Police Stops in the City of Berkeley: Are People of Color Still Being Stopped More Despite Changes in Police Policy?

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Introduction

Berkeley, California is known as one of the cities with the most progressive police departments in the US. However, recent reports have said that while the city is better than most, there are still racial disparities found in recent crime data from 2012-2016. This report analyzes city of Berkeley Police stops data since 2015 as well as consider new RIPA (Racial Identity and Profiling Act) compliant features from stops data since 2020 to verify some existing claims, and test new ones specifically regarding disparities in race. Key questions for this analysis include:

- How much does prior perception of race play a role in the result of a stop, particularly if the citizen being stopped is a person of color?
- Can environmental factors like income, residential demographics, and/or amount of previous police activity affect and/or reduce how many stops occur in an area? Do these vary by neighborhood, or are they largely consistent throughout the city?
- Can RIPA-Compliant data reveal more nuanced relationships between features of a stop? Can and/or will more detailed data echo previous discoveries about race and law enforcement?

Background

In 2018, the Center for Police Equity released a report on the Berkeley Police Department saying that there were racial disparities in arrest rates between white and nonwhite people of Berkeley (Buchanan, K. S., Pouget, E., & Goff, P. A. , 2018). Their study found that people of color were 4.5x-6.5x more likely to be stopped than white citizens, 4.5x-20x more likely to be searched per capita, and 2x as likely to be arrested overall. It's worth noting that additional analysis found that black and hispanic searches yielded less stops, however this didn't affect overall arrest rates. Use of force disparities were also found, but due to the complexity of classifying force in stop data we will not be considering this in our report. The report also requested that the city of Berkeley collect more race specific data in their reports, particularly surrounding the perceived race of the subject and if their race had been perceived prior to the stop.

Since the time of this report, the city has begun collecting RIPA-compliant (since 2020) and very recently (discussed later in report) approved a batch of departmental and policy changes that will radically alter how traffic stops are handled in the city of Berkeley. There is a unique opportunity here to conduct a more pointed analysis of stops and race, both in comparison to the broader non-RIPA stops data of the past, and before/in preparation for the very different data that will follow the intensive re-organization of Berkeley transportation laws and their enforcement. We will look to see if those specific racial disparities actually do exist in better data, and set up opportunities for clear comparisons as future policies change.

Methods

Study Design

We use multiple logistic regression to observe how likelihood (specifically *odds ratios*) of arrest (and other outcomes) vary depending on factors like race, area median income, age, distance from the university, etc. This is done with the understanding that while stop data is not directly equivalent to crime or arrest data, analyses here can at least reveal disparities in stop rates for different populations, and what goes into those disparities. Study variables are based on the previously mentioned project done by the Center for Police Equity and the first portion of their analysis focused on stop rates. While our data is limited and we can't directly infer differing stop rates just with data recorded after the stop, we do take the same variables and use them to analyze stop outcomes at scale.

Data

The data used in this project was collected by the city of Berkeley Police Department from 2015-2022 and downloaded in March of 2022 from its publicly available open access data portal. The data comes in two formats: RIPA and Non-RIPA Compliant data. All data since October of 2020 is RIPA-Compliant and as a result provides increased insights. Non-RIPA Compliant data has been kept to attempt to comprehensively represent the city, but some variables have been changed to match with new RIPA terminology, and certain models may vary in observation size due to lacking shared features between the two datasets. This is unfortunate, but some key assumptions can still be tested regardless of the differences in data.

Long-term crime and arrest data is also not directly available through the city and will be left out of this analysis. While it is still beneficial to look at stops to analyze police activity, it's important to clarify the difference between stops and arrests, and admit that while comprehensive, the presently available stops data do not paint the whole picture. Inferences made in previous reports surrounding the likelihood of being stopped, and the full volume of occurring crime cannot be equivalently made with only stops data.

Measurements

Outcomes

Arrest is the main dependent variable examined in this study. In the logistic regression model, it is a simple arrested/not arrested classification variable. Alternative dependent variables include *noactions* and *warning*, although these aren't given as much focus.

Longstop and/or *duration of stop* are also in focus as a dependent variable, but only apply for the data from 2020 and later. RIPA data mandates that the length of the stop be recorded. In the case of this study, and stops over 270 minutes, or 4.5 hours were excluded. In the context of this study, this classification variable essentially asks "based on certain conditions, what are the odds a person has a longer than average stop?"

