identify the appropriate motivational threat.

**Contemporary Group Threat Theory: Racial/Minority, Economic, Community Violence, and Place-Based Threat**

Blalock (1967) certainly provided social scientists with a lot to grapple with when it came to his theory. Contemporary group threat literature and theory have taken elements of his work and adapted it to the study of various social outcomes. These adaptations have resulted in four distinct types of group threat: racial/minority, economic, community violence, and place-based threat. Below I will provide a brief explanation of each threat, including the various hypotheses derived from each. I will then summarize the literature on group threat theory and PIH.

**Racial/Minority Threat**

Racial threat is derived from Blalock’s (1967) power threat hypothesis which assumes that as the percentage of Blacks in the population increases, so does the view of Blacks as a threat to the political ascendancy of Whites (Eitle et al. 2002). In turn, dominant group political actors turn to social control as a means of maintaining their political power. This relationship is posited to be curvilinear with a critical point of fifty percent where the slope begins to decrease. Within the group threat literature, political threat is often measured in one of two distinct ways, either as the proportion or Black to White total population, or the ratio of Black-to-White voting. Eitle et al. (2002: 564) argue that voting is a better measure of political threat because it requires the expenditure of time and effort on the part of an individual, which also demonstrates a degree of
activism that “captures group-level political mobilization.” However, one might also argue that political activism such as voting may also be related to the level of social control a group experiences (i.e. voter suppression efforts and increased social control).

**Economic Threat**

Eitle, D'Alessio, and Stolzenberg (2002) assert that economic threat derives from competition between Whites and Blacks for jobs and other finite resources, which results in greater amounts of social control imposed on Blacks. According to Blalock (1967), this relationship is expected to be curvilinear, with a positive but declining slope (Eitle et al. 2002). Conflict theorists suggest the socioeconomic conditions can alter the extent of overlap between “occupational niches” that Blacks and Whites occupy (Barth 1969; Olzak 1990). As overlap continues to develop, Whites may perceive this as Blacks taking White jobs, even if this is not occurring. Blalock (1967) conceptualizes this relationship as power potential. Power potential is the actual sources of power, or those properties of the individual or group that provide the power potential or ability to exercise power, in this case, competing for and taking a job from a White worker. Power potential or potential competition can be measured in multiple ways. In their work, Eitle et al. (2002) measure economic threat as the ratio of White-to-Black unemployment. The validity of this measurement rests on the assumption that a split labor market exists, or that Whites and Blacks are paid different wages, thus employers may have an incentive to employ Blacks over Whites. Certainly, this assumption can be questioned, and research testing the economic threat hypothesis has found mixed support for it (Smith 2004). Largely ignored in the literature on economic threat are the other sources of power posited by Blalock. These sources include knowledge and competence, key factors in determining one’s chances of landing a job. Though it is important to note that previous
research has found that even with similar credentials, Blacks are less likely to find employment vis-à-vis Whites (Pager 2003).

**Place-Based Threat**

Previous research has shown that minority populations in the United States are disproportionately concentrated in segregated urban neighborhoods (Holmes, Painter II, and Smith 2019; Massey and Denton 1993). Often these populations experience various forms of socioeconomic disadvantage, which are posited to influence how police understand and react to these populations. The place-based threat hypothesis maintains that "the residential segregation of these populations is central to the deployment of coercive strategies of policing" (Holmes et al. 2019: 757). The segregation of perceived dangerous populations thus serves the interests of more powerful groups, specifically White populations who may view people of color as a threat. In this way, policing strategies, whether more or less coercive, may act to defend White neighborhoods from perceived threatening intrusions. The place hypothesis is effectively spatial but has not been tested as a spatial arrangement as it relates to PIH.

**Community Violence**

The Community violence hypothesis posits that the objective threats confronted by police officers in a community are positively associated with the level of social control in that community. Jacobs and O’Brien (1998: 845) state, "Some police killings undoubtedly are a reaction to difficult conditions in departmental environments. If findings of social divisions or direct political hypotheses are to be credible, it is crucial to include extensive controls for these problematic urban conditions. For example, the police should be especially likely to use violent methods where they must deal with a violent population. This most fundamental reactive explanation suggests that police departments in cities with higher civilian murder rates should be more likely to use deadly
force.” In other words, those groups which are more violent, are more likely to experience higher levels of social control. Community violence is often operationalized using the violent crime rate and arrest rate (Holmes, Painter II, and Smith 2019). However, research has also found that law enforcement may be less likely to engage with communities characterized by high levels of violence. Notably, Lautenschlager and Omori (2019) and Smith (2004) find that social control efforts are conditional on the level of violence present in a neighborhood, meaning that law enforcement may be less likely to police and patrol particularly violent neighborhoods out of fear of potential harm. Ultimately, questions still remain as to whether community violence is associated with more or less social control.

**Group Threat and Police-Involved Homicide**

Research testing the main tenets of the threat hypothesis has produced studies on various aspects of social control, such as police use of deadly force (Liska and Yu 1992; Legewie and Fagan 2016; Klinger et al. 2016; Jacobs and O’Brien 1998; Lautenschlager and Omori 2019; Gray and Parker 2020; Helms and Constanza 2020; Holmes et al. 2019), police force size (Jackson 1989), arrest rates (Liska, Chamlin, and Reed 1985; Eitle and Monahan 2009; Eitle, D’Alessio, and Stolzenberg 2002), incarceration rates (Inverarity 1992), mob lynching (Tolnay and Beck 1992), executions (Jacobs, Carmichael, and Kent 2005), and interracial crime (D’Alessio, Stolzenberg, and Eitle 2002). Recent, notable police shootings have reignited social science interest in the structural determinants of police violence leading to studies that have helped elucidate the theoretical connections between the two. It is both important and informative to begin this literature review with some of the formative studies on PIH and build toward contemporary studies.

An early group threat study by Jacobs and Britt (1979) applies what they call a conflict theory model to explore police shootings at the state level for a ten-year period from 1961 through 1970.
Specifically, the authors explore the extent to which inequality at the state level explains variations in police-caused homicides. Jacobs and Britt (1979) employ the Gini coefficient, computed from state income distributions supplied by the Internal Revenue Service, as a measure of inequality. Additionally, multiple regression models also controlled for the violent crime rate and the number of riots in each state. The violent crime index was computed using data from 1960-1962, and riot data were computed using data on the number of riots in cities between 1960 and 1969. Lastly, they control for percentage Blacks in a state, percent change in population and percent residents in large cities. Certainly, there are some concerns about the data measures used in their analysis, notably measures for violent crime do not capture the full breadth of relevant time points, and data on riots is limited to cities only, but findings from their regression analyses still revealed that economic inequality, changes in population, and violence index were positively and significantly associated with police-caused homicides, even when controlling for the region. While important, the authors do not acknowledge that they were testing the main tenets of group threat theory.

Fyfe (1980) explores the geographic distribution of all reported shootings in New York City police officers between 1971-1975 (n = 2,746) and indices of police exposure to violent crime and public safety. Arrest rate is measured as the number of violent felony arrests by the resident population, and the same for the homicide rate. Linear regression models and Pearson’s r's were calculated to describe the relationship between police shooting rates and the independent variables. Results indicate a significant relationship between arrest rates and shootings. Furthermore, analysis reveals a significant and positive relationship between homicide rates and police shootings. Fyfe (1980) concludes that police shootings are closely associated with the index for public safety, with busier areas in terms of reported murders and nonnegligent manslaughters reporting higher percentages of police shootings by on-duty officers. Again, while not directly mentioning it, Fyfe
Fyfe’s (1980) work has also been central to claims that community violence is the most important factor in predicting police-involved homicides.

The work of Jacobs and Britt (1979), and Fyfe (1980), while important to the literature itself, represent what Liska (1992) might describe as atheoretical and largely descriptive. Thanks to the work of Liska and Yu (1992), the application of group threat to PIH, is more systematic than it was in the past. In their analysis of police shootings using data from 1975 through 1979, they found that police-involved homicides were significantly, and positively associated with segregation and percent non-White, and that the non-White crime rate did not mediate the non-White population effect. This finding is important and has been replicated in more contemporary studies of group threat theory.

Smith (2004) examines what factors influence police killings of felons. Specifically, he tests three competing arguments posited to impact police killings. The first is the threat hypothesis, the second is the community violence hypothesis, and the last, the organizational hypothesis, is broken into two distinct parts. Part one, the professionalism hypothesis posits that hiring highly educated officers, and providing them with extensive training should reduce police killings. The second part, the bureaucratic control model, suggests that officers are subject to rules and guidance and that boundaries on police discretion will limit police killings. Data on police killings is gathered from the 1994-1998 FBI supplemental Homicide Reports, and US census data from 1990. Racial threat was measured as the proportion of African American and Hispanic residents within each city analyzed. Economic inequality was measured using the Gini index. Community violence was measured as the rate of violent crime, consisting of murder, rape, robbery, and assault. Measures of organizational characteristics consisted of 12 items gathered from the Law Enforcement
Management and Administrative Statistics Survey. Additional measures for training were also included. Poisson regression models were estimated.

Findings from this study provide evidence for the threat and community violence hypotheses, but the findings are much more nuanced than expected. For example, while community violence and the proportion of African Americans was found to be significantly related to police killings of felons, economic threat was not related to killings. Furthermore, limited support was found for the organizational hypotheses. Analyses indicated a significant negative relationship between in-service training and fatal killings of White felons; however, this was not a consistent finding across models. Furthermore, results indicated that the greater number of field hours after police academy was positively and significantly related to killings. These findings should be interpreted with caution. Smith (2004) argues the explanation for this finding may lie in police culture. This finding is related in many ways to the findings of Legewie and Fagan (2016) in that it is important to recognize the police as a significant social group, capable of influencing police shooting rates on their own through collective culture. Legewie and Fagan (2016) also found that race-specific killings, notably those of African Americans, are not simply driven by population characteristics. Instead, they found race-specific patterns in the ways police respond to crime. More so, they find that Black-White homicide rates are a significant predictor of officer-involved killings, whereas Black-Black homicides are not.

Klinger et al. (2016) sought to test two competing arguments related to police shootings of citizens. The first is that the prevalence of violence in a neighborhood is the focal concern leading officers to use deadly force, and the second is that the racial composition of neighborhoods influences an officer’s decision to shoot. To test these competing threat arguments, Klinger et al. (2016) use police shooting data from the St. Louis Metropolitan Police Department that took place
between 2003 and 2012. Data during this 10-year period returned a total of 239 separate incidents of officers intentionally firing shots at citizens. However, after cleaning data, a total of 230 cases remained. The two key predictor variables in the study are the racial composition of neighborhoods and firearm violence in St. Louis Neighborhoods. The latter variable consists of an index of the average yearly homicide rate, firearm assault rate, and firearm robbery rate. The former variable was measured as the percentage of neighborhood population that is Hispanic, percentage Black, unemployment rate, median household income, and percentage of persons older than 25 years with a college education, residential stability (percentage owner-occupied dwellings and percentage of population residing in the same residence 5 years before), age composition (percentage age 18-24, and percentage age 50 years and older), and population size. The predictor variable data were gathered from the 2005-2009 ACS at the block-group level. The authors analyze their data at the census block group level which is the smallest geographic unit for which diverse population characteristics are available. Analysis of the data consisted of both a micro-spatial analysis of block groups and multivariate OLS and Poisson analyses which included a spatial lag variable to capture spatial variation.

Overall, the study identifies that shootings in St. Louis tend to occur in the most disadvantaged neighborhoods with relatively large Black populations and elevated firearm violence. Through multivariate OLS and Poisson regression analyses, which included a spatial lag variable, findings from this study reveal that the frequency of police shooting incidents is a function of serious crime, specifically firearm violence. In other words, while race was an important variable, race only mattered insofar as it increases the level of firearm violence. Adding to this finding, Klinger et al. (2016) find the relationship between violent crime and police shootings to be curvilinear in that police shootings are less likely to occur in neighborhoods with the highest levels of criminal
violence, while neighborhoods with moderate violence experience higher levels of police shootings. This finding represents what is known as the curvilinear hypothesis. The hypothesis posits that police are less likely to respond to highly violent areas due to fear of potential injury or death. In some ways, this reflects the idea that police may abandon certain areas, which may give rise to vigilante justice.

Holmes et al. (2019) test competing structural threat hypotheses, the racial threat hypothesis, the place hypothesis, and the community violence hypothesis on police-involved-homicide. Like previous studies, racial threat was measured as the percent Black population in a given city. However, a major contribution of this study is the examination of place, and how levels of Black-White segregation influence PIH. The place hypothesis maintains that “the residential segregation of these populations is central to the deployment of coercive strategies of policing” (Holmes et al. 2019: 757). The segregation of perceived dangerous populations thus serves the interests of more powerful groups, specifically White populations who may view people of color as a threat. In this way, policing strategies, whether more or less coercive, may act to defend White neighborhoods from perceived threatening intrusions. In their study, Holmes et al. (2019) set the groundwork for the development of spatially informed hypotheses, though do not test them. Lastly, the authors test the community violence hypothesis, which posits that the extent of crime and violence in a community reflects the objective threats confronted by officers and is positively associated with cases of PIH.

To test these relationships, the authors use data from the Supplemental Homicide Report (SHR) of “felon killed by police officer” between 2008 and 2013 for US cities with populations 100,000 or more. Data from the 2010 US Census were used to construct measures on racial threat, while data from the US 2010: Discover America in a New Century website were used to construct
variables on Black-White segregation. Data from the Uniform Crime Report were used to measure community violence. Negative binomial models were used to analyze the data due to overdispersion within the data, and the highly skewed nature of PIH. Results from their study support racial threat, place, and community violence hypotheses, in the predicted directions.

Lautenschlager and Omori (2019) identify that cases of police use of force are often framed as incidents that take place between two individuals, largely disconnected from their surroundings. In other words, place is not often considered an important factor in where and why cases of police use of force occur, which has limited our understanding of how community characteristics shape patterns and consequences resulting from police use of force. Drawing on criminological literature which has been often applied to understanding community-level crime, the authors test the applicability of racial threat theory, social disorganization theory, and Klinger's ecological theory of policing, to police use of force. Their study is limited to census tracts within New York City, and data from the New York Police Department's Stop, Question, and Frisk database from 2003-2012. They employ multilevel random intercept models to test the extent to which racial threat (measured as percent Black), measures of social disorganization such as residential instability and concentrated disadvantage, and measures of police perceptions of neighborhood crime, influence levels, and severity of police use of force. Results from their analyses indicate that the percent Black population is both positively and statistically significant even after controlling for theoretically relevant variables and that this relationship is nonlinear. Notably, they find that areas with high levels of racial heterogeneity experience fewer instances of police use of force, but that the severity of instances is higher. Theoretically, this finding led the authors to conclude that gentrifying neighborhoods might experience lower incidences of force, but that law enforcement may engage in protective responses due to higher levels of intergroup interaction, including
intergroup and interethnic crime and victimization. What is important to note here is that the findings may be biased in significant ways, especially considering they excluded measures of spatial lag due to concerns with multicollinearity, or simply that there may be spatial factors not accounted for in their findings. However, despite these concerns, their study prompts questions regarding the spatial relationship between localized incidents, such as cases of police use of force, and the larger spatial context surrounding such incidents. Notably, the authors point to the possibility that the larger spatial context of a neighborhood plays an even more important role in police actions, especially in cases where a place is gentrifying, with law enforcement acting as gatekeepers and protectors of a potentially new economic oasis.

Gray and Parker (2020) also consider the structural factors related to deadly police shootings by testing three theoretically driven sets of hypotheses drawn from the work of Blalock (1967): political threat, economic threat, and racial threat. To assess these theoretical constructs, the authors utilize newly available crowdsourced data from the Mapping Police Violence database (MPV) and construct their independent variables through multiple state-level databases including the 2010 census population estimates, 2010 American Community Survey 1-year estimates, and a unique state-level political indicator database. Results from negative-binomial regression indicate a positive and significant relationship between racial threat (measured as percent Black) in all models, except those specifically testing White-specific police deadly shootings, and this relationship was found to be curvilinear. Limited support was found for political threat, with analyses revealing a negative and significant relationship (p < .1) for liberal ideology. Overall, Gray and Parker (2020) provide a framework through which to further test racial threat's applicability to police shootings. It is important to note that the application of racial threat at the state level may mask spatial heterogeneity of police shootings and may even account for the lack
of significance with some of the economic and political threat measures. Thus, the ability to extrapolate out what their findings mean is tenuous at best.

Helms and Constanza (2020) complement the work of Gray and Parker (2020) and take a structural approach with the goal of providing new insight into how space and place matter in fatal interactions with police. Drawing on racial threat literature, the authors test whether economic and racial threat in US counties impacts fatal interactions with police. They utilize data from the Killed by Police database, which compiles crowdsourced data on police-citizen encounters. They also construct county-level variables for economic and racial threat, and control for violent crime, drug offenses, and rate of police officers per 100,000 population. Using negative binomial regression, the authors find that economic threat (measured with three separate indicators: Gini index, % unemployment, and population age 20-34, median income) and racial threat (measured as percent Black and percent Hispanic) were both positively and significantly associated with fatal police interactions. The finding regarding economic threat is particularly important given the relative dearth of evidence supporting it. The authors identify that Messner and Rosenfeld's (2012) American Dream argument is particularly salient in explaining this finding. Specifically, they hypothesize that "under conditions of gross economic inequality, economic tensions are conceptualized as contributing to a general heightened risk of conflict between police and citizens," due to the pressures placed on groups to achieve material success (Helms and Constanza 2020: 52). More so, as communities fail to meet basic needs to fulfill economic expectations, and the effects of economic strain are magnified, those who are most socially marginalized are least able to overcome opportunistic deficits, which is likely to produce conditions that push groups toward a critical threshold, increasing the risk that aggression will spill over into deadly violence (Helms and Constanza 2020: 52).
The literature exploring group threat and its application to police-involved homicide is far from being conclusive, and debates within the community have only recently begun to heat up as the national discourse on police brutality has once again emerged as a hot-button issue. Fortunately, this reignition has prompted many scholars to take a harder look at the literature, and new insights are likely to follow, evident with the current debate on proper risk factors for analysis. But it is important to recognize that in the pursuit of findings surrounding disproportionate minority outcomes, that theory is not monopolized by certain ideological perspectives. Whereas the current debate is largely surrounding whether police disproportionately shoot and kill minorities, it is just as important to explore and understand the structural determinants of police shootings, including group threat. The threat literature has inconsistently found support for all three measures of group threat. However, recent studies have begun to elucidate the theoretical linkages between group threat and PIH. The current literature has also set the groundwork for the application of spatial econometrics and any theoretical insights gleaned from such an approach. Perceptions of threat are not likely to emerge exclusively from conditions in a focal community and are likely to spill over into surrounding communities. As Lautenschlager and Omori (2019) find in their work, police may engage in protective measures to contain potentially threatening groups from the interests of more powerful groups, as is the case in areas that are gentrifying, or characterized by a high level of socioeconomic disadvantage. Ultimately, communities are not islands, and space and place matter for both focal and surrounding communities. Below I will begin to explicate how spatial econometrics will be integrated into the current study and the benefits from such an approach.

