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Understanding misdemeanor enforcement: The roles of calls for service and community characteristics

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Abstract

This study examines the roles of calls for service (i.e., police-related 911 calls) and community characteristics in explaining variation in enforcement rates for low-level, misdemeanor offenses, which make up the large majority of police enforcement activity. The study site is Prince George's County, Maryland, and the unit of analysis is the police department's 65 patrol beats, studied over a 10-year period, during 2006–2015. Overall, misdemeanor enforcement rates vary at the beat level, and that variation can be largely explained using a combination of indicators about community characteristics and calls for service. The findings indicate, though, that the calls for service rate is the most important variable in explaining misdemeanor enforcement variation. These findings inform both future research on police activity, and current policy debates about what drives enforcement rates and the role of discretion in enforcement outcomes.

KEYWORDS

calls for service, community characteristics, Misdemeanor enforcement, police discretion

1 | INTRODUCTION

Despite the significant proportion of time and resources devoted by police agencies to the enforcement (e.g., citations, summonses, arrests) of low-level, misdemeanor offenses, relatively little is known about misdemeanor enforcement practices and the mechanisms driving variation in such enforcement across and within police jurisdictions. According to official statistics, police enforcement activities are mostly focused on misdemeanor offenses, as opposed to more serious, felony offenses. Data from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program show that, of 11.3 million reported arrests, approximately 18.1% are attributable to “Part I” violent or property offenses, most of which are felonies (e.g., murder, rape, robbery, aggravated assault, burglary). Therefore, misdemeanors and ordinance violations (i.e., “Part II” offenses) make up the majority of reported arrests, accounting for the remaining 81.9% (Lum & Nagin, 2017). Lum and Nagin (2017) conducted a survey of police departments and found that, on average, officers spend between two and 4 hours processing an arrest for a Part II offense. Given that there were 9.2 million arrests for these offenses in 2013 alone, arrests for misdemeanor offenses take a “major bite out of officers' time” (Lum & Nagin, 2017, p. 4). This time estimate from Lum and Nagin's (2017) survey does not account for other enforcement activities, such as citations, warrant services, or summonses, suggesting that the total allocation of police time toward misdemeanor enforcement is even higher.

In the current study we use 10 years of data (2006–2015) from Prince George's County, Maryland, to examine misdemeanor enforcement across police administrative units (i.e., beats) within a single jurisdiction. Specifically, we address two interrelated research questions:

1) What proportion of law enforcement activity involves misdemeanor versus felony offenses, and do misdemeanor enforcement rates vary across patrol beats within a single jurisdiction?
2) To what extent can beat-level variation in misdemeanor enforcement rates be explained by community characteristics, including demographic composition, economic disadvantage, population density, and rate of calls for police service?

Extant literature on policing provides several avenues for exploring such beat-level variation. First, incident-level studies highlight the considerable amount of discretion that individual police officers exercise in the activities they perform, how they interact with citizens, and the processes by which they invoke and uphold the law (Black, 1970; Engel et al., 2018; Klinger, 1994; Mastrofski, Snipes, & Supina, 1996; Skogan & Frydl, 2004; Wilson, 1968). Discretion-related studies also highlight the importance of context in informing police decision-making, particularly the relationship between neighborhood characteristics (e.g., racial-ethnic composition) and aggregate enforcement outcomes such as low-level drug arrest rates (Eitle & Monahan, 2009; Parker & Maggard, 2005; Warner & Coomer, 2003) or traffic citation counts (Ingram, 2007). Findings also suggest that requests for service and state and agency-level policies are also important for informing the ways in which misdemeanor offenses are policed.

In the following section of this paper we outline several related literatures, all of which have important implications for understanding misdemeanor enforcement. We begin by reviewing the existing data on the relative composition of misdemeanor and felony offense processing in the criminal justice system. Next, we discuss the literature on determinants of police behavior. Because the current study is focused on explaining aggregated misdemeanor enforcement rates, we provide only a brief discussion on police discretion and individual/incident-level outcomes before introducing the related literature on neighborhood context and enforcement rates. Then, we contextualize the literature on calls for service to highlight the potential explanatory power of community members' demand for service. Finally, we review extant work on the importance of state and agency-level policies in shaping police enforcement practices.

2 | BACKGROUND

2.1 | Misdemeanor justice

The empirical study of crime and criminal justice in the United States has traditionally focused on felony, rather than misdemeanor, offenses. However, in recent years, misdemeanor justice has come to the forefront of policy conversations, especially those surrounding criminal justice reform (Natapoff, 2015). As highlighted in the introduction to this paper, most enforcement activity by police is directed toward misdemeanor offenses, and that skew continues in successive stages of the criminal justice system. According to Natapoff (2015), approximately ten million misdemeanor cases are filed per year (compared to two to three million felony cases) and 80% of cases on state court dockets are misdemeanors. These estimates are mirrored in Stevenson and Mayson's (2018) assessment of misdemeanor case filings, which showed that misdemeanors represented between 74 and 83 percent of total caseloads, and the ratio of misdemeanor-to-felony cases remained relatively stable at about three-to-one during the period of 2007–2017.

2.2 | Explaining variation in police enforcement outcomes

2.2.1 | Police discretion

Extant literature on enforcement outcomes (e.g., arrest, stop and frisk, police use of force) focuses heavily on the exercise of discretion in police decision-making in individual police-citizen encounters. Research suggests that police discretionary decisions are informed by legal and extra-legal situational factors, officers' characteristics and outlooks, organizational characteristics and policies, as well as community characteristics (Skogan & Frydl, 2004). Generally, incident-level research on discretion suggests that legal factors (e.g., seriousness of the offense, suspect noncompliance) have a stronger influence over arrest decisions compared to extra-legal characteristics (Skogan & Frydl, 2004). However, in a more recent meta-analysis, Kochel, Wilson and Mastrofski (2011) find that minority suspects are more likely to be arrested than white suspects, even after controlling for important legal factors such as offense severity, prior record of the suspect, and quantity of evidence at the scene, reinforcing that extralegal characteristics do inform discretion.

The incident-level findings pertaining to police discretion and decision-making have several unique implications for misdemeanor justice. Results show that offense severity has a strong influence on officer decision-making, at least when it comes to arrest decisions. Seriousness of the offense (along with the strength of evidence) often removes discretion from officers' arrest decisions, suggesting that officers have fewer options to invoke arrest alternatives (i.e., less discretion) for more serious offenses (Engel et al., 2018). Therefore, officers may exercise greater discretion when policing misdemeanor versus felony offenses. Although findings from studies of police discretion are often presented at the individual or incident levels, they provide guidance for aggregate-level examinations of enforcement outcomes, specifically the impact of socioeconomic and cultural context of neighborhoods in which police-citizen encounters occur.

2.2.2 | The importance of community context

In his seminal work, Smith (1986) examined the influence of neighborhood context on police behavior in 60 neighborhoods in three U.S. cities. He found that, in more racially heterogeneous neighborhoods, police provide more assistance to residents and initiate more contacts with suspected law violators. Additionally, variation in police use of coercive authority is linked to the racial composition of the neighborhood, rather than the race of individuals confronted by the police (Smith, 1986). Regarding offense seriousness, Smith (1986) suggests that there may be a threshold effect at work, in which, before police report an incident, the offense must reach a higher level of seriousness in higher-crime neighborhoods. This “threshold” suggests that offense severity (e.g., misdemeanor, felony) may differentially influence discretion in certain neighborhood contexts.

In a more recent study, Ingram (2007) used data from a large metropolitan city in the Southwest United States to investigate the effect of neighborhood characteristics on traffic citation practices of the police. Ingram (2007) concluded that levels of disorganization, disadvantage, violent crime, and racial composition in neighborhoods significantly predict the number of citations issued by officers in traffic encounters, independent of specific encounter-level characteristics.

