Reducing Fatal Crashes, Fighting Crime, and Social Control
Evaluating Three Models of Police Traffic Stops

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Abstract

This paper presents an analysis of over 11 million traffic stops conducted by the San Diego Police Department using geolocated traffic stop data. The study examines the relationship between traffic enforcement and traffic accidents, with a particular focus on the racial composition of neighborhoods where enforcement occurs. The results show that police tend to enforce traffic laws in areas with high numbers of crashes but are less likely to conduct enforcement during times of the day when there is a high number of accidents. Additionally, the study finds that the racial composition of neighborhoods explains a significant portion of the variance in police-stopping behavior. These findings highlight the need for more nuanced approaches to traffic enforcement that take into account both traffic safety concerns and issues of equity and fairness in policing.

Keywords: Criminal Justice, Race and Politics, Traffic Stops

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Introduction: Three Models of Traffic Stops

We propose three alternative explanations of police traffic stops. First and most straightforwardly, police agencies may allocate their resources according to observed automobile accidents, particularly those crashes that result in injury or death. Second, they may use traffic stops as a means to fight the war on drugs and/or the war on crime. Because every motorist is breaking some kind of law, the traffic code provides law enforcement officers the opportunity to have a short conversation with any motorist (see Harris 1998, Seo 2019). Police nation-wide use this tool in order to pull over 20 million motorists each year, making the traffic stop the most common form of interaction between members of the public and the police. While many of these interactions are clearly related to speeding or dangerous driving, the fact that a majority of drivers are indeed speeding if they are moving with traffic means that a police officer may “pick and choose” which car to stop and with whom to have a conversation. Further, the courts have routinely validated this police strategy and it is widely used as a method of looking for drugs and contraband or simply as showing members of certain communities that the police are active and aware (see Baumgartner et al. 2018). This “pretextual” use of traffic stops as a way to fight the war on crime may be an effective crime-reduction tool (that is, after all, its official justification from law enforcement sources). On the other hand, commentators have long suggested that the pretextual use of the traffic code as a tool of crime-control is ineffective and is more focused on social control than on crime control (see Epp et al. 2008). Racial and class-based disparities are clearly present in these traffic stops, even more than in moving violations.

We use publicly available data from San Diego to assess what we will call the “public health,” the “crime fighting,” and the “social control” models of traffic stops. We leverage variation in location (e.g., which of 122 police beats, or neighborhoods); traffic stop type (e.g. moving v. non-moving violations); and time of day/week associated with each traffic stop. Our analysis suggests that the public health and crime control models carry some weight in predicting at least certain types of traffic stops (e.g., moving violations for white drivers), but the social control model is fundamental to the system.

The paper proceeds as follows. In the following section, we describe the dataset available for San Diego, give an overview of its main characteristics, and describe how we assess the public health threat (e.g., crashes), the crime threat (e.g. calls for service and reported crimes), and the demographic factors that allow us to assess the social control model. Next, we present our analytic model and results. Finally, we conclude.

Data

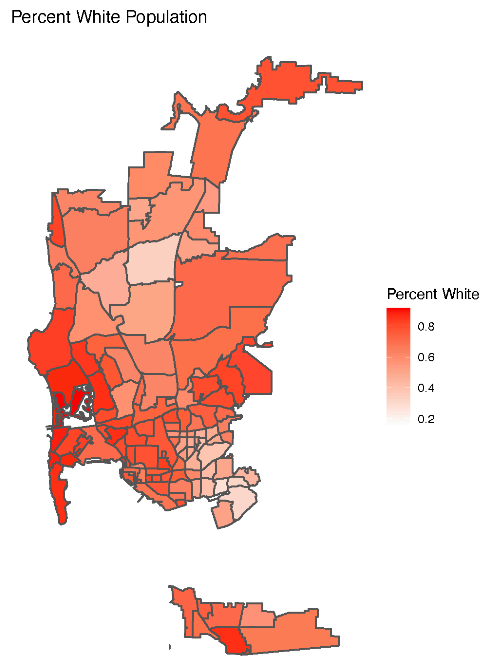
In constructing our analysis, we consider policing factors such as traffic stops, calls for service, and index crimes as well as non-police factors like the demography of an area as well as the traffic flows in a given area. Our geographic unit of analysis is the "police beat"; San Diego is divided into 122 beats, which are used for reporting purposes are correspond to neighborhoods in the community. There are also data important to understanding police activity that are not collected at the beat level, like income data and racial demographics. These data were collected by the U.S Census Bureau at the census block group level. The process of estimating census block group data at the police beat level is done through a process of dasymetric mapping. The city of San Diego is divided into 123 distinct, geographically delineated beats. Of the 28,633 census blocks in San Diego County, 11,416 are located in San Diego's municipal boundaries that are covered by the San Diego Police Department's beats. Of these beats, 9,498 are inhabited by at least 1 resident. Of these 9,498 inhabited census blocks, 9,234 (97.2%) are entirely located within one beat. Importantly, population data is available at the census block level. This means that while race and income data are only available at the census block group level (and census block groups are more frequently split between beats), data at the block group level can be weighted into beats based on the distribution of underlying census blocks into beats. All census blocks fit exactly into census block groups. This method of data weighting is superior to areal interpolation, which would just use the area of overlap between census block groups and police beats to weight data (see Amos et. al 2017).

