CRIME AND JUSTICE

RESEARCH REPORT

Catalyzing Policing Reform with Data

Policing Typology for Los Angeles Neighborhoods

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Catalyzing Policing Reform with Data

Public scrutiny of police in the US—especially regarding racial disparities—has increased in recent years, with many communities experiencing strained relations with their local police. Police departments have also increased transparency by making some data about their activity (primarily arrests and reported crimes) public. However, access to high-quality, disaggregated police data is insufficient—these data must also be analyzed to inform and empower people in communities most affected by crime and the justice system as well as to benefit law enforcement agencies and policymakers. When meaningfully analyzed and shared, these data can support conversations between communities and police and catalyze local reforms.

Local organizations in the National Neighborhood Indicators Partnership (NNIP)—a learning network coordinated by the Urban Institute that connects independent partner organizations in 30 cities—regularly provide data and analysis to support discussions about key issues in their communities. The NNIP's mission is to ensure all communities can access data and have the skills to use information to advance equity and well-being across neighborhoods. In 2018, NNIP and Microsoft partnered to use the network to spur data-driven and community-led criminal justice reforms with the goal of building police-community trust and improving public safety.[1]

As one of the project's activities, we selected one city—Los Angeles—to explore how we could create a comprehensive measure of community-police engagement using publicly available police data. Our motivating research questions are the following:

- Are there different patterns of community-initiated and police-initiated engagement?
- How many distinct patterns are there, and what makes them distinct?
- How do the patterns of community-police engagement vary across neighborhoods?

In collaboration with the Microsoft Criminal Justice Reform team, the Microsoft Data Science team, and the University of Southern California's Sol Price Center for Social Innovation (Los Angeles's local NNIP partner), we synthesized data sources (including information on calls for service, stops, arrests, and crime) to develop a typology that elucidates the relationship between resident-initiated and police-initiated activity, as well as how that relationship varies across Los Angeles neighborhoods. Our typology of community-police interactions reveals patterns in how calls to police and police activity (which varies by the severity of crime and levels of economic hardship) differ across neighborhoods.

We also discuss how this neighborhood-policing typology can inform conversations about police reform and support local movements for a more equitable criminal justice system. We hope this report informs conversations in Los Angeles and demonstrates how open data can be a powerful tool for local data organizations and criminal justice advocates nationwide.

Background

Our typology of policing in Los Angeles neighborhoods builds on the body of research on community-police relations and policing approaches. We expect resident-initiated contact to vary across neighborhoods because of differences in reported crime, police-initiated activity, and community trust in and sentiments toward police. Similarly, we anticipate police-initiated activity to vary by reported crime and departmental priorities.

Community Trust in Police

Strong community-police relationships are essential to public safety, and these relationships influence how communities engage with the police. Public sentiment toward and trust in police varies by demographics, rates of reported crime, and types of police activity. Surveys and interviews have found disparities between Black and white residents' attitudes toward police, though not between their willingness to report crime (Bobo and Thompson 2005). White residents are the most likely to report satisfaction with city and neighborhood police, followed by Hispanic and Black residents (Weitzer and Tuch 2005). Spanish-speaking Hispanic residents are the least likely to call the police, even if they perceive big neighborhood problems (Skogan 2005). Moreover, studies exploring the influence of neighborhood characteristics show that people living in high-crime areas are less satisfied with the police.[2] Furthermore, neighborhoods with concentrated economic disadvantage are more dissatisfied with the police (Sampson and Bartusch 1998). Fear of crime and victimization is also associated with lower satisfaction (Carter 1985).

The types of police activity and the nature of community-police contact can also influence neighborhoods' sentiment toward police. Skogan (2005) found that residents are more satisfied with resident-initiated (voluntary) encounters than police-initiated (involuntary) encounters. Moreover, when police use procedural justice principles (e.g., fairness, transparency) during interactions, residents often feel more satisfied and consider the police more legitimate (Mazerolle et al. 2013). Vicarious police interactions—interactions that people hear others have had with police—also significantly influence people's satisfaction with police (Rosenbaum et al. 2005; Weitzer and Tuch 2005). Community sentiment is difficult to measure and researchers often use calls for service as an easily accessible (although imperfect) metric for gauging residents' views of police legitimacy. However, high-profile police misconduct can make residents less willing to call the police and report crime (Desmond, Papachristos, and Kirk 2016). In our analysis, we treat calls for service as a proxy for community trust in the police and anticipate that levels and types of calls will vary depending on neighborhoods' demographics, crime levels, and experiences with policing.

Policing Strategies

Just as community engagement with and sentiment toward police vary across cities, so do the police's strategies and activities. Primary policing activities (which fit into various policing strategies) include patrol, incident response, emergency response, and criminal investigation. Reactively responding to calls for service is one long-standing strategy. Others are more proactive, such as problem-oriented policing, where police identify and respond to specific problems contributing to crime and disorder (Eck and Spelman 1987; Goldstein 1979). Other common approaches include hot spot policing—concentrated, place-based policing in small geographic areas with high levels of crime (Sherman and Weisburd 1995)—and disorder policing—focusing on physical and social disorder to prevent neighborhood decline and more serious crime.[3] Another popular strategy is community policing, where the police partner with community members to identify problems and develop and implement solutions (Trojanowicz and Bucqueroux 1990).

Policing in Los Angeles

Although this report does not examine the Los Angeles Police Department's (LAPD's) specific policing approaches, we anticipate that the varying levels and types of police activity across neighborhoods will signal differences in how LAPD deploys various strategies, differences that community stakeholders can explore. Understanding local context is critical when analyzing people's experiences with policing and when considering how to leverage findings to improve community-police relations. The LAPD had 9,988 sworn officers in 2017, and it currently serves more than 4 million people (Kaplan 2019). The department has a multifaceted history that includes being a national leader in major policing innovations while also experiencing high-profile occurrences of police violence and misconduct. Like the criminal justice system nationally, the department has long faced concerns about racially disparate practices. Black residents constitute 9 percent of the city's population but experience 31 percent of LAPD arrests (Bryan et al. 2019). During traffic stops, Black and Hispanic residents are more likely to be searched than white residents, but searches of white residents yield illegal items at a slightly higher rate.[4] The LAPD has aided examinations of these disparities by publicly sharing data dating back to 2010 on calls for service, stops, arrests, and crimes. In our examination of patterns of resident-initiated and police-initiated activity, we anticipate varied levels of community trust (as measured by community-initiated calls for service), different policing patterns across the city, and demographic disparities among residents' and neighborhoods' engagement with the police.

Methodology

In this analysis, we explore how a typology of policing activity—one reflecting indicators of resident-initiated and police-initiated activity—elucidates how Los Angeles residents in different neighborhoods experience policing differently. Moreover, we document the characteristics of crime and of residents across the typology's different groups. To do this, we use several publicly available data sources and cluster analysis (a type of machine learning) to create and test the typology. A detailed explanation of our data sources and analytic methodology are available in a companion technical appendix.[5] In addition, with the assistance of the Microsoft Data Science and Analytics team, we have created an interactive Power BI data tool that allows users to visualize and explore the typology and individual indicators from the analysis.[6]

Data and Key Indicators

Our data come from three sources: (1) policing data from the City of Los Angeles Police Department, (2) data on resident characteristics from the American Community Survey, and (3) quantities of addresses from the US Postal Service. We do not use data from other law enforcement agencies that have jurisdiction in Los Angeles.[7]

POLICING DATA

The policing-related data are publicly available on the City of Los Angeles's open data portal and include all LAPD arrests, calls for service, stops, and crimes since 2010.[8] The data are published at the incident (i.e., call for service, stop, arrest, or crime) level. For each unique event, the portal provides information on the incident type and the person's demographic characteristics if applicable and available.[9] Each observation in the LAPD data is coded with the reporting district (a geographic unit used for police operations) where it occurred. At the time of our analysis, LAPD had 1,135 reporting districts with an average district size of 0.42 square miles. We aggregate 2018 events to the reporting-district level such that our unit of analysis is a reporting district in 2018. We include all reporting districts regardless of their population size because policing activity can occur in nonresidential areas.