Most of the aggregate-level literature focuses on the community factors that explain drug-related crime rates. Using drug possession and trafficking arrest data from the UCR, along with socioeconomic data from the 1990 Census for a sample of 187 U.S. cities, Mosher finds that a city's racial composition is the strongest predictor of drug arrest rates, controlling for economic deprivation variables. Similarly, Warner and Coomer (2003) analyze the extent to which police arrest rates can be accounted for by neighborhood-level variables thought to be associated with police discretion (e.g., percentage below poverty, percentage African American, percentage below high school degree, percentage female-headed households with children under the age of 18, and a measure of residential stability). They find that, after statistically controlling for residents’ self-reported levels of visible drug trafficking in their neighborhoods, trafficking arrests are not significantly affected by neighborhood disadvantage. They conclude that disadvantage may increase the likelihood of visible drug-trafficking, the variable which was most strongly related to drug-trafficking arrests (Warner & Coomer, 2003).

Parker and Maggard (2005) examine the impact of similar structural level factors on race-specific drug arrests (measured as a count). They find that, contrary to their hypothesis, concentrated disadvantage is associated with a statistically significant decrease in both total arrests and possession drug arrests for African Americans (but not for whites). They also find that a rise in the black population is associated with a decline in all types of drug arrests among African Americans over time. Alternatively, changes in percentage black did not significantly increase or decrease white arrests. Lastly, increases in police presence were positively associated with increases in arrests for drug sales among African Americans (Parker & Maggard, 2005).

Relatedly, Eitle and Monahan (2009) use data from 260 cities to examine the impact of structural disadvantage and disorganization indicators and police organizational factors on race-specific arrest rates for drug offenses. They categorized police organizational factors as indicators of “structural complexity” (e.g., task differentiation, ratio of sworn to non-sworn officers, unionization, and salary differentials) and “structural control” (e.g., count of formal written policies for police conduct, employee drug testing, and pre-employment training and education). Eitle and Monahan (2009) found racial differences in the relationship between social disorganization, disadvantage, and arrest rates. First, disadvantage (measured as an index of poverty rate and percentage of males who are unemployed) was associated with a statistically significant increase in black arrest rates, but not white arrest rates. Additionally, race-based economic competition (measured by a racial inequality index) was found to be a significant predictor of both black and white drug arrest rates, increasing arrest rates for both groups. Police organizational factors also had differential impacts on white versus black arrest rates. While greater functional (e.g., task scope and civilianization) and spatial (e.g., pay differentials and number of facilities) differentiation were both associated with increased drug arrests for blacks and whites, police force size only increased the white (not black) drug arrest rate. Formalization (i.e., the number of formal, written policies) was found to influence both black and white drug arrest rates but in opposite directions, where increases in formalization were associated with increases in black arrest rates and decreases in white arrest rates (Eitle & Monahan, 2009). In addition to the direct associations of police organization factors, Eitle and Monahan (2009) also illustrate that increased formalization mitigates the effect of political and economic competition on the black arrest rate, suggesting that, in addition to community structural factors, departmental administrative policies serve as important mechanisms for informing enforcement rates.

2.2.3 | State and agency policy

In addition to situational factors and neighborhood context, state and agency policies place relevant constraints on police behavior and the enforcement of certain misdemeanor crimes like drug offenses, as found by Eitle and Monahan (2009). Specifically, jurisdictions may have mandatory arrest policies for certain crimes (Engel et al., 2018), while other jurisdictions may promote civil (noncriminal) responses to such offenses. For example, using group-based trajectory models to sort jurisdictions by their use of misdemeanor arrests over time, Lum and Vovak (2018) found that there were no covariates that explained membership of any agency in any trajectory. Within trajectories, there were no commonalities on crime, poverty, population density, racial and ethnic heterogeneity, or percentage of the population that was foreign born. Therefore, Lum and Vovak (2018) conclude that: "… the use of misdemeanor arrests might well be a policy choice by agencies" (pp. 549–550) or based on other factors not detected or analyzed in their paper. The complex relationship between misdemeanor policing and discretion provides further motivation for the exploration of the potential mechanisms explaining misdemeanor enforcement rates.

2.3 | Calls for service

In addition to the individual and community characteristics discussed above, calls for service influence enforcement practices, as the majority of incidents are reported directly to police by victims and witnesses (Varano, Schafer, Cancino, & Swatt, 2009). Therefore, while incident-level factors (e.g., suspect's race), neighborhood context (e.g., socioeconomic disadvantage) and agency policy may inform enforcement rates through their effects on officer behavior, calls for service may inform enforcement rates first by bringing incidents to officers' attention and by signaling community residents' preferences about enforcement.

Criminal justice research primarily uses calls for service (CFS) data as an indicator of the spatial and temporal distribution of criminal activity (Bursik, Grasmick, & Chamlin, 1990; Sherman, Gartin, & Buerger, 1989). In a National Institute of Justice report, Travis (1997) suggested that data from computer-aided-dispatch systems are useful for measuring daily police activities, as well as for determining the types of services community members seek from police. According to Kessler (1993), calls for service are the most important source of information available to police agencies about problems in their jurisdictions.

Because one role of the police is to respond to community members' requests, calls for service data are critical to understanding lower-level misdemeanor offenses, such as those related to disorder and other public nuisance crimes (e.g., loitering, disorderly conduct, public drunkenness). Long ago, Wilson (1968) suggested that calls for service (what he called citizen-invoked enforcement and order maintenance) must be followed by a police response to "avoid the charge of doing nothing" (p. 89). While not *all* calls for service will result in formal enforcement, in a report on "broken windows" policing in New York City, Bratton (2015) suggests that many misdemeanor arrests (and other police responses to quality-of-life offenses) stem from 911 and 311 calls for service, and that these arrests correlate closely with origin points for calls for service, especially those regarding disputes and disorderly behavior. That is, misdemeanor arrests occur in areas where community members request police service (through 911 or 311 calls) because police officers are deployed to areas in which complaints originate. However, it is important to note that while enforcements closely parallel calls for service in communities, there is not a one-to-one relationship between calls and arrests, because not every call for service results in police enforcement, some calls may result in multiple arrests, and multiple calls can stem from the same originating crime or problem, leading to a singular enforcement (Bratton, 2015; Warner & Pierce, 1993).

While it is somewhat intuitive that the rate at which community members request police service should inform the rate at which police enforce crimes, some suggest that this dynamic will vary with the characteristics of a community. Varano et al. (2009) summarize the established competing perspectives on the relationship between community characteristics, requests for service, and police behavior. One perspective states that the allocation of police resources increases as social status increases, suggesting that economically advantaged neighborhoods receive the most and best services while poor and minority neighborhoods receive fewer. Relatedly, others suggest police officers exert more coercive authority in disadvantaged neighborhoods, but more assistance-like behavior in relatively advantaged neighborhoods (Smith, 1986; Varano et al., 2009). Proponents of an alternative perspective posit that public resources are disproportionately concentrated in disadvantaged neighborhoods due to over-policing and more formalized (e.g., arrests rather than warnings) responses to crime. A third perspective argues that police behavior is a function of crime levels and the “tolerance of deviance” within neighborhoods. For example, if members of disadvantaged communities are more tolerant of deviance (as found by Sampson & Jeglum-Barusch, 1998), police may also view certain levels or types of crime as acceptable in these areas. In this case, higher levels of deviance could be accepted as normal and, therefore, formal intervention not warranted (Varano et al., 2009).

3 | METHODOLOGY

3.1 | Prince George's County as a study site

Prince George's County is located to the east of Washington, D.C. and is one of 24 counties in the state of Maryland. The county has grown appreciably in recent decades, from a reported population in the 1970 Census of 661,719, to 728,553 in the 1990 Census, to 863,420 in the 2010 Census. Overall, the county covers 483 square miles with a population per square mile of 1,788.8 in 2010. The 2010 Census found that Prince George's County was 85.1% minority, up from 75.7% in 2000. In 2010, the median household income in Prince George's County was $71,260, compared to the median income of $51,914 for the nation (U.S. Census Bureau, 2010a, U.S. Census Bureau, 2010b).

