

ONLINE APPENDIX: CLASS DISPARITIES AND DISCRIMINATION IN TRAFFIC STOPS AND SEARCHES

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A Data Appendix

We merge traffic stop data to commercial address history data from Infogroup using full name and address. We first use an address standardization algorithm, the Stata function `stnd.address`, to ensure that addresses are structured analogously across the two data sets, with separate fields for street address, unit number, etc. We also extract the address number. In addition, we manually standardize Texas city and town names in the traffic stop data. We standardize full names and extract suffixes. We then use the Stata command `reclink2` to perform a probabilistic linkage across the two data sources. We fuzzy match using the following fields: last name, first name, middle name, suffix, address number, street name, city, and zip code. We require that observations match exactly on the first letter of the first name and the first letter of the last name. For zip code, we define agreement discretely based on whether the fields match exactly. For all other fields, we utilize the bigram string comparator to assess the degree of agreement. The address history data includes an identifier that matches the same individual to multiple addresses. We use this identifier to match multiple stops to the same person. We are able to match 75% of stops to the address history data. For stops that we are unable to match, we create identifiers based on full name, street address, and zip code.

We then match the criminal history data to traffic stops using the full set of addresses associated with each person. We apply the same address and name standardization to the criminal history data, and apply the same fuzzy match.

Though Diamond et al. (2019) and Phillips (2020) find that similar address history data from Infutor are of high quality, we are unable to match every stop to the address history data and these data may be incomplete. Hence, we may not correctly associate all stops and criminal history with the corresponding motorist.

To match geocoded stops to sergeant patrol areas, we use the sergeant area boundaries shapefile received in response to a Texas Public Information Act request. This shapefile includes two sergeant area identifiers: *sgt_area* and *sgt_area_n*. In practice, the *sgt_area* identifier includes a significant

number of unique values corresponding to identical geographies and the same value of *sgt_area_n*. For example, the boundaries for *sgt_area* 1B03 and *sgt_area* 1B05 are identical; both objects are assigned to the same value of *sgt_area_n* (1B03.1B05). As such, we rely on the *sgt_area_n* identifier to map stops to sergeant areas, and we reassign stops associated with the small number of remaining *sgt_area_n* values that are themselves unique but correspond to identical geographies. There are also instances in which distinct *sgt_area_n* objects are partially overlapping. In the fewer than 4% of cases in which a stop is associated with multiple distinct but partially overlapping *sgt_area_n* values, we randomly select one observation to include. The sergeant area(s) associated with each geocoded stop were identified using the **Spatial Join** analysis tool in ArcGIS.

B National Household Travel Survey Analyses

We use data from the 2017 NHTS survey wave in order to examine the associations between reported household income, educational attainment, vehicle group, and location of residence.

In the NHTS, household income is partitioned into 11 intervals in the 2017 survey and five educational attainment levels are reported. To characterize economic status based on vehicle grouping, we follow the approach employed in the stop data and classify vehicles based on make, car type (passenger car, pick up truck, or SUV), and vehicle age. While the NHTS does not provide residential location at a more disaggregated level than core-based statistical area (CBSA), to analyze the association between respondent years of schooling and area-level income, we group Texas respondents based on response values for the following variables: (1) Category of the percent of renter-occupied housing in the census block group of the household's home location, (2) Category of population density (persons per square mile) in the census block group of the household's home location, (3) Category of housing units per square mile in the census block group of the household's home location, (4) Block group urban/rural status, (5) Urban area size where home address is located, and (6) CBSA for the respondent's home address. Note that a unique set of response values will typically correspond to multiple block groups, limiting the predictive power of our measure of average income based on block group characteristics.

In the text, we summarize results based on several analyses. First, we report the 0.35 rank correlation between reported income and vehicle group average income (using the grouping approach described above). Next, we reference the results shown in Appendix Table D.6. In columns 1 and 2 of that table, we report results from regressions of log household income on log average household income by vehicle group, with and without demographic controls. In columns 3 through 6, we report results from regressions of years of schooling on log average household income by vehicle group and by block group characteristics, with and without demographic controls and a control for log household income.

C Survey on Fairness in Policing

While prior opinion polls routinely ask about perceived racial bias in policing, to the best of our knowledge, no nationally scoped surveys examine perceived class bias. To fill this gap, we surveyed a national sample of 1,001 individuals on Prolific, a technology platform that facilitates such data collection efforts. Through Prolific, we requested a “representative sample” of survey respondents. In practice, Prolific achieves “representativeness” by selecting among prospective respondents to ensure that the survey sample meets pre-specified quotas with respect to age, gender, and ethnicity.

For this brief (5-minute) survey, we randomly assigned one half of the study sample to respond to questions pertaining to fairness in policing and economic class. The other half of respondents were randomly assigned to respond to questions pertaining to fairness in policing and race. All respondents were then asked about their demographic background (age, race/ethnicity, gender), household income, and political ideology/party affiliation.

Given that race, but not economic disadvantage, is a protected class under anti-discrimination law, our primary survey objective was to understand how perceptions of fairness, concerns about inequitable treatment, and support for policies promoting equal treatment, vary when respondents are asked to consider treatment based on class versus race. A secondary objective was to explore how political polarization (i.e., the alignment between survey responses and Democratic versus Republican Party affiliation) varies when respondents are asked to consider class versus race.

In Appendix Figure D.13, we present histograms characterizing the distribution of responses to five sets of questions about beliefs and policy preferences (asked in the context of race or class depending on the survey frame assigned to a given respondent). The three sets of questions related to beliefs are as follows: (1) whether “police treat low-income (Black) drivers less fairly compared to high-income (White) drivers”; (2) whether the amount of attention paid to equal treatment is “too little”, “too much” or “about right”; and (3) whether any perceived unfair treatment is “a very big problem”, “a moderately big problem”, “a small problem” or “not a problem at all”. Turning to policy preferences, we then ask whether respondents “strongly favor”, “somewhat favor”, “somewhat oppose” or “strongly oppose” the following: (1) a policy “requiring police departments to collect and publicly report data on traffic stops, searches, and arrests, so that disparities between low-income and high-income (Black and White) drivers can be identified” and (2) “a law that would make it illegal for police to treat civilians differently because of their income level.” Broadly speaking, Appendix Figure D.13 indicates that both perceptions related to fairness and policy preferences are similarly distributed with respect to race and class. Two exceptions are that unfair treatment by race is more likely to be viewed as “a very big problem”, while respondents are more likely to report that “too little attention” is paid to equal treatment by class.

Panel A of Appendix Table D.12 formally tests whether beliefs and policy preferences vary across the race and class frames; these estimates confirm that the two largest differences (and the only two differences that are statistically significant at conventional levels) relate to the measures of problem severity and attention paid to inequitable treatment. In Panel B, we explore heterogeneity in political polarization by regressing the same outcome measures on an indicator for respondent

assignment to the class frame, an indicator for Republican Party (as opposed to Democratic Party) affiliation, and the interaction between the two. Across outcome measures, we find that those whose views align more closely with the Republican Party perceive treatment by race as less inequitable and are less supportive of policies intended to address disparate treatment. Republican versus Democratic respondent views align more closely for each outcome when respondents are instead surveyed about class differences, although the difference in polarization is only statistically significant when respondents are asked about support for mandated data collection and reporting in the context of class (as opposed to race).¹

¹Although omitted for the sake of brevity, Appendix Table D.12 estimates are insensitive to the inclusion of controls for respondent demographics and household income.

D Additional Exhibits

TABLE D.1
SAMPLE SELECTION

Sample step	Observations	
	Dropped	Remaining
1. All stops conducted by Texas Highway Patrol between 2009 and 2015		15,761,299
2. Drop stops with missing demographics, trooper ID or stop outcomes	2,320	15,758,979
3. Retain stops of motorists with Texas addresses	1,872,228	13,886,751
4. Retain stops of motorists with valid addresses	1,958,381	11,928,370
5. Retain stops of valid passenger cars, pick-up trucks, and SUVs	577,405	11,350,965
6. Drop stops with missing time or location information	329,246	11,021,719
7. Drop stops with miscoded or toll violations	14,834	11,006,885

TABLE D.2
TRAFFIC STOP DESCRIPTIVE STATISTICS, NON-DWI SPEEDING STOPS

	All Stops			All Searches		
	Below Median	Above Median	All	Below Median	Above Median	All
Black	9.63	7.80	8.86	19.68	16.84	18.82
Hispanic	33.10	20.71	27.93	37.75	26.70	34.40
White	54.71	67.81	60.18	40.53	53.32	44.41
Female	37.62	36.00	36.94	18.60	17.00	18.11
Log Household Income	10.08	11.48	10.67	10.02	11.41	10.44
	(0.62)	(0.46)	(0.89)	(0.63)	(0.43)	(0.86)
Search Rate	0.964	0.586	0.806	100	100	100
Unconditional Hit Rate	0.259	0.194	0.232	26.56	32.91	28.49
Implied percent pretextual	0	0	0	0	0	0
Moving	100	100	100	100	100	100
Driving while intoxicated	0	0	0	0	0	0
Speeding	100	100	100	100	100	100
Equipment	4.19	2.97	3.68	6.17	5.48	5.97
Regulatory	23.51	17.55	21.02	40.74	30.25	37.55
Prior felony arrests	0.105	0.0553	0.0844	0.547	0.426	0.510
	(0.652)	(0.456)	(0.578)	(1.543)	(1.333)	(1.484)
Prior misdemeanor arrests	0.254	0.154	0.212	1.145	0.959	1.088
	(1.132)	(0.835)	(1.020)	(2.609)	(2.247)	(2.506)
Observations	3,771,791	2,703,234	6,475,025	36,344	15,829	52,173

Sample restrictions are described in section I. We further restrict to stops with a speeding warning or citation, and no DWI warning or citation. All values, excluding log household income and prior arrests, are expressed as percentage points. ‘Below Median’ and ‘Above Median’ refer to stops where household income is below and above the median value for all stops (not limiting to non-DWI speeding stops). Section I.B discusses the construction of the household income measure, which divides household income into 16 intervals.

