The Pennsylvania State University The Graduate School

PATTERNS OF FORCE: A COMPARISON OF DATA SOURCES ON OFFICER-INVOLVED HOMICIDE RATES

A Dissertation in

Sociology

by

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ABSTRACT

In this dissertation, I develop a model for measurement of homicide by police that draws on multiple sources of data and then utilize this measurement model to examine potential city/agency-level predictors of homicide by police. The issue of data choice is of key importance to research on geographic variations in homicide by police. I utilize data from one official data source on homicide by police (the Supplementary Homicide Reports) and three media-based data sources (Fatal Encounters, Mapping Police Violence, and The Counted) as indicators of the latent, "true" 2015 to 2016 homicide by police rate. I then use this measurement model to examine various potential predictors of the homicide by police rate including city-specific and agency-specific factors. I then compare the model predicting latent rates of homicide by police to models where only one data source is used as the outcome. A key finding regarding city-specific predictors is that a city's percent Black and Black-White housing segregation are associated with lower homicide by police rates. Some key findings from the agency-specific predictors tested are that more restrictive vehicle pursuit policies, requiring more new recruits to engage in community policing training, and authorizing the use of chemical weapons (like tear gas) are associated with lower homicide by police rates while having more specialized unit types and authorizing officers to use soft projectiles or neck restraining techniques (such as chokeholds or vascular neck restraint) are associated with higher homicide by police rates. In terms of the findings related to measurement, I find that all four of the data sources on homicide by police appear to relate to the same underlying factor. However, one data source (Mapping Police Violence) is very strongly related to the estimated latent homicide by police rate and models using it are nearly identical to the more complex model using all four indicators of the latent rate.

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Chapter 1: INTRODUCTION

This dissertation seeks to improve the literature on city-level homicide by police by 1) developing a model for measurement of city differences in levels of homicide by police in 2015 and 2016 that draws on multiple sources of data and 2) utilizing this measurement model to examine potential city/agency-level predictors of homicide by police. These predictors are taken from the 2012-2016 American Community Survey, the 2015 and 2016 Uniform Crime Reports, and the 2013 Law Enforcement Management and Administrative Statistics survey. In doing so I will illustrate that the choices surrounding which data source to use in creating rates of homicide by police remain key issues that must be addressed by anyone attempting to do research in this area.

Homicide by police (HbP) should be of interest to researchers. Individual incidents of homicide by police have implications for cultural narratives surrounding police legitimacy as well as implications for individual human lives lost and those who personally suffer from those losses. Higher rates of homicide by police can also be viewed as an organizational outcome for police agencies, with lower rates potentially indicating a better functioning agency.

The last several years have seen a rise in public interest, and outrage, regarding the use of lethal force by the police. Despite the apparent political importance of police use of force, we lack answers to basic questions about police killing. While attempts to study violence are often hampered by a so-called "dark figure" (i.e., the amount of violence that goes unreported), the problem is especially egregious when it comes to police use of force. As a field, we have known since at least the late 1970s (Sherman & Langworthy, 1979) that official sources of data are woefully inadequate for determining how many people are killed by police (or during encounters with police). However, during the past several years public outrage toward police shootings has

converged with the trend of "data journalism," leading to the creation of several media-based sources of data that attempt to count the number of police-involved deaths. According to these media-based sources, roughly twice as many people are killed by law enforcement officers as would be indicated by the official data sources (see Figures 1.1 and 1.2).

Because of the extreme discrepancies between the traditional sources of data on police homicides and the newer media-based data sources in the counts of homicide by police, researchers interested in geographic variation in police lethal force rates have largely abandoned the older sources of data. From 2016 onward, only three agency-level studies (Dirlam, 2018; Pang & Pavlou, 2016; Renner, 2019) have utilized the SHR (Supplementary Homicide Reports) to create their outcomes, whereas prior work (Bailey, 1996; Jacobs & O'Brien, 1998; MacDonald & Parker, 2001; Nowacki, 2015; Smith, 2004; Sorensen et al., 1993; Willits & Nowacki, 2013) almost exclusively utilized the SHR.

Because there is so little overlap in the studies that utilized the SHR and those that utilize media-based data sources, it is unclear when discrepant findings between the older and newer studies are due to the data source, model specification, or unit of analysis.¹ For instance, many of the older studies found a positive association between cities' percent minority and their police homicide counts or rates (Jacobs & O'Brien, 1998; Smith, 2004; Sorensen et al., 1993; Willits & Nowacki, 2013) whereas studies using media-based data sources have found no statistical association (Jennings & Rubado, 2017; Legewie & Fagan, 2016; Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016). One study that used the SHR (Jacobs & O'Brien, 1998) found that the

¹ Most studies comparing police homicide counts or rates across geographies utilize cities or agencies as the unit of analysis. Others have used states (Jacobs & Britt, 1979; Kivisto et al., 2017; Tennenbaum, 1994), core-based statistical areas (Hehman et al., 2017; Renner, 2019), counties (Delehanty et al., 2017; Renner, 2019), or block groups (Klinger et al., 2016).

presence of a Black mayor was associated with lower rates of Blacks killed by police whereas another study that used media-based data (Legewie & Fagan, 2016) found no such association. Similarly, a study that utilized the SHR (Willits & Nowacki, 2013) found that minority representation on the police force was associated with lower justifiable homicide rates while a study using newer, media-based data (Jennings & Rubado, 2017) found no association between minority representation and officer-involved gun deaths.

Although it is critical to our ability to compare findings across studies, only a few studies have attempted a comparative assessment of the older and newer data sources (Dirlam, 2018; Pang & Pavlou, 2016; Renner, 2019). Although the newer, media-based data sources seem to represent more accurate counts of police homicides, it is possible that the predictive capacity of the Supplementary Homicide Reports is not meaningfully different from the newer data sources. In addition, while two studies (Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016) have presented models predicting more than one media-based source and one study (Legewie & Fagan, 2016) has used multiple media-based sources to create an integrated media-based dataset, no one has attempted to use structural equation modeling to incorporate multiple media-based sources as indicators of a latent level of homicide by police.

Homicide by Police as an Outcome of Interest

The rate of homicide by law enforcement is an important sociological outcome of interest for several reasons. First, it has a high degree of political and social relevance to the general public and this relevance has increased in recent years. Google Trends data (see Figure 1.3) shows that searches for the terms "homicide by police," "police shooting," "police killing," and "police brutality" began increasing in 2014, coinciding with the 2014 protests in Ferguson, Missouri in response to the shooting death of Michael Brown and several other high-profile police-involved homicides in that year. Average yearly searches for these terms increased between 2014 and

2016 but declined and appeared to stabilize between 2017 and 2019. However, searches for these terms increased again in 2020 following the highly publicized killing of George Floyd in May of that year and subsequent national protests in response to that event.

Another important reason to look at homicide-by-police is that it disproportionately impacts some racial/ethnic groups more than others. The history of law enforcement in the United States is intimately tied with the changing racial and ethnic context of the country. In the early 1800s, modern policing systems emerged in the South as a means of controlling enslaved and formerly enslaved people (Reichel, 1988) while their appearance in northern cities was tied to civil disorder related to racial conflict and the influx of new immigrant groups from Ireland and Germany (Walker, 1977). The current phenomenon of public outcry in response to particular events of police brutality against Black or other minority individuals is by no means new. For instance, the Harlem riots of 1964 were sparked by the death of 15-year-old James Powell after he was shot by an off-duty New York City police officer (Fyfe, 1988). Other such instances include the 1966 Los Angeles Watts Riots, sporadic riots in Miami throughout the 1980s, the 1992 Los Angeles riots after the beating of Rodney King, and the 2001 Cincinnati riots, to name only a few. Whether because of structurally racialized policing practices, individual-level racial prejudice among police, or structural and individual-level issues outside of police practices, it is clear that Black civilians are disproportionately killed by law enforcement officers when compared to their proportion of the U.S. population. While Non-Hispanic Blacks made up about 12.3% of the U.S. population in 2015 (U.S. Census Bureau, n.d.), they made up between 23% and 29% of those killed by law enforcement in 2015, depending on the data source used (see Figure 1.4). Similarly, Native Americans appear to be disproportionately killed by officers. Non-Hispanic American Indians and Alaskan Natives made up about 0.6% of the U.S. population in

2015 and between 0.9% and 2.1% of those killed by law enforcement, depending on the lethal force data being used.² Interestingly, Hispanics are not killed at a rate that is greatly out of proportion with their share of the US population. In 2015, people of Hispanic origin made up about 17.6% of the U.S. population and between 17% and 20% of those killed by law enforcement.

Accounting for Multiple Sources of Data

The first issue of interest to this dissertation is whether and how to account for the multiple sources of data on homicide by police (HbP). There is some unknown number of what can be termed "fatal encounters with law enforcement officers," that is, law enforcement encounters that result in the death of one or more civilians. Many, though not all, of these incidents can also be termed "officer-involved homicides," that is, incidents where a law enforcement officer *causes* the death of a civilian. Each of the potential sources of data on officer-involved homicides represents an imperfect attempt to count the number of such incidents.

Measurement error can occur both with official data sources and media-based sources. In official data generated by police, a death could fail to be reported because of a lack of compliance with the UCR and SHR, a lack of complete knowledge on the part of the agency (e.g., if a person is injured by police but died later at the hospital), definitional confusion (e.g., the person filling out the SHR form may think that the death was not a legally justifiable homicide), a lack of clarity on the SHR report forms,³ poor quality internal records keeping on

² Comparing these percentages should be done cautiously given the small numbers of indigenous people identified in these lethal force datasets. For instance, Native Americans make 1.3% of the decedents in 2015 according to Mapping Police Violence, but this is a total of 15 individuals.

³ The sample SHR form provided in the UCR Handbook is two pages long. The first page has the heading "1a. Murder and Nonnegligent Manslaughter" and the second page has the heading "1b. Manslaughter by Negligence." Justifiable homicides do not technically fall into either of these categories. If the respondent reads the full text on the instructions on the first page, they will see that they are meant to add justifiable homicides under the first heading. If

the part of the agency, or purposeful obfuscation on the part of the agency or individual officers. An incident could also potentially be logged in the SHR when it was not actually a justifiable homicide. For instance, the agency may think that a person died when they did not or the person filling out the SHR form may think that a justifiable homicide occurred when it was actually a death of a different kind (e.g., an officer killing someone for reasons of personal revenge while off duty, an officer killing someone who was not in the process of committing a felony, an officer killing someone due to negligence or gross recklessness, or a death that was self-inflicted or due to accident on the part of the decedent). An officer-involved homicide may fail to be reported in media-based data sources because a person died later due to injuries received during the encounter and initial media reports did not pick this up, a lack of local reporting on homicides by police (e.g., journalists local to the incident did not report on the death when it occurred), poor quality search techniques on the part of the journalists or activists or an uneven focus on certain kinds of incidents (e.g., the group may focus on finding incidents involving Black decedents and neglect to search for incidents involving White decedents), or because the group inaccurately understood the incident as falling outside of their exclusion restrictions (e.g., the data source only wants to catalogue incidents where officers were on-duty and reporting on the incident made it seem like the officer was off-duty). Within the media-based sources, incidents could also be inaccurately linked to a given geography. For instance, the original media reports may not have accurately recorded the city that the death occurred in, may have misattributed the death to the wrong agency, or may have given vague attributions to the agency

the person filling out the form does not fully read the instructions, they may not know that justifiable homicides are supposed to be reported on these forms.

or agencies involved (e.g., county-level law enforcement were involved but the reporting indicated that city-level law enforcement caused the death).

Error in the dependent variable is sometimes not a major concern in correlational research. However, it can be an issue if independent variables of interest predict both the true values of the dependent variable and measurement error in the dependent variable. For instance, a commonly used predictor of geographic differences in homicide by police is the local crime rate. If agencies that experience high crime rates are both more likely to have homicide by police incidents and less likely to report those incidents through the SHR, then the effect size of the crime rate would tend to be underestimated. Alternatively, if agencies that experience high crime rates are more likely to both have homicide by police incidents and report them through the SHR, then the effect size of crime rate would tend to be overestimated. This could be an important issue when the independent variables of interest are agency policies and organizational factors. For instance, if agency professionalization both decreases the number of homicides by police and increases the accuracy of reporting on those incidents to the SHR, the impact of professionalization on homicide by police rates would tend to be underestimated.

It is also important to note that there is no uniform definition for what should count as an "officer-involved" incident. Some definitions include only intentional acts on the part of the officer (e.g., an officer intentionally shoots someone during the commission of a crime), whereas other definitions may include accidental deaths caused by the officer (e.g., an officer crashes their car during a high-speed chase, killing a civilian). Different sources of homicide by police data capture different, though equally important, operationalizations of officer-involved homicide.

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Because of the potential sources of error in the measures of officer-involved homicide and because there are different ways of conceptualizing the term, researchers should view the officerinvolved homicide rate as a latent variable with several observed measures. Rather than use only one observed measure as an indicator of officer-involved homicide, researchers can employ multiple measures by combining them into a single factor or using structural equation modelling to estimate the latent construct. In this dissertation, I develop a measurement model that takes into account multiple sources of data on homicide by police. I then build on this model to examine local contextual factors as predictors of the latent homicide by police rate.

Policing and Local Context

There are good reasons to think that local context would shape local police behavior. In the U.S., law enforcement is territorial and decentralized (Klinger 1997). While state and federal law enforcement agencies do exist, most law enforcement agencies in the United States are operated at the county or municipal level. County sheriffs are generally elected while municipal police chiefs are appointed by a member of the local government (e.g., the mayor or the city manager). In large part then, law enforcement is accountable to the local citizenry, and that local ecological context likely shapes an agency and its officers.

Macro-level associations must function through individual or situational level associations (Coleman, 1990). I therefore introduce the framework summarized in Figure 1.5 as a way of understanding how structural factors shape interactions between police and citizens and how those interactions accumulate into macro-level outcomes (like lethal force rates). In short, this framework suggests that local context can shape officer perceptions of situational dangerousness (Bittner, 1970; Klinger, 1997; Skolnick, 1966) and the options that officers perceive as being available to them when responding to that dangerousness (Klinger, 1997; Maguire, 2003;

Walker, 1993). These factors together determine the level of force applied by an officer in a given situation and by aggregation create the local homicide by police rate.

For instance, journalists and activists point to racial tension and inequality as potential predictors of high homicide by police rates. Within the framework I have introduced, this could be interpreted in the following manner: cities where racial tensions are strained and racial inequality is high may produce more situations in which officers have a higher perception of dangerousness. Because there are a large number of perceptually dangerous situations, more police-citizen interactions will end in the use of lethal force, which will lead to higher homicide by police rates.

However, certain agency policies and practices may expand or contract officers' perceived options for action. For instance, the purpose of introducing less-lethal weapons (e.g., batons, Tasers, takedown techniques) is to reduce the number of lethal force incidents. In theory, it does this by increasing the number of less-lethal options that officers can take in a given situation, meaning that fewer police-citizen interactions will end in the use of lethal force.

In this dissertation I examine several categories of variables as predictors of the homicide by police rate. These factors are related to the populations that an agency serves as well as factors related to the agency's own demographics, organizational context, policies, and practices. Amongst the characteristics of the population served I examine the local firearm violence rate, population size, measures of general socio-economic status in the city, indicators of family structure, the percent Black and percent Hispanic/Latino, Black-White socioeconomic inequality and housing segregation, and Hispanic/Latino-White socioeconomic inequality and housing segregation. Agency demographic characteristics of interest include the agency's size, gender composition, and racial/ethnic composition. Agency organizational factors include salary

disparity between the chief and entry-level officers, the number of specialized unit types, and the presence of an active collective bargaining agreement. Agency policies and practices include educational requirements for officers, training requirements for officers, restrictions place on vehicle and foot pursuits of suspects, the documentation required for different forms of the use of force, the use of body cameras and dashboard cameras, and whether the agency authorizes particular kinds of less-lethal use of force options.

Dissertation Overview

This dissertation seeks to improve the literature on city-level homicide by police (HbP) rates by 1) developing a model for measurement of homicide by police that draws on multiple sources of data and 2) utilizing this measurement model to examine potential city/agency-level predictors of homicide by police. These two goals are explored in the following chapters. In "Chapter 2: Measurements of Lethal Police Violence," I discuss in greater detail the prior work that has been done regarding this first goal. Specifically, I discuss potential sources of data on officer-involved homicide and how other studies attempt to account for multiple sources. In "Chapter 3: Theory and Prior Literature," I address background relevant to the second goal by discussing the framework I use for understanding local contextual factors as predictors of policing, which predictors have been explored in the past, and why these predictors would theoretically impact homicide by police rates. In "Chapter 4: Data and Methods," I describe the particular data sources used in these analyses (i.e., 2015 to 2016 homicide by police data from the Supplementary Homicide Reports, Mapping Police Violence, The Counted, and Fatal Encounters; the 2012-2016 American Community Survey; the 2015 and 2016 Uniform Crime Reports; and the 2013 Law Enforcement Management and Administrative Statistics survey) and give an overview of the variable coding and analytic methods used. In "Chapter 5: Measurement of Latent Homicide by Police," I create and assess a measurement model using structural

equation modelling that takes into account multiple sources of data on homicide by police. In "Chapter 6: Local Context and Latent Homicide by Police," I utilize the measurement model to examine the associations between city and agency factors and homicide by police rates. In "Chapter 7: Conclusion," I summarize the results from chapters 5 and 6 and discuss their implications for the literature on geographic variation in officer-involved homicide, their potential policy implications, and the limitations of this study.

Figures

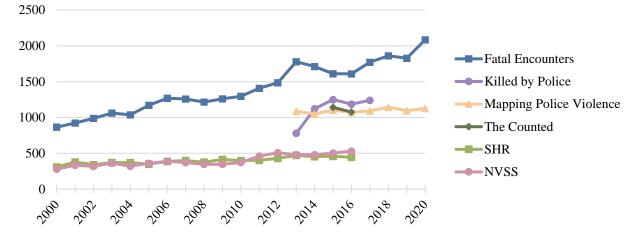
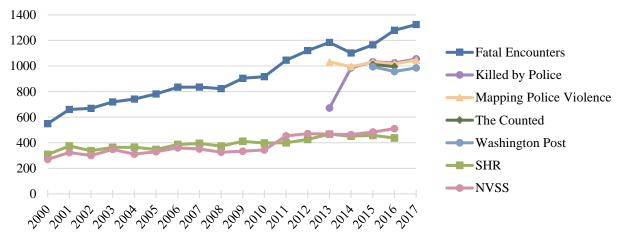


Figure 1.1: Number of Homicides by Law Enforcement as Reported by Different Data Sources, 2000-2020

Counts come from the following datasets: Fatal Encounters, Killed by Police, Mapping Police Violence, The Counted, Supplementary Homicide Reports (SHR), and National Vital Statistics System (NVSS).

Figure 1.2: Number of Shooting Fatalities by Law Enforcement as Reported by Different Data Sources, 2000-2017



Counts come from the following datasets: Fatal Encounters, Killed by Police, Mapping Police Violence, The Counted, The Washington Post's fatal shootings data (WP), Supplementary Homicide Reports (SHR), and National Vital Statistics System (NVSS).

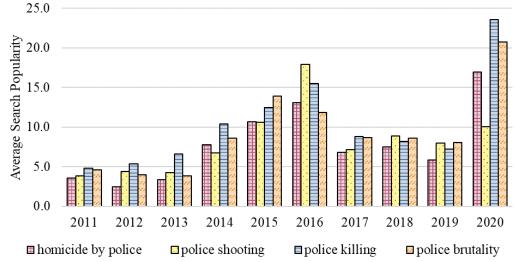


Figure 1.3: Google Trends Search Popularity for Homicide by Police Terms, 2011 to 2020

Search popularity is relative to the peak popularity for a given search term across a given time period. For instance, score of 20 in a given month would indicate that the search term was 20% as popular as its peak month. For this figure, average yearly search popularity is calculated as the 12-month average of a term's monthly search popularity score. From the period of January 2011 to December 2020, the peak popularity for "police shooting" occurred in July 2016 and the peak popularity for "homicide by police," "police killing," and "police brutality" occurred in June 2020. Google Trends data can be found at https://trends.google.com/trends/.

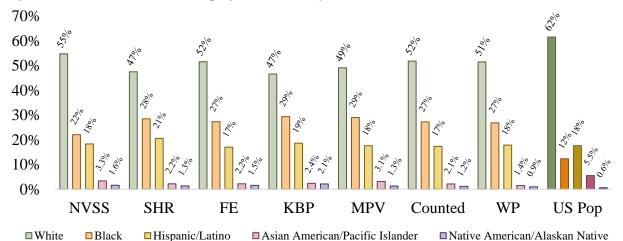


Figure 1.4: Racial/Ethnic Group of Decedents by HbP Data Source, 2015

Percentages come from the following datasets: National Vital Statistics System (NVSS), Supplementary Homicide Reports (SHR), Fatal Encounters (FE), Killed by Police (KBP), Mapping Police Violence (MPV), The Counted (Counted), The Washington Post's fatal shootings data (WP), 2015 American Community Survey 1-Year Estimates (US Population). The NVSS, SHR, and ACS collect race and Hispanic origin as separate variables. To create consistency with media-based lethal force datasets, the four racial groups are recoded to exclude Hispanics.

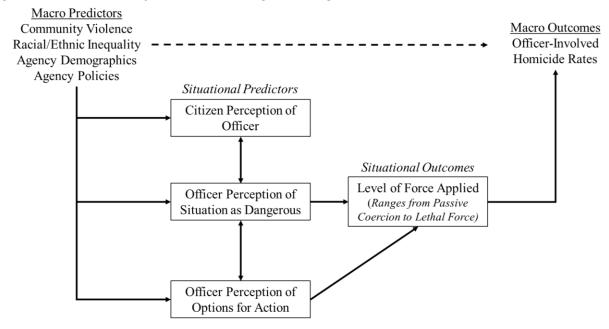


Figure 1.5: Framework for Understandings Policing, Local Context, and Individual Actions

Chapter 2: MEASUREMENTS OF LETHAL POLICE VIOLENCE

The goals of this dissertation are to 1) develop a model for measurement of homicide by police that draws on multiple sources of data and 2) utilize this measurement model to examine potential city/agency-level predictors of homicide by police (HbP). In this chapter I discuss important considerations and prior work relevant to the first goal.

Data sources that can be used to compare the use of lethal force across agencies, cities, or other geographies come in two broad varieties: "traditional," official data sources and newer, media-based data sources. In the following section, I will give an overview of the two data source types (i.e., official and media-based) and then discuss the studies that utilize more than one source (Dirlam, 2018; Legewie & Fagan, 2016; Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016; Renner, 2019). In doing so, I will illustrate how different sources vary in quality, how they pick up different aspects of homicide by police, and why there is utility in trying to account for more than one data source when attempting a comparison of homicide by police rates across geographies.

Types of Data Sources

Official Data

A paucity of high-quality data has limited attempts to compare the use of lethal force across agencies, cities, or other geographies. When looking for official sources of data on lethal force, researchers have turned to two main sources: law enforcement data and vital statistics. Studies examining geographic variation in lethal force published prior to 2016 have most often based their outcome on justifiable homicides as reported in the Supplementary Homicide Reports (Bailey, 1996; Jacobs & Britt, 1979; Jacobs & O'Brien, 1998; MacDonald & Parker, 2001;

Nowacki, 2015; Smith, 2003, 2004; Sorensen et al., 1993; Tennenbaum, 1994; Willits & Nowacki, 2013).

The Supplementary Homicide Reports

The SHR is a supplement to the FBI's Uniform Crime Reporting (UCR) Program, which is a major source of information on crime and crime rates in the U.S. The SHR therefore covers a greater length of time (from 1976 to 2017) than any other major source of lethal force data. The SHR is fully public use and can be downloaded at the incident, victim, or offender level and then collapsed to the agency, county, or state level. Because the FBI distributes it, it is easy to merge the data with other official data sources (like overall crime rates from the UCR) or government-produced surveys (such as Law Enforcement Management and Administrative Statistics, which is distributed by the Bureau of Justice Statistics).

The issues with the SHR as a source of data on police use of deadly force are welldocumented (Fyfe, 2002; Klinger, 2012; Loftin et al., 2003; Sherman & Langworthy, 1979; Zimring, 2017). The SHR is limited in scope because it counts only "justifiable homicides" by police officers, which excludes incidents that did not result in death and homicides not deemed legally justifiable. More detrimental is the fact that a large number of agencies that participate in the UCR program do not fill out the SHR forms or fill them out inconsistently month-to-month, creating a large amount of missing data (Loftin et al., 2003). Comparisons between SHR counts of justifiable homicides and internal counts gathered from police agencies suggest that the undercounting problem is severe (Fyfe, 2002; Klinger, 2012).

National Vital Statistics System

Another potential source of national data on police lethal force is the National Vital Statistics System. The NVSS collects death certificates from coroners and other medical professionals and categorizes deaths using the International Classification of Diseases (ICD). Deaths caused by police use of force fall under the ICD classification "legal intervention," which includes "injuries inflicted by the police or other law-enforcing agents, including military on duty, in the course of arresting or attempting to arrest lawbreakers, suppressing disturbances, maintaining order, and other legal action" (WHO 2016).

While the NVSS provides important information on deaths generally, it is limited in the kinds of sub-national geographic units it can compare. Its operationalization of "legal intervention" deaths includes more incidents than the SHR, but this makes the data less useful for researchers interested in deaths caused by municipal police only. There is no way to distinguish these deaths from those caused by other types of law enforcing agents. In addition, the county-level is the smallest geographic division that the NVSS provides in its public-use data and it suppresses information at *any* geographic level if too few incidents occurred during a given period.

Another important issue regarding the utility of NVSS as a measure of officer-involved homicides is that medical professionals do not directly select the classification "legal intervention." Instead, they are asked to fill in a list of the causes of death (from the most immediate cause to the underlying cause) and a manner of death statement with an open text field that describes how the death occurred (Loftin et al. 2003; NCHS 2003). This data is later translated into an ICD category. This system can be inaccurate because of simple misidentification, lack of awareness of ICD categories, purposeful obfuscation (for instance to avoid stigma to victims or their families), vague instructions for how to complete the death certificate, purposeful or unaware omission of the police role in the death, potential transmission and coding errors, and individual variability among medical professionals in the decision-making processes involved in reporting (Sherman & Langworthy, 1979). Loftin and colleagues (2003) found that the SHR and NVSS have only a moderate level of agreement about sub-national officer-involved homicide rates. Comparing justifiable homicides from the SHR to deaths by legal intervention in the NVSS from the years 1976-1998, they find that the SHR consistently reports higher national counts of justifiable homicide than the NVSS, but that this varies at the state level with over half of the states reporting more justifiable homicides through the NVSS than the SHR. This is related to state population size — larger states tended to have higher SHR reported rates than NVSS reported rates. The correlation between mean state population size over the period of study and the ratio of SHR counts to NVSS counts is 0.58. The national counts tracked fairly closely, with a correlation of 0.73 and a correlation between their change scores (i.e. the number of homicides in year t minus the number in year t-1) of 0.58. The authors indicate that while the national trends do seem to follow broadly similar patterns, either data source should be used with caution because of the way that both sources systematically underreport incidents.

National Violent Death Reporting System

A third major source of potential official data on officer-involved homicides is the National Violent Death Reporting System (NVDRS) (CDC 2014). The NVDRS is an effort by the Centers for Disease Control to integrate traditional sources of vital statistics (i.e., death certificates, coroner reports, medical examiner reports) with law enforcement reports in an attempt to track all violent deaths in the U.S. The NVDRS began data collection with six states in 2002, but expanded to include programs in all 50 states, Puerto Rico, and the District of Columbia by 2018.

The process of identifying officer-involved homicides within the NVDRS may be laborintensive. Researchers using this data for analyses of officer-involved homicides have had to utilize multiple variables in the dataset (specifically, the five variables type of death, death circumstance, victim–suspect relationship, underlying cause of death, and whether the death occurred in custody) to identify which violent deaths can be classified as "officer-involved" and then check these against the narrative descriptions of the deaths provided by the NVDRS (Barber et al., 2016; Conner et al., 2019). This is a time-consuming process, but apparently a necessary one (at least given the current state of the NVDRS program), since Conner and colleagues (Conner et al., 2019) found that only 81.5% the death initially identified as possible legal intervention deaths could actually be classified as "legal intervention homicides" based on the authors' criteria (i.e., line-of-duty homicides by a law enforcement officer) after being checked against their narrative descriptions.

Another issue for the utility of the NVDRS is the ability to link the data to the specific police agency responsible for a death. The restricted use version of the data contains information on the location of death down to the Census block group (CDC 2021) and therefore deaths could easily be attached to a given municipality. However, there is not currently a variable identifying the specific law enforcement agency associated with the death.

Media-Based Data

With increasing public interest in police use of lethal force, journalists and activists have attempted to compile their own datasets in order to count the number of people killed by police each year. These datasets are based largely on media reports of people who have died subsequent to police encounters, with some datasets supplementing this information with internal agency data obtained through public records requests. To varying extents, the journalists and activists who publish this data rely on crowd-sourcing techniques where volunteers systematically scour the internet for media reports fitting the particular data source's operationalization of lethal force. There are reasons to find the media-based data more trustworthy than agency-based data submitted to the FBI through the SHR. News media tends to focus on serious acts of violence (especially homicides), those incidents with a certain level of drama, and those that "can be grouped together as a moral panic" (Chermak 1994:580). This means that deaths related to law enforcement intervention are always newsworthy events and media outlets are therefore incentivized to report such events.

Police, on the other hand, receive little to no direct benefits from reporting justifiable homicides to the FBI. Individual agencies with high justifiable homicide counts run the risk of public scrutiny. The SHR also requests other kinds of information that agencies may not already keep track of internally, and the SHR takes time and resources to complete without seemingly being useful to police in helping them carry out their duties.

However, it is important to note the processes by which media-based police homicide data are generated. In order to be reported in a media-based database, an incident must first be reported on by one or more news sources. These articles must then be located by the group working to compile the data. These groups are generally composed of journalists, activists, and/or crowd-sourced volunteers. Because they are likely interested in illustrating that the issue of police-involved homicides is a significant problem, journalists and activists are institutionally incentivized to locate and add to the database as many incidents as possible. In one sense, this is beneficial — it means that media-based databases will report closer to the real number of police-involved homicides. However, the extent to which police are involved in a death is sometimes fuzzy, so some media-based databases may "overcount" the number of police-involved homicides for certain operationalizations of the term "police involvement." For instance, imagine an incident of what has been called "suicide by cop" — that is, an individual who wishes to

commit suicide and commits a crime (or pretends to commit a crime) so that police will shoot them. Or consider the case of someone who ingests their supply of drugs in order to "hide" them from the police and dies of an overdose. The person would not have ingested the drugs without the threat of police presence, yet the police did not directly cause the death. There is not a clear consensus about whether such incidents as these should be counted as a "police-involved homicide." Importantly, incidents are only added to a database if the group creating it considers those incidents as falling under their definition of "police-involvement." Because these databases are not primarily run by quantitative researchers, the operationalization of "police involvement" is often unclear.

There are several different media-based sources of data, which vary in terms of comprehensiveness and methods used to collect the data (as I discuss below). Three data sources — The Counted, Mapping Police Violence, and The Washington Post's shootings data — appear largely interchangeable in terms of absolute counts. The dataset Killed by Police is also similar in terms of absolute counts, although the process used to gather the data is less clear. The dataset Fatal Encounters covers a longer period of time, potentially giving it greater utility as a dataset than the others. Lastly, the USPD (U.S. Police Shootings Data) produced by Deadspin should be avoided, at least in its current form, given a clear problem of undercounting.