We only use data from 2018, the most recent full year for which data were available at the time of our analysis. Using multiple years would produce multiple observations for each reporting district, and the same reporting district could be assigned to multiple clusters. We tested models that include variables on changes over time and found they did not meaningfully change the results. We decided that the value of incorporating multiple years did not merit complicating the analysis with cluster assignments over time.

With the LAPD data, we created measures for analysis in three primary categories: resident-initiated activity, police-initiated activity, and reported crime. We define the proxy measure of *resident-initiated activity* as calls for service made by people in Los Angeles. Calls for service are incidents where people call 911 to request police services for emergencies and nonemergencies. People can make calls to report things including crimes, traffic crashes, road hazards, suspicious activity, injured persons, and missing persons. With input from LAPD, we narrowed the data on calls for service to resident-initiated calls only by excluding calls generated by the dispatch system or police. This is how we define "calls" and "calls for service" throughout this report. Within the category of resident-initiated calls for service, we distinguish calls for serious emergencies, defined as murder, kidnapping, robbery, battery, assault with a deadly weapon, or child abuse. We created rates of calls for service for each reporting district based on the city's population rather than each reporting district's population because calls for service in particular districts may not have originated from people living in them.

Our analysis also contributes an aggregate measure of *police-initiated activity*, including stops and arrests. Police can stop (i.e., temporarily detain for investigative purposes) both vehicles and pedestrians. Traffic (vehicle) stops can occur for many reasons, including moving violations, equipment violations, and reasonable suspicion of criminal activity. Police also use reasonable suspicion of criminal activity to justify pedestrian stops, such as when a person matches a reliable lookout, displays characteristics of being armed, or engages in activity perceived as suspicious and unusual. Officers must base reasonable suspicion on specific and articulable facts, and it often involves multiple factors that in totality lead a reasonable officer to suspect a person's engagement in criminal activity. Pedestrian and vehicle stops can both lead to protective pat downs (frisks), searches, and/or arrest. An arrest occurs when police have probable cause to believe a person committed a specific crime and take them into custody. We also created variables that distinguish juvenile from adult arrests.

We created rates of overall stops, traffic stops, pedestrian stops, and arrests for each LAPD reporting district. As with calls for service, police-initiated activity may involve people who reside outside the reporting district. Thus, we use the relevant Los Angeles population (e.g., total population, juvenile population) as the denominator. We calculated rates of stops and arrests by race by dividing the number of people of a given race stopped or arrested in a reporting district by the total population of that race in Los Angeles.[10]

We measure *reported crime* as crime reported to and recorded by LAPD. Although a crime may be associated with an arrest, many crimes do not result in arrest. Crimes are commonly categorized by severity. Following the Uniform Crime Report classification system for LAPD,[11] we categorize crimes into Part 1 Violent (homicide, rape, robbery, and aggravated assault), Part 1 Property (burglary, motor vehicle theft, and theft), and Part 2 (all other crime categories). For each reporting district, we created rates for overall crime and the subcategories by dividing a given reporting district's crime count by the total Los Angeles population.

RESIDENT CHARACTERISTIC DATA

We used the 2013–17 American Community Survey[12] (the most recent data available at the time of our analysis) for data on resident demographics and other characteristics, such as racial composition, immigration status, poverty, educational attainment, and share of renter households.[13] The University of Southern California (USC) Sol Price Center for Social Innovation team assisted with the processing of the American Community Survey data. Because our focus is creating a typology that demonstrates how policing varies across Los Angeles, we only use resident characteristics to describe the groups resulting from the cluster analysis and to analyze who is most affected by greater police contact, not to determine the cluster assignments.

ADDRESS DATA

We hypothesize that the number of stops in a reporting district as well as the breakdown of vehicle versus pedestrian stops is influenced by the reporting district's built environment. We suspect that denser neighborhoods will experience more stops and that the proportion of pedestrian stops is likely to be higher in denser, more walkable areas. We use the US Department of Housing and Urban Development aggregated census tract–level US Postal Service data on address vacancy to determine neighborhood address density as a proxy for the built environment of neighborhoods.[14] For each reporting district, we calculated the density of business, residential, and overall addresses per square mile.

Analysis Method

To create a typology of community-police activity, we conduct a machine learning cluster analysis of reporting districts based on their resident-initiated activity, police-initiated activity, and crimes in 2018. Researchers have used cluster analysis widely to develop neighborhood typologies that illuminate various patterns, including commuting behavior (Manaugh, Miranda-Moreno, and El-Geneidy 2009), immigrant neighborhood types (Vicino, Hanlon, and Short 2011), social capital (Sampson and Graif 2009), social problems (Chow 1998), and socioeconomic and demographic characteristics (Li and Chuang 2009). In the criminal justice literature, researchers have used cluster analysis to develop typologies of officers by occupational attitudes and burnout types (Loo 2004; Paoline 2004). Cluster analysis is valuable for generating typologies because it enables researchers to distill numerous input variables into a discrete number of types. Broadly, the goal of any cluster analysis is to create groupings of observations that maximize the similarity of observations in the same group and the differences between groups (Bahr, Bielby, and House 2011). Cluster analysis allows us to group reporting districts together based on their similarities regarding the 17 input variables on calls for service, crime, stops, and arrests.[15] This enables us to draw novel connections between similar reporting districts that would not be apparent by simply looking at geographic relationships or analyzing our input variables in isolation.

We tested three clustering algorithms that take different approaches to grouping observations into clusters: k-means clustering, agglomerative hierarchical clustering, and gaussian mixture models clustering. Each algorithm assigns reporting districts to clusters to simultaneously optimize for maximizing the similarity of the members of the same cluster and the difference between clusters. Each approach has unique strengths and weaknesses based on several factors, including computational intensity, alignment with the underlying distribution of the data, and parameters that researchers must define or let the machine learn. Ultimately, we found that the gaussian mixture model algorithm with five clusters produced was the best fit for the underlying data and had a more even distribution of reporting districts across groups. Using the clusters, we then conducted several descriptive analyses to explore how the clusters vary in terms of policing activity types, racial disparities, and neighborhood characteristics.

Limitations

Our typology has several data and methodological limitations. First, our measures of stops and arrests are based on officially reported police data, which may contain errors or biases. Second, we only include reported crime, which often vastly underestimates actual crime (Biderman and Reiss 1967; Skogan 1977). Ideally, we would include more metrics that capture resident views and policing activity, such as public sentiment, complaints, use-of-force incidents, or assaults on officers. It also would have been helpful to include all law enforcement agencies operating in Los Angeles County, which would allow us to create a comprehensive measure of policing activity in the City of Los Angeles and the surrounding areas. Finally, our cluster analysis only focuses on one year of data (2018). Repeating the analysis for multiple years could clarify how crime, resident-initiated activity, and police-initiated activity change over time.