TABLE D.3
CONTRABAND TYPE BY MOTORIST INCOME AND VEHICLE
STATUS

	Vehicle Status Quintile				
	Q1	Q2	Q3	Q4	Q5
<i>Contraband Type (%)</i>					
Currency	0.3	0.4	0.7	0.6	0.8
Drugs	53.2	50.4	50.5	51.8	55.2
Other	43.0	45.3	44.9	43.9	40.3
Weapons	3.5	3.9	3.9	3.8	3.7
Observations	27,907	18,499	13,258	10,335	7,046
	Log Income Quintile				
	Q1	Q2	Q3	Q4	Q5
<i>Contraband Type (%)</i>					
Currency	0.7	0.4	0.4	0.4	0.3
Drugs	51.6	51.6	52.3	52.2	53.4
Other	44.0	44.1	43.7	43.7	42.8
Weapons	3.6	4.0	3.6	3.8	3.5
Observations	19,905	19,504	15,120	12,578	9,938

This table summarizes the distribution of contraband type by motorist economic status among motorists found with contraband. The top panel groups motorists into quintiles by vehicle status. The bottom panel groups motorists into quintiles by log household income.

TABLE D.4
PRETEXT STOP SHARES BY MOTORIST INCOME: ALTERNATIVE
DEFINITIONS

<i>Panel A</i>	Pretextual Share Based on Bottom Decile Search Rate Troopers($\times 100$)				
	(1)	(2)	(3)	(4)	(5)
log household income	-1.02 (0.00)	-0.79 (0.00)	-0.72 (0.00)	-0.68 (0.00)	-0.62 (0.00)
Mean of DV	7.32				
Observations	11,006,234				
<i>Panel B</i>	Infraction-Specific Share of Stops by No Search Troopers ($\times 100$)				
	(1)	(2)	(3)	(4)	(5)
log household income	0.015 (0.000)	0.011 (0.000)	0.010 (0.000)	0.0089 (0.000)	0.0084 (0.000)
Mean of DV	1.76				
Observations	11,006,234				
Sgt. Area $\times$ Time of Week $\times$ Year FEs		✓	✓	✓	✓
Motorist Demographics			✓	✓	✓
Motorist Criminal History				✓	✓
Trooper FE					✓

This table reports regression coefficients from estimates of equation (5). In Panel A, the outcome is the infraction-specific pretext share associated with a given stop (multiplied by 100), where all troopers in the bottom search rate decile are considered troopers without a search motive. In Panel B, the outcome is the infraction-specific share of stops conducted by troopers without a search motive. Section I.B discusses the construction of motorist household income. The sample includes all stops, which are assigned to either one of the ten most common infraction types or a residual “Other” category. For stops with multiple associated infractions, the assigned pretext share is the minimum value across infractions, and the assigned share of troopers without a search motive is the maximum value across infractions. Robust standard errors are provided in parentheses.

TABLE D.5
SEARCH RATES BY MOTORIST INCOME, CONTROLLING FOR
INFRACTION CATEGORY

Outcome:	Search ($\times 100$)				
	(1)	(2)	(3)	(4)	(5)
log household income	-0.31 (0.00)	-0.35 (0.00)	-0.32 (0.00)	-0.24 (0.00)	-0.22 (0.00)
Sgt. Area $\times$ Time of Week $\times$ Year FEs		✓	✓	✓	✓
Motorist Demographics			✓	✓	✓
Motorist Criminal History				✓	✓
Trooper FE					✓
Infraction Category FEs	✓	✓	✓	✓	✓
Mean of DV			1.92		
Observations			11,006,234		

This table reports regression coefficients from estimates of equation (5), where the outcome is an indicator (multiplied by 100) for whether a stop leads to a search. Section I.B discusses the construction of motorist household income. The sample includes all stops, which are assigned to either one of the ten most common infraction types or a residual “Other” category. For stops with multiple associated infractions, the assigned infraction category is determined based on the minimum pretext share across infractions. Robust standard errors are provided in parentheses.

TABLE D.6
NATIONAL HOUSEHOLD TRAVEL SURVEY (NHTS) CORRELATIONAL ANALYSES

	Outcome: Log HH Income		Outcome: Years of Schooling			
	(1)	(2)	(3)	(4)	(4)	(6)
Log Average Income by Vehicle Group	0.760 (0.021)	0.744 (0.021)	1.405 (0.053)	0.756 (0.052)		
Log Average Income by Block Group Characteristics					0.790 (0.037)	0.252 (0.037)
Race and Gender Controls		✓		✓		✓
Log Household Income Control				✓		✓
Observations	40,106					

This table reports results from regressing respondent log household income/years of schooling on leave-out log average household income by vehicle group (make, car type, and age) and leave-out log average household income by block group characteristics. Data is from the 2017 NHTS sample of Texas respondents. Average income measures are constructed as described in Appendix B. Robust standard errors are provided in parentheses.

TABLE D.7
WITHIN-MOTORIST VEHICLE STATUS GRADIENT BY INFRACTION (ALL STOPS)

	Outcome: Δ Infraction										
	Speeding	Fail to Signal	Expired Plates	Lane Viol.	Seatbelt Viol.	Lights Viol.	Disregard Sign	Tinted Windows	DWI	Tailgating	Other Viol.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Δ Vehicle Status	0.379 (0.002)	-0.016 (0.001)	-0.152 (0.002)	-0.014 (0.001)	-0.069 (0.001)	-0.140 (0.001)	-0.015 (0.001)	-0.023 (0.001)	-0.002 (0.000)	-0.005 (0.000)	-0.087 (0.001)
Observations	2,320,044										

This table relates first differences in indicators for the given infraction type for sequential pairs of stops of the same motorist to changes in vehicle status. The sample includes all stops, including those with multiple associated infractions. Standard errors are clustered at the motorist level.

TABLE D.8
SPEEDING VIOLATION SEVERITY BY VEHICLE STATUS
(WITHIN-MOTORIST ANALYSIS)

Outcome:	Δ MPH Over Limit			
	(1)	(2)	(3)	(4)
Δ Vehicle Status	1.05 (0.09)	0.85 (0.12)	1.48 (0.09)	1.14 (0.29)
Restricted to Speeding-Only Violations		✓		
Speed Limit FEs			✓	
Restricted to Same Road Segment				✓
Mean of DV	-0.15	-0.14	-0.15	-0.51
Observations	103,411	56,677	103,411	10,977

This table relates first differences in MPH over the speed limit for sequential pairs of speeding stops of the same motorist to changes in vehicle status. The sample includes all speeding stops in column (1) and speeding-only stops in column (2). Column (3) controls for the speed limit associated with each within-pair stop and Column (4) restricts the sample to pairs of stops taking place on the same road number/type and in the same Sergeant Area. Standard errors are clustered at the motorist level.