Fatal Encounters

"Fatal Encounters" (Burghart, 2018), first released in March 2014, is now one of the most comprehensive media-based data sources as it includes incidents from January 2000 to the present date. This effort is founded by journalist D. Brian Burghart, former editor/publisher of the Reno News and Review and former instructor at the University of Nevada, Reno. Data are collected via a combination of public records requests of police agencies and media reports located by paid researchers and crowdsourced volunteers. As of June 2015, about 15% of records are submitted by "the crowd." As of August 2018, this had decreased to about 4%. The remaining 96% are added to the database by known, non-crowd individuals (i.e., paid researchers, D. Brian Burghart himself, and one unpaid volunteer contributor).⁴ Decedent entries submitted by volunteers are checked by paid researchers before being added into the downloadable data. All entries have a link to a webpage where the information can be verified. In Chapters 5 and 6, I use Fatal Encounters data from 2015 and 2016 as one indicator of the latent homicide by police rate.

U.S. Police Shootings Data

Another early data source "U.S. Police Shootings Data" (Wagner, 2014, 2018), whose efforts began in August 2014, has been less successful. The USPSD is distributed by sports news and blog website Deadspin and journalist Kyle Wagner oversaw the project until his departure from the company in November 2015. Unlike Fatal Encounters, the USPSD is an entirely crowd-sourced dataset. Volunteers are asked to choose a single day between January 1, 2011 and December 31, 2014. Volunteers then use Google to search for any incidents of police shootings reported on that day, checking all links within the first 10 pages of the search results. This piecemeal method has yielded poor results. Approximately 62% of dates had been checked by August 23, 2018, corresponding to about 319 incidents of police shooting on average per year over the period of 2011 to 2014 — a smaller count than both the SHR and NVSS.

Killed by Police

"Killed by Police" (KBP, 2018), originally released in December 2014, is provided online seemingly through the efforts of a single individual. According to reporting by FiveThirtyEight, he is "an instructor on nonviolent physical-intervention techniques [and] he prefers to remain

⁴ These percentages are obtained through correspondence between the researcher and D. Brian Burghart.

anonymous" (Fischer-Baum & Johri, 2014). KBP is presented as a series of spreadsheets for the years 2013 to 2018 and includes links to media reports for each decedent. However, this source does not provide information on its methods for compiling the data.

Mapping Police Violence

Three activists associated with Campaign Zero, a police reform campaign, released "Mapping Police Violence" (Sinyangwe et al., 2018) in March 2015 (McCray, 2015). MPV combines the three data sources discussed above — Fatal Encounters, the U.S Police Shootings Data, and Killed by Police. In addition, the planning team for MPV performed additional research to identify the race/ethnicity of decedents when it is not identified in the underlying data sources, utilizing various sources including obituaries, criminal records databases, and social media accounts.

The Counted and The Washington Post

In June 2015, the Guardian (a British newspaper) and The Washington Post released their own datasets counting lethal force incidents. The Guardian data, called "The Counted" (Swaine et al., 2018), attempts to count all people killed by police or other law enforcement agents in the U.S. from January 1, 2015 to December 31, 2016. The Washington Post data (Arthur et al., 2018) is narrower in focus but covers a longer time period. The Post attempts to count all shooting deaths since January 1, 2015 by police officers in the line of duty. The Post's own report series based on their data is called "Shot by Cops and Forgotten," although the dataset is usually identified with the company's name. Both The Counted and The Washington Post's shooting data compiled data by monitoring local news sources, social media, and databases like those discussed already (i.e., Fatal Encounters and Killed by Police).

Studies that Attempt to Account for Multiple Sources

Two city/agency-level studies (Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016) present models using different data sources side-by-side.⁵ These studies illustrate that the choice of data source may lead to different findings. However, both studies compare findings using different time periods for different data sources, which makes it difficult to ascertain whether differences between models are due to the time period chosen or to the choice of data.

In their study focusing on agency demographics and city-level lethal force, Nicholson-Crotty and colleagues (2017) utilize both Mapping Police Violence and The Washington Post's fatal shootings data to create their outcomes — counts of Black citizens killed by police in 2014 (derived from MPV) and counts of Black citizens shot and killed by on-duty police in 2015 (from the Washington Post data). Testing the quadratic relationship between the percent of Black officers and both outcomes, they find that the percent of Black officers has a statistically significant and strong non-linear (positive-decreasing) relationship with the 2015 Washington Post count but no statistically significant relationship with the 2014 MPV count, although the coefficients were in the same direction. In addition, the count of White citizens killed is a strong and statistically significant positive predictor of the 2014 MPV count of Blacks killed but not the 2015 Washington Post count of Blacks shot and killed, although the coefficient was in the same direction for both sources.⁶

Pang and Pavlou (2016) examine various types of technology utilized by police as potential predictors of the logged count of police shooting fatalities. They use three data sources on

⁵ One study (Delehanty et al., 2017) technically compares two data sources on police-involved fatalities, however I do not review that study in this section because one of the data sources is the Puppycide Database Project, which logs deaths of dogs killed by police.

⁶ Nicholson-Crotty and colleagues (2017) do not offer an assessment of why there would be a difference between the two data sources and make no attempt to combine MPV and WP data.

homicide by police — The Washington Post's fatal shootings data for 2015 (WP), Killed by Police data for 2013-2014 (KBP), and the Supplementary Homicide Reports for 2013-2014 (SHR). Several key variables are consistent across data sources. For instance, they find that agencies that gather crime data and use it to conduct statistical analyses have between 2.5% and 3.7% lower logged counts of fatal shootings and that every standard deviation increase in number of assaults experienced by police officers is associated with an increase between 8.1% and 13.9% in the logged counts of fatal shooting. However, the authors find several differences in the strength and statistical significance of coefficients based on the data source used. For instance, the authors find that agencies that equip officers with smartphones for use in data collection have about 2.4% lower logged counts of fatal shootings when using WP or KBP but only 0.2% lower logged counts using the SHR (which is statistically insignificant). The use of body cameras is associated with 3.6% higher logged counts when using WP but this association is small (i.e., between 1.2% and -0.2%) and statistically insignificant when using KBP or the SHR. A one standard deviation increase in the number of community policing training required by the agency is associated with a 1.3% increase in the logged count when using the SHR but this association is negligible (i.e., less than 0.5%) and statistically insignificant when using KBP and WP.⁷

In one set of models, Pang and Pavlou (2016) attempt to combine data from the Washington Post and Killed by Police. Given that their WP data only covers the year 2015 and their KBP data covers the years 2013 and 2014, they choose to simply combine these counts together to create a measure that covers the years 2013 to 2015. Coefficients in this model tend to be of a similar or greater strength compared to the WP-only and KBP-only models. Exceptions to this

⁷ Pang and Pavlou (2016) do not offer assessments for why these differences are present.

are the coefficients for body camera use, median household income, and the Gini coefficient for income inequality — the first two of which have moderately-sized, statistically significant associations in the WP-only model and the last of which has a have moderately-sized, statistically significant association in the KBP-only model. All three of these factors have small, statistically insignificant associations with fatal shootings in the combined model. The authors do not provide methodological reasons for combining the WP and KBP data, do not report correlations between the three data sources, and do not provide descriptive statistics for the KBP and SHR counts they use.

Pang and Pavlou's method of combining information from two data sources may be superior to using data from only one source. However, the method of merging homicide by police counts from multiple years *and* multiple sources implicitly takes as granted that WP and KBP represent the same kind and quality of data. As an analogy, consider a repeated longitudinal survey where a given variable of interest, say parental attachment, is measured with a different question wording from one year to the next — for instance, if it makes reference to a child's mother in one year and a child's mother *and* father the next year. Certainly, the two measures are related, but a researcher would be wary about combining them together. This is especially true given that the Washington Post used a clear, concise operationalization of police-involved fatal shooting incidents, that is, "only those shootings in which a police officer, in the line of duty, shoots and kills a civilian" (Arthur et al., 2018), while Killed by Police gives no clear statement defining its scope.

In another noteworthy study, Legewie and Fagan (2016) use three sources (Fatal Encounters, The Counted, and The Washington Post data) to create a fourth integrated dataset. The authors' operationalization of officer-involved killings includes only intentional, purposeful killings by police or unintentional deaths caused by recklessness or negligence on the part of the officer. This eliminated 17.5% of the incidents in FE, 4.2% of the incidents in The Counted, and 2.7% of the cases from the WP data. The different datasets contributed to the integrated dataset (which includes 1,147 decedents) to different degrees. FE is missing 33 decedents found in one or both of the other two data source; The Counted is missing 49 decedents found in one or both of the other sources; the Washington Post data is missing 184 decedents found in one or both of the other two data sources.

Legewie and Fagan's (2016) integrated data is more complete (at least for their operationalization of officer-involved homicide) than any of the three media-based data sources would be alone. However, they rely on one type of data only (i.e., media-based data). Taking into account both official and media-based data may be important because the two types of data may capture different aspects of officer-involved homicide — that is, the SHR captures justifiable homicide by law enforcement, The Counted and Mapping Police Violence capture deaths arising from the actions of law enforcement officers, and FE captures fatalities where an officer was present or involved. In addition, the SHR has a certain benefit as a data source that often goes overlooked. By its nature, it is always accurate in attaching deaths (at least those that are reported within the SHR) to the agency responsible. Media-based sources rely on the accuracy of local journalists, who may not easily distinguish between agencies. In addition, multiple agencies can be *involved* in a death even if only one of these agencies' officers are *responsible* for a death. This creates difficulties for researchers interested in agency-specific predictors. However, because the SHR is distributed as homicides-within-agencies, it is easy to identify the agency responsible for the death.

Dirlam (2018) employs multiple imputation to improve the SHR and utilizes Fatal Encounters as a benchmark to assess whether his method of imputation appears to make the SHR more valid. One major issue for the SHR is that agencies fill out the monthly forms inconsistently. Dirlam uses Poisson multiple imputation methods to estimate the number of justifiable homicides that occurred during missing agency-months based on the year, month, and city in which the missing data occurred. Estimated values are then averaged across multiple imputed datasets and missing agency-months are filled in with these averages. Dirlam finds that the imputed total for the SHR comes closer to the totals reported by Fatal Encounters,⁸ although the degree of similarity varies by time period. For the years 2001 to 2003, the un-imputed SHR total is 8% lower than the FE total while the imputed SHR total is 37% higher than the FE total. For the years 2011-2013, the un-imputed SHR total is 46% lower than the FE total while the imputed SHR total is only 16% lower than the FE total. This imputation method may be a viable method for overcoming the missing data issues in the SHR. However, using FE counts to assess SHR counts implicitly assumes that Fatal Encounters is accurate, even though it may be very different from other media-based data sources. In addition, in multi-variate models Dirlam (2018) uses the SHR only.⁹ He uses FE only to assess his multiple imputation method of dealing with missing agency-months.

One study attempts to account for data from both official and media-based sources using a latent variable model. Renner (2019) uses a repeated measures, multiple indicators confirmatory factor analysis and three data sources — the Supplementary Homicide Reports, the National

⁸ Because of the difference in operationalization of officer-involved homicide between the SHR and FE, Dirlam attempts to limit the FE counts to those incidents that would fall under the term "justifiable homicide."

⁹ Because Dirlam is interested in homicide by police over the period from 1981 to 2013, utilizing FE (which covers 2000 to the present) would not be feasible.

Vital Statistics System, and Fatal Encounters. He finds that the measurement models combining all three data sources that include only large counties or only MSAs have good quality fit. The model that includes all U.S. counties has poor quality fit. In addition, he performs multivariate regression using a small list of predictors¹⁰ and finds substantive differences between models using each of the sources on their own versus a model using a factor score derived from the three sources.

Given that the smallest geographic unit available for the NVSS is the county, Renner's analysis is at the county and MSA level. This means that multiple agencies — including municipal police, county police, tribal police, county sheriffs, state law enforcement, and federal law enforcement — are grouped together. That is, no attempt is made to attribute deaths to the particular agency or agencies involved. While some macro-structural factors (e.g., poverty, crime rates, racial/ethnic conflict) may be meaningful predictors at the county or MSA, this method cannot be used to test the impact of agency-specific factors (e.g., agency demographics, organizational control, technology use), which Renner affirms are easier and more practical to change.

In addition, there are methodological and conceptual problems with aggregating the SHR to the county or MSA level. Multiple agencies exist within a single county, often of different types, and each agency may have different reporting practices. Two counties may seemingly have the same number of justifiable homicides when in actuality one of the counties has several agencies that do not report deaths to through the SHR.

¹⁰ Renner's uses the following independent variables to predict homicide by police rates: percent in poverty, percent Black, violent crime rate, population density, police per capita, and whether the geographic area is in the South.

In summary, those studies that attempt to account for multiple data sources indicate that these data sources are descriptively different (Dirlam, 2018; Legewie & Fagan, 2016) and that findings in multi-variate analyses can differ based on the choice of data source (Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016) even amongst media-based data sources. Renner (2019) illustrates that multiple data sources can load on the same underlying latent trait, ideally creating a stronger measure of officer-involved homicide than any one measure can on its own. However, his level of analysis (the county) is not the one best suited for the SHR and cannot be used to examine agency-specific predictors of homicide by police. In addition, it remains to be seen whether one of the potential data sources is actually superior to the others. Potentially, one of the media-based sources could be used as the "gold" (or at least silver) standard for researchers interested in geographic variation in lethal force. In order to assess this, a measurement model that estimates the latent homicide by police (HbP) rate should be constructed, used in multivariate analyses, and then findings should be compared to models using only one of the potential sources of HbP data. I will do this in later chapters, combining HbP data for 2015 and 2016 for four indicators of the latent rate (the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted).

Chapter 3: THEORY AND PRIOR LITERATURE

The second goal of this dissertation is to examine potential city/agency-level predictors of homicide by police. In the following section, I discuss why local contextual factors would matter for policing by developing a framework for understanding how such factors can impact policecitizen interactions. Then, I describe categories of factors that have been proposed as predictors of homicide by police (HbP) rates, specifying why these predictors would theoretically impact homicide by police rates and what prior studies find regarding these predictors.

A Framework for Understanding Policing, Local Context, and Individual Actions

In the U.S., law enforcement is territorial and decentralized (Klinger 1997). While state and federal law enforcement agencies do exist, most law enforcement agencies in the United States are operated at the county or municipal level. County sheriffs are generally elected while municipal police chiefs are appointed by a member of the local government (e.g., the mayor or the city manager). In large part then, law enforcement is accountable to the local citizenry, and that local ecological context likely shapes an agency and its officers.

Macro-level associations must function through individual or situational level associations (Coleman, 1990). I therefore introduce the framework summarized in Figure A as a way of understanding how structural factors shape interactions between police and citizens and how those interactions accumulate into macro-level outcomes like homicide by police rates. As illustrated in the figure, macro-level predictors (which include agency demographics, policies, and practices as well as aspects of the population served by an agency) can impact the overall homicide by police rate in one of two ways. All else being equal and if the likelihood that an officer will kill a citizen does not differ between police-citizen interactions, areas with more total police-citizen interactions will have more homicide by police incidents than areas with fewer

total police-citizen interactions. Therefore, the first way that a macro-predictor can change the overall homicide by police rate is by changing the absolute volume of police-citizen interactions.

The second way that macro-level factors can shape homicide by police rates is through their impact on individual police-citizen interactions themselves. A particular police-citizen interaction has three elements — the officer or officers involved, the citizen(s) or suspect(s) involved, and the environment in which the officer and citizens find themselves. In studies of police-citizen interactions (for examples, see: Garner et al., 2002; Lawton, 2007; Schuck, 2004; Terrill & Mastrofski, 2002), officer factors include officer demeanor or disposition, prior training, time spent on the force, race/ethnicity, age, and gender. Citizen or suspect factors include demeanor or disposition, offense type, weapon use, drug or alcohol use, race/ethnicity, age, and gender. Environmental factors can include neighborhood, number of onlookers, and the availability of cover.

These situational predictors shape the perceptions that officers and citizens/suspects have about their situation, which in turn shapes the level of force applied by an officer or officers in a particular situation. Fundamentally, this framework suggests that local context shapes officercitizen situational factors that in turn impact officers' perceptions of *situational dangerousness* and the *options for action* that officers perceive as being available to them when responding to that dangerousness. These factors together determine the level of force applied by an officer in a given situation and by aggregation create the local homicide by police rate.

The Police Role and Perceived Situational Dangerousness

A major factor determining perceived situational dangerousness is whether a given officer thinks they have lost or may lose control over a situation. The necessity of maintaining control is built into the work of policing. Skolnick (1966) argues that their social position as authority figures and their sense of on-the-job danger shapes police officers' "working personality." Officers are placed into circumstances with a high degree of uncertainty regarding their welfare and the welfare of others. Moreover, in an environment where nearly every officer is issued a firearm,¹¹ any encounter is a potentially lethal one for bystanders if a suspect is able to subdue an officer and take his or her gun. This creates a high level of motivation for officers to seek compliance from suspects.

Bittner (1970) points to the capacity to use force as core to the police role, which means that officers' main tool in responding to the potential loss of control during interactions with citizens is their coercive authority. The police wield this coercive authority in almost all of their crime control, order maintenance, and service tasks. This includes a wide range of activities from those dealing directly with preventing or investigating crime to more mundane tasks, such as being present during parades or protests, transporting those in need of psychiatric services to local hospitals, settling interpersonal disputes, or keeping traffic flowing. In each of these cases, the police wield the *capacity* to use force, although the force itself is not always necessary. The police have the authority to question you or move you somewhere because if you do not do as they ask, they can make trouble for you. Frequently then, the implied threat that force could be used is all that is necessary to control crime, enforce laws, maintain order, and provide various other services.

Attributions of Dangerousness

Officers may perceive certain kinds of subjects as more or less dangerous and/or likely to cause trouble than other kinds of subjects. In the literature on violence, these are called

¹¹ Based on the 2013 LEMAS, 99.7% of county and municipal police departments authorized some form of firearm for *all* sworn personnel (BJS 2013).

"adversary effects" (Felson, 2009; Felson & Pare, 2010a, 2010b) - individuals (including police) are more likely to adopt an aggressive posture when they perceive their targets as more threatening. These perceptions of people and places as dangerous are influenced by personal experiences, cultural messages, and interactions with other officers. Cultural messages about whether the police can trust the citizens they encounter come from both the wider culture (i.e., cultural aspects of their city, state, and nation) and the particular working culture of the agency they belong to. To different extents, an agency's particular working culture may reflect what has been called "traditional police culture," which "tends to incorporate distrust toward and isolation from citizens, a desire to 'maintain the edge' in encounters with citizens, a crime-fighting orientation, a desire to avoid supervisor scrutiny, loyalty to fellow police officers, concerns about danger and bravery, and permissiveness toward misconduct" (Silver et al. 2017:1273). Officers vary in the extent to which they endorse traditional ideas and attitudes (Paoline, 2003; Silver et al., 2017; Terrill et al., 2003). Agency or city factors that tend to uphold traditional police culture would tend to reinforce mistrust between police and citizens. This would create more policecitizen encounters where perceived situational danger is high. Agency or city factors that move agency culture towards greater confidence in the populace (and vice versa) and towards greater levels of police-community cooperation would tend to create fewer police-citizen encounters where perceived situational danger is high.

It is also important to note that officer perceptions influence and are influenced by citizen perceptions of officers and situations. There is feedback between citizen and officer demeanor. Citizens perceiving officers as dangerous, unjust, or untrustworthy will react to officers differently than those perceiving officers as friendly, helpful, or understanding, and vice versa. Simultaneously, both citizens and officers bring prior information into any given situation. For instance, citizens who have had bad experiences with police before are likely to enter into new encounters with police with apprehension.

Options for Action in Response to Dangerousness

In addition to perceived situational dangerousness, officers' perceptions of their *options for action* are important for understanding the level of force applied in a given situation. Officers have a high degree of discretion when it comes their work (Walker, 1993) and therefore have a range of potential options for action. This is reflected in the use-of-force continuums, used by the majority of agencies (Terrill & Paoline, 2013), which categorize potential use of force actions on a scale usually beginning with mere officer presence or verbal direction at the lower end of the scale and deadly force at the highest end of the scale.

Perceived options for action are circumscribed by an officer's training, available weapons and techniques, departmental or legal restrictions, and departmental norms. In addition, the variety of options available may decrease or increase officers' perceptions of danger. For instance, officers who are trained in de-escalation techniques may perceive a situation as less dangerous than officers not trained in these techniques. Simultaneously, officers' perceptions of danger may change their perceptions of what kinds of options for action are available to them.

Summary of Theoretical Framework

In summary, officers make decisions about the level of force to apply in a given situation (ranging from mere officer presence to lethal force) largely based on their perceptions of that situation as dangerous (i.e., their perceptions of whether they lack control or could potentially lack control over the situation). Officers' perceptions of situational dangerousness are determined by the demeanor of the citizen(s)/suspect(s) involved, their perceptions of particular places or particular kinds of people as generally dangerous, and the options for action that they perceive as available based on agency policy and training. In the following sections, I turn to a discussion of those local contextual factors which may influence officers' cumulative perceptions of situational dangerousness.

The predictors I will test fall into two broad categories — demographic and social aspects of the populations served by the agencies in the sample (i.e., city-specific predictors) and demographics, policies, and practices of the agencies themselves (i.e., agency- specific predictors). City-specific factors include community violence, percent minority, minority-White socio-economic inequality, minority-White housing segregation, indicators of the general socioeconomic status of the city, and family structure variables. Agency-specific factors include the demographic composition of the agency, organizational complexity, and organizational control. All of the city-specific and most of the agency-specific factors have been used in the prior literature on geographic variation in the police use of force. However, issues about data choice make the validity of prior findings unclear. In addition, agency-specific policies and practices are understudied in the literature on geographic variation in lethal force and some of the agencyspecific predictors tested here have not be included as predictors in prior studies. These new predictors are training requirements for lateral hires, restrictive foot and vehicle pursuit policies, whether the agency authorizes specific less-lethal weapons and techniques, and the percentage of authorized less-lethal options that require documentation when they are used.

Demographic and Social Aspects of the Population Served

Community Violence

Of all the possible predictors of police use of force one might propose, using local violence or crime rates perhaps makes the most logical sense. Using lethal force as an example, if police in all areas have the same probability of shooting and killing suspects of violent crimes, then we would expect those places with more violence to also have more suspects killed simply due to the volume of potentially lethal incidents. At the individual level, police are constitutionally authorized to take the severity of a crime that the officer thinks has been committed into account (Oyez, 2017), and, in practice, officers do respond to more severe crimes with greater force (Garner et al., 2002). A greater volume of suspect-police encounters where the suspect has supposedly committed a violent crime would naturally lead to more officer-involved homicides.

Community violence could also affect lethal force for reasons other than increasing the number of potentially lethal interactions with citizens. In terms of the framework discussed above, crime or violence rates can impact officers' perceptions of danger. Officers develop a sense of the crime or deviance in their city through personal experience with their workloads, observations about people they interact with on their beats, the general environment of those beats, and second-hand information from other officers or from monitoring the police radio (Klinger, 1997). This has a direct effect on perceptions of danger at the situational level. Local crime or violence rates also shape agency or work-group level perceptions of the community served. Given the overlap in those who offend and those who are victimized and because many victims precipitate their victimization to some extent, officers in higher crime areas tend to see a greater percentage of the population as undeserving of help (Klinger, 1997). For these reasons, the overall level of crime or violence in an area may increase the overall level of police use of force (or police use of lethal force specifically).

The above arguments lead to the following hypothesis:

 H1) Agencies serving populations with <u>higher levels of violence</u> will have <u>higher</u> <u>levels of homicide-by-police</u>. Studies based on the justifiable homicides reported in the SHR generally find that the local crime, violence, or murder rate are meaningful predictors of police use of force, although this may vary based on the units of analysis. Jacobs and Britt (1979) find that, among the independent variables they test, the violent crime rate is the strongest predictor of the state-level justifiable homicide rate. Studies comparing cities with populations of 100,000 or more¹² find that the murder rate (Jacobs & O'Brien, 1998; MacDonald & Parker, 2001),¹³ violent crime rate (Smith, 2003, 2004; Sorensen et al., 1993), or general crime rate (Willits & Nowacki, 2013) predict differences in justifiable homicide between cities. However, using his imputed SHR data and a longitudinal study design, Dirlam (2018) finds that the changes in the violent crime rate have a small, statistically insignificant relationship with changes in the justifiable homicide rate, although a 1 standard deviation increase in the number of officers killed in a city is associated with a 6% increase in the justifiable homicide count.

The relationship between violence and the justifiable homicide rate may not hold up for particularly large cities or smaller cities. As with earlier studies, Willits and Nowacki (2013) find that the crime rate is a strong predictor of the justifiable homicide rates in cities of more than 100,000 residents. However, it has a small, statistically insignificant association in models limited to smaller cities (i.e., those between 25,000 and 100,000).When comparing cities with populations of 250,000 or more, Sorensen and colleagues (1993) find that violent crime is predictive when a control for economic disadvantage is operationalized as the percent in poverty but not when it is operationalized as the Gini index. However, Smith (2004, 2003) finds that the

¹² Studies using samples of cities with populations of 100,000 or more range from samples of size n=169 (Sorensen et al., 1993) to n=266 (Legewie & Fagan, 2016) because the number of cities in the U.S. with populations of that size has increased over time.

¹³ It should be noted that the MacDonald and Parker (2001) study included justifiable homicides by both civilians and police in the outcome.

violent crime rate is predictive of justifiable homicides in large cities even when controlling for the Gini index.

Findings have been more mixed among studies using newer, media-based datasets, with some studies finding a strong, positive association between measures of crime or violence and lethal force outcomes (Hemenway et al., 2018; Kivisto et al., 2017; Legewie & Fagan, 2016; Pang & Pavlou, 2016) and others finding no statistically significant association (Delehanty et al., 2017; Hehman et al., 2017; Nicholson-Crotty et al., 2017). It should be noted that two of the studies that find no association have uncommonly used geographic units — core-based statistical areas (Hehman et al., 2017) and counties (Delehanty et al., 2017). In addition, Nicholson-Crotty and colleagues (2017) find no association between community violence measures and the number of officer-involved homicides. However, in this study, the authors control for both the violent crime rate and the murder rate simultaneously. These two measures have a high correlation (r=0.76), which can lead to problems detecting statistical significance. Alternatively, because the models include only the nation's 100 largest cities, this study could provide further evidence that the violent crime rate is not predictive of lethal police violence when comparing only particularly large cities.

Legewie and Fagan (2016) find that the association between community violence and racespecific lethal force outcomes may vary by the type of community violence measure being used. They find that the violent crime rate is predictive of the count of Whites killed by police and the rate per resident of Whites killed by police but is not predictive of any Black-specific measure.¹⁴ Conversely, the Black-on-White homicide rate is a statistically significant predictor of the count of Blacks killed by police, the rate of Blacks killed by police per Black resident, and the rate of

¹⁴ The violent crime rate is also not predictive of the officer-involved homicide rate of Whites per arrest.

Blacks killed by police per Black arrest. The Black-on-Black homicide rate, however, is not predictive of any outcome.

Using block group-level data from St. Louis, Missouri from 2003 to 2012, Klinger and colleagues (2016) find a non-linear relationship between community violence and officerinvolved shooting incidents (an operationalization that includes both lethal and non-lethal incidents). He finds a positive-decreasing relationship between high levels of firearm violence (i.e., the sum of the homicide rate, firearm assault rate, and firearm robbery rate, each per 100,000 residents) and the officer-involved shooting incident rate per resident. The positive association peaks at a firearm violence rate of 4.17 per 1000 and becomes negative thereafter. This non-linear association provides support for Klinger's earlier argument (1997), which states that police tend to expend less energy and be less engaged with the community in very high crime areas because of resource limitation and cynicism about the population they serve. This non-linear association has not been tested in studies using other geographic units.

Socio-Economic Context and Concentrated Disadvantage

High socioeconomic inequality, concentrated disadvantage, and overcrowding create more areas in a city where physical disorder is present. This can lead a city's residents (including police) to develop negative attributions about those places and the people who live there. Vacant housing, buildings and streets in disrepair, graffiti, and smashed windows prompt "attributions and predictions in the minds of insiders and outsiders alike" (Sampson and Raudenbush 1999:604). In general, then, low city-level SES could increase the volume of police-citizen interactions where perceived situational dangerousness is high.

This leads to the following hypothesis:

H2) Agencies serving populations that experience <u>higher levels of concentrated</u> <u>disadvantage</u> will have <u>higher levels of homicide-by-police</u>.

Evidence from multi-level studies supports the idea that police make different decisions in different environments. These studies find that measures of structural disadvantage are predictive of the level of force applied in police-citizen encounters net of situational factors (Lee et al., 2010; Sun et al., 2008; Terrill & Reisig, 2003). For instance, in their study of arrest situations nested within agencies, Lee and colleagues (2010) find that high unemployment rates are associated with officers choosing to apply more serious forms of coercion (e.g., use of a weapon) over less serious forms of coercion (e.g., verbal commands) net of arrestee and officer demographic characteristics and whether the suspect is resisting arrest. Terrill and Reisig (2003) find that, net of suspect demeanor and resistance, police apply a higher level of force in policesuspect encounters¹⁵ when those encounters took place in neighborhoods with higher levels of concentrated disadvantage than in neighborhoods with lower concentrated disadvantage. Using the same data, Sun and colleagues (2008) similarly find that police used a greater number of coercive actions during police-citizen encounters¹⁶ when those encounters take place in neighborhoods with higher concentrated disadvantage. In addition, they find that neighborhood disadvantage and citizen demeanor interact — police took more noncoercive actions (i.e., helpful actions towards the citizen, like offering physical assistance or information, advising the citizen on the legal process, or reassuring the citizen) with "irrational" citizens (i.e., those showing signs of intoxication, mental illness, or a heightened emotional state) in areas of low concentrated

¹⁵ Police-suspect encounters are those between police and individuals "defined as wrongdoers, peace disturbers, or persons for whom a complaint is received" (Terrill and Reisig 2003:298).

¹⁶ Police-citizen encounters include both confrontational encounters (i.e., police-suspect encounters) and more mundane encounters between police and citizens not suspected of wrongdoing.

disadvantage. That is, police are more helpful toward belligerent citizens when encounters take place in more affluent areas.

Several studies examine measures of economic disadvantage or inequality. Two studies find that the Gini Index is predictive of lethal force when using the SHR (Jacobs & Britt, 1979; Pang & Pavlou, 2016), while others find no statistically significant association between the two (Dirlam, 2018; Jacobs & O'Brien, 1998; MacDonald & Parker, 2001; Smith, 2003, 2004). Using newer data, studies find a relationship between the Gini Index when using Killed by Police (Pang & Pavlou, 2016) and Fatal Encounters (Jennings & Rubado, 2017), but not when using the Washington Post (Pang & Pavlou, 2016). No study thus far finds a statistical association between the percent unemployed or percent jobless and lethal force outcomes (Dirlam, 2018; Hehman et al., 2017; MacDonald & Parker, 2001) or between the percent of residents in poverty and lethal force outcomes (Hemenway et al., 2018; Nicholson-Crotty et al., 2017). Willits and Nowacki (2013) use a disadvantage index (a factor score composed of the percent of female-headed households, the percent in poverty, the unemployment rate, and the median household income) and find no statistically significant association between it and the justifiable homicide rate.