Table 1: Description of Variables

Name	Description
Beat	One of 122 policing neighborhoods used for reporting statistics
Population	Beat-level information about population and racial composition obtained from the US Census
Traffic	Estimate of the average annual traffic passing through a beat. Obtained from Kalibrate's TrafficMetrix for the United States and arcGIS.
Index Crimes	Crimes reported to the FBI's Uniform Crime Reporting (UCR) Program. These crimes include the most heinous and violent offenses like rape, murder, and assault, and also include property crime, robbery, and other serious offenses.
Urgent Calls for Service	The San Diego Police provide data on all calls for service made, identified by beat. We do not believe that all calls are not going to be considered equal by police—a call about an ongoing assault is going to be taken much more seriously than a man who calls the police several time in one day because his neighbor has left trash cans in the street after trash pick-up. Our models use "urgent" calls for service, those identified by the dispatcher as priority 0, 1, or 2. Priority level 0 (the highest priority) indicate ongoing serious crimes involving immediate threat to life or serious injury. Priority 1 includes ongoing serious crimes like child abduction, domestic violence, or disturbances involving weapons. Finally, priority 3 includes robberies where a suspect is standing by to give a witness report, disturbing people at a scene, "prowlers," and other suspicious individuals. Beyond priority 3 are calls about cold cases, nuisances, welfare checks, or other non-immediately pressing issues—they are excluded from our analysis. We also exclude from our analysis any calls that were cancelled before an action could be taken.
Median Income	Beat-level information about median income from the US Census
Crashes	Count of Crashes published by the City of San Diego. For all analyses, we restrict to include only crashes with injuries
Moving Violation	Violations that occur as a result of the vehicle being in motion such as speeding or disobeying traffic signals
Non-Moving Violation	Violations that do not require the vehicle to be in motion such as equipment violations or expired registration

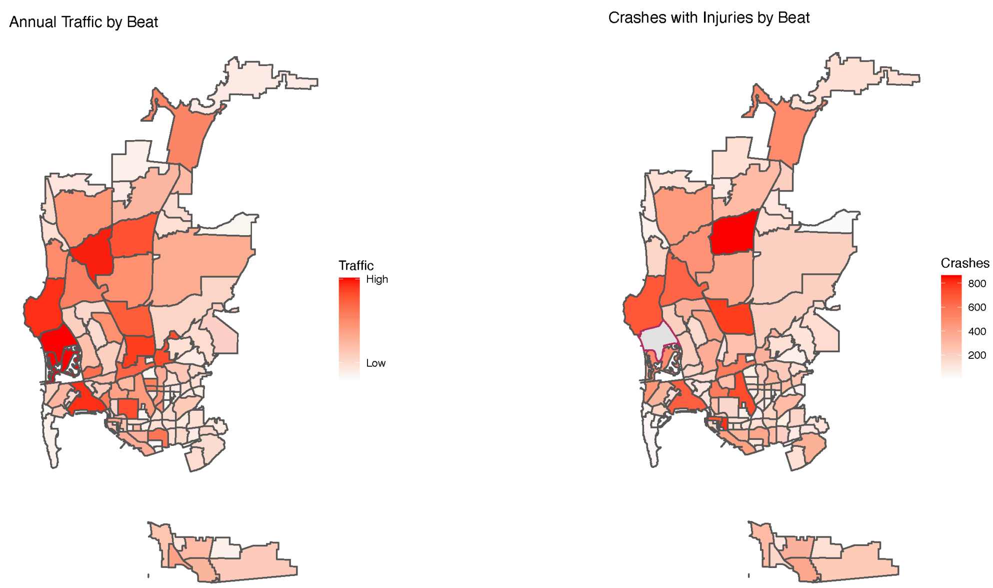
Focusing on San Diego allows us to highlight fine-grained geographic variation that occurs within one policing jurisdiction. The San Diego Police Department divides the city into 122 "beats" or neighborhoods for the purposes of policing and reporting. Like many American cities, San Diego displays a significant amount of racial segregation where certain areas are "majority-minority" while others are almost entirely white. This creates numerous challenges for equitable policing. Beats with the highest percentage of non-white residents are clustered in the southeast corner of San Diego while beats on the western side a predominately white. Figure 1 shows the percent white population in each beat:

Figure 1: Percent White Population by Beat



Driving behavior also differs from beat to beat. The left panel of Figure 2 shows the annual traffic estimates for each beat and the right panel shows the number of crashes with injuries for each beat.

Figure 2: Traffic and Crashes by Beat[1]



Stops are not uniformly distributed throughout the city of San Diego. Some beats have a significantly larger population than others as well as more traffic running through them.

Figure 3 shows the raw distribution of stops in the city as well as the distributions after controlling for population and traffic volume. While stops are not distributed evenly among the beats, controlling for population and especially traffic explains some of the spatial variations in traffic stops. This is to be expected since more traffic leads to a larger number of potential cars to pull over.

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[1] Beats outline in red are outliers.

Figure 3: Choropleth Map of Stops, Stops per Capita, and Stops Accounting for Traffic