**Introducing a Spatial Approach to Group-Threat Theory**

While many of the previous studies discussed in this chapter have highlighted the importance of space and place, and the ecological nature of PIH, few studies have incorporated spatial
econometrics in ways that allow for the examination of contextual characteristics and PIH. The incorporation of the spatial perspective into macro-criminology is imperative, as many macro theories posit spatial relationships without directly testing them. As previously noted, this may result in findings that obfuscate causal mechanisms. Additionally, the incorporation of spatial econometrics may elucidate new understandings about how space and place interact with one another in important theoretical ways, by helping to identify new causal mechanisms.

As I will discuss later in chapter three, the spatial Durbin model (SDM) allows for more interesting and potentially useful hypotheses to be tested, through testing of both local or direct effects and neighboring or indirect effects of independent variables on police-involved homicide. In this way, I argue as Yang et al. (2015: 20) do for mortality rates, that the rate of PIH of a certain area could be "explained not only by the features of this area but also by the characteristics of the surrounding areas." Below, I will attempt to synthesize the work of Blalock with a spatial approach grounded in spatial spillover and social relativity.

*Spatial Spillover, Social Relativity, Spatial Incongruity and Blalock*

How is police-involved homicide related to, or influenced by focal and surrounding communities? This is the key question guiding my research. To a certain extent, the answer to this question is grounded in two theoretical perspectives: spatial spillover and social relativity (Yang et al. 2015). The term spatial spillover is drawn from research in regional development and economics. The term itself has multiple meanings, including knowledge spillover, industry spillover, and growth spillover (Yang et al. 2015: 20). However, the general meaning is that change, whether that be of mortality, crime, or some other outcome of interest, in one place, is related to the behaviors of the neighboring units. The idea is that the spatial structure and dynamics of space lead to the diffusion of ideas, people, and goods and resources across and between spatial
units. Borrowing from Yang et al. (2015: 20), I conceptualize a spatial unit as “a geographically
limited system in which all necessary resources could not be produced, but those resources
exceeding local demands would spillover to nearby units for survival and growth.” However,
unlike Yang et al. (2015), I note that the spillover between spatial units is not mutually beneficial,
and that competition pervades these relationships, and some units may benefit from spatial
spillovers while others suffer from them. For instance, while spatial units may benefit from a public
health standpoint if neighbors have extra hospital beds, the same cannot be said for structural
covariates of police-involved homicide, such as criminal activity, and concentrated disadvantage.
In fact, such undesirable aspects of neighboring counties may be understood and perceived as
threats to other counties. For example, a county with a particularly high level of violent crime may
be viewed as a threat to another county, which may potentially influence how law enforcement
engage with and deal with individuals and groups belonging to that neighboring county.

According to Blalock, discrimination against minority groups is most likely to occur in
situations where (1) minorities must be directly relevant to at least some of the means to important
goals, and (2) that these particular means are appropriate for large segments of the dominant group.
In other words, for discrimination to take place, minority groups must be impeding the means of a
dominant group, and that group must have limited alternatives to dealing with the issue other than
through action such as discrimination. Blalock further notes that discrimination will be most
common in situations where the minority may be a serious competitor, and discrimination may
serve as a means of restricting or eliminating such competition. For example, Blalock (1967) notes
that a minority population may be understood as a major competitor when there is a relatively large
population of unemployed, or underemployed minorities in a given area who may take jobs of
those already employed at pay far below those already employed. So, in this way, as the levels of
unemployment between a dominant and minority group bifurcate, the level of threat between the
two groups is posited to increase, and thus levels of social control are expected to increase to
maintain this power relationship.

Blalock notes that certain conditions may produce specific outcomes when it comes to minority
discrimination. Specifically, he states that “prejudice towards negroes, for example, may in part
be due to the fact that the individual habitually rejects any members of the lower class, regardless
of race, creed, or color. Under some conditions, such as when the minority is especially numerous
or when overt power struggle is occurring, we would naturally expect the minority to be defined
as a distinct out-group” (Blalock 1967: 52). In these cases, Blalock contends that when competition
is especially high, or the minority group is competing with those of the dominant group for control
of resources, stereotyping will serve to set the minority apart from others, and they may be lumped
in with a lower-class group. While Blalock does not posit a spatial relationship with the various
forms of group-threat and social control, research focused on spatial incongruity provides some
insight into how this might play out.

From a law enforcement perspective, this may play out in ways related to what Capers (2009)
terms spatial incongruity. Capers (2009) explores the way segregation has played an important
role in criminal and procedural law and continues to play a role in maintaining racialized spaces.
Capers begins with an exploration of how racialized spaces influence social capital and opportunity
for racial minorities living in racially segregated communities. Spatial separateness, according to
Capers, breeds racial divisiveness, through the process of race-making. Race-making is the process
through which people understand issues of spatial separateness as related to race, and not place.
Spatial separateness further contributes to race-making, by “producing and reproducing racial
difference and White privilege” (Capers 2009: 45), which reinforces and maintains social and economic inequality by limiting access to education, employment, and political power.

Capers further explores how racial segregation influences policing practices, notably the effect it has on the idea of racial incongruity, and its relation to suspicion building and Terry stops. The practice of police stops is largely influenced by the ruling Terry v Ohio, in which the Supreme Court lowered the evidential standard for justifying a police stop to reasonable suspicion that a person is or may engage in criminal activity. Notable ramifications of this ruling include the now controversial New York City Stop and Frisk policy, which was found to be unconstitutional and racially biased. According to Capers, this ruling, and other similar ruling lowering the evidential bar for search and seizure, has had the de facto effect of reinforcing the idea of racial incongruity, or the practice of using race as a factor in determining reasonable suspicion. The oft cited idea of “driving while Black” plays an important role, especially when driving through a largely White neighborhood. According to Capers, segregation has played a role in delineating in the minds of law enforcement, which neighborhoods are White, and which are Black, which are crime ridden, and which are peaceful. This has the effect of reinforcing in the minds of everyday citizens, the idea that there are places you can and cannot go, and that crossing certain geographic borders is prohibited. For some people of color, especially the majority of whom are law abiding citizens, a “racial tax” comes with crossing geographic borders, thus creating, reinforcing, and maintaining barriers to equal access to opportunity. In doing so, police also, whether knowingly or not, engage in race-making by continuing the Black-White binary, reinforcing White privilege, and associating Blackness with criminality. As it relates to the current study, often obscured in the deluge of stops of people of color, is the disproportionate targeting of minorities with threats of violence. The legitimacy of the law, after all, comes from its threat of lawful violence, and this is understood
most acutely by people of color, which has prompted many parents to have “the talk” with their children.

At the heart of spatial incongruity is the concept of social relativity. Building on spatial spillover, the social relativity perspective is drawn from social comparison theory (Festinger 1954). This perspective posits that people and groups will compare themselves to others to assess the differences between one another. These assessments are then used as motivators for changes in actions, attitudes, and behaviors in order to reduce this discrepancy. This perspective assumes a power differential between groups, with those who are of a lower socioeconomic position striving to reduce the gap between them and those of higher socioeconomic standing. However, in aligning this perspective with the work of Blalock (1967), we can assume that those of higher standing wish to maintain their privileged position and will thus work to limit the ascension of those of the lower class, especially when the lower class is assumed to be an impediment to the goals of the higher class. Recent work by Lynch et al. (2013) Stuart (2016), and others, has identified the ways in which socioeconomic status, race, and crime, influence both local power elites and law enforcement to engage in practices of spatial containment and exclusion of threatening groups.

In their study, Lynch et al. (2013) examine how drug law enforcement practices are influenced by place-based structural factors, and how these factors help to shape discriminatory enforcement patterns. Their work approaches the concept of space and spatiality and the law enforcement practices that manifest, as a product of power relations between various groups, and that the character of such relations and resulting policing strategies, take on a racial aspect. In their case study of San Francisco, they find that drug law enforcement is not evenly distributed, but rather spatially concentrated in areas of the city where political and economic interests are greatest. This often manifested in targeted policing strategies aimed at predominantly Black, segregated areas,
with higher levels of crime, with the goal of containing potential racial, economic, and political threats to communities deemed economically important. As Lynch et al. (2013: 350) state, “those residents who transgress the Tenderloin’s (an area located in the central downtown district of San Francisco) boundaries are subject to arrest through ‘order maintenance’ policing aimed at panhandling, sleeping in public, and open drug use.” Similar to the work of Stuart (2016), San Francisco maintains areas known as containment zones, where police are positioned as “coercively inclusive resource officers” who wield their power to benevolently arrest addicts into treatment (Lynch et al. 2013: 350). Ultimately, Stuart (2016) and Lynch et al. (2013) demonstrate how political and economic pressures drive law enforcement practices to maintain economic and political power relations through the use of exclusionary policing strategies aimed at containing threatening groups and limiting the potential for spillover effects.

The effect of race and place has been demonstrated in studies on police stops. For instance, Meehan and Ponder (2002) find that African Americans are subject to higher levels of surveillance in areas where a predominantly White area borders a predominantly Black area, and are thus more likely to be stopped, regardless of the level of criminality of the Black area. Ingram (2007) explores the impact of neighborhood characteristics on traffic citation practices of officers of a large, metropolitan city. The study starts by initially considering how neighborhood structural characteristics impact citation practices by examining variables such as low economic status, racial composition, crime rates, and residential instability. Secondly, the study explores these characteristics using spatial econometric models to test the impact of larger geographical areas. Data for the study were gathered from two sources, the Southwest City Police Department traffic citation data from January 1, 1999, to October 10, 1999, and the 2000 U.S. Census. A total of 87,792 traffic encounters resulted in 211,689 citations. After data cleaning, a total of 85,432 usable
encounters across 1,006 neighborhoods were used for subsequent analysis. The dependent variable for the study was the number of citations issued by officers during encounters. Independent variables included a grouping of neighborhood-level characteristics including residential stability, measured as the percentage of single-parent households, renter-occupied residences, and vacant households. Low economic status was measured as a factor score between median household income, the percentage living below the poverty line, and the percentage of people 16 years and older who are unemployed. Lastly, percent Black and Hispanic were included. Encounter level control variables were also included. Multiple analyses were used, including bivariate associations, and multi-level modeling. Spatial analysis began with a test for spatial dependence, with a Moran's I test indicating the presence of spatial dependence. With this finding, the author preceded to run spatial regression models.

Initial multi-level models revealed significant variation across neighborhoods in police citations. Further tests indicated that the odds of citation increase by 11% for each increase in standard deviation for logged violent crime, and 35% increase for every standard deviation increase in low economic status. Increases were also observed for percent Hispanic, residential instability, and natural log percent Black. Overall, these findings support the claim that place does matter. Even after controlling for encounter level characteristics, violent crime rates and lower economic status played a role in citations. Overall, multilevel findings indicate significantly greater odds of a citation for non-Whites, males, and southwest city residents. Turning to the spatial results, Ingram (2007) utilizes spatial regression models and introduces a spatial lag variable. Spatial lag models represent a global indicator for spatial dependence and account for spatial correlations for both diffusion and externality processes. While initially significant, after the introduction of the spatial lag variable, violent crime, residential instability, and percent Black are
no longer significant. However, low SES is still significant, but less so. Additional models find that the percent Hispanic in the immediate neighborhood on citation issuance is greatest when surrounding neighborhoods have lower percentages of Hispanics. Two competing arguments are at play here. The first is that officers' assessments of citizens are based on the racial composition of a neighborhood, where officers know which communities are Whiter, Blacker, and so on. This knowledge filters down to inform decisions on where to police and whom to stop. The second explanation combines race and class to argue minorities are more likely to reside in disadvantaged communities.

Roh and Robinson (2009) test racial threat theories applicability to traffic stops utilizing spatial analysis. In total, data collected by the Houston Police Department, Texas between January 2003 through December 2003 on 333,760 traffic stops across 121 beats were analyzed. Macrolevel data from the 2000 Census were used to estimate populations and racial proportions for the police beats. Initial analysis included a test for spatial dependence between predictor and outcome variables. Results indicated significant spatial dependence. Building on this finding, the authors test both spatial error and lag models. Spatial regression models were then estimated to take into account spatial effects. Results from their analysis revealed that the likelihood of being stopped and being subjected to unfavorable police treatment was greater in predominantly Black and Hispanic beats, and where more police force was deployed. Overall, these findings indicate that racial disparity of stops by police may be explained by differential policing strategies dependent on who resides in those areas (Roh and Robinson 2009).

Carrol and Gonzalez (2014) examine how race and place interact with one another to influence police stops, searches, and frisks. In their study, they apply a recently developed theory in Smith and Alpert’s (2007) social conditioning theory. Their theory posits that racial disparities in
enforcement are the product of unconscious racial profiling and implicit stereotypes developed through implicit and explicit experience. Often these perceptions and biases inform cognitive schema and scripts, beliefs, attitudes, and behavioral predispositions, that are automatically triggered and guide behavior in certain situations. The authors of the study derive four hypotheses predicting post-stop investigations from this theory and place-based theories of crime control: (1) that racial disparities in post-stop investigations will be greater for frisks than searches; (2) that these disparities will be greater in communities with predominantly White populations; (3) that searches will not be conditioned by the context of the stop (i.e. threshold of suspicion); and (4) that “hit rates” or the productivity of a stop in finding contraband should be lower for Whites who are investigated. To test these hypotheses the authors, use traffic stop data from the Rhode Island State Police from in 2006. In total their dataset contained 47,913 stops after it was cleaned, involving 176 frisked individuals and 356 searches. The authors estimate their models using multinomial and binary logistic regressions. The authors find support for all four hypotheses. Important in these findings is their relevance to place-based theories of crime control. Notably, the authors find that while Blacks were more likely to be stopped, searched, and frisked, and more likely to be carrying contraband, Black drivers were more likely to be stopped in White communities.

What these studies demonstrate is that race and place are often intertwined and that they interact with other socioeconomic structural determinants, such as segregation and inequality, to influence police behavior. Specifically, these studies point toward how police work to maintain racial, economic, and political boundaries between various groups, but also, indirectly, how dominant groups reinforce socioeconomic barriers. This set of literature also highlights the relative lack of attention paid to the importance of space and place for PIH. Certainly, police work to contain
threats, whether they be real or perceived, and this often manifests in more contacts between police and people of color, especially in areas where bordering communities vary significantly with one another. Research has already demonstrated that Black men are disproportionately shot and killed by police (Edwards et al. 2019) and that this is dependent on the structural characteristics of an area (Lautenschlager and Omori 2019; Gray and Parker 2020; Helms and Constanza 2020). The position of the current study is that PIH is not only dependent on the structural characteristics of the focal area, but also the surrounding areas due to policing strategies aimed at containing threatening groups. Because of these strategies, police may be more likely to come into contact with people of color, especially in areas people of color are not expected to be, and this may result in higher levels of PIH.

In conclusion, previous theoretically informed research has begun to identify the mechanisms through which power and social control interact with space and place in ways that work to maintain existing power relationships between disparate groups. On the one hand, this manifests in increased stops of people belonging to groups which do not align with predetermined understandings of who should and should not be in a given place, what Capers calls spatial incongruity. On the other hand, this may take the form of purposeful policy aimed at containing or excluding specific groups from various places. When these “rules” or “codes” are broken, agents of social control are within their jurisdictional purview to control these people through necessary means, including stopping, frisking, arresting, or lethal force. The idea of spatial incongruity also reflects the ideas inherent in the work of Blalock (1967), which itself is based on ideas of social relativity and the maintenance of power relations, whether they be local or spatial in nature. In essence, minority groups, notably Blacks, those who are impoverished, and those residing in high crime areas, are more likely to catch the eye of law enforcement who are presumed to be working
on behalf of those in power, and thus more likely to experience higher levels of social control. From this perspective, we are also able to contend with the question of why various forms of threat, notably racial threat, might increase police-involved homicides of Whites as well. In the same way that a young, Black male is presumed to be a threat when they are driving through an affluent White neighborhood, the same can be said for a White male driving through or stopping in a predominantly Black neighborhood, especially if that neighborhood has higher crime. Building on these ideas I present the current study below.

**Current Study**

While many studies approach the question of what factors influence police-involved homicide through the use of nonspatial methods, recent advances in spatial econometrics provide social scientists with new tools to examine this question and provides new theoretical insights. Previous research has demonstrated the connections between group threat and police-involved homicide; however, the relationship has been tenuous. The incorporation of spatial factors into the equation allows for greater precision in our understanding of not only why these tragic events occur, but also where. And I believe that the where is every bit as important and tied intimately to the why. Below I formulate the spatial hypotheses derived from group-threat theory.