Median household income seems to be negatively associated with counts of lethal force incidents, with some caveats. Pang and Pavlou (2016) find that jurisdictions with higher median household incomes tend to have fewer officer-involved gun deaths when using the Washington Post data and fewer justifiable homicides with a gun when using the SHR. However, no such relationship is found when using Killed by Police data. Delehanty and colleagues (2017) find that counties in Connecticut, Maine, Nevada, and New Hampshire with higher median household income tend to have fewer officer-involved fatalities (calculated using data from Fatal Encounters). However, median household income is not predictive of the change in officerinvolved fatalities or the count of officer-involved killings of dogs. Interestingly, Klinger and colleagues (2016) find that block groups in St. Louis with higher median incomes tended to have more officer-involved shooting incidents (which included non-fatal incidents). They speculate that this may be due to the high number of incidents in their data that occur off-duty when officers are at or near their homes (which tend to be medium- or high-income neighborhoods). This block group level association may not translate to larger geographic units. Still, the positive association between median income and officer-involved shooting incidents is reduced to non-significance in the final models, which controlled for the square of firearm violence. Using an imputed version of the SHR, Dirlam (2018) finds no association between the change in median family income and the change in the justifiable homicide rate.

Only three studies (Klinger et al., 2016; Pang & Pavlou, 2016) examine housing related measures of disadvantage. Klinger and colleagues (2016) find that the percentage of owneroccupied households in a block group is not significantly related to the count of officer-involved shooting incidents. Using the SHR, Pang and Pavlou (2016) find that jurisdictions with a larger number of vacant homes per person have more justifiable homicides, yet jurisdictions with a greater percentage of residents who moved in the last year have fewer justifiable homicides.

There is weak evidence for a relationship between education levels and lethal force outcomes. Jennings and Rubado (2017) find that jurisdictions where a higher percentage of the populations has a higher education degree also tend to have lower counts of officer-involved gun homicides. Other studies that examine education predictors find not statistical association (Kivisto et al., 2017; Klinger et al., 2016; Pang & Pavlou, 2016).

Age and Gender

Population demographics, specifically the percentage of the population that are young males, could also play a role in producing lethal force outcomes by increasing the total volume of police-citizen encounters and the proportion of encounters with citizens/suspects that police may view as "dangerous." Young males are the age-gender grouping most involved in violence and serious property crime (Bouffard, 2009; Davidson & Chesney-Lind, 2009; Hirschi & Gottfredson, 1983; Kanazawa & Still, 2000). Even outside of their actual criminal activity, the activities of young males are more likely to be scrutinized and lead to police calls for service than other age-gender combinations (Bittner, 1970; Brunson, 2007; Brunson & Miller, 2006; Brunson & Pegram, 2018; Brunson & Weitzer, 2009; Hagan et al., 2005; Meehan, 1992). Interactions between police and young males are produced by and recreate attributions of young males as dangerous and particularly likely to pose a threat to officers' ability to gain or keep control over a situation. These "adversary effects" (Felson, 2009; Felson & Pare, 2010a, 2010b) could accumulate to increase the number of perceptually dangerous situations police are involved in, which in turn would increase the rate of fatalities (see Fig. A of Appendix B).

The above arguments lead to the following hypotheses:

 H3) Agencies that serve populations made up of a <u>high percent of young males</u> will experience <u>higher levels of homicide-by-police</u>.

The effect of percent young may differ by data source. Using the SHR, MacDonald and Parker (2001) find no statistically significant relationship between cities' percentage of residents between the ages 18 to 24 and their justifiable homicide rates. Pang and Pavlou (2016) similarly find no statistical relationship between cities' percentage of residents between the ages 15 to 24 and their count of justifiable homicides with a gun. However, when using the Washington Post and Killed by Police, Pang and Pavlou (2016) find a negative association between percent young and the count of officer-involved gun homicides. Using The Counted, Kivisto and colleagues (2017) find that median age is positively associated with state-level counts of officer-involved homicides, although this association is reduced to non-significance in some models.

Gender composition has not been adequately explored as a predictor. Only one study (Pang & Pavlou, 2016) has examined percent male as a predictor. Pang and Pavlou find that, regardless of data source (i.e., the SHR, Killed by Police, or the Washington Post), percent male is not a statistically significant predictor of officer-involved gun homicides.

Percent Minority

Percent Black and, less commonly used, percent Hispanic or Latino have been proposed as possible predictors of the homicide by police rate. Other than measures of community crime or violence, percent Black is the most commonly tested variable in studies of geographic variation in homicide by police. The reasoning for using this measure comes from racial threat theory.

Arguments based on racial threat theory have dominated the discussion regarding the relationship between racial context and police use of force. The basic premise of threat theory is that as the dominant group feels their social, economic, or political ascendency threatened, it will exert greater social control over subordinate groups. As police are an agency of social control, studying them would be an obvious way to test this theory.

Hubert Blalock's (1967) minority threat perspective, which builds off the work of Herbert Blumer (1958), specifically connects minority group size to the dominant group's motivation to discriminate. He argues that as minority group size increases, so too will the dominant group's sense of competitive threat (also called economic threat) and power threat (also called political threat) to its position in society. Regarding competitive threat — as percent minority increases so will the sense of economic competition between minority group and dominant group members. Perceived economic competition leads to discriminatory behavior meant to handicap members of the minority group. If this discriminatory behavior is successful, it increases the economic inequality of the two groups. Discrimination due to threats to power takes on a different form. The power and influence of a group is a function of the group's relative size, the resources available to group members, and the group's capacity to mobilize those resources. As percent minority increases, the dominant group must increase its resources or mobilization (or decrease the resources or mobilization of the minority group) to maintain its power advantage.

Blalock's threat theory makes the most conceptual sense when it's used to explain discrimination with clearly political or economic outcomes (e.g., socioeconomic status, educational attainment, or voting patterns). It may seem odd to relate economic and political threat to criminal justice outcomes, especially lethal force by police. The most obvious (though dubious) claim would be that elimination of minority group members reduces economic competition and political power. Police do not kill citizens at such an extreme rate that this would be a viable method for limiting minority group threat towards the dominant group.

However, disparity in lethal force may be a byproduct of over-policing minority group members relative to dominant group members, which could have consequences for the economic or political power of minority group members. Policing does not exist in isolation but is part of the larger criminal justice process. Criminal justice contact may reduce job prospects and literally disenfranchise some individuals. From a conflict perspective, the entire criminal justice system (including police) may be viewed as a means of controlling subordinate group members and limiting their ability to compete with dominant group members over jobs and political policy. Political or economic threat could also influence lethal force rates through the relationship between officers and minority group members. In an environment where the motivation to discriminate is high, officers may make more negative attributions about minority group members, especially if the police force is largely made up of dominant group members. That is, political or economic threat could influence officers to view minority group members as less trustworthy and more threatening so that when police interact with minority group members they will perceive those interactions as more dangerous and more likely to require the use of lethal force. Overall, the general expected pattern between percent minority and the homicide by police rate is a positive association that is possibly non-linear (i.e., positive-decreasing).

This leads to the following hypotheses:

- H4) Agencies serving populations with a <u>higher percent of Black residents</u> will have <u>higher levels of homicide-by-police</u>.
- H5) Agencies serving populations with a <u>higher percent of Hispanic/Latino residents</u> will have <u>higher levels of homicide-by-police</u>.
- H6) The positive relationship between percent Black or percent Hispanic/Latino and homicide by police rates will be <u>stronger at lower levels of percent Black or percent Hispanic/Latino</u> than at higher levels of percent Black or percent Hispanic/Latino.

Studies using the SHR generally find a positive association between percent Black and at least one of the justifiable homicide outcomes they test (Bailey, 1996; Jacobs & O'Brien, 1998; Smith, 2003, 2004; Sorensen et al., 1993; Willits & Nowacki, 2013), although these studies do not test for a non-linear association. However, there are inconsistencies between studies in whether percent Black is predictive of overall justifiable homicide or Black-specific justifiable homicides. Of the three studies that examined percent Black as a predictor of Black-specific counts or rates of justifiable homicide, two found a positive association (Jacobs & O'Brien, 1998; Smith, 2004) while one found no statistically significant association (Bailey, 1996). Of the nine studies that examined percent Black as a predictor of overall counts or rates of justifiable homicide, five find a positive association (Bailey, 1996; Smith, 2003, 2004; Sorensen et al., 1993; Willits & Nowacki, 2013) while three find not statistical relationship (Jacobs & Britt, 1979; Jacobs & O'Brien, 1998; MacDonald & Parker, 2001). The few studies published prior to 2014 that test percent Hispanic/Latino find no statistically significant association between it and overall justifiable homicide counts or rates (Smith, 2003, 2004; Willits & Nowacki, 2013). This indicates that the linear association between percent minority and homicide by police may be sensitive to model specification, although there is no clear pattern signaling that the inclusion of any particular control variable or style of regression (e.g., OLS versus negative binomial) is to blame. Alternatively, if the association is truly non-linear, it may be picked up as positive in some studies testing a linear term and null in other studies testing a linear term.

Studies relying on media-based, crowdsourced data generally do not find a meaningful relationship between percent minority and lethal force outcomes (Hemenway et al., 2018; Jennings & Rubado, 2017; Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016). One exception is Legewie and Fagan (2016), who find that percent Black is *negatively* associated with the count of officer-involved homicides of *Whites*, although it did not predict the rate per resident or rate per arrest for Whites. They find that every one standard deviation increase in the percent Black of the population served is associated with a 51% decrease in the number of Whites killed by police. Percent Black has no statistical association with the count, rate per resident, or rate per arrest for officer-involved homicides of Blacks.

At the block-group level, Klinger and colleagues (2016) find a significant bivariate correlation between percent Black and the count of officer-involved shooting incidents (r = 0.463). However, after adding basic controls, this association became only marginally significant. The association is reduced to non-significance after controlling for the square of the firearm violence rate.

Dirlam (2018) tests for non-linear and interaction effects of percent minority, which has not been done in prior work, and finds that the association between percent minority and justifiable homicide is conditional on time period and segregation. Using repeated-crossectional models with four time periods (1981-1983, 1991-1993, 2001-2003, and 2011-2013), he finds that citylevel percent Black does not have a direct or non-linear association with the justifiable homicide rate. However, percent Black interacts with time period dummies and with a measure of Black-White segregation. The interaction with time period indicates a general positive association between percent Black and the justifiable homicide rate that has decreased in intensity over time. The interaction with segregation indicates that cities with both a high percent Black and high segregation have the smallest justifiable homicide rates. This provides support for the theory of benign-neglect, which states that segregation creates less threat for Whites.

Unlike with percent Black, Dirlam finds a non-linear association between percent Hispanic and the justifiable homicide rate. In cities located in the Western U.S. (which tend to have a higher percent Hispanic than non-West cities), the association is positive-decreasing. That is, in the West, percent Hispanic generally has a positive relationship with the justifiable homicide rate except at very high levels of percent Hispanic. In non-Western U.S. cities, the relationship is the opposite — negative-increasing. As with percent Black, Dirlam finds an interaction between percent Hispanic and Hispanic-White segregation. The interaction term indicates that the association between percent Hispanic and the justifiable homicide rate (whether positive or negative) is stronger at higher levels of segregation. That is, among non-Western cities, those with both a high percent Hispanic and high Hispanic-White segregation have the *smallest* justifiable homicide rates. Among cities in the West, those with both a high percent Hispanic and high Hispanic-White segregation have the *highest* justifiable homicide rates.

To summarize the findings regarding percent minority, only studies that use the SHR data find a positive association between percent Black or percent Hispanic/Latino and homicide by police outcomes, although this association seems to lack robustness as it is not consistent across studies. No crossectional study at the agency- or city-level has examined the non-linear association between percent minority and homicide by police.¹⁷ In a longitudinal study, Dirlam (2018) finds that the association between percent minority and justifiable homicide is conditional on time period and segregation. Percent Black has a general positive association with the justifiable homicide rate that decreases in size over time. In addition, percent Black has a weaker association with the justifiable homicide by threat theory (i.e., positive-decreasing) among cities in the West but the association is the opposite (i.e., negative-increasing) among other cities. Percent Hispanic has a stronger negative association with justifiable homicide in non-Western cities.

Racial/Ethnic Socio-Economic Inequality and Housing Segregation

Some studies have gone beyond simply using percent minority and examine other kinds of racial/ethnic contextual variables. These include the socio-economic status of minority group

¹⁷ Or at least no crossectional study has *published* findings regarding the non-linear association between percent minority and homicide by police outcomes.

members and housing segregation. These are sometimes backed up with arguments related to racial threat theory, albeit with a broader reading of the theory than Blalock gives. These studies often argue that a low socio-economic status for minority group members and high housing segregation indicate that a city has high levels of minority threat. Beyond threat theory, arguments based on the ideas of structural and systemic racism can also be employed to support the idea that minority SES and housing segregation may be related to homicide by police rates. These arguments tend to view race discrimination as a wholistic system, of which criminal justice is only one part.

Bonilla-Silva (1997) argues that the idea of "racism" is too often linked to individual feelings of racial hatred. He instead argues for a move toward the concept of "racialized social systems," that is, societies in which racial categories exist and in which members of those categories are differentially rewarded across several domains, including the economic, the political, the social, and the psychological. This system creates and is supported by a racial ideological structure which provides both explicit and implicit rationalizations for the racialized social system. This racialized system can change in character over time as a product of "racial contestation," that is, the positional struggle between racial groups, but its purpose is always to differentially distribute rewards based on racial group membership.

Similarly, Reskin (2012) views race discrimination as a set of inter-linking sub-systems which create a system of "emergent discrimination." These sub-systems include the educational system, the labor market, the housing and mortgage markets, credit and consumption markets, health services, and the criminal justice system. Each sub-system has reciprocal feedback with the other systems (e.g., educational disparities have implications for labor market disparities and vice versa). This creates a system of what Reskin calls "emergent" or "über" discrimination,

which she argues has its own emergent properties. For instance, "in social psychological terms, it distorts how we see others, the attributions we make about them, and our predictions of their performance" (Reskin 2012:24). That is, emergent discrimination can have implications for individual psychologies and attributions made about minority group members.

The emergent impact of structural discrimination has implications for police perceptions of minority group members and minority-group member perceptions of police. Minority-group members do not experience situations in isolation (Murphy & Walton, 2013). They bring into situations their prior understanding of experienced prejudice as well as historical and cultural narratives of prejudice, both from the police and otherwise. This influences their perceptions of the police as hostile, dangerous, or untrustworthy. Similarly, where discriminatory outcomes are higher generally (e.g., high residential segregation, high minority unemployment, low minority educational attainment, high racial income inequality), police may view minority group members as more hostile, dangerous, or untrustworthy. This can be due to attributions generally made about highly-disadvantaged people and places and because of police perceptions that minority-group members will not trust them.

It is important to note that while I will refer to segregation and socio-economic disparity as "predictors" and police lethal force rates as "outcomes," predictions based in arguments concerning structural racism would view the causal ordering of these factors as recursive. That is, segregation, educational disparities, economic disparities, and criminal justice disparities are each part of their own systems which create and recreate one another. Given that the potential associations between these factors have been inadequately explored (which will be discussed in greater detail below), I am also not interested in disentangling the temporal order of these factors as arguments regarding causality ought to first be based on strong observed associations.

The above arguments lead to the following hypothesis:

- H7) Agencies serving populations that experience <u>higher levels of Black-White socio-</u> economic inequality and housing segregation will have <u>higher levels of homicide-</u> <u>by-police</u>.
- H8) Agencies serving populations that experience <u>higher levels of Hispanic/Latino-</u> <u>White socio-economic inequality and housing segregation</u> will have <u>higher levels</u> <u>of homicide-by-police</u>.

Very few studies examine racial or ethnic group specific measures of socioeconomic status (that is, racial or ethnic group specific measures of income, income inequality compared to Whites, unemployment, or educational attainment). Two studies (Jacobs & O'Brien, 1998; Willits & Nowacki, 2013) that use the SHR look at racial income inequality and find that Black-White income inequality is predictive of higher justifiable homicide rates, at least in large cities. However, Willits and Nowacki (2013) do not find this relationship in smaller cities. They also test for Hispanic-White income inequality and find no relationship between it and the justifiable homicide rate.

Using media-based data, Hehman and colleagues (2017) examine Black overrepresentation in officer-involved homicides (i.e., the difference between the percent of all officer-involved homicides where the victim is Black and the percent Black of the geographic unit of interest). Their key predictors (macro-level psychological factors) are strong and statistically significant, but all other independent variables in their models have weak, statistically insignificant associations with the outcome. These other independent variables include Black median income, White median income, the percentages of Black and White residents with a high school degree, and the percentages of Black and White residents with a bachelor's degree. Using media-based data, Legewie and Fagan (2016) find that race-specific unemployment is predictive of race-specific officer-involved homicide counts and rates. That is, the Black unemployment rate is predictive of Black-only officer-involved homicide counts and rates per resident and the White unemployment rate is predictive of the White-only counts and rates per resident. Group-specific unemployment is not predictive of rates per arrest.

Only five studies (Dirlam, 2018; Hehman et al., 2017; Jennings & Rubado, 2017; Legewie & Fagan, 2016; Willits & Nowacki, 2013) test the relationship between housing segregation and lethal force outcomes. Two studies examining overall measures of lethal force find no relationship between segregation and either the justifiable homicide rate (Willits & Nowacki, 2013) or the count of officer-involved gun deaths (Jennings & Rubado, 2017). However, Dirlam (2018) finds that the change in Black-White and Hispanic-White segregation has a statistically significant negative relationship with the change in the justifiable homicide rate. In addition, when testing square terms for both he finds that both kinds of segregation have positive-decreasing associations with the justifiable homicide rate. As stated above, segregation also interacts with percent Black and percent Hispanic. In general, he finds that when both percent minority and segregation are high, cities have lower justifiable homicide rates.

When examining race-specific outcomes, Legewie and Fagan (2016) find that Black-White segregation (measured by the dissimilarity index) is predictive of higher counts and rates per resident of Whites killed by police. Segregation is not predictive of the White rate per arrest or of any Black-specific outcomes. Similarly, in another study the Black isolation index is not predictive of Black overrepresentation amongst those killed by police.

Agency Demographics, Policies, and Practices

Studies in this area have generally neglected to test agency-specific factors (other than agency demographics) that could contribute to homicide by police rates. Such factors are

important if we are interested in reducing homicide by police rates because they may be easier to change than the city-level contextual factors discussed above. I will be testing several agency policies and practices that have not been tested in prior studies.

Agency Demographics

Diversifying the police force is a common recommendation for reducing police violence (Bergman et al., 2016; Campaign Zero, 2018; Fifield, 2016; National Research Council, 2004; Spillar, 2015). Police agency demographics have been an issue of interest to police reformers since at least the 1960s (National Research Council, 2004), yet police agencies remain largely White and male. Despite increasing representation over time, in 2013 about 72.8% of full-time sworn municipal police officers are non-Hispanic Whites and about 87.8% are male (Reaves, 2015), although these percentages varied greatly by department. It is important to note that agency racial composition can be assessed using percentages (e.g., percent of sworn officers who are Black) or representation ratios (e.g., the ratio of the percent of sworn officers who are Black to the percentage Black in the population served). Gender composition is measured using percentages, as there is not as much variance between large cities in the gender composition of the population served to warrant a representation ratio.

In theory, agency demographics may impact agency-level use of force outcomes because interactions between citizens and female and/or minority officers are different from interactions between citizens and White-male officers. For instance, officers from racial/ethnic minority groups may be better at communicating with and relating to minority group members than White officers (National Research Council, 2004). This suggests that a racially representative agency will have police-citizen interactions with lower perceived dangerousness on the part of both officers and citizens and therefore have fewer interactions that end in deadly force. Citizens may also react differently to White and racial minority officers. For instance, Cochran and Warren (2012) find that respondents to the 2005 Police-Public Contact Survey (a national survey) are more likely to say that officers did not have a legitimate reason for stopping them when officers are White than when they are Black, even controlling for the officers' stated reasons for the stop. This suggests that agencies with more Black officers will have police-citizen interactions where citizens perceive the officers' actions as legitimate, meaning that officers would be less likely to respond with deadly force.

Female officers may also utilize different options for action or be perceived differently by suspects than male officers. For instance, differences in socialization between men and women could lead female police officers to be less overtly confrontational than male officers (Archbold & Schulz, 2012; Rabe-Hemp, 2008). Female officers may also be less likely to utilize weapons, cause injury, or use excessive force (Brandl et al., 2001; Hoffman & Hickey, 2005; National Center for Women and Policing, 2002). This implies that agencies with more female officers would have fewer police-citizen interactions that end in deadly force.

Agency demographics may also impact agency-level homicide by police rates through shifts in the agency culture and norms or the public's perception of the police as legitimate. "Traditional police culture" (Silver et al., 2017) tends to engender a sense of distrust or hostility towards community members. Inasmuch as demographic shifts may push agency norms toward greater community cooperation and mutual respect between officers and the population they serve, we would expect agencies with more racial/ethnic minority officers and agencies with more female officers to have lower HbP.

All of this leads to the following hypotheses:

- H9) Agencies with a larger percentage of Black and/or Hispanic/Latino officers will have lower levels of homicide-by-police.
- H10) Agencies that are more <u>racially/ethnically representative</u> of the populations they serve will have <u>lower levels of homicide-by-police</u>.
- H11) Agencies with a <u>larger percentage of female officers</u> will have <u>lower levels of</u> <u>homicide-by-police</u>.

However, there are also reasons to think that statistical diversity alone would not create real change. The literature tends to find that minority and/or female officers are not that different from White-male officers. Many studies find small or no differences between female and male officers' decision-making and occupational attitudes (Archbold & Schulz, 2012; National Research Council, 2004; Poteyeva & Sun, 2009) and research comparing Black and White officers tends to find more similarities than differences (National Research Council, 2004). Less research has been done comparing Hispanic/Latino and White officers.

This apparent minimization of differences may be due to the occupational socialization into "traditional police culture" (Silver et al., 2017). The police identity may supersede officers' other identities (Weitzer, 2000; Wilkins & Williams, 2008). It could also be due to the fact of selection into training. That is, there may be dispositional similarities between police officers regardless of race, ethnicity, or gender such that interactions between citizens and female and/or minority officers are not substantially different from interactions between citizens and White-male officers.

"Active" rather than "passive" representation shifts organizational norms (Bradbury & Kellough, 2011; Mosher, 1968). In the theory of representative bureaucracy, passive representation is the simple calculation of whether an organization is statistically representative

of the demographics of the population it is drawn from or the population it serves. An agency employing minority group members at percentages approximately equivalent to their percentages in the population served by the agency is, at minimum, passively representative. However, institutions often seek passive representation in the hope of achieving active representation of historically under-represented group members. Active representation is achieved when bureaucrats (consciously or otherwise) act in ways that support the interests of the group or groups that they are part of. These more meaningful changes in departmental culture would not be picked up by the variables percent minority, minority representation, or percent female.

To summarize, the idea minority and/or female officer may not interact with citizens differently than White, male officers (due to selection or socialization into the police role) and "passive" forms of representation may not shift departmental norms. *This means that the*

following <u>null hypotheses</u> also have theoretical support:

- H9₀) Agencies will <u>not vary</u> in their <u>levels of homicide-by-police</u> based on their <u>percentages of Black and/or Hispanic/Latino officers</u>.
- H10₀) Agencies will <u>not vary</u> in their <u>levels of homicide-by-police</u> based on whether they are <u>racially/ethnically representative</u> of the populations they serve.
- H11₀) Agencies will <u>not vary</u> in their <u>levels of homicide-by-police</u> based on their <u>percentages of female officers</u>.

While only a small number of studies have tested these demographic factors, most find no meaningful relationship between minority representation (Dirlam, 2018; Jennings & Rubado, 2017; Smith, 2003) or percent female (Dirlam, 2018; Jennings & Rubado, 2017; Legewie & Fagan, 2016; Pang & Pavlou, 2016) and lethal force outcomes, however, a few studies have actually found that agencies with a higher percentage of racial/ethnic minority officers

(Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016) or agencies with a higher percentage of female officers (Smith, 2003) actually have *more* homicide by police incidents than those with fewer minority officers or fewer female officers, respectively. Only one study (Willits & Nowacki, 2013) has found that minority representation is associated with lower HbP.

The two studies that examine the percentage of racial/ethnic minority group members within police agencies find a positive association between percent minority and lethal force outcomes. Pang and Pavlou (2016) find that a higher percentage of Whites on the force is associated with *fewer* justifiable homicides. This association is small — an increase from 0% White to 100% White is associated with a 4.6% lower predicted count of justifiable homicides. The direction of the coefficient is the same when they use the Washington Post data or Killed by Police data (i.e., negative), although the coefficients in those models are smaller and not statistically significant. Using the Washington Post data, Nicholson-Crotty and colleagues (2017) find a non-linear, positive-decreasing relationship between percent Black and the count of officer-involved gun homicides of Blacks. As the percent Black increases, the predicted count of officer-involved gun homicides of Blacks also increases until an inflection point at about 42% Black.¹⁸ Large confidence intervals make it unclear whether the association levels out, becomes negative, or is simply less certain at higher levels of percent Black officers.¹⁹ The effect was meaningfully large — at lower levels of percent Black officers, a 1% increase in the percent of Black officers was associated with a 12.5% increase in the predicted count of officer-involved homicides of Blacks.

¹⁸ It is important to note that this positive association between the percent Black on the force and the number of officer-involved gun homicides of Blacks is not simply a function of the percent Black in the population served. Nicholson-Crotty and colleagues control for the total Black population size and the percentage Black of the population served.

¹⁹ Given the small sample size (n=100), the small number of agencies in the sample with more than 30% Black officers (n=12), and the change in the confidence interval size for agencies with a very large percent Black, my speculation is that the association they find is positive and simply becomes less certain at large values of percent Black.

The authors find a similar, though only marginally statistically significant, relationship when using data from Mapping Police Violence. They do not provide speculation about why findings might differ between the Washington Post and MPV.

One study using the SHR (Willits & Nowacki, 2013) finds that minority representation (i.e., the percent minority in the department divided by the percent minority in the population) is negatively associated with the justifiable homicide rate. That is, departments that have a percent minority that is more similar to their percentage in the population tended to have a lower justifiable homicide rate. In large cities, standard deviation increase in the minority representation ratio was associated with a 12% decrease in the predicted justifiable homicide rate. This association was not present in the sub-sample of small cities (i.e., those with populations between 25,000 and 100,000) or in the full model. Other studies that look at representation find no statistical association between minority representation and the count of officer-involved gun homicides (Jennings & Rubado, 2017) or between either Black representation or Hispanic/Latino representation and the count of justifiable homicides (Dirlam, 2018; Smith, 2003).

Only one study out of four finds a statistical association between percent female and lethal force outcomes. Smith (2003) finds that cities with agencies that have a larger proportion of sworn female officers actually have *higher* counts of justifiable homicides. This association is statistically significant in the large city model (i.e., the one that included cities with populations over 100,000) but not in the very large city model (i.e., the one that included cities with populations over 250,000). Other studies that examine agencies' percent female find no statistical association with officer-involved homicide outcomes (Dirlam, 2018; Jennings & Rubado, 2017; Legewie & Fagan, 2016; Pang & Pavlou, 2016).

Agency Policies and Practices

Agency policies and practices may create important controls on the police use of force (Smith, 2004; Walker, 1993). These factors come in two broad categories: organizational complexity and organizational control. Organizational complexity refers to the amount of hierarchy and job types within an organization. Organizational control refers to policies and practices meant to limit or influence the discretion of workers. Some key elements of control in police organizations are formalization (i.e., written rules and required documentation), professionalization (i.e., educational and training requirements), community policing, video surveillance of officers, and additional options for action in the form of less-lethal weapons and techniques that provide alternatives to firearms. For many of these issues, there is a conflict in the recommendations provided by the older police reform movements of the 1920s to 1970s (and their modern adherents) (Kelling & Moore, 1988; Maguire, 2003; Redlinger, 1994; Walker, 1977) and newer community policing reformers (Maguire, 2003; Maguire et al., 2003; Skolnick & Bayley, 1986, 1988; Zhao et al., 2010).

Organizational Complexity

In Maguire's (2003) theory of police organizational structure, the complexity of an organization has three elements — its vertical differentiation, functional differentiation, and spatial differentiation. Vertical differentiation is the degree of hierarchy within an organization. A pyramid is often used to represent organizational hierarchy, with the lowest level of command (e.g., patrol officers) at the bottom and higher levels of command stacked above tapering off to the highest level of command (e.g., police chief) at the top. Researchers operationalize vertical differentiation as "segmentation" (i.e., the number of command levels), "concentration" (i.e., the proportion of people working at different levels), or "height" (i.e., the social or economic distance between the lowest level and highest level). Functional differentiation is the degree of

specialization in task types. Organizations with more task-groups or many specialized roles have greater functional differentiation. Spatial differentiation is the degree to which an organization is distributed geographically. In some organizations, this may be operationalized as the number of operating sites or branch offices. For law enforcement it can be operationalized as the number of station houses or specific beats.

A fourth element of complexity is occupational differentiation (Maguire et al., 2003), which is conceptually distinct from functional differentiation. While functional differentiation represents differences in task division among workers after they are hired, occupational differentiation represents the degree to which an organization hires workers from different occupational sectors or with different specialized training or certification. Within organizational literature on policing, the concept of occupational differentiation is tied to the concept of the "civilianization" of policing — the degree to which an agency employs non-sworn, civilian personnel. Civilian personnel enter into an agency with a different set of skills and qualifications compared to sworn personnel, meaning that they belong to different occupational groups from sworn officers. Non-sworn personnel can include administrative or clerical workers, financial management, forensic scientists, crime analysts or statisticians, vehicle maintenance, and call dispatchers, among other job types.

The recommendations of police reform advocates regarding organizational complexity have changed over time. Professionalization and bureaucratization were the themes of police reform beginning in the early 1920s and lasting into the 1970s (Kelling & Moore, 1988; Redlinger, 1994; Walker, 1977). Reformers promoted increased vertical differentiation to reduce corruption and the influence of local politics on policing (Maguire, 2003; Walker, 1977) and increased

functional differentiation because specialized squads could be set up to deal with emerging issues.

However, the recent trends among reformers have reversed these recommendations and called for a flattening of hierarchies and a shift towards general rather than specialized skill sets for officers (i.e., decreased vertical and functional differentiation). Modern police reformers, especially community policing advocates, argue that the earlier trend towards professionalization and increased organizational complexity, which they term "traditional policing," had unintended consequences. They contend that complex bureaucratic organizational structures are inefficient and ineffective at delivering services to citizens (Maguire, 2003; Maguire et al., 2003; Zhao et al., 2010). More fundamentally, "traditional policing" deemphasizes the order maintenance and service functions of police in favor of the crime control function alone (Redlinger, 1994). This de-personalizes policing and fosters resentment between police and the communities they serve.

While modern police reform advocates argue that agencies should work to decrease organizational complexity in terms of vertical differentiation and functional differentiation, they promote increased complexity in terms of spatial differentiation and occupational differentiation (Maguire et al., 2003). Increased occupational differentiation, or "civilianization," may help sworn officers form a more positive disposition towards community members. In addition, civilian workers can free up sworn officers' time so that they are more able to effectively engage in community policing and civilian workers may function as community liaisons that engage community members in crime prevention programs (Skolnick & Bayley, 1986, 1988). Civilian workers, if they are drawn from the communities served by an agency, may also hold important linguistic and cultural understandings that sworn personnel lack since many sworn officers do not live in the cities that they serve or do not live in the areas that receive the most police attention (Skolnick & Bayley, 1986). Increased spatial differentiation within an agency means increasing the number of headquarters or sub-stations within a jurisdiction or the number of beats/patrol areas. Doing so is meant to make police-work more personal and localized. While one study found that the number of facilities had a negative relationship with the justifiable homicide rate (Willits & Nowacki, 2013), the data I use does not have a measure of spatial differentiation.