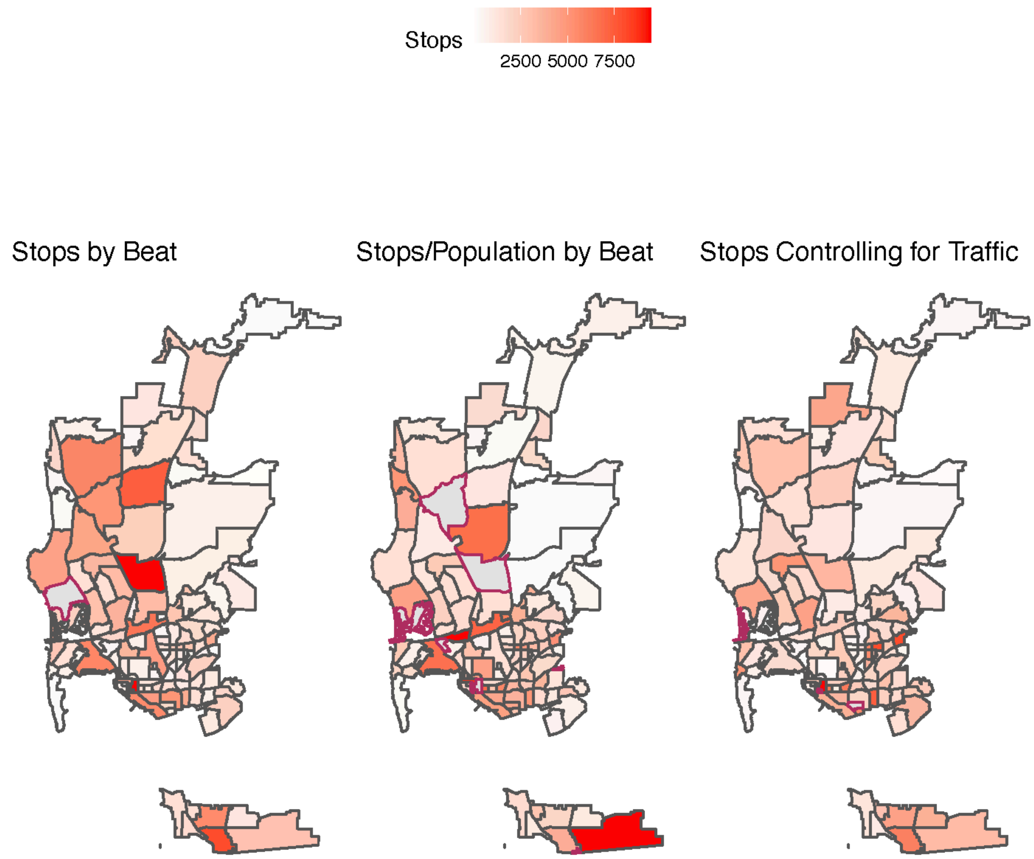


Table 2: Correlation Matrix of Variables of Interest

	Stops	Searches	% Movement Stops	% White Pop.	Total Pop.	Median Income	Traffic	Crashes	Index Crimes	Calls for Service
Stops	1	.	.	.	.	.	.	.	.	.
Searches	.71	1	.	.	.	.	.	.	.	.
% Movement Stops	.02	-.41	1	.	.	.	.	.	.	.
% White Pop.	.07	-.31	.56	1	.	.	.	.	.	.
Total Pop.	.52	.19	.14	.16	1	.	.	.	.	.
Median Income	.41	.03	.23	.34	.90	1	.	.	.	.
Traffic	.56	.27	.08	.26	.43	.42	1	.	.	.
Crashes	.88	.53	.07	.22	.60	.56	.67	1	.	.
Index Crimes	.46	.27	.07	.16	.39	.35	.48	.44	1	.
Calls for Service	.87	.64	.01	.17	.49	.43	.55	.88	.50	1

Empirical Strategy

Most people want safe roads and low levels of crime, but people also want to be free from police harassment and abuse. In light of these goals, an ideal policing regime would use traffic stops to increase road safety (public health) and deter crime (crime fighting), but as many commentators have observed, police forces often focus instead on enforcing social or racial hierarchies (social control). We test which of these three models best explains the use of traffic stops through three analytical frames: temporal variation within days and weeks, spatial variation across police beats, and a cross-sectional time-series (CSTS) analyzing changes in police behavior in response to changes in traffic and crime trends. In each section, our empirical goals are to understand how police do or do not meet the demands of residents for traffic safety and crime prevention. We also aim to illustrate how police may instead be acting in a way that enforces social control rather than traffic safety and crime prevention.

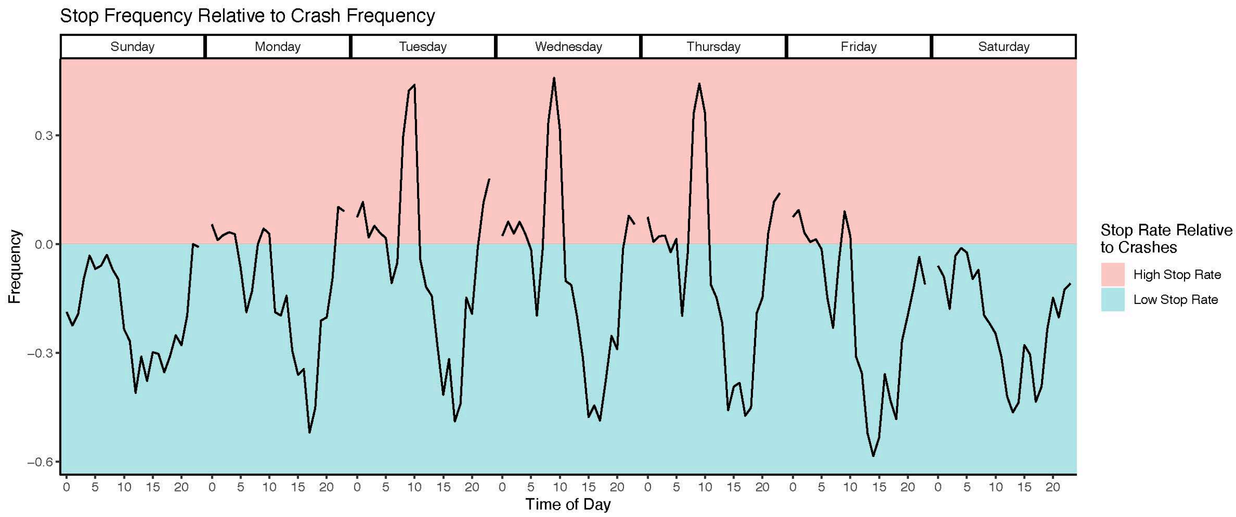
Time Trends

In this section, we review how police practices change depending on the hour of the day and the day of the week. In Figure 4, the x-axis represents the time of day, and the text at the top of each cell shows the day of the week. The y-axis represents the relative frequency of stops or collisions. This is calculated by summing all of the stops or collisions in our data for each hour of the day and day of the week and then dividing that number by the maximum value. The solid line represents collisions with injuries while the dashed line represents traffic stops. We can see that traffic stops are most common on Tuesday, Wednesday, and Thursday mornings while collisions are most common in the afternoon of any day of the week.