**Spatial Hypotheses**

The first major challenge in formulating spatial hypotheses related to group-threat is elucidating the mechanisms, both direct and indirect, measured and unmeasured, through which group-threat interacts with spatial units. For example, why might economic threat in one county influence the PIH of another county? Through what mechanisms does this relationship emerge? The work of authors like Forrest Stuart (2016), and Bittner (1967) discuss how areas with a high level of perceived threat, whether that be racial, criminal violence, or economic, are often understood to
be the focus of more intensive policing. When areas are identified as threatening, police presence often increases, as a means of containing the threat. Lynch (2013) specifies models of containment with proactive policing strategies implemented in multiple cities throughout the country. However, this is not always the case, and conflicting accounts of which forms of threat influence social control are present in the literature. Notably, Lautenschlager and Omori (2019) find social control efforts to be conditional on the violence present in a neighborhood, with areas characterized as high in violence exhibiting lower levels of social control due to fear among law enforcement about potential harm. On the other hand, Stuart’s (2016) work in Los Angeles’s Skid Row neighborhood describes the way political and economic elites from surrounding areas of the city come together to develop and implement policies and programs aimed at containing threatening groups in specific areas. In this way, Stuart (2016) posits a spatial arrangement between different groups based on threat. While not directly measured, perceived threat acts as a key mechanism triggering between and within spatial unit shifts in social control. This perceived threat may manifest in either political or economic elites, triggering calls for changes in policing strategies, or may emerge from perceived threats understood directly by law enforcement on the ground of potentially violent groups. In this way, local economic and political elites play a role in how law enforcement understand who and what is a threat. Borrowing from the literature on social relativity and spatial incongruity, this may manifest into social control activities aimed at limited access to certain groups, or instances of the proverbial “driving while Black” hypothesis where Blacks are stopped at disproportionate rates when traveling within or through predominantly White areas.

Building on this, Blalock also contends that racial threat is not the only factor influencing threat and social control, and that we must also account for economic and political threat. Regardless of which factor it is, it is assumed that police already have an intimate understanding of the beats they
police, and readily identify individuals who do not “belong.” Previous research by Klinger et al. (2016) has highlighted the notion that law enforcement are intimately familiar with the beats they police. As Klinger et al. (2016: 214) notes, “within beats, officers’ territorial knowledge involves understanding the threat contours of specific neighborhoods, including hotspots, with particularly high levels of crime.” These threats are assumed to be the product of their own understanding of their immediate environment, the surrounding communities, and the policies and procedures of their department which are themselves, dependent on the communities they police. Below, I provide my spatial hypotheses, broken down by threat category, beginning with racial threat, moving to economic threat, followed by place-based threat, and finishing with hypotheses derived from the community threat hypothesis.

**Racial Threat**

While racial threat plays out in a rather straightforward manner in nonspatial hypotheses, building spatial hypotheses brings with it important complications. On the one hand, racial threat is derived from Blalock’s (1967) power threat hypothesis which assumes that as the percentage of Blacks in the population increases, so does the view of Blacks as a threat to the political ascendancy of Whites (Eitle et al. 2002). In turn, dominant group political actors turn to social control as a means of maintaining their political power. Not present in this hypothesis is how we are supposed to understand how racial threat of surrounding areas influences social control in focal communities. For example, how does the percent Black population of a neighboring county influence a focal community?

Research on police stops of Blacks driving through largely White neighborhoods finds that Blacks are subject to increasingly high levels of social control (Meehan and Ponder 2002). From a spatial spillover perspective, it would be expected that Blacks from neighboring communities
will inevitably spillover into neighboring communities whether that be due to work, entertainment, or social ties, and oppositely that Whites will also spillover into neighboring Black communities. Tying this understanding to the spatial incongruity perspective, we might assume that as the percent Black of neighboring communities increases, so do the chances that Blacks will find themselves traveling through neighboring communities, which will also increase the level of social control in focal communities where Blacks may be traveling through. In the same manner, I might also expect Whites in neighboring communities to travel and or pass through Black communities. Based on the spatial incongruity perspective, we would expect law enforcement to draw conclusions about who belongs and who does not, based on their own interpretations about the characteristics of their local communities. As previously noted, it is assumed that law enforcement already has a deep understanding of the threat contours of their communities and are quite capable of spotting potential threat vectors. Thus, I posit that as the percent Black of neighboring communities increases, so will the level of police-involved homicides of a focal community.

However, recent research in Cleveland, Ohio indicates that police have engaged in policing tactics that proactively targeted "those in the poorest, predominantly Black Eastside neighborhoods in the city, despite evidence of similar low-level drug offending in other neighborhoods" (Lynch 2013:339). According to Lynch (2013: 339), this has been the result of political maneuvering between the Mayor's office, police union, and county district attorney, which gave rise to a racialized arrest policy that persisted for 25 years. Of additional importance, and as justification for my use of county-level data, is that Cleveland, like many large cities across the United States, straddles five different counties, with each county having its unique socioeconomic and racial makeup. This research is also in-line with previous research on racial threat and aligns with my nonspatial hypothesis that the percent Black of a focal county will be positively associated with
police-involved homicide. That said, a recent study by Holmes et al. (2019) found percent Black to be negatively and significantly associated with the total police-involved homicide of major cities. However, unlike the previous study, the current study relies on crowdsourced data, instead of the supplemental homicide report. The findings in Holmes et al. (2019) buck the trend in previous research which has largely found percent Black to be positively and significantly associated with police-involved homicide. With this in mind, I align with the previous research which has posited a positive relationship for percent Black and police-involved homicide. I posit the following hypothesis:

\[ H1a: \text{Percent Black (racial threat) in focal county will be positively associated with police-involved homicide in that focal county, and percent Black of neighboring counties will be positively associated with police-involved homicide in that focal county.} \]

The second spatial hypothesis reflects no spatial relationship between neighboring counties. In effect, percent Black of neighboring counties may not be an important determinant of a focal county’s police-involved homicide and may not factor in as a real threat.

\[ H1b: \text{Percent Black (racial threat) in focal county will be positively associated with police-involved homicide in that focal county, but percent Black of neighboring counties will not be associated with police-involved homicide in that focal county.} \]

\[ Economic \text{ Threat} \]
Eitle, D'Alessio, and Stolzenberg (2002) assert that economic threat derives from competition between Whites and Blacks for jobs and other finite resources, which results in greater amounts of social control imposed on Blacks. However, economic threat is also derived from the view that certain groups are not advantageous to be around, such as those who are disadvantaged and/or impoverished. Regardless of whether it is disadvantage, competition for jobs, or inequality, those in power will work to limit the perceived threat of these groups. Thus, when economic elites perceive a threat from a particular group, it is posited that they will lobby for protection from agents of social control. From a social relativity perspective, groups are expected to engage in social comparison, and these assessments are used as the basis for changes in behavior. For example, I might posit that as the concentrated disadvantage of neighboring counties increases relative to a focal county, a focal county may engage in higher levels of social control to protect themselves from the economic threat of its neighbors. The question which can be answered by the spatial Durbin model is, which effect is greater, the threat of neighbors, or the threat that is right in your own backyard? This is a question SDM is uniquely situated to answer. Based on this understanding I posit the following hypothesis:

\[ H2a: \text{Economic threat in focal county will be positively associated with police-involved homicide in that focal county, and economic threat of neighboring counties will be positively associated with police-involved homicide in that focal county.} \]

Similar to racial threat, it may be possible that economic threat bears no relationship spatially between neighboring units, only resulting in local effects. With this in mind, I posit the following hypothesis:
**H2b:** Economic threat in a focal county will be positively associated with police-involved homicide in that focal county but economic threat of neighboring counties will not be associated with police-involved homicide in that focal county.

**Place-Based Threat**

Previous research has shown that minority populations in the United States are disproportionately concentrated in segregated urban neighborhoods (Holmes, Painter II, and Smith 2019; Massey and Denton 1993). Often these populations experience various forms of socioeconomic disadvantage, which are posited to influence how police understand and react to these populations. Research has also shown a positive association between residential segregation and PIH (Liska and Yu 1992), showing that as residential segregation increases (measured as less interaction), police-involved homicide also increases. In defining place-based threat, Holmes et al. (2019: 757) acknowledge that segregated populations often experience “various socioeconomic disadvantages—social isolation, poverty, crime, drugs, weapon availability, violence, and social disorder/incivilities.” As such, Whites may believe that people living in such squalid conditions are threats to social order, and that efforts should be made to contain such threats. The important point made by Holmes et al. (2019: 758) is that “the use of violence might protect the interests of police officers on the street who feel threatened when patrolling racial segregated minority areas.” In their study, Holmes et al. (2019) test this hypothesis, and find that segregation was positively and significant associated with police-involved homicide. Building from their study, I utilize the interaction index, which measures the extent to which various racial groups are exposed to one
another, with a higher index reflecting lower levels of segregation. Based on previous studies, I posit:

\[ H3a: \text{The interaction index in a focal county will be negatively associated with police-involved homicide in that focal county, and the interaction index in neighboring counties will be negatively associated with police-involved homicide in that focal county.} \]

Similar to the other forms of group-threat, place-based threat may not interact spatially, especially in cases where the overriding perception by local officials and law enforcement is that the threatening group is adequately contained to a specific area. In these cases, there would be no relationship between the surrounding areas and the focal county. Based on this, I posit the following hypothesis:

\[ H3b: \text{The interaction index in a focal county will be negatively associated with police-involved homicide in that focal county, and the interaction index in neighboring counties will not be associated with police-involved homicide in that focal county.} \]

**Community Violence Hypothesis**

Community violence threat posits that the level of crime and deviance a minority group engages in will be positively associated with increased discrimination and social control against that minority group. Spatially, law enforcement is likely to engage in behaviors directly relevant to their local community, but also surrounding areas. This may be particularly salient in cases where
an area high in violent crime neighbors another area of low crime. In these situations, crime may spill-over into neighboring areas, and police may work to limit this spill-over in neighboring areas.

Previous research has shown that race and community levels of crime play an important role in how law enforcement form suspicion. Alpert et al. (2005) adopt a mixed-methods approach utilizing qualitative observations of police officers in Savannah, Georgia. Officers were observed and then debriefed after incidents when they formed suspicion either about an individual or a vehicle. Trained observers accompanied selected officers on 132, 8-hour shifts, observing officers forming suspicion 174 times. These variables were used as the dependent in logistic regression models. For independent variables, the researchers used officer characteristics including race, education, and the number of years in service. Additionally, variables were included measuring neighborhood composition where suspicion was formed and were based on police officer perceptions of the area being patrolled, and also included whether officers felt neighborhoods were "troubled". Findings from the study reveal that race plays an important role in suspicion development. Notably, people were more likely to be arrested in lower-class Black neighborhoods than in affluent ones. However, police were less likely to stop suspicious people in high-crime neighborhoods. This speaks to a divide between race and crime rates or competing arguments for what influences police behavior.

Unlike racial and economic threat, community violence is expected to work through mechanisms that directly inform how police do their job. If an officer is aware of a particularly violent area neighboring their jurisdiction, they may perceive people coming from those communities as a greater threat for violence. For example, Jacobs and Britt (1979) found that that economic inequality, population changes, and violence index were positively and significantly associated with police-caused homicides. These findings were largely echoed by Fyfe (1980) who
found a significant relationship between arrest rates and shootings. Furthermore, analysis reveals a significant and positive relationship between homicide rates and police shootings. Fyfe (1980) concludes that police shootings are closely associated with the index for public safety, with busier areas in terms of reported murders and nonnegligent manslaughters reporting higher percentages of police shootings by on-duty officers. Smith (2004) found that community violence and the proportion of African Americans were significantly related to police killings of felons, while economic threat was not related to killings. Though, they note that officers may be less likely to enter areas and neighborhoods with high levels of violent crime. This reflects the ideas of Klinger et al. (2016) vigilante justice hypothesis, or that law enforcement will only engage with a violent population when they cross a border into a place they do not belong, while adopting a more hands off approach within the violent community, allowing them to police themselves. Based on Klinger et al.’s (2016) vigilante justice hypothesis, and findings from Lautenschlager and Omori (2019), and Smith (2004), we may expect the violent crime of a focal community to exhibit a negative relationship with police-involved homicide because law enforcement may be less likely to intercede in communities with high levels of violence. On the other hand, the violent crime of neighbors is likely to have a positive effect on a focal community’s police-involved homicide, especially in cases where violent communities border non-violent communities. In these situations, law enforcement may also be more likely to respond with higher levels of force, including violence. As Jacobs and O’Brien (1998) note, police may undoubtedly respond to a violent population with violence themselves. However, it is important to point out that questions still remain as to whether community violence works directly within a community, or indirectly vis-à-vis external threats. With this in mind, I posit the following hypothesis:
**H4a**: Violent crime in a focal county will be negatively associated with police-involved homicide in that focal county and violent crime of neighboring counties will be positively associated with police-involved homicide in that focal county.

Alternatively, the total level of crime of a particular focal county is likely to exhibit a positive relationship with police-involved homicide. Based on this, I posit the following hypothesis:

**H4b**: Total crime in a focal county will be positively associated with police-involved homicide in that focal county and total crime of neighboring counties will be positively associated with police-involved homicide in that focal county.

Lastly, the Black arrest rate is likely to exhibit a similar relationship with the total crime rate. Therefore, I posit:

**H4c**: Black arrest rate in a focal county will be positively associated with police-involved homicide in that focal county and Black arrest rate of neighboring counties will be positively associated with police-involved homicide in that focal county.

Future research should explore how the relationship between Black arrest and police-involved homicide varies based on the type of arrest. For example, similar to the hypothesis on violent crime, might we expect arrests of Blacks for violent crime to have a negative relationship with police-involved homicide within a focal county, but a positive relationship when considering Black violent crime of neighboring counties? Either way, the proposed hypotheses on total crime and
Black arrest posit a spillover effect from neighboring counties, while violent crime is proposed to exhibit a socially relative or socially incongruous response from law enforcement.
CHAPTER 3: DATA AND METHODS

One of the more important marriages between criminological inquiry and methodological advancement has been the application of spatial analysis to the study of crime. According to Baller et al. (2001), criminologists have begun to devote more attention to the spatial relationship of crime. Spatial analysis has been applied in the study of multiple criminological theories including anomie/strain, social disorganization, routine activities, and crime hot spot mapping (Anselin, Cohen, Cook, Gorr, and Tita 2000). More recent studies have also begun to explore the nature of police shootings concerning place and space (Klinger et al. 2016; Ross 2015). However, recent attempts, while important, have been only applied spatial econometrics in a limited fashion. Often, spatial analyses are relegated to including a spatial-lag variable within larger statistical models. However, doing so also introduces potential issues of interpretation, because the dependent variable is treated as both a dependent and independent variable. While I will discuss this later, it is important to note that the spatial research on PIH is rather limited, except for the few recent studies cited above. These recent studies have begun to shed light on the spatial relationships between communities of color and policing outcomes. However, methodological shortcomings have limited the scope of what we know about these spatial relationships.

The application of spatial econometrics to the study of crime emerged in the 1990s along with advancements in computer technology. Furthermore, advancements in geographical information systems (GIS) were crucial to our ability to measure and represent spatial relationships in data (Anselin et al. 2000). The goal of spatial analysis, in addition to understanding spatial relationships, is to account for violations in the basic assumptions underlying regression analysis (Anselin et al. 2000; Baller et al. 2001; Wheeler and Tiefelsdorf 2004). The argument is that much
of the inconsistency in the empirical application of criminological theories may come down to the problem of multicollinearity, and variations in error terms which represent potential "spill-over" effects. Thus, the main concern of regression modeling comes down to accounting for issues of spatial autocorrelation. The goal then of spatial analysis is to treat spatial effects, not as a nuisance, but as a substantive part of theoretical application (Anselin et al. 2000). This is realized in spatial econometrics by purposely including a spatial interaction variable as a predictor in a regression model.

Spatial autocorrelation refers to the situation where values of variables are systematically related to geographic location (Baller et al. 2001). Spatial analysts are generally concerned with understanding the influence of neighboring areas, in addition to "spillover" effects. As an example of spillover effects, a criminologist or crime analyst might be interested in how gang drug trafficking might be related to homicide. The issue is that, unlike standard regression analysis, the spatial analyst would be able to account for effects that move beyond simple geographical boundaries. So, for instance, a gang may have a territory that takes up parts of two distinct geographical boundaries. A rival gang may encroach on their territory, and someone might be killed. This results in a retaliatory killing in a different territory. While classical regression analysis might see this as a problem, spatial analysts specifically account for these types of occurrences by including a spatial predictor.

The literature on police-involved homicides has only recently begun to test spatial models. For example, Klinger et al. (2016) in their analysis of St. Louis neighborhoods included a spatial lag (SLM) variable into their OLS models. Spatial lag refers to the influence one community has on another, as it relates to a variable of interest. Take the example from above, a spatial lag would attempt to measure how a homicide in one neighborhood influences homicides in neighboring
communities. Another way of accounting for spatial dependence is through the use of spatial error models (SEM). SEM attempts to account for what is called "spatial disturbance," also known as those spatial effects which are omitted or unaccounted for by nonspatial models. In other words, SEM "implies that it is unnecessary to posit distinctive effects of the lagged dependent variable. The observed spatial clustering in homicide rates is accounted for simply by the geographic patterning of measured and unmeasured independent variables” (Baller et al. 2001: 567). One of the clear drawbacks of Klinger et al.’s (2016) spatial lag model, is that it incorporates a spatial lag into an OLS model and is very likely to yield biased or inefficient estimates. This is because the spatial lag of the dependent variable is treated as a dependent and independent variable, which produces results that do not clearly separate the dependent variable from the independent variable. Furthermore, Klinger et al.’s (2016) spatial lag model is based on first-order neighbors and does not allow for decomposition of results, which is a specific goal of this study. Overall, my study looks to build on previous research by addressing many of the methodological pitfalls inherent in standard spatial lag and error models by introducing the spatial Durbin model (SDM) as a superior spatial model for teasing out direct and indirect effects.