Results

Our cluster analysis of policing-related variables results in five unique groupings, each with a distinct[16] combination of resident-initiated activity, police-initiative activity, and reported crime. We refer to the five unique clusters as groups. Table 1 shows the average value of our policing indicators by group and includes total population for reference (see appendix table A.1 for additional information). The groups range from very low rates of resident- and police-initiated activity in group one to high rates in group five. The five groups are sets of reporting districts with similar levels of crime, calls for service, stops, and arrests. In this section, we present key takeaways based on overall patterns and differences in policing variables and resident characteristics between the groups.

TABLE 1

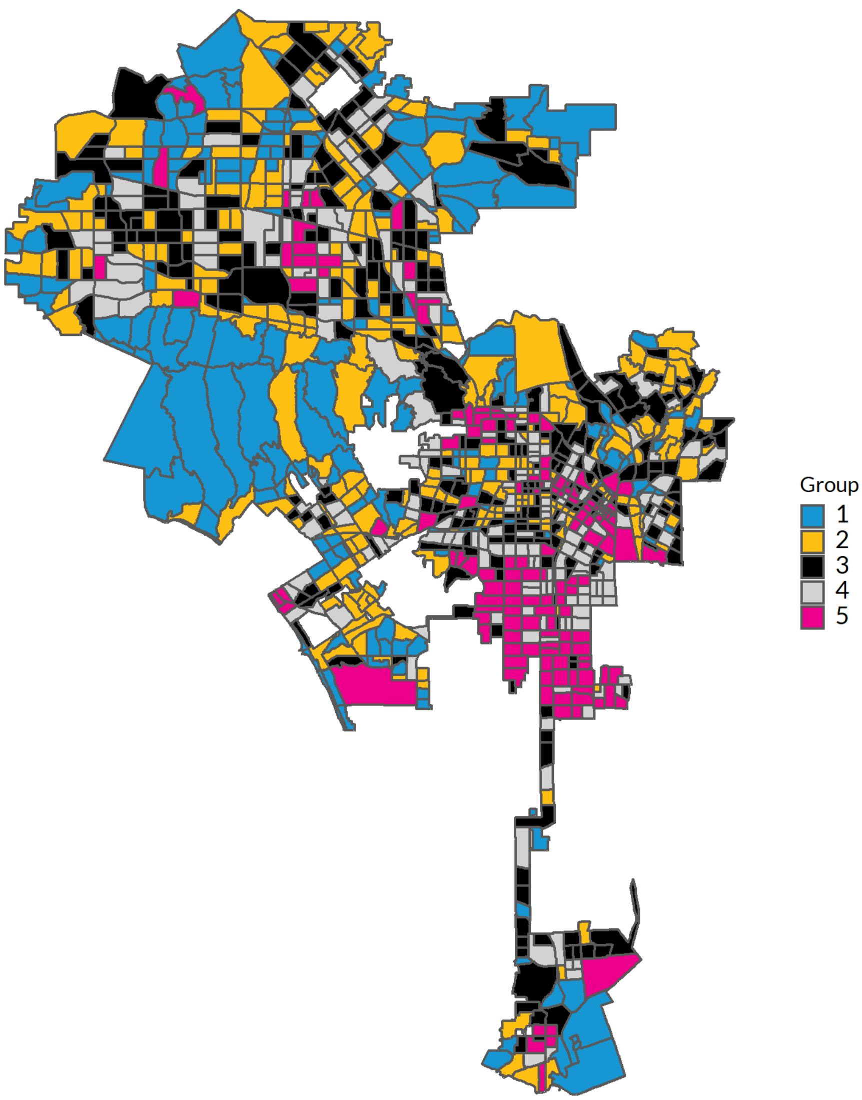
Average Value of Key Metrics in Reporting District by Group

	Group 1 (n=231)	Group 2 (n=271)	Group 3 (n=284)	Group 4 (n=201)	Group 5 (n=148)
Variable					
Calls for service	196	488	762	1,121	1,753
Part 1 violent crimes	10	31	56	88	172
Pedestrian stops	21	78	134	222	580
Traffic stops	94	244	389	625	1,373
Arrests	15	44	67	111	306
Population	1,612	3,051	4,031	4,631	4,563

The groups vary across LAPD reporting districts (figure 1). Some areas have concentrated patterns, including group 1 (blue) in Westside (which includes the Brentwood, Westwood, and Pacific Palisades neighborhoods) and group five (pink) in south Los Angeles (which includes the Florence and Watts neighborhoods). However, most of the city has a mix of adjacent groups. This confirms that one cannot make broad assumptions about policing experiences based on geography, and it raises useful questions about local drivers of differences. Appendix figure A.1 provides a map of the reporting districts with a neighborhood overlay.

FIGURE 1

Reporting District Group Assignment Map



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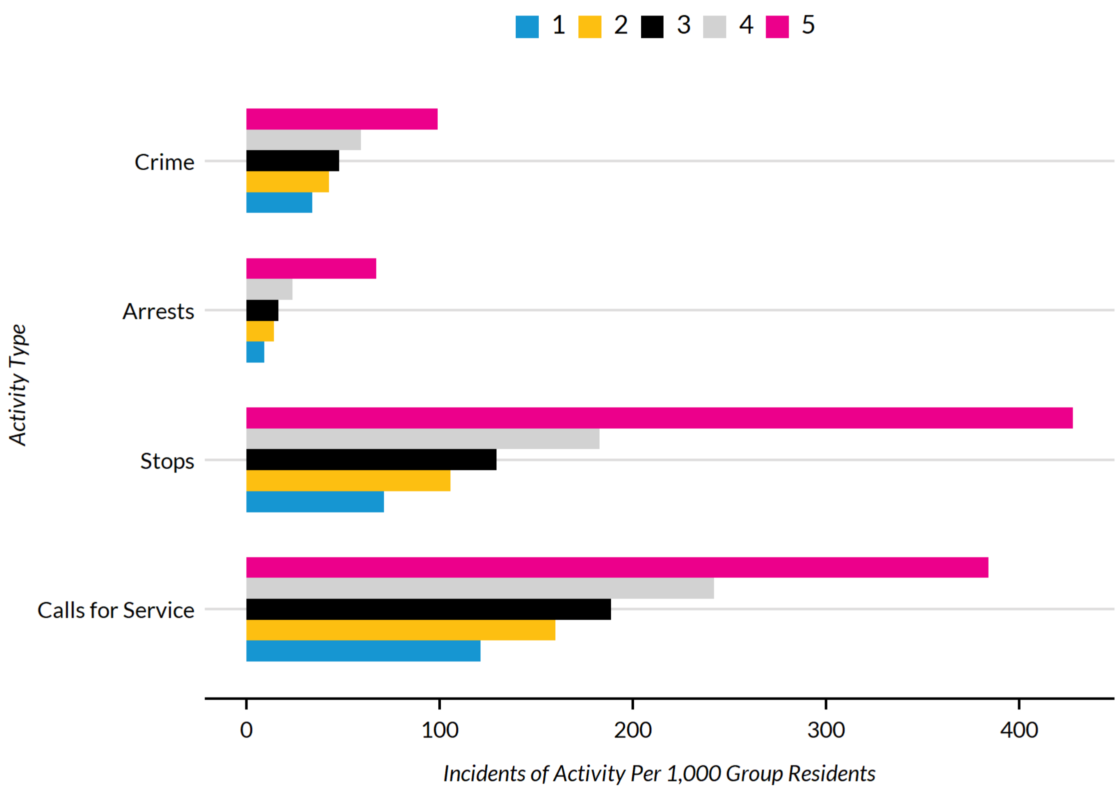
Levels of the measures of interest vary across the groups but generally increase from group one to group five. Group one has the lowest rates of calls for service, crime, arrests, and stops, whereas group five has the highest (figure 2). The increase in each activity type is steady from group one to group four, but a much larger increase exists from group four to group five. We refer to this pattern of all the activity types (i.e., calls for service, crime, stops, and arrests) increasing together as "increasing activity." The rest of this report's results section examines patterns in this increasing activity.