Figure 4: Relative Frequency of Stops and Collisions by Weekday-Hour

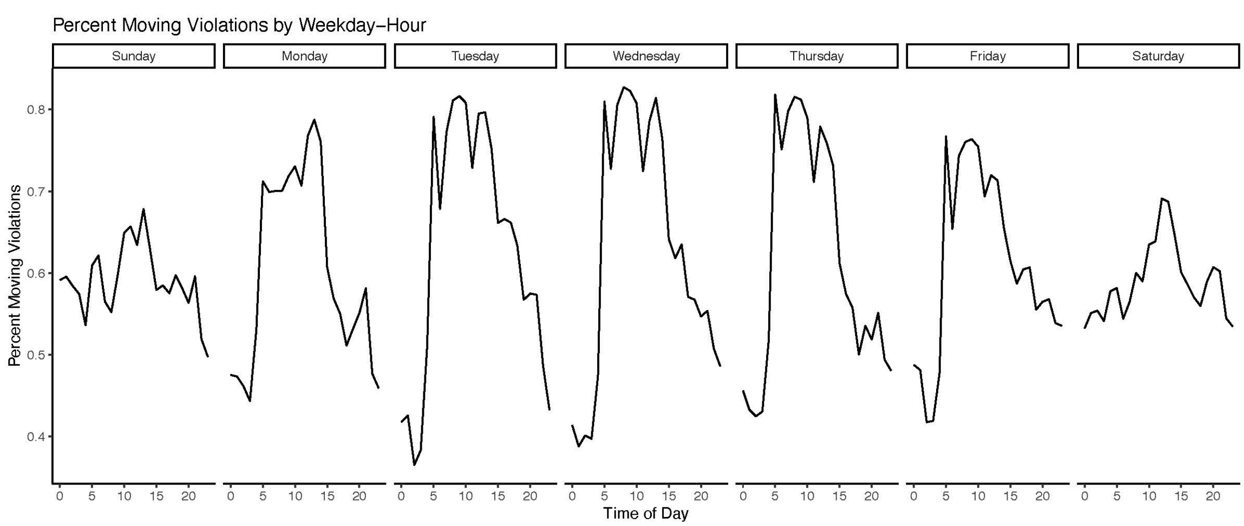
From Figure 4, it is clear that there is a discrepancy between when traffic stops are occurring and when collisions are occurring. To better visualize this gap, we subtract the frequency value of stops from the value for collisions and plot this. This generates one measure, which is the disparity between stops and crashes which is plotted in Figure 5. Values greater than zero represent police conducting many stops relative to crashes while values less than zero represent police conducting few stops relative to crashes.

Figure 5: Stop Frequency Relative to Crash Frequency



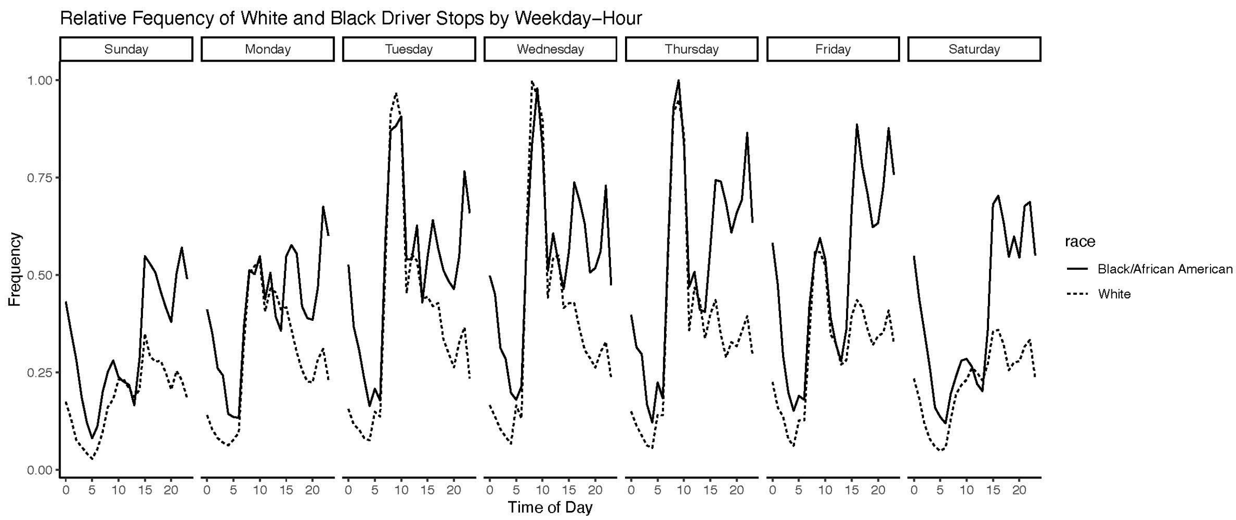
Again, Tuesday, Wednesday, and Thursday mornings stand out as a time with few crashes, but many stops. Alternatively, afternoons and evenings, especially on Fridays have many crashes but few stops. Throughout the day, police also change the mix of moving and non-moving stops that they conduct. Figure 6 shows that in the morning, almost 80% of stops are for moving violations like speeding or disobeying traffic signals. However, this number drops below half in the night and early hours of the morning. During these periods, a majority of traffic stops are equipment, or "pretextual" stops.

Figure 6: Percent Moving Violations by Weekday-Hour



The racial mix of stops excepts a strikingly similar trend to that of the moving violations shown in Figure 7. During the day, stops of white and black drivers track closely, but in the afternoon and evening, stops of black drivers remain high while stops of white drivers greatly decrease.

Figure 7: Racial Makeup of Stops by Weekday-Hour



In Table 2 and Figures 2-3, it seems that police are responsive to traffic safety objectives; beats with higher crashes and traffic receive more enforcement than beats with lower values. However, the time trends indicate that traffic enforcement does not align temporally with the times of the day with the most crashes and in fact, racialized trends in enforcement become apparent when examining stop trends over time. This discrepancy may reflect police prioritizing certain models of policing such as crime prevention and social control over the model of traffic safety. In the next section, we fit various regressions to test the explanatory power of each of the three models of policing.

Analytic Model

How we use crashes to evaluate whether there is a response in a CSTS set-up, separately for all crashes, and those with deaths or injuries. How we use calls for service (which types) and index crimes, and how these are or are not available by the time of day. How we use moving v. other traffic stops and race to assess the different focus of law enforcement, and how we will interpret the results based on that. Also, the benchmarking we do by neighborhood population and anything else needed to interpret the results to be presented.

Finally, we test the relationship between crashes and traffic stops using panel data analysis. The outcomes of interest include the frequency of moving and equipment stops for each ethnic group. For beat i in week t, we create the outcome variable by first dividing the total number of moving or equipment stops made for drivers from an ethnic group by the population size of the ethnic group in the beat, and then taking the logarithm of the number. The independent variable is the logged number of crashes in the previous week. We rely on the two-way fixed effects model with both beat and week fixed effects. The standard errors are clustered at the level of beats. We first estimate the effects on the whole sample and then explore the heterogeneity of the effects by fitting the same model on various subsamples, such as beats whose share of minority residents is above the median versus those whose share is below the median. We also examine whether the effects are larger for traffic stops in the morning. In the end, we present four regression models in each set of analyses.