In summary, organizational complexity may impact homicide by police rates by shaping officers' relationships with the communities they serve, thereby also changing the nature of police-citizen interactions. Reformers argue that vertical differentiation (i.e., the degree of hierarchy within an agency) and functional differentiation (i.e., the degree of specialization among sworn personnel) de-personalize police work and leave communities without important order maintenance or service functions from a governmental agency. This creates apathy or resentment between police and the community they serve, which would increase the number of police-citizen interactions that police will perceive as dangerous enough to warrant the use of lethal force. However, increased occupational differentiation (i.e., the percentage of civilians working at an agency) would tend to increase an agency's effectiveness at providing services and foster greater police-community cooperation, thereby decreasing the number of police-citizen interactions that end in the use of lethal force.

This leads to the following hypotheses about organizational complexity:

- H12) Agencies with a greater degree of <u>vertical differentiation/hierarchy</u> will have <u>higher levels of homicide-by-police</u>.
- H13) Agencies with a greater degree of <u>functional differentiation/specialization</u> will have <u>higher levels of homicide-by-police</u>.

H14) Agencies with a greater degree of <u>occupational differentiation/civilianization</u> will have <u>lower levels of homicide-by-police</u>

Only two studies (Pang & Pavlou, 2016; Willits & Nowacki, 2013) have examined organizational complexity variables as predictors of homicide by police outcomes, but these studies provide some evidence that vertical and functional differentiation are related to higher homicide by police rates, as predicted by theory. Willits and Nowacki (2013) find that agencies with more "vertical differentiation," which they operationalize as the salary disparity²⁰ between entry-level patrol officers and the police chief, tend to have higher justifiable homicide rates. A one standard deviation increase in the salary disparity is associated with 29% increase in the predicted justifiable homicide rate in the large city sample. (Salary disparity was not predictive of justifiable homicides in the small city sample, although the coefficient was in the same direction.) Willits and Nowacki do not find a relationship between functional differentiation, operationalized as the number of specialized unit types an agency has, and the justifiable homicide rate. However, using a similar measure, Pang and Pavlou (2016) find that agencies with more specialized unit types have higher counts of officer-involved gun homicides. A one standard deviation increase in number of specialized units (i.e., an increase of 3.8 specialized unit types out of 14 possible types) was associated with a 4% increase in the predicted count of officer-involved gun homicides when using the Washington Post data. The coefficient was similar when using Killed by Police data and the SHR. One possible reason for the discrepancy between Pang and Pavlou's (2016) findings and Willits and Nowacki's (2013) findings regarding functional differentiation is that the specialized unit types asked about in LEMAS 2000 (used by

²⁰ Respondents to LEMAS 2013 gave salary ranges for different job levels at their agencies. The salary disparity is calculated as the difference between the mid-point salary offered to entry-level patrol officers and the mid-point salary available for the position of agency chief divided by the mid-point salary offered to patrol officers.

Willits and Nowacki) and those asked about in LEMAS 2013 (used by Pang and Pavlou) are different.²¹ Another potential reason for the discrepancy is that Pang and Pavlou do not control for agency size (i.e., the number of sworn officers employed by the agency). Larger departments tend to have greater functional differentiation (Maguire, 2003). In 2012, large local police agencies (i.e., those with 100 or more full-time sworn personnel) had on average about 4.9 types of specialized units whereas smaller police agencies (i.e., those with 99 or fewer full-time sworn personnel) had on average about 0.8 types of specialized units.²²

Occupational differentiation has only been examined by Willits and Nowacki (2013), and their finding is contrary to what would be expected based on recommendations by modern police reformers (and the hypothesis stated above). They find that agencies with a higher percentage of non-sworn personnel have a higher rate of justifiable homicides. In large cities, a one standard deviation increase in the percent non-sworn (about 8.0%) is associated with a 21% increase in the predicted justifiable homicide rate.²³ The authors suggest that the common measure of civilianization may actually be picking up aspects of what Maguire (2003) calls "administrative intensity," an element of organizational control (discussed in more detail below). Agencies that employ more civilians may be using them mainly for administrative roles. In 2012, about 65.0%

²² Personal calculations based on 2013 Law Enforcement Management and Administrative Statistics Survey (LEMAS) data. Sampling weights were used to estimate the national averages for all local police agencies.

²¹ LEMAS 2000 and LEMAS 2013 both ask about specialized unit types for dealing with the following 7 issues: bias/hate crimes, child abuse/endangerment, cybercrime, domestic/intimate partner violence, drug or alcohol impaired driving, gangs, and juvenile crime. LEMAS 2000 asks about specialized unit types for dealing with the following 11 issues not asked about in LEMAS 2013: community crime prevention, community policing, crime analysis, drug education, environmental crimes, internal affairs, missing children, prosecutor relations, repeat offenders, research, and victims and youth outreach. LEMAS 2013 asks about specialized unit types for dealing with the following 7 issues not asked about in LEMAS 2000: bomb/explosive disposal, fugitives or warrants, human trafficking, re-entry surveillance, terrorism/homeland security, victim assistance, and special operations (e.g., SWAT, SRT).

²³ The coefficient for percent non-sworn in the small city sample was not statistically significant but was in the same direction and still moderate in size. In small cities, one standard deviation increase in the percent non-sworn (about 8.7%) is associated with a 16% larger predicted justifiable homicide rate.

of all local police agencies used employed non-sworn personnel for administrative or clerical duties and nearly all large agencies (99.5%) employed non-sworn personnel for such duties.²⁴ Unfortunately, recent LEMAS data cannot be used to calculate the number or percentage of personnel in administrative roles, although a question about the number of administrative personnel was available in earlier versions of LEMAS (Maguire et al., 2003). This means that Willits and Nowacki were unable to examine the association between civilianization and justifiable homicide controlling for administrative intensity.

Organizational Control

While organizational complexity deals with how an organization divides up work, organizational control deals with how that work is carried out. Maguire (2003) refers to this concept as "structural coordination and control" while Walker (1993) uses the term "administrative rulemaking" to refer to a similar concept. Both point to the importance of organizational bureaucracy and rulemaking for placing limits on officers' discretion (i.e., their ability to make decisions). While some police reform advocates, especially community policing advocates, argue for decentralizing organizational control (Maguire, 2003; Maguire et al., 2003; Redlinger, 1994; Zhao et al., 2010), Walker argues that, "Administrative rulemaking, promoted by vigorous political advocacy, remains a viable avenue for reform" (1993:53).

Maguire (2003) says that structural coordination and control has three elements administrative intensity, centralization, and formalization. Administrative intensity (or administrative density) is the relative size of an agency's administrative component, that is, the percentage of workers whose primary duties involve organizational maintenance rather than the

²⁴ ²⁴ Personal calculations based on 2013 Law Enforcement Management and Administrative Statistics Survey (LEMAS) data. Sampling weights were used to estimate the national percentage for all local police agencies. "Large local police agencies" are those agencies designated by LEMAS as "self-representing," that is, those agencies with 100 or more sworn officers.

main goals of the organization itself. Centralization is the degree of concentration of discretion, that is, the extent to which decision-making power is held by one or a small number of individuals. Organizations where all or most decisions are made or approved by a chief or a small number of administrators are more centralized than organizations that allow lower-level supervisors or "on-the-ground" workers to make most of their decisions without approval beforehand. Formalization is the degree to which an organization uses formal policies, standards, and procedures to direct the actions of workers.

Measures of an agency's formalization (i.e., its particular formal rules and procedures) are generally more readily available than measures of centralization and administrative intensity. A centralization measure requires information about who makes decisions within an agency.²⁵ A measure of administrative intensity requires the number or percentage of personnel in administrative roles. Measures of centralization and administrative intensity are not available in the LEMAS 2013 data I use, nor have they been used as predictors of homicide by police in prior work. I therefore do not offer hypotheses regarding either of these aspects of organizational control.

Formalization

In general, community policing advocates argue for decreases in some forms of control over officers' decision-making (Maguire, 2003; Maguire et al., 2003; Redlinger, 1994; Zhao et al., 2010). This is part of a larger effort to push a form of police-work that is more personalized,

²⁵ An example would be "How much discretion does the typical first-line supervisor have [regarding] hiring and firing personnel?" (Maguire 2003:145).

proactive, and focused on order maintenance and service over mere crime control. One proponent of community policing, Lee P. Brown,²⁶ has said:

The command-and-control culture of the police department doesn't treat officers as intelligent, creative, and trustworthy people. It allows them very little discretion. It's designed to make sure that they don't get into trouble, don't embarrass the department, and don't get their supervisors into trouble (Webber 1991:116).

Formalization and other aspects of organizational control may therefore have disadvantageous consequences for homicide by police outcomes. If formalization decreases officers' job satisfaction and job-related well-being, de-personalizes police-work, creates departmental inefficiency, and/or degrades the police-community relationship, we would expect formalization to increase homicide by police rates. However, this is not the only perspective on organizational control.

Earlier researchers have argued that administrative rulemaking (i.e., formalization) had a large impact on the country's transition from the older "fleeing felon" standard to the current "defense of life" standard regarding the use of lethal force (Fyfe, 1988; Walker, 1993). While the *Tennessee v. Garner* Supreme Court decision had a meaningful impact on the state-level justifiable homicide rate as measured by the SHR (Tennenbaum, 1994), most large police departments had already adopted a more restrictive lethal force policy prior to the *Garner* decision (Fyfe, 1988; Walker, 1993).

Organizational control through formal policy may instead place important limits on police discretion, especially when it comes to discretion over the lethal use of force (Fyfe, 1988; Reiss,

²⁶ Lee P. Brown has held positions as the Police Chief of Houston, Police Commissioner of New York City, Director of the Office of National Drug Control Policy, and Mayor of Houston. The cited interview is from 1991 when Brown was the Police Commissioner of New York City.

1980; Walker, 1993). Within the framework I have discussed (see Figure A), formal policies place limits on officers' perceived options for action. This could decrease the likelihood that officers will resort to the use of lethal force in a given situation.

This leads to the following hypotheses:

- H15) Agencies with more <u>restrictive policies regarding pursuing suspects</u> will have <u>lower levels of homicide-by-police</u>.
- H16) Agencies that require <u>more restrictive use of force documentation</u> will have <u>lower</u> <u>homicide-by-police</u>.

The few studies that have examined formal policies have found that general measures of formalization are not predictive of homicide by police (Smith, 2004; Willits & Nowacki, 2013), although one study found that agencies with a policy requiring documentation for the display of a firearm had lower counts of officer-involved homicides with a gun than those without such a policy (Jennings & Rubado, 2017). Smith (2004) finds no relationship between the number of formal written policies²⁷ and the count of justifiable homicides. Willits and Nowacki (2013) find no relationship between the justifiable homicide rate and either the presence of a written maximum hours policy or protection orders policy. Unlike earlier studies, Jennings and Rubado (2017) find one formal policy that seems to be associated with lethal force outcomes — agencies that required officers to file a report any time they displayed a firearm (rather than only requiring a report when the firearm is fired) have lower counts of officer-involved gun homicides. Local police agencies and Sheriff's offices serving populations of 25,000 or more with a firearm

²⁷ Smith (2004) measured formalization as the number of written policy directives that the agency had out of 15 possible types regarding: using of deadly force, handling people with mental illness, handling homeless people, handling domestic disputes, handling juveniles, using less-than-lethal force, relationships with private security firms, off-duty employment, strip searches, conduct and appearance, confidential funds, employee counseling assistance, citizen complaints, and maximum hours worked by officers.

display report policy had about 0.32 fewer deaths on average during the period from 2000 to 2015 than those agencies that did not have a firearm display report policy. This is a large association given that the average number of deaths in their sample is 1.75 across agencies.

Given that Jennings and Rubado (2017) find an association between having a firearm display report policy and fewer officer-involved gun homicides while other authors find not association between the presence of other written policies and homicide by police outcomes (Smith, 2004; Willits & Nowacki, 2013), policies that have a more direct relationship with the use of force may be more relevant to homicide by police than general measures of formalization. Therefore, I employ the same measure of whether agencies require a report for the display of firearms used by Jennings and Rubado (2017) along with a measure that captures the degree to which agencies require use of force reports for less-lethal weapons and techniques. I also test measures regarding restrictions on foot and vehicle pursuits in particular have a potential to cause damage given that they involve the legally justifiable violation of the normal "rules of the road." I hypothesize that greater formal restriction on the use of force, operationalized as restrictive policies regarding pursuits and use of force documentation, is associated with lower HbP

Professionalization

Professionalization variables deal with pre-service requirements and training (Flynn, 2002; Smith, 2004; Willits & Nowacki, 2013). As discussed above, professionalization and bureaucratization were the main themes of the first wave of police reform, which lasted roughly from the 1920s to the 1970s (Kelling & Moore, 1988; Redlinger, 1994; Walker, 1977). These reformers argued that professionalization would reduce police corruption and increase police legitimacy in the eyes of the public. Education and training continue to be seen as important even by the new wave of community policing advocates.

The above arguments lead to the following hypotheses:

- H17) Agencies that <u>require higher levels of educational attainment from new hires</u> will have <u>lower levels of homicide-by-police</u>.
- H18) Agencies with <u>more training requirements for new hires</u> will have <u>lower levels of</u> <u>homicide-by-police</u>.

There is some evidence that professionalization variables are predictive of officer-involved homicide outcomes, although not always in the expected direction. Smith (2004) finds that agencies that require more hours of *field training* for new officer recruits tended to have *higher* counts of justifiable homicides (including total counts, White-specific counts, and Black-specific counts). This association is only present in his models of large cities (i.e., those with populations of 100,000 or more) and not in his models of very large cities (i.e., those with populations of 250,000 or more). However, agencies in very large cities that required more *in-service training* have *lower* counts of justifiable homicides of Whites. This association is not present in models including large cities or in models predicting total or Black-specific counts. Similarly, Dirlam (2018) finds that in large cities, changes in in-service training hours are not predictive of changes in the total justifiable homicide rate.

In contrast to Smith (2004), Willits and Nowacki (2013) find that training hours for new officer recruits are not predictive of the justifiable homicide rate. They suggest that this may be due to their more extensive list of police agency controls. However, it is also possible that the difference in findings is due to a difference in outcome calculation (i.e., counts versus rates).

Of the four studies of geographic variation in lethal force that examine agencies' educational requirements for service (Dirlam, 2018; Pang & Pavlou, 2016; Smith, 2004; Willits & Nowacki, 2013), only one (Dirlam, 2018) finds a statistical relationship between them and lethal force

outcomes. Willits and Nowacki (2013) and Smith (2004) use the same data source — the Supplementary Homicide Reports — and the same operationalization of educational requirements — whether agencies require a college degree. Pang and Pavlou (2016) test whether agencies require a high school degree and find no relationship between this variable and officerinvolved gun homicides using any of their three data sources (i.e., the Washington Post data, Killed by Police, and the Supplementary Homicide Reports). However, using an imputed version of the SHR, Dirlam (2018) finds that agencies that begin requiring college have lower justifiable homicide rates.

Community Policing

Community policing refers to a policing philosophy that focuses on involving private citizens in the crime control process (DeLong, 2002). It emerged as a paradigm beginning in the late 1970s and early 1980s (Oliver, 2000). This philosophy pushes for pro-active, creative solutions to crime control that center around the general quality of life of community members, rather than a traditional, reactive, and offense-focused method of policing. Community policing advocates think officers should have a more personalized, intimate understanding of the communities they serve.

If the community policing philosophy is correct, community policing could impact homicide by police rates by reducing the amount of crime or violence in the population served and by shaping the perceptual dangerousness of police-citizen interactions. Agencies that demonstrate a commitment to the philosophy would have better relationships and mutual trust with the communities they serve compared to agencies that do not try to implement community policing tactics. When implemented well, community-oriented policing can improve officers' job satisfaction, job performance, and perceptions of community support (Gill, 2017). In addition, by increasing collaboration with the community and reducing officers' anonymity towards community members, individuals that officers interact with may be more likely to value rather than resent officer presence. In summary, effective community policing could change officers' and citizens' demeanors when interacting with each other and reduce the number of policecitizen interactions that police perceive as dangerous enough to warrant lethal force.

Because it can be a nebulous concept, potential measures of community policing may vary in quality. Most agencies endorse community policing principles in theory. In 2012, about 68% of *all* local police agencies and about 88% of *large* local police agencies had written mission statements with a community policing component.²⁸ An ideal measure would be able to distinguish between those agencies that show a strong commitment to the community policing philosophy and those agencies that only partially incorporate community policing language or ideas into their policies and organizational culture. Measures that may relate to agencies' commitment to community policing include the number of officers who receive community policing training, the number of officers who are actively engaged in SARA-type²⁹ problem-solving projects, whether officers are evaluated based on their involvement in collaborative problem-solving projects, whether the agency has active partnerships or written agreements with local community organizations, whether the agency surveys local residents to assess the agency's effectiveness, or some scale that combines one or more of these kinds of factors.

This leads to the following hypothesis:

²⁸ Personal calculations based on 2013 Law Enforcement Management and Administrative Statistics Survey (LEMAS) data. Sampling weights were used to estimate the national percentage for all local police agencies. "Large local police agencies" are those agencies designated by LEMAS as "self-representing," that is, those agencies with 100 or more sworn officers.

²⁹ SARA stands for "Scanning, Analysis, Response, and Assessment" (Eck & Spelman, 1987) and is a commonly used decision making model encouraged by advocates of community policing and the related concept of problemoriented policing.

H19) Agencies that demonstrate <u>a greater commitment to the community policing</u> philosophy will have <u>lower levels of homicide-by-police</u>.

Despite the high hopes of the community policing philosophy, prior studies incorporating measures of community policing and community oversight do not find that they are associated with lower lethal force outcomes. Legewie and Fagan (2016) find no relationship between a count of community policing policies and practices and homicide by police counts or rates. Similarly, Jennings and Rubado (2017) find no relationship between the proportion of officers who received in-service training on community policing issues and the count of officer-involved gun homicides. Pang and Pavlou (2016) also find no relationship between officers receiving community policing training and the count of officer-involved gun homicides when using Fatal Encounters (the same data used by Jennings and Rubado) or the Washington Post data. However, when using the SHR, Pang and Pavlou (2016) find that a higher proportion of officers who receive community policing training actually predicts *higher* counts of justifiable homicides with a gun, although the size of the association was small — an increase from none of the officers receiving community policing training to all of the officers receiving training was associated with a 4% higher count of justifiable homicides with a gun. It is also important to note that Pang and Pavlou include both county Sherriff's offices and local police in their sample and that the agencies range in size from 1 full-time sworn officer to over 34,000 full-time sworn officers.³⁰ Local police are more likely to incorporate community policing into their policies and practices compared to county Sherriff's offices and larger agencies are more likely to incorporate them compared to smaller agencies. Pang and Pavlou do not include controls for agency size or type in their models despite including such a large variety of agencies. The community policing

³⁰ Pang and Pavlou do not provide the range of agency sizes, but they use LEMAS 2013 data

association they find may simply be due to the propensity of larger local police agencies to have more officer homicide incidents.

Video Surveillance

Video surveillance is another potential avenue for control over police discretion (Campaign Zero, 2018; Harris, 2010; Nowacki & Willits, 2016). Police administrators can review body cams and dash cams to evaluate officers' effectiveness and footage can be used as potential evidence in possible cases of misconduct. Alternatively, as argued by Pang and Pavlou (2016), police may view cameras as providing evidence that *justifies* their use of force decisions, which could make them more likely to engage in lethal force.

The above arguments lead to the following hypotheses:

H20) Agencies that monitor officer behavior through <u>video surveillance devices</u> (i.e., dashboard cameras and body cameras) will have <u>lower levels of homicide-by-police</u>.

Pang and Pavlou (2016) examined several forms of technology employed by agencies and find that some kinds of technology that provide officers with more information are associated with lower counts of officer-involved gun homicides while the use of body cameras is associated with higher counts. The authors suggest that technology used for intelligence analyses and access (like the collection and use of computerized data) reduces the uncertainty officers feel, thus decreasing their likelihood of using deadly force. However, the presence of evidence-gathering technologies (like body cameras and dash cameras) would increase the likelihood of deadly force because officers will feel that video evidence will provide legal support for their use of deadly force.

Indeed, agencies that used body cameras (i.e., video cameras that are attached to the patrol officers as part of their armor or clothing) tended to have higher counts of officer-involved gun

homicides when using the Washington Post data. This association is not present when using Killed by Police or the SHR. The use of dash cameras (i.e., video cameras mounted in or on patrol vehicles) is not statistically associated with officer-involved gun homicides.

Less-Lethal Weapons and Techniques

Use of force options other than firearms are available to officers. "Less-lethal" weapons include impact weapons (like batons), soft projectiles (e.g., bean-bag rounds or soft bullets that can be loaded and fired similarly to traditional bullets or rounds), OC spray or foam, tear gas, mace, and conducted energy devices (including Tasers). Officers can also employ devices other than handcuffs for restraining suspects, which are called severe restraints (an example of which is the "leg hobble" device). In addition, officers may be authorized to use chokeholds or lateral neck restraints or to physically slap or punch suspects.

Agencies vary in their policies regarding less-lethal weapons and techniques, but in all cases these alternatives to the use of a firearm may reduce the number of lethal police-citizen interactions by providing officers with different options for action (see Figure A). These options may have a direct effect on the level of force applied in a situation. They may also indirectly impact the level of force applied by an officer by influencing an officer's perceptions about an interaction's dangerousness. If the availability of less-lethal options reduces perceived dangerousness, we would expect fewer police-citizen interactions to end in the death of the citizen.

However, some less-lethal options may increase perceived dangerousness. For instance, being authorized to use neck restraining techniques could lead officers to get closer to a subject than they would if they were not authorized to use neck restraint. Maintaining distance and keeping barriers between officers and resistant subjects can be important tactics for preventing interactions from becoming lethal (Klinger, 2005). No study on geographic variation in police homicide rates has controlled for the kinds of less-lethal options an agency authorizes for its officers. Given this, my hypothesis will err towards the assumption that less-lethal options will be associated with the outcome their use intends to produce (i.e., fewer homicides by police).

This leads to the following hypothesis:

H21) Agencies that <u>authorize less-lethal weapons and techniques for use by all officers</u> will have <u>lower levels of homicide-by-police</u>.

I will now discuss three less-lethal options utilized by some police departments: neck restraints, soft projectiles, and chemical weapons. Neck restraining techniques are controversial, with some activist groups calling for a ban on all neck holds because of their potential lethality (Campaign Zero, 2022; Task Force on Policing, 2021) while officers and some academics argue that some types of neck holds pose less danger and should be authorized in some circumstances (Bozeman et al., 2022; Hickman et al., 2021; Winkley, 2019). There are two major kinds of neck holds: "true" chokeholds (also called respiratory restraints or "air chokes") and vascular neck restraint (also called "blood chokes") (Hall & Butler, 2007; Vilke, 2006). True chokeholds involve placing pressure directly on the airway of a subject (i.e., on the front of the neck below the chin). There is widespread agreement among the medical, law enforcement, and activist communities that chokeholds are very likely to result in serious bodily harm or death of the subject. In contrast, vascular neck restraint involves placing pressure on the carotid arteries of the subject (i.e., on the sides of the neck), restricting blood flow to the brain while leaving the airway unobstructed. There is evidence that when correctly implemented by law enforcement officers vascular neck restraint is able to induce unconsciousness without leaving the subject with serious, long-term injuries (Bozeman et al., 2022; Hickman et al., 2021). For instance, in a study

of data from three agencies (San Diego Police Department, North Carolina State Highway Patrol and the Royal Canadian Mounted Police) that included 944 instances of the use of vascular restraint, no fatalities related to neck restraint occurred and only 9 subjects experienced injuries, all of which were categorized as "mild" (Bozeman et al., 2022). In addition, the vast majority of subjects (92.6%) were apprehended by law enforcement and only a minority of subjects (23.7%) actually lost consciousness. In a study of the Spokane Police Department (Hickman et al., 2021), researchers found that use of force incidents involving vascular restraint were less likely to involve visible injuries or complaints of injury by the suspect (64.8%) than use of force incidents where vascular restraint was not used (85.1%). In addition, of the 230 uses of vascular restraint examined, no suspect deaths occurred.

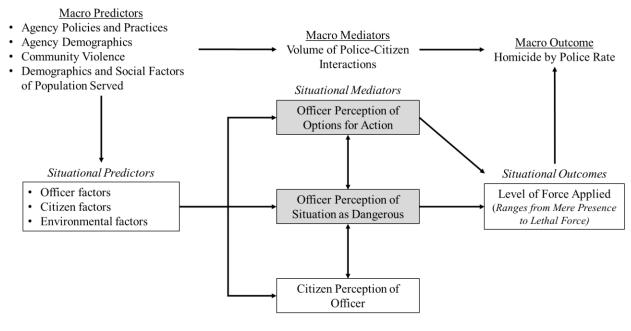
A wide variety of less-lethal munitions (also called "soft projectiles") are potentially available to law enforcement officers including bean-bag rounds, foam grenades, and bullets made from plastic, rubber, or wood. Less-lethal munitions can be an attractive choice of lesslethal weapon for law enforcement. Unlike a baton, they can be used at a distance (Fourkiller, 2002; Ijames, 2021) and that distance could give officers more time to assess a citizen's intentions or de-escalate a potentially lethal situation (Klinger, 2005). In addition, their operation is similar to traditional firearms, which officers generally receive a great deal of training in. In particular, bean bag projectiles fired from a standard 12-gauge shotgun appear to be a popular option for law enforcement (Fourkiller, 2002; Hubbs, 1997; Ijames, 2021; Mesloh et al., 2008) because the shotgun requires few if any modifications to be an effective launcher, most officers already have access to shotguns, and the projectiles are relatively cheap.

The probability of a subject's death or injury may differ significantly based on the kind of projectile, its brand and model, the impact site on the body, the number of impacts the subject

experiences, and the distance at which the projectile was fired from (Beatty et al., 2020). Impacts to the neck and head are associated with the most severe outcomes, followed by impacts to the chest and abdomen, with impacts to the extremities being least severe (Burki, 2023; Haar, Iacopino, Ranadive, Dandu, et al., 2017). At very close range, soft projectiles become much deadlier. For instance, manufactures of bean bag rounds for shotguns typically recommend a minimum distance of around 10 feet or 3 meters (Hubbs, 1997; Manhas et al., 2021).

While OC spray (also called pepper spray) is commonly authorized by most departments, the use of other chemical weapons, including various forms of tear gas (like CN and CS gas), are less common. While the experience of being exposed to tear gas is by no means pleasant, most of its physical effects are "acute and transient" (Tsang et al., 2020, p. 151). Tear gas irritates the skin and eyes, possibly causing burns (Agrawal et al., 2009; Carron & Yersin, 2009; Danto, 1987; Sivathasan, 2010). A person who is exposed to it for an extended period or at a high concentration may have more serious physical impairments, but "from a biological point of view, both CN and CS have wide margins of user safety" (Danto, 1987, p. 320). Figures

Figure 3.1: Framework for Understanding Policing, Local Context, and Individual Actions, Detailed



Chapter 4: DATA AND METHODS

Construction of a Homicide by Police Dataset

This study requires a dataset combining multiple sources of lethal force data to create the outcome measures and data on local agency and city context to create the predictors. To that end, I link data about homicides by police (HbP) that occurred in 2015 and 2016 from the Supplementary Homicide Reports (SHR), Fatal Encounters (FE), Mapping Police Violence (MPF), and The Counted (Cou) with the 2012-2016 American Community Survey (ACS), the 2015 and 2016 Uniform Crime Reports (UCR), and the 2013 Law Enforcement Management and Administrative Statistics survey (LEMAS). These dates are chosen because The Counted only includes deaths that occurred in 2015 and 2016.

The final dataset is crossectional but represents a time period from 2012 to 2016. It contains 254 police agencies and is representative of large municipal police departments in the U.S. (specifically those that served populations of 100,000 or more and employed 100 or more officers in 2012). This is a near-population sample of agencies fitting the exclusion criteria. All HbP variables combine data from 2015 and 2016 for decedent counts. Predictor variables related to police agency policies and practices are taken from LEMAS 2013 and therefore refer to an agency's circumstances in 2012. City crime rates come from the 2015 and 2016 UCR. Other city characteristics come from the ACS 5-year estimates for 2012-2016.

Description of Data

Lethal Force Data

All four lethal force data sources utilized in this analysis provide information on individuals who have died during or as a result of an encounter with the police, although the exclusion restrictions beyond this vary by data source. These analyses utilize the SHR (the more "classic" data source) and three media-based data sources (specifically, Fatal Encounters, The Counted, and Mapping Police Violence). I use these sources to create rates of homicide by police in 2015 and 2016. These are the two years available for all four lethal force data sources. The criteria used to decide whether an incident is entered into each of these databases varies by source. Other than limiting the years to 2015 and 2016 I will not attempt to make the data sources more comparable by adding additional exclusion criteria.³¹ I do this because I am interested in comparing the data sources as they are.

Supplementary Homicide Reports: The SHR are a supplement to the FBI's Uniform Crime Reporting (UCR) Program, which is a major source of information on crime and crime rates in the United States. City, county, and state law enforcement agencies report information about crime incidents and arrests for the eight "index" crimes — criminal homicide, rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson — on UCR Return A. The FBI also requests but does not require that agencies fill out the SHR form, which gives greater detail on homicide incidents, including the demographic characteristics of the victim and offender and circumstances surrounding the incidents. In addition to criminal homicides, the SHR asks for information regarding justifiable homicides (which are not included among the index crimes reported by the UCR).

The basic unit of analysis in the SHR is "homicide incidents," which can include more than one victim and more than one offender. In order to create local counts or rates of those killed by police, the researcher must first reshape the data to the victim level and restrict the data to justifiable homicides by police (that is, criminal homicides and justifiable homicides by citizens must be excluded). Counts can then be aggregated to the agency level.

³¹ An example of adding additional exclusion criteria can be found in Pang and Pavlou (2016). The authors use The Washington Post data, Killed by Police, and the SHR. Because The Washington Post data is limited to shooting homicides, the authors exclude incidents from Killed by Police and the SHR where firearms were not used.

Fatal Encounters: Fatal Encounters (FE) is an effort to create a comprehensive database of deaths related to law enforcement intervention that occurred from January 2000 to the present (Burghart, 2018). Data collection is carried out by a combination of paid researchers and crowd-sourced volunteers who make public records requests and systematically search for media reports on deaths occurring after law enforcement intervention. When creating new entries or submitting corrections, volunteers fill out an online form and provide links to the news articles or official documents that they utilized. This information is verified and checked for accuracy before being added to the database. As of June 2015, about 15% of records were submitted by "the crowd." As of August 2018, this had decreased to about 4%. The remaining 96% were added to the database by known, non-crowd individuals (i.e., paid researchers, D. Brian Burghart himself, and one unpaid volunteer contributor).³² As of January 2018, Fatal Encounters considered its information complete for the years 2000 to 2017 and included 23,569 individuals who died as a result of law enforcement intervention during this period.

FE is the most thorough of the media-based datasets and covers the largest time period. However, its definition of officer-involved deaths is very broad. It includes all deaths which occurred during or subsequent to encounters with law enforcement officers. This ranges from incidents where law enforcement intentionally or unintentionally caused direct harm to suspects to incidents of intentionally or unintentionally self-inflicted harm on the part of the decedent immediately prior to, during, or subsequent to a police encounter. This difference from other data sources is most evident when comparing the percentage of "vehicle deaths" between different data sources. For instance, an incident where police driving at high speeds or recklessly hit a pedestrian uninvolved with a criminal act would likely appear in Fatal Encounters, Mapping

³² These percentages were obtained through correspondence between the researcher and D. Brian Burghart.