Spatial Durbin Models (SDM) are a more recent spatial analysis advancement that attempt to marry spatial error and spatial lag models. LeSage (2014) notes, spatial Durbin models can be used in cross-sectional research and can be interpreted as depicting or reflecting a comparative static slice at one point in time of a long-run steady-state equilibrium relationship, and the partial derivatives viewed as reflecting a comparative static analysis of changes that represent new steady-state relationships that would arise. This would seem to fit well with my research, given not only the limitations in data but also the level of analysis used. I will explore SDM more fully in the proposed analysis section. It is important to note that previous studies exploring police-involved
homicide tend to use counts as the dependent variable. This is due to the highly skewed nature of police-involved homicides in US counties. Furthermore, previous research has also relied on statistical techniques that help account for the overdispersion of zeros within the data, such as negative binomial regression models. Unfortunately, spatial analysis has not matured enough to allow for such analysis at this time, even with recent advancements such as geographically weighted negative binomial regression.

Level of Analysis

The present study uses data at the county-level. Baller et al (2001) note that counties may be an arbitrary unit of analysis when studying homicides, and this is likely to hold when those homicides are by police specifically. Additionally, county-level data may be subject to the ecological fallacy problem. Furthermore, the unit of analysis has important impacts on spatial analysis. For example, a county may be too large a unit of analysis when detecting the diffusion of certain social processes, such as PIH. Ideally, the unit of analysis should be determined theoretically, but data availability often necessitates certain accommodations. However, this does not mean the county is not a valid unit of analysis for PIH. While the county level may pose problems for homicides writ large, specifically focusing on counties for PIH may be of more use. Eitle et al. (2002: 563) notes that counties “typically represent the legal jurisdictions of governments and criminal justice systems and given most law enforcement personnel operate at the local level, using counties as the unit of analysis for examining differences” – in their case, in local law enforcement practices, was not problematic. Additionally, Eitle et al. (2002) utilize similar measures of group threat to those I am using. Recent studies such as Ross (2015) and Edwards et al. (2018) have demonstrated the usefulness of examining PIH at the county-level, and the present study aims to build on this. Below I will explore the data and measures used for this study.
Data

Police-Involved Homicide Data

Police shooting data has been notoriously inadequate at capturing the extent to which citizens are shot and killed by police in the United States (Campbell et al. 2018). Recent studies have begun to shed light on data quality issues with police shooting data, such as the Uniform Crime Report’s Supplemental Homicide Report (SHR), and the National Vital Statistics System (NVSS). For example, Williams, Bowman, and Jung (2016), when comparing government databases recording officer-involved shooting fatalities, found that the SHR and NVSS were subject to various inconsistencies, such as underreporting, and classification errors, and that these shortcomings applied statewide, such as with Texas and California. Further analysis of the data, when compared to crowdsourced or open-sourced data, indicated that governmental databases reported 30 percent to 45 percent fewer cases than crowdsourced/open-sourced databases. However, it is important to note that these new databases, such as MPV, may also be subject to similar inconsistencies, such as classification errors and underreporting, though to a lesser extent than governmental databases. Despite this, crowdsourced databases, and the research utilizing them, can reveal critical questions and understandings that governmental data is unable to shed light on, such as the extent of police-involved homicides in certain places, and the events surrounding these shootings. Additional benefits of crowdsourced data include their timeliness and cost. For example, most crowdsourced databases are updated regularly and have processes in place to catch and resolve irregularities within the data. Furthermore, because these databases are updated regularly, it allows for researchers to quickly identify patterns, and produce analyses that are more relevant to current social issues. Additionally, because these databases are freely available to anyone with an internet connection, the costs associated with doing such analyses are minimal.
Given the current limitations of governmental data, the current study will utilize crowdsourced data from the Mapping Police Violence database (Sinyangwe, Samuel, DeRay McKesson, and Johnetta Elzie 2021). The MPV database shares many similarities with other internet databases, such as The Counted, Fatal Force, and The Washington Post’s Police Shooting Database, such that they all use data sources from the internet, articles from the news, and some direct police records (Gray and Parker 2019). However, MPV also uses crowdsourcing efforts to collect data, something Fatal Force does not. MPV has been collecting data since 2013 and is regularly updated. The database is overseen by three individuals who “have held varying roles in policy analysis, data science, education, activism, youth leadership, and so on, with a special emphasis on working within communities of color for racial justice and equity” (Gray and Parker 2019: 29). According to MPV, their data has been “been meticulously sourced from the three largest, most comprehensive and impartial crowdsourced databases on police killings in the country: FatalEncounters.org, the U.S. Police Shootings Database, and KilledByPolice.net” (MPV 2020). Furthermore, recent estimates by the Bureau of Justice Statistics between June 2015 and May 2016 closely mirror those of MPV, 1,200 to 1,104 respectively. Moreover, the curators of the database have run their research to add to the quality and completeness of the data (Gray and Parker 2019). Ultimately, it is the goal of the curators that this data will help bring an end to police violence.

Measures

Dependent Variable

The main dependent variable for this study is the overall county-level average police-involved homicide rate from 2013 to 2019. The choice of average rate is in line with the design of the spatial

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1 For more information, please visit https://mappingpoliceviolence.org/planning-team/.
2 For more information, please visit https://mappingpoliceviolence.org/aboutthedata.
Durbin model, which assumes a continuous dependent variable. The rate of PIH is calculated by first averaging the number of PIHs for one county for the years 2013 to 2019, and then dividing it by county population total data from the 2012 American Community Survey five-year estimates, and then multiplying it by 1,000 to arrive at the average rate of police-involved homicide per 1,000 population. The Spatial Durbin model also relies on the normality assumption, that the original dependent variable is normally distributed. However, data on police-involved homicide are highly skewed, with many zeros. To correct for this, I transform the dependent variable by taking the square-root of the average police involved homicide rate. While this is unlikely to completely correct the skewness of the data, I will also run additional negative-binomial regression models of the police-involved homicide count data and compare across models to determine if the findings vary drastically. If the findings do not vary drastically, it can be assumed that the dependent variable is not a cause for concern in the spatial models.

The use of average rates has been demonstrated in the work of Balle et al. (2001), in their spatial examination of county-level homicide using a national dataset. In their study, three-year averages of county homicide counts were used, centered on each decennial census year between 1960 and 1990. The averages were then divided by single-year census population figures. This approach is common in studies where the dependent variable is highly skewed toward zero. This is done for both White and Black PIH, with each average being divided by the race-specific population.

While the data gathered by MPV should be commended, it is not without issues, and some cleaning of the data is required. Notably, MPV has a very broad definition for PIH as identified above. For this study, I limit cases to only those where the race and gender of the victim are known, the officer was on duty during the incident, and the official cause of death does not involve a
vehicle. On the one hand, limiting cases only to those where the race and gender of the suspect are known allows for me to explore racial dynamics in PIH, it may also introduce potential bias into results. For instance, I may artificially underrepresent the extent of PIH, both statistically and spatially. A review of the data shows that a total of 645 PIH cases omitted the race of the victim between 2013 and 2019. An additional 8 cases did not include the gender of the victim. However, the choice to exclude these cases is justified based on the theoretical aims of the study to explore racial threat and the goal of disentangling the spatial effects of group-threat on PIH.

By vehicle, I mean situations where police pursue a suspect by car and the official disposition or cause of death is vehicle. It is possible for these situations to cross county boundaries, or the suspect themselves precipitates their own death by getting into an accident. For example, if a suspect is pursued by an officer of a focal county, and they cross into a neighboring county during a pursuit, there may be concern of whether I am measuring the effect of the neighboring county or focal county threat. In total, 29 cases reported the official cause of death to be vehicle. Unlike some studies exploring PIH, I do not limit my inquiry to only those cases where the victim was shot by police. There may be concern regarding this decision, especially when it comes to the question of controlling for extraneous circumstances which may call into question the validity of findings regarding PIH. For example, there may be instances in which an officer was attempting to subdue a suspect, and in doing so, decided to use a TASER™. It is possible, that while the intent was to subdue, the suspect experiences sudden cardiac arrest, and succumbs to it. In these situations, it is clear the officer in question did not intend to kill the suspect. This may seem like a clear case that should be excluded from the sample of PIHs. The question of whether to include cases such as these is one of focus. If the focus of this study was to explore the decision-making processes of officers who engaged in actions with the intent to kill, then it would make sense not to include
these cases, as there would be clear and direct evidence demonstrating that the officer did not intend to kill the suspect. However, if the focus of the study is to explore and understand the nature of PIH, where they occur, in what frequency they occur, and the social and economic determinants of such phenomena, as is the case with this study, then arbitrarily limiting cases to instances where the intent was clear is exactly that, arbitrary. Even in studies where cases are limited to only those involving a firearm, and the shooting of a suspect, it is unclear whether such limits enrich or are even necessary. If for example, the researcher plans to study only police shootings, and they have a valid theoretical justification or model to do so, then it is of no issue to limit cases to only those utilizing a firearm.

Of notable relevance regarding this point, often the only evidence researchers have to determine the intent of a PIH is a police report of a situation, which previous research has already shown to be biased. Even more concerning is the relative lack of criminal charges laid on officers who may have engaged in unlawful killings of citizens. In fact, between 2013 and 2019, MPV identified only 114 cases where criminal charges were laid out of a total of 7,646 PIHs. It is then assumed that for the remaining cases, the officers were acting lawfully and within their rights to take the life of another person. The penultimate point I am trying to make is that even if the goal of this study was to explore whether various PIHs were justified, or whether there is indeed a racial bias in how officers make their decisions, doing so would require a different set of data. As such, the goal for this study remains the exploration and uncovering of what Durkheim coined, social facts. After cleaning the data, the final sample size includes 6,575 police-involved homicides across 3,108 US counties.

Independent Variables
Intending to test various aspects of group threat, the current study utilizes data from multiple databases, including the 2012 American Community Survey 5-year estimates, and the 2012 Uniform Crime Report. In testing group threat theory, I have divided variables from these sources into four distinct measures of group threat: racial threat, economic threat, place-based threat, and the community violence hypothesis. Below I will describe how these variables are measured.

Racial Threat

Political threat is derived from Blalock’s (1967) power threat hypothesis which assumes that as the percentage of Blacks in the population increases, so does the view of Blacks as a threat to the political ascendancy of Whites (Eitle et al. 2002). In line with Blalock’s work, I use percent Black as my main measurement for racial threat. Racial threat is constructed using data from the 2012 ACS five-year estimates.

Economic Threat

As noted in Chapter 2, economic threat refers to the competition between two or more groups for jobs and finite resources. Economic threat has been measured in multiple ways within the literature, but the most accepted measure is the ratio of Black-to-White unemployment ratio. As Eitle et al. (2002) note, the validity of this measurement rests on the assumption that a split labor market exists, or that Whites and Blacks are paid different wages, thus employers may have an incentive to employ Blacks over Whites. However, threat should also be considered from the perspective of social relativity. According to Blalock (1967), an economic threat may result in the loss of social status when lower status groups interact with or enter higher status areas. Economic threat should thus be understood as both the competition between two groups for finite resources, but also the potential for one group to threaten the status of another group. Thus, higher unemployment between one group and another may indicate a difference in status between the
two, and result in negative interactions between them, especially when the higher status group works to limit contact or access to resources to the lower status group. With this in mind, I calculate the ratio of Black-to-White unemployment using data from the 2012 ACS 5-year estimates. Additionally, I also include another measure of economic threat in the Gini Coefficient. The Gini coefficient measures the dispersion of income across the entire income distribution and ranges from 0 to 1. A Gini coefficient of 0 indicates perfect equality, where everyone receives an equal share, while 1 represents perfect inequality where only one recipient or group receives all the income.

In addition to the Black-to-White unemployment ratio and the Gini coefficient, I also include a measure for concentrated disadvantage. This variable is calculated as a composite score using principal component analysis on three factors: percent unemployed, percent living in poverty, and percent female-headed households. The extract command was used in SPSS, with the default choice to factor the correlation matrix. This is the equivalent to standardizing variables first, then factoring the covariance matrix. After the factor analysis, a factor score is generated resulting in a mean of 0 and a standard deviation of 1. The factor scores for each variable are .843, .864, and .870 respectively.

Place-Based Threat

Previous research has shown that minority populations in the United States are disproportionately concentrated in segregated urban neighborhoods (Holmes, Painter II, and Smith 2019; Massey and Denton 1993). Often these populations experience various forms of socioeconomic disadvantage, which are posited to influence how police understand and react to these populations. The place-based threat hypothesis maintains that "the residential segregation of these populations is central to the deployment of coercive strategies of policing" (Holmes et al.
To assess the extent to which place-based threat plays a role in PIH, I include a measure of segregation in the interaction index. There are two basic measures of exposure, the isolation index, and the interaction index. The interaction index measures the extent of interaction between the minority and majority groups and is calculated as the minority weighted average of the majority proportion of the population in each areal unit (Massey and Denton 1988: 288). Because I am interested in exploring the spatial causes of PIH, the interaction index seems to be a plausible construct to use, given the necessity of contact for PIH to occur.

\[
\text{Interaction} = \sum_{i=1}^{n} \frac{b_i}{B} \times \frac{w_i}{t_i}
\]

In the formula above, the Interaction index represents the reverse of segregation, meaning that as the interaction index increases, the level of segregation decreases. It is calculated by taking the within tract Black population represented as \(b_i\), and dividing it by the total sum of the Black population for the aerial unit used, represented as \(B\). In this study, I use the total sum of the minority population for a county. This is then multiplied by the within tract White population notated as \(w_i\), divided by the total population of that tract, represented as \(t_i\). This is summed for the number of tracts within a county.

Community Violence Hypothesis

Community violence hypothesis posits that the level of crime and deviance a minority group engages in will be positively associated with increased discrimination and social control against that minority group. For example, the police should be especially likely to use violent methods where they must deal with a violent population. “This most fundamental reactive explanation
suggests that police departments in cities with higher civilian murder rates should be more likely to use deadly force” (Jacobs and O’Brien 1998: 845). In other words, those groups which are more violent, are more likely to experience higher levels of social control. However, more recent research has identified that community violence may exhibit the opposite effect on social control (Klinger et al. 2016; Smith 2004; Lautenschlager and Omori 2019), in that as community violence increases, the level of social control drops, with law enforcement allowing violent communities to police themselves, giving rise to vigilante justice. To capture this concept, I include measures for Black arrest rate, violent crime rate, and total crime rate. The rates for violent and total crime are taken from the 2012 Uniform Crime Report, while the Black arrest rate is calculated using data collected by the Inter-university Consortium for Political and Social Research (ICPSR) on arrests by race, age, and sex in the United States, by reporting agency for the year 2012. The data in its raw form only provides the reporting agency, and not the county GEOID. To resolve this issue, I used the Law Enforcement Agency Identifier crosswalk for US counties and summed total arrests by agencies within each county. The resulting raw count data was then divided by the total population for each racial group, and then multiplied by 1,000 to calculate the rate. While the overall, the literature posits a positive relationship between community threat variables and PIH, recent work by Klinger et al. (2016) and Lautenschlager and Omori (2019) indicate that this relationship may not hold for the most violent communities, and that police may be less likely to engage with communities with high levels of violence.

Control Variables
I also control for several variables that are expected to influence the findings if not present including percent male, percentage of population 15 to 24, the number of officers assaulted\(^3\) and the number of suicides by firearm. The first two variables are taken from the 2012 ACS 5-year estimates, while the last two are taken from the 2012 UCR and 2012 Centers for Disease Control mortality data respectively. The decision to control for officers assaulted and suicide by firearm is based on the idea that these variables may capture the direct threats officers in the field may face, while also accounting for the potential to encounter an armed suspect. Previous research (Nagin 2020; Kleck 2004) reports that the use of suicide by firearm is a validated approach and a widely used measure for gun availability in criminological and criminal justice research and is shown to be associated with levels of community violence. Research from Miller, Azrael, and Hemenway (2002) find that from 1988 to 1997, firearm ownership was positively and significantly associated with homicide across the United States. Additionally, they found that this relationship held when examined regionally, and at the state level, even after controlling for poverty, urbanization, unemployment, alcohol consumption, and nonlethal violent crime. Overall, their research found that in areas with “higher levels of firearm ownership, a disproportionate number of people died from homicide” (Miller et al. 2002: 1988). In another study, Miller, Hemenway, and Azrael (2007) note that in the United States, two out of every three homicide victims are killed by a firearm. In their study, they examine the unexplored link between household firearms and homicide victimization. Their research used data survey data on gun ownership from 2001, for all 50 states, and homicide mortality data aggregated from 2001 to 2003. After controlling for structural variables related to socioeconomic status, crime, and race, they found that states with higher rates

\(^3\) There were some missing data on the number of officers assaulted. The original data consisted of 3,135 counties. Data was imputed for 66 missing counties, or 2.1\% of the total cases. The average imputation was used, 14.45.
of household firearm ownership had significantly higher rates of homicide victimization, and that these rates were largely driven by firearm ownership (Miller et al. 2007: 656). Linking this to police-involved homicide, Nagin (2020) finds that at the state level, gun ownership (measured as the percentage of suicides committed by firearms), is positively associated with fatal police shootings. Ultimately, the potential threats encountered by law enforcement while in the field present an important ingredient in police-involved homicides and must be controlled for.

While potentially important, data limitations do not allow for me to control for the racial makeup of police departments. Previous research is mixed on whether diversifying policing organizations impacts policing outcomes (Brown and Frank 2006; Nicholson-Crotty, Nicholson-Crotty, and Fernandez 2017). However, future work should explore the racial and gender makeup of policing organizations, and its impact on policing outcomes.