Results: Aggregate Level Variation in Policing Tactics

The following tables regress various measures of policing on covariates that are typically understood to explain patterns in police behavior. In all models, the unit of analysis is the police beat. In all tables, the first model includes "public health model" explanations for police behavior. Most important in this model is the number of collisions in a given beat. From a public health standpoint, policing of the roads aiming to improve public safety should take place where collisions are most frequent. Beyond public health, police may also consider crime levels as a legitimate reason to increase policing activity. These models are labelled as Crime and Health. We consider both crimes reported to the FBI crime database (index crimes) and demand for policing measured via calls for police service that are deemed by the dispatcher to be "high priority." If police use data on criminal activity or demand for policing as a heuristic for deciding where to engage in policing activity, then these measures of crime should be associated with policing activity.

Finally, there are factors like race and income that may affect policing activity. While police cannot legally use these factors to shape their policing activity, extant work has demonstrated that policing in the United States is frequently racialized. We label models including race and income information as ‘Social Control’ factors. Finally, we also include a `Full Model’ with all of the covariates included. Dependent variables considered are stops per capita (measured as all traffic stops divided by the total estimated beat population), stops per traffic (measured as all traffic stops divided by the level of traffic estimated for the beat), the percent of all beat traffic stops that occur at night, the odds of a contraband search taking place during traffic stops in a beat, and the ratio between moving and non-moving violations cited as reasons for traffic stops in a beat.

The first set of models use traffic stops per capita as the dependent variable. In the public health model, lower population, and higher traffic both are associated with a greater number of stops. Given that the outcome is stops per person, this finding is intuitive, police engage in traffic stops where the traffic is. The association between collisions and stops per person is statistically significant in the public health model and public health and social control model, but the effect is substantively minimal. Moving to the crime and health model, calls for service are statistically significant and associated with more stops per person. Between the Public Health Model and Crime and Health Model, the adjusted R^2 for the model nearly doubles. The covariates added in the Social Control model do not meaningfully improve the fit of the model. The same exact models using stops divided by the level of traffic as the dependent variable show similar results (see appendix).

Table 3: Stops Per Population

	Dependent variable:			
	Stops Per Capita			
	Public Health Model	Crime and Health Model	Public Health and Social Control	Full Model
	(1)	(2)	(3)	(4)
Population (logged)	-0.474***	-0.014	-0.466***	-0.078*
	(0.048)	(0.036)	(0.076)	(0.044)
Traffic (logged)	0.134**	0.010	0.129**	0.024
	(0.058)	(0.032)	(0.060)	(0.032)
Collisions (involving injured person)	0.002***	0.0003	0.002***	0.0004*
	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Index Crimes Per Capita		0.008		0.007
		(0.019)		(0.019)
Urgent Service Calls Per Capita		0.211***		0.218***
		(0.023)		(0.023)
Beat Share Latino			-0.133	0.280**
			(0.272)	(0.140)
Beat Share Black			-0.339	0.338
			(0.846)	(0.431)
Median Income (logged)			-0.010	0.135**
			(0.109)	(0.056)
Constant	2.223**	-0.083	2.414*	-1.273*
	(0.889)	(0.484)	(1.259)	(0.674)
Observations	122	122	122	122
R^2	0.470	0.859	0.473	0.867
Adjusted R^2	0.457	0.853	0.446	0.858
Residual Std. Error	0.528 (df = 118)	0.275 (df = 116)	0.533 (df = 115)	0.270 (df = 113)
F Statistic	34.909*** (df = 3; 118)	141.273*** (df = 5; 116)	17.207*** (df = 6; 115)	92.017*** (df = 8; 113)
Note:				*p<0.1; **p<0.05; ***p<0.01

The next set of models use the odds of being searched as a result of a traffic stop in a beat as the outcome variable. Here, traffic, population, collisions, calls for service, and crime levels are all insignificant. Instead, the only variables that reach statistical significant are the share of a beat that are Latino (in the Public Health and Social Control Model and the Full Model) and the share of a beat that are Black (in the Full Model only). The R^2 value of the Crime and Health Model is .029 but rises to .466 with the inclusion of racial and income covariates. Importantly, income has no distinguishable effect, meaning that there is no evidence that the racial effect is driven by racial differences in income level.

Table 5: Search Rate

	Dependent variable:			
	Search Rate			
	Public Health Model	Crime and Health Model	Public Health and Social Control	Full Model
	(1)	(2)	(3)	(4)
Population (logged)	-0.004	-0.003	-0.006	0.001
	(0.005)	(0.007)	(0.006)	(0.007)
Traffic (logged)	-0.006	-0.007	-0.002	-0.005
	(0.006)	(0.007)	(0.005)	(0.005)
Collisions	-0.00000	-0.00000	0.00001	0.00001
	(0.00002)	(0.00003)	(0.00002)	(0.00002)
Index Crimes Per Capita		0.0001		0.003
		(0.004)		(0.003)
Urgent Calls for Service Per Capita		0.001		0.0001
		(0.004)		(0.003)
Share Latino			0.144^{***}	0.150^{***}
			(0.022)	(0.022)
Share Black			0.107	0.120^{*}
			(0.068)	(0.068)
Median Income (Logged)			-0.006	-0.004
			(0.009)	(0.009)
Constant	0.212^{**}	0.205^{**}	0.161	0.122
	(0.094)	(0.099)	(0.100)	(0.104)
Observations	122	122	122	122
R^2	0.028	0.029	0.449	0.466
Adjusted R^2	0.003	-0.013	0.420	0.429
Residual Std. Error	0.056 (df = 118)	0.056 (df = 116)	0.043 (df = 115)	0.042 (df = 113)
F Statistic	1.129 (df = 3; 118)	0.683 (df = 5; 116)	15.594^{***} (df = 6; 115)	12.341^{***} (df = 8; 113)
Note:				*p<0.1; **p<0.05; ***p<0.01

Finally, the moving Equipment to Moving Violation Ratio outcome variable is also best explained by the inclusion of the social control covariates. The Equipment to Moving Violation ratio is higher in beats where a greater portion of the total traffic stops are based on non-moving violations like a faulty headlight or broken windshield wiper. The only covariates statistically associated with this measure of policing behavior across all models are the share of a beat that is Latino and a beat's median income level. Although these equipment violations are often thought of as pre-textual reasons to investigate suspicious people or activities, these stops are not associated with measures of crime---they are associated with the racial demographics and income level of an area. More Latinos in a beat are associated with a greater ratio of equipment to moving violations, and higher incomes are associated with the opposite.