TABLE D.9
DESCRIPTIVE STATISTICS FOR SEQUENTIAL STOPS WITH MOVING
INFRACTIONS

	Single Stop	Multiple Stops	
		Same Vehicle	Different Vehicle
Black	10.22	7.99	8.13
Hispanic	28.41	26.72	31.13
White	57.18	63.04	58.56
Female	42.42	37.61	28.73
Log household income	10.68 (0.873)	10.63 (0.904)	10.64 (0.907)
Search rate	1.347	0.951	1.079
Unconditional hit rate	0.409	0.293	0.314
Search rate in prior stop	.	0.864	1.090
Unconditional hit rate in prior stop	.	0.241	0.278
Implied percent pretextual	4.924 (12.70)	3.919 (11.84)	4.106 (12.02)
Moving	100	100	100
Driving while intoxicated	1.183	0.680	0.786
Speeding	84.99	88.54	87.93
Equipment	3.756	3.956	3.948
Regulatory	23.12	17.92	19.30
Prior felony arrests	0.0557 (0.468)	0.0898 (0.592)	0.133 (0.730)
Prior misdemeanor arrests	0.139 (0.823)	0.232 (1.037)	0.328 (1.289)
Vehicle status	10.63 (0.227)	10.62 (0.201)	10.64 (0.221)
Change in vehicle status	. (.)	-0.0214 (0.0305)	0.0256 (0.245)
Change in vehicle age	. (.)	0.729 (0.928)	-0.657 (5.947)
Months between stops	. (.)	9.128 (10.38)	17.02 (15.34)
Absolute change in vehicle status	. (.)	0.0214 (0.0305)	0.188 (0.160)
Absolute change in vehicle age	. (.)	0.729 (0.928)	4.410 (4.044)
Observations	2,997,832	1,117,506	1,155,932

This table presents descriptive statistics for three sets of stops: stops that involve motorists that we only observe in one stop (column 1); stops that involve motorists that were previously stopped in the same vehicle (columns 2); and stops that involve motorists that were previously stopped in a different vehicle (column 3). We restrict the sample to stops (and prior stops) associated with moving violations.

TABLE D.10
DESCRIPTIVE STATISTICS FOR SEQUENTIAL STOPS, BY INCOME TERCILE

	Bottom Tercile			Top Tercile		
	Single Stop	Multiple Stops		Single Stop	Multiple Stops	
		Same Vehicle	Different Vehicle		Same Vehicle	Different Vehicle
Black	11.93	8.81	8.60	8.70	7.50	7.73
Hispanic	39.81	39.25	43.80	20.00	20.00	24.35
White	45.24	50.26	46.07	66.27	69.59	65.12
Female	40.38	34.57	26.67	41.18	32.00	24.52
Log household income	9.72 (0.56)	9.66 (0.59)	9.66 (0.59)	11.61 (0.41)	11.61 (0.41)	11.61 (0.41)
Search rate	2.753	2.150	2.347	1.181	1.334	1.323
Unconditional hit rate	0.972	0.761	0.770	0.480	0.561	0.537
Search rate in prior stop	.	2.041	2.381	.	1.208	1.345
Unconditional hit rate in prior stop	.	0.708	0.710	.	0.518	0.493
Implied percent pretextual	12.05 (15.04)	11.40 (15.08)	11.35 (15.29)	8.536 (13.60)	8.453 (13.33)	8.245 (13.61)
Moving	67.12	66.35	68.28	76.24	73.29	76.30
Driving while intoxicated	3.078	1.686	2.102	1.195	1.038	1.169
Speeding	52.18	54.14	55.39	64.82	63.94	66.36
Equipment	21.87	22.76	22.16	13.84	16.21	14.70
Regulatory	39.13	32.11	33.52	26.76	29.05	27.52
Prior felony arrests	0.0978 (0.634)	0.170 (0.841)	0.247 (1.006)	0.0409 (0.393)	0.0761 (0.532)	0.112 (0.661)
Prior misdemeanor arrests	0.230 (1.120)	0.408 (1.485)	0.569 (1.782)	0.112 (0.714)	0.223 (1.012)	0.305 (1.246)
Vehicle status	10.54 (0.198)	10.54 (0.185)	10.55 (0.200)	10.69 (0.252)	10.64 (0.226)	10.67 (0.246)
Change in vehicle status	. (.)	-0.0171 (0.0266)	0.0168 (0.227)	. (.)	-0.0233 (0.0328)	0.0230 (0.269)
Change in vehicle age	. (.)	0.624 (0.876)	-0.401 (6.802)	. (.)	0.783 (0.975)	-0.533 (5.982)
Months between stops	. (.)	7.828 (9.755)	15.53 (14.76)	. (.)	9.757 (11.02)	18.14 (15.83)
Absolute change in vehicle status	. (.)	0.0172 (0.0266)	0.175 (0.146)	. (.)	0.0234 (0.0328)	0.204 (0.177)
Absolute change in vehicle age	. (.)	0.624 (0.876)	5.126 (4.489)	. (.)	0.783 (0.975)	4.416 (4.070)
Observations	1,544,358	798,211	897,249	1,332,172	607,856	657,950

This table presents descriptive statistics for motorists in the bottom income tercile (columns 1-3) and in the top income tercile (columns 4-6). Descriptive statistics are shown for three sets of stops: stops that involve motorists that we only observe in one stop (columns 1 and 4); stops that involve motorists that were previously stopped in the same vehicle (columns 2 and 5); and stops that involve motorists that were previously stopped in a different vehicle (columns 3 and 6).

TABLE D.11
ALTERNATIVE SEARCH YIELD MEASURES BY VEHICLE STATUS

<i>Panel A</i>	Expected Sentence Length				
	(1)	(2)	(3)	(4)	(5)
Vehicle status	-3.79 (1.87)	-2.69 (1.88)	5.79 (1.87)	5.53 (1.89)	5.89 (1.92)
log household income				0.41 (0.39)	0.40 (0.40)
Observations	211,533				
<i>Panel B</i>	Charges of Above Median Severity				
	(1)	(2)	(3)	(4)	(5)
Vehicle status	-0.61 (0.19)	-0.53 (0.20)	0.46 (0.19)	0.41 (0.20)	0.47 (0.20)
log household income				0.09 (0.04)	0.09 (0.04)
Observations	211,533				
Sgt. Area $\times$ Year FEs	✓	✓	✓	✓	✓
Motorist demographics		✓	✓	✓	✓
Motorist criminal history			✓	✓	✓
Trooper FEs					✓

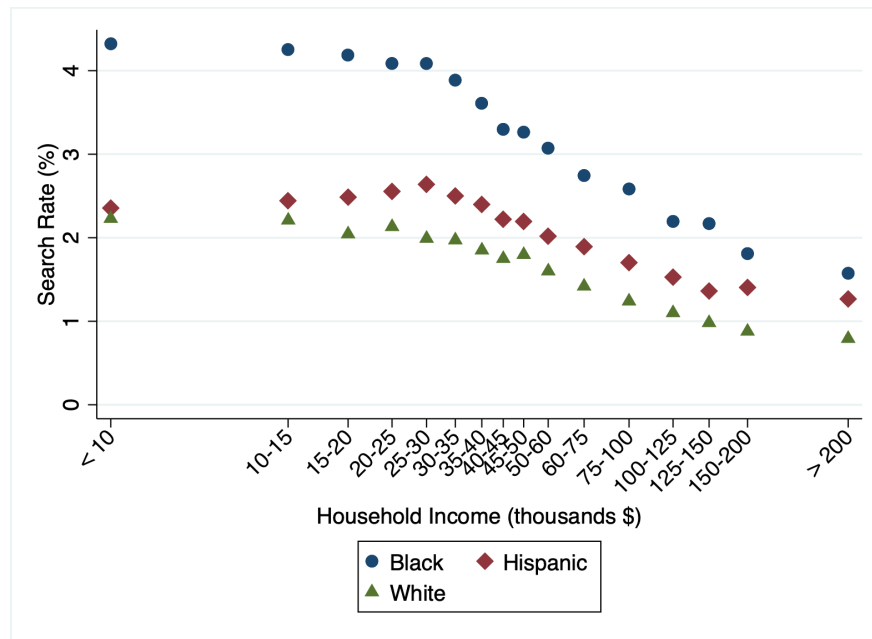
This table reports regression coefficients from estimates of equation (5), where the outcome is expected incarceration sentence (Panel A) or an indicator (multiplied by 100) for whether a motorist is arrested for criminal charges of above median severity (Panel B). Section I.B discusses the construction of motorist household income. Vehicle status measures expected log household income for people driving vehicles of the same make, type, and age. Robust standard errors are provided in parentheses.