FIGURE 2

All Activity Rates Increase from Group One to Group Five

Calls for service, stops, arrests, and crimes per 1,000 group residents



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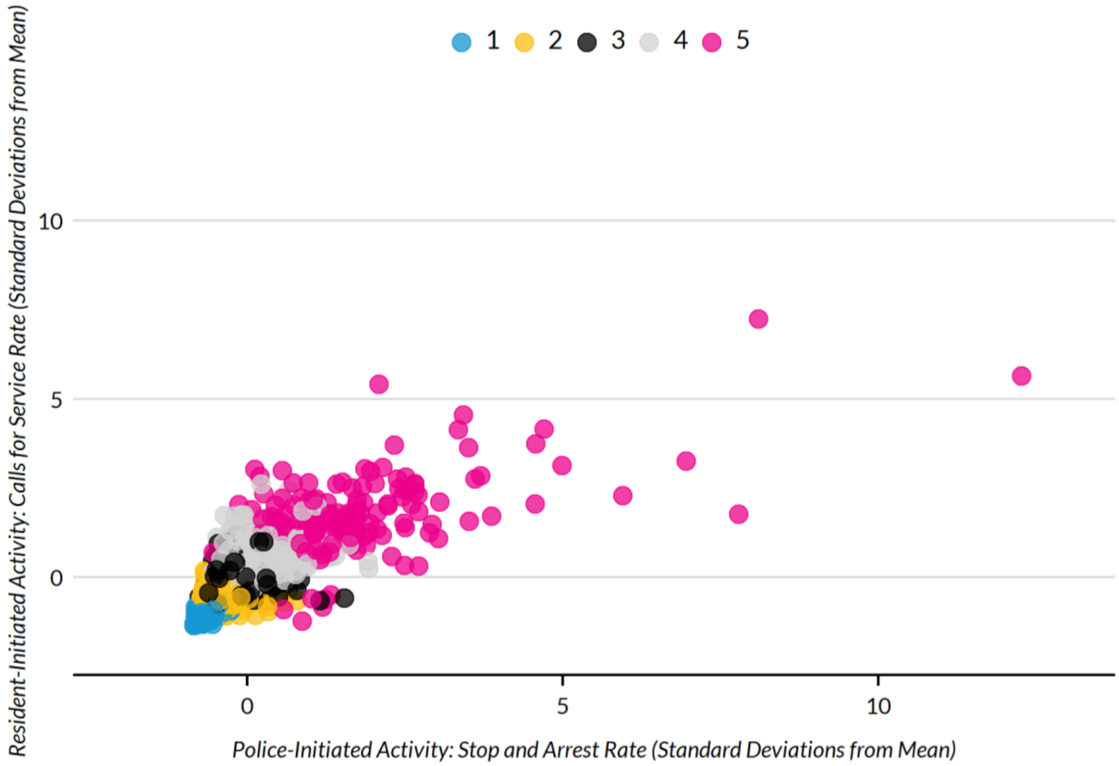
Resident- and Police-Initiated Activity Increase Together

Resident- and police-initiated activity generally increase across groups (figure 3). The group-one reporting districts have resident- and police-initiated activity lower than the city average. Groups two and three have activity close to the city average, and activity in groups four and five is generally higher than the city average. This finding is intuitive because police may dedicate more resources in areas with more calls for service, leading to more stops and arrests.

FIGURE 3

Resident Calls and Police Activity Increase across Groups

Resident-initiated activity by police-initiated activity for each reporting district by group assignment



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Interestingly, resident-initiated and police-initiated activity do not increase at the same rate across the groups (table 2). That is, moving from group one to group five, the increase in police-initiated activity outpaces the increase in resident-initiated activity. Notably, group five is the only group that experiences more police-initiated contact than resident-initiated contact on average. This suggests that the police use different strategies in higher-activity groups and/or that residents in these groups are less willing to call the police.

TABLE 2

Highest-Activity Group Has Significantly Lower-than-Expected Resident Calls Given Police Activity

Ratio of resident-initiated contact to police-initiated contact by group

	Group 1	Group 2	Group 3	Group 4	Group 5
Ratio of resident-initiated to police-initiated contact	1.51	1.33	1.29	1.17	0.78

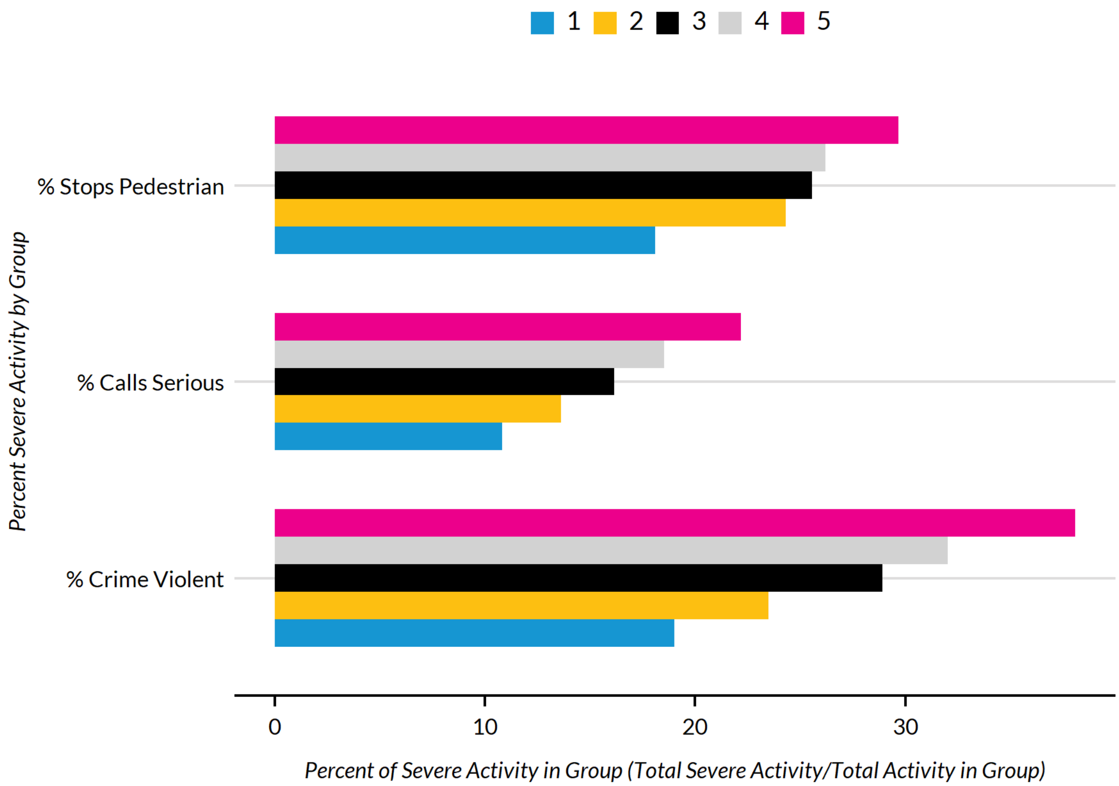
As Activity Increases, So Does Severity

The high-activity districts in groups four and five experience more calls for service, crime, and police activity. As activity increases across groups, the composition of each activity also changes. The higher-activity groups have a greater share of calls for service that are serious and crimes that are violent (figure 4). For example, 11 percent of group one's calls are serious, compared with 22 percent of group five's. The high-activity groups also have a higher percentage of stops that are of pedestrians rather than vehicles. The high-activity groups have different built environments (i.e., greater address density), which may influence the higher pedestrian-stop rate. For people stopped on foot rather than in a vehicle, stops can feel more intrusive and strongly influence views of police legitimacy. The increased activity and severity indicate that the neighborhoods have greater public safety concerns and that resident perceptions of safety and experiences with the police likely differ from those in neighborhoods with low activity.