Explanatory Variables

Perceived Race or Ethnicity represents the race of the person stopped. This variable is a combination of "race" from the non-RIPA dataset and "perceived race" from the RIPA dataset.

Race Perceived Prior to Stop is a binary variable representing (1) the subject's race was perceived by the officer before the stop and (0) the subject's race was not perceived before the stop. This data, while insightful, is only available for the models based on the RIPA-compliant data. For this analysis, single and double race categories have been simplified into "White", "Black/African American", "Hispanic/Latino", "Asian", and "Other". Any perceived racial categories with more than 3 mentioned races were classified as "Other". The 2017 report on Berkeley PD specifically cited concerns with enforcement towards black and Hispanic populations, so these categories are focused on most here.

Whitepop, aapop, na_aipop, hawaiian, and mixed2 all represent specific estimated counts of racial demographics per Berkeley census tract in 2020 based on data from the US Census.[1] These are useful in the multilinear regression as well as in the mapping portion of the analysis.

Totalpop, BIPOCpop, and *Pocpop* are the estimated total racial population numbers per census tract from the same census data and city information from geolocation maps.[2] Nonwhite includes all other racial categories outside of white, and POC includes Black, Hispanic, Hawaiian, and Mixed races.

BIPOCcomp and *Focus Group Comp* are a simple calculation of the estimated proportion of BIPOC residents and Focus Group Residents (The Black and Hispanic

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[1] American Community Survey, B02001_RACE

[2] (Census Tract Polygons 2010) Census tract polygons built from US Census Bureau 2010 decennial data for the City's redistricting process

populations that were the focus of the CPE report) per census tract. This is a broad representation but is acceptable for creating simple variables regarding “whiter” neighborhoods where stops would supposedly occur less.

Distancefromcal, Far, and *Close* represent another variable mentioned in the earlier study, distance from the university. Although we later find that this is at best curvilinear, it’s still worth including to see if it is still statistically significant.

Longstop represents if the duration of a stop was longer than average (in this case > 20 minutes). This is slightly over the mean, and approximately 80% of stops were within this range.

Results

We provide the descriptive statistics in Table 1. We did not find multicollinearity issues with any variables. Notably, certain variables had less observations as they could only be generated from information in the RIPA-Compliant dataset. Because of this, multiple models were run both for the larger and smaller datasets based on what variable information was available. This will be discussed more in later sections of the paper.

The results of the from the larger logistic regression models are displayed in Tables 2 & 3. Results show that that the subject race variable was significant and increased likelihood of arrest, and that in models where the subject was white this lowered the likelihood of arrest.

Table 1. Descriptive statistics (RIPA and Non-RIPA)

DESCRIPTIVE STATISTICS	Obs	Mean	Std. Dev.	Min	Max
Subject Arrested	61,702	0.018	0.133	0	1
Perceived Age of Subject	61,702	37.342	12.995	5	99
Stop Distance from Cal	61,702	1.435	0.704	0.25	2.5
Census Tract Total # of Stops	61,702	546.984	469.688	13.00	1454.000
Census Tract Median Income	61,702	87675.090	35424.510	20579.00	206199.000
Census Tract Annual Average # of Stops	61,702	68.377	58.837	2.00	182.000
Census Tract Racial Composition (BIPOC/W)	61,702	0.388	0.184	0.00	0.768
Perceived Race of Subject	61,702	2.765	1.007	1.00	5.000
BIPOC Person	61,702	0.647	0.478	0.00	1.000
Focus Group Person (Black/Hispanic)	61,702	0.583	0.493	0.00	1.000
Far From University	61,702	0.236	0.424	0.00	1.000
Reasonable Suspicion Based Stop	61,702	0.435	0.496	0.00	1.000
Traffic Stop	61,702	0.944	0.229	0.00	1.000
Result of Stop	61,702	6.798	4.263	1	11
Duration of Stop	8,088	16.613	17.631	1.00	270.000
Race Perceived Prior to Stop	8,088	0.425	0.494	0.00	1.000
Stop Duration Longer Than Average	8,086	0.297	0.457	0.00	1.000