TABLE D.12
FAIRNESS IN POLICING: BELIEFS AND POLICY PREFERENCES

Treatment Unfair	Unfair: Big Problem	Unfair: Big/ Moderate Problem	Unfair: Insufficient Attention Paid	Support Data Collection & Reporting	Support Equal Protection
(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A</i>					
Class Frame	0.008 (0.029)	-0.072 (0.029)	-0.031 (0.031)	-0.034 (0.032)	0.006 (0.031)
Observations	985	981	970	956	948
<i>Panel B</i>					
Class Frame	-0.051 (0.033)	-0.104 (0.046)	-0.094 (0.040)	-0.144 (0.047)	-0.048 (0.042)
Republican	-0.346 (0.040)	-0.148 (0.045)	-0.370 (0.042)	-0.331 (0.046)	-0.213 (0.045)
Class $\times$ Republican	0.086 (0.058)	0.046 (0.061)	0.095 (0.062)	0.193 (0.067)	0.081 (0.064)
Observations	870	868	858	847	839
Mean of DV	0.705	0.293	0.608	0.494	0.666

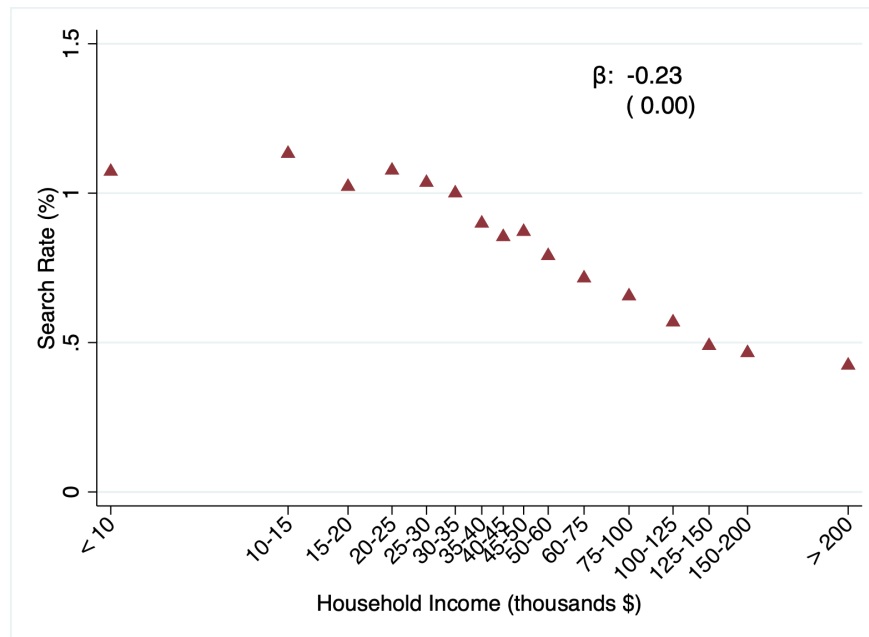
Panel A of this table reports estimates from regressions of survey-based indicator variables on an indicator for whether the survey respondent was asked about fairness in policing related to economic class (as opposed to race). Panel B also includes as regressors an indicator for Republican party affiliation and the interaction between Republican and the economic class frame indicator. The outcome in column 1 is an indicator for whether an individual reports that "police treat low-income (Black) drivers less fairly compared to high-income (White) drivers". Columns 2 and 3 dependent variables are indicators equal to 1 if an individual reports unfair treatment and states that this is a "big problem" (column 2) or "moderate or big problem" (column 3). Column 4 is an indicator for whether the respondent believes insufficient attention is paid to unfair treatment based on class (race). Column 5 is an indicator for whether an individual strongly favors "requiring police departments to collect and publicly report data on traffic stops, searches, and arrests, so that disparities between low-income and high-income (Black and White) drivers can be identified." Column 6 is an indicator for whether an individual strongly favors "a law that would make it illegal for police to treat civilians differently because of their income level (race)." Observations are set to missing if the respondent answers "Don't know / Prefer not to answer" (Panels A-B) or does not identify with either the Republican or Democratic Party (Panel B). Robust standard errors are provided in parentheses.

FIGURE D.1
SEARCH RATES BY MOTORIST INCOME AND RACE



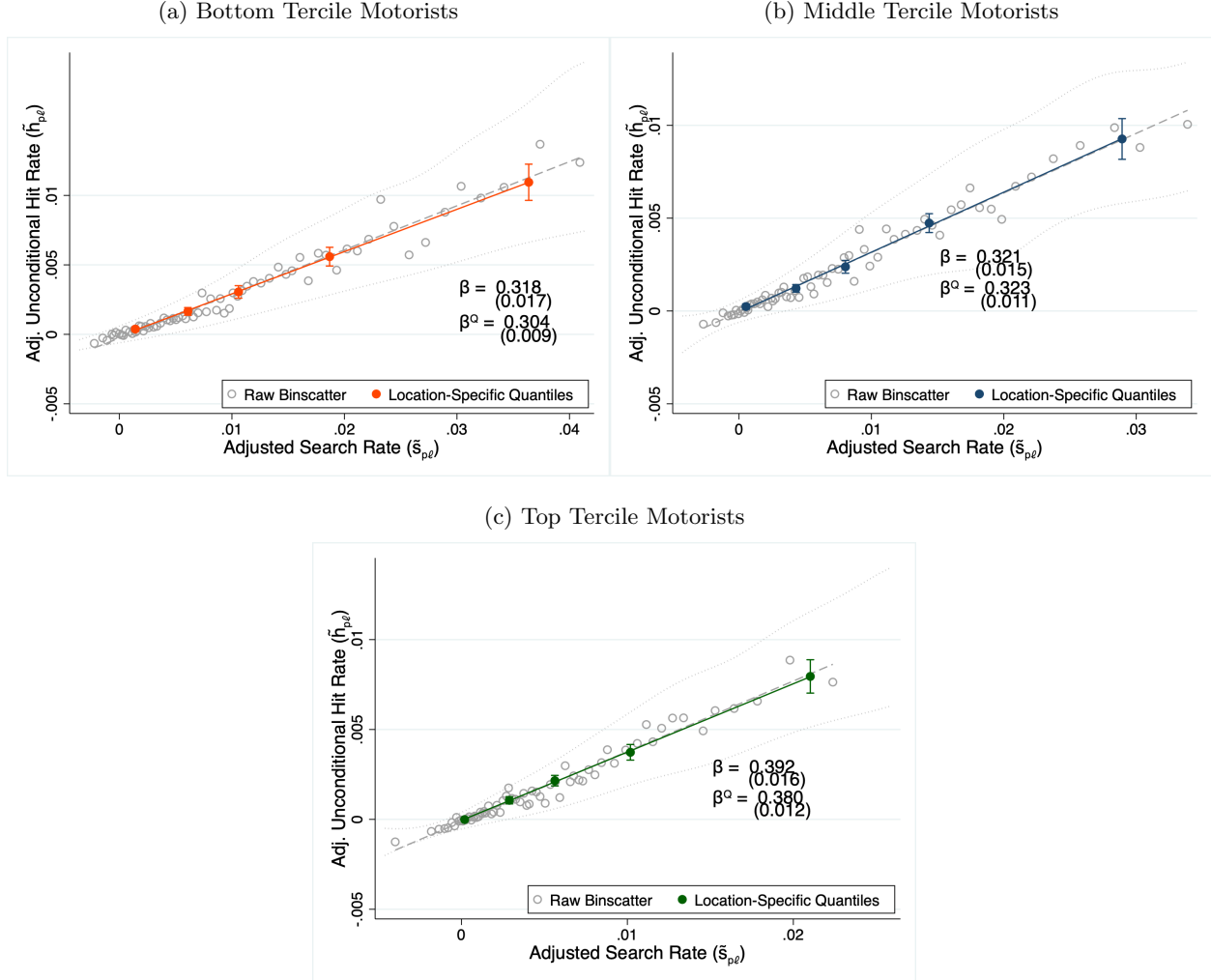
Note: This figure plots search rates as a function of motorist income, separately by motorist race. Household income is depicted on a log scale. Section I.B discusses the construction of the household income measure, which partitions household income into 16 intervals.

FIGURE D.2
SEARCH RATES ARE DECREASING IN MOTORIST INCOME, NON-DWI SPEEDING STOPS



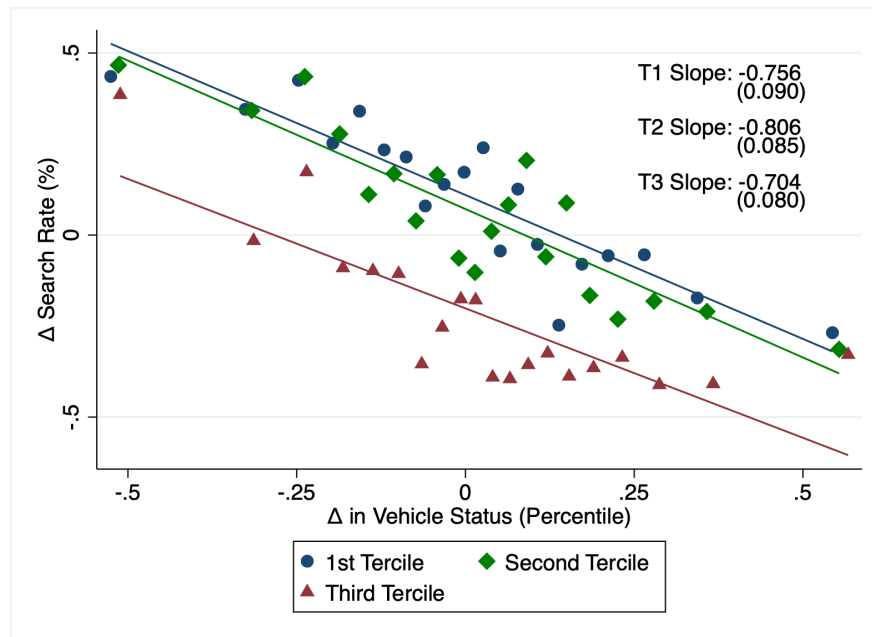
Note: This figure plots search rates as a function of motorist income. Household income is depicted on a log scale. Section I.B discusses the construction of the household income measure, which partitions household income into 16 intervals. We use the average household income for all Texas households in a given interval as the horizontal axis coordinate. The sample is limited to stops with a speeding warning or citation, and no DWI warning or citation.