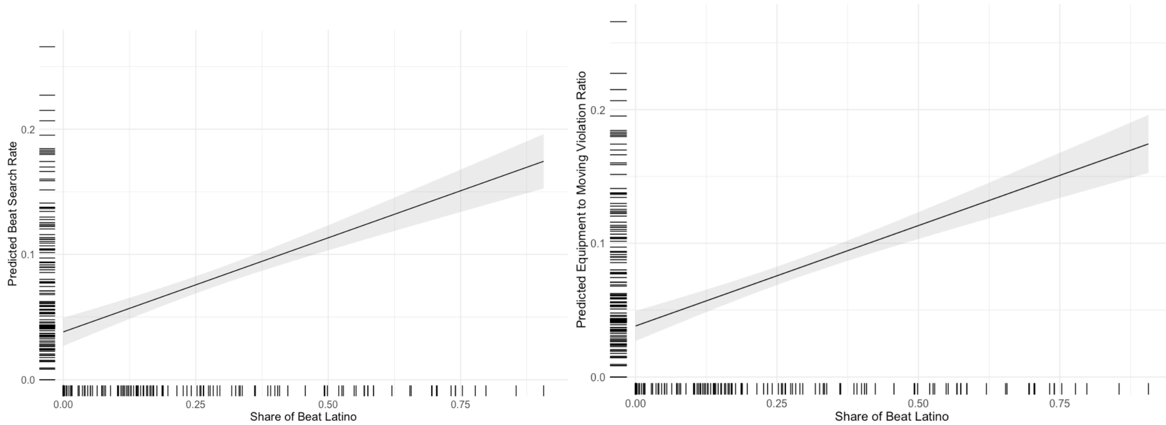
Table 6: Equipment to Moving Violation Ratio

	Dependent variable:			
	Equipment to Moving Violation Ratio			
	Public Health Model	Crime and Health Model	Public Health and Social Control	Full Model
	(1)	(2)	(3)	(4)
Population (Logged)	0.003	-0.021	0.054	0.063
	(0.036)	(0.052)	(0.045)	(0.052)
Traffic (Logged)	-0.039	-0.030	-0.023	-0.030
	(0.043)	(0.046)	(0.035)	(0.037)
Collisions	-0.00005	-0.00002	0.00000	0.00001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Index Crimes Per Capita		-0.004		0.017
		(0.028)		(0.023)
Urgent Calls for Service Per Capita		-0.006		-0.013
		(0.028)		(0.022)
Share of Beat Latino			0.720***	0.725***
			(0.161)	(0.164)
Share of Beat Black			0.603	0.625
			(0.500)	(0.506)
Median Income (Logged)			-0.149**	-0.150**
			(0.064)	(0.065)
Constant	1.111*	1.207*	1.656**	1.700**
	(0.662)	(0.693)	(0.740)	(0.780)
Observations	122	122	122	122
R^2	0.015	0.019	0.383	0.386
Adjusted R^2	-0.010	-0.023	0.351	0.342
Residual Std. Error	0.393 (df = 118)	0.395 (df = 116)	0.315 (df = 115)	0.317 (df = 113)
F Statistic	0.618 (df = 3; 118)	0.448 (df = 5; 116)	11.894*** (df = 6; 115)	8.874*** (df = 8; 113)
Note:				*p<0.1; **p<0.05; ***p<0.01

The effects of beat demographics on policing tactics are substantively meaningful. Figure 8 plots the marginal effect of the share of a beat that is Latino on the search rate and equipment-to-moving violation ratio in police beats estimated in the Full Models of Tables 5 and 6. Search rates vary widely across beats, from less than two percent of stops resulting in searches to well over a fifth. A beat that is a quarter Latino (roughly the mean share Latino) is predicted to have a search rate of 7-8 percent. A beat that is half Latino---a one standard deviation increase in the share of a beat that is Latino---is predicted to have a search rate of 11-13 percent. Given that this marginal effect includes controls for crime, the finding is concerning.

The marginal effect for the share of a beat that is Latino on the predicted equipment-to-moving violation ratio is similar. A beat that is a quarter Latino is predicted to have an equipment-to-moving violation ratio of about .5. A beat that is half Latino---a one standard deviation increase in the share of a beat that is Latino---is predicted to have an equipment-to-moving violation ratio of .65-.8.

Figure 8: Marginal Effects of Latino Population on Search Rate and Equipment-to-Moving Violation Ratio



Place-Based Variation in Racial-Group Outcomes

Beyond variation in search rate based on local demographics, we also measure differences in outcomes in different beats due to variation in individual characteristics. The results above suggest that police work differently in different beats. In particular, police conduct more searches, stop more cars due to non-moving violations, and conduct more stops at night in beats that have greater concentrations of Black and Latino drivers.

A key question then is whether this is actually due to differences in how police work in different areas, as we suggest, or if these results are driven by differences in how Black and Latino drivers are policed. For instance, our findings above could be driven by racially motivated searches, equipment stops, and night stops of Black and Latino drivers. If these drivers are disproportionately in beats where greater shares of Latino and Black drivers live, we would expect the above results. In this section, we look specifically at rates of searches on Black, Latino, and white drivers. The models in Table 7 regress the odds of Black, Latino, and White drivers being searched on the covariates included in the Full Models in previous tables.

Model 1 shows an association between the odds a Black driver is searched and urgent calls for service. In beats with greater demand for police action, Black drivers are more likely to be searched when stopped. Model 2 uses the same outcome but adds beat demographic information---the R^2 value quadruples, roughly. Black drivers are more likely to be searched when stopped in beats that have greater shares of Black and Latino residents. This finding holds for the odds of Latino drivers being stopped and the odds of white drivers being stopped. That white drivers are also searched at higher rates shows that racially disparate outcomes in search rates by beat are not motivated exclusively by officers choosing to search racial or ethnic minority drivers at higher rates---all individuals in beats with high concentrations of minority populations are more likely to be searched relative to other beats.