Police Violence, and The Counted. However, an incident where police were engaged in pursuit of a fleeing suspect who then crashed his or her own car would likely appear in Fatal Encounters but is unlikely to appear in Mapping Police Violence or in The Counted.

The Counted: Distributed by the Guardian, a United Kingdom based newspaper, The Counted attempts to log every person killed by law enforcement agents in the United States in 2015 and 2016 (Swaine et al., 2018). The Guardian collected its data by monitoring local news outlets as well as open-source databases like Fatal Encounters. The Counted includes only deaths directly caused by law enforcement agents. This includes shooting deaths as well as deaths due to being tasered or struck by police vehicles. The Counted also includes individuals who died in police custody after being arrested or booked. Unlike FE, The Counted does not include suicides, self-inflicted deaths, or vehicle deaths where the subject was speeding away from police. The Counted utilizes a combination of independent research by the Guardian's journalists (who monitored local news sources, social media, and existing databases, like Fatal Encounters, Killed by Police, and Deadspin's U.S. Police Shootings Database) and crowdsourcing from volunteers. Crowdsourced entries are verified by the Guardian's staff.

Mapping Police Violence: MPV is produced by activists associated with Campaign Zero, a police reform campaign (McCray, 2015; Sinyangwe et al., 2018). MPV combines data from three sources — Fatal Encounters, the U.S. Police Shootings Data (distributed by Deadspin), and Killed by Police. These were the three earliest efforts at compiling data on police-involved homicides. In addition, the planning team for MPV performed additional research to identify the race/ethnicity of decedents when it was not identified in the underlying data sources, utilizing various sources including obituaries, criminal records databases, and social media. MPV includes only deaths that result from being harmed, chased, arrested, or restrained by police officers. This

includes deaths caused by both on-duty and off-duty police officers, regardless of whether caused intentionally or unintentionally.

LEMAS 2013 and LEAIC 2012

The Bureau of Justice Statistics sporadically conducts the Law Enforcement Management and Administrative Statistics (LEMAS) survey, usually at intervals of three to four years, with the latest released prior to the 2015-2016 data used as indicators of the latent HbP rate being LEMAS 2013 (Bureau of Justice Statistics, 2013). LEMAS 2013 is a nationally representative sample of state and local law enforcement agencies and contains information on the organization, policies, and practices of the surveyed agencies. LEMAS uses a stratified sample design based on agency size and type. All 50 state agencies and all local agencies with 100 or more sworn officers were considered "self-representing." The BJS attempted to contact and survey all selfrepresenting agencies. Smaller agencies were divided into six strata³³ and randomly sampled from within those strata. The final sampling frame called for 2,353 local police departments, of which 2,059 responded (i.e., an 88% response rate).

The Law Enforcement Agency Identifiers Crosswalk (Bureau of Justice Statistics, 2012) is provided by the BJS to assist in linking law enforcement agency datasets to other agency datasets, crime data, and Census data. It also provides some additional information about law enforcement agencies, including the size of the population served by the agency. I use information from LEMAS and LEAIC to create exclusion criteria for the agencies used in these analyses. The agencies in these analyses are all self-representing municipal police serving populations of 100,000 or more. These criteria will be discussed in more detail below.

American Community Survey

³³ The six categories based on agency size are as follows: 50-99 officers, 25-49 officers, 10-24 officers, 5-9 officers, 2-4 officers, and 1 officer.

The American Community Survey is a periodic survey conducted and distributed by the Census Bureau (U.S. Census Bureau, 2018b). It is meant to provide estimates of social, demographic, housing, and economic factors between decennial censuses. From 2005 to 2012, the ACS surveyed respondents through paper mail questionnaires, phone interviews, and personal visits. From 2013 onward, survey respondents also had internet response options. From 2017 onward, phone interviews are no longer conducted. The ACS has high response rates, with response rates in the past six years generally being around 95%.³⁴ The ACS program provides both single-year and multi-year estimates. I utilize the 2012-2016 5-year estimates rather than the 1-year estimates because I consider precision more important than currency for this analysis.

Linking Data Sources

The basic unit of analysis varies across the data sources discussed above. The SHR reports justifiable homicides at the incident level, that is, a given incident in the SHR may have multiple subjects/victims. The other lethal force datasets (i.e., Fatal Encounters, The Counted, and Mapping Police Violence) report police-involved homicides at the subject/victim level. LEMAS reports data at the agency level while the ACS data I will use will be at the "city" (i.e., incorporated places) level. For ease of merging, I use LEMAS 2013 as the "base" data and merge all other data sources into LEMAS.

Exclusion Criteria: I use information from LEMAS and LEAIC to create exclusion criteria regarding which agencies to include in this analysis. The 254 agencies in these analyses are <u>self-representing municipal police departments that served populations of 100,000 or more in 2012</u>. Within LEMAS, agencies are "self-representing" if they employ 100 or more officers. These

³⁴ The response rates to the 2012 through 2017 ACS are as follows (U.S. Census Bureau, 2018a). Housing Units: 2012: 97.3%; 2013: 89.9%; 2014: 96.7%; 2015: 95.8%; 2016: 94.7%; 2017: 93.7% Group Quarters: 2012: 95.1%; 2013: 95.2%; 2014: 95.9%; 2015: 95.3%; 2016: 95.7%; 2017: 94.7%

agencies were not sampled — the BJS attempted to contact all self-representing agencies. The term "municipal police department" excludes state agencies and sheriff's offices as well as local police agencies operated by county or tribal governments.

Population size is a commonly used criteria for exclusion in studies of homicide by police rates, with most studies choosing to include only cities with populations of 100,000 or more. Population data can either come from Census bureau estimates of the population served by the local government associated with the agency or from UCR estimates of the population served by the agency itself. These estimates are generally close for municipal police departments³⁵ and 2012 estimates for both are provided by LEAIC. I use the UCR estimate for the population-based exclusion criteria because it seems more in line with the unit of analysis (i.e., the agency). Doing so includes two agencies that would be excluded³⁶ and excludes three agencies that would be included³⁷ if I used the Census estimate.

Linking LEMAS Agencies to the American Community Survey: LEMAS can be connected to the ACS using the 2012 Law Enforcement Agency Identifiers Crosswalk (Bureau of Justice Statistics, 2012). The LEAIC was created to assist with merging law enforcement agency data to both agency and non-agency data with no identifiers in common. LEAIC 2012 can be merged to LEMAS 2013 using agencies' ORIs (Originating Agency Identifiers), which

³⁵ There are usually large differences between the two when examining sheriff's departments, given that they generally serve the non-urban population of a county whereas the population served by the county government will include both the urban and non-urban population.

³⁶ Tyler Police Department in Texas and Lewisville Police Department in Texas have a 2012 population served of 100,040 and 100,216 respectively. They have 2012 local government populations of 99,323 and 99,453, respectively.

³⁷ Las Cruces Police Department in New Mexico, Kenosha Police Department in Wisconsin, and Ramapo Town Police Department in New York have 2012 population served counts of 99,824, 99,993, and 85,443, respectively. They have 2012 local government populations of 101,047, 100,150, and 126,595, respectively.

are commonly used to identify agencies in Bureau of Justice Statistics datasets. The merged LEMAS-LEAIC data can then be attached to ACS data through FIPS codes.

Of the 254 agencies, 248 are easily attached to the 2016 5-year ACS through Census place codes. One agency, the Louisville Metro Police Department, serves a consolidated city-county government (i.e., the consolidated city of Louisville and Jefferson County). Two agencies, the Savannah-Chatham Metro Police Department and the Charlotte-Mecklenburg Police Department, serve both a city and the surrounding county, although the city and county are not a consolidated entity otherwise. The two combined city-county departments are linked to the ACS using the place codes for the corresponding city. The consolidated city department is linked using the consolidated city's FIPS code.

Three agencies serve towns or townships that are not designated as Census "places" — the Amherst Police Department in New York, the Edison Township Police Department in New Jersey, and the Woodbridge Township Police Department in New Jersey. These locations are defined by the Census as "county subdivisions." I therefore link these agencies to the corresponding county subdivisions in the 2016 5-year ACS.

Linking LEMAS Agencies to the UCR and SHR: General data on crime rates comes from the Uniform Crime Reports, distributed by the FBI. The unit of analysis in the UCR is also the agency. Therefore, all 254 agencies are easily linked to the UCR using their ORIs (Originating Agency Identifiers).

In order to link LEMAS to the SHR, the latter must be reshaped and aggregated. The Supplementary Homicide Reports are provided at the incident level — a given justifiable homicide incident could involve more than one decedent. The SHR is reshaped to the decedent level. This data is then aggregated up to the agency that reported the death to create counts of

justifiable homicides by officers in a given agency for a particular year. As with the UCR, this agency-level data is easily linked to LEMAS using agencies' ORIs.

Linking LEMAS Agencies to Media-Based Data: The media-based lethal force data sources used in this analysis (i.e., Fatal Encounters, The Counted, and Mapping Police Violence) provide data at the decedent level. As with the SHR, the decedents must be aggregated up to the agency listed as responsible for the death or to the city in which the death occurred. These media-based sources present a challenge for aggregation and merging

These data sources report the name of the city, county, and state where the death occurred as well as the agency or agencies involved in the death. All of this information is in text format and cannot be linked to outside datasets using uniform identifiers like FIPs codes or ORIs. In addition, there can also be variability within a given media-based data source in the spelling of agency or city names. For instance, if aggregating based on the name of the agency involved in the death, the entries "St. Louis PD," "Saint Louis PD," "St Louis Police," and "St. Louis Police Department," would all aggregate as if they were different agencies. Similarly, the department's name as spelled in LEMAS 2013 may differ from the spelling used in a given media-based data source. This means that merging media-based data to LEMAS must occur in two phases, each of them an iterative process: 1) assuring that agencies are uniformly identified within a given media-based source and 2) linking to LEMAS using a simplified form of the agency's name.

During Phase 1 I do not attempt to differentiate between agency types, that is, cleaning is carried out for police departments, sheriff's offices, state agencies, and federal agencies. Phase 1 begins with collapsing the media-based subject/decedent data by agency name and state, sorting names alphabetically, then visually checking for similar agency names in the same state. During

this process, several obvious misspellings or inconsistent entries in agency names are detected.³⁸ These issues appear in about 1.8% of decedent entries in The Counted (n=40), 5.5% of decedent entries in Mapping Police Violence (n=312), and 0.1% of decedent entries in Fatal Encounters (n=19).³⁹

After changing these more obvious issues, adjustments are made in agency names to create consistency in entries.⁴⁰ Again, these consistency issues are detected by collapsing the subject/decedent data by agency name and state, then visually checking for similarly named agencies. Changes for consistency are made to about 3.8% of decedents that appear in The Counted (n=85), 5.1% of decedents that appear in Mapping Police Violence (n=289), and 4.5% of decedents that appear in Fatal Encounters (n=1,055).

Because subject/decedent data is collapsed by agency name *and* the state in which the death occurred, special attention must be paid to large cities that exist on state borders. In particular, the Washington (DC) Metropolitan Police Department is likely to have incidents that occur in Maryland or Virginia, the Louisville Metro Police Department in Kentucky is likely to have incidents that occur in Indiana, the Kansas City (MO) Police are likely to have incidents that occur in Missouri. Where necessary, the state where the death occurred is changed to the state of the agency involved with the death. Changes of this nature are made to seven entries in Fatal Encounters, one entry in Mapping Police Violence, and one entry in The Counted. In addition,

³⁹ The Counted has 2,238 subject/decedent entries for the years 2016 and 2017. Mapping Police Violence has 5,673 subject/decedent entries for the years 2013 to 2017. Fatal Encounters has 23,574 for the years 2000 to 2017.
 ⁴⁰ Examples of consistency issues include the entries "Colorado Springs Police Department" and "Colorado Springs

³⁸ Examples of these issues include spelling "Department" as "Dpeartment" or "Deartmentt," "Sheriff's" being entered as "Sheriffâ€TMs," inconsistent use of capitalization, and using a single quotation mark (') rather than an apostrophe (').

Police;" "Pittsburgh Bureau of Police" and "Pittsburgh Police Department;" and "St. Louis Police Department," "Saint Louis Police Department," and "St Louis Police Department."

all deaths attributed to Kansas City, Missouri and Kansas City, Kansas police are doublechecked with media reports to make sure that they are attached to the correct Kansas City. In Mapping Police Violence, two deaths⁴¹ are mistakenly attributed to Kansas City, KS police when Kansas City, MO police were actually the ones involved. Misattributions of this nature are not found in The Counted or Fatal Encounters.

Phase 2 (i.e., linking the media-based data to LEMAS) begins with creating a simplified version of the agency name variable. This simplified name is entirely lowercase and includes only the place name associated with the agency. For example, "Little Rock Police Department" has the simplified agency name of "little rock." Some agencies in LEMAS have what I will call a "special designation" in their name. Examples include "Amherst (Town) Police Dept," "Buffalo (City) Police Dept," and "Woodbridge TWP Police Dept." LEMAS seems to use this format if there is a possibility that one agency could confused for another, for instance, if there is a town and a city with the same name in the same state. Most of these special designations are not included in the simplified agency name, although in all cases "TWP" is changed to "township." I check for agencies with these special designations in the media-based data to ensure that their simplified agency names are consistent with the simplified agency names in LEMAS. Adjustments of this nature are made to 0.3% of decedents in The Counted (n=6), 0.2% of decedents in Mapping Police Violence, and 0.2% of decedents in Fatal Encounters.

After merging a media-based source into LEMAS based on the simplified agency name, I take steps to ensure that no entries are incorrectly linked and that unmatched agencies are unmatched because they did not appear in the media-based source. First, I check to see if the LEMAS-reported name of the agency (i.e., not the simplified name) is exactly the same as the

⁴¹ These decedents are Patrick Pippin and Michael Bitters.

name the agency had in the media-based data source. For those that are not exactly the same, I visually check the names against one another to ensure that any differences are not indicative of the linked agencies actually being different entities. Second, for any of the focal 254 municipal police agencies that do not link to agency names in a given media-based data source, I use tabulations to check if any similarly named agencies exist in the media-based data. Lastly, it is still possible that some agencies have names that were not standardized within a given data source in Phase 1. Therefore, I use tabulations to check whether similarly named agencies exist amongst the unlinked media-based data for all of the focal 254 municipal police agencies that *successfully* linked to the media-based data. Adjustments to agency names are made as needed. Any adjustments detected at this point in Phase 2 are fixed earlier in the process and therefore are enumerated amongst those adjustments that are already discussed above.

At this point, I am reasonably certain that any of the focal 254 municipal police in LEMAS that do not merge with a given media-based data source do so because they do not appear in than data source. Out of the focal 254 municipal police departments, 68.9% (n=175) merge with The Counted, 89.5% (n=227) merge with Mapping Police Violence, and 99.2% (n=252) merge with Fatal Encounters. Note that the differences in percentage merged has more to do with the fact that the full Fatal Encounters and Mapping Police Violence datasets cover more years than The Counted. For the year 2015, 54.7% (n=139) merge with The Counted, 54.7% (n=139) merge with Mapping Police Violence, and 59.4% (n=151) merge with Fatal Encounters. For the year 2016, the percentages are 50.0% (n=127), 50.8% (n=129), 61.4% (n=156), respectively. Any agency that cannot be linked to a media-based data source should be considered as having no homicide by police incidents in that media-based source for that year.

Description of Variables

Homicide by Police

The measure of agency-level differences in homicide by police used in this dissertation are based on one official data source (the Supplementary Homicide Reports) and three media-based data sources (Fatal Encounters, Mapping Police Violence, and The Counted). The only years of data available for all four data sources are 2015 and 2016. It is common within this literature to combine multiple years of data in order to maximize variability between cities and minimize the impact of single-year fluctuations with a rare event like homicide by police.

For each rate, total counts of deaths attributed to police at a given agency are combined for the years 2015 and 2016. These total combined counts are divided by the size of the population served by the agency according to the 2012-2016 ACS 5-year estimates and multiplied by 1,000,000. I use the ACS estimates here rather than the single-year 2012 UCR-based estimates that I use for the population-based exclusion criteria because the 5-year estimates cover the two years of data I draw from.

Agencies Missing SHR Data: The FBI does not directly report whether an agency filled out the SHR in a given month. In addition, an agency may choose not to fill out a Supplementary Homicide Reports form if no homicides (including both criminal homicides and justifiable homicides) occurred in a given month. That is, an agency may choose not to fill out the SHR for arbitrary reasons *or* because it had nothing to report. Therefore, the researcher must infer which agencies have a zero count in the SHR for a given year because no homicides occurred or because the agency did not fill out the forms. Only two other studies have attempted to adjust for missing SHR reports (Dirlam, 2018; Renner, 2019). Other studies that utilize the SHR simply code all agencies without reported justifiable homicides as have zero counts of justifiable homicides. An agency is considered missing its SHR rate for a given year if the agency has no justifiable homicides reported to the SHR and either a) did not submit a Uniform Crime Report for any months of that year or b) submitted information to the UCR during that year and reported at least one criminal homicide (i.e., murder or manslaughter) to the UCR but did not report any criminal homicides through the SHR. In the first case, this indicates that the agency did not fill out the UCR and therefore also did not fill out the SHR during that year. In the second case, this implies that the agency filled out the UCR but did not fill out the SHR during that year.⁴² If an agency appears to have not filled out the SHR in either 2015 or 2016, it is set to missing for the SHR-based rate. This leaves 226 agencies (89%) with SHR-based rates out of the total 254 agencies in the sample. Analyses in this study use MLMV (maximum likelihood with missing values) estimation so that agencies missing SHR data can be retained.

Predictors of Agency-Level Differences in Homicide by Police

The predictors I will test fall into two broad categories — demographic and social aspects of the populations served by the agencies in the sample (i.e., city-specific predictors) and demographics, policies, and practices of the agencies themselves (i.e., agency- specific predictors). The coding of these predictors is discussed in greater detail in Chapter 5. The firearm violence rate comes from the Uniform Crime Reports. City-specific measures of general socio-economic status of the city, family and age structure variables, percent minority, minority-White socio-economic inequality, and minority-White housing segregation come from the American Community Survey. Agency-specific measures of demographic composition of the agency, organizational complexity and organizational control come from LEMAS 2013.

⁴² Note that this method still leaves the possibility that an agency that had no criminal homicides in a given year but did have justifiable homicides in that year and did not report them through the SHR would be coded as having zero justifiable homicides in that year.

Analytic Method

Benefits of Structural Equation Modeling for the Study of Homicide by Police

Structural equation modeling provides a number of benefits over traditional regression techniques. The primary utility of SEM is that researchers can model relationships among multiple latent constructs and between latent constructs and observed variables. In the following analyses, I will conceptualize the "true" agency-level homicide by police (HbP) rate as a latent variable measured imperfectly by the observed indicators of HbP discussed above (that is, the agency-level HbP rates derived from the SHR, Fatal Encounters, Mapping Police Violence, and The Counted). I do this because, as discussed in Chapter 2, the justifiable homicide rate has many known flaws that make it an imperfect measure of HbP and the media-based data sources on HbP are new and poorly understood by researchers.

Using a latent variable measurement model is preferable over simply combining or averaging observed indicators because SEM assumes that the residual variance of each indicator is composed of both traditional measurement error and another type of error specific to latent variable models (Bowen & Guo, 2012). Specifically, SEM assumes that some of the residual of an observed indicator is due to factors other than the latent variable. For instance, media-based measures of HbP may be influenced by the quality or frequency of reporting by local media in a given city or by what local media consider to be newsworthy law enforcement-involved deaths. SEM measurement models take this kind of error into account.

This relationship between latent factors, observed indicators, and their residual variances is beneficial when moving from a measurement model (which examines how well a set of observed indicators measures a latent construct) to a structural model (which examines directional relationships between exogenous/"independent" variables and endogenous/"dependent" variables). Specifically, the relationship between a latent factor and another variable is only based on the variance in the observed indicators that is due to the latent factor, rather than variation due to measurement error or to factors other than the latent factor (Bowen & Guo, 2012). For instance, if the MPV-based rate of HbP is created by a combination of the "true" HbP rate and the quality of reporting by local media, SEM will only use the variance in the MPV-rate that is related to the "true" latent HbP rate to estimate the relationship between agency policies and the latent HbP rate.

SEM Model Considerations

The assumptions of a SEM analysis are similar to the assumptions of other regression-based analyses. For instance, the default estimation in SEM (i.e., the maximum likelihood estimator) assumes that observed variables are measured at the interval or ratio level and that their distributions follow a normal curve. Violating these assumptions "can lead to biased estimates, misleading significance testing, and erroneous conclusions about model fit" (Bowen and Guo 2012, p. 58). Researchers using SEM should therefore first consider the measurement level and distributional properties of their variables of interest, examining the skew, kurtosis, and presence of outliers. Various methods can be used to deal with such issues if they are detected, including data transformations, the use of modified chi-square tests, or bootstrapping. More advanced methods include the use of an alternative estimator, such as the use of a weighted least squares estimator as opposed to the default maximum likelihood estimator, or using a generalized SEM framework, which allows for the incorporation of forms of regression commonly used for non-continuous outcomes (such as logistic regression or negative binomial regression) (Kline, 2015).

A topic related to measurement and distribution is the issue of "ill-scaling." Ill-scaling occurs when the variances of the observed variables entered into a SEM vary widely. This can cause issues of non-convergence. Researchers should examine the variances of the observed variables in their datasets and determine if the ratio of the largest variance to the smallest variance is greater than 10, which indicates an issue of ill-scaling (Bowen & Guo, 2012). Ill-scaling can be dealt with by multiplying certain variables by a constant. Because this does not change a variable's correlation with other variables, doing so does not create issues in running a SEM.

Large sample sizes are also recommended. Small sample sizes lead to unstable results (i.e., results that aren't robust to minor changes in model specification) and issues with nonconvergence (Bowen & Guo, 2012). Commonly, samples of fewer than 100 cases are considered small, samples of 100 to 200 cases are thought of as moderately sized, and samples of more than 200 cases are considered large (Kline, 2015). However, simple cutoffs for what counts as "large" should not be utilized in isolation. More complex models with variables that aren't continuous or normally distributed require larger samples. Another method for assessing sample size requirements in the N:q rule, where the number of cases (N) is considered relative to the number of parameters to be estimated (q). A recommended ratio would be 20:1, with ratios falling below 10:1 being far less trustworthy (Kline, 2015).

Like many other statistical procedures, SEM assumes that cases are independent of each other. One way this assumption might be violated in the current study is that agencies in the same county or state may be more similar to each other than agencies in different counties or states. To adjust for this, all models adjust the standard errors for clustering within states.

SEM assumes that measurement errors between observed indicators of the same latent construct are uncorrelated, unless the user specifically models them that way. This can be tested for in a post-hoc fashion. It is noteworthy that modeling errors as correlated can only be done under a traditional SEM framework and not under the generalized SEM framework. Methods for dealing with missing data depend on the estimator and framework used.⁴³ Under the traditional SEM framework, most estimators (such as ML, QML, and ADF) deal with missingness through listwise deletion. An alternative estimator is MLMV (maximum likelihood with missing variables), also called FIML (full information maximum likelihood), which retains all cases in a model. Missingness under the generalized SEM framework is dealt with through equationwise deletion. That is, cases that are missing in one equation may still be used in other equations.

In the next two analytic chapters, I will discuss the following considerations relative to the measurement model (Chapter 5) and structural model (Chapter 6) that I wish to test.

- Adequacy of the sample size
- The measurement level and distributional characteristics of variables
- Whether clustering is present in the data
- The potential need to model correlated measurement errors
- How missing data will be handled

I will then establish an initial model and some alternative models, which I will then assess using applicable fit statistics. Finally, substantive conclusions will be drawn.

⁴³ The options that I discuss for dealing with missing data are specific to the sem and gsem commands available in Stata.

Chapter 5: MEASUREMENT OF LATENT HOMICIDE BY POLICE

The Current Study

This chapter examines a latent variable measurement model that combines information from four different sources of data on homicide by police (HbP) — the Supplementary Homicide Reports, The Counted, Mapping Police Violence, and Fatal Encounters. No other studies have utilized multiple sources of data to estimate a latent HbP rate at the agency level, which is arguably a more appropriate unit of analysis for examining geographic variation in HbP than the larger geographic areas (e.g., counties, MSAs, states) utilized in some prior work. This analysis contributes to the literature by examining the descriptive and correlational similarity of multiple sources of HbP data and exploring the viability of an HbP measurement model that draws on multiple sources of data as a potential solution to the issue of data choice.

The overall counts from the SHR compared to the counts from media-based sources are used as an indicator of the poor data quality of the SHR. However, most geographic analyses on homicide by police are performed on samples of agencies serving populations of 100,000 or more. Agencies serving larger populations are more likely to complete the UCR — in 2016, 97.76% of the agencies serving populations of 100,000 or more completed the UCR for all 12 months while 71.05% of the agencies serving populations of fewer than 100,000 completed the UCR for all 12 months while 71.05% of the agencies serving data in the SHR may therefore actually be less prominent when examining the subset of agencies most often examined in geographic analyses. Therefore, I am interested descriptively in how close the SHR rates are to the media-based rates in large cities.

⁴⁴ These percentages come from personal calculations using the UCR data for 2016.

Data choice is a key issue in the literature on geographic variation in homicide by police. Discussions of the flaws in older, official data sources are abundant (Fyfe, 2002; Klinger, 2012; Loftin et al., 2003; Sherman & Langworthy, 1979; Zimring, 2017). However, less attention is paid to the potential flaws or simple operational differences in the newer, media-based data sources. Overall lethal force counts differ substantially between the official data sources and media-based sources, but they also differ amongst media-based sources. This could indicate that data choice remains an issue of concern even for those researchers who wish to use media-based data.

Therefore, the following two questions are explored in this chapter.

- Descriptively, how similar are different sources of HbP data when examining large cities only?
- What is the strength of the relationship between each data source and the latent HbP rate? Can they be considered indicators of the same construct?

Data

The analyses throughout this dissertation utilize the merged dataset described in Chapter 3. The unit of analysis is municipal police departments that were serving populations of 100,000 or more in 2012 and responded to the LEMAS 2013 survey as self-representing agencies. The full sample is made up of 254 agencies.

The analysis below draws on four variables in this dataset, each a rate of homicides by police at a given agency during the years 2015 and 2016. For each rate, total counts of deaths attributed to police at a given agency are combined for the years 2015 and 2016 (which are the only years available for all four data sources). These counts come from four sources — the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. For each data source, the total combined count for the years 2015 and 2016 is divided by the size of the population served by the agency according 2012-2016 ACS 5-year estimates and multiplied by 1,000,000.

An agency is considered missing its SHR rate for a given year if the agency has no justifiable homicides reported to the SHR and either a) did not submit a UCR crime report for any months of that year or b) submitted information to the UCR during that year and reported at least one criminal homicide (i.e., murder or manslaughter) to the UCR but did not report any criminal homicides through the SHR. In the first case, this indicates that the agency did not fill out the UCR and therefore also did not fill out the SHR during that year. In the second case, this implies that the agency filled out the UCR but did not fill out the SHR during that year. If an agency appears to have not filled out the SHR in either 2015 or 2016, it is set to missing for the SHR-based rate. This leaves 226 agencies (89%) with SHR-based rates out of the total 254 agencies in the sample. All analyses use MLMV (maximum likelihood with missing values) estimation, therefore, these agencies are retained in the measurement model.

Method

In this analysis, I use standard linear structural equation modeling. Structural equation modeling allows researchers to model relationships between variables in complex ways that cannot be done when using normal regression techniques. For the current analysis, I view the "true" homicide by police (HbP) rate as a latent, unmeasured construct. Each of the four sources of data on the HbP rate (the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted) is a potentially flawed indicator of the "true" rate, measured with error. This measurement model, which is in essence a confirmatory factor analysis, is illustrated in Figure 5.1. If these four observed rates are actually indicators of the same

underlying construct, the SEM model will show that their estimated associations with the underlying model are strong.

One utility in the use of structural equation modeling is the ability to test for correlations between errors in measurement. In the current analysis, there is a possibility that the measurement errors in the media-based data sources are correlated. These sources draw on the same base data (i.e., media reports of people who die subsequent to encounters with law enforcement). They also rely on one another — for instance, the distributors of Mapping Police Violence explicitly state that they draw on Fatal Encounters to create their database. In addition, correlated errors could exist between the official data and the media-based data. In reporting on deaths related to law enforcement involvement, local media necessarily relies to some extent on the information law enforcement provided to them.

Analysis

The analysis proceeds in the following order. First, I will compare the four homicide by police indicators descriptively based on their univariate characteristics. Second, I will present bivariate comparisons of the indicators. Then, I will discuss some of the discrepancies between agencies in their counts and rates of HbP. Fourth, I present a measurement model that utilizes the four data sources as indicators of the latent HbP rate and assess the overall model fit. Lastly, I test six alternative error structures and assess their fit relative to the first measurement model.

Univariate Characteristics of HbP Indicators

Table 5.1 displays descriptive statistics for HbP rates derived from different sources. For the subset of municipal police agencies serving large cities in this sample, the differences between rates by data source replicate the pattern for the U.S. totals (compare to Figure 1.1). In this sample, the average rate reported by Fatal Encounters (11.8 deaths per million residents) is about

2.5 times as large as the average SHR rate (4.8 deaths per million residents). The average rates reported by The Counted (8.4 deaths per million residents) and Mapping Police Violence (8.1 deaths per million residents) are about 1.7 times as large as the average SHR rate. These average rates for large cities are slightly closer than the national rates by data source. At the national level for 2015 and 2016, Fatal Encounters reports about 3.5 times as many deaths as the SHR, Mapping Police Violence reports about 2.6 times as many, and The Counted reports about 2.5 times as many.⁴⁵

The SHR rate's divergence from the rates drawn from media-based sources seems to have more to do with "missing" incidents on the individual reports rather than missing months of reporting. The SHR mean in Table 5.1 only includes those agencies that appeared to report to the SHR in both 2015 and 2016.⁴⁶ If the divergence was only due to missing months of reporting, we would expect the agencies that reported to the SHR to have similar rates of homicide-by-police as the media-based sources. However, the mean of the SHR-based rate is still much lower than the media-based rates even when limiting the SHR rate to reporting agencies. Therefore, the difference between the SHR rate and the media-based rates appears to be due to a difference in operationalization (i.e., "justifiable homicides" versus homicides by police) or to agencies leaving deaths off of the SHR forms that by operationalization should have been included (whether deliberately or unintentionally).

Figure 5.2 displays histograms for each HbP rate indicator while Figure 5.3 displays their box plots. As one would expect, all of the rate variables are highly right skewed. For each HbP

⁴⁵ The total counts of deaths by data source, combining 2015 and 2016 counts are as follows — SHR: 904, FE: 3,179, MPV: 2,316, The Counted: 2,218.

⁴⁶ Descriptives for limited to these 226 agencies are similar for the media-based data sources as those descriptives reported in Table 1.

indicator, the modal number of decedents attributed to an agency is 0. About 52.2% of the agencies had no justifiable homicides in 2015 or 2016 according to the SHR, 23.2% had no decedents according to Fatal Encounters, 31.9% had no decedents according to Mapping Police Violence, and 31.1% had no decedents according to The Counted. HbP rates derived from the SHR, The Counted, and Mapping Police Violence also had distinct secondary peaks at around 8 or 9 deaths per million. The Fatal Encounters rate does not have this feature.

Bivariate Relationships of HbP Indicators

Despite differences in the average rates, Table 5.2 shows that the correlations between the measures are moderate to large in size. The largest correlation is between Mapping Police Violence and The Counted (r = 0.95). Reflecting this, MPV and The Counted have similarly size correlations to each other with Fatal Encounters (r = 0.80 for MPV and FE; r = 0.77 for The Counted and FE) and the SHR (r = 0.70 for both correlations). The lowest correlation is between these measures are further illustrated by the LOWESS curves displayed in Figures 5.4 through 5.9.