Table 2. Logistic Regression Model (RIPA & Non-RIPA Compliant) (Subject is Black)

VARIABLES (Large)	Model 1	Model 2	Model 3
Subject is Black	1.574***	1.371***	1.359***
	(0.096)	(0.086)	(0.087)
Age of Subject	1.009***	1.006*	1.006*
	(0.003)	(0.002)	(0.002)
Perceived Gender of Subject	0.471***	0.676***	0.673***
	(0.039)	(0.057)	(0.057)
Traffic Stop		0.076***	0.069***
		(0.005)	(0.005)
Tract Distance from University			1.154
			(0.095)
Tract Total Population			1.000***
			(0.000)
Tract Median Income			1.000***
			(0.000)
Tract Average Annual Stops			0.999***
			(0.000)
Tract BIPOC Composition			1.644
			(0.465)
Constant	0.028***	0.084***	0.028***
	(0.004)	(0.012)	(0.011)
Observations	61,702	61,702	60,897

seEform in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 3. Logistic Regression Model (RIPA & Non-RIPA Compliant) (Subject is White)

VARIABLES	Model 1	Model 2	Model 3
Arrest	.	.	.
	(.)	(.)	(.)
Subject is White	0.966	0.820**	0.820**
	(0.062)	(0.054)	(0.055)
Age of Subject	1.009***	1.008**	1.008**
	(0.003)	(0.002)	(0.002)
Perceived Gender of Subject	0.465***	0.678***	0.674***
	(0.038)	(0.057)	(0.057)
Traffic Stop		0.074***	0.067***
		(0.005)	(0.005)
Tract Distance from University			1.168
			(0.096)
Tract Total Population			1.000**
			(0.000)
Tract Median Income			1.000***
			(0.000)
Tract Average Annual Stops			0.999***
			(0.000)
Tract BIPOC Composition			1.707
			(0.481)
Constant	0.034***	0.095***	0.033***
	(0.005)	(0.013)	(0.012)
Observations	61,702	61,702	60,897

seEform in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The results from the smaller logistic regression models are displayed in Tables 4 and 5. These more nuanced models, while smaller, echo the earlier significant race variables and add that when available, the race perceived prior to stop variable was very significant.

The models above indicate continued disparities surrounding race and likelihood of arrest in the city of Berkeley. There are both direct differences in likelihoods of arrest for Black and White subjects in our models, but also other indicators that race plays a role exist in the significance of the race perception and BIPOC composition variables. These suggest not only that there are differing odds of arrest for people of color, but more interestingly that there are general perceptions around race held by Berkeley Police that affect how stops are conducted.

Table 4. Logistic Regression Model for Arrest (RIPA-Compliant Only)

VARIABLES	Model 1	Model 2	Model 3
Subject is Black	1.490***	1.430***	1.429***
	(0.098)	(0.097)	(0.098)
Age of Subject	1.001	0.997	0.996
	(0.003)	(0.003)	(0.003)
Perceived Gender of Subject	0.544***	0.572***	0.571***
	(0.046)	(0.050)	(0.050)
Traffic Stop		0.306***	0.301***
		(0.033)	(0.033)
Race Was Perceived Prior		2.769***	2.730***
		(0.193)	(0.195)
Tract Distance from University			1.001
			(0.086)
Tract Total Population			1.000
			(0.000)
Tract Median Income			1.000***
			(0.000)
Tract Average Annual Stops			1.000*
			(0.000)
Tract BIPOC Composition			2.782**
			(0.885)
Constant	0.271***	0.538***	0.173***
	(0.039)	(0.097)	(0.076)
Observations	8,086	8,086	8,008

seEform in parentheses

Table 5. Logistic Regression Model for Arrest (RIPA-Compliant Only)

VARIABLES	Model 1	Model 2	Model 3
Subject is White	0.977	0.840*	0.836*
	(0.067)	(0.060)	(0.060)
Age of Subject	1.002	0.998	0.998
	(0.003)	(0.003)	(0.003)
Perceived Gender of Subject	0.540***	0.572***	0.571***
	(0.046)	(0.050)	(0.050)
Traffic Stop		0.309***	0.302***
		(0.033)	(0.033)
Race Was Perceived Prior		2.877***	2.834***
		(0.201)	(0.203)
Tract Distance from University			1.002
			(0.086)
Tract Total Population			1.000
			(0.000)
Tract Median Income			1.000***
			(0.000)