FIGURE D.3
BETWEEN-TROOPER SEARCH PRODUCTIVITY CURVE, BY MOTORIST INCOME TERCILE



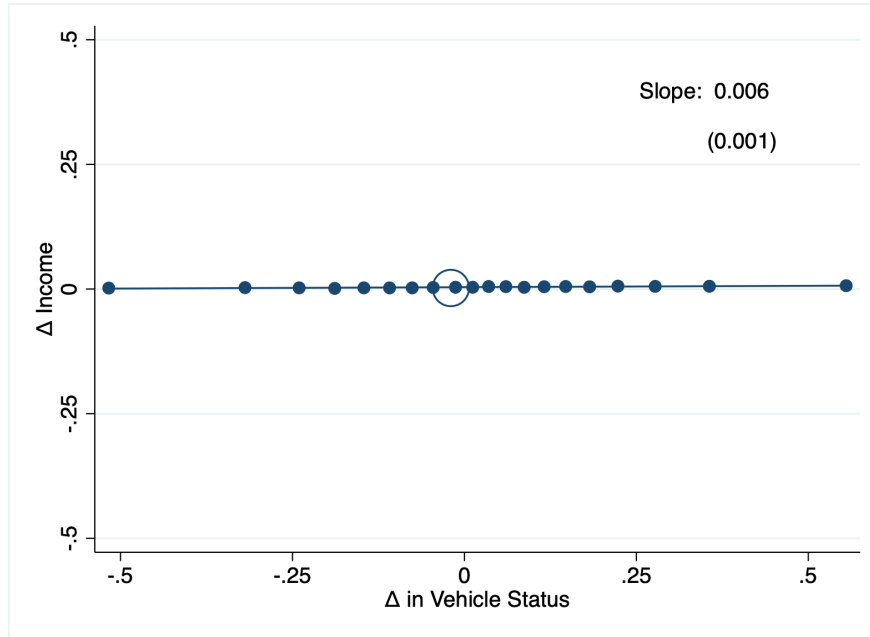
Note: In this figure we plot adjusted trooper unconditional hit rates ($\tilde{h}_{p\ell}$) against trooper search rates ($\tilde{s}_{p\ell}$) using two approaches, where $\tilde{s}_{p\ell}$ and $\tilde{h}_{p\ell}$ take on values between zero and one (before each is residualized). The first approach is a simple binscatter, where we choose the integrated mean square error-optimal number of bins as in Cattaneo et al. (2019) (using the Stata package `binsreg`). The figure includes 95% confidence bands for the local linear relationship between adjusted trooper search rates and unconditional hit rates and the best linear fit and its slope. The local linear fit is derived using a Gaussian kernel with a rule-of-thumb bandwidth. In the second approach we divide troopers into quantiles by search rate within locations, group quantiles across locations, and then plot the relationship between search rates and unconditional hit rates across quantiles. From this approach, the figure includes the mean values for each quintile and the best linear fit and its slope. Bootstrap standard errors for the estimated slopes are provided in parentheses. Panel A, Panel B, and Panel C plot the search productivity curve (SPC) for bottom income tercile motorists, middle income tercile motorists, and top income tercile motorists, respectively. As in Feigenberg and Miller (2022), the sample is restricted to highway speeding stops.

FIGURE D.4
SEARCH RATES FOR MOTORISTS IN SEQUENTIAL STOPS BY TIME BETWEEN STOPS



Note: This figure looks at differences in search rates for pairs of stops of the same motorist in different vehicles. Sequential pairs are partitioned by the time between the stops. For the first tercile, there is less than 7 months between stops. For the second tercile, there is between 7 and 19 months between stops. For the third tercile, there is at least 19 months between stops.

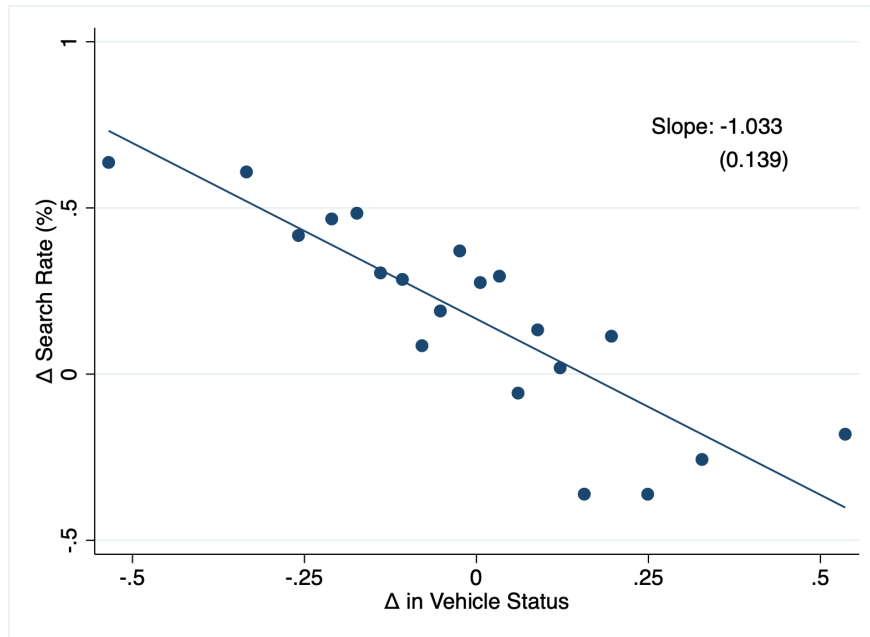
FIGURE D.5
CHANGE IN MOTORIST INCOME BETWEEN STOPS IN WITHIN-MOTORIST DESIGN



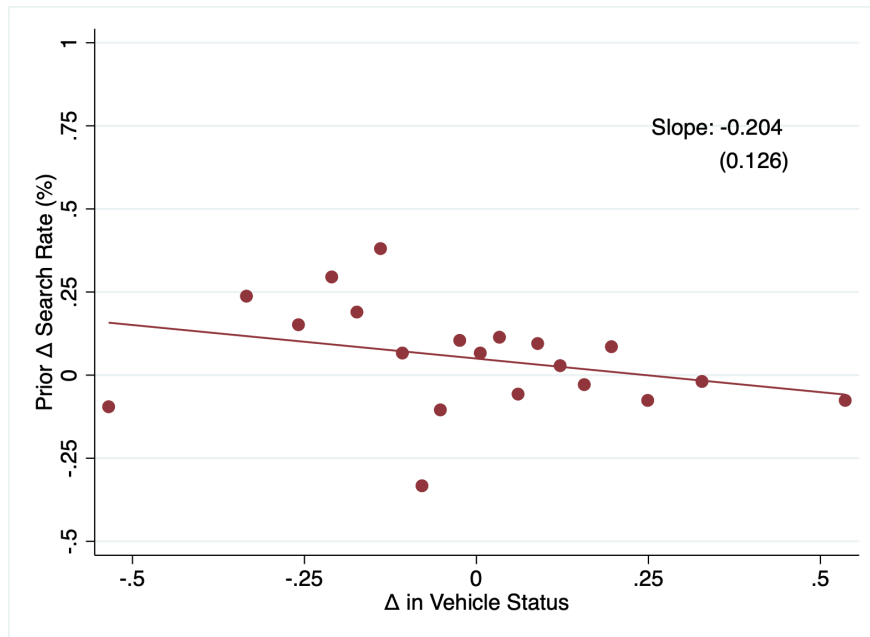
Note: This figure looks at the change in log household income between sequential stops (as described in section IV.A) as a function of the change in vehicle status between stops. A motorist's log household income may change if they change addresses between stops.