Agencies with high homicide by police rates based on one indicator are not necessarily high on all indicators. Table 5.3 displays agencies with outlier or high value rates on at least one HbP indicator. I categorize agencies as "outliers" if they had rates above the upper adjacent value⁴⁷ for a particular HbP indicator and as "high value" if they had rates below the upper adjacent value but at or above the 90th percentile. Of these outlying and high value agencies (n=48), only 19% (n=9) had high or outlying values on all four HbP indicators, 17% (n=8) had high or

⁴⁷ The upper adjacent value of a distribution is used to calculate outliers for the purposes of a box plot. It is equal to the third quartile of a distribution plus 1.5 times the size of the interquartile range (Q3 + 1.5(Q3 - Q1)). The upper adjacent values for each of the HbP rate indicators used in this chapter are as follows: Supplementary Homicide Reports: 21.614, Fatal Encounters: 39.666, Mapping Police Violence: 32.644, The Counted: 32.342.

outlying values on three out of four HbP indicators, 21% (n=10) had high or outlying values on two out of four indicators, and the remaining 44% (n=21) had high or outlying values on only one indicator.

Exploration of Discrepancies

Of the four HbP indicators examined in this paper, Fatal Encounters provides the highest number of decedents at the national level, the Supplementary Homicide Reports has the lowest number, and Mapping Police Violence and The Counted lie between them. Therefore, if the pattern of decedent presence or missingness was uniform across all agencies and data sources, then (of the four HbP indicators examined in this paper) we would expect an agency to have its highest rate based on Fatal Encounters, its lowest based on the SHR, and its rates based on The Counted and Mapping Police Violence to be between those two.

Some noteworthy discrepancies between the SHR and Fatal Encounters occur in Chicago (SHR: 6 total deaths, FE: 33 total deaths), Houston (SHR: 17, FE: 41), and Los Angeles (SHR: 30, FE: 54). All of these agencies had a difference between officially-reported justifiable homicides and decedents attributed to them by Fatal Encounters of more than 20 people. In the other direction are the Washington Metropolitan Police, which had 13 decedents according to the SHR and only 10 according to Fatal Encounters.

Measurement Model

Table 5.5 displays the results of a structural equation model that views the homicide by police rate as a latent variable with four indicators — the SHR justifiable homicide rate, the FE rate of fatal police encounters, the MPV rate of homicides by police, and the rate of homicides by police taken from The Counted. The model presented in Table 5.5 includes the full sample of all 254 agencies. The coefficients in the standardized model indicate a strong relationship

between each of the indicators and the latent construct. The weakest relationship is between the SHR rate and the latent rate (beta = 0.71). These factor loadings indicate that about 50% of the variance in the SHR is due to the "true" value of the latent HbP rate ($0.71^2 = 0.50$), while about 64% of the variance in Fatal Encounters ($0.80^2 = 0.64$), 91% of the variance in The Counted ($0.956^2 = 0.91$) and 99% of the variance in MPV ($0.996^2 = 0.99$) is due to variation in the "true" latent rate.

It could be possible that the lower strength of the SHR's coefficient is due to agencies inconsistently reporting to the FBI. To account for this, Model 2 of Table 5.6 is limited to the 226 agencies that filled out the SHR in 2015 and/or 2016. That is, agencies missing SHR data are removed from Model $2.^{48}$ The SHR's standardized coefficient in this restricted model (beta = 0.70) is virtually identical to its coefficient in the full model. This indicates that the relatively lower strength of the SHR's relationship to the latent rate is not an artifact of the missing SHR data.

Alternatively, the high strength of the coefficients for MPV (beta = 0.996) and The Counted (beta = 0.956) in Table 5.5 could be due to the high correlation between those two measures (see Table 5.2). To test this, Model 3 of Table 5.6 excludes The Counted as an observed indicator of the latent rate and Model 4 of table 5.6 excludes MPV as an indicator. In these models, The Counted and MPV continue to have strong relationships with latent HbP — in Model 3, MPV has a standardized coefficient of 0.999, and in Model 4, The Counted has a standardized

⁴⁸ As discussing in Chapter 4, agencies are coded as missing their SHR rate if they either a) did not submit a Uniform Crime Report for 2015 or 2016 or b) submitted information to the UCR during 2015 or 2016 and reported at least one criminal homicide (i.e., murder or manslaughter) to the UCR but did not report any criminal homicides through the SHR. In the first case, this indicates that the agency did not fill out the UCR and therefore also did not fill out the SHR during that year. In the second case, this implies that the agency filled out the UCR but did not fill out the SHR during that year. Note that this method still leaves the possibility that an agency that had no criminal homicides in a given year but did have justifiable homicides in that year and did not report them through the SHR would be coded as having zero justifiable homicides in that year.

coefficient of 0.970. This indicates that the strength of the association between MPV and latent HbP and between The Counted and latent HbP is not due to the high correlation between MPV and The Counted. In addition, the standardized coefficient sizes for the SHR and Fatal Encounters are similar across models in Table 5.6.

The model fits the data well. Goodness-of-fit statistics are displayed in the first row of Table 5.7 under the label "Simple Model." A chi² test of this model versus the saturated model (i.e., a model that reproduces the variances, covariances, and means of the four indicators without applying paths to latent HbP) indicates that there is no statistically significant difference between the two. Because of the small sample size (n = 254), the chi² test is likely to be statistically insignificant even if the model fits poorly (Hox & Bechger, 2009), therefore other goodness-of-fit indicators are included. The CFI (comparative fit index) and TLI (Tucker-Lewis index) are both less sensitive to sample size (Cangur & Ercan, 2015; Hox & Bechger, 2009). For both the CFI and TLI a value close to 1, which the Simple Model has, is better. An RMSEA (root mean square error of approximation) close to zero indicates good fit. The point estimate for the RMSEA is approximately zero and the confidence interval (displayed next to the RMSEA in brackets) has an upper limit of only 0.04. The AIC (Akaike's information criterion) and BIC (Bayesian information criterion) are not highly informative on their own. They are useful for comparisons between models, with lower values indicating better fit.

Analysis of Alternative Error Structures

I test several models with alternative error structures. Specifically, I test models that include terms for covarying errors for each pair of the four sources on homicide by police for a total of six alternative models. Table 5.7 compares goodness-of-fit statistics for the Simple Model predicting latent HbP (i.e., the model presented in Table 5.5 and Model 1 of Table 5.6) and the six alternative models that add covarying error components.

Table 5.6 shows that the goodness-of-fit statistics for the alternative error structure models are similar to those for the Simple Model. In addition, likelihood-ratio tests (displayed in Table 5.8) indicate that the alternative error models are not statistically different from the Simple Model. The more parsimonious model (that is, the one without covarying error terms) is carried forward for the analyses in the next chapter.

Discussion

In this chapter, I was interested in examining the similarity of homicide by police (HbP) rates based on four different data sources (the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted) and in constructing a measurement model that takes all four sources into account when estimating the latent HbP rate. Despite differences in the average rate of individuals killed by police and differences in their operationalizations, the four data sources utilized here appear to work as indicators of the same latent construct, here referred to as the latent homicide by police (HbP) rate. Mapping Police Violence and The Counted produce very similar rates and are highly correlated. They both load extremely strongly onto the latent HbP rate, with standardized coefficients close to 1. Despite their differences in operationalization compared to MPV and The Counted, the SHR and FE rates also have strong associations with the latent HbP rate. The measurement model has indications of high-quality model fit. Therefore, in the next chapter this measurement model will be used to examine potential predictors of the latent HbP rate.

Figures

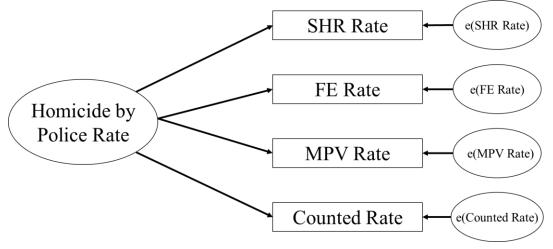
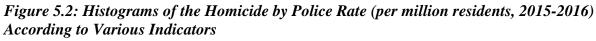
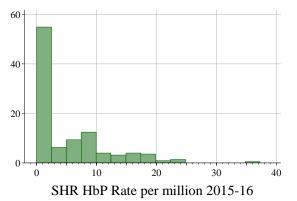
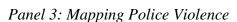


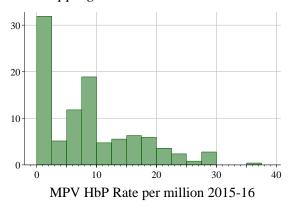
Figure 5.1: Measurement Model Predicting Latent Homicide by Police Rate



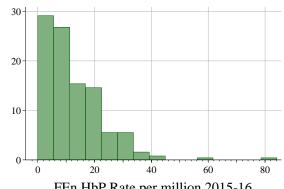
Panel 1: Supplementary Homicide Reports







Panel 2: Fatal Encounters



FEn HbP Rate per million 2015-16

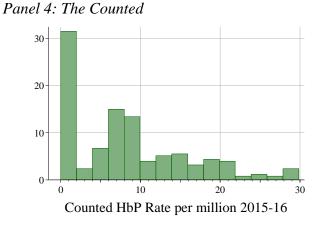
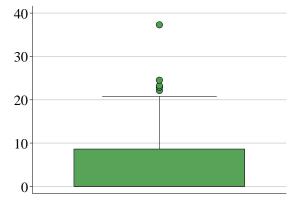
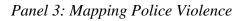


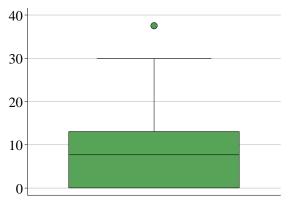
Figure 5.3: Box Plots of the Homicide by Police Rate (per million residents, 2015-2016) According to Various Indicators

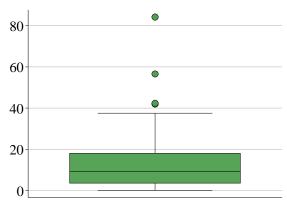
Panel 1: Supplementary Homicide Reports

Panel 2: Fatal Encounters











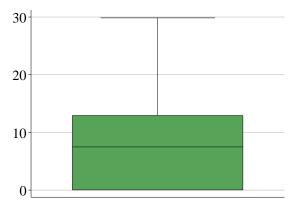


Figure 5.4: LOWESS Curves of HbP Rates and Counts based on the Supplementary Homicide Reports and Fatal Encounters

Panel 1: Rates (per million, 2015-2016)

Panel 2: Counts (2015-2016)

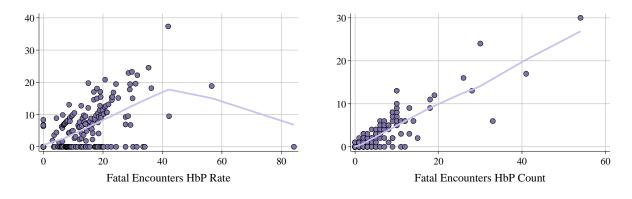
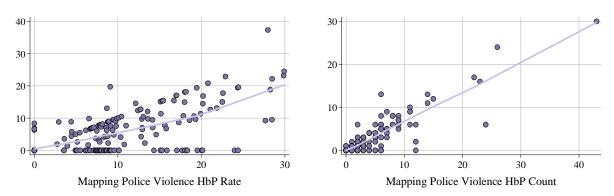
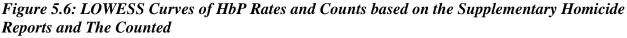


Figure 5.5: LOWESS Curves of HbP Rates and Counts based on the Supplementary Homicide Reports and Mapping Police Violence

Panel 1: Rates (per million, 2015-2016)

Panel 2: Counts (2015-2016)





Panel 1: Rates (per million, 2015-2016)

Panel 2: Counts (2015-2016)

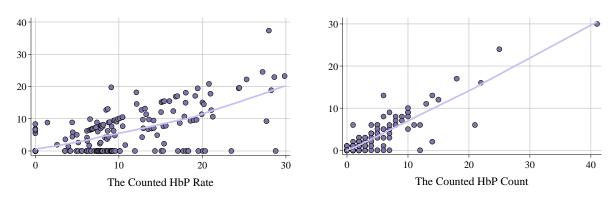


Figure 5.7: LOWESS Curves of HbP Rates and Counts based on the Fatal Encounters and Mapping Police Violence

Panel 1: Rates (per million, 2015-2016)

Panel 2: Counts (2015-2016)

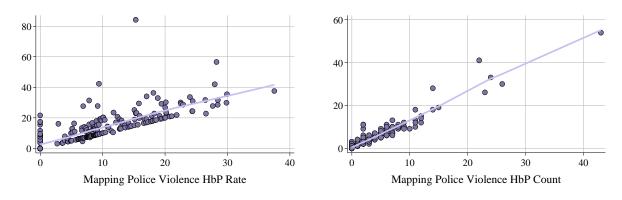
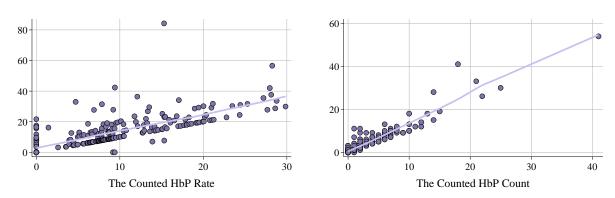
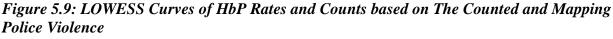


Figure 5.8: LOWESS Curves of HbP Rates and Counts based on the Fatal Encounters and The Counted

Panel 1: Rates (per million, 2015-2016)

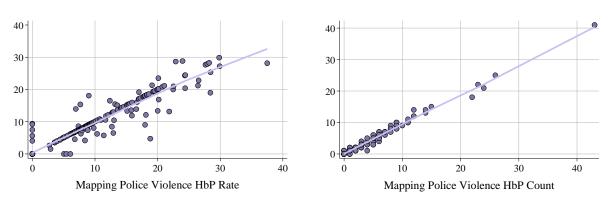
Panel 2: Counts (2015-2016)





Panel 1: Rates (per million, 2015-2016)

Panel 2: Counts (2015-2016)



Tables

	Mean	Std Dev	Minimum	Maximum	Skewness	Kurtosis
Supplementary Homicide Reports	4.81	6.51	0.00	37.28	1.51	5.51
Fatal Encounters	11.89	11.09	0.00	84.19	1.76	9.92
Mapping Police Violence	8.40	8.02	0.00	37.53	0.85	3.19
The Counted	8.12	7.62	0.00	29.86	0.79	2.95

Table 5.1: Descriptive Statistics for Homicide by Police Rates from Different Sources

Descriptives for FE, MPV, and The Counted are based on 254 large police agencies.

Descriptives for the SHR are based on 226 large police agencies.

Rates calculated per 1,000,000 residents based on the 2016 ACS 5-year estimates.

Table 5.2: Pairwise Correlations between Homicide by Police Rates

	SHR	FE	MPV	Counted
Supplementary Homicide Reports	1.000			
Fatal Encounters	0.545***	1.000		
Mapping Police Violence	0.693***	0.799***	1.000	
The Counted	0.675***	0.765***	0.952***	1.000

*** p < 0.001, ** p < 0.001, * p < 0.05

AgencyStateCountRateRat
Bakersfield PoliceCalifornia924.491335.371129.931027.21Stockton PoliceCalifornia723.22929.86929.86929.86Tempe PoliceArizona422.9528.62422.9528.62St. Louis Metropolitan PoliceMissouri722.151031.64928.48825.31Syracuse PoliceNew York320.78320.78320.78320.78320.78Washington Metropolitan PoliceNew York320.78320.78320.78320.78320.78Fontana PoliceCalifornia419.49524.36524.36524.36524.36El Cajon PoliceCalifornia219.571930.981524.66524.36528.77328.27Springfield PoliceMissouri318.1766.63.33318.17212.1111Inglewood PoliceCalifornia218.02218.02218.02218.02218.02Cong Beach PoliceCalifornia817.03919.16817.03919.16817.03919.16Beaumont PoliceCalifornia516.83723.56620.19516.89Cong Beach Police
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Modesto Police California 0 0 7 33.57 5 23.98 6 28.78
Norfolk Police Virginia 0 0 6 24.42 6 24.42
Rialto Police California 0 0 2 19.53 2 19.53
Richmond Police Virginia 0 0 6 27.68 2 9.23 2 9.23
Sunnyvale of Public SafetyCalifornia00320.05320.05
Topeka Police Kansas 0 0 4 31.38 1 7.84 1 7.84
Waco Police Texas 0 0 11 84.19 2 15.31 2 15.31
Birmingham Police Alabama 7 32.95 4 18.83 1 4.71
Huntsville Police Alabama 6 31.75 5 26.46 4 21.17
Kansas City Police Kansas 4 26.71 3 20.03 2 13.36
Orlando Police Florida 6 22.79 7 26.59 6 22.79
Palm Bay Police Florida 4 37.53 4 37.53 3 28.15

Table 5.3: HbP Rates and Counts for Agencies with Outlier or High Value Rates

Note: Outlying rates (i.e., rates at or above the upper adjacent value within the HbP indicator) are highlighted in **Black**. High values (i.e., non-outlying rates at or above 90th percentile) are highlighted in gray. The upper adjacent values and 9th percentile values for each dataset are: SHR: 21.61, 14.99; FE: 39.67, 26.71; MPV 32.64, 19.93; Counted: 32.34, 19.30.

	Difference Between	Between	Difference Between	Difference Between	Difference Between	Difference Between
	FE & SHR	MPV& SHR	Cou & SHR	FE & MPV	FE & Cou	MPV & Cou
	(n=226)	(n=226)	(n=226)	(n=254)	(n=254)	(n=254)
-2 or less	0.4%	1.8%	2.2%	0.0%	0.0%	0.4%
-1	3.1%	3.5%	4.9%	1.6%	1.6%	6.3%
0	30.5%	46.5%	43.4%	56.3%	54.7%	77.6%
1	24.3%	21.7%	27.0%	18.5%	18.9%	13.0%
2	13.3%	14.2%	12.4%	9.4%	9.4%	1.6%
3	10.2%	4.9%	3.5%	7.9%	7.1%	0.8%
4 or more	18.1%	7.5%	6.6%	6.3%	8.3%	0.4%

Note: Differences in counts are calculated as the number of decedents an agency has according to the first dataset listed in each column minus the number of decedents it has according to the second dataset listed in each column. The first dataset listed in each column is the one with a larger overall count of decedents.

Dataset abbreviations: FE – Fatal Encounters, SHR – Supplementary Homicide Reports, MPV – Mapping Police Violence, Cou – The Counted

	Colum	Column 1		n 2
	Coef.	SE	Std. Coef.	SE
Supplementary Homicide Reports				
HbP	1.000		0.705***	(0.034)
Constant	4.847***	(0.426)	0.737***	(0.073)
Fatal Encounters				
HbP	1.916***	(0.160)	0.802***	(0.023)
Constant	11.892***	(0.695)	1.074***	(0.079)
Mapping Police Violence				
HbP	1.718***	(0.120)	0.996***	(0.006)
Constant	8.404***	(0.502)	1.050***	(0.078)
The Counted				
HbP	1.568***	(0.113)	0.956***	(0.008)
Constant	8.121***	(0.477)	1.068***	(0.079)
var(e.SHR)	21.746	(2.076)	0.503	(0.048)
var(e.FE)	43.660	(4.003)	0.356	(0.037)
var(e.MPV)	0.565	(0.802)	0.009	(0.013)
var(e.Counted)	4.991	(0.802)	0.086	(0.016)
var(HbP)	21.497	(3.524)	1.000	

 Table 5.5: Measurement Model for Latent Homicide by Police Rate (Simple Model)

Based on the full sample of 254 agencies serving large populations. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for state clusters (44 clusters in M1 and 42 clusters in M2). Standard errors are displayed in parentheses. *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1

		odel 1	Model 2		Model 3			odel 4
	-	e Model	SHR Complete		No Counted		No MPV	
	(n=	=254)	(n=	=226)	(n=254)		(n=254)	
	Unstd	Std	Unstd	Std	Unstd	Std	Unstd	Std
HbP \rightarrow SHR	1.000	0.705	1.000	0.696	1.000	0.703	1.000	0.695
Constant	4.847	0.737***	4.812	0.741***	4.857	0.737***	4.753	0.732***
HbP \rightarrow FE	1.916	0.802***	1.937	0.788***	1.910	0.799***	1.934	0.789***
Constant	11.892	1.074***	11.949	1.076***	11.892	1.074***	11.892	1.074***
HbP \rightarrow MPV	1.718	0.996***	1.715	0.996***	1.726	0.999***		
Constant	8.404	1.050***	8.325	1.070***	8.404	1.050***		
HbP \rightarrow Counted	1.568	0.956***	1.625	0.965***			1.634	0.970***
Constant	8.121	1.068***	8.227	1.081***			8.121	1.068***
var(e.SHR)	21.746	0.503	21.778	0.516	21.927	0.505	21.794	0.517
var(e.FE)	43.660	0.356	46.744	0.379	44.233	0.361	46.317	0.378
var(e.MPV)	0.565	0.009	0.453	0.007	0.068	0.001		
var(e.Counted)	4.991	0.086	3.986	0.069			3.366	0.058
var(HbP)	21.497	1.000	20.418	1.000	21.466	1.000	20.390	1.000

Table 5.6: Simple Measurement Model and Alternative Models

Model 1 uses the full sample of 254 agencies and is the same as the model presented in Table 5.5. Model 2 uses a limited sample of 226 agencies that filled out the SHR in 2015 and/or 2016. That is, agencies missing SHR data are removed from this model.

Model 3 uses the full sample and does not include The Counted as an indicator of the latent HbP rate.

Model 4 uses the full sample and does not include Mapping Police Violence as an indicator of the latent HbP rate. For all models, parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for state clusters (44 clusters in M1, M3, and M4 and 42 clusters in M2).

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1

	$p > chi^2$	CFI	TLI	RMSEA	AIC	BIC
Simple HbP Model						
M1: Simple Model	0.933	1.000	1.006	0.00 [0.00, 0.04]	5976	6018
Error Covariance Models						
M2: $e(SHR) * e(FE)$	0.737	1.000	1.005	0.00 [0.00, 0.12]	5978	6024
M3: e(SHR) * e(MPV)	0.784	1.000	1.006	0.00 [0.00, 0.11]	5978	6024
M4: e(SHR) * e(Counted)	0.918	1.000	1.006	0.00 [0.00, 0.06]	5978	6024
M5: $e(FE) * e(MPV)$	0.918	1.000	1.006	0.00 [0.00, 0.06]	5978	6024
M6: e(FE) * e(Counted)	0.784	1.000	1.006	0.00 [0.00, 0.11]	5978	6024
M7: e(MPV) * e(Counted)	0.737	1.000	1.005	0.00 [0.00, 0.12]	5978	6024

Table 5.7: Goodness-of-Fit Statistics for Simple Model and Error Covariance Models

The simple HbP model is the same as Model 1 of Table 5.5. The error covariance models are the same as the simple model except that each allows the errors between two HbP indicators to covary.

The RMSEA confidence interval is displayed in brackets. For all RMSEAs displayed, the pclose is statistically insignificant, indicating that the estimates are not statistically different from zero.

The above fit statistics other than AIC and BIC cannot be obtained when clustering standard errors. Therefore, the chi² test, CFI, TLI, and RMSEA are obtained from models that do not cluster the standard errors by state.

Table 5.8: Likelihood-Ratio Tests Against Simple Model

Error Co	vari	ance Models	chi	i^2 $p > chi^2$
e(SHR)	*	e(FE)	0.0	0.8687
e(SHR)	*	e(MPV)	0.0	0.7996
e(SHR)	*	e(Counted)	0.1	3 0.7193
e(FE)	*	e(MPV)	0.1	3 0.7193
e(FE)	*	e(Counted)	0.0	0.7996
e(MPV)	*	e(Counted)	0.0	0.8687

The simple HbP model is the same as Model 1 of Table 5.5. The error covariance models are the same as the simple model except that each allows the errors between two HbP indicators to covary.

Chapter 6: LOCAL CONTEXT AND LATENT HOMICIDE BY POLICE

The Current Study

The goal of the current study is to utilize the measurement model developed in the prior chapter to examine potential city and agency-level predictors of homicide by police (HbP). I also compare the models predicting the latent HbP rate with models using each of the four indicators, alone, as an outcome. The predictors I will test fall into two broad categories: (1) demographic and social aspects of the populations served by the agencies in the sample (i.e., city-specific predictors); and (2) demographics, policies, and practices of the agencies themselves (i.e., agency-specific predictors).

City-specific factors include the firearm violence rate, indicators of the general socioeconomic status of the city, the percent of the city who are young males, percent minority, minority-White socio-economic inequality, and minority-White housing segregation. The general predictions for these variables are displayed in Table 6.1.

Agency-specific policies and practices are understudied in the literature on geographic variation in lethal force and some of the agency-specific predictors tested here have not be included as predictors in prior studies. These new predictors are training requirements for new hires, restrictive foot and vehicle pursuit policies, whether the agency authorizes specific less-lethal weapons and techniques, and the percentage of authorized less-lethal options that require documentation when they are used. Overall, the agency-specific factors included in these analyses fall into the following broad categories: the demographic composition of the agency, organizational complexity, formalization, professionalization, community policing training, video surveillance, and less-lethal options for force. The general predictions for these variables are found in Table 6.1

Data

The analyses throughout this dissertation utilize the merged dataset described in Chapter 4. The unit of analysis is municipal police departments that were serving populations of 100,000 or more in 2012 and responded to the 2013 Law Enforcement Management and Administrative Statistics (LEMAS) survey as self-representing agencies. The full sample is made up of 254 agencies. The dependent variables in this analysis come from the Supplementary Homicide Reports and three media-based databases of individuals killed by police in the U.S. (i.e., Fatal Encounters, Mapping Police Violence, and The Counted). Predictors related to the demographic and social aspects of the population served by the agency are drawn from the 2012-2016 5-year American Community Survey. Predictors related to the demographics, policies, and practices of the agency itself are drawn from LEMAS 2013.

Description of Variables

Dependent Variables: Homicide by Police

The analysis below draws on four variables in this dataset, each a rate of homicides by police at a given agency during the years 2015 and 2016. For each rate, total counts of deaths attributed to police at a given agency are combined for the years 2015 and 2016 (which are the only years available for all four data sources). These counts come from four sources — the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. For each data source, the total combined count for the years 2015 and 2016 is divided by the size of the population served by the agency according 2012-2016 ACS 5-year estimates and multiplied by 1,000,000.

An agency is considered missing its SHR rate for a given year if the agency has no justifiable homicides reported to the SHR and either a) did not submit a UCR crime report for any months of that year or b) submitted information to the UCR during that year and reported at least one criminal homicide (i.e., murder or manslaughter) to the UCR but did not report any criminal homicides through the SHR. In the first case, this indicates that the agency did not fill out the UCR and therefore also did not fill out the SHR during that year. In the second case, this implies that the agency filled out the UCR but did not fill out the SHR during that year. If an agency appears to have not filled out the SHR in either 2015 or 2016, it is set to missing for the SHR-based rate. This leaves 226 agencies (89%) with SHR-based rates out of the total 254 agencies in the sample. All analyses use MLMV (maximum likelihood with missing values) estimation, therefore, these agencies are retained in the measurement model.

Firearm Violence

A measure of crime or violence is a key control when examining geographic variation in homicide by police. In this analysis I use the *firearm violence rate*, proposed by Klinger and colleagues (2016), because it may be more indicative of local violence that would be particularly likely to raise officers' sense of situational dangerousness than the general violent crime index. The firearm violence rate is the total number of homicides, firearm assaults, and firearm robberies in 2015 and 2016 per 100,000 residents. Crime totals are taken from the Uniform Crime Reports.

City Predictors

Demographic and social data about the city served by an agency is taken from the 2012-2016 American Community Survey. Because all of the agencies in the sample serve large populations, I use a binary measure for the size of the population served where agencies are coded 1 if they serve *populations of 250,000 or more* and 0 if they serve populations smaller than 250,000. The general socio-economic context of the city served by an agency is assessed using a *disadvantage index* made by taking mean of three standardized measures: the unemployment rate for 20- to 64year-olds and the percent of residents who do not have a college degree, and the percent of female-headed households (alpha = 0.622). The *percent young males* is the percent of residents who are 15- to 24-year-old males (the demographic group most likely to engage in delinquency).

The <u>percent Black</u> is the percent of the population who identify as Black or African American and the <u>percent Hispanic/Latino</u> is the percent of the population who identify as Hispanic or Latino. I assess racial/ethnic minority inequality using a <u>Black-White inequality</u> <u>index</u>, which is the mean of three standardized measures: the ratio of White residents' median income to Black residents' median income, the ratio of the Black unemployment rate to the White unemployment rate, and the ratio of White residents with at least a college degree to Black residents with at least a college degree (alpha = alpha = 0.824). The <u>Hispanics/Latino-White</u> <u>inequality index</u> is calculated similarly (alpha = 0.354). <u>Black-White segregation</u> and <u>Hispanic/Latino-White segregation</u> are assessed using isolation indexes.

Agency Predictors

Agency predictors come from the 2013 Law Enforcement Management and Administrative Statistics survey. <u>Agency size</u> is included as a control variable in some models. It is measured as the number of full-time sworn personnel working at the agency as of January 1, 2013. <u>Percent</u> <u>female</u>, <u>percent Black</u>, and <u>percent Hispanic/Latino</u> all refer to the percentage of full-time, sworn personnel working at the agency that belong to those groups. <u>Black representation</u> and <u>Hispanic/Latino representation</u> are calculated as the ratio of the percent of sworn personnel who are Black or Hispanic/Latino to the percent Black or Hispanic/Latino in the population served.⁴⁹

⁴⁹ The percent Black and percent Hispanic/Latino for the population served are taken from the 2016 5-year ACS.

Values below zero indicate under-representation of a racial/ethnic group while values above zero indicate over-representation.

An agency's organizational complexity refers to its degree of vertical differentiation, functional differentiation, and occupational differentiation. Vertical differentiation/hierarchy is assessed through the amount of <u>salary disparity</u> between the chief executive and entry level officers, calculated as the difference between the mid-point of the chief's allowable salary and the mid-point of the entry level officers' allowable salary divided by the latter. The agency's functional differentiation/specialization is measured as the <u>number of specialized unit types</u> with full-time personnel. In total, there are 14 different types of specialized units that respondents were asked about.⁵⁰ The agency's occupational differentiation/civilianization is assessed using the <u>percent non-sworn</u> (i.e., the percent of total full-time personnel who are not sworn officers).⁵¹

Aspects of an agency's organizational control include the degree of formalization and professionalization in the agency. Agencies are more formalized when they have more restrictive written policies and require more documentation from officers. Whether agencies had a *restrictive foot pursuit policy* is measured using a count of the number of policies agencies had regarding foot pursuit out of the six that were asked about on the survey.⁵² Whether agencies had a *restrictive vehicle pursuit policy* is measured using a binary variable where 1 indicates some

⁵⁰ The possible specialized unit types are as follows: bias/hate crime unit, bomb/explosive disposal unit, child abuse/endangerment unit, cybercrime unit, domestic/intimate partner violence unit, terrorism/homeland security unit, human trafficking unit, drug/alcohol impaired driving unit, juvenile crime unit, gangs unit, re-entry surveillance unit, fugitives/warrants unit, or victim assistance unit.