Tract Average Annual Stops			1.000**
			(0.000)
Tract BIPOC Composition			2.849***
			(0.906)
Constant	0.314***	0.611**	0.210***
	(0.044)	(0.109)	(0.091)
Observations	8,086	8,086	8,008

seEform in parentheses
*** p<0.001, ** p<0.01, * p<0.05

While the larger models lacked more specific racial data, we were still able to find broad differences in Black and White arrest odds. In the model where Subjects were white, initially the White variable did not have a significant relationship, and by the third stage had a slightly significant relationship with arrest but was still ultimately less likely to be arrested. In the model where the Subjects were black, there was always a very significant relationship ($p < .001$), and by the third stage the higher likelihood of arrest had very little change. Black subjects in these large models were not 2x as likely to be arrested, but approximately 1.6x as likely instead. It's also worth noting that in the larger models, the tract BIPOC composition variable was not significant and therefore did not play any role in affecting the likelihood of arrest. This is in contrast with the smaller models, where it was a significant or very significant variable. This could suggest that like the other tract features, BIPOC composition does not matter, or it could necessitate further examination of the interaction of the race perception and tract BIPOC composition variables.

The smaller models also had differences in white and black arrest odds and added that tract BIPOC composition and prior perception of race were also significant. Being white had a slightly significant relationship with arrest and made subjects less likely to be arrested, while being black consistently had a very significant relationship with arrest and made subjects more likely to be arrested. Black subjects were approximately 1.7x more likely to be arrested in the same scenario. Prior perception of race was consistently very significant in both models and had a major increase in the likelihood of arrest. And in the smaller models where race had been perceived, tract BIPOC composition was consistently very significant and also had a major increase in likelihood of arrest.

The smaller models were also tested for likelihood of a longer stop than usual, or the variable *Longstop*. The results of this are presented in Figure 6 and Tables 7 & 8. Duration data was only available in the RIPA-Compliant dataset, and so the number of observations was much smaller. In these models the Black variable had a very significant relationship with longer stops, and consistently substantially increased the likelihood of a longer stop. The White variable had no significance or some significance depending on the model, and when significant lowered odds of a longer stop. Black odds of a longstop stay at around 1.8X that of white odds, and again perception of race and tract BIPOC composition variables were both very significant and had the largest increase in likelihood of a longstop among other variables (> 2.0, where anything > 1.0 indicates higher likelihood and lower than < 1.0 indicates lower likelihood). Interestingly, in both models, the odds of longstop based on the race perceived prior variable actually *increased* when tract BIPOC composition was accounted for. This was unusual, but likely indicates how much of a role race perception affects a stop. When checked for correlation between the two variables, the resulting score was .11, showing that while they did influence each other, there was no risk of the two being the same and somehow affecting the integrity of the models.

These tests confirm the existing likelihoods that were produced by the previous report and strengthen the broader disparities surrounding race that were not available for analysis with older data. While there are less observations in the RIPA dataset, the high significance levels of the perception of race and BIPOC composition variables across Arrest and Longstop models suggest that if the officer perceives the race of the subject prior to stop, the race of the subject and the racial composition of the surrounding area play a large role in the larger result of the stop, particularly if the subject is not white or if the percent of BIPOC residents in that area is high. This suggests that officers behave differently based on race, and that there are disparities in police practices in the city of Berkeley.

Figure 6. Boxplot of Durations of Stops by Race (RIPA-Compliant Only)