FIGURE 4

Group Five Has Greatest Percentage of Severe Activity across Types

Percent of severe activity by group



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Crime, calls for service, stops, and arrests are generally concentrated in groups four and five. This may owe to police increasing activity in crime "hot spots" or spending more time in those areas because of frequent calls for service. Despite having the greatest share of serious calls for service and violent crime, group five had less resident-initiated contact than we would expect given its level of police-initiated contact. Moreover, group five had the greatest share of serious calls for service and violent crime. The lower ratio of calls for service, combined with the increased severity of the calls and crime, may indicate that residents have a higher severity threshold for when they call the police or that they are less willing to request police services.

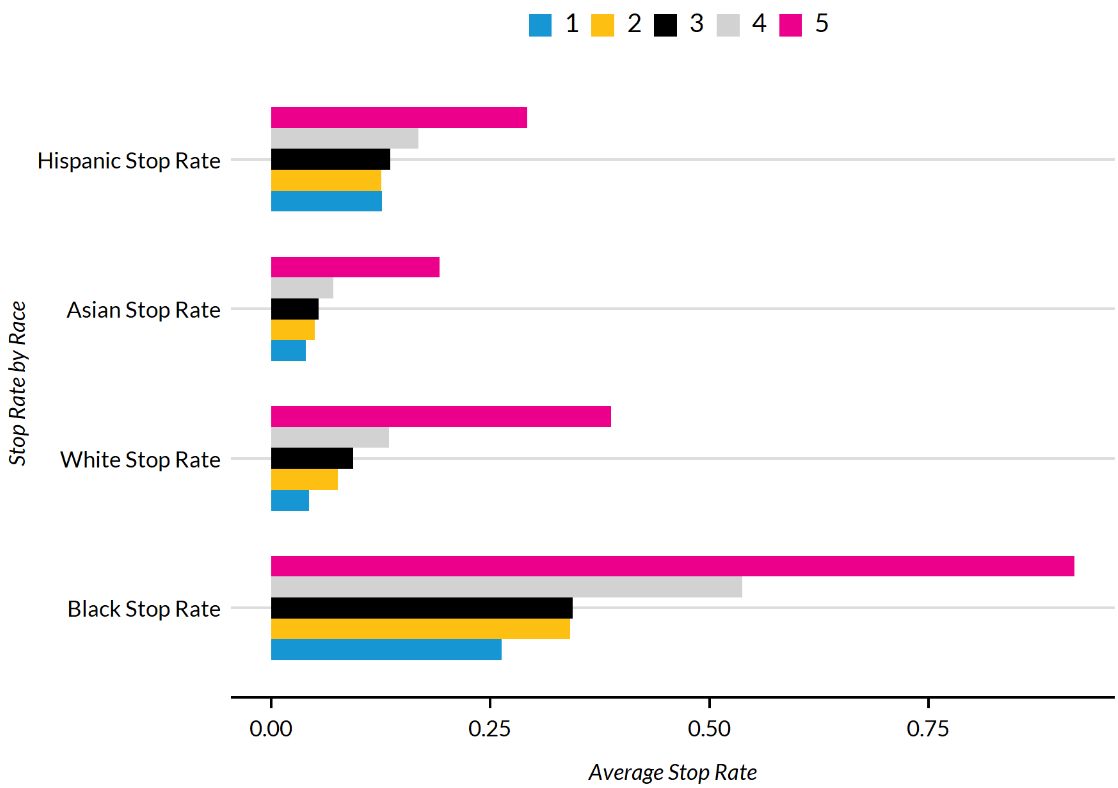
As Activity Increases, So Do Racial Disparities

As activity increases from groups one to five, racial and ethnic disparities in stops and arrests generally widen. Figure 5 shows the per capita stop rate for each racial and ethnic group increasing from group one to group five. The stop rates in figure 5 are calculated by summing the number of stops of people of a given race across all reporting districts in the group and dividing by the total population of that race across all reporting districts in the group. Although the people stopped in a particular group may not live in one of that group's reporting districts, calculating the rates in this way is important to account for the different racial composition by group (table 3). For example, the Black population rate in group five is six times that in group one.

FIGURE 5

Though Stop Rates Increase for All Races across Groups, the Stop Rate Is Highest among Black People

Stop rate per capita by race and by group



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Across all groups, the per capita stop rate is lowest for Asian people, followed by white, Hispanic, and Black people (figure 5). When examining stop rates per capita for each race separately, the rate of increase between groups varies. For example, Black people in group five are three times more likely to be stopped than in group one, and white people in group five are nine times more likely to be stopped than in group one. However, across all groups and their varied activity levels, Black people are stopped at the highest rate. Reporting districts in groups four and five have a greater share of Black and Hispanic residents and still have higher per capita stop rates of Black and Hispanic people. We also find the same patterns of racial disparity for arrest rates. Although people of all races experience increased police contact in the high-contact groups, this experience is especially frequent for Black and Hispanic people.

TABLE 3

Racial/Ethnic Composition of Reporting Districts by Group

	Group 1 (n=231)	Group 2 (n=271)	Group 3 (n=284)	Group 4 (n=201)	Group 5 (n=148)
Population Percentage					
Asian	13.4	14.3	12.0	10.5	7.4
Black	3.4	4.2	6.9	8.3	20.1
Hispanic	22.9	39.8	51.5	58.0	56.2
White	56.5	38.3	26.8	20.9	14.1

Residents Experiencing Economic Hardship Are More Likely to Live in Areas with Higher Activity

We also explore how different groups of people in Los Angeles are affected by policing, particularly in the high-activity groups, because people's circumstances and neighborhood resources influence their engagement with police, crime patterns and opportunity, and policing activity. People facing economic hardship—as measured by the share of people with incomes less than 200 percent of the poverty line[17]—are more likely to live in areas with high activity (figure 6). Greater economic hardship may impact the types of community resources available. Similarly, the share of people with limited English proficiency increases across groups, meaning more people in high-activity groups may have difficulty communicating with local police. The share of noncitizen immigrants is also higher in the higher-contact groups, and noncitizens may be less likely to engage with the police or make calls for service. Regarding housing factors, the share of people who rent is also higher as activity rises, which could affect community connections because renters move more often than people who own their homes.