Prince George's County is a unique jurisdiction, particularly due to its status as the wealthiest majority-minority county in the country (Brigham, 2018; Rowlands, 2018). Despite this status, Prince George's neighborhoods are largely segregated, with a recent increase in the number of neighborhoods in the county with more than 85% of the residents of the same race (Wiggins, Morello, & Keating, 2011). Rowlands (2018) examined racial-ethnic homogeneity in the county's seven planning sub-regions (defined by the Maryland-National Capital Park and Planning Commission). In five of the seven sub-regions, most residents are African American (between 67% and 88% of sub-region population). Only the remaining two sub-regions are heterogeneous, in that no single racial-ethnic group is dominant. Police beats, used as the unit of analysis in the present study, mirror the distributions presented by Rowlands (2018). Of the 65 beats studied here over 10 years, 51 beats are majority African American, five are majority white, and two are majority Hispanic.

3.2 | Data

3.2.1 | Prince George's County Police Department enforcement data

Record data provided by Prince George's County Police Department (PGPD) contained information for all adults and juveniles subject to enforcement action during the period of January 1, 2006 through December 31, 2015, including incidents involving law enforcement service or response not necessarily related to an offense (N = 193,373). In this study, enforcement actions include arrests (for felonies and misdemeanors) and criminal citations (for misdemeanors). The underlying offense leading to the enforcement action is described in the records management system by a set of classification codes, and for each enforcement action, up to three classification codes may be recorded, in decreasing order of seriousness. In the data provided, 153 different classification codes were recorded at least once.

In the original, administrative data, the classification codes were not additionally categorized as being felonies or misdemeanors. Among the authors of this article, two independent coders assigned the 153 classification codes to one of

TABLE 1 Distribution of Classification Codes by Offense Severity & Incident Type

Category	N	Percent
Misdemeanor	131,759	68.1%
Felony	35,477	18.3%
Distress-Related	349	00.2%
Warrant	25,432	13.2%
Other	356	00.2%
Total	193,373	100.0%

the following five categories: Felony, Misdemeanor, Warrant Service, Distress-Related Police Service, and Other Miscellaneous/Official Record Keeping. Table 1 shows the distribution of enforcements according to these five categories.

Enforcement actions categorized as warrants designated that the officer encountered an individual with an open warrant. The distress category included events that are not inherently offense-related, but rather police responding to individuals in distress, such as "narcotic overdose," "missing person," or "injured person." The other category captured internal police record-keeping codes, such as "police criminal transport" and "other incidents." The distress-related, warrant, and other categories were easily categorized, and collectively represented 14% of the 153 classification codes. The remaining 86% of classification codes were assigned to either the felony or misdemeanor enforcement category.[1]

In addition to the misdemeanor/felony indicator, the PGPD enforcement data included information on date and time of enforcement and the type of enforcement (e.g., arrest, citation, warrant service). Demographic information about individuals subject to enforcement was also available (e.g., age, race, sex). We used these data to identify the number of misdemeanor arrests and citations (combined) against individuals aged 16 and older in each beat year to compose the numerator for the dependent variable of interest in this study (misdemeanor enforcement rate, described in more detail below).

3.2.2 | Prince George's Police Department calls for service data

Record data for all 911-dialed calls for service received by PGPD between 2006 and 2015 are included in this study (n = 5,773,420). During this ten-year period, there were six consequential changes to the record management system housing calls for service data, in terms of either the adoption of a new operational system, or changes in the data fields recorded for each call for service. Information which was consistently and continuously collected throughout the study period is analyzed in this study, including the following: date and time for dispatch and response (to assign the call to the correct year) and the beat location to which the call was assigned.

For the latter portion of the study period (2011 onwards) there was also information about the urgency and type of call. The "priority" data field included a priority rank score of 0 through 4. Calls designated at dispatch with

[1]The assignment of PGPD's classification codes was guided by the charging manual used in Maryland by District Court Commissioners, which includes for each potential criminal charge in Maryland the following information: an offense description, statutory citation, associated punishment, and a categorization of misdemeanor/felony. The inter-rater reliability for the misdemeanor/felony categorization was 73%. Of the codes for which there was not agreement, only 4% involved complete disagreement on the categorization of misdemeanor versus felony, while the other 23% were cases in which one coder assigned a matching charge to the classification, and the other did not. Among the handful of classification codes where a consensus could not be reached (due to insufficient details, often regarding dollar amounts in larceny offenses), the first 500 "incident summaries" (in which police officers provided additional incident information) were reviewed for each classification code by the authors, and codes which still could not be resolved were reviewed further in consultation with PGPD. Ultimately, all codes that involved disagreement were resolved and categorized as misdemeanors, except for one (larceny from a building), which was assigned to the felony category, despite being associated with misdemeanor and felony theft thresholds, to preserve the homogeneity of the misdemeanor category.

a priority of 0 are of the highest priority, and 3 are assigned as lowest priority. The priority category of 4 is not part of the hierarchical priority ranking system, but instead designates a different type of call. Priority 4 calls are police officer-initiated and closed calls for recording purposes, and do not require community member reporting via 911 calls. Except for Table 4 (presented later), all calls for service rates reported here include all priority level calls (0–4) for consistency throughout the study period.

3.2.3 | Prince George's County shape files and census data

The Census data used for this study includes population counts aggregated to Prince George's County at county-wide, police district, and police beat levels. Using data from the 2000 and 2010 Censuses (downloaded from American Fact Finder), we used linear interpolation to calculate the population base for study years 2006–2010. In the absence of post-2010 decennial Census estimates, we used American Community Survey (ACS) five-year estimates to interpolate population data for study years 2011–2015.

Beat-level population estimates were used to create variables of interest, such as proportions and rates (e.g., the proportion of beat residents aged 16–20-years-old). Because Prince George's County includes 217 Census tracts, and 67 police beats (i.e., boundaries drawn by the police agency to allocate officers and resources), shape files of beat maps were used to assign Census estimates to the 67 beats. Specifically, we used a land mass approach to determine the overlap between beat and Census tract, and then allocated the proportion of each age-race-gender group accordingly.[2] The population for Census tracts wholly contained within a beat were attributed totally to that beat (e.g., if Tract B falls entirely within the boundary of beat B2, 100% of Tract B's population was allocated to beat B2). The beat shape files also allowed calculation of the size of each beat in square miles.

3.3 | Study unit of analysis: 650 Beat-Years

Prince George's County's police beats vary in size, urbanicity, and population density. Data were not sampled for this study – the study data represents population data, and our final analyses include 65 police beats. During the study period, PGPD's jurisdiction encompassed 66 beats. However, beat B11 was excluded from analysis because it contains two hospital centers and a nursing home. Because of this, beat B11 has a very low noninstitutionalized population, but a high rate of calls for service due to the filing of reports by healthcare providers (e.g., the hospital will notify police of a shooting victim being treated). The study population's unit of analysis is the beat-year resulting in a sample size of 650 beat-years, representing 65 beats over the ten-year study period. During the ten-year study period, there were no changes in beat boundaries within the county.

3.4 | Measures

3.4.1 | Enforcement rates

In this study, the primary outcome of interest is the misdemeanor enforcement rate. The *misdemeanor enforcement rate* was created by dividing the total number of misdemeanor enforcements (combined arrests and citations) that occurred in a beat in a given year by the total population of the beat aged 16 and older in that year, multiplied by 1,000. This

[2]For example, if 40% of Census Tract A's land mass fell within beat B1, then 40% of Tract A's population was allocated to beat B1 (e.g., 40% white population, 40% black population, etc.).

calculation generates the rate of enforcement per 1,000 beat residents. We also examine two additional enforcement rates. The *felony enforcement rate* was calculated using only felony arrests, while the *total enforcement rate* was calculated by combining all misdemeanor and felony enforcements.