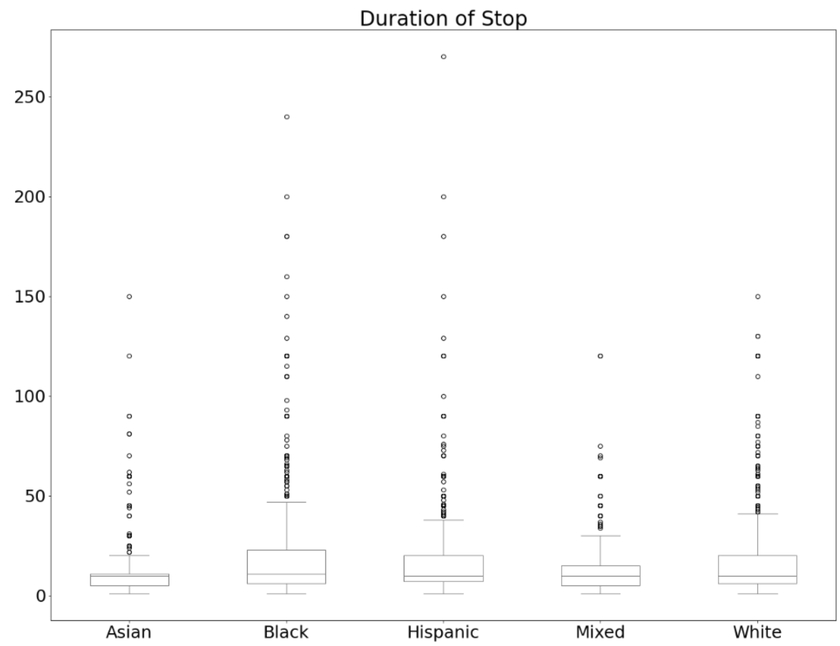


Table 7. Logistic Regression Model for Longstop (RIPA-Compliant Only)

VARIABLES (Small)	Model 1	Model 2	Model 3
Subject is Black	1.590***	1.534***	1.534***
	(0.080)	(0.078)	(0.079)
Age of Subject	0.993***	0.990***	0.990***
	(0.002)	(0.002)	(0.002)
Perceived Gender of Subject	0.784***	0.788***	0.776***
	(0.045)	(0.046)	(0.046)
Traffic Stop		1.101	1.057
		(0.118)	(0.114)
Race Was Perceived Prior		2.132***	2.222***
		(0.108)	(0.116)
Tract Distance from University			1.100
			(0.071)
Tract Total Population			1.000

			(0.000)
Tract Median Income			1.000***
			(0.000)
Tract Average Annual Stops			1.000*
			(0.000)
Tract BIPOC Composition			2.036**
			(0.497)
Constant	0.610***	0.451***	0.194***
	(0.065)	(0.067)	(0.066)
Observations	8,086	8,086	8,008

seEform in parentheses

Table 8. Logistic Regression Model for Longstop (RIPA-Compliant Only)

VARIABLES	Model 1	Model 2	Model 3
Subject is White	0.941	0.858**	0.868**
	(0.049)	(0.046)	(0.046)
Age of Subject	0.995**	0.991***	0.991***
	(0.002)	(0.002)	(0.002)
Perceived Gender of Subject	0.779***	0.787***	0.775***
	(0.045)	(0.046)	(0.046)
Traffic Stop		1.106	1.059
		(0.118)	(0.114)
Race Was Perceived Prior		2.211***	2.297***
		(0.112)	(0.120)
Tract Distance from University			1.109
			(0.071)
Tract Total Population			1.000
			(0.000)
Tract Median Income			1.000***
			(0.000)
Tract Average Annual Stops			1.000**
			(0.000)
Tract BIPOC Composition			2.127**
			(0.517)
Constant	0.720**	0.523***	0.240***
	(0.075)	(0.076)	(0.081)
Observations	8,086	8,086	8,008

seEform in parentheses
*** p<0.001, ** p<0.01, * p<0.05

In both models, the majority of the local census tract features proved to either be insignificant, or to neither increase nor decrease likelihood of arrest. Besides racial composition of the area following perception of subject race, other factors like distance from the university, median income, or even historical stop rates did not influence likelihood of arrest.

Discussion

Ultimately, it appears that there are still racial disparities in law enforcement in the city of Berkeley. Both broad and detailed models reveal that not only does the race of the subject increase or decrease your likelihood of arrest, but also that the officer's perception of the subjects race and the surrounding neighborhood racial composition also play a role. From what this analysis has been able to observe with just stop data, the likelihoods of arrest mentioned in the CPE's previous report have remained somewhat consistent, and the new features in RIPA-compliant data have revealed that their intuitions towards race perception were also accurate. Perceived (or non-perceived) BIPOC subjects are more likely to be arrested following a stop, are more likely to be stopped for longer than white subjects and are more at risk if the surrounding area is less white than others.