**Analytic Models and Strategy**

**Analytic Strategy**

The analysis portion of this study is broken down into four separate analyses. The first analysis will include an exploration of the descriptive statistics. Next, I will begin my initial spatial exploration by running tests for spatial autocorrelation in the baseline model, and each variable. This is accomplished through the use of two separate methods, the Moran’s I statistic for spatial autocorrelation, and the examination of spatial maps, or local indicator of spatial association (LISA) maps. This step allows the researcher to identify spatial clustering, while also providing initial insight into potential spatial relationships between variables. Following this analysis, I will move onto the full spatial analyses, which will include spatial lag, spatial error, and finally spatial Durbin models. The goal of these analyses is to compare the standard spatial approach, using spatial lag and error models, with the spatial Durbin approach. Ultimately, I will test whether the
spatial Durbin model is analytically superior to other spatial models, while also testing whether findings from the model provide more substantive and theoretically important findings regarding the spatiality of covariates on police-involved homicide. Lastly, I will partition the results of the spatial Durbin model into direct and indirect effects. The partitioning of results allows researchers to assess the extent to which outcome variables are influenced by more localized effects or are the result of neighboring effects spilling over into local communities.

The decision to use spatial Durbin modelling for the current study is based on two important and related justifications. First, theoretically and substantively, the spatial Durbin model allows me to test seemingly contradictory relationships across space that have been captured within the literature. For instance, research on economic threat and the community violence hypothesis have highlighted the importance of accounting for both local area structural determinants, such as inequality, disadvantage, and violence, but also how neighboring communities influence local community responses to threats. As previously noted, the work of qualitative researchers has identified that the characteristics of surrounding communities matter when it comes to policy initiatives and policing strategies (Lynch et al. 2013; Stuart 2016). The spatial Durbin model is uniquely situated to be able to help me answer the question of whether local community characteristics or surrounding community characteristics drives these changes. For example, to what extent is the violence of surrounding communities responsible for the level of police involved homicide in a focal county? At the same time, to what extent is a focal county’s level of police-involved homicide driven by local or neighboring community factors? Taken together, this analysis provides an initial step toward understanding the complex interplay between communities from a quantitative perspective.
Second, the spatial Durbin model allows researchers to overcome some of the initial limitations of previous spatial models in terms of model specification and interpretation. LeSage (2014) notes that in applied work, regional scientists and practitioners interested in understanding local and global spillovers need only model one of two model specifications. Either the spatial Durbin error model (SDEM) or the standard spatial Durbin model (SDM). The current study relies on the spatial Durbin model approach. The decision to use the global spillover model is based on theoretical and substantive justifications related to the spatial relationships between counties. For example, if I assume that neighboring counties are all in competition with one another, and an aspect of that competition is the regulation and control of law enforcement activities to protect the interests of a given county, then I would be assuming a global spillover process. If, on the other hand, I was interested in understanding how a local governments policy provisions simply result in a local spillover phenomenon, I would want to estimate a SDEM. Given the focus on threat, and competition between units, the SDM is recommended. From here, the partitioning of results into direct and indirect effects allows for an unbiased estimation of the results. Below, I will describe my methods more thoroughly, beginning with the initial spatial exploration, including an explanation of how I will calculate and use spatial weighting.

*Spatial Weighting and Exploratory Spatial Data Analysis (ESDA)*

The weight matrix essentially determines which spatial units are considered neighbors. Choosing a weight matrix should be based on the theoretical and practical relationships between variables. For example, I could employ a larger weight matrix using nearest neighbors, where X nearest counties are considered neighbors to the focal county, a strategy sometimes employed in spatial research. Other techniques include using adaptive weight matrices, which are often employed in geographic weighted regressions (GWR) but are of limited theoretical value in the
Regardless of which spatial weight is employed, recent research on spatial weighting has begun to call into question prevailing myths about choice of spatial weight.

Recent work by LeSage and Pace (2014: 218) debunks the long prevailing myth that the explanatory effects and inferences of spatial models are sensitive to the particular weight matrix employed. While it is still the case that different spatial weights may produce different estimates, a modest approach to spatial weighting is not likely to greatly influence model estimates.

Potentially more likely to influence estimates in spatial modeling is model misspecification. As LeSage and Pace (2014) identify in their critique of previous spatial studies, weight matrix variation is more likely to produce differences in significance of estimates. Variation in estimates is likely to result from omission of key variables from spatial modeling. This is not to say this is always the case, but comparison of model estimates seems to be a reliable approach when determining model specification, while variation in significance across model estimates is likely a result of spatial weighting decisions. Though, LeSage and Pace (2014) note that this is not likely, even as you move up in spatial ordering. Regardless of which spatial weighting matrix is used, discussion regarding alternatives should be had based on theoretical and substantive implications for research.

In the case of the current study, I will employ a first-order Queen adjacency matrix. This matrix determines whether two counties are neighbors by whether they share a boundary or vertex geographically. If they do, then they are defined as neighbors. This approach varies with respect to alternative approaches such as Rook contiguity, which determines neighbors by shared border. The decision to use a Queen matrix is likely to result in a larger number of neighbors per county, as counties must only share vertex. Based on research from LeSage and Pace (2014), it is unlikely
this will produce drastically different estimates as the number of neighbors is unlikely to vary greatly between the two weight matrices.

After constructing the spatial weights, I will begin the explanatory analysis stage by determining whether spatial analysis is a valid approach. Exploratory spatial data analysis (ESDA) is the first opportunity for researchers to identify potential spatial clustering, also known as spatial autocorrelation. Baller et al. (2001) define spatial autocorrelation as a situation in which values on a variable of interest are systematically related to geographic location. If significant and positive spatial autocorrelation is present, it suggests the clustering of cases in and across space, rejecting the assumption of spatial randomness. To test for spatial autocorrelation, I will employ the Moran’s I Statistical test for global autocorrelation of both the dependent variable and independent variables. A positive and significant Moran’s I statistic indicates spatial clustering, or spatial autocorrelation, meaning that the variables vary spatially. In addition to testing for spatial autocorrelation, I will also construct a series of basic visualization techniques, mapping both dependent and independent variables to identify spatial clustering. Between directly testing for spatial autocorrelation and mapping the results, researchers are better able to justify the use of spatial techniques, such as SDM.

While useful for justifying spatial analysis, global Moran’s I only provide an overall sense of the data using a single statistic. Further exploration can be made by examining local indicators of spatial association, also known as LISA statistics. To assess the extent of spatial clustering in counties across the United States, I will borrow a technique from Baller et al. (2001) by using a scatterplot of the LISA statistics combined with values for significant local Moran statistics. The resulting maps will then be classified into four categories, based on the relationships between neighboring counties: High-High, Low-Low, Low-High, and High-Low. These relationships
describe the extent to which a particular variable is spatially clustered around values of that variable that are similar or different in terms of magnitude. For example, a High-High significant relationship for Black arrest rate would indicate high levels of Black arrest rate surrounded by other counties with similarly high Black arrest rates. This will also be indicated on the map, as counties with various relationships will be color coded as such.

Spatial Lag, Spatial Error, and Spatial Durbin Modelling

Following the Moran’s I test and LISA maps, and assuming that significant and positive spatial autocorrelation is evident, I will begin full spatial modeling. Following previous studies employing SDM, I will introduce spatial lag and spatial error modeling into the county-level dataset, as these models will be used to assess if the SDM statistically outperforms the other models (Yang, Noah, and Shoff 2015), using the Akaike information criterion (AIC). An AIC of 10 or greater would indicate that the SDM statistically outperforms other spatial models (Yang et al. 2015).

The final analyses will test the effects of racial threat, economic threat, place-based threat and variables for the community violence hypothesis on police-involved homicide using the spatial Durbin model. The benefits of SDM allow me to partition the results between direct and indirect effects, allowing me to explore the extent to which PIH is largely driven by factors within a community, or characteristics of surrounding communities.

Spatial Durbin Model

LeSage (2014) concludes in his treatise on spatial econometrics, that while much emphasis has been placed on spatial autoregressive models (SAC), they should be largely ignored and/or avoided by researchers given their numerous drawbacks in applied use. He recommends that only two spatial specifications should be estimated, either the spatial Durbin error model (SDEM) or spatial
Durbin model (SDM). The spatial Durbin model (SDM) is a "global spillover specification,” taking the form (LeSage 2014: 17) shown below.

\[ y = pWy + \alpha_n + X\beta_1 + \varepsilon \]

The model includes a spatial lag variable in Wy, representing a linear combination of values of the dependent variable vector from neighboring observations, as well as a matrix of own-region characteristics X (LeSage 2014: 17). In the case of the current study, y would represent a cross-section of county-level average PIH rate, and X would represent theoretical variables of counties. The idea is that global spillovers may occur or arise due to concerns with threatening groups in adjacent or neighboring counties, instigating or influencing potential interactions in police-citizen interactions. Direct and indirect effects from SDM shown above, describe for the \( r \)th explanatory variable in the matrix X, are given by the matrix partial derivative expression below.

\[ \frac{\partial y}{\partial X^r} = (I_n - pW)^{-1}(I_n\beta_1^r + W\beta_2^r) \]

The presence of spillovers can be seen by recognizing that: \( (I_n - pW)^{-1} = I_n + pW + p^2W^2 + \cdots \). According to LeSage (2014), this means that an n X n matrix of partial derivatives is associated with a change in each of the explanatory variables. LeSage and Pace (2014: 18) further note that direct effects can be “measured as the average of the main diagonal elements of this matrix as a scalar summary measure of the own-partial derivatives, which they label direct effects. An average of the cumulative sum of off-diagonal elements reflecting cross-partial derivative provides a summary measure of spillovers which they label indirect effects.” LeSage (2014: 18) further
comments that the “literal interpretation of the partial derivatives from a cross-sectional model such as the SDM would be that the cross-partial derivative impacts on neighboring regions (indirect effects or spillovers) arise simultaneously.” Thus, spatial Durbin models can be used in cross-sectional research and can be interpreted as depicting or reflecting a comparative static slice at one point in time of a long-run steady-state equilibrium relationship, and the partial derivatives viewed as reflecting a comparative static analysis of changes that represent new steady-state relationships that would arise. In the case of justifying the use of SDM, LeSage (2014) recommends that researchers need only estimate SDM when the case of global spillover is implied by theoretical or substantive aspects of the problem, as is the case in the current study where concerns of spatial threat play out writ large between and within counties.

Ultimately, the SDM approach represents a potentially significant step forward in our understanding of the factors influencing PIH, but also new theoretical avenues of exploration for group threat theory. It is my opinion that group threat theory has been relatively stagnant in its application and usefulness to social phenomena, and this new direction allows for both substantively important and useful findings to help inform where and potentially how to solve the problems of police use of force.
CHAPTER 4: RESULTS

As noted in the previous section, the analysis portion of this study is broken down into four separate analyses. I will begin with the presentation and discussion of the descriptive statistics, and then move to exploratory spatial data analysis (ESDA). Following this, I will present findings from the full spatial model analysis, and finish with the portioning of results from the SDM into direct and indirect effects.

[Insert Table 1]

Descriptive Analysis

Table 1 presents a summary of the data on police-involved homicide and group threat variables measured at the county-level. For purposes of the analysis, I will use the square-root of the average rate of police-involved homicides. In total, the current study explores the structural determinants of 6,575 police-involved homicides across 3,108 US counties between 2013 and 2019. The mean number average rate of police-involved homicide is .0031 per 1,000 population. However, the standard deviation (.007) is much higher than the mean value, indicating the distribution of police-involved homicide varies greatly across US counties, and as expected, the distribution of police-involved homicides is highly skewed. Specifically, 1,661 counties reported zero police-involved homicides, which is about 53% of the 3,108 counties in the sample. On the other hand, some counties reported very high levels of police-involved homicide. For example, Foard County, Texas, has the highest average rate of police-involved homicide across the period under study at .109, with an average yearly rate of about .142 per 1,000 population. Other notable counties include
Concho County, Texas with an average rate of .071 per 1,000 population, and a yearly average rate of .285, and Sherman County, Oregon with an average rate of .082. All three counties do not have large metropolitan areas, with populations ranging from about 1,300 to 4,000.

Similar to police-involved homicide, some of the covariates for this study also vary greatly. While presented in raw form in the descriptive analysis, I do transform some of the variables to account for the skewness observed in the data. The mean percent Black across US counties is 8.93%, with a standard deviation of 14.56%, and a maximum range of 86.2%, with many counties reporting no people of color. In fact, 50% of US counties report percent Black populations of 2% or less. US counties have a mean Gini coefficient of .43, and a standard deviation of .03. Building on this, the mean Black-to-White Unemployment ratio in US counties is 2.87, with a standard deviation of 6.59, indicating a higher level of unemployment among Blacks in the United States. The interpretation of this figure indicates the rate of unemployment among Blacks is nearly three times as high for Blacks as it is for Whites and varies greatly from county to county. Disadvantage is constructed using factor analysis of three separate measures, percent unemployment, percent living in poverty, and percent female-headed households. The measure has a mean of 0 and a

4 One concern with the current study relates to the reliability of estimates due to skewness observed in both the dependent and independent variables. Previous studies exploring police-involved homicide have often limited analysis to urban areas with populations of at least 100,000 (Holmes et al. 2019). Holmes et al. (2019) note that the inclusion of cities with less than 100,000 population, will likely skew data on covariates related to race. However, given the current studies focus on group-threat, and the effects of covariates between counties, instances where the percent Black of one county is relatively small or nonexistent, and neighboring county percent Black is high, may provide important insights into the ways group-threat plays out across space in ways that are masked by previous studies focused on urban epicenters. While it still may be the case that cities play an important role in the dynamics of police-involved homicide, and previous studies would certainly point to this, discounting the impact of surrounding counties may obscure spatial dynamics at play. For example, it is possible that the relatively high level of police-involved homicide within urban centers is both a product of internal functions within a given urban center, and the product of forces external to a city center aimed at containing or curtailing perceived racial and criminal threats.
standard deviation of 1. A higher disadvantage score indicates higher levels of concentrated disadvantage for a given county.

The interaction index is a measure of exposure and varies from 0 to 1. The interaction index measures the exposure of minority group members to members of the majority group, as the minority weighted average of the majority proportion of the population in each areal unit (Massey and Denton 1988). The interaction index has a negative relationship with segregation, with higher interaction index values representing lower levels of segregation. According to the data, the mean interaction index is .57, with a standard deviation of .2, with many counties representing both ends of the index.

Measures of community threat hypothesis include Black arrest rate, the total crime rate, the violent crime rate, officers assaulted, and total number of suicides by firearm. The Black arrest rate has a mean of 139.24 per 1,000, with a standard deviation of 499.16. This figure, similar to PIH, is driven by larger metropolitan areas, which arrest Blacks at rates far and above the expected rate. To account for the skewness of this figure, I use the logged Black arrest rate in my statistical models. The mean of the total crime rate is 22.69, with a standard deviation of 13.66, and a maximum figure of 89.47, while the violent crime rate has a mean of 2.36 and a standard deviation of 1.99. In addition to measures of criminality for each county, I have also included the number of officers assaulted and suicide by firearm, each reflecting the level of danger a community may pose to law enforcement. The mean number of officers assaulted per county is 15.27, but this number varies greatly as the standard deviation of 80.59 demonstrates. Similar variability is found in suicide by firearm, with a mean value of 4.47 and a standard deviation of 15.93. For purposes of analysis, the natural log of officers assaulted, and suicide is taken. Lastly, I provide results for my variance inflation factor (VIF). Generally, a VIF value greater than 10 suggests
multicollinearity may lead to imprecise coefficients (Yang et al. 2015). As demonstrated in the last column of Table 1, multicollinearity is not a concern for this study. Even when considering a more conservative cut-off point of 3, crime rate and violent crime rate approach this, but are still below it at 2.89 and 2.57 respectively.

Moran’s I Statistical Analysis and Local Indicators of Spatial Association (LISA)

I will begin the spatial component of this study by examining the Global Moran’s I statistics for the dependent and independent variables, followed by an exploration of the spatial clustering of the variables across the United States. The classic test of spatial autocorrelation is the Moran’s I (Anselin et al. 2000) and is used to make an assessment about the degree of global spatial autocorrelation in data (Anselin and Tam Cho 2002). In my analysis, I use a first-order Queens contiguity matrix, or spatial weight, to test the extent to which spatial autocorrelation is present in my data. Overall, the mean number of neighbors per county is 5.94, with a minimum of 1 and a maximum of 14. Table 3 presents the Moran’s I values for both the dependent variable, and the independent variables, including officers assaulted and suicide. A positive and significant Moran’s I statistic indicates clustering in space of a given variable (Baller et al. 2001). As displayed, all of the variables exhibit a positive and significant Moran’s I statistic, indicating spatial clustering of the data, and a rejection of the null hypothesis of spatial randomness. It is important to note that some of the Moran’s I values are small (<0.1), indicating that some of the variables are more spatially clustered than others.

[Insert Table 2]
While useful for justifying spatial analysis, global Moran’s I only provide an overall sense of the data using a single statistic. Further exploration can be made by examining local indicators of spatial association, also known as LISA statistics. Borrowing from Baller et al. (2001), the figures below present modified scatterplot maps of the square root average rate of police-involved homicide, and the independent variables. The format is presented in a way to allow for the easy identification of spatial clustering. The scatterplot is combined with values for significant local Moran statistics, and are then classified into four categories: High-High, Low-Low, High-Low, and Low-High (Anselin et al. 2000). Each LISA map was created using permutation method, with 999 permutations for each map.

[Insert Figure 1 – PIH LISA Map]

An initial observation of police-involved homicide indicates a high level of clustering in the West, and the Southeast, with some clustering in Northern Florida, and parts of Oklahoma, with other scattered clusters of High-High throughout the United States. Low level clustering is evident in the central and North central counties. These clusters are an indication of potential spatial dynamics not accounted for in nonspatial models. Of note for the current study is relatively high prevalence of low-high and high-low areas. Specifically, we find that many counties with high levels of PIH are neighbored by counties with low levels of PIH, and these differences are statistically significant. Generally, high levels of spatial autocorrelation are justification enough to include either a spatially lagged dependent variable or utilize a spatial error model to account for potential confounding factors not accounted for in nonspatial modeling. However, because the
goal of the current study is to explore and analyze the way in which group-threat influences PIH spatially, it is also informative to examine LISA maps of key independent variables.