FIGURE 6

High-Activity Groups Have Greater Share of People in Poverty and Renting

Average percentage of residents with characteristic by group

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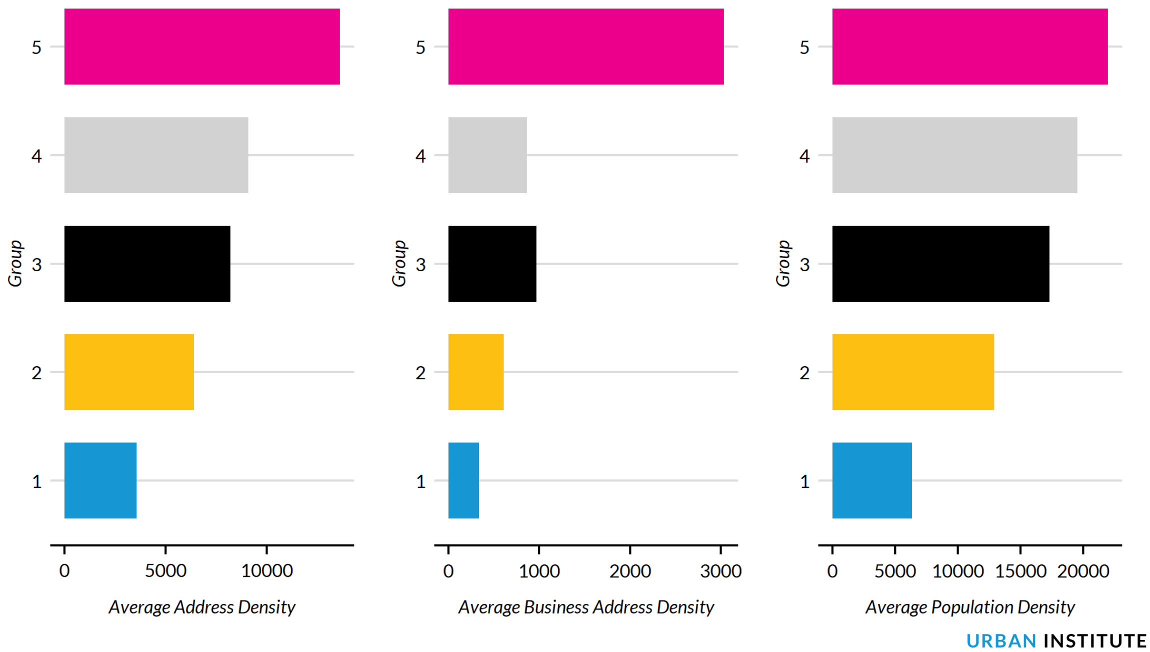
Though this project's limited scope prevented in-depth exploration of land use and built environments, we do consider how these can affect crime and social interaction (figure 7). The high-activity groups have slightly more businesses; commercial areas often have different patterns of social activity, crime, and policing. For example, commercial areas may have more daytime activity, greater opportunity for property crime, and regular policing patrol. The high-activity groups also have greater population and address density, meaning they may be denser areas with increased social interaction.

FIGURE 7

High-Activity Groups Have Greater Population and Address Density

Density per square mile by group



Although the groups show general demographic and land-use patterns, the neighborhoods in each group assignment vary. Not all neighborhoods in the high-activity groups have the same levels of economic hardship or types of built environment. Moreover, two adjacent neighborhoods that may be quite similar in terms of these characteristics may be in different groups because of their varied levels of crime, police-initiated activity, and resident-initiated activity.

Despite These Trends, Notable Outliers Exist

The previous sections show aggregate patterns of resident-initiated contact compared with police-initiated contact. However, we recognize the complexity of neighborhoods and that some reporting districts may diverge from the general patterns. Most reporting districts follow the trend of either low resident-initiated contact and low police-initiated contact, or high resident-initiated contact and high police-initiated contact. However, a few reporting districts have a combination of high and low activity. Thirty-four reporting districts (3.0 percent) have greater-than-expected resident-initiated contact given their levels of police-initiated contact, and 32 reporting districts (2.8 percent) have greater-than-expected police-initiated contact given their levels of resident-initiated contact.[18] Compared with the rest of the reporting districts, the high resident-initiated contact outliers have a significantly greater share of white and Asian people, adults with college degrees, renters, and property crime. The outliers with high police-initiated contact have significantly more businesses and violent crime. They also have a significantly smaller immigrant population (both citizen and noncitizen) and a smaller population of people with incomes less than 200 percent of the poverty line, suggesting these are more affluent commercial areas. For example, a few of the outliers are the areas around the Los Angeles International Airport, Hollywood Walk of Fame, and Venice Beach Boardwalk. The high police-initiated contact outliers also include major university areas (like the University of Southern California and the University of California, Los Angeles) and Skid Row in downtown Los Angeles, an area with a large concentration of unsheltered people experiencing homelessness. Most of these areas are not traditional residential neighborhoods, and many have separate police departments and security agencies that also patrol the areas.

Further examination of the outlier reporting districts that had high and low combinations of resident-initiated and police-initiated contact (rather than all high and all low) would be important in any community engagement plan. These districts have unique demographic and economic characteristics and may be neighborhoods that are experiencing more rapid change or are largely nonresidential. Moreover, their levels of police-initiated activity are not proportionate to the levels of resident calls for service, indicating that the police may be implementing different strategies there. The patterns and outliers in the policing typology highlight several areas for further exploration.

Community-Police Conversations

Neighborhood-level analyses of policing activity can support conversations between community members and police. From NNIP's experience, having a common set of facts focuses conversations more on solutions. Our analysis confirms the importance of analyzing small areas (rather than just citywide data) to understand the range of experiences across neighborhoods. For the NNIP network, democratizing data also means including marginalized people and communities so they can better advocate for themselves. In this section, we provide examples and resources for community-based organizations, government agencies, and law enforcement agencies in Los Angeles. We also discuss how local data organizations and criminal justice advocates could implement this approach in their communities.

Resources for Los Angeles

In Los Angeles, we hope that community-based organizations, government representatives, and the LAPD will use our analysis to start or inform conversations about policing reform and strengthening communities' trust in police. For example, the Reporting District Explorer in our Power BI website offers a map where people can zoom in and see the types of groups represented in their neighborhood (which are larger than reporting districts).[19] Users can also select key statistics for each reporting district (e.g., calls for service, stops, arrests, and crime) and compare their values with reporting districts across Los Angeles. With this information, residents and other stakeholders will understand the patterns of resident-initiated and police-initiated activity in their neighborhood and whether those levels of activity are higher or lower than in other neighborhoods. In conversations, residents can share their lived experiences with the factors influencing whether and when neighbors call the police, and police can clarify how they determine strategies in particular neighborhoods. If reporting districts in residents' neighborhoods have been assigned to multiple groups, they can initiate a conversation to explore the drivers of differences between those districts.

One local initiative using this data is the Criminal Justice Data Initiative within the Neighborhood Data for Social Change project at USC.[20] Through this initiative, the Sol Price Center for Social Innovation and Safe Communities Institute at USC are collecting and sharing many neighborhood-level criminal justice indicators and hosting community trainings on using the data. They convene representatives from community-based organizations, law enforcement agencies, and local government to start conversations about the data, opportunities for future data collection, and ideas to promote public safety. Publicly accessible criminal justice data and regular communication between communities, police, and government ensure residents' experiences supplement quantitative analysis with their insights and provide a foundation for improving neighborhood trust and safety.

Representatives in city and county government may also have applications for a neighborhood typology of policing activity. They may be interested in examining calls for service, policing activity, or crime in the neighborhoods they represent to inform their outreach to LAPD or provide context about public safety. They may also want to further democratize data by requesting that all law enforcement agencies in Los Angeles and adjacent jurisdictions publicly release their data.