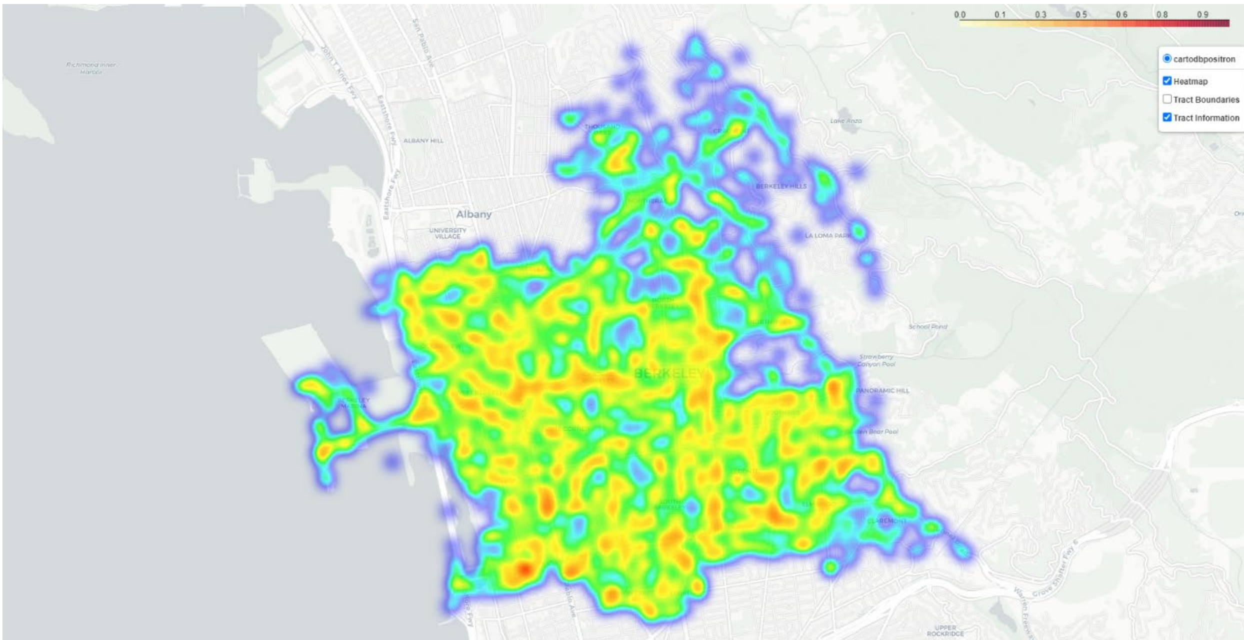
It is important to note however that these points are still new – the insights provided by RIPA-compliant data are based on data that has only been collected this way for less than two years. It is possible that certain variables will be less significant or may change in scale when tested again with more data. Additionally, the < two-year period in which this data was collected was also during the COVID-19 pandemic. While it is difficult to say just how different the RIPA data would be if it was collected in a non-quarantine environment, it is important to recognize that the data is not exactly equivalent.

Future policy changes in the city of Berkeley may prove to address these disparities as well. In late 2021, Berkeley City Council approved a package of policy changes proposed by a city working grouped launched by the mayor in 2020 composed of city officials, police, and community stakeholder organizations (Raguso, E, 2021). Key changes include that police would no longer be able to conduct traffic stops for low-level traffic violations, and written consent would have to be obtained for a search to be conducted, suggesting that the city is trying to reduce not only the volume of discriminate stops/searches, but also make them safer when they do happen. More recent updates from the city include hints towards centralizing all transportation related work into one department and possibly including citizen volunteers (BerkDOT), spending approximately $200k on municipal code and staffing analyses, and creating a new “specialized care unit” (SCU) to handle behavioral health crisis response (Raguso, E, May 2022). Implementation will likely take at least 2-3 years, although a pilot program for the SCU may be launched in late 2022.

Considering that traffic stops made up the vast majority of interactions in our analysis and that all of these stops were made by police, it will be interesting to see the effect of these changes on future analyses.

Appendices

Appendix A: Interactive Heatmap of BPD Stops Since 2015 (Linked Here)



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