3.4.2 | Demographic composition

Using the Census data described above, we created multiple indicators to examine the relationships between beat-level demographic composition and enforcement rates. Race and ethnicity measures were created by dividing the total number of individuals of each race and ethnicity by the total beat population aged 16 and older, to create a proportion of the total beat belonging to each category in each beat-year. The resulting indicators provided proportions for each race/ethnicity category of interest (*Non-Hispanic white* (reference category), *Non-Hispanic black, and Hispanic*).[3]

Similarly, age variables (*proportion aged 16–20*; *proportion aged 66 and older*) were created by dividing the total number of beat residents within that age range by the total number of individuals (of all ages) in that beat. These measures allow us to isolate the effect of population age skews in beats, which may have an impact on enforcement rates when beats are on average either younger or older in age composition.

3.4.3 | Population density

A measure of beat *population density* was created by dividing the total beat population aged 16 and older by the total square miles of the beat, producing a rate of individuals per square mile. Given the layout of beats within the county, more urbanized and smaller beats are concentrated in the western half of the county.

3.4.4 | Disadvantage indicators

A dummy variable was created to identify the 16 beats directly adjacent to Washington, D.C. (*DC-Adjacent Beat*). These beats have higher rates of both calls for service and enforcement, and a significant number of D.C. residents subjected to enforcement action in the county. The northeast and southeast quadrants of D.C., which are the D.C. quadrants that share a border with Prince George's County, have much higher rates of crime compared to the other two D.C. quadrants and are more socioeconomically disadvantaged.

Additionally, we include a disadvantage index composed of the percent female-headed households, percent on public assistance, and unemployment rate.[4] The Census data used to create these measures came from the 2010 Census and so, although our unit of analysis is the beat-year, the disadvantage index score remains constant within beats over time (i.e., the disadvantage index score for beat A1 in 2006 is equivalent to A1's disadvantage score in 2015). Higher scores on the index represent higher levels of disadvantage in a given beat.

[3]Prince George's Police Department enforcement data included additional race/ethnicity categories of Asian/Pacific Islander and American Indian, but due to their small representation within Prince George's County and due to the lack of differentiation in the Census' "Non-Hispanic Other" category, our racial and ethnicity variables focuses on the larger segments of White, Black, and Hispanic residents. However, enforcement events involving individuals identified as Asian/Pacific Islander or as American Indian were not excluded from the enforcement totals and rates.

[4]Both a principal components analysis and an exploratory factor analysis confirmed that additional, commonly used disadvantage indicators (percent of 18–24-year-olds with no high school diploma and percent below poverty) were not appropriate for inclusion in the index.

3.4.5 | Calls for service rate

The *total calls for service rate* was calculated by dividing the total number of calls for service originating in a given beat in a given year by the total population (aged 16 and older) of the beat in that year, multiplied by 1,000. This calculation provides a rate of calls for service per 1,000 beat residents.

3.4.6 | Year dummies

Lastly, in our nested regression models (see Tables 5 and 6), we include ten dichotomous year variables, for each year in our study period, to isolate the impact of crime, legal, and law enforcement practice changes in the county during the decade under study. As previously mentioned, Lum and Vovak (2018) highlighted the importance of policy choices in understanding misdemeanor arrests. During our study period, Prince George's County experienced several relevant “policy shocks”, including the state-level legal changes in the enforcement of marijuana possession and the county-wide increase in patrol hours and police resources as a result of the early-2011 homicide spike. Given the nature of state and agency-level policy changes over time, we control for year-to-year changes in our models.

3.5 | Descriptive statistics

Table 2 presents descriptive statistics for our sample of 650 beat-years. Examining the outcome variable of interest, the average misdemeanor enforcement rate is 21.86 enforcements per 1,000 beat residents. The average beat-year has a calls for service rate of 922.63 calls per 1,000 beat residents. The racial-ethnic make-up of the beat-years in the sample was 15% white, 67% black, and 13% Hispanic on average. The average proportion of residents aged 16–20 is 10 percent and the average proportion of residents aged 66 or older is 11percent. One quarter of

TABLE 2 Descriptive Statistics for All Variables, across 650 beat-years in Prince George's County, 2006–2015

Variable	Mean	St. Dev.	Min	Max
Total Enforcement Count	230.38	169.73	4	911
Enforcement Rate per 1,000	27.70	26.02	0.38	215.57
Total Misdemeanor Enforcement Count	182.50	137.32	4	780
Misdemeanor Enforcement Rate per 1,000	21.86	20.83	0.38	187.91
Total CFS Count	8,830	4,890	476	59,995
CFS Rate per 1,000	992.63	634.00	47.23	5,043.29
Total Population (Aged 16+)	10,367	4,354	2,736	26,179
Proportion White (Aged 16+)	0.15	0.14	0.00	0.63
Proportion Black (Aged 16+)	0.67	0.22	0.08	0.93
Proportion Hispanic (Aged 16+)	0.13	0.15	0.01	0.87
Proportion Aged 16–20	0.10	0.04	0.06	0.42
Proportion Aged 66+	0.11	0.03	0.02	0.18
Disadvantage (Index)	0.00	0.90	−1.55	1.56
Population Density	3,241.54	3,293.90	84.52	28,969.46
Beat Square Miles	7.25	10.93	0.33	59.47
DC-Adjacent Beat	0.25	0.43	0	1

the beats are D.C.-adjacent, and the population density of beat-years ranges from 84.52 residents per square mile to 28,969 residents per square mile.

3.6 | Analysis

In the analyses presented below, we first display the changing trends in enforcement and calls for service in Prince George's County during the study period. Next, we present a series of bivariate correlations to show the relationship between misdemeanor enforcement, calls for service, and population. Then, we employ two nested ordinary least squares regressions to assess the explanatory power of beat-level characteristics, calls for service, and year-to-year policy changes in explaining the beat-level variation in misdemeanor enforcement rates over time. The first nested regression models show the results for the full study period, 2006–2015 ($N = 650$).

Then, we repeat the same procedure for the subset of study years in which Prince George's County had an active 311 call system (2013–2015; $n = 195$). Nonemergency and nonpublic safety related calls constitute a large portion of 911 calls, which has led to many jurisdictions adopting parallel 311 call systems. These alternate 311 call systems allow members of the community to request services from appropriate city government departments, whether by phone, internet, or smartphone applications (O'Brien, Sampson, & Winship, 2015). By diverting nonemergency and nonpolice-related calls, 311 systems work to reduce the demand on 911 dispatchers and police (Sampson, 2004). The motivation for this sub-group analysis is to examine the role of calls for service when it is a purer measure of community members' requests for police service.

The nested regression procedure is as follows for both the full study and sub-sample regression models: Demographic composition variables (*proportion black*, *proportion Hispanic*, *proportion aged 16–20 and proportion aged 66+*) are introduced first. Then, *population density* is added to the model. Third, disadvantage variables (*DC-Adjacent Beat* and *Disadvantage*) are added to each model, followed by *Calls for Service Rate* (fourth). Finally, in the fifth step we add the dichotomous year variables. This depiction of the results highlights how the explanatory variables of interest perform as additional groups of variables are added to the model.

In the regression, we used robust standard errors, clustered on the district, to address potential spatial correlation in the data. PGPD's jurisdiction is separated into six districts, police drawn boundaries within which varying numbers of beats are assigned. It is necessary to cluster on district because beats within the same district likely have more similar characteristics than to beats in other districts.[5] Because the explanatory variables differ in measurement level, we present standardized coefficients to facilitate appropriate comparison of their effects on the misdemeanor enforcement rate.

4 | RESULTS

4.1 | Trends in misdemeanor enforcement and calls for service

Figure 1 displays the trends in misdemeanor and felony enforcements during the study period. As previously indicated in Table 1, PGPD recorded 131,759 misdemeanor enforcement actions between 2006 and 2015. Overall, arrests make up 69% of all misdemeanor enforcements, while citations make up the remaining 31%.[6] The three most common misdemeanor offense types are those that are categorized as disorder-related (26.95%), property

[5]To address potential concerns of multi-collinearity, we calculated variance inflation factors (VIFs) for our *Beat Characteristics and Calls for Service* model (containing all control variables). All variables were well below the threshold of 5 (Menard, 1995), except for proportion Hispanic (VIF= 5.40). After removing proportion Hispanic from the model, there were marginal changes in coefficients and standard errors for *proportion aged 16–20* and *disadvantage*, affecting their significance levels. Because we have population data and therefore rely less on statistical significance, the substantive results do not change, and proportion Hispanic is theoretically relevant to the current research question, we include it in the final analysis.