The LAPD could use the typology to examine more detailed information about neighborhoods in terms of their levels of crime and calls for service, or how their policing activity varies throughout the city. Although police officers may believe they know the areas with more crime and resident calls, the typology may counter their assumptions and provide insights about where calls are significantly more serious or where the number of calls does not match the level of crime. With these neighborhoods identified, police could focus on community engagement to increase trust (which may in turn make people more willing to call) or adopt a more inclusive, problem-oriented policing strategy. The LAPD could also use this analysis during community meetings to, for example, describe neighborhood variation in calls for service or stops or conduct similar analyses regularly to see how resident-initiated activity and policing strategy evolve over time.

With the baseline understanding of how resident-initiated activity varies throughout the city that this analysis provides, community organizations and the LAPD may be interested in digging deeper to understand how public trust and sentiment toward police varies across neighborhoods. As an example of what could be done with additional data collection and collaboration, the Urban Institute partnered with the Austin Justice Coalition in Austin, Texas, on the Community Voices Project to survey residents in areas with high police presence about their views on the law and role of the police as well as their perceptions of police fairness, procedural justice, and legitimacy.[21] Survey findings were presented back to the community in a data walk that resulted in recommendations for the Austin Police Department. Further exploration of community views in Los Angeles could lead to more robust conversations and solutions-development between communities and police.

Analyses of open police data and surveys of community perceptions not only support community-police conversations; they can also help support trust-building efforts between communities and police. The National Network for Safe Communities at John Jay College has helpful resources on how to implement reconciliation processes between police and communities at the neighborhood level.[22] Recently, six cities implemented reconciliation discussions between communities and police, along with officer trainings and departmental policy changes, through the National Initiative for Building Community Trust and Justice and found some improvements in police-community relations.[23] Community organizations, local government, and police in Los Angeles may be able to draw from models implemented in other cities to build trust between police and communities.

Resources for Other Cities

Outside of Los Angeles, we hope this analysis inspires local data organizations and criminal justice advocates in other communities to conduct similar analyses. We recommend that any analysis like ours be done collaboratively with analysts and advocates to be relevant to local audiences and community questions. The first step is to acquire the data. The NNIP's 2019 brief highlights the wide range of commonly available local criminal justice data, which is not restricted to data sources on policing.[24]

Local groups can check the US City Open Data Census or the Police Data Initiative to find their city's or county's open data portal.[25] For unpublished data sets, NNIP's "Lessons on Local Data Sharing" provides tips for people advocating for their police to release new data.[26]

The next step is to analyze the data. Our GitHub site shares the detailed methodology and programming used to process the files.[27] Community data organizations like NNIP partners, other applied research centers at universities, or data-for-good volunteer groups like the Code for America brigades or DataKind chapters are promising sources of analytic expertise about adapting the machine learning techniques we used. Our Power BI site gives examples of how to visualize the findings.[28]

The final and most important step is to work with community groups to interpret and share the findings. Our local partner at USC was already cultivating relationships with community groups and residents, and it provided us invaluable insights about the city's geography and local advocates' potential interests. People living in the neighborhoods should be involved to provide critical context to validate or critique the indicators and categories, as well as surface ideas about other forums for the findings.

As one example of a local data organization working with residents, Data You Can Use is working with residents of the Amani neighborhood in Milwaukee, Wisconsin, to build their capacity around neighborhood conditions, safety, and policing. They paired an analysis of crime trends and hot spots with a resident-conducted survey about public safety and police legitimacy. The survey found that residents felt secure with police presence in their neighborhood, were willing to call police to report crime, and were more concerned about traffic safety than violent crime. The residents shared the survey results with their neighbors in "data chats" and took action to improve traffic safety in their neighborhood.

Although this report focuses on a policing typology, NNIP's 2019 brief highlights examples of action-oriented analysis from across the US on a host of criminal justice issues.[29] Data are a powerful though still underused tool for advancing community conversations about criminal justice reform. Learning from one another can benefit this challenging journey and we welcome examples of other places using data for justice reform at nnip@urban.org.