[Insert Figure 2 – PNHB LISA Map]

For example, figure 2 depicts the spatial clustering of percent non-Hispanic Black in US counties. What is notable is the high level of clustering in Southern counties, up through parts of the mid-Atlantic. Comparing it to the PIH map, there seems to be little relation between the percent Black population and PIH, except for a few clusters around the South, and up into areas of Virginia. Alternatively, looking at figure 3, we see that concentrated disadvantage overlaps a bit more with PIH, though a cursory look at the maps is not enough to conclude that a spatial relationship does not exist. That said, looking at figure 4, officers assaulted does seem to overlap far more than both disadvantage and percent Black population. This provides initial evidence that PIH and the number of officers assaulted may be significantly related to one another. Similar overlap is found with the total crime rate, and the violent crime rate, which may indicate that PIH may be more a product of communities with high levels of crime and violence, and a history of violence against police. Previous research has found overwhelming support for the community threat hypothesis (Liska and Yu 1992; Smith 2004; Legewie and Fagan 2016; Holmes et al. 2019; Lautenschlager and Omori 2019; Helms and Constanza 2020), and it is possible that community violence may interact in a spatial manner, as indicated by initial findings from Klinger et al. (2016).

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5 Please see Appendix A for the full set of LISA maps covering all variables tested.
Univariate local Moran’s I LISA maps are generally useful for identifying spatial regimes. However, in building on this, I have also run bivariate LISA maps, using the square root average rate of police-involved homicide and key independent variables. Figure 5 depicts in similar fashion, the bivariate associated between police-involved homicide and percent non-Hispanic Black population. Initial observations of the bivariate LISA map indicate spatial clustering of high levels of police-involved homicide and large percent non-Hispanic Black populations in Southeastern counties in the United States. However, this is also accompanied by many counties with low levels of police-involved homicide and large Black populations. Alternatively, there is also spatial clustering of high levels of police-involved homicide and small Black populations throughout North Central and Northwestern counties, as well as in counties in the Northeast and South Texas. Based on this initial observation, it does not seem that percent Black is associated with police-involved homicide, at least in the sense that high rates of police-involved homicide tend to spatially cluster in counties with both low and high Black populations.

Figure 6 depicts spatial clustering between concentrated disadvantage and police-involved homicide. Initial observations reveal similar spatial clustering to percent Black, with the caveat that new High-High clusters emerge in some counties in California, while previous spatial clusters
in the Northwest and Northeast are no longer significant. Interestingly, the extent of High-Low relationships that were present with percent Black has dropped from 321 counties to 172 counties. This may provide some initial evidence for a relationship between concentrated disadvantage and police-involved homicide. Unlike concentrated disadvantage, spatial clustering between police-involved homicide and the Gini coefficient (Figure 7) is not as apparent. However, areas like South Texas, and areas throughout the Southeast still reflect similar relationships between inequality and police-involved homicide.

[Insert Figure 6 – PIH/DISADV LISA Map]

[Insert Figure 7 – PIH/GINI LISA Map]

Moving to place-based threat, Figure 8 depicts the bivariate relationship between police-involved homicide and the interaction index. Initial observations do not indicate a particularly strong spatial relationship between the two.

[Insert Figure 8 – PIH/COINT LISA Map]

Figures 9 and 10 depict the bivariate relationship between violent crime and the Black arrest rate and police-involved homicide, respectively. Starting with Figure 9, initial observations indicate much more High-High spatial clustering between the violent crime rate and police-involved homicide in counties within California, New Mexico, and Arizona, and in other regions such as the Southeast, Florida and Georgia specifically. Alternatively, Low-Low relationships tend to cluster in North Central counties. The relative absence of Low-High and High-Low relationships
compared to other covariates may provide initial evidence for a positive relationship between the violent crime rate and police-involved homicide. Moving to Figure 10, initial observations indicate similar spatial clustering in the North Central for Low-Low relationships, with counties in Illinois demonstrating a high level of variability between Low-Low and High-Low relationships. Additionally, the relationship in the Southeast is quite different from violent crime. In fact, the majority of counties in these states exhibit a High-Low relationship, indicating high levels of police-involved homicide, but low levels of Black arrest rate. In positing what might be driving these relationships, it is certainly possible that a high level of violent crime is occurring, but it is not being committed by Black communities, and may represent threats from other groups, such as Hispanic and Latinx populations. Future research should elaborate more on the relationship between different racial and ethnic groups and police-involved homicide.

[Insert Figure 9 – PIH/VCRMR LISA Map]

[Insert Figure 10 – PIH/LNBARRT LISA Map]

Overall, observations from the univariate and bivariate LISA maps provide initial evidence for spatial dependence, and spatial relationships between key covariates and police-involved homicide.

[Insert Table 3 – Full Model]

Full Spatial Modeling Results
Following the proposed analytic strategy, four separate regression models were implemented, and the results are presented in Table 3. Before exploring the results, it is important to first examine model fit, using the Akaike information criterion (AIC). As noted in the analytic strategy section, a lower AIC is desirable, but it is just as important to assess the differences between models, with differences greater than 10 demonstrating preference for the model with the smaller AIC value. The base OLS model has an AIC of -10,823, compared to the spatial Durbin model (SDM) at -10,841, a difference of 18. This alone provides evidence that the SDM is the superior model, and future research exploring PIH should consider the spatial nature of PIH. Moving from left to right, the spatial lag model has an AIC of -10,833, and the spatial error model has an AIC of -10,832, differences of 8 and 9 respectively. Based on this, the spatial Durbin model does not statistically outperform other spatial models. While this is an important finding and does call into question the applicability of the spatial Durbin model, it still remains important for its theoretical and substantive usefulness.

On the one hand, while the spatial Durbin model did not statistically outperform other spatial models, there are substantive and theoretical contributions gleaned from use of the spatial Durbin model. Notably, the spatial error model exhibited a significant Lambda which reflects the presence of omitted variables not captured by the spatial error model. It is possible that by using the spatial Durbin model, I am helping to explain the significant Lambda by capturing and measuring the

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6 Appendix C provides an analysis for second order neighbors for the full spatial modeling results. The AIC for the second order neighbor is -10,853 for SDM, -10,838 for the spatial lag model, and -10,836 for the spatial error model, indicating that the SDM outperforms the other spatial models for second order neighbors.
7 In attesting to questions regarding changes in spatial weighting, I have also tested second order queen contiguity matrix. The results for this analysis can be examined in Appendices C and D. Of importance with the direct and indirect effect findings is the lack of significance for violent crime outside of 1st order neighbors, indicating that neighbors outside of a focal county’s contiguous neighbors, do not exhibit a significant influence on a focal county’s police-involved homicide. However, the findings for this analysis also indicate a greater effect for second order neighbors than first order neighbors for measures of inequality, specifically, the Gini index.
indirect effects of independent variables in adjacent counties. Furthermore, the spatial Durbin model builds on results from the spatial lag model by taking the independent variables in the spatial lag model, which are assumed to be unmeasured, and measures them directly, teasing out the actual effects of the independent variable on a focal county as opposed to assuming the relationship as unmeasured. In other words, the spatial Durbin model moves beyond other spatial models by measuring the “true” independent effects of covariates in neighboring counties. This is not to say that the other models are not useful, but from a theoretical and substantive standpoint, the spatial Durbin model enriches our understanding of the endogenous effects of covariates.

Moving to the results, I will begin with the spatial effects (Rho in Table 3), for both the spatial lag and spatial Durbin models. This statistic demonstrates that “the endogenous interaction relationship accounts for the” PIH variation across US counties (Yang et al. 2015: 27). The endogenous effect relates to the effect of covariates within a county, while an exogeneous effect relates to the effect of covariates on police-involved homicide originating outside of a focal county (i.e. neighboring counties). The Rho is .0975 and .0795 for the spatial lag and spatial Durbin models respectively. Interpreted, a Rho of .0795 means that for a 1% increase in the average PIH rate of a particular county, the average PIH rate of a neighboring county will increase by about .08%, net of other explanatory variables. Regarding the statistically significant spatial error effect (Lambda in Table 4), it suggests that there may be variables that contribute to county-level PIH that are not accounted for or included in the models (Yang et al. 2015). However, I have also run a Lagrange multiplier (LM) test of the results from each model. Figures 11 and 12 depict a map of the residuals between the OLS model and the spatial Durbin model. As you can see, the spatial clustering between the two has been drastically reduced, and this is also represented in Table 3,
where the LM value of .070 is not statistically significant, meaning the SDM has accounted for spatial autocorrelation in the residuals.

[Insert Figure 11 – OLS RESIDUALS]

[Insert Figure 12 – SDM RESIDUALS]

[Insert Table 4 - IMPACTS]

**Direct and Indirect Effects of Spatial Durbin Modelling Estimates**

Spatial Durbin coefficients should be interpreted with the direct and indirect impacts shown in Table 4. As already discussed, SDM modelling results are “richer” than other conventional spatial approaches, notably for the ability to disentangle direct and indirect effects of independent variables on outcomes of interest (Yang et al. 2015). I have bolded key significant findings in Table 4. Significant indirect effects provide strong evidence that the structural characteristics of surrounding counties are important determinants of PIH, however, some of these variables exhibit greater direct effects. It is important to remember that direct effects reflect the endogenous dynamic, or the within county effects of covariates on the average rate of police-involved homicide, while the indirect effects reflect the exogenous dynamic, or those effects related to the covariates of neighboring counties on a focal county’s average rate of police-involved homicide. With the spatial Durbin model, indirect effects will equal the sum of all the off-diagonal elements, meaning that the indirect effect reflects the collective influence of neighboring counties on a focal county. So, a significant direct effect means that covariates within a focal county are directly associated with changes within that focal county, while a significant indirect effect means that the sum of neighboring covariates is significantly associated with a local county’s average rate of
police-involved homicide. It is expected that the effects will vary between direct and indirect, and that some covariates may only exhibit a direct effect as highlighted in the hypotheses. However, in situations where there exist significant direct and indirect effect, comparison of the direction provides guidance as to whether the exhibited relationship between the endogenous and exogenous effects represents a form of spatial incongruity or social relativity, or if a spatial spillover is being observed. Similar to Yang et al. (2015), a significant direct and indirect effect, and in the same direction, indicates a spatial spillover, while opposite effects indicate underlying social relativity processes. Below I will highlight important findings from this analysis, beginning with racial threat, moving to economic and place-based threat, and then finishing with the community threat hypothesis.

Starting with racial threat, I hypothesized that percent Black of both focal and neighboring counties would be positively and significantly associated with police-involved homicide. The results indicate percent Black is not a significant predictor of police-involved homicide. This finding is not entirely surprising, given the findings across models. Notably, the spatial lag and spatial error models find percent Black to be negatively and significantly related to police-involved homicide. The reason for the lack of a finding may be related to the spatial clustering of Black populations in the US, and when accounted for by the SDM, it is no longer significant.

Economic threat was measured in three separate ways, the Gini coefficient, Black/White unemployment ratio, and concentrated disadvantage. I previously hypothesized that police-involved homicide would be positively and significantly influenced by economic threat of both the focal and neighboring counties. I only find partial support for this hypothesis, and only for two of the three variables, the Gini coefficient and concentrated disadvantage. Specifically, I find that the Gini coefficient exhibits both a significant direct and indirect effect on focal county police-
involved homicide, but in opposite directions. This finding is surprising given the hypothesized relationship of a positive effect of inequality on police-involved homicide. Looking at the direct and indirect effects, for a one-unit increase in the Gini coefficient in neighboring counties, there is a .1 per 1,000 increase in the average rate of police-involved homicide in the focal county, while the same increase in a focal county results in a reduction of the average rate of police-involved homicide by .06 per 1,000 population. Situating these results in the larger picture, it may be that local communities who are experiencing gentrification, thus rising levels of inequality, may adopt less forceful practices when it comes to controlling threatening populations, with the goal of making these communities seem attractive to would-be investors. Alternatively, in situations where there is high inequality in neighboring communities, law enforcement may be engaged in more forceful policies aimed at keeping out those groups deemed most threatening to the economic interests of focal communities.

In the same way that Harvey (1973) posits that secret mechanisms are used by political and economic elites to fortify their own standing, the use of police as a means of maintaining their standing may be reflected in the findings from this study. For example, the work of Lynch et al. (2013) note that political and economic elite often engage with law enforcement in ways that explicitly limit who has access to specific areas within cities. Notably, those groups that are highly impoverished are often understood to be threats to the economic ascendancy of certain communities, especially in cases where a community is attempting to attract investment from outside groups, or is in the process of revitalizing an area, and economically disadvantaged populations are viewed as problematic to the economic goals of investors. However, at the same time, high levels of economic inequality may also reflect differences in the types of job available to residents of a particular community, with higher levels of inequality possibly reflecting more
service-based jobs, or lower-wage jobs. According to Fainstein (1997), political economy theory posits that economic inequality is an important factor when considering how people and groups draw distinction from one another and provides the impetus for conflict between groups.

On the other hand, concentrated disadvantage only exhibits a positive and significant direct effect on police-involved homicide. In effect, a one unit increase in the concentrated disadvantage of a focal county results in an increase in the average rate of police-involved homicide of .0074 per 1,000 population. The lack of an indirect finding lends support to hypothesis H2b, which posited no significant relationship between the economic threat of neighboring counties and police-involved homicide of a focal county. What this means is that not all forms of economic threat work in the same way. On the one hand, high levels of inequality within a focal county may be inherently beneficial to the political and economic ascendancy of those in power, in that the concentration of income is overly contained to those of the political elite, and may even reflect areas undergoing gentrification. However, it may still be expected that certain populations, notably those who are unemployed, single-mother households, and those highly impoverished, are viewed as direct threats to the goals of the political and economic elite. In some ways, these findings mimic the findings from Lynch et al. (2013), in the sense that those groups that are most disadvantaged pose a significant threat to the economic and political goals of powerful groups, and are thus subject to higher levels of social control.

I did not find support for either of my place-based threat hypotheses. In fact, the spatial Durbin model did not find the interaction index to be a significant predictor of police-involved homicide directly or indirectly. Reasons for this null finding may lie in the general demographic shifts in the United States over the past 50 years. For instance, Iceland, Sharp and Timberlake (2013) examine declining trends in segregation using Census data from 1970 through 2000. Notably, they find that
large shifts in Black population from the south to the north, along with other shifts from the north back to sunbelt states, only accounted for a small proportion of the overall change in segregation. Moreover, they find that overall changes in the largest metropolitan areas in the US accounts for a larger proportion of the change, with the most dramatic shifts occurring in the West and South, despite relatively small changes in actual population. In this way, while Blacks in the west tended to live in neighborhoods with higher levels of segregation in 1970, by 2014 those levels were substantially lower.

Because of this, it is possible the use of the interaction index does not capture the complexity of an evolving multiracial landscape of American communities. Notably, recent research on segregation has demonstrated the importance of incorporating larger demographic shifts in the United States. For example, Fowler, Lee, and Matthews (2016) implement both the entropy index, and Theil’s H to examine changes and shifts in racial diversity and segregation across 50 U.S. metropolitan areas. Their findings indicate that principle cities in 1980, or those with high levels of diversity, have decreased in diversity over time, while other cities have increased in diversity, most notably in outlying suburbs which account for the greatest increase in diversity. This study is notable for several reasons, including its use of the entropy index as opposed to the dissimilarity index because it can more adequately accommodate multiple racial categories. Additionally, the null finding for segregation may also be related to a recent study by Freeman and Cai (2015) who found that, while White entry into Black neighborhoods is historically rare, data between the period of 2000-2010 indicate a reverse in this trend, with a substantial increase in White entry into Black neighborhoods. The authors propose several reasons as to why this is occurring, such as declining crime rates, and lower levels of racism featuring prominently. Additionally, the authors point toward factors associated with gentrification as a promising explanation (Freeman and Cai
2015). Future research would do well to account for gentrification and a more diverse and multicultural community landscape, as spatial drivers of social control. Some research has already begun this trend (Hwang and Sampson 2014), though not from a spatial econometric approach.

Findings from variables measuring the community threat hypothesis are likely the most substantive findings from this study. Overall, I find partial support for all three community threat hypotheses, and in the predicted directions. First, hypothesis H4a posited a significant and negative direct effect of violent crime on police-involved homicide in a focal county, and a positive indirect effect from neighboring counties on a focal county. My results support the latter part of this hypothesis. More specifically, a one unit increase in neighboring county violent crime rate is associated with an increase in focal county average police-involved homicide rate of .0029 per 1,000 population. While not significant, the direction of the direct effect is in the opposite direction, which is in line with hypothesis H4a.

This finding lends support to findings from Lautenschlager and Omori (2019) and Smith (2004) who found social control efforts to be conditional on the violence present in a neighborhood, with areas characterized as high in violence exhibiting lower levels of social control due to fear among law enforcement about potential harm. This demonstrates that law enforcement may be aware of the spatial threats surrounding their communities. In this way, law enforcement may be quicker to the trigger if they believe a particularly violent element of a neighboring community has entered their jurisdiction, exhibited by the positive indirect effect. In total, I find support for elements of my hypotheses. Specifically, I find that Black arrest and the total crime rate are not significant indirect predictors of police-involved homicide in focal communities, but that they do exhibit significant direct effects. Alternatively, violent crime does exhibit significant indirect effects in the predicted direction, but not direct effects. The null finding for direct effects is unexpected but
taken together with the other measures indicate that Black crime and minor offenses are more important predictors of local communities. Muhammad (2010) notes how disentangling race and criminality are difficult propositions, and that by simply being Black, one is presumed to be criminal.