⁵¹ Non-sworn personnel can include administrative or clerical workers, financial management, forensic scientists, crime analysts or statisticians, vehicle maintenance, and call dispatchers.

⁵² The individual foot pursuit policies are binary variables for the presence or absence of a given policy. These policies are as follows: restricts foot pursuit when the officer is acting alone, restricts foot pursuit when the officer loses sight of the suspect, restricts foot pursuit when two or more officers become separated, restricts foot pursuit when officers loses radio contact, restricts foot pursuit when suspects are armed with firearms, and encourages the use of containment tactics. Together, these foot pursuit policies have an alpha score of 0.958.

amount of restriction placed on vehicle pursuits and 0 indicates that the pursuing officer has full discretion over whether and how to proceed with a vehicle pursuit.⁵³ <u>*Firearm display*</u> <u>*documentation*</u> is a binary variable indicating whether an agency requires use of force documentation for any display of a firearm (rather than only when an officer actually discharges a firearm). <u>*Less-lethal documentation*</u> is the percentage of less lethal weapons and techniques authorized by the agency that require documentation (alpha = 0.745).⁵⁴

Agency professionalization is assessed using educational requirements for hiring and training requirements for new hires. An agency's educational requirements are measured with a binary variable indicating whether the agency had a *college requirement* for new hires. The *new hire additional training index* is an agency's total across two other scales: a new lateral hire additional training scale and a new pre-service hire additional training scale. New lateral hires are individuals who have both law enforcement certification and prior law enforcement experience. New pre-service hires are individuals with law enforcement certification but no prior law enforcement experience. Both sub-scales are coded 0 if the new hire type receives no additional training, 1 if they receive at least some additional training, and 2 if they receive the same training as new hires without any certification or experience. The combined scale therefore ranges from 0 to 4.

An agency's commitment to community policing is assessed with two scales regarding the number of full-time personnel who received community policing training over the course of a

⁵³ Restrictions range from simple policy restrictions that limit vehicle pursuit to specific circumstances to explicitly discouraging vehicle pursuits. All agencies in the sample had some form of written vehicle pursuit policy and no agency fully prohibited all vehicle pursuits.

⁵⁴ These less-lethal weapons and techniques are batons, other impact weapons, soft projectiles, OC spray or foam, other chemical agents, conducted energy devices, neck restraining techniques, takedown techniques, open-hand techniques, close-hand techniques, and leg hobbles or other severe restraints.

year. Respondents were asked whether, over the 12-month period ending on December 31, 2012, all, half or more, less than half, or no full-time personnel received at least 8 hours of community policing training as part of 1) in-service training or 2) recruit training.⁵⁵ Both the <u>in-service</u> <u>community policing training scale</u> and <u>recruit community policing training scale</u> are coded such that a higher value indicates more officers of that type completed community policing training t

The presence of cameras is measured with two binary variables for whether the agency collects information using video cameras in patrol vehicles, referred to as *dash cams*, or attached to patrol officers, referred to as *body cams*. The extent to which an agency utilized less-lethal weapons and techniques is measured using three binary variables indicating whether the agency authorized the use of a specific weapon or technique for all sworn personnel.

Utilization of less-lethal weapons and techniques is assessed based on whether an agency *authorizes soft projectiles* (e.g., bean-bag rounds or soft bullets that can be loaded and fired similarly to traditional bullets or rounds), *authorizes chemicals* (that is, chemical agents other than OC spray of foam, which can include tear gas and mace), or *authorizes neck restraining techniques* (which includes lateral neck restraints and chokeholds).

Method

In order to simultaneously account for multiple sources of data on homicide by police, I build a structural model onto the measurement model discussed in the prior chapter. In the current analysis, all predictors are specified with paths to the latent HbP rate. The latent HbP rate has

⁵⁵ LEMAS 2013 provided a "not applicable" option for both community policing training variables. The survey instructions indicate that respondents are to select this option if the agency did not offer that particular kind of training over the 12-month period. "Not applicable" responses are therefore coded as "0," the same as "none" responses, because they both indicates that no officers completed the training during the 12-month period.

four indicators of homicide by police, each measured with error — the SHR justifiable homicide rate, the FE rate of fatal encounters with police, the MPV homicide by police rate, and the homicide by police rate derived from The Counted.

Analysis

Descriptives

Table 6.2 displays descriptive statistics of the measures used in this analysis for the 254 agencies in this sample. Pairwise correlations for each domain of independent variables can be found in the Appendix. Missing values for the independent variables are not a severe issue. No values for independent variables from the ACS are missing because all 254 agencies were successfully linked to the ACS. About 30% of the sample serve populations of 250,000 or more. Although all of the agencies in the sample are self-representing LEMAS agencies, meaning that the BJS thought they had 100 full-time sworn officers, some agencies had fewer than 100 full-time sworn officers, with one agency having as low as 89 officers when it filled out the survey. The use of dash cams was fairly common — about 69% of agencies used video cameras mounted on police vehicles — while the use of body cameras was fairly uncommon — about 22% of agencies used them.

City Factors Predicting HbP

Results of a series of linear structural models predicting the latent HbP rate using demographic and social aspects of the populations served by the agencies in the sample are displayed in Tables 6.3, 6.4, and 6.5. These tables show that firearm violence⁵⁶ and population

⁵⁶ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, a city at the 25th percentile for firearm violence (50.38 homicides, firearm assaults, and firearm robberies per 100,000 residents) and a city at the 90th percentile for firearm violence (406.30 per 100,000) would have an MPV rate of 6.96 and 11.00 decedents per

size are consistent, strong predictors of the latent HbP rate. The disadvantage index only becomes a statistically significant predictor after controlling for Black-White inequality and segregation in Table 6.5. Percent young males is not a statistically significant predictor in any model.

Tables 6.3 and 6.4 focus on testing the racial threat hypothesis that areas with higher percentages of minority groups will be the subjects of greater levels of police violence, with Table 6.3 looking at percent Black as a predictor and Table 6.4 looking at percent Hispanic/Latino as a predictor. The percent minority threat hypothesis not consistent with my findings. Table 6.3 shows that cities with a higher percent Black have <u>lower</u> levels of homicide by police.⁵⁷ Table 6.4 shows no statistically significant relationship between percent Hispanic/Latino and the latent HbP rate. The threat hypothesis also states that we should expect a curvilinear, positive-decreasing relationship between percent minority and police violence. However, Model 2 and Model 4 in both tables show that the square terms of percent Black and percent Hispanic/Latino are not statistically significant.

Table 6.5 focuses on minority inequality and segregation as predictors of the latent HbP rate. Although percent Black was a statistically significant predictor in Table 6.3, I do not include it in the table because of its high correlation with Black-White inequality (r = 0.423) and segregation (r = 0.939). While the association between Black-White inequality and the latent HbP rate is in the predicted direction, Black-White segregation and Hispanic/Latino-White inequality are in the

million, respectively. For the Counted, the difference is 6.80 and 10.50; for the SHR it is 4.00 and 6.36; for Fatal Encounters it is 10.27 and 14.80.

⁵⁷ This is a fairly large association. Predictive marginal means for Model 3 of Table 6.3 indicate that if all other independent variables in the model are held constant at their means, a city with a population that is 10% Black and a city with a population that is 80% Black would have an MPV rate of 9.24 and 0.79 decedents per million, respectively. For the Counted, the difference is 8.89 and 1.15; for the SHR it is 5.33 and 0.40; for Fatal Encounters it is 12.83 and 3.38.

opposite direction. Controlling for all else in Model 4, agencies serving cities with higher levels of Black-White inequality experience <u>higher</u> rates of homicide by police while agencies serving cities with high levels of Black-White segregation and/or Hispanic/Latino-White inequality have <u>lower</u> rates of homicide by police.

Agency Factors Predicting HbP

Most city predictors are retained in Tables 6.6 and 6.7 as control variables. However, percent Black, percent Hispanic/Latino, percent young males, and Hispanic/Latino-White segregation are not included in these models. Given the high correlation between percent Black and Black-White segregation (r = 0.939), only one could be retained without facing issues of multi-collinearity. The latter three variables are not included because of their lack of statistically significant association with the outcome in Tables 6.3, 6.4, and 6.5.

Table 6.6 focuses on agency demographics as predictors of the latent HbP rate. Counter to the hypothesized associations, none of the variables indicating greater gender or racial diversity in a department were statistically significant predictors of the outcome. While this is not consistent with common policy recommendations (Bergman et al., 2016; Campaign Zero, 2018; Fifield, 2016; National Research Council, 2004; Spillar, 2015), it is consistent with the body of literature that distinguishes between "active" and "passive" representation (Bradbury & Kellough, 2011; Mosher, 1968).

Table 6.7 focuses on organizational complexity and control. Findings indicate that agencies with greater levels of functional differentiation/specialization and occupational differentiation/civilianization experience greater levels of homicide by police. Agencies that have more specialized units tend to have higher HbP rates.⁵⁸ This is consistent with the arguments of modern police reform advocates (Maguire, 2003; Maguire et al., 2003; Zhao et al., 2010). The finding that agencies with a higher percentage of non-sworn personnel tend to have a higher HbP rate⁵⁹ is consistent with the findings of the only other study to test this predictor (Willits & Nowacki, 2013) but inconsistent with the advice of police reform advocates, who argue that agencies should hire more non-sworn personnel (Maguire, 2003). Salary disparity, which is used here as a measure of vertical differentiation/hierarchy, was not a statistically significant predictor.

Only a few of the organizational control variables shown in Model 2 of Table 6.7 were statistically significant predictors of the latent homicide by police rate. As hypothesized, agencies with more restrictive vehicle pursuit policies⁶⁰ and those that required more recruits to engage in community policing training⁶¹ had lower levels of homicide by police. Results were mixed regarding the authorization of less-lethal weapons and techniques. Authorizing the use of

⁵⁸ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency with no specialized units would and an agency with 14 types of specialized units would have an MPV rate of 6.51 and 10.84 decedents per million, respectively. For the Counted, the difference is 6.38 and 10.35; for the SHR it is 3.73 and 6.26; for Fatal Encounters it is 9.77 and 14.62.

⁵⁹ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency with 10% civilian personnel and an agency with 45% civilian personnel would have an MPV rate of 6.97 and 10.77 decedents per million, respectively. For the Counted, the difference is 6.81 and 10.29; for the SHR it is 4.00 and 6.22; for Fatal Encounters it is 10.29 and 14.54.

⁶⁰ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency that gave officers full discretion for vehicle pursuits and an agency that placed some restrictions on vehicle pursuits would have an MPV rate of 12.21 and 8.11 decedents per million, respectively. For the Counted, the difference is 11.61 and 7.85; for the SHR it is 7.06 and 4.67; for Fatal Encounters it is 16.15 and 11.56.

⁶¹ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency with no recruits trained in community policing in the past year and an agency where all recruits received community policing training would have an MPV rate of 10.27 and 7.77 decedents per million, respectively. For the Counted, the difference is 9.83 and 7.54; for the SHR it is 5.93 and 4.47; for Fatal Encounters it is 13.98 and 11.19.

chemical agents was associated with lower latent HbP.⁶² However, authorizing the use of soft projectiles⁶³ or neck restraining techniques⁶⁴ were associated with higher levels of HbP.

Comparison Across Sources

To illustrate how findings can differ based on the outcome used, in Tables 6.8, 6.9, and 6.10 I compare models predicting the latent HbP rate to those predicting each HbP indicator separately. In each table, Model 1 is similar to the prior models presented (i.e., a structural equation model where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted with all exogenous variables predicting latent HbP). Model 2 is a structural equation model where the exogenous variables are used to predict each of the indicator HbP rates separately. These are estimated together in a single model so that I can test for differences between coefficients.

These tables show that there is variability between models such that if these sources were viewed in isolation, researchers would come to different conclusions about the findings. For instance, percent Black is a statistically significant predictor of the latent HbP rate in Model 1 of Table 6.8. However, in Model 2, it is only a significant predictor when using MPV or The Counted as an outcome and not when using the SHR or Fatal Encounters. Another example is

⁶³ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency that does not authorize officers to use soft projectiles and one that does would have an MPV rate of 5.42 and 8.80 decedents per million, respectively. For the Counted, the difference is 5.39 and 8.48; for the SHR it is 3.10 and 5.07; for Fatal Encounters it is 8.55 and 12.33.

⁶² This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency that does not authorize officers to use chemical weapons and one that does would have an MPV rate of 10.20 and 7.39 decedents per million, respectively. For the Counted, the difference is 9.77 and 7.19; for the SHR it is 5.89 and 4.25; for Fatal Encounters it is 13.90 and 10.75.

⁶⁴ This is a moderately sized association. Predictive marginal means for Model 2 of Table 6.7 indicate that if all other independent variables in the model are held constant at their means, an agency that does not authorize officers to use neck restraining techniques and one that does would have an MPV rate of 7.79 and 9.61 decedents per million, respectively. For the Counted, the difference is 7.56 and 9.23; for the SHR it is 4.48 and 5.55; for Fatal Encounters it is 11.21 and 13.25.

that in Table 6.10, authorizing soft projectiles is a statistically significant predictor of latent HbP and all of the indicators except Fatal Encounters while authorizing chemicals is predictive of latent HbP and all of the indicators except the SHR. Some, though not all, of these differences between coefficients are statistically different between the outcomes used (as indicated by letters placed next to the normal significance tests in the tables).

Of key importance is that the coefficients predicting the Mapping Police Violence rate alone are closest to the model that uses all four sources as indicators of the latent HbP rate in terms of the pattern of which predictors are found to be significant and the relative size of the coefficients in the standardized models. This is perhaps not surprising given its strong association with the latent HbP rate shown in Chapter 5.

Discussion

The goal of the current study was to utilize the measurement model developed in the prior chapter to examine potential city- and agency-level predictors of homicide by police (HbP). I also test models predicting each HbP indicator separately. The substantive findings are summarized in Table 6.11. In addition, I find that the model using Mapping Police Violence for its outcome closely replicates the measurement model that uses all four indicators to predict the latent HbP rate. This provides evidence that using MPV alone may be a viable alternative to the SEM method used in this article.

As is consistent with the theoretical framework described in Chapter 3 and prior research, cities with more firearm violence and those that experience higher levels of concentrated disadvantage also experience greater levels of homicide by police. This suggests that cities that experience more violence and socio-economic hardship have a greater number of perceptually dangerous interactions between police and the public, leading to greater levels of force used by officers in order to gain control in these situations.

In the past, racial threat theory (Blalock, 1967; Blumer, 1958) has been used to suggest that percent minority will have a positive-decreasing association with homicide by police. Many older studies using the SHR find this positive association (Jacobs & O'Brien, 1998; Smith, 2004; Smith & Holmes, 2003; Sorensen et al., 1993; Willits & Nowacki, 2013); however, most recent studies that incorporate media-based data (Hemenway et al., 2018; Jennings & Rubado, 2017; Nicholson-Crotty et al., 2017; Pang & Pavlou, 2016) find no association between percent Black and the homicide by police rate, with two even finding a negative association (Legewie & Fagan, 2016; Renner, 2019). My findings align with these last two studies.

This is a statistically significant and fairly large association. Predictive marginal means for Model 3 of Table 6.3 indicate that if all other independent variables in the model are held constant at their means, a city with a population that is 10% Black and a city with a population that is 80% Black would have an MPV rate of 9.24 and 0.79 decedents per million, respectively. For the Counted, the difference is 8.89 and 1.15; for the SHR it is 5.33 and 0.40; for Fatal Encounters it is 12.83 and 3.38.

I suggest that the seemingly contradictory findings between older and newer studies are not a function of data source, since although it is statistically insignificant in this study, the coefficient for percent Black predicting the SHR rate still has a negative sign (see Table 6.8). Instead, the fact that older studies find a positive association while newer studies find a negative or insignificant association may be an indication that the association has changed over time. All of the aforementioned studies are cross-sectional. However, in his longitudinal study using the SHR, Dirlam (2018) finds that while percent Black has an overall positive association with homicide by police, this association has decreased in strength over time. The older studies use older data when the positive association between percent Black and homicide by police was

stronger. Newer studies are unlikely to find a positive association because they use more recent data.

The negative association between percent Black and homicide by police may also be a consequence of the high correlation between percent Black and Black-White segregation. Racial threat theory (Blalock, 1967; Blumer, 1958) and structural discrimination theories (Bonilla-Silva, 1997; Murphy & Walton, 2013; Reskin, 2012) have been used to suggest that minority-White socio-economic inequality and housing segregation would be associated with higher levels of police violence. This is consistent with the association between Black-White socio-economic inequality and HbP in this study, but not with the associations between Black-White housing segregation and Hispanic/Latino-White socio-economic inequality and HbP.

Taken together with the findings for percent minority, this suggests that future research should consider more nuanced versions of threat and structural discrimination theories. From a threat perspective, segregation and minority inequality could be associated with *lower* levels of state violence if they are effectively limiting the economic and political threat of minority communities on their own. For instance, high Black-White housing segregation could mean fewer interactions between Black and White residents, leading to a lower sense of group threat from White people in the community. Another possible explanation for the negative association between Black-White segregation and homicide by police is benign neglect (Liska et al., 1981; Liska & Chamlin, 1984; Myer & Chamlin, 2011; Stolzenberg et al., 2004). According to this theory, marginalized groups may be less able to mobilize support from social control agents and issues faced by segregated marginalized communities may be seen as less worthy of intervention. A third alternative explanation is one of empowerment. Areas with high Black populations may actually be better at mobilizing police or preventing police violence, for instance, by pushing for

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the installment of Black mayors (Saltzstein, 1989) or Black police chiefs (Shoub & Christiani, 2023). This complexity means that it is difficult to discern whether a negative association should be viewed as favorable or unfavorable for Black communities.

Studies using the SHR find that Black-White income inequality is positively predictive of the overall justifiable homicide rate (Jacobs & O'Brien, 1998; Willits & Nowacki, 2013). My findings align with these earlier studies. In addition, although it was weak and only marginally significant, Willits and Nowacki (2013) found a negative relationship between Hispanic-White income inequality and the justifiable homicide rate. I also found this negative relationship, which was statistically significant in my models.

Some police reform advocates point to increasing agencies' gender and racial diversity as potential avenues for reducing police violence (Bergman et al., 2016; Campaign Zero, 2018; Fifield, 2016; National Research Council, 2004; Spillar, 2015). However, prior research also suggests that increasing simple numerical diversity may not be enough to change departmental cultures. Many studies find that officers have similar outcomes and attitudes regardless of their own race or gender (Archbold & Schulz, 2012; National Research Council, 2004; Poteyeva & Sun, 2009). This could be due to socialization of female and minority officers into traditional police culture or selection into police work by individuals who already share behavioral and attitudinal characteristics (Silver et al., 2017; Weitzer, 2000; Wilkins & Williams, 2008). My findings (which show no statistically significant associations between percent female, percent minority, or minority representation and the latent homicide by police rate) are consistent with this criticism of numerical diversity.

Debate exists among police reform advocates regarding the proper amounts of organizational complexity. Police reform movements of the 1920s to 1970s advocated for greater levels of

vertical differentiation/hierarchy to reduce corruption and the influence of local politics on policing and increased functional differentiation/specialization so that squads of officers could develop expertise to deal with emerging issues (Kelling & Moore, 1988; Maguire, 2003; Walker, 1977). However, more modern police reformers focused on community policing advocate a flattening of hierarchies and a shift towards general rather than specialized skill sets for officers (Kelling & Moore, 1988; Maguire, 2003; Maguire et al., 2003; Zhao et al., 2010). This study finds partial support for the position of community police reformers. Police agencies with a greater number of specialized unit types experienced higher levels of homicide by police. However, salary disparity between patrol officers and police administrators (which was used as an indicator of vertical differentiation/hierarchy) was not significantly associated with latent HbP.

Contrary to most of their recommendations regarding organizational complexity, community policing advocates generally recommend increased occupational differentiation/civilianization (Maguire et al., 2003). However, I find that agencies with a higher percentage of civilian workers (as opposed to sworn officers) experienced *higher* rates of homicide by police. This could indicate that the specialization of job types brought on by hiring from different occupational sectors (i.e., civilianization) functions similarly to the specialization brought on by functional differentiation between sworn officers.

As with organizational complexity, debate exists over the effectiveness of organizational control. Traditional police reform movements argued that increased organizational control through formal policies, greater levels of documentation, and increased education and training requirements placed important limits on police discretion, especially when it came to discretion over the lethal use of force (Fyfe, 1988; Reiss, 1980; Walker, 1993). However, community

policing advocates argue for decreases in some forms of control over officers' decision-making in favor of a style of police-work that is more personalized, proactive, and focused on order maintenance and service rather than merely on crime control (Maguire, 2003; Maguire et al., 2003; Redlinger, 1994; Zhao et al., 2010). I find that higher formalization in the form of more restrictive vehicle pursuit policies is associated with lower homicide by police rates. However, other measures of formalization (i.e., more restrictive foot pursuit policies and use of force documentation requirements) and professionalization (i.e., educational requirements and additional training requirements for new hires with prior experience or certification) are not statistically significant predictors of HbP.

Unlike prior studies (Jennings & Rubado, 2017; Legewie & Fagan, 2016; Pang & Pavlou, 2016), I find some evidence that community policing may work to reduce homicide by police rates. Specifically, requiring more new recruits to engage in community policing training is associated with lower HbP. Although this measure has been used as part of a community policing index in prior work (Holmes & Smith, 2014; Legewie & Fagan, 2016) it has not been tested as a predictor on its own (at least in the literature reviewed in Chapter 3).

There was no statistically significant difference between agencies that used video cameras in patrol vehicles (i.e., dash cams) or on patrol officers (i.e., body cams) and those that did not in terms of the levels of homicide by police that they experienced. This is consistent with some of the models tested by Pang and Pavlou (2016), who found no statistically significant relationships between dash or body cams and officer-involved gun deaths derived from Killed by Police or the SHR. However, Pang and Pavlou (2016) did find a statistically significant positive association when using an outcome based on The Washington Post's fatal shootings data. Body cameras and dashboard cameras may have complicated impacts on officers' use of force. Advocates call for

their use with the idea that officers will be more hesitant to use unnecessary force because they know that they are being recorded. Alternatively, as argued by Pang and Pavlou (2016), police may view cameras as providing evidence that *justifies* their use of force decisions, which could make them more likely to engage in lethal force.

Less-lethal weapons and techniques are authorized by agencies as alternatives to the use of firearms with the intention that these alternatives will reduce the number or deadly interactions between officers and civilians. However, of the three policies authorizing less-lethal options for use of force shown in Model 2 of Table 6.7, two were associated with a *higher* latent homicide by police rate and one was associated with a *lower* rate. Controlling for other measures of organizational complexity and control, agencies that authorized neck restraining techniques and the use of soft projectiles had higher HbP rates. In contrast, the authorization of chemical agents (like tear gas) had a statistically significant association with lower HbP rates.

These findings regarding less-lethal options are somewhat in alignment with the medical literature, which tends to find greater severity and longer lasting injuries in studies of those subjected to neck restraints (Bozeman et al., 2022; Hall & Butler, 2007; Hickman et al., 2021; Vilke, 2006) or soft projectiles (Beatty et al., 2020; Burki, 2023; Fourkiller, 2002; Haar, Iacopino, Ranadive, Weiser, et al., 2017; Hubbs, 1997; Ijames, 2021; Manhas et al., 2021) than in studies of those subjected to chemical weapons like tear gas (Agrawal et al., 2009; Carron & Yersin, 2009; Danto, 1987; Sivathasan, 2010; Tsang et al., 2020). From the standpoint of the theoretical framework established in Chapter 3, I argue that chemical agents may reduce perceptual dangerousness because they can be used at a distance. Officers are more likely to feel in danger when suspects are in closer proximity. Related to this, neck restraining techniques must be used while officers are physically touching suspects. Lateral vascular neck restraints are

sometimes touted as necessary training for officers and as less dangerous than traditional chokeholds (Marcou, 2015). However, this study indicates that they may be a dangerous policy for police agencies to authorize. Soft projectiles, while useable at a distance, behave similarly to traditional firearm ammunition. Again, this study suggests that the use of soft projectiles by police may be ineffective at reducing lethal force incidents.

Tables

Table 6.1: Summary of Hypotheses

Category		Hypothesis
City Predictors		
Community Violence	H1.	Firearm Violence 7 HbP
Socio-Economic Context	H2.	Concentrated Disadvantage 7 HbP
Age and Gender	H3.	Percent of Young Males 7 HbP
Percent Minority	H4.	Percent Black 7 HbP
	H5.	Percent Hispanic/Latino 7 HbP
	H6.	Percent Black ルオ HbP
		Percent Hispanic/Latino オレ HbP
Racial/Ethnic Inequality and Segregation	H7.	Black-White Socio-Economic Inequality 7 HbP
		Black-White Housing Segregation 7 HbP
	H8.	Hispanic/Latino-White Socio-Economic Inequality 7 HbP
		Hispanic/Latino-White Housing Segregation 7 HbP
Agency Predictors		
Agency Demographics	H9.	Percent Black V HbP
		Percent Hispanic/Latino א HbP
	H10.	Racial/Ethnic Representativeness ム HbP
		Percent Female L HbP
Organizational Complexity	H12.	Vertical Differentiation/Hierarchy 7 HbP
	H13.	Functional Differentiation/Specialization 7 HbP
	H14.	Occupational Differentiation/Civilianization ビ HbP
Organizational Control	H15.	Restrictive Pursuit Policies 凶 HbP
	H16.	Restrictive Use of Force Documentation ビ HbP
	H17.	Education Requirements 凶 HbP
	H18.	New Hire Training Requirements ビート HbP
		Community Policing ビ HbP
	H20.	Video Surveillance ↘ HbP
	H21.	Less-Lethal Authorization 凶 HbP

HbP: Homicide by Police; 7 Positive relationship; V Negative relationship; 7 Ucrvilinear, positive-decreasing relationship

Table 6.2: Descriptives

HbP Indicators	Mean or %	SD	Min	Mav	Missing		
Supplementary Homicide Reports	4.81	6.51	0	37.28	28		
Fatal Encounters	11.89	11.09	0	37.28 84.19	20		
	8.40			37.53			
Mapping Police Violence		8.02	0				
The Counted	8.12	7.62	0	29.86			
City Predictors	Mean or %	SD	Min	Max 1	Missing	Bivaria	te Model [†]
Firearm Violence	186.43	183.38	0	1114.94	5	0.01	[0.22]***
Disadvantage Index	0.00	0.88	-2.04	3.23		0.97	[0.18]
Percent Young Males	7.52	2.06	3.86	17.93		0.10	[0.04]
Percent Black	17.27	16.44	0.30	80.80		0.02	[0.06]
Percent Hispanic/Latino	24.09	19.71	1.30	96.30		0.02	[0.09]
Black-White Inequality Index	0.00	0.88	-1.45	3.34		0.50	[0.10]*
Black-White Segregation	0.27	0.23	0.01	0.90		1.09	[0.05]
Hispanic/Latino-White Inequality Index	0.00	0.73	-1.47	2.42		-0.01	[0.00]
Hispanic/Latino-White Segregation	0.32	0.21	0.04	0.96		2.31	[0.10]
Population of 250,000 or more	30.3%	0.21	0.01	1		2.34	[0.23]***
r opulation of 250,000 of more	50.570		0	1		2.34	[0.23]
Agency Demographics	Mean or %	SD	Min	Max 1	Missing	Bivaria	te Model [†]
Agency Size	781.57	2439.73	89	34454		0.00	[0.01]
Agency % Female	12.32	4.90	3.01	42.20	1	0.02	[0.02]
Agency % Black	10.91	12.50	0	85.41	6	0.01	[0.04]
Agency % Hispanic/Latino	12.61	14.51	0	97.51	6	0.02	[0.05]
Black Representation	0.82	1.43	0	21.28	6	-0.07	[-0.02]
Hispanic/Latino Representation	0.49	0.28	0	2.09	6	-0.09	[-0.01]
Organizational Complexity	Mean or %	SD	Min	Max 1	Missing	Bivaria	ite Model [†]
Salary Disparity (Hierarchy)	1.53	0.54	0.48	3.80	17	0.18	[0.02]
Num. of Spec. Unit Types (Specialization)	6.36	3.48	0	14.00	4	0.28	[0.21]***
Percent Non-Sworn (Civilianization)	23.45	8.26	6.23	47.83		0.04	[0.08]
Organizational Control	Mean or %	SD	Min	Max 1	Missing		te Model [†]
Restrictive Foot Pursuit Policy	0.69	1.74	0	6	9	0.00	[0.00]
New Hire Additional Training Index	2.67	1.18	0	4		-0.26	[-0.07]
In-Service Community Policing Scale	1.35	1.22	0	3	9	0.03	[0.01]
Recruit Community Policing Scale	2.19	1.29	0	3	9	-0.31	[-0.09]
Restrictive Vehicle Pursuit Policy	91.8%		0	1	9	-2.16	[-0.13]*
Firearm Display Documentation	33.6%		0	1	4	-1.20	[-0.12]**
Less-Lethal Documentation	86.5%		0	1	4	-0.35	[-0.01]
College Requirement	4.0%		0	1	6	-2.20	[-0.09]+
Dash Cams	69.2%		0	1	1	-0.09	[-0.01]
Body Cams	22.1%		0	1	1	0.77	[0.07]
Authorizes Soft Projectiles	89.3%		0	1	2	1.21	[0.08]
Authorizes Chemicals	60.3%		Ő	1	2	-1.02	[-0.11]*
Authorizes Neck Restraining Techniques	34.1%		ů 0	1	2	1.29	[0.13]*
* Bivariate models are structural equation m				-			

[†] Bivariate models are structural equation models with four indicators of latent HbP (SHR, FE, MPV, and Counted) and one independent, exogenous variable and are estimated using mlmv and clustered standard errors. Standardized coefficients are listed in brackets. *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

Sample Size: n=254

Table 6.3: City Percent Black Predicting the Latent HbP Rate

	Model 1	Model 2	Model 3	Model 4
Structural Model	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Population of 250,000 or more	2.445 0.242***	* 2.481 0.246***	* 1.770 0.175**	1.804 0.179**
Disadvantage Index	1.136 0.214+	1.132 0.214 +	0.890 0.168	0.889 0.168
Percent Young Males	0.188 0.083	0.193 0.085	0.174 0.077	0.178 0.079
Percent Black	-0.026 -0.094	-0.053 -0.186	-0.070 -0.249*	-0.090 -0.318+
Percent Black Squared		0.000 0.098		0.000 0.075
Firearm Violence			0.007 0.262**	0.007 0.259**
HbP Measurement Model	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Supplementary Homicide Reports	1.000 0.706	1.000 0.706	1.000 0.706	1.000 0.706
Fatal Encounters	1.917 0.803***	* 1.917 0.803***	* 1.917 0.803***	1.917 0.803***
Mapping Police Violence	1.714 0.994***	* 1.714 0.994***	* 1.714 0.994***	1.714 0.994***
The Counted	1.570 0.958***	* 1.569 0.958***	* 1.569 0.957***	1.569 0.957***

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

Structural equation models where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, constants from the measurement model are not displayed.