[6]Only 0.50% of enforcements are accounted for by summonses or juvenile curfew violations.

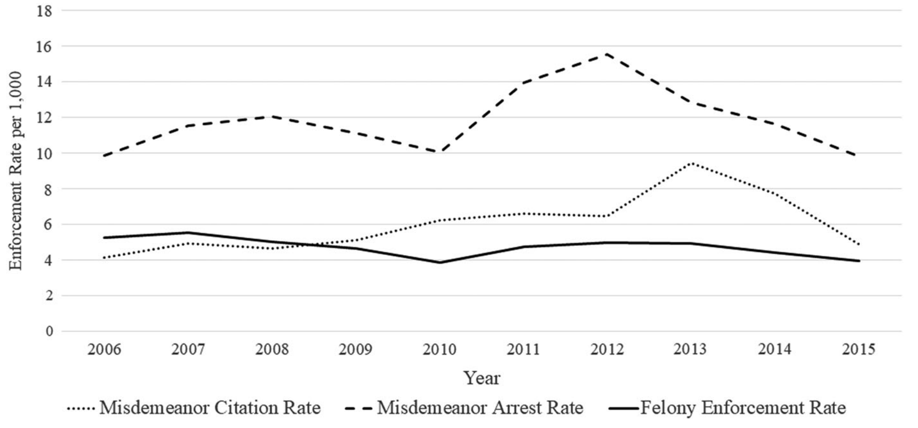

FIGURE 1 Prince George's County Police Department Enforcement Rates per 1,000

(21.27%), and drug-related (19.70%).[7] Comparatively, PGPD recorded 35,471 felony enforcement actions from 2006 to 2015. Given the severity of such offenses, arrests make up 98% of all felony enforcements. The three most common felony offense types are those that are categorized as drug-related (42.26%), violent/person-related (31.65%), and property-related (26.06%). In 2010, the midpoint of our study period, the misdemeanor enforcement rate (citations and arrests, collectively) was 20 enforcements per 1,000 beat residents, while the felony enforcement rate was 5 enforcements per 1,000 beat residents.

During the study period, the county experienced relevant changes governing state drug enforcement laws, and changes in crime trends, coinciding with police and county leadership changes. First, misdemeanor enforcement trends were shaped by Maryland state law changes governing the enforcement of marijuana possession of amounts less than 10 grams. In October 2012, possession of less than 10 grams became subject to criminal citation rather than arrest; then, in October 2014, enforcement via criminal citations was replaced with civil citations. In the above figure depicting overall enforcement trends, the large increase in 2013 in misdemeanor citations reflects the first full year of implementation of the new criminal citation policy. Similarly, in 2015, the first full year of civil citation enforcement is represented by the misdemeanor-criminal citation trend line, returning to more typical levels of the pre-2012 study period. Second, during the study period, the county experienced a homicide spike in early 2011, to which new county and police leadership responded with increased patrol activity. The county devoted additional resources, and sought external grant funding, to support expansion of authorized overtime to address the homicide spike, resulting in greater overall enforcement activity during 2011 and 2012.

Table 3 displays annual frequencies and rates for calls for service and total enforcements (80% of which are misdemeanor-related). Comparing just the 2006 and 2015 figures would suggest a period of relatively stability in the county, but the annual statistics reflect changes in crime trends and reactions to them, as well as legal changes involving marijuana enforcement and the county's response to the homicide spike. As indicated in the descriptive statistics and reiterated here, the average calls for service rate for the study period was about 933 calls per 1,000 beat residents. Calls for service rates ranged from a low of 875 calls per 1,000 residents in 2006 to a high of 1,113 calls per 1,000 residents in 2009. These rates are similar to those found in other studies, with one study examining a sample of 61 cities across 26 states identifying an average calls for service rate of 1,005 per 1,000 residents

[7]In addition to categorization of classification codes as felonies or misdemeanors discussed previously, classification codes were also categorized as well by type of offense. The 153 classification codes were divided into seven categories of offense types: Person/Violent, Property, Drugs, Traffic, Weapon, Disorder, and Other.

TABLE 3 Prince George's County Police Department Enforcements and Calls for Service

Year	Total Calls for Service	Average Calls for Service Rate per 1,000	Total Enforcements	Average Enforcement Rate per 1,000
2006	467,668	874.94	11,284	22.45
2007	575,898	1,064.98	14,275	28.01
2008	614,614	1,057.76	14,222	25.91
2009	656,450	1,112.62	13,740	24.15
2010	654,020	1,093.83	13,453	24.43
2011	624,077	1,050.33	17,009	31.33
2012	527,404	915.05	18,235	33.60
2013	540,211	919.36	18,433	34.10
2014	551,915	946.91	16,244	29.80
2015	527,200	890.50	12,854	23.21

(McCabe, n.d.). In their recent review of 911 call systems and policing, the Vera Institute of Justice reported that Maryland's 2017 call rate was 82 per 100 persons in the population (or, 820 per 1,000 persons), comparable to the combined average for all states in their sample (19 states) -- 85 per 100 persons. (Neusteter, Mapolski, Khogali, & O'Toole, 2019).

One additional programmatic change not yet discussed occurred in October 2012, involving the county's full, public implementation of a new 311 call system, to redirect calls for service demand from the 911 system. The 311 system handles nonpublic safety related concerns among residents to appropriate county agencies for resolution. In the table above, the total calls for service to the 911 system fell by almost 100,000 calls between 2011 and 2012, after which call volume remained relatively stable through 2015. (It should be noted, though, that not all of 2012's decline should be attributed to the formal launch of the 311 service, since the launch was implemented between July and October 2012.)

TABLE 4 Bivariate correlations among Misdemeanor Enforcements, Calls for Service, and Population (2006–2015; $N = 650$ beat-years)

Year	Total Calls for Service	Total Misdemeanor Enforcements	CFS Rates-Misdemeanor Enforcement Rates Correlation*	CFS Rates-Misdemeanor Enforcement Rates (Priority 0–3) Correlation*	Total Misdemeanor Enforcements – Population Correlation
2006	467,668	8,235	0.745		−0.050
2007	575,898	10,701	0.797		−0.101
2008	614,614	10,949	0.751		−0.009
2009	656,450	10,672	0.611		−0.082
2010	654,020	10,889	0.641		−0.023
2011	624,077	13,842	0.829		−0.097
2012	527,404	14,857	0.844	0.874	−0.115
2013	540,211	15,106	0.868	0.843	−0.127
2014	551,915	13,228	0.846	0.851	−0.129
2015	527,200	10,149	0.901	0.896	−0.037

*Note: All coefficients in these two columns are significant, at $p < 0.05$. No significant coefficients in the last column.

4.2 | Bivariate correlations

Table 4 describes year-to-year changes in the bivariate correlations, at the beat level, between calls for service rates and misdemeanor enforcement rates, and between misdemeanor enforcements and population. Total counts are included in the first two data columns to display changes in enforcements and calls for service levels during the study period. Recall that the period 2011–2013 was especially unstable due to multiple policy and practice changes.

The number of misdemeanor enforcements at the beat-year level appears to have no correlation with total population, as indicated in the coefficients in the last column of Table 4. Beats are drawn by law enforcement agencies for managerial and operational purposes, to account for officer workload and population considerations. Still, they are not standardized -- there remains considerable diversity among the 65 beats, in terms of size, population, and enforcement activity. To find no association between population count and misdemeanor enforcement activity levels suggests more refined measures are needed to explain variation in misdemeanor enforcement rates.