Next, I find partial support for hypothesis H4b, which posited a significant and positive direct effect of total crime on police-involved homicide in a focal county, and a positive indirect effect from neighboring counties on a focal county. Specifically, I find only the direct effect to be significant, and in the predicted direction.

Lastly, hypothesis H4c posited a significant and positive direct effect of Black arrest rate on police-involved homicide in a focal county, and a positive indirect effect from neighboring counties on a focal county. For Black arrest rate, the direct effect is significant, and the indirect effect is not. The direct effect may be interpreted as, for a one unit increase in a focal county’s Black arrest rate, there is a coinciding increase in the average police-involved homicide rate of 0.002 per 1,000 population. This finding reflects previous research demonstrating that Black populations are often the subject of increased supervision and social control. The findings for the total crime rate are similar to that of the Black arrest rate. In effect, I do not find support for spatial spillover of Black arrest and total crime. As noted previously in this study, decomposing the findings between Black violent arrests and nonviolent arrests may unearth different findings.

Building on these results, I also find number of officers assaulted and suicide have positive and significant direct effects on police-involved homicide. Specifically, a one unit increase in either the number of officers assaulted or suicides by firearm are associated with a .0025 and .0036 increase in the average rate of police-involved homicide in a focal county respectively. This finding is in line with previous research exploring the association between firearm availability,
homicide, and police-involved homicide (Miller et al. 2002; Miller et al. 2007; Nagin 2020).
However, the number of officers assaulted of neighboring counties exhibits a negative and
significant relationship with the police-involved homicide of a focal county. This is an unexpected
finding, and in the opposite direction as predicted and may require further exploration in future
studies to see if it is replicated. That said, the significant direct effects are in the expected
directions, reflecting local law enforcement’s awareness of contours of threat woven into the
communities they police. These findings also reflect research by Klinger et al. (2016) and Donahue
and Horvath (1991) which find that police are more likely to respond to incidents with higher
levels of force when significant threats to life are present. Specifically, Donahue and Horvath
(1991) find that suspects killed by police were more likely to have been found with a weapon and
were more likely to have assaulted an officer.

Results Conclusion

Overall, my analysis reveals many interesting, and sometimes, unexpected results. Notably, I
find no support for the racial threat hypothesis, nor the place-based hypothesis. When it comes to
economic threat, the findings for both the Gini coefficient and concentrated disadvantage do not
support economic threat theory. More specifically, concentrated disadvantage exhibits a positive
and significant direct effect, but does not have a significant indirect effect. The Gini coefficient on
the other hand, has a negative direct effect which was hypothesized to interact positively with
police-involved homicide, and a positive indirect effect which is in line with the predicted indirect
effect. I also find the violent crime rate exhibits a significant and positive direct effect, meaning
that as the violent crime of surrounding counties goes up, so does the police-involved homicide of
a focal county. However, I do not find a significant direct effect, which is against the posited
hypothesis. If anything, the analysis opens up more questions than it likely answers. The fact that
I find economic threat to be a significant predictor of police-involved homicide goes against the grain of the many studies which find that economic threat is not a significant predictor of social control outcomes (Liska and Yu 1992; Smith 2004; Legewie and Fagan 2016; Holmes et al. 2019), but also expands our understanding of economic threat as a mechanism which is inherently tied to space and place. In the same way that home values are tied to one’s neighbors, so too are the goals and ambitions of those in power tied to their local communities and their neighbors. I will expand and elaborate on these results in the following chapter.
CHAPTER 5: DISCUSSION

The current dissertation contributes to the prior literature on police-involved homicide in the following ways. First, this research incorporates theoretical perspectives on group-threat and spatial econometrics to develop a theoretical approach for the exploration of the spatial dynamics of group-threat theory and police-involved homicide. The importance of this research objective is predicated on the belief that nonspatial studies may be misleading, or at least, obfuscating the spatial determinants of police-involved homicide. More specifically, previous research has focused almost exclusively on the nonspatial determinants of police-involved homicide. This research attempts to build on this work by calling into question the extent to which neighboring community characteristics influence police-involved homicide of a focal community.

The second way this research contributes to the prior literature on police-involved homicide was to test a new spatial approach in the spatial Durbin model. From a statistical standpoint, the spatial Durbin model is a potential step forward in our understanding of the spatial dynamics of police-involved homicide and allows for the testing of new hypotheses not testable with previous spatial econometric approaches. Notably, the ability to disentangle direct and indirect effects of covariates, or the distinguishing of the effects of focal community characteristics from neighboring community characteristics, on police-involved homicide represents an important step forward in the literature and uncovers potentially new and interesting theoretical questions and findings.

However, it is also important to recognize some of the ways the spatial Durbin model does not outperform other spatial models. As noted in the findings section, the AIC indicates the spatial Durbin model did not statistically outperform the spatial lag or the spatial error models. It is important to recognize the ways in which this null finding is important, while also noting the ways
in which the spatial Durbin model remains an important tool for criminologists and other social scientists interested in understanding the spatial relationship of policing outcomes. In his article “What Regional Scientists Need to Know about Spatial Econometrics”, LeSage (2014: 14) notes that for a host of “historical reasons, most regional science applications of spatial regression models have not: 1) used the appropriate spatial regression specification to produce valid estimates of spatial spillovers, 2) correctly interpreted estimates of spillovers, or 3) produced valid inferences regarding the statistical significance of spillovers.” According to LeSage (2014), one of the primary reasons for this is the daunting task of sifting through the literature to determine the appropriate modeling approach. On the one hand, the majority of spatial research has taken the oft-quoted approach that “all spatial spillovers are local,” or that issues of importance are most often issues of concern within a local area. LeSage (2014) identifies that when examining localities for the presence of local spillovers, the spatial lag (SLX) and spatial Durbin error models (SDEM) are the most common specifications. It is important to recognize as well, that when considering models exploring local spillovers, endogenous interactions and feedback effects are not present, or situations where changes in one region/agent/entity set into motion a sequence of adjustments in all regions in the sample (LeSage 2014: 14-15). In effect, local spillover specifications are most appropriate in situations where we believe that, for example, the actions of an officer killing someone in one location, would not have a feedback effect on the neighboring area. LeSage (2014: 15) provides an example where an individual crosses a state border to buy cigarettes to avoid higher taxes in their home state. In this situation, we have a spillover whereby more people are crossing a state border to buy cigarettes, but there is no further spillover from these bordering states to their neighbors. This is a key concern with studies utilizing spatial lag and spatial error models, that they do not account for the feedback effect of neighboring locales, and thus only purport
results reflecting local spillovers, and not the endogenous effects of spillovers occurring in both directions. Whereas the spatial error model assumes that error present in the analysis, represented by a significant Lambda, represents potential omitted variables, the spatial Durbin model directly measures the omitted variables as indirect effects. The spatial lag model, on the other hand, assumes the independent variables to be unmeasured, producing potentially biased estimates of independent effects. The spatial Durbin model overcomes this issue, by measuring the actual effect of the independent covariates of surrounding counties, allowing for comparison between direct within county effects, and the endogenous interaction of surrounding covariates on a focal county dependent variable. This is also a key advantage of using the spatial Durbin model. So, while the spatial Durbin model does not statistically outperform the other models, given the plausibility of expected endogenous effects or feedback effects between neighbors, the spatial Durbin model still remains theoretically and substantively important and appropriate to the current study. With that said, below I will highlight the important findings and conclusions from the current study.

The analyses yield several significant findings. Beginning with racial threat, research has traditionally maintained that the relative size of the Black population is an important determinant in various policing outcomes, ranging from stop and frisks to police-involved homicide. The basis for this association has been predicated on the perceived threat Black populations have on the continued ascendency of Whites. However, unexpectedly, and contradictory to the prior literature, percent Black does not seem to be associated with police-involved homicide, directly or indirectly. This is at odds with previous nonspatial and spatial research which has consistently found race to be a salient factor when it comes to policing outcomes (Liska and Yu 1992; Smith 2004; Legewie and Fagan 2016; Klinger et al. 2016; Holmes et al. 2019; Lautenschlager and Omori 2019; Gray and Parker 2020; Helms and Constanza 2020), though no other study has attempted to test the
spatial relationship between racial threat and police-involved homicide using the methods in the current study. While this study will not settle the debate, it does raise additional questions about the salience of race as a factor in the spatial dynamics of police-involved homicide. Previous research into less serious forms of police coercion has consistently found race to be an important predictor in police behavior. For example, the work of Carrol and Gonzales (2014) find that officers are likely to develop cognitive schema and scripts, beliefs, attitudes, and behavioral dispositions based on the characteristics of the communities they police, notably the racial composition of their community. Furthermore, the work of Roh and Robinson (2009) indicate that police are more likely to stop drivers in predominantly Black and Hispanic beats. Additionally, the work of Ingram (2007) finds that police are more likely to issue citations in communities of color, especially in situations where surrounding neighborhoods have a lower percentage of Hispanics. Lastly, research by Lautenschlager and Omori (2019) find that Black neighborhoods are more likely to experience low-level police harassment, and that more severe incidents of police use of force are likely in neighborhoods with higher levels of racial and ethnic heterogeneity. The current research thus adds to this literature by suggesting that in addition to race, the level of violence in surrounding communities is likely to influence police behavior of a focal community. Ultimately, questions remain as to how racial threat manifests across space.

In the same way that Wilson (2011) acknowledges it is about more than just race, it may also be the case that it is about more than just one race. A significant limitation of the current study is the focus paid to Black and White populations, to the detriment of other racial and ethnic groups that make up this country. Specifically, the omission of Latinx populations likely obfuscates the relationship between race and police-involved homicide in Western and Southwestern counties. More so, the high level of spatial clustering of police-involved homicide in Western counties in
the United States also mirrors high levels of Latinx population clustering and may be an important avenue for future research to consider.

Second, analysis revealed partial support for the effect of economic threat on police-involved homicide. On the one hand, the Gini coefficient was a significant predictor of police-involved homicide, but in the opposite direction for direct effects, and in the predicted direction for indirect effects. On the other hand, the Black-to-White unemployment ratio was not significant, and concentrated disadvantage only exhibited a significant direct effect on police-involved homicide. Putting these findings in context, the current study suggests that the inequality of surrounding counties matters when it comes to police-involved homicide.

Blalock (1967) contends that competition for scarce resources breeds conflict between groups, especially in cases where the distribution of resources is unequal. Conflict theorists also contend that inequality breeds conflict, but that the distribution of power between groups also varies and is an important determinant in the way social control manifests across space. Jacobs and Britt (1979: 410) note that when it comes to studies of the modern police, most researchers assume that the “police employ force when they must deal with a violent populace.” And while this is important to account for, Jacobs and Britt (1979) contend that it is just as important to study how the police work to protect the interests of those in power. Recent research exploring gentrification has identified that law enforcement employed in areas encountering gentrification may use less force within the community they patrol, as police-involved homicide is not likely to attract would be investors. Bringing this down to the ground level, law enforcement may be more likely to engage with suspects who are perceived as a threat to the economic goals and interests of the gentrifying class. In this way, the finding that the Gini coefficient has a positive indirect effect, but negative direct effect may be plausible. As noted earlier, these findings seem to mimic those of Lynch et al.
(2013) and their qualitative study of how law enforcement maintain and defend economic and political boundaries from threatening populations. This study also raises more questions about how this plays out on the ground. For example, to what extent do police really know who lives where? In the same way that notable Black celebrities have been stopped in their driveways in upper class neighborhoods, how do police contend with, and construct spatial boundaries? And, of course, how do these perceived boundaries influence police behavior? Furthermore, why does concentrated disadvantage not exhibit the same indirect effect?

Sharkey (2014) integrates spatial econometrics, through the use of lagged measures of neighborhood characteristics, to examine neighborhood inequality of different racial and ethnic groups across metropolitan areas. Data are obtained from the Neighborhood Change Database and supplemented with updated data from the American Community Survey. At the heart of his study are two competing claims. The first by Patillo (1999), asserts that while some segments of the Black population enjoy a reasonable level of success, exhibited by higher incomes, their status is particularly tenuous, as their spatial proximity to disadvantage and disorder is much greater than that of other middle- to upper-class people. A second set of research by Lacy argues that a new Black middle-class has emerged, that is socially and spatially separated from problems and disadvantage. This set of research reflects the argument made by Wilson (1987) who observed the flight of middle- and upper-class Blacks from socially disorganized city centers. At the same time that middle- and upper-class Blacks are leaving areas characterized by concentrated disadvantage, recent research (Freeman and Cai 2015) has begun to indicate that trends in White flight may be reversing, as data between 2000 to 2010 indicate a substantial increase of White entry into Black neighborhoods, and with it, likely increases in social control against socioeconomically disadvantaged Blacks. Ultimately, Sharkey (2014) finds evidence of a non-class-based segregation
occurring. Some scholars have begun to argue that class has replaced race as the most salient variable with respect to segregation. However, this article argues that race may still play an important role in the segmentation of Black populations throughout urban areas. As Sharkey (2014: 935) notes, racial and ethnic gaps in neighborhood disadvantage and spatial disadvantage are not driven by group-level differences in income. This is most apparent when comparing elite Black middle-class, those making over $100,000, to Blacks living in largely disadvantaged neighborhoods. Results from his study reveal that upper- and middle-class Black households still live in areas and are surrounded by communities that are more disadvantaged than low-income White households (those making less than $30,000 a year).

Other research into this area by Ingram (2007) has demonstrated that low socioeconomic status is still a significant predictor of police citations, at least within a community. The current research builds on this literature by suggesting the level of inequality of surrounding communities may play an important role in police-involved homicide. Given how severe a response police-involved homicide is on the continuum of police responses, it may seem plausible that other forms of economic threat (e.g. inequality, concentrated disadvantage, or unemployment) may influence others forms of social control such as arrest or police stops. Future research would do well to extend the current research into other forms of social control including police arrests and citizen stops.

Third, variables measuring the community violence hypothesis lend partial support to the hypotheses posited. Notably, the Black arrest rate exhibits a significant positive, direct effect on police-involved homicide, as does the total crime rate. Alternatively, the violent crime rate was found to have a positive and significant indirect effect on police-involved homicide but did not have a significant direct effect in either direction. While these results do not lend support to
previous findings by Klinger et al. (2016), Lautenschlager and Omori (2019), and Smith (2004) that high levels of community violence is inversely related to police-involved homicides, they do deepen our understanding of how surrounding communities influence police-involved homicide through perceived threats of violence. In building on prior research, neighboring community violence exhibits a spillover effect. In other words, the level of community violence of neighboring counties is indirectly related to the police-involved homicide of a focal county in that as the violence of neighboring counties increases, so does the police-involved homicide of a focal county. Placing this in context, Klinger et al. (2016) and Lautenschlager and Omori (2019) indicate that violent crime is likely to cluster in communities that are most disadvantaged, and previous research on social disorganization and collective efficacy (Sampson, Raudenbush, and Earls 1997) support this claim. Klinger et al. (2016) contend that police-involved homicides are less likely to occur in areas with the highest levels of violence. Klinger et al. (2016: 213) note that in these neighborhoods, it is possible that people “adapt to conditions in extremely violent neighborhoods in ways that reduce the frequency of police shootings. It is possible that, on average, individuals in such neighborhoods who carry weapons, commit crimes, or otherwise engage in activities that are likely to draw the attention of the police behave in ways that reduce the likelihood that officers will fire at them.” On the other hand, police may also be better equipped to deal with situations and encounters with a particularly violent population, and thus may be able to diffuse situations so that they do not end in violence. Klinger et al. (2016: 213) identifies that:

“Officers are trained that how they structure encounters with citizens (e.g., how many officers are present, how they approach citizens, and where and how they stand) can affect the chances they will resort to their firearms. When officers are attentive to the dangers they face
and use sound tactics in encounters with potentially dangerous citizens, according to this line of reasoning, the odds are lower that suspects will take actions that would warrant deadly force and that officers might misidentify innocuous citizen actions as a threat necessitating gunfire.”

Lastly, Klinger et al. (2016) note that police officers may also avoid or invest less energy in policing areas with high levels of violent crime. This perspective assumes that police withdraw from their community out of fear and resentment to their community. This perspective sees officers as becoming more cynical, less engaged, and less likely to come into contact with suspects, resulting in fewer instances in which a situation can escalate. At the same time, it is also possible that officers may be fearful of a particularly violent population and may not want to enter these communities. If the latter of these conclusions is true, then it may seem plausible that violent crime could spillover into neighboring communities, especially in cases where law enforcement have largely withdrawn from policing their communities.

As Klinger et al. (2016) notes, police are often intimately aware of their surroundings, and the contours of threat woven into their communities and neighboring areas. If law enforcement is aware of a particular violent group that is weakly controlled by the neighboring authorities, it seems plausible that they may feel the need to take action before an encounter gets out of control when members of the violent group cross over into their community. This may in turn, trigger responses using increasingly higher levels of coercive control, which may result in more police-involved homicides. Ultimately, how police officers form and act on suspicion may play an important role in who is stopped, and why, and it seems that the characteristics of neighboring communities may play an important role in how suspicion is formed, and eventually acted upon.
Specifically, the concept of spatial incongruity may play an important role in how police officers form suspicion, and then act upon it.

Previous research by Donahue and Horvath (1991) find that suspects killed by police are more likely to have an extensive criminal background. Furthermore, they note that while officers may not be familiar with the criminal background of every suspect, it may be that the suspect’s criminal background mediates the relationship between suspect behavior and police encounter outcome, especially in cases where there is a stressful situation where the chance of being reincarcerated is at the front of a suspect’s mind. This in turn may result in an increased likelihood to run from an officer, and as the authors state, "desperate behavior invites desperate countermeasures” (Donahue and Horvath 1991: 29). For example, recently, a former Vallejo, California police officer killed a Black man, Ronnel Foster, who was riding his bicycle through traffic at night without lights on his bike. When Ronnel was stopped, words were exchanged, and Ronnel fled from the officer on foot. Eventually the officer caught up with him and jumped on top of him, and a struggle ensued. During the struggle, the police officer Ryan McMahon, used his Taser on Ronnel, followed by gunfire, seven shots total. Ronnel Foster was dead. Ronnel Foster was on community supervision for a car theft conviction a month earlier (Thompson 2021). Tragically, McMahon was not charged for this incident, and went on a year later to shoot another man, Black rapper Willie McCoy, who was asleep in his car outside a Taco Bell, blocking the drive through. Unfortunately, these encounters are not uncommon in the United States.