FIGURE D.6
SEARCH RATES FOR MOTORISTS THAT ALTERNATE BETWEEN VEHICLES

(a) Contemporaneous Change in Vehicle



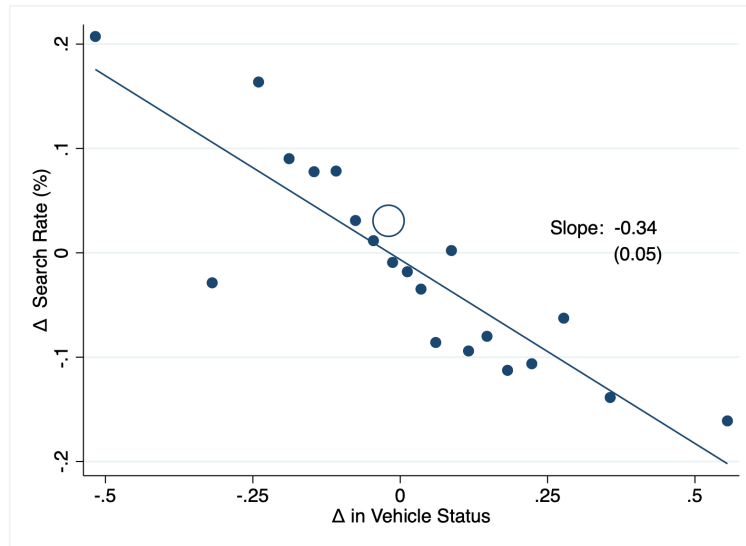
(b) Stops of Same Vehicle Bracketing Stops of Other Vehicles



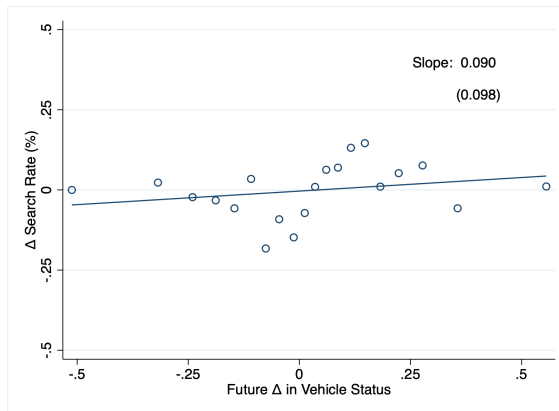
Note: This figure looks at differences in search rates for pairs of stops of the same motorist, limiting to motorists that alternate back and forth between vehicles. Panel A limits to sequential pairs of stops involving two vehicles (vehicle A then vehicle B). Panel B looks at the pairs of stops of the original vehicle (vehicle A) that bracket stops of other vehicles.

FIGURE D.7
TROOPERS PROFILE MOTORISTS AT THE SEARCH MARGIN, NON-DWI SPEEDING STOPS

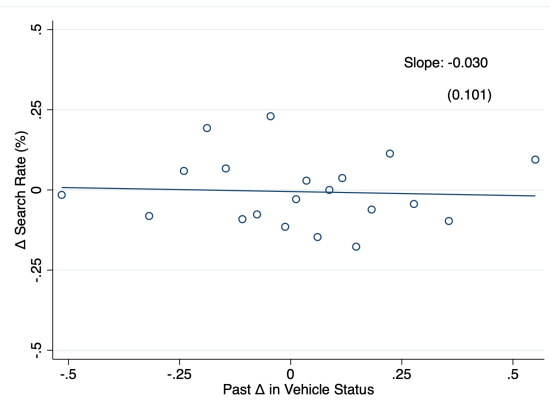
(a) Contemporaneous Change in Vehicle



(b) Future Change in Vehicle



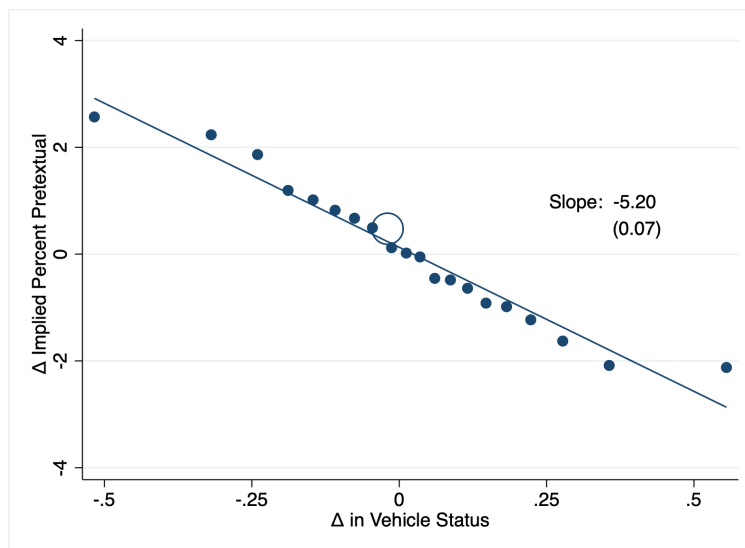
(c) Past Change in Vehicle



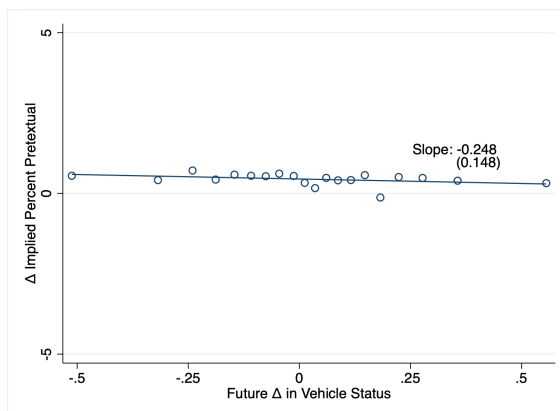
Note: These figures look at first differences in search rates for sequential pairs of stops of the same motorist as a function of changes in vehicle status. Stops are limited to those with a speeding warning or citation, and no DWI warning or citation. Panel A plots first differences in search rates against first differences in vehicle status. The open circle depicts the change in search rates for sequential pairs of stops where the same vehicle is involved in both stops. Panel B looks at whether future changes in vehicle status predict contemporaneous changes in search rates. Panel C looks at whether past changes in vehicle status predict contemporaneous changes in search rates.

FIGURE D.8
TROOPERS PROFILE MOTORISTS AT THE STOP MARGIN, MOVING VIOLATIONS

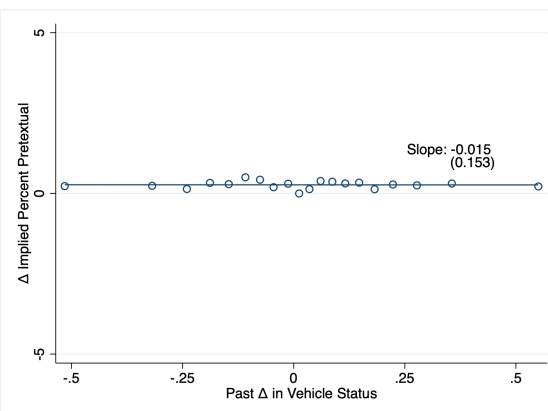
(a) Contemporaneous Change in Vehicle



(b) Future Change in Vehicle



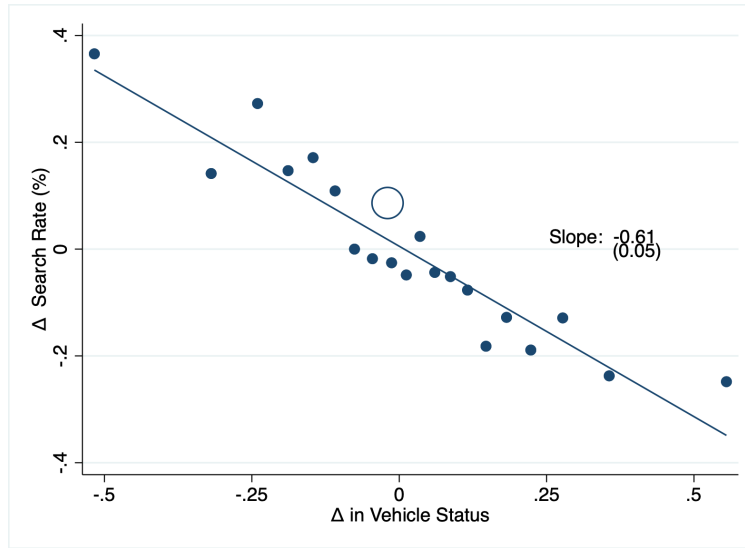
(c) Past Change in Vehicle



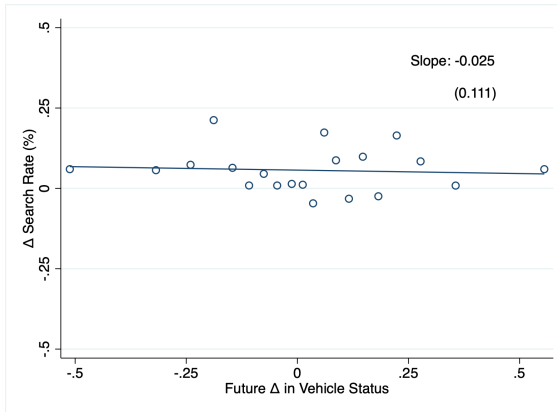
Note: These figures look at first differences in the implied pretextual stop percentage for sequential pairs of stops of the same motorist as a function of changes in vehicle status. The sample is restricted to sequential pairs of stops with associated moving violations, and we define the implied pretextual stop percentage based only on these moving violations. Panel A plots first differences in the implied pretext share against first differences in vehicle status. The open circle depicts the change in pretext share for sequential pairs of stops where the same vehicle is involved in both stops. Panel B looks at whether future changes in vehicle status predict contemporaneous changes in pretext share. Panel C looks at whether past changes in vehicle status predict contemporaneous changes in pretext share.