Appendix. Additional Metrics

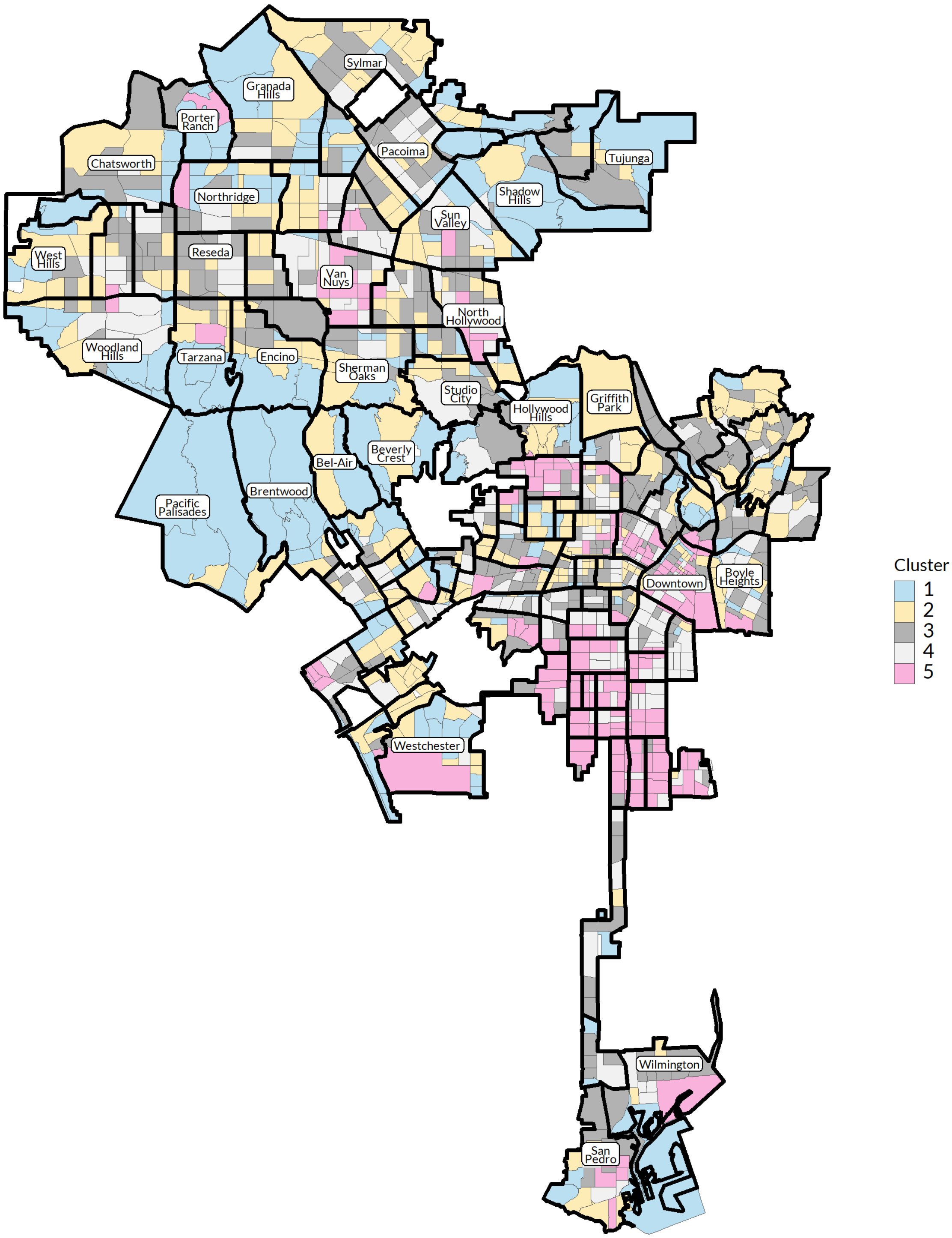
TABLE A.1

Mean Count of Key Metrics for Each Group

	Group 1	Group 2	Group 3	Group 4	Group 5
Variable					
Number of reporting districts (n)	231	271	284	201	148
Calls for service	196	488	762	1,121	1,753
Part 1 violent crimes	10	31	56	88	172
Part 1 property crimes	29	65	88	120	183
Part 2 crimes	15	35	50	67	96
Pedestrian stops	21	78	134	222	580
Traffic stops	94	244	389	625	1,373
Arrests	15	44	67	111	306
Total population of all reporting districts in group	372,418	826,689	1,144,751	930,867	675,305
Average population in reporting district	1,612	3,051	4,031	4,631	4,563
Asian population %	13.4	14.3	12.0	10.5	7.4
Black population %	3.4	4.2	6.9	8.3	20.1
Hispanic population %	22.9	39.8	51.5	58.0	56.2
White population %	56.5	38.3	26.8	20.9	14.1
Average population % under age 18	17.0	19.1	20.7	22.9	20.9
Average address density (address/mile2)	3,562	6,393	8,209	9,076	13,613
Average business address density (business address/mile2)	341	611	970	868	3,036

FIGURE A.1

Reporting District Group Assignment Map with Neighborhood Overlay



Notes

[1] For more information, see the NNIP cross-site project page at http://www.neighborhoodindicators/justicereform.

[2] Jesilow, Meyer, and Namazzi (1995), Langan and coauthors (2001), LaVigne, Fontaine, and Dwivedi (2017), Murty, Roebuck, and Smith (1990), Reisig and Parks (2000), and Sampson and Bartusch (1998).

[3] George L. Kelling and James Q. Wilson, "Broken Windows: The Police and Neighborhood Safety," *Atlantic Monthly*, March 1982, https://www.theatlantic.com/magazine/archive/1982/03/broken-windows/304465/.

[4] Ben Poston and Cindy Chang, "LAPD Searches Blacks and Latinos More. But They're Less Likely to Have Contraband than Whites," *Los Angeles Times*, October 8, 2019, https://www.latimes.com/local/lanow/la-me-lapd-searches-20190605-story.html.

[5] *Catalyzing Policing Reform with Data: Technical Appendix* is available at https://www.urban.org/research/publication/catalyzing-policing-reform-data-technical-appendix.

[6] Visit the interactive data tool at http://neighborhoodindicators.org/CJinteractive.

[7] The LAPD has the most sworn personnel out of the law enforcement agencies in the County of Los Angeles, and only has jurisdiction within the City of Los Angeles. However, the Los Angeles Sheriff's Department is nearly as large as LAPD and has jurisdiction throughout the rest of the County of Los Angeles. In the city, there are many smaller agencies based out of localities (e.g., Santa Monica, Pasadena) or universities (e.g., UCLA, USC). There are also state and federal agencies that operate in Los Angeles (e.g., California Highway Patrol, FBI). Our analysis only looks at LAPD activity within LAPD reporting districts. However, other agencies may conduct activities in those reporting districts that we are unable to measure.

[8] The LAPD's open data are available at https://data.lacity.org/browse?Data-Owner_Department=LAPD.

[9] Age, sex, and race/ethnicity information is available for arrests and sex and race/ethnicity information is available for stops. Age, sex, and race/ethnicity information is also available for victims of crime, but we do not use this information in our analyses. No demographic information is available for calls for service.

[10] In this analysis, we use four primary race/ethnicity categories, non-Hispanic Asian, non-Hispanic Black, Hispanic, non-Hispanic white, and other following the terminology used by LAPD. The other group includes American Indian/Alaskan Native, other, and unknown. LAPD uses 19 unique descent codes, which we group into these five categories.

[11] Information on how LAPD classifies crimes according to the UCR categories is available at https://data.lacity.org/api/views/63jg-8b9z/files/fff2caac-94b0-4ae5-9ca5-d235b19e3c44?download=true&filename=UCR-COMPSTAT062618.pdf.

[12] For all subsequent plots, 22 reporting districts are excluded from analysis because the 2010 census blocks that fall within the reporting district all have populations of zero. Therefore, we could not crosswalk the reporting districts to census tracts using our population-weighted crosswalk methodology and assign demographic data from the American Community Survey to these 22 reporting districts. Of the 22 reporting districts, 18 are in group one and four are in group two.

[13] Because our unit of analysis is a reporting district and American Community Survey data are reported at the census-tract level, we create a crosswalk that weights the American Community Survey information according to the reporting district size.

[14] The US Department of Housing and Urban Development aggregated US Postal Service data on address vacancy reports quarterly data on total, vacant, and no-stat residential and business address counts at the tract level. We

use the average counts of total, residential, and business addresses across the four quarters of 2018 for our analysis.

15 The 17 variables included in the cluster analysis include: rates for serious and nonserious calls for service; vehicle and pedestrian stops; total stops by race (Asian, Black, Hispanic, white); adult and juvenile arrests; total arrests by race (Asian, Black, Hispanic, white); Part 1 violent and property crime; and Part 2 crime. A full discussion of the variables is available in the technical documentation.

16 To assess whether our clusters are meaningfully distinct, we perform two-sided *t*-tests of our cluster means against the population means (the average across all reporting districts in Los Angeles) for each of the variables used in the cluster analysis, as well as the following other variables of interest: non-Hispanic Asian, non-Hispanic Black, Hispanic, and non-Hispanic white population percentage, total stops, total arrests, and total calls for service. For nearly all variables, our cluster averages are significantly different from the population average at the 0.05 significance level. The notable exception is cluster 3, for which the cluster means for 8 of the 17 variables used for clustering as well as non-Hispanic Asian and non-Hispanic Black population percentage are not significantly different from the population average. This suggests that our ”middle” cluster 3 is most reflective of the overall population.

17 In 2017, 200 percent the poverty threshold set by the US Census Bureau was $24,976 for a single person, or $49,716 for a household with two adults and two children. The threshold changes based on the number of adults and children in the household. For more information on poverty thresholds, see https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html.

18 We define the outliers as those reporting districts that are one standard deviation above the mean in the difference in scaled resident-initiated contact and scaled police-initiated contact.

19 See http://neighborhoodindicators.org/CJinteractive.

20 For more information, visit the USC website at https://socialinnovation.usc.edu/announcing-the-ndsc-criminal-justice-data-initiative/.

21 Findings from the survey and recommendations from the data walk are available at https://www.austinjustice.org/reports.

22 Resources for implementing reconciliation conversations are available at https://www.nnscommunities.org/innovations/racial-reconciliation/

23 Information about the National Initiative can be found at https://www.urban.org/policy-centers/justice-policy-center/projects/national-initiative-building-community-trust-and-justice.

24 See “The Potential for Catalyzing Community Criminal Justice Reform with Data” at https://www.urban.org/research/publication/potential-catalyzing-community-criminal-justice-reform-data.

25 See http://us-cities.survey.okfn.org/ or https://www.policedatainitiative.org/participating-agencies/.

26 The data sharing guide is available at https://www.neighborhoodindicators.org/library/guides/nnip-lessons-local-data-sharing.

27 See https://github.com/UrbanInstitute/la-policing-typology.

28 See http://neighborhoodindicators.org/CJinteractive.

29 See “The Potential for Catalyzing Community Criminal Justice Reform with Data” at https://www.urban.org/research/publication/potential-catalyzing-community-criminal-justice-reform-data.

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