Importantly, these results are not driven by higher rates of crime or demand for service in these racially diverse beats. For one thing, calls for service have a significant effect on search rates across all racial groups, but calls for service are uncorrelated with the share of a beat that is Latino or Black. Indexed crimes are unassociated with search rates across all groups. Going further, Model 5 regresses the contraband hit rate, or the success of these searches, on the Full Model covariates---the share of a beat that is Latino or Black is negatively associated with searches finding any contraband. Police are conducting more searches in diverse beats despite no indication in the data of crime or elevated levels of contraband hits.

Table 7: Odds of a Driver Search

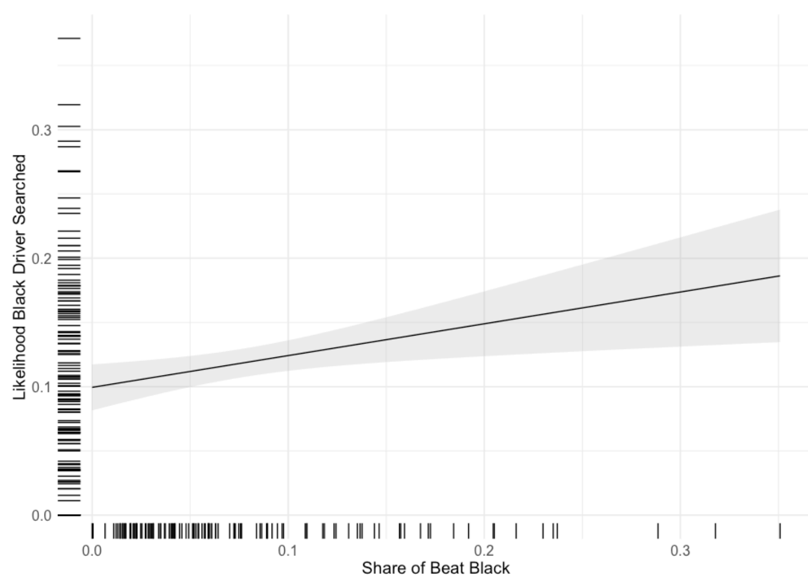
	Odds Black Driver Searched		Odds Latino Driver Searched	Odds White Driver Searched	Contraband Hit-Rate
	(1)	(2)	(3)	(4)	(5)
Population (logged)	0.015	-0.0004	0.006	0.005	0.043
	(0.012)	(0.015)	(0.010)	(0.011)	(0.027)
Urgent Calls for Service	0.098^{***}	0.118^{***}	0.076^{***}	0.071^{***}	-0.022
	(0.033)	(0.028)	(0.019)	(0.020)	(0.053)
Crime Index	-0.004	-0.003	-0.003	-0.002	0.002
	(0.005)	(0.004)	(0.003)	(0.003)	(0.008)
Traffic Collisions	-0.00004	-0.00002	-0.00003	-0.00003	-0.0001
	(0.00004)	(0.00003)	(0.00002)	(0.00002)	(0.0001)
Traffic (logged)	-0.013	-0.010	-0.005	-0.003	0.026^{*}
	(0.009)	(0.007)	(0.005)	(0.005)	(0.014)
Share Black		0.247^{***}	0.140^{**}	0.120^{*}	-0.569^{***}
		(0.094)	(0.063)	(0.068)	(0.173)
Share Latino		0.158^{***}	0.136^{***}	0.154^{***}	-0.188^{***}
		(0.027)	(0.018)	(0.019)	(0.050)
Median Income		0.014	0.003	0.007	-0.036^{*}
		(0.011)	(0.008)	(0.008)	(0.021)
Constant	0.167	0.010	0.025	-0.074	-0.033
	(0.132)	(0.115)	(0.078)	(0.083)	(0.235)
N	121	121	121	121	119
R^2	0.109	0.402	0.478	0.459	0.266
Adjusted R^2	0.070	0.359	0.441	0.421	0.212

Residual Std. Error	0.074 (df = 115)	0.062 (df = 112)	0.042 (df = 112)	0.045 (df = 112)	0.114 (df = 110)
F Statistic	2.807** (df = 5; 115)	9.397*** (df = 8; 112)	12.841*** (df = 8; 112)	11.891*** (df = 8; 112)	4.974*** (df = 8; 110)

*p < .1; **p < .05; ***p < .01

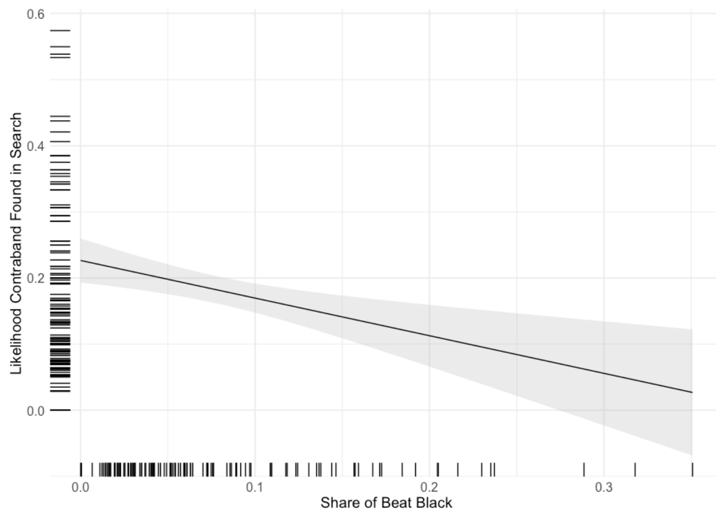
Figures 9 and 10 plot the marginal effects of the share of a beat that is Black on the likelihood of a Black driver being searched and the likelihood that contraband is found during a search. Both effects are substantively meaningful---drivers in a beat that is 7.5 percent Black, the sample mean, are predicted to be searched about 11 percent of the time. A standard deviation increase in the share of a beat that is Black, to 15 percent, and a Black driver is expected to be searched roughly 14 percent of the time. In beats with the greatest concentration of Black residents, search rates of Black drivers rise to about 14 to 22 percent.