Calls for service rates, on the other hand, are highly correlated with misdemeanor enforcement rates, and especially so beginning in 2011. From 2010–2011, there was a 5% decline in total calls for service and a 27% increase in total misdemeanor enforcements. Additionally, the bivariate correlation improved from $r = 0.641$ to 0.829. The correlation between calls for service rate and enforcement rate remained stable through the end of the study period in 2015, and the difference between total calls for service rates, and the pure resident-initiated calls for service rate was negligible (identifiable in 2012–2015 as priority 0–3 only).[8] Even the implementation of the county's 311 system, which contributed to a drop in 911 calls for service starting in 2012, did not appear to impact the correlation between calls for service rates and misdemeanor enforcement rates.

4.3 | Nested regression models for misdemeanor enforcement, including beat characteristics and calls for service

While the bivariate correlation analyses showed a strong relationship between calls for service and misdemeanor enforcement rates, and almost no relationship between misdemeanor enforcement and population counts, the nested regression models presented next seek to identify those beat-level characteristics that still hold explanatory power when controlling for calls for service.

Table 5 displays results for a nested ordinary least squares regression model examining beat characteristics, calls for service, and year-to-year policy changes on misdemeanor enforcement rates for the full study period ($N = 650$). The results for the five regression models are presented side-by-side, to highlight how demographic composition (Model 1), population density (Model 2), and disadvantage (Model 3) variables perform before and after calls for service rates (Model 4) and year dummies (Model 5) are included. Models 4 and 5 have relatively strong explanatory power overall, resulting in relatively high R^2 coefficients in the realm of social science research. The R^2 coefficients indicate the proportion of the variation in beat-year level misdemeanor enforcement rates explained by the control variables, as the model seeks to minimize overall divergence of the beat-year level observations from the predicted linear relationship. Since we are trying to predict variation in misdemeanor rates, although also interested in the relative contributions of the control variables, comparing the overall model R^2 coefficients is the statistical test appropriate to this inquiry.

Comparing across Models 1, 2, and 3, the addition of population density and disadvantage variables improves the model's explanatory power of the variation in beat-year misdemeanor enforcement rates (from $R^2 = 0.277$ in Model 1 to $R^2 = 0.382$ in Model 3). Comparing Model 3 to Model 4, the addition of the total calls for service rate markedly strengthens the explanation of the variation in misdemeanor enforcement rates (from $R^2 = 0.382$ to $R^2 = 0.694$). After

[8]As previously mentioned, to preserve continuity within the full study period, and because these bivariate differences are negligible, the regressions in the following section use the total calls for service measure.

TABLE 5 Multiple Regression Models for Misdemeanor Enforcement Rates (2006–2015; *N* = 650 beat-years)

Outcome: Misdemeanor Enforcement Rates	(1) *Demographics* R^2= 0.277 β (RSE)	(2) *Density* R^2 = 0.352 β (RSE)	(3) *Disadvantage* R^2 = 0.382 β (RSE)	(4) *Calls for Service* R^2 = 0.694 β (RSE)	(5) *Year Dummies* R^2 = 0.742 β (RSE)
Proportion Aged 16–20	0.102 (0.053)	0.0579 (0.058)	0.027 (0.062)	0.044 (0.016)**	0.031 (0.020)
Proportion Aged 66+	−0.021 (0.101)	0.049 (0.095)	0.045 (0.093)	−0.001 (0.050)	−0.019 (0.056)
Proportion Black (Aged 16+)	0.677 (0.142)***	0.509 (0.103)***	0.269 (0.114)*	−0.000 (0.083)	−0.042 (0.085)
Proportion Hispanic (Aged 16+)	0.586 (0.072)***	0.142 (0.180)	0.058 (0.169)	−0.001 (0.092)	−0.060 (0.107)
Population Density	--	0.481 (0.211)*	0.437 (0.162)**	0.314(0.043)***	0.325 (0.053)***
DC-Adjacent Beat	--	--	0.031 (0.103)	0.072 (0.065)	0.077 (0.061)
Disadvantage (Index)	--	--	0.245 (0.081)**	0.113 (0.054)*	0.116 (0.054)*
Total Calls for Service Rate	--	--	--	0.655 (0.174)**	0.680 (0.170)**
2007 (all years = 0/1)	--	--	--	--	0.008 (0.028)
2008	--	--	--	--	0.000 (0.023)
2009	--	--	--	--	−0.034 (0.036)
2010	--	--	--	--	−0.013 (0.034)
2011	--	--	--	--	0.084 (0.044)
2012	--	--	--	--	0.153 (0.045)**
2013	--	--	--	--	0.160 (0.067)*
2014	--	--	--	--	0.095 (0.051)
2015	--	--	--	--	0.027 (0.036)
_cons	−9.26e-10	−2.09e-10	−6.35e-10	0	5.91e-09

RSE = Robust Standard Error
2006 is used as the reference year in Model 5
Significance
***=$p < 0.01$.
**=$p < 0.05$.
*=$p < 0.10$.

adding dichotomous year variables, the explanatory power is again improved to an R^2 of 0.742, suggesting that the final model (Model 5) explains approximately 74% of the beat-year variation in misdemeanor enforcement rates. Therefore, as much as misdemeanor enforcement is often regarded as the highest-discretion area of police activity, that discretion is still consistently related to community characteristics and problems, as well as the demands from the community. The implications of this finding are examined further in the conclusion section.

Across the five models, *population density*, *disadvantage*, and *total calls for service rate* remain significant in their explanatory power. Before the inclusion of calls for service (i.e., in Models 1–3) *proportion black* significantly contributed to the misdemeanor enforcement rate. However, after the inclusion of total calls for service (Model 4) and year effects (Model 5) *proportion black* does not significantly predict variation in misdemeanor enforcement rates. Similarly, *proportion Hispanic* was a significant predictor of variation in enforcement in Model 1, but lost significance after the inclusion of population density in Model 2. Proportion aged 16–20, representing the peak risk age period for offending, was significant only in Model 4 (before the inclusion of yearly indicators). Additionally, the years 2012 and 2013 significantly predicted variation in enforcement, consistent with expectations given the increase in patrol activity and financial resources which occurred due to a policy response to the 2011 homicide spike. Therefore, in beat-years with higher population densities, relatively more disorder, and higher calls for service rates among residents, experience greater rates of misdemeanor enforcement.

By way of comparison, less of the overall variation in felony enforcement rates was explained using the same variables and nested display of the regressions, but there still was improvement – from $R^2 = 0.313$, to $R^2 = 0.519$ – by adding the calls for service.[9] The important difference between felony rates and misdemeanor rates being explained, by the same set of control variables, was that none of the year variables were significant in predicting felony enforcement variation. It is not a surprising finding that less variation in felony enforcement is explainable with the available control variables. Misdemeanor enforcement is well-understood to involve greater discretion.

4.4 | Sub-Sample analysis: Post-311 implementation

The results displayed in Table 4 (presented earlier) showed that in the post-311 implementation period (i.e., years 2013–2015), the total number of calls for service was approximately 100,000 less than at their peak in 2009. Given that calls for service are so important in understanding enforcement outcomes, we further explore how the change in the composition of calls for service may have affected their explanatory power following 311's implementation. Table 6 reproduces the stepwise regression model displayed in Table 5, using a sub-sample of beat-years during the period of 2013–2015 ($n = 195$). [10]

Consistent with results from the full sample (shown in Table 5), the explanatory power of the sub-sample models (Table 6) improves as demographic, density, and disadvantage variables are added, but is most notably strengthened by the inclusion of the calls for service rate (Model 4) which improved the R^2 to 0.782 (from 0.355 in Model 3). Approximately 81% of the variation in misdemeanor enforcement rates can be explained in the sub-sample analysis (Model 5, Table 6), when calls for service more likely represented public safety concerns. This result indicates a slight improvement over the variance explained for the full study period (Model 5, Table 5; $R^2 = 0.742$). The variables that retain their significance across models are disadvantage and total calls for service rate. Beat-years with higher disadvantage scores and those with higher rates of calls for service have higher rates of misdemeanor enforcement. As in the full sample analysis, *proportion black* significantly contributed to the misdemeanor enforcement rate before the inclusion of

[9] Appendix displays the results of the multivariate regression models for felony enforcement rates discussed here.