The interpretations of the findings must be made while considering the limitations of this dissertation. Like others, this research is limited in many ways, including data reliability and model specification. I identify the major limitations of my research below. First, caution should be made when interpreting the findings due to concern with the construction of the dependent variable.
Notably, the dependent variable is an average rate for the years 2013 through 2019. While consistent with other studies on police-involved homicide, questions about the adequacy of this measurement should be considered when interpreting the findings.

Second, are concerns with the normality of the dependent variable. Despite multiple efforts at transformation, the data remains highly skewed. To account for this concern, I compared coefficients across models, including estimates from a negative binomial regression model of the count variable which is the preferred nonspatial method for analysis on police-involved homicide and other variables with an overdispersion or overrepresentation of zero values (see Appendix B). Comparison across models did not yield significant differences in estimates or significance. As LeSage and Pace (2014) note, significant differences between estimates is likely the result of model misspecification, while differences in significance reflect concerns with spatial weighting. That said, interpretation of findings should be made with caution.

Third, questions still remain as to whether the use of county as the level of analysis is a useful approach in studying police-involved homicide and group-threat. While the use of counties is consistent with prior research, there are still some questions about this approach. For instance, to what extent is county the appropriate aerial unit when discussing spatial spillover? In some cases, as discussed previously, many major cities are comprised of multiple counties, resulting in a high level of spatial spillover. However, in counties where the impetus to leave the county either for work or pleasure is lower, to what extent can we assume that the county is the proper aerial unit, and not something smaller, such as the census tract? That said, there are obvious issues with data availability for smaller spatial units. Previous research has tended to focus on individual cities, though none have applied the spatial Durbin model. Cogent to this discussion, Lynch et al. (2013) and Stuart (2016) explore individual neighborhoods within larger cities. It may be the case that
race becomes a salient factor in police-involved homicide for smaller spatial units and is obscured by data at the county level. Along the same lines, questions about whether segregation plays an important role in police-involved homicide remain unanswered. Though not significant in the current study, the interaction index may not be best measure of segregation, especially as communities across the nation diversify. The notable absence of measures for Latinx populations also points to directions for future exploration, especially considering the spatial clustering of police-involved homicide in areas characterized by larger Latinx populations.

Lastly, concerns remain about the usefulness of the spatial Durbin model in the study of police-involved homicide. Certainly, the spatial Durbin model is not meant to be tested with data that contains a high proportion of zeros, and as such may not be the appropriate method for studying police-involved homicide at this time. However, the spatial Durbin model may prove incredibly useful in exploring data with more occurrences, such as arrest or police stops.

With these limitations in mind, this dissertation offers a number of theoretical and methodological implications. First, prior research has not examined group-threat spatially, and the current study extends this research into the spatial realm. Notably, the inclusion of spatial incongruity taps into the heart of Blalock’s (1967) group-threat theory by providing a potentially useful lens through which to understand how differences in power and resources between groups may play out between communities to influence police-involved homicide. But more so, the current study indicates that group-threat may influence police-involved homicide in ways that are fundamentally different from nonspatial applications. The current research extends previous understandings into how inequality of surrounding communities influences police-involved homicide within a focal county, and in some ways points to qualitative research which has explored the ways in which law enforcement may work to protect the interests of the political and economic
elite (Lynch et al. 2013; Stuart 2016). Future research should consider the role gentrification and changes in community demographics play in police-involved homicide, notably entrance of Whites into historically Black neighborhoods.

Second, the current study suggests that the level of violence of surrounding communities may play an important role in the way police respond in a specific county. Notably, as the level of violence of surrounding counties increases, police-involved homicides in a focal county also increase. While caution should be used with the findings, there are still questions about why these findings emerged. In fact, the current study suggests that fear of threatening groups is not a local phenomenon, reflected by issues within a community, but can emerge from sources outside of a community. In this way, future research should consider how the level of violence of surrounding communities influences how police officers determine who or what is a threat, and why.

Lastly, police-involved homicide of Black men has received considerable attention in the media, and the current post-Ferguson era has given way to renewed calls for policing reform, including the calls for defunding the police. The current study does not find racial threat to be a significant factor in the overall average rate of focal county police-involved homicide. This, of course, does not mean race is not a salient factor, it just is not significant as it relates to the overall average rate of police-involved homicide. It is possible that racial threat may influence police-involved homicides of Blacks, and not Whites, or other racial or ethnic groups, something future spatial research should explore.

**Conclusion**

This dissertation’s empirical findings are based on police-involved homicide data from 2013 to 2019. During this period, we have witnessed the rise of the Black Lives Matter movement, the death of countless Black men at the hands of police and the ensuing riots and protests across the
nation. Since then, we have witnessed the indictment, guilty finding and sentencing of a Minneapolis police officer for the death of George Floyd. We have seen, heard, and read about renewed calls for changes to law enforcement practices and policies, and for law enforcement to be held accountable for the harm they cause. Yet, despite all of this, 1,126 people were killed by police in 2020, a strikingly similar total to previous years, and 564 people have already been killed by police in 2021 as of July 21, 2021, despite the fact that the United States has been plagued by a pandemic since early 2020 (Sinyangwe, Samuel, DeRay McKesson, and Johnetta Elzie 2021).

In situating this dissertation within the larger conversation on police violence, at the macro-level, police-involved homicide remains remarkably stable year to year seemingly regardless of changes to policing policies, calls for reform, or even societal awakening to the problems faced by our most vulnerable communities. In building on research exploring police-involved homicide, the current dissertation explores how social forces structures police-involved homicide at the macro-level, by examining the ways in which group-threat influences these tragic events within and between communities.

Police officers occupy a critical position within American Society and are important arbiters of public policy (Smith 1996), but they are not immune to the larger social structures they find themselves embedded within. As street-level bureaucrats, the choices made by police officers constitute the services delivered by government to the public (Lipsky 1980: 3). Police also have significant power, being the only branch of government, whose discretion affords them the option of force against the citizenry. This power is often drawn upon in situations that are complex, and with little guidance or tools with which to handle them. These situations range from health-related emergencies, public safety concerns, welfare issues, and include many situations for which there are no criminal or legal aspects. As Bittner (1967) summarily remarks, the domain of law
enforcement is virtually limitless. In fact, he goes on to state, “there is scarcely a human predicament imaginable for which police aid has not been solicited and obtained at one time or another” (Bittner 1967: 703). However, previous research has shown police-involved homicide to be remarkably consistent across time and place, with areas characterized by high levels of violence and inequality, bearing the brunt of these tragic events. Furthermore, previous research has often focused on individual-level or encounter-level characteristics, assessing the extent to which police-involved homicides are justified, whether bias was at play, whether there was evidence to indict the victim, and whether individual officers or departments have a history of violence. The current study deepens our understanding of police-involved homicide by examining the social forces which structure these encounters, both within specific communities. In this way, the current study takes the additional step of situating communities within a larger web of influence, by considering how neighboring communities influence a local community and their responses to threatening groups. More specifically, my dissertation finds that economic threat (i.e. inequality) and the community violence hypothesis (violent crime rate) exhibit spatial dependence that should not be ignored. In some ways, I find that violence begets violence, in that as violence of surrounding communities increases, so do instances of police-involved homicide in focal communities. Even more important, inequality also structures police-involved homicide in that as the inequality of surrounding communities increases, so do instances of police-involved homicide in a focal community.

With the innovative approach of spatial Durbin modeling, this dissertation spatially explores how communities are intimately connected to one another and contributes to our understanding of how violence and inequality breach spatial divides to influence police-involved homicide. Overall,
this dissertation adds to our understanding of the complex dynamics of group-threat theory and its impact on police-involved homicide.
REFERENCES


### TABLE 1: Descriptive statistics for police involved homicide, independent, and control variables

<table>
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<th>SD</th>
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<th>Maximum</th>
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<td>1.00</td>
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<td>Black Arrest Rate (per 1,000)</td>
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<td>Crime Rate (per 1,000)</td>
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Table 2. Moran’s I test for spatial autocorrelation of dependent and independent variables

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<td>Gini</td>
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<td>Black/White Unemp</td>
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<tr>
<td>Interaction Index</td>
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<td>Disadvantage</td>
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<td>Crime Rate</td>
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<td>Suicide</td>
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*p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001
Table 3. Coefficient estimates of different regression approaches (n=3,108)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>OLS model</th>
<th>Spatial lag model</th>
<th>Spatial error model</th>
<th>Spatial Durbin Model</th>
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</thead>
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<td>Estimate</td>
<td>Estimate</td>
<td>Estimate</td>
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<td>Intercept</td>
<td>.0356†</td>
<td>.0376†</td>
<td>.045*</td>
<td>-.0922*</td>
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<td>-.00034***</td>
<td>-.00035***</td>
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</tr>
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<td>GINI</td>
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<td>-.0276</td>
<td>-.032</td>
<td>-.060†</td>
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<td>Black/White Unemp</td>
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<td>-.00014</td>
<td>-.00014</td>
<td>-.0001</td>
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<tr>
<td>Interaction Index</td>
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<td>.00568</td>
<td>.0062</td>
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<td>Disadvantage</td>
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<td>.0092***</td>
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<td>.0017***</td>
<td>.0018***</td>
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<td>Crime Rate</td>
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<td>.00038***</td>
<td>.00039***</td>
<td>.0004***</td>
</tr>
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<td>Violent Crime</td>
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<td>-.00029</td>
<td>-.0009</td>
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<td>Control Variables</td>
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<td>Percent Male</td>
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<td>-.0005</td>
</tr>
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<td>-.00022</td>
<td>-.0001</td>
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<td>.00186**</td>
<td>.002**</td>
<td>.002***</td>
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<td>.00374***</td>
<td>.0038***</td>
<td>.0036***</td>
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<td></td>
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<tr>
<td>Lambda (spatial error)</td>
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<td>.098***</td>
<td></td>
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<td>Model diagnostics AIC</td>
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<td>-10.833</td>
<td>-10.832</td>
<td>-10.841</td>
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<td>Lagrange multiplier test</td>
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<td>.021</td>
<td>N/A</td>
<td>.070</td>
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Notes: AIC, Akaike information criterion.
The coefficient estimates for the spatial Durbin model should be interpreted with direct and indirect impacts shown in table 4.
†p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001

Table 4. Decomposition estimates of the direct and indirect effects of selected conditions on police involved homicide (SQRTAVGRT)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Direct</th>
<th>Indirect</th>
<th>Total</th>
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</thead>
<tbody>
<tr>
<td>Percent Black</td>
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<td>-0.0001</td>
<td>-0.0004***</td>
</tr>
<tr>
<td>GINI</td>
<td>-0.058*</td>
<td>0.1*</td>
<td>0.041</td>
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<tr>
<td>Black/White Unemp</td>
<td>-0.0001</td>
<td>-0.0003</td>
<td>-0.0004</td>
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<tr>
<td>Interaction Index</td>
<td>0.004</td>
<td>0.0002</td>
<td>0.004</td>
</tr>
<tr>
<td>Disadvantage</td>
<td>0.0074***</td>
<td>0.0022</td>
<td>0.0096***</td>
</tr>
<tr>
<td>Black Arrest</td>
<td>0.002***</td>
<td>-0.0003</td>
<td>0.0017**</td>
</tr>
<tr>
<td>Crime Rate</td>
<td>0.0004***</td>
<td>-0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td>Violent Crime</td>
<td>-0.0009</td>
<td>0.0029*</td>
<td>0.002†</td>
</tr>
<tr>
<td>Age 15-24</td>
<td>-0.0001</td>
<td>-0.00028</td>
<td>-0.00038</td>
</tr>
<tr>
<td>Percent Male</td>
<td>-0.0005</td>
<td>0.002***</td>
<td>0.0056**</td>
</tr>
<tr>
<td>Officer Assaulted</td>
<td>0.0025**</td>
<td>-0.002†</td>
<td>0.0004</td>
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<tr>
<td>Suicide</td>
<td>0.0036***</td>
<td>0.002</td>
<td>0.0056***</td>
</tr>
</tbody>
</table>

†p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001
FIGURES:
Figure 1. LISA MAP of Square Root Average Rate of Total Police-Involved Homicide (per 1,000 population)

Figure 2. LISA MAP of Percent Non-Hispanic Black Population
Figure 3. LISA MAP of Concentrated Disadvantage

Figure 4. LISA MAP of Logged Number of Officers Assaulted
Figure 5. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Percent Non-Hispanic Black Population

Figure 6. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Concentrated Disadvantage
Figure 7. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Gini Coefficient

Figure 8. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Interaction Index
Figure 9. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Violent Crime Rate (per 1,000 population)

Figure 10. Bivariate LISA Map of Square Root Average Rate Police Involved Homicide (per 1,000 population) and Logged Black Arrest Rate (per 1,000 population)
Figure 11. LISA MAP of OLS Model Residuals

Figure 12. LISA MAP of Spatial Durbin Model Residuals
APPENDIX A:
Figure A1. LISA MAP of Percent Male

Figure A2. LISA MAP of Total Crime Rate
Figure A3. LISA MAP of Total Violent Crime Rate

Figure A4. LISA MAP of Percent Age 15 to 24
Figure A5. LISA MAP of Black-to-White Unemployment Ratio

Figure A6. LISA MAP of Gini Coefficient
Figure A7. LISA MAP of the Interaction Index

Figure A8. LISA MAP of Logged Black Arrest Rate
Figure A9. LISA MAP of Logged Suicide Count
## APPENDIX B:
### Coefficient estimates of different regression approaches (n=3,108) SQRTAVGRT

<table>
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<tr>
<th>Independent Variables</th>
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<th>Spatial lag model</th>
<th>Spatial error model</th>
<th>Spatial Durbin Model</th>
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<td>.27</td>
<td>.0376†</td>
<td>.045*</td>
<td>-.0922*</td>
</tr>
<tr>
<td>Percent Black</td>
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<td>-.013***</td>
<td>-.00034***</td>
<td>-.00035***</td>
<td>-.0002</td>
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<td>GINI</td>
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<td>.718</td>
<td>-.0276</td>
<td>-.032</td>
<td>-.060*</td>
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<tr>
<td>Black/White Unemp</td>
<td>-.00015</td>
<td>-.039***</td>
<td>-.00014</td>
<td>-.00014</td>
<td>-.0001</td>
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<td>Interaction Index</td>
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<td>.00568</td>
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<td>.0047</td>
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<tr>
<td>Disadvantage</td>
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<td>.186***</td>
<td>.0088***</td>
<td>.0092***</td>
<td>.0074***</td>
</tr>
<tr>
<td>Black Arrest</td>
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<td>.077***</td>
<td>.0017***</td>
<td>.0018***</td>
<td>.002***</td>
</tr>
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<td>.022***</td>
<td>.00038***</td>
<td>.00039***</td>
<td>.0004***</td>
</tr>
<tr>
<td>Violent Crime</td>
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<td>.023</td>
<td>-.00022</td>
<td>-.00029</td>
<td>-.0009</td>
</tr>
</tbody>
</table>

### Control Variables

- Percent Male: -.0001, -.037**, -.00019, -.00024, -.0005, -.0024***
- Percent Age 15-24: -.0002, .014*, -.0002, -.0002, -.0001, -.0002
- Suicide: .00398***, .548***, .00374***, .0038***, .0036***, .001

| Rho (spatial lag) | .0975*** | .0795*** |
| Lambda (spatial error) | .098*** |
| Model diagnostics AIC | -10.823 | 8.018, -10.833, -10.832, -10.841 |
| Lagrange multiplier test (residuals autocorrelation) | 11.24***, 22.02***, 0.21, N/A, 0.070 |

Notes: AIC, Akaike information criterion.
The coefficient estimates for the spatial Durbin model should be interpreted with direct and indirect impacts shown in table.
†p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001
## APPENDIX C:

Coefficient estimates of different regression approaches, including second order SDM (n=3,108)

<table>
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<th>OLS model 2nd Order</th>
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<tr>
<td>Intercept</td>
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<td>-.00033***</td>
<td>-.0003***</td>
<td>-.0022**</td>
<td>-.0019**</td>
</tr>
<tr>
<td>Percent Black</td>
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<td>-.041</td>
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<td>-.073**</td>
</tr>
<tr>
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<td>.0018***</td>
<td>.002***</td>
<td>.0021***</td>
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<td>.00046</td>
<td>.0003***</td>
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<td>-.00019</td>
<td>-.0002</td>
<td>-.0005</td>
<td>-.0024***</td>
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<td>-.0002</td>
</tr>
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<td>.0037***</td>
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<td>Lambda (spatial error)</td>
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<td>.085</td>
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Notes: AIC, Akaike information criterion.
The coefficient estimates for the spatial Durbin model should be interpreted with direct and indirect impacts shown in Table 4.
†p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001
APPENDIX D:

Decomposition 2nd order estimates of the direct and indirect effects of selected conditions on police involved homicide (SQRTAVGRT)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Direct</th>
<th>Indirect</th>
<th>Total</th>
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<td>.146*</td>
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<td>Violent Crime</td>
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<td>-.001*</td>
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<tr>
<td>Officer Assaulted</td>
<td>.002**</td>
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<td>.0002</td>
</tr>
<tr>
<td>Suicide</td>
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<td>.002</td>
<td>.0057**</td>
</tr>
</tbody>
</table>

†p ≤ 0.1; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001