FIGURE D.9
TROOPERS PROFILE MOTORISTS AT THE SEARCH MARGIN, MOVING VIOLATIONS

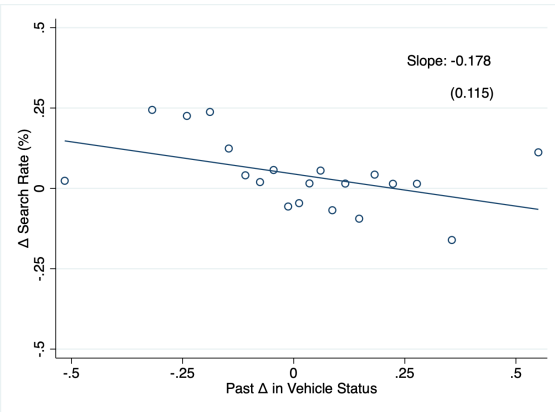
(a) Contemporaneous Change in Vehicle



(b) Future Change in Vehicle

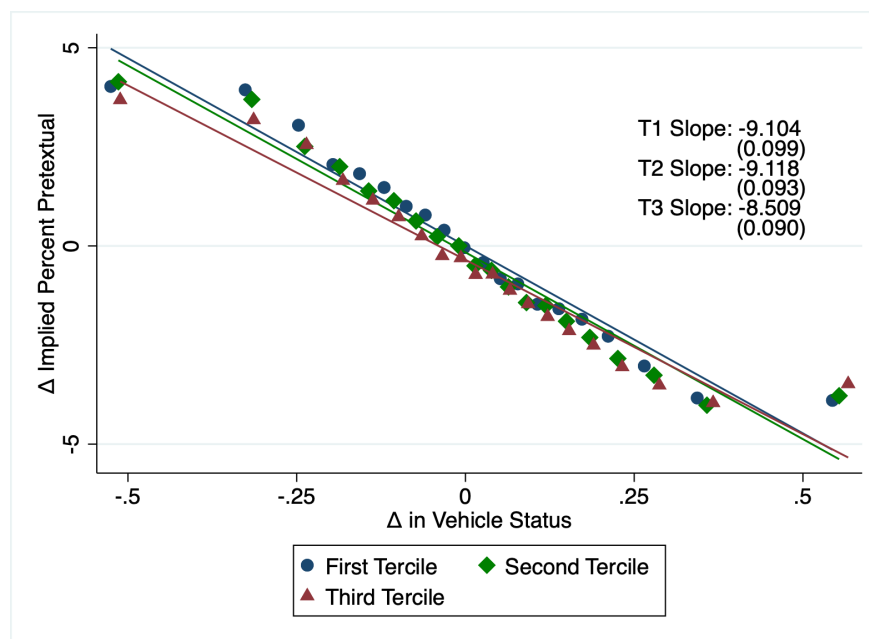


(c) Past Change in Vehicle



Note: These figures look at first differences in search rates for sequential pairs of stops of the same motorist as a function of changes in vehicle status. The sample is restricted to sequential pairs of stops with associated moving violations. Panel A plots first differences in search rates against first differences in vehicle status. The open circle depicts the change in search rates for sequential pairs of stops where the same vehicle is involved in both stops. Panel B looks at whether future changes in vehicle status predict contemporaneous changes in search rates. Panel C looks at whether past changes in vehicle status predict contemporaneous changes in search rates.

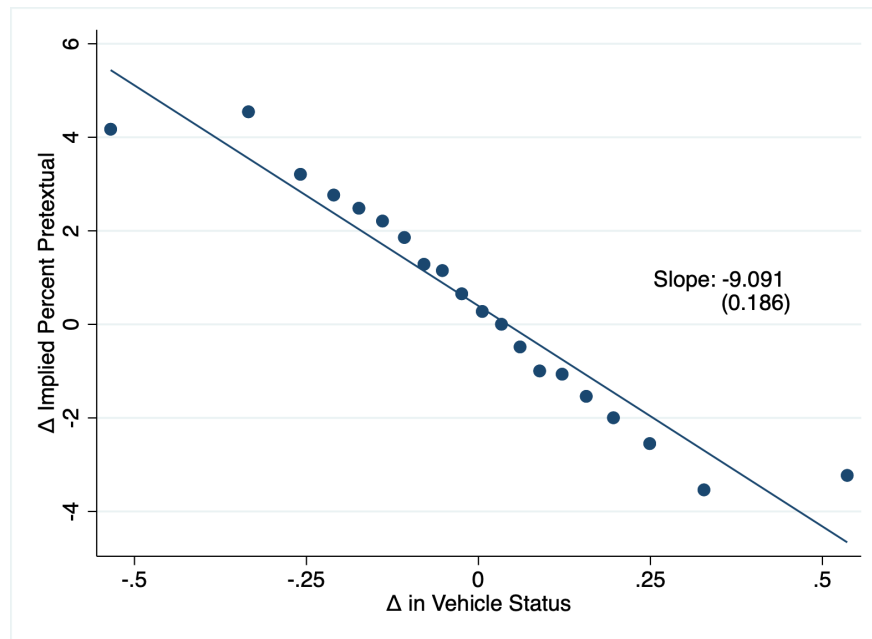
FIGURE D.10
PRETEXT STOP SHARES FOR MOTORISTS IN SEQUENTIAL STOPS BY TIME BETWEEN STOPS



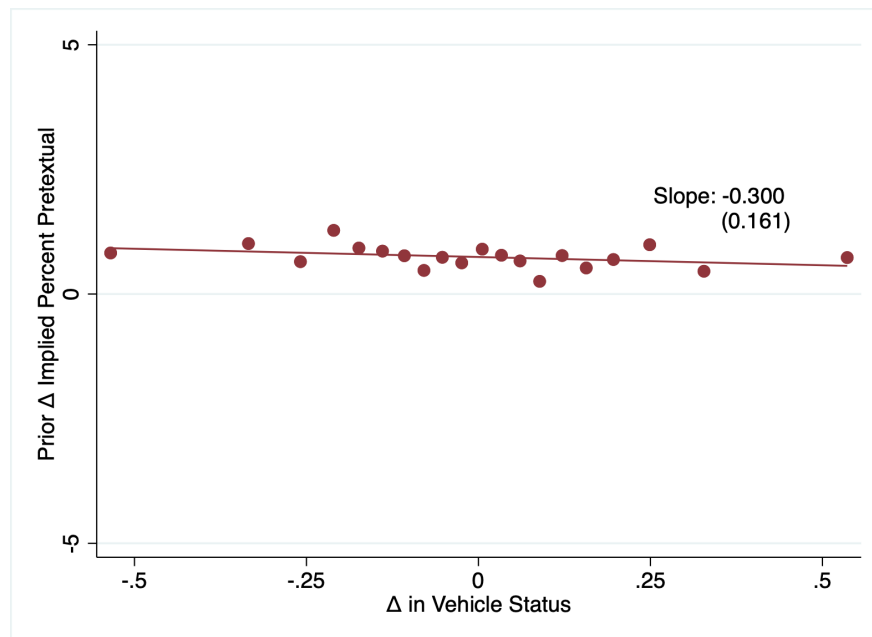
Note: This figure looks at differences in pretext stop shares for pairs of stops of the same motorist in different vehicles. Sequential pairs are partitioned by the time between the stops. For the first tercile, there is less than 7 months between stops. For the second tercile, there is between 7 and 19 months between stops. For the third tercile, there is at least 19 months between stops. The sample is constructed using all stops, which are assigned to either one of the ten most common infraction types or a residual “Other” category. For stops with multiple associated infractions, the assigned pretext share is the minimum value across infractions.