[10] Per reviewer suggestion, we also estimated the regression model for the full study period (2006–2015) with an interaction term combining a dummy indicating post-311 status (i.e., equal to 1 for years 2013–2015) and calls for service rate included in the fourth model. The results of this analysis were substantively similar to those presented in the paper -- calls for service rates have a significant, differential impact in post-311 years, compared to pre-311 years. Results available upon request.

TABLE 6 Multiple Regression Models for Misdemeanor Enforcement Rates Post-311 Implementation (2013–2015; *N* = 195 beat-years)

Outcome: Misdemeanor Enforcement Rates	(1) *Demographics* R^2 = 0.228 β (RSE)	(2) *Density* R^2 = 0.291 β (RSE)	(3) *Disadvantage* R^2 = 0.355 β (RSE)	(4) *Calls for Service* R^2 = 0.782 β (RSE)	(5) *Year Dummies* R^2 = 0.808 β (RSE)
Proportion Aged 16–20	0.098 (0.089)	0.058 (0.106)	−0.000 (0.111)	0.043 (0.031)	0.043 (0.031)
Proportion Aged 66+	−0.004 (0.122)	0.068 (0.107)	0.046 (0.113)	−0.004 (0.080)	−0.005 (0.080)
Proportion Black (Aged 16+)	0.745 (0.168)***	0.588 (0.132)***	0.207 (0.132)	−0.116 (0.080)	−0.114 (0.079)
Proportion Hispanic (Aged 16+)	0.502 (0.119)***	0.086 (0.291)	−0.095 (0.275)	−0.061 (0.095)	−0.057 (0.096)
Population Density	--	0.400 (0.224)	0.400 (0.224)	0.163 (0.035)***	0.163 (0.034)***
DC-Adjacent Beat	--	--	0.110 (0118)	0.149 (0.062)*	0.149 (0.062)*
Disadvantage (Index)	--	--	0.334 (0.098)**	0.199 (0.051)**	0.199 (0.050)**
Total Calls for Service Rate	--	--	--	0.854 (0.166)***	0.850 (0.163)***
2014 (all years = 0/1)	--	--	--	--	−0.067 (0.031)**
2015	--	--	--	--	−0.131 (0.050)**
_cons	0.041 (0.182)	0.061 (0.180)	0.075 (0.129)	0.177(0.040)***	0.330 (0.095)**

RSE = Robust Standard Error
2013 is used as the reference year in Model 5
Significance
***= $p < 0.01$.
**= $p < 0.05$.
*= $p < 0.10$.

calls for service rate, but does not significantly predict variation in misdemeanor enforcement rates in Models 4 and 5. *Proportion Hispanic* was again a significant predictor of variation in enforcement in Model 1, but lost significance after the inclusion of population density in Model 2. Interestingly, population density and D.C.-adjacent beat become significant predictors of variation in enforcement only after the inclusion of calls for service rates. Based on the results from the final model (Model 5, Table 6), higher population densities and being located D.C.-adjacent is associated with higher rates of misdemeanor enforcement. Year variables for 2014 and 2015 are also significant, and in this period, represent the county's declining enforcement rates, relative to the preceding peak enforcement period that continued into 2013.[11]

In the current study we find that the relationship between calls for service rates and misdemeanor enforcement rates was not substantially impacted by "purer" calls for service (post-311 implementation). One explanation for this outcome can be contextualized by a U.S. Department of Justice, Office of Justice Programs, National Institute of Justice (2005) report on 311-implementation in Baltimore, Maryland. Baltimore's implementation of a 311-call system was expected to have several implications for policing practices including reductions in response time, changes in dispatch policy, and increases in officer discretionary time. However, the implementation of 311 did not have the expected impacts in these areas. Notably, implementation resulted in only marginal gains in officers' un-committed, discretionary patrol time and approximately two-thirds of surveyed officers did not perceive a change in their available time (U.S. Department of Justice, Office of Justice Programs, National Institute of Justice, 2005). Given these previous results observed in Baltimore, it is reasonable to suspect that the impact of calls for service rates remained relatively constant pre-and-post-311 implementation in Prince George's County for similar reasons – implementation did not impact officers' work routines.

5 | DISCUSSION AND CONCLUSION

5.1 | Summary of findings and discussion

At the outset, we introduced two research questions. The results here indicate that misdemeanors make up the large majority of all arrests, and that, even within a single jurisdiction, at the patrol beat level, misdemeanor enforcement rates vary across the jurisdiction. Previous research has already established the former point, but, for the purposes of this study, establishing the latter was a precondition of pursuing the second research question – can such variation be explained using community characteristics and calls for service, and to what extent?

The results indicate that much of the variation in misdemeanor enforcement rates may be explained with variables measuring demographics, population density, disadvantage, calls for service, and changes in policing effort. However, the inclusion of the disadvantage and calls for service variables in the nested regression models indicate that demographic and population density variables lose significance as a consequence.

In this paper, although we mention calls for service as a variable to be considered *in addition to* community characteristics, research on calls for service has emphasized their usefulness as a data source in providing information to police about offenses and problems to address, but also as a mechanism by which the community can compel police attention and response. Much of the extant empirical research on calls for service, however, is operationally-oriented, and has particularly focused on how quickly police respond to calls for service, rather than the relationship between crime, calls for service, and enforcement rates (Neusteter et al., 2019).

The work output of a law enforcement agency as a whole, just as it is for the individual officer, is subject to a set of constraints, but is also a product of discretion. When an agency deploys extra personnel, there will be an impact on enforcement rates. When laws change what is or is not subject to enforcement, there will be an impact on

[11]While the overall explanatory power of the final model is greater in the post-311 period, an equality of coefficients test (see Paternoster, Brame, Mazerolle, & Piquero, 1998) shows that the independent effect of calls for service is only marginally different ($z = -1.519$) for the post-311 period (2013–2015) compared to pre-311 period (2006–2011, model not shown).

enforcement rates. And, especially when residents, employees, and visitors call and demand service or attention, there will be an impact on enforcements rates.

However, the findings of this study also suggest something of a paradox in understanding discretion in enforcement. It is widely accepted that there is more discretion in misdemeanor policing than in felony policing. Felonies almost universally involve one or more persons or businesses as victims, who file complaints, and whose victimization motivates a response not just from police, but throughout case processing, including prosecutors and judges. Misdemeanors, in comparison, represent a hybrid group of offenses, including both victimless and victim-impacted offenses. Thus, it may be assumed that the constraints on enforcement discretion are greater for felonies than misdemeanors.

But, according to the current findings, it does not mean that misdemeanor enforcement is unconstrained, and thus less accountable, activity. Misdemeanor enforcement rate variation is more accountable than felony enforcement rate variation (recall the R^2 values were 0.742 vs. 0.539 for the complete models). Discretion employed with accountable variation – especially at the aggregate level of an agency's activity, measured across 65 beats for 10 years – is conceptually a somewhat surprising finding. This finding ultimately points to an interrelationship between varying problems in a community, the varying demands for service from a community, and the resulting variation in law enforcement response to those demands.

This study could measure only the latter two elements – the varying demands for service from a community and the enforcement rate response to those demands, while also controlling for community characteristics. We do not have any measures of actual beat-level problems or crimes. But the amount of the beat-level variation in misdemeanor enforcement rates that can be accounted for by calls for service rates suggests that overall enforcement rates are likely being driven to some degree by the volume of calls for service from the community (although this study design does not allow determining the extent and significance of the causal relationship).