Figure 9: Marginal Effect of Population Share Black on Odds that a Black Driver is Searched



Searches lead to the discovery of contraband much less frequently in the beats with the greatest concentration of Black residents. Searches in a beat that is 7.5 percent Black, the sample mean, are predicted to be successful about 20 percent of the time. A standard deviation increase in the share of a beat that is Black, to 15 percent, and a contraband search is predicted to discover contraband 17 percent of the time. In beats with the greatest concentration of Black residents, predicted contraband hit rates fall to at or below 10 percent.

Figure 10: Marginal Effect of Population Share Black on Likelihood of Contraband Found



Results from panel data analysis

In the left plot of Figure 11, we present the effect estimates for three variants of the independent variable: crashes, crashes with injuries or fatalities, and crashes without injuries, for all traffic stops, moving stops, and equipment stops. We can see that the effect is the largest for moving stops. When the number of crashes increases by 10%, the number of moving stops will increase by 0.8%. For equipment stops, the effect size is less than 0.2% and insignificant. In addition, crashes with injuries or fatalities have a larger impact than those without injuries. We thus focus on the effect generated by the latter in the analyses that follow.

Figure 11: Estimated Effect of Crashes on Enforcement

In the right plot of Figure 11, we present results from applying the same model to two separate sets of beats, depending on whether its share of minority residents is above or below the median. It turns out that the effect of crashes on moving stops is mainly driven by beats with a low share of minority residents. We also find that crashes lead to more equipment stops of minority drivers in beats with a low share of minority residents (although the estimate is imprecise), but not more equipment stops of white drivers in any type of beats. In the appendix, we show that the effect estimates are significant only for traffic stops in the morning but not for those in the nighttime.

Conclusion

In San Diego, when a driver happens to be stopped matters. Collisions are most frequent in the afternoon, but moving violations are handed out by police more frequently in the morning. Black and white drivers are stopped at roughly the same rates in the morning, but Black drivers are stopped at higher rates in the evening and at night.

Where a driver happens to be stopped also matters. Regardless of race, drivers more likely to be searched if they're pulled over in a beat with a larger share of Black or Latino residents. Given a beat's base-rate of moving violations, an individual is more likely to be ticketed for a non-moving violation in beats with larger Black or Latino shares of the population.

Our analyses indicate that these racial disparities are not the side-effect of police working to improve road safety or to deter crime. In fact, searches and equipment violations are uncorrelated with crime, crashes, and calls for service. Instead, we find that they are driven by police working to enforce social control. Controlling for crime, traffic safety conditions, and residents' calls for service, beats with large shares Latino and Black populations are over-policed. White drivers are affected by this too—being pulled over in these over-policed beats results in a higher search rate for whites too. Of course, the searches taking place in these beats are less effective than searches conducted by police in San Diego, overall.

Indeed, how police engage in traffic stops appears to be heavily influenced by factors other than crime prevention and traffic safety in whatever way they are framed. Temporally, collisions happen most frequently in the afternoon and evening, but traffic stops are disproportionately made in the morning. Although there are collisions on Sunday, Monday Friday and Monday, San Diego police do not make many traffic stops on these days at all.

Of course, police do make stops where collisions cause injuries to occur, but even in this regard, we see racial bias. When traffic collisions increase, police respond with more moving violations, but this finding is driven primarily by police increasing their traffic stops in whiter beats where collisions occur. Beats with higher minority populations are defined more by their demographics than their need for traffic safety.

Appendix

Stops Per Traffic

	Dependent variable:			
	Stops Per Traffic			
	Public Health Model	Crime and Health Model	Public Health and Social Control	Full Model
	(1)	(2)	(3)	(4)
Population (logged)	-0.011	0.070*	-0.057	0.026
	(0.028)	(0.039)	(0.043)	(0.048)
Traffic (logged)	-0.246***	-0.273***	-0.230***	-0.260***
	(0.033)	(0.034)	(0.033)	(0.034)
Collisions (involving injury)	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index Crimes Per Capita		0.010		0.014
		(0.021)		(0.020)
Urgent Service Calls Per Capita		0.027		0.031
		(0.025)		(0.024)
Share of Beat Latino			0.361**	0.453***
			(0.154)	(0.149)
Share of Beat Black			0.340	0.490
			(0.479)	(0.460)
Median Income (logged)			0.072	0.099*
			(0.062)	(0.060)
Constant	4.016***	3.687***	3.288***	2.634***
	(0.516)	(0.521)	(0.709)	(0.709)
Observations	122	122	122	122
R^2	0.335	0.379	0.371	0.435
Adjusted R^2	0.318	0.353	0.338	0.395
Residual Std. Error	0.306 (df = 118)	0.298 (df = 116)	0.302 (df = 115)	0.288 (df = 113)
F Statistic	19.798*** (df = 3; 118)	14.178*** (df = 5; 116)	11.317*** (df = 6; 115)	10.893*** (df = 8; 113)
Note:				*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	Percent of Stops at Night			
	Public Health Model	Crime and Health Model	Public Health and Social Control	Full Model
	(1)	(2)	(3)	(4)
Population (logged)	-0.008	0.004	0.006	0.019
	(0.008)	(0.011)	(0.012)	(0.013)
Traffic (logged)	-0.002	-0.004	-0.001	-0.004
	(0.009)	(0.010)	(0.009)	(0.010)
Collision at Night (involving injuries)	0.00005	0.00001	0.00004	0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index Crimes Per Capita		-0.002		0.0004
		(0.005)		(0.004)
Night Calls for Urgent Service (Per Capita)		0.018^{*}		0.017^{*}
		(0.010)		(0.009)
Share of Beat Latino			0.039	0.053
			(0.043)	(0.042)
Share of Beat Black			0.170	0.183
			(0.134)	(0.132)
Median Income (logged)			-0.028	-0.025
			(0.017)	(0.017)
Constant	0.333^{**}	0.255^{*}	0.466^{**}	0.353^{*}
	(0.143)	(0.144)	(0.196)	(0.195)
Observations	122	122	122	122
R^2	0.011	0.057	0.122	0.178
Adjusted R^2	-0.014	0.016	0.076	0.120
Residual Std. Error	0.088 (df = 118)	0.087 (df = 116)	0.084 (df = 115)	0.082 (df = 113)
F Statistic	0.429 (df = 3; 118)	1.397 (df = 5; 116)	2.653^{**} (df = 6; 115)	3.055^{***} (df = 8; 113)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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