FIGURE D.11
PRETEXT STOP SHARES FOR MOTORISTS THAT ALTERNATE BETWEEN VEHICLES

(a) Contemporaneous Change in Vehicle



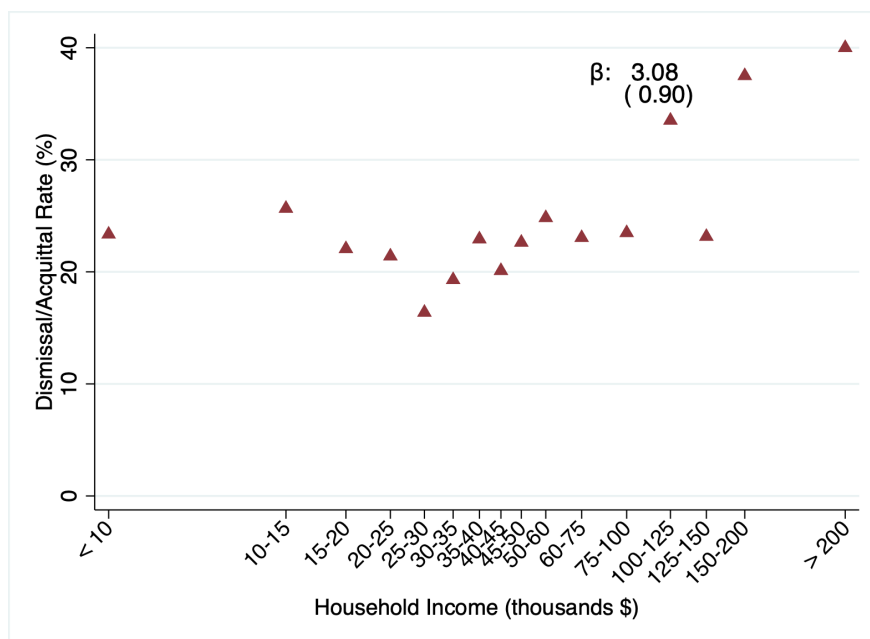
(b) Stops of Same Vehicle Bracketing Stops of Other Vehicles



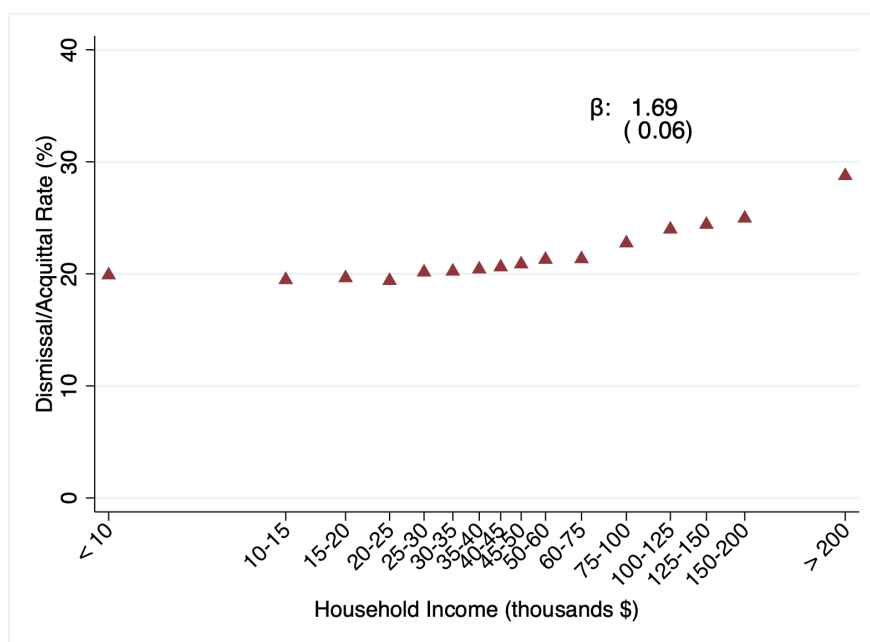
Note: This figure looks at differences in pretext stop shares for pairs of stops of the same motorist, limiting to motorists that alternate back and forth between vehicles. Panel A limits to sequential pairs of stops involving two vehicles (vehicle A then vehicle B). Panel B looks at the pairs of stops of the original vehicle (vehicle A) that bracket stops of other vehicles. The sample is constructed using all stops, which are assigned to either one of the ten most common infraction types or a residual “Other” category. Across panels, for stops with multiple associated infractions, the assigned pretext share is the minimum value across infractions.

FIGURE D.12
DISMISSAL/ACQUITTAL RATES ARE INCREASING IN MOTORIST INCOME

(a) DPS Searches



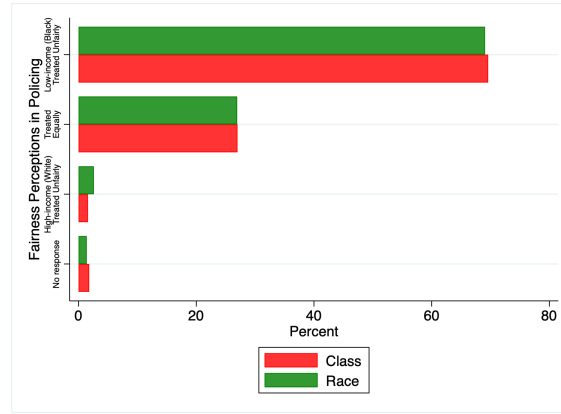
(b) All Drug Arrests



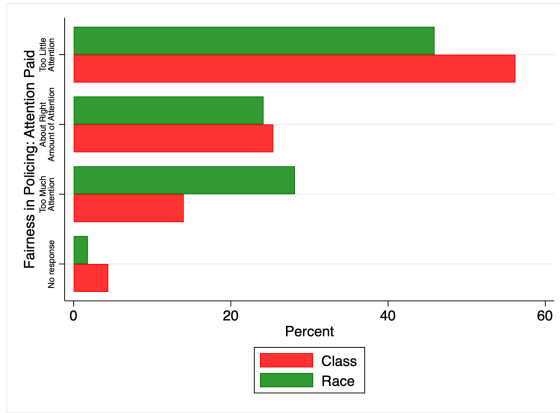
Note: These figures plot dismissal or acquittal rates as a function of motorist income. Section I.B discusses the construction of the household income measure, which partitions household income into 16 intervals. We use the average household income for all Texas households in a given interval as the horizontal axis coordinate. In Panel A the sample includes traffic stops that lead to a search, contraband recovery, and arrest. In Panel B the sample is all arrests in the CCH data for those drug charges most commonly associated with contraband-related arrests in the traffic stop data. See footnote 52 for details.

FIGURE D.13
FAIRNESS IN POLICING: BELIEFS AND POLICY PREFERENCES

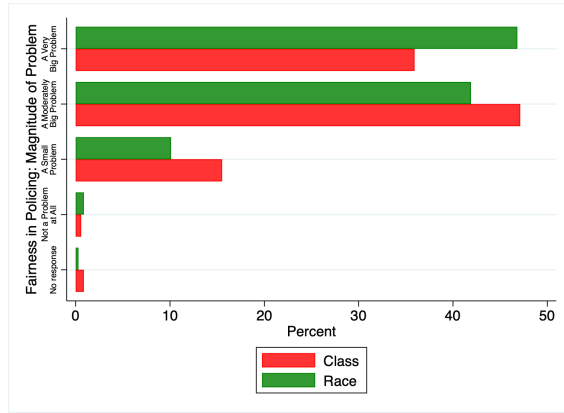
(a) Equality of Treatment by Police



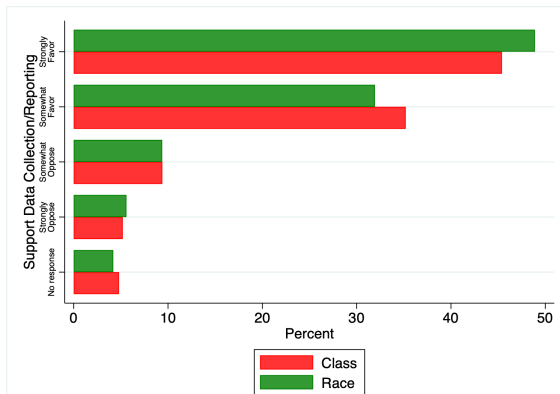
(b) Attention Paid to Equal Treatment



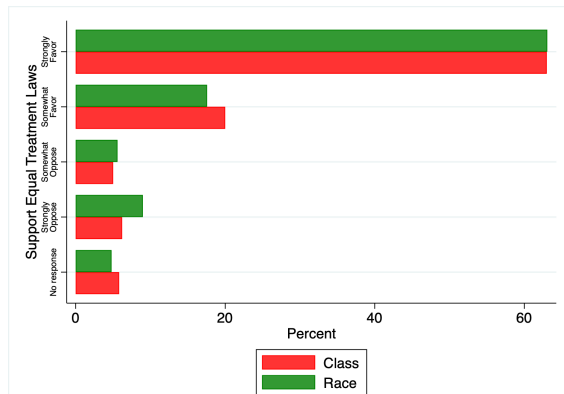
(c) How Big a Problem is Unequal Treatment?



(d) Support for Increased Data
Collection/Reporting



(e) Support for Equal Treatment Laws



Note: These figures present histograms characterizing the distribution of responses to questions included in a survey conducted by the authors on Prolific (see Appendix C). The five questions are as follows: (a) “In general, do you think police treat low-income (Black) drivers less fairly, more fairly, or about equally compared to high-income (White) drivers?”; (b) “How much attention do you think the issue of class (race) differences in how police treat drivers receives today?”; (c) “How big of a problem do you think this unfair treatment of low-income (Black) drivers by the police is today?”; (d) “Would you favor or oppose requiring police departments to collect and publicly report data on traffic stops, searches, and arrests, so that disparities between low-income and high-income (Black and White) drivers can be identified?”; (e) “Would you favor or oppose a law that would make it illegal for police to treat civilians differently because of their income level (race)?” Note that respondents only answer question (c) if they report that low-income (Black) drivers are treated less fairly.