	Model 1	Model 2	Model 3	Model 4
Structural Model			Unstd Std	Unstd Std
Population of 250,000 or more	2.305 0.228***	2.307 0.229***	1.810 0.179**	1.800 0.178**
Disadvantage Index	0.848 0.160	0.854 0.161 +	0.400 0.076	0.398 0.075
Percent Young Males	0.171 0.076	0.177 0.078	0.153 0.068	0.162 0.072
Percent Hispanic/Latino	0.006 0.024	0.018 0.075	0.020 0.083	0.041 0.174
Percent Hispanic/Latino Squared		0.000 -0.054		0.000 -0.095
Firearm Violence			0.004 0.140+	0.004 0.144+
HbP Measurement Model			Unstd Std	Unstd Std
Supplementary Homicide Reports	1.000 0.706	1.000 0.706	1.000 0.706	1.000 0.706
Fatal Encounters	1.917 0.803***	1.917 0.803***	1.916 0.803***	1.917 0.803***
Mapping Police Violence	1.715 0.994***	1.714 0.994***	1.715 0.994***	1.714 0.994***
The Counted	1.569 0.957***	1.569 0.957***	1.568 0.957***	1.569 0.957***

Table 6.4: City Percent Hispanic/Latino Predicting the Latent HbP Rate

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

Structural equation models where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, constants from the measurement model are not displayed.

	Model 1	Model 2	Model 3	Model 4
Structural Model	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Population of 250,000 or more	2.393 0.237***	2.592 0.257***	2.639 0.261***	2.137 0.212**
Disadvantage Index	1.448 0.273*	0.899 0.170+	1.725 0.325**	1.252 0.236*
Percent Young Males	0.165 0.073	0.190 0.084	0.160 0.071	0.153 0.068
Black-White Inequality Index	0.728 0.138+		1.350 0.256**	1.176 0.223**
Black-White Segregation	-4.425 -0.217*		-5.281 -0.258**	-7.183 -0.351**
Hispanic/Latino-White Inequality Index		-0.670 -0.106*	-1.173 -0.185**	-1.167 -0.184***
Hispanic/Latino-White Segregation		0.631 0.028	-0.338 -0.015	0.496 0.022
Firearm Violence				0.006 0.244**
HbP Measurement Model	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Supplementary Homicide Reports	1.000 0.706	1.000 0.706	1.000 0.706	1.000 0.706
Fatal Encounters	1.918 0.804***	1.916 0.803***	1.918 0.804***	1.916 0.803***
Mapping Police Violence	1.712 0.993***	1.715 0.994***	1.712 0.993***	1.716 0.995***
The Counted	1.571 0.959***	1.569 0.957***	1.571 0.959***	1.568 0.957***

Table 6.5: City Minority Inequality and Segregation Predicting the Latent HbP Rate

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

Structural equation model where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, constants from the measurement model are not displayed.

	Ν	Model 1	Ν	Model 2	
Structural Model	Unstd	Std	Unstd	Std	
City Context Controls					
Firearm Violence	0.007	0.258**	0.006	0.238**	
Population of 250,000 or more	2.149	0.213**	2.149	0.213**	
Disadvantage Index	1.443	0.272*	1.332	0.251*	
Black-White Inequality Index	1.235	0.234**	1.224	0.232**	
Black-White Segregation	-6.115	-0.299*	-7.332	-0.359**	
Hispanic/Latino-White Inequality Index	-1.095	-0.173**	-1.174	-0.185**	
Agency Predictors					
Agency Size	0.000	-0.002	0.000	0.001	
Agency % Female	0.015	0.016	0.000	0.001	
Agency % Black	-0.048	-0.130	-	-	
Agency % Hispanic/Latino	-0.013	-0.041	-	-	
Black Representation	-	-	-0.056	-0.017	
Hispanic/Latino Representation	-	-	-0.624	-0.038	
HbP Measurement Model	Unstd	Std	Unstd	Std	
Supplementary Homicide Reports	1.000	0.707	1.000	0.706	
Fatal Encounters	1.918	0.804***	1.917	0.804***	
Mapping Police Violence	1.712	0.993***	1.712	0.993***	
The Counted	1.570	0.959***	1.570	0.958***	

Table 6.6: Agency Demographics Predicting the Latent HbP Rate

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

Structural equation models where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, constants from the measurement model are not displayed.

Structural Model Unstd Std Unstd Std City Context Controls			odel 1	M	odel 2
Firearm Violence 0.006 0.246^{**} 0.007 0.264^{***} Population of 250,000 or more 2.071 0.205^{**} 1.504 0.149^{*} Disadvantage Index 1.310 $0.247+$ 1.071 $0.202+$ Black-White Inequality Index 1.217 0.231^{**} 1.061 0.201^{**} Black-White Segregation -7.446 -0.364^{***} -4.939 -0.242^{**} Hispanic/Latino-White Inequality Index -1.132 -0.179^{***} -0.937 -0.148^{**} Organizational ComplexitySalary Disparity (Hierarchy)- -0.383 -0.045 Num. of Specialized Unit Types (Specialization)- -0.181 0.135^{*} Percent Non-Sworn (Civilianization)- -0.140 -0.052 Restrictive Foot Pursuit Policy- -0.140 -0.052 Restrictive Vehicle Pursuit Policy- -0.620 -0.063 Less-Lethal Documentation- -0.050 -0.002 College Requirement- -0.100 -0.026 Restrictive Community Policing Scale $ -$ - -0.060 -0.015 In-Service Community Policing Scale $ -$ - -0.099 0.010 Body Cams $ -$					

Table 6.7: Agency Complexity and Control Predicting the Latent HbP Rate

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.) Structural equation models where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. Parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, constants from the measurement model are not displayed.

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Table 6.8: City Percent Minority Predicting HbP Rates from Different Sources

	Model 1	Model 2				
	Latent HbP	SHR	Fatal Encounters	MPV	The Counted	
	Unstd Std	Unstd Std	Unstd Std	Unstd Std	Unstd Std	
Firearm Violence	0.006 0.257**	0.010 0.274*	0.016 0.269** ^C	0.011 0.265**	0.009 0.224** ^F	
Population of 250,000 or more	1.811 0.179**	3.027 0.214**	1.820 0.076	3.059 0.176**	3.043 0.184***	
Disadvantage Index	0.979 0.185	0.528 0.071 ^C	2.009 0.159	1.601 0.175	1.911 0.220* ^S	
Percent Young Males	0.174 0.077	0.236 0.075	0.540 0.100	0.296 0.076	0.272 0.074	
Percent Black	-0.074 -0.263*	-0.074 -0.187	-0.100 -0.148	-0.128 -0.262**	-0.137 -0.295***	
Percent Hispanic/Latino	-0.005 -0.023	0.036 0.110	-0.018 -0.032	-0.009 -0.023	-0.010 -0.026	

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

S: Significantly different from the coefficient predicting SHR based on a post-estimation Wald test (p<0.05).

F: Significantly different from the coefficient predicting Fatal Encounters based on a post-estimation Wald test (p<0.05).

M: Significantly different from the coefficient predicting MPV based on a post-estimation Wald test (p<0.05).

C: Significantly different from the coefficient predicting Counted based on a post-estimation Wald test (p<0.05).

Model 1: Structural equation model where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. All exogenous variables are predicting latent HbP.

Model 2: Structural equation model where all exogenous variables are used to predict observed rates from each indicator separately. Coefficients were similar in models that only included one indicator each.

In all models, parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, the measurement model in Model 1 and constants in Model 2 are not displayed.

	Model 1		Mo		
	Latent HbP	SHR	Fatal Encounters	MPV	The Counted
	Unstd Std	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Firearm Violence	0.006 0.244**	0.009 0.263*	0.017 0.277** ^{MC}	0.011 0.252** ^F	0.008 0.205** ^F
Pop. of 250,000 or more	2.137 0.212**	3.046 0.216**	$2.083 0.086^{M}$	3.641 0.209*** ^F	3.504 0.212***
Disadvantage Index	1.252 0.236*	0.934 0.126 ^C	2.669 0.211*	2.047 0.224*	2.320 0.267* ^S
Percent Young Males	0.153 0.068	0.196 0.062	0.488 0.091	0.260 0.067	0.228 0.062
Black-White Inequality	1.176 0.223**	1.828 0.248**	2.554 0.203**	1.948 0.214**	2.096 0.242**
Black-White Segregation	-7.183 -0.351**	-8.167 -0.286**	-12.662 -0.260*	-12.233 -0.347***	-12.786 -0.382***
H/L-White Inequality	-1.167 -0.184***	-1.738 -0.196**	-2.068 -0.137**	-1.981 -0.181***	-1.868 -0.180***
H/L-White Segregation	0.496 0.022	5.585 0.179*	0.501 0.009	0.717 0.019	1.162 0.032

Table 6.9: City Minority Inequality and Segregation Predicting HbP Rates from Different Sources

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

S: Significantly different from the coefficient predicting SHR based on a post-estimation Wald test (p<0.05).

F: Significantly different from the coefficient predicting Fatal Encounters based on a post-estimation Wald test (p<0.05).

M: Significantly different from the coefficient predicting MPV based on a post-estimation Wald test (p<0.05).

C: Significantly different from the coefficient predicting Counted based on a post-estimation Wald test (p<0.05).

Model 1: Structural equation model where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. All exogenous variables are predicting latent HbP.

Model 2: Structural equation model where all exogenous variables are used to predict observed rates from each indicator separately. Coefficients were similar in models that only included one indicator each.

In all models, parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, the measurement model in Model 1 and constants in Model 2 are not displayed.

	Model 1		Mod	lel 2	
	Latent HbP	SHR	Fatal Encounters	MPV	The Counted
	Unstd Std	Unstd Std	Unstd Std	Unstd Std	Unstd Std
Salary Disparity	-0.383 -0.045	1.121 0.093 ^{FMC}	-1.071 -0.052 ^s	-0.652 -0.044 ^s	-0.772 -0.055 ^s
Num. of Spec. Unit Types	0.181 0.135*	0.268 0.142+	$0.498 0.156^{**C}$	0.317 0.137*	0.277 0.126+ ^F
Percent Non-Sworn	0.063 0.113*	0.169 0.213**	0.235 0.175*** ^{MC}	0.106 0.109* ^F	0.084 0.091* ^F
Restrictive Foot Pursuit	-0.140 -0.052	0.064 0.017	-0.223 -0.035	-0.257 -0.056	-0.173 -0.040
Restrictive Vehicle Pursuit	-2.394 -0.141**	-0.913 -0.038 ^{MC}	-3.006 -0.075	-4.377 -0.150** ^S	-4.043 -0.146* ^s
Firearm Display Doc.	-0.620 -0.063	-0.476 -0.034	-1.761 -0.075	-1.005 -0.059	-1.432 -0.089+
Less-Lethal Doc.	-0.050 -0.002	-3.848 -0.093+	-2.281 -0.032	-0.065 -0.001	-0.251 -0.005
College Requirement	-1.827 -0.077	-0.918 -0.028	-3.979 -0.071	-3.037 -0.075	-3.018 -0.078
New Hire Ad. Training	-0.060 -0.015	0.124 0.022	-0.391 -0.041	-0.130 -0.019 ^c	$0.172 0.027^{M}$
In-Service Com. Pol.	-0.100 -0.026	-0.288 -0.054	-0.722 -0.079 ^M	-0.201 -0.031 ^{FC}	$0.086 0.014^{M}$
Recruit Com. Pol.	-0.485 -0.134*	-0.496 -0.098	-0.560 -0.065	-0.884 -0.142*	-0.668 -0.113*
Dash Cams	0.099 0.010	-1.350 -0.095 ^{FM}	2.660 0.111* ^{SMC}	0.226 0.013 ^{SFC}	-0.719 -0.044 ^{FM}
Body Cams	0.780 0.070	-0.543 -0.035	1.613 0.060	1.318 0.068	1.617 0.088+
Authorizes Soft Projectiles	1.972 0.131*	2.258 0.107*	1.486 0.042	3.489 0.135**	2.966 0.121*
Authorizes Chemicals	-1.642 -0.173***	$-1.044 -0.078^{M}$	-3.876 -0.171**	-2.864 -0.175*** ^s	-2.254 -0.145**
Authorizes Neck Restraint	1.064 0.109*	0.569 0.041	2.198 0.094	1.799 0.107*	1.696 0.106+

Table 6.10: Agency Complexity and Control Predicting HbP Rates from Different Sources

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1 (Significance tests are taken from the unstandardized model.)

S: Significantly different from the coefficient predicting SHR based on a post-estimation Wald test (p<0.05).

F: Significantly different from the coefficient predicting Fatal Encounters based on a post-estimation Wald test (p<0.05).

M: Significantly different from the coefficient predicting MPV based on a post-estimation Wald test (p<0.05).

C: Significantly different from the coefficient predicting Counted based on a post-estimation Wald test (p<0.05).

Model 1: Structural equation model where latent HbP has four indicators based on rates derived from the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. All exogenous variables are predicting latent HbP.

Model 2: Structural equation model where all exogenous variables are used to predict observed rates from each indicator separately.

All models control for city context (firearm violence, population size, disadvantage index, Black-White inequality, Black-White segregation, and

Hispanic/Latino-White Inequality). Findings for these covariates are similar to those shown in Table 6.8.

In all models, parameters are estimated using maximum likelihood with missing values (mlmv) and standard errors are adjusted for 44 state clusters. To conserve space, the measurement model in Model 1 and constants in Model 2 are not displayed.

Category		Hypothesis	Table	Finding
City Predictors				
Community Violence	H1.	Firearm Violence 7 HbP	All	\checkmark
Socio-Economic Context	H2.	Concentrated Disadvantage 7 HbP	All	\checkmark
Age and Gender	H3.	Percent of Young Males 7 HbP	6.3, 6.4	X
Percent Minority	H4.	Percent Black 7 HbP	6.3	X (Inverse)
	H5.	Percent Hispanic/Latino 7 HbP	6.3	X
	H6.	Percent Black フレ HbP	6.3	X
		Percent Hispanic/Latino レトレー HbP	6.3	X
Racial/Ethnic Inequality and	H7.	Black-White Socio-Economic Inequality 7 HbP	6.4, 6.5, 6.6	✓
Segregation		Black-White Housing Segregation 7 HbP	6.4, 6.5, 6.6	X (Inverse)
0.0	H8.	Hispanic/Latino-White Socio-Economic Inequality 7 HbP	6.4, 6.5, 6.6	X (Inverse)
		Hispanic/Latino-White Housing Segregation 7 HbP	6.4	X
Agency Predictors				
Agency Demographics	H9.	Percent Black V HbP	6.5	X
		Percent Hispanic/Latino ≥ HbP	6.5	X
	H10.	Racial/Ethnic Representativeness → HbP	6.5	X
	H11.	Percent Female Y HbP	6.5	X
Organizational Complexity	H12.	Vertical Differentiation/Hierarchy 7 HbP	6.6	X
	H13.	Functional Differentiation/Specialization 7 HbP	6.6	\checkmark
	H14.	Occupational Differentiation/Civilianization ビ HbP	6.6	X (Inverse)
Organizational Control	H15.	Restrictive Pursuit Policies V HbP	6.6	 ✓ (Only vehicle pursuits)
	H16.	Restrictive Use of Force Documentation ⊌ HbP	6.6	X
	H17.	Education Requirements ビ HbP	6.6	X
	H18.	New Hire Training Requirements レ HbP	6.6	X
	H19.	Community Policing ┙ HbP	6.6	$\checkmark (Only for new recruits)$
	H20.	Video Surveillance ビ HbP	6.6	X
	H21.	Less-Lethal Authorization 凶 HbP	6.6	\checkmark /X (Mixed results)
		Soft Projectiles ビート HbP	6.6	X (Inverse)
		Chemical Weapons ┙ HbP	6.6	\checkmark
		Neck Restraining Techniques	6.6	X (Inverse)

Table 6.11: Summary of Findings

 \checkmark Supported; X Not supported; \checkmark /X Mixed results; Inverse: Finding was in the opposite of the predicted direction

Chapter 7: CONCLUSION

Summary of Results

This dissertation sought to improve the literature on city-level homicide by police rates by 1) developing a model for measurement of homicide by police that draws on multiple sources of data and 2) utilizing this measurement model to examine potential city/agency-level predictors of homicide by police. To create the measurement model, I utilized homicide by police rates derived from four different sources — the Supplementary Homicide Reports, Fatal Encounters, Mapping Police Violence, and The Counted. I found that all four indicators, but especially the rates derived from MPV and The Counted, are strongly associated with the estimated latent homicide by police rate.

In multivariate analyses, I used this measurement model to test several categories of potential predictors including demographic and social aspects of the population served by an agency and agency-specific demographics, policies, and practices. A summary of the substantive findings can be found in Table 6.11. Agency-specific policies and practices are understudied in the literature on geographic variation in lethal force and some of the agency-specific predictors tested here have not be included as predictors in prior studies. These new predictors are additional training requirements for new hires who have prior experience or a certification, whether agencies had restrictive foot or vehicle pursuit policies, whether agencies authorized specific less-lethal weapons and techniques, and the percentage of authorized less-lethal options that require documentation when they are used.

Amongst the variables that related to the population served by the agency, I find that firearm violence and population size are strong predictors of a higher latent homicide by police rate. Percent Black was associated with a lower HbP rate, while percent Hispanic/Latino was not significantly associated with HbP. Black-White socioeconomic inequality was associated with

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higher HbP while Black-White segregation and Hispanic/Latino-White socioeconomic inequality were associated with lower HbP. These findings create complications for how racial threat theory (Blalock, 1967; Blumer, 1958) and structural discrimination theory theories (Bonilla-Silva, 1997; Murphy & Walton, 2013; Reskin, 2012) have been used in the past by researchers interested in police violence.

Variation in agency demographics was not predictive of the latent HbP rate. Agencies with more minority representation and agencies with a higher percent of female officers were not statistically different than agencies with less minority representation or a lower percent of female officers. This suggests that simple numerical diversity may not have a strong impact on departmental culture, as some have argued before (Silver et al., 2017; Weitzer, 2000; Wilkins & Williams, 2008).

Agencies with greater organizational complexity in terms of the number of specialized unit types (i.e., functional differentiation) and a higher percentage of civilian personnel (i.e., occupational differentiation) had statistically significantly higher levels of homicide by police. The former finding is in alignment with community policing advocates' calls for more generalists rather than specialists within agencies (Kelling & Moore, 1988; Maguire, 2003; Maguire et al., 2003; Zhao et al., 2010). However, the latter finding contradicts community policing advocates' recommendations to civilianize police agencies (Maguire et al., 2003).

Agencies with higher levels of organizational control in the form of more restrictive vehicle pursuit policies had lower homicide by police rates. This is aligned with arguments made by older police reform movements, which said that greater formalization would be associated with less police violence (Fyfe, 1988; Reiss, 1980; Walker, 1993). However, other measures of formalization (i.e., more restrictive foot pursuit policies and use of force documentation requirements) and professionalization (i.e., educational requirements and additional training requirements for new hires with prior experience or certification) were not statistically significant predictors of HbP.

Agencies that showed greater commitment to the community policing philosophy by requiring more new recruits to engage in community policing training experienced statistically significantly lower levels of homicide by police. This is in alignment with the recommendations of community policing advocates (Kelling & Moore, 1988; Maguire, 2003; Maguire et al., 2003; Zhao et al., 2010) but contradicts prior research that has attempted to measure the impact of community policing on homicide by police (Jennings & Rubado, 2017; Legewie & Fagan, 2016; Pang & Pavlou, 2016).

I find no statistically significant association between the agencies' use of body cameras or dashboard cameras and the latent homicide by police rate. Any impacts that body camera and dashboard camera usage may have on HbP may be mixed. Advocates call for their use with the idea that officers will be more hesitant to use unnecessary force because they know that they are being recorded. Alternatively, as argued by Pang and Pavlou (2016), police may view cameras as providing evidence that *justifies* their use of force decisions, which could make them more likely to engage in lethal force.

Policies authorizing less-lethal options for the use of force are mixed in their associations with homicide by police levels. Specifically, agencies that authorize chemical agents other than OC spray or foam (such as tear gas and mace) have a lower homicide by police rate. However, agencies that authorize the use of soft projectiles (including rubber bullets and bean bag rounds) and those that authorize neck restraining techniques (including vascular neck restraints and chokeholds) have higher homicide by police rates. In addition to displaying models that take multiple sources of data into account, I also test models that predict each HbP indicator separately. These models illustrate that the issue of data choice can lead to different findings. As expected, the models predicting SHR rates are substantively different from the models predicting media-based rates. However, the media-based models are also different from one another. Of key importance, the models predicting the MPV rate are nearly identical to the models predicting the latent HbP rate using all four indicators. Some of these differences in coefficient sizes are statistically significant (see Table 6.8, 6.9, and 6.10).

Discussion

This dissertation set out to develop and test a model for measurement that utilizes several different indicators of homicide by police rates to estimate the latent, "true" HbP rate. The hope was that this would be a viable method for overcoming data quality issues amongst these different sources of police homicide data. Instead, this measurement model indicates its own redundancy. All of the indicators used here load strongly onto the same factor, meaning that they do relate to the same latent construct. However, the rate based on Mapping Police Violence has a particularly strong association with the latent factor. Related to this, multi-variate models using the MPV rate as the outcome are virtually identical to the model predicting the latent HbP rate using all four indicators. This implies that, at least for the sample type used in this dissertation (i.e., municipal police agencies serving large populations), using a rate based on MPV data is just as good as using the more complex measurement model developed here.⁶⁵

⁶⁵ This endorsement comes with the caveat that MPV required slightly more alterations when cleaning the data than FE or The Counted, which are detailed in Chapter 3 of this dissertation. This is based on a download of the data from August 2018. The media-based datasets are sometimes adjusted by their distributors when errors or missing decedent come to their attention. These inconsistencies and misspellings in agency names may be less prominent in later versions of the data.

Some of the findings regarding agency-specific predictors are encouraging, others less so. Community policing is often touted as a solution to issues around police legitimacy. I find that agencies that have more recruits who train in community policing techniques tend to have lower HbP. In addition, authorizing chemicals for use by police is associated with lower HbP rates, although whether such chemicals have other severe consequences for suspects cannot be explored in this study. Restricting officer discretion regarding vehicle pursuits is also associated with lower HbP. However, the authorization of soft projectiles and neck restraining techniques, which are ostensibly provided to officers as alternative to the use of lethal force, are associated with higher homicide by police rates.

Limitations

These analyses have several limitations. Of primary importance — the study is crosssectional, so its findings should be taken with caution, especially those findings regarding agency policies and practices. For instance, this study examined whether authorization of certain lesslethal weapons and techniques is associated with the homicide by police rate. Several potential less-lethal options available in LEMAS 2013 could not be adequately tested because there is little variation in their authorization. Conducted energy devices (e.g., Tasers) in particular have become ubiquitous but the potential impact that their introduction over time into departments may have had on homicide by police rates cannot be detected by this kind of study. Indeed, any of the policies and practices that have a cross-sectional association with homicide by police rates in this dissertation may have no appreciable effect if they are introduced into a department. Some unmeasured factor that leads to both the use of a particular policy and the homicide by police rate (for instance, some aspect of departmental culture) could lead to the cross-sectional associations seen here.

This study is also limited by the agency-specific variables available. Because they are drawn from LEMAS 2013, the agency demographics, policies, and practices tested here reflect the agencies' situations during the year 2012 or on January 1st of 2013. The agencies' demographics, policies, and practices may have changed between then and the years of homicide by police data used here (i.e., 2015 and 2016). In addition, this study could only use those measures available in LEMAS 2013. For instance, detailed information about use of force policies (e.g., whether the agency requires officers to give a verbal warning before using deadly force, whether the agency requires officers to exhaust other possible alternatives before using deadly force, or the kind of use of force continuum or matrix used by the agency) are not available through LEMAS. In addition, some policies and practices tested in prior studies could not be tested here because they were only asked about in earlier versions of LEMAS (e.g., the number of formal policies the agency has, whether the agency has an internal affairs unit, the number of pre-screening tools used in hiring, and the presence of a citizen complaint review board were all predictors in prior studies of geographic variation in homicide by law enforcement that used prior versions of LEMAS).

This analysis is limited to municipal agencies serving large populations. Like much of the prior literature in this area, this means that agencies serving smaller populations have been neglected. Based on Mapping Police Violence, the agencies in this sample were responsible for about 32.6% of law enforcement officer deaths that occurred in 2015 and 2016.⁶⁶ That means that a large proportion of officer-involved homicides are due to other agency types, which are unaccounted for in most agency-level studies of variation in homicide by police.

⁶⁶ According to the MPV data, 754 individuals died due to involvement with the agencies in this sample and 2,316 individuals dies due to law enforcement involvement in the years 2015 and 2016.

Relatedly, the restriction to municipal agencies serving large populations give the study a small sample size (n = 254), meaning that false negative findings are more likely because of issues of statistical power. SEM analyses are best conducted on large samples. Commonly, samples of fewer than 100 cases are considered small, samples of 100 to 200 cases are thought of as moderately sized, and samples of more than 200 cases are considered sufficiently large (Kline, 2015). This study is in line with many other published SEM studies; for instance, a review of 74 SEM studies found that these studies had a median sample size of about n=260 (Westland, 2010). However, SEM sample considerations are highly dependent on the number of parameters being estimated (Jackson, 2003; Kline, 2015; Westland, 2010) and this analysis involves a large number of covariates. The final model in Table 6.7 includes 22 exogenous variables, 4 observed endogenous variables, and 1 latent variable. It must also include parameter estimates of the variance and covariance matrix for all of these variables. For all of the models presented in the paper, I also checked for simpler models with fewer covariates. For the most part, findings were robust to the number of covariates entered into the models, but there is still a chance that some covariates were found to be statistically insignificant predictors because of a lack of power rather than a real lack of association with the outcome.

Conclusion

The goals of this dissertation were to develop a model for measurement of homicide by police that draws on multiple sources of data and utilize this measurement model to examine potential city/agency-level predictors of homicide by police. I find that the measurement model developed is seemingly redundant — utilizing rates derived solely from Mapping Police Violence yields nearly identical results. Future studies, at least those using a similar subset of agencies (i.e., municipal police agencies serving large populations), should consider using MPV rates as their outcome. In addition, older studies using the SHR should not be entirely abandoned

as researchers explore geographic variation in homicide by police rates. The SHR is still strongly associated with the underlying latent HbP rate. However, findings from older studies should be approached with caution. SHR-based rates may yield substantively different findings, although many findings were similar across models. In addition, utilizing Fatal Encounters should also be done with caution for similar reasons.

Future work should continue to explore the differences between these data sources. The SHR and Fatal Encounters both use different operationalizations of officer-involvement. It remains unclear the extent to which the SHR rates differ from the MPV and The Counted rates due simply to missingness or to operational differences. Findings therefore may be different due to missing cases or due to effects being different for "justifiable homicides" compared to "officer-involved homicides." Fatal Encounters spans a longer period of time than MPV and The Counted and most of the incidents logged in MPV and The Counted are likely logged in FE as well. If researchers find an easy way of identifying which incidents in FE follow the MPV operationalization, then it will be easier for them to engage in longitudinal analyses of homicide by police.

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Appendix: Pairwise Correlations Between Independent Variables

	1	2	3	4	5	6	7
1. Firearm Violence	1.000						
2. Population of 250,000 or more	0.356***	1.000					
3. Disadvantage Index	0.480***	0.069	1.000				
4. Percent Young Males	0.036	-0.120+	-0.019	1.000			
5. Percent w/o a College Degree	0.232***	-0.024	0.843***	-0.107+	1.000		
6. Unemployment	0.509***	0.110 +	0.857***	0.039	0.511***	1.000	
7. Percent Female-headed Households	0.520***	0.097	0.931***	0.018	0.707***	0.743***	1.000
***p<0.001, **p<0.01, *p<0.05, +p<0.1							

Table A.1: City Economic and Demographic Context

Table A.2: City Percent Black and Black-White Inequality

	8	9	10	11	12	13
8. Percent Black	1.000					
9. Black-White Inequality Index	0.423***	1.000				
10. Black-White Segregation	0.939***	0.540***	1.000			
11. White-Black Median Income Ratio	0.290***	0.896***	0.410***	1.000		
12. Black-White Unemployment Ratio	0.375***	0.865***	0.449***	0.659***	1.000	
13. White-Black College Educ Ratio	0.454***	0.884***	0.570***	0.709***	0.628***	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.3: City Percent Hispanic/Latino and Hispanic/Latino-White Inequality

	14	15	16	17	18	19
14. Percent Hispanic/Latino	1.000					
15. Hispanic/Latino-White Inequality Index	0.030	1.000				
16. Hispanic/Latino-White Segregation	0.956***	0.169**	1.000			
17. White-H/L Median Income Ratio	-0.095	0.797***	-0.013	1.000		
18. H/L-White Unemployment Ratio	-0.147*	0.736***	-0.063	0.452***	1.000	
19. White-H/L College Educ Ratio	0.308***	0.668***	0.449***	0.302***	0.169**	1.000
***n < 0.001 $**n < 0.01$ $*n < 0.05$ $+n < 0.1$						

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.4: Agency Demographics

20	21	22	23	24	25
1.000					
0.232***	1.000				
0.184**	0.523***	1.000			
-0.001	0.017	0.023	1.000		
0.097	-0.094	-0.154*	0.316***	1.000	
0.153*	0.219***	0.133*	0.156*	0.477***	1.000
	1.000 0.232*** 0.184** -0.001 0.097	1.000 0.232*** 1.000 0.184** 0.523*** -0.001 0.017 0.097 -0.094	1.000 0.232*** 1.000 0.184** 0.523*** 1.000 -0.001 0.017 0.023 0.097 -0.094 -0.154*	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.5: Organizational Complexity

	26	27	28
26. Salary Disparity (Hierarchy)	1.000		
27. Num. of Specialized Unit Types (Specialization)	0.299***	1.000	
28. Percent Non-Sworn (Civilianization)	-0.181**	-0.123+	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.6: Organizational Control: Formalization

	29	30	31	32
29. Restrictive Foot Pursuit Policy	1.000			
30. Restrictive Vehicle Pursuit Policy	-0.001	1.000		
31. Firearm Display Documentation	0.051	0.054	1.000	
32. Less-Lethal Documentation	0.106+	0.069	0.275***	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.7: Organizational Control: Professionalization

	33	34	35	36
33. College Requirement	1.000			
34. New Hire Training Index	0.055	1.000		
35. New Lateral Hire Training Scale	0.047	0.874***	1.000	
36. New Pre-Service Hire Training Scale	0.046	0.892***	0.560***	1.000
	510.10		0.000	2100

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.8: Organizational Control: Community Policing

	37	38
37. In-Service Community Policing Scale	1.000	
38. Recruit Community Policing Scale	0.244***	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.9: Organizational Control: Video Surveillance

	39	40
39. Dash Cams	1.000	
40. Body Cams	0.150*	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

Table A.10: Organizational Control: Less-Lethal Weapons and Techniques

	41	42	43
41. Authorizes Soft Projectiles	1.000		
42. Authorizes Chemicals	0.348***	1.000	
43. Authorizes Neck Restraining Techniques	0.168**	0.139*	1.000

***p<0.001, **p<0.01, *p<0.05, +p<0.1

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Education

2024	Ph.D, Sociology [expected], The Pennsylvania State University
	Certificate in Quantitative Methodology
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	Committee: Eric Baumer (chair), Richard Felson, John Iceland, and Eric Plutzer
	Dissertation Title: "Patterns of Force: A Comparison of Data Sources on Officer-
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2015	M.A., Criminology, The Pennsylvania State University
	Committee: Corina Graif (chair), Richard Felson, Derek Kreager
	Thesis Title: "Residential Poverty, School Neighborhood Poverty, and Adolescent
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2012	B.A., Liberal Arts, Westminster College, Fulton, MO
	Major: Anthropology/Sociology, Minor: French
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Employment

2019 - present	Instructor of Criminal Justice, Social Sciences Department, Northwestern
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Publications

- Felson, R. B., Savolainen, J., Whichard, C., Fry, S. & Ellonen, N. (2021). Opportunity and the sexual abuse of adolescents. *Child Abuse & Neglect*, 122, Article 105363. https://doi.org/10.1016/j.chiabu.2021.105363
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