5.2 | Limitations

While the current study provides a key first step in exploring the relationship between aggregate-level community characteristics, community members' calls for service, and police enforcement of misdemeanor offenses, there are several limitations that warrant acknowledgement. First, considering the cross-sectional nature of our analysis, we cannot define the relationship between calls for service rates and enforcement rates as causal. Our findings suggest that having higher rates of calls for service is significantly associated with higher rates of misdemeanor enforcement by police. In other words, beats where community members request service at a higher rate, have higher rates of police enforcement (for misdemeanors) than those beats where calls for service rates are comparatively lower. However, despite the relationship between calls for service and enforcement rates, the mechanism (or mechanisms) linking these two processes remains unknown.

One possibility is that calls for service rates are a proxy for crime rates. Therefore, the positive association between calls for service rates and enforcement rates is a result of police officers responding directly to crime rates. Another potential mechanism relates to the reaction prompted by calls for service. When a community member calls 911, the appropriate police resources are subsequently dispatched to the scene of the incident. So, if a beat has relatively high rates of calls for service, police are dispatched to these areas at higher rates. Therefore, enforcement rates may be relatively higher in these areas for two reasons. First, police may react to calls for service through direct, one-to-one enforcement, such that areas with higher calls for service experience higher rates of enforcement. Alternatively, higher rates of calls for service may result in a greater police presence on the street at any given time. Even if officers do not respond to all calls for service with a subsequent enforcement (e.g., the call turns out to be unfounded, or a warning is issued instead of a citation/arrest), once on the scene, they may proactively encounter additional incidents in these areas, which then leads to enforcement actions.

Next, given the lack of research seeking to explain misdemeanor enforcement variation, we have no comparative information against which to evaluate the strength of the research design and data used. We cannot point to the findings or conclusions of other studies and assess whether any variables performed differently than previously demonstrated.

Most law enforcement research has been conducted using large cities as study sites. Prince George's County is a member agency of the Major Cities Chiefs Association, a national membership group which includes the 69 largest law enforcement agencies in the United States, but it is not a city *per se*. It has areas that are urban with high population density, and it is part of the larger Washington, D.C., metropolitan area – but much of the county is suburban or rural in character.

Another concern regarding generalizability of these findings has to do with the county's position as the wealthiest majority-minority jurisdiction in the United States. Despite its comparative affluence, Prince George's County still has areas of concentrated disadvantage and poverty. Also, as is typically the pattern in majority-white jurisdictions, the relatively economically disadvantaged areas are more racially and ethnically diverse than the county overall.

Finally, with the data available, we could not link individual calls for service to subsequent enforcement actions, but studying such linked records would allow a more accurate, incident-level understanding of enforcement variation and the dominant role of calls for service in explaining such variation.

6 | CONCLUSION

The dominant debate today about the future of policing is focused on the appropriate level of enforcement –in terms of both the overall quantity and form, whether arrests or citations or summonses, and against whom enforcement actions are directed. Understanding the variation in enforcement rates, especially for misdemeanor offenses that contribute most to arrests, is the first step to understanding what kinds of reforms should be contemplated, are even possible, and are likely to succeed.

This study's results inform future study in two areas that are especially salient in current policy reform discussions about law enforcement: bench-marking disparate outcomes and measuring police legitimacy.

When any organization's activities are analyzed, but especially those of a law enforcement agency, an important question is whether their activities are racially and ethnically neutral. This is certainly among the most important issues facing policing today. Police document the demographic information about those subjected to enforcement actions, and the resulting statistics are compared to some reference population. Typically, the reference population is described as the residents of the jurisdiction. This causes difficulty in accurately assessing the specific nature and extent of potentially disparate enforcement activity.

Appropriate benchmarks consider the racial composition of both the population of individuals who engage in criminal activity and the racial composition of those exposed to police enforcement (Ridgeway, 2007; Tregel et al., 2019). Both Ridgeway (2007) and Tregel et al. (2019) explain the limitations of using arrests as estimates of contact with police, because arrest outcomes are affected by bias in pre-arrest decisions. Tregel et al. (2019) propose that, instead of using arrests, police-citizen interactions may be a more appropriate benchmark. Additionally, both studies (Ridgeway, 2007; Tregle, Nix, & Alpert, 2019) conclude that without appropriate benchmarks, estimates may distort the magnitude of the disparity or racial biases in police activity.

By factoring in calls for service data, this study begins a new line of inquiry into potential benchmarks, to assess differences in enforcement rates by community characteristics, and methods for measuring disparity more precisely. Notwithstanding the unique situation of Prince George's County (or perhaps because of it), the findings here suggest that comparing enforcement rates to population and community characteristics, without factoring in the demands for service, may result in incomplete benchmarking.

Studying calls for service could also improve understanding of police legitimacy. Absent regular and rigorous survey research, which is increasingly difficult and expensive to conduct, further analysis of calls for service data could illuminate the relationship between enforcement and calls for service, and whether legitimacy itself may be measured using calls for service record data. Research about the willingness of individuals to make calls for service is not nearly as developed as research about what prompts individuals to report their victimizations to police. But the fact that calls for service are the most common interaction between the public and police means that the general public's perception of police legitimacy must be influenced by how calls for service are handled. The most common way this has been studied has focused on response times, measured in minutes, as a performance metric, rather than as a measure of demand for police service. In the jurisdiction studied here, over a 10-year study period, there were about 200,000 enforcement actions, and almost 6 million calls for service. That is a ratio of about 30-to-one. This article began by discussing how the bulk of police work is devoted to misdemeanor enforcement, and how little of that activity was understood. That same sentiment is equally appropriate when discussing police activity devoted to responding to calls for service.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to report.

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Appendix: Multiple Regression Models for Felony Enforcement Rates (2006–2015; *N* = 650 beat-years)

Outcome: Felony Enforcement Rates	(1) *Demographics* R^2= 0.230 β (RSE)	(2) *Density* R^2 = 0.0.258 β (RSE)	(3) *Disadvantage* R^2 = 0.313 β (RSE)	(4) *Calls for Service* R^2 = 0.519 β (RSE)	(5) *Year Dummies* R^2 = 0.539 β (RSE)
Proportion Aged 16–20	0.098 (0.038)*	0.070 (0.047)	0.029 (0.047)	0.045 (0.019)*	0.055 (0.025)*
Proportion Aged 66+	−0.057 (0.096)	−0.014 (0.095)	−0.013 (0.078)	−0.051 (0.049)	−0.038 (0.052)
Proportion Black (Aged 16+)	0.637 (0.144)***	0.534 (0.142)**	0.208 (0.121)	−0.010 (0.074)	0.003 (0.077)
Proportion Hispanic (Aged 16+)	0.397 (0.066)***	0.125 (0.141)	0.014 (0.107)	−0.034 (0.071)	−0.007 (0.085)
Population Density	--	0.295 (0.156)	0.238 (0.107)*	0.136 (0.038)**	0.126 (0.043)*
DC-Adjacent Beat	--	--	0.014 (0.064)	0.048 (0.028)	0.046 (0.029)
Disadvantage (Index)	--	--	0.347 (0.081)***	0.243 (0.071)**	0.235 (0.069)**
Total Calls for Service Rate	--	--	--	0.533 (0.058)***	0.549 (0.065)***
2007 (all years = 0/1)	--	--	--	--	−0.014 (0.024)
2008	--	--	--	--	−0.075 (0.050)
2009	--	--	--	--	−0.114 (0.060)
2010	--	--	--	--	−0.146 (0.075)
2011	--	--	--	--	−0.083 (0.051)
2012	--	--	--	--	−0.027 (0.033)
2013	--	--	--	--	−0.036 (0.041)
2014	--	--	--	--	−0.062 (0.037)
2015	--	--	--	--	−0.077 (0.053)
_cons	−0.002 (0.123)	−0.002 (0.114)	−0.002 (0.053)	−0.005 (0.051)	−0.005 (0.052)

RSE = Robust Standard Error.

2006 is used as the reference year in Model 5

Significance

*** = $p < 0.01$.

** = $p < 0.05$.

* = $p < 0.10$.