Class Disparities and Discrimination in Traffic Stops and Searches

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Motivation

- Class may shape how police engage with civilians (Robison, 1936)
- Low-status neighborhoods are policed more aggressively (Fagan et al., 2010; MacDonald, 2021; Chen et al., forthcoming)
- Q: in the same context, are low-status civilians policed more aggressively?
- Potential implications for:
  - Mobility and inequality
  - Trust in criminal justice institutions
  - Effectiveness of policing

This Paper

- Study class disparities and discrimination in traffic stops and searches conducted by Texas Highway Patrol
  - Measure motorist household income using ACS and residential property value data
  - Estimate class differences in search rates, contraband yield, and “pretext” stops
  - Exploit within-motorist variation in perceived class to test for class *discrimination*
  - Investigate how class disparities in the court system may influence stop and search decisions

Preview of Findings

- Class disparities in search rates are *large*
- Searches of low-income motorists are *less* likely to yield contraband
- Pretext stops: low-income motorists are stopped by more search-intensive troopers
- Class disparities at least in part reflect class *discrimination*
  - Same motorist is more likely to be searched in a low-status vehicle and is stopped by more search-intensive troopers
- Downstream hassle costs may help to explain trooper behavior
  - Low-income motorists are more likely to plead guilty/no contest after arrest
  - Supporting evidence: search rates are lower in jurisdictions where local institutional factors imply higher hassle costs

Related Literature

- Research on profiling that has documented racial disparities in
  - Vehicle stops: Grogger and Ridgeway (2006); Pierson et al. (2020)
  - Searches: Knowles et al. (2001); Anwar and Fang (2006); Close and Mason (2007); Antonovics and Knight (2009); Marx (2022); Feigenberg and Miller (2022)
  - Pre-trial detention: Arnold et al. (2018, 2022)
  - Charging decisions, sentencing: Rehavi and Starr (2014)
- Regressive burden of criminal justice policies
  - Agan et al. (2021); Gupta et al. (2016); Makowsky (2019); Clair (2020); Mello (2021); Finlay et al. (2023); Lieberman et al. (2023)
- Class discrimination in other contexts
  - Kraus and Keltner (2009); Nelissen and Meijers (2011); Bjornsdottir and Rule (2017); Kraus et al. (2017, 2019); Rivera and Tilcsik (2006); Besbris et al. (2015); Glied and Niedell (2010)

Talk Outline

1. Institutional Context and Data
2. Search and Hit Rates by Income
3. Class Differences in Pretext Stops
4. Test for Trooper Discrimination
5. Hassle Costs and Trooper Objectives

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Institutional Context

- We study traffic stops conducted by Texas Highway Patrol
- Most stops occur on state and interstate highways
- Trooper can:
  - Stop motorists if they observe or have reasonable suspicion of a violation
  - During stop, investigate if motorist is carrying contraband, including illicit drugs and weapons
  - Conduct a search if they have probable cause to believe a law has been broken
  - Ask for and receive motorist consent to conduct a search

Data

- 16 million vehicle stops conducted by Texas Highway Patrol (2009-2015)
  - Information on stop time and location, vehicle characteristics, motorist race and gender, stop and search outcomes, trooper ID
  - Unique feature: includes motorist's full name and address
    - Match multiple traffic stops to the same motorist
- Individual-level criminal histories from Texas Computerized Criminal History System
  - Measure arrest and court outcomes associated with stop
- Commercial address history data (Infogroup/Data Axle) used to facilitate matching traffic stops and criminal history to a given motorist

Sample Selection

Measuring Household Income

- 2009-2013 ACS block group-level income data and ATTOM property assessment data used to infer household income
    - Single-family residential properties: assign to p^{th} percentile of homeowner household income distribution if property value falls in p^{th} percentile
    - For all others (multifamily housing, apartment complexes, etc.): assign median household income category among renters
    - Finally, allocate across 16 income intervals available for pooled block group sample
    - Results insensitive to alternative approaches, including assigning all motorists to block group median income

- While imperfect due to ACS measurement error, mismeasurement of owner/renter status and imperfect correlation between property value and income, measure captures important dimension of economic well-being

Descriptive Statistics

Figure: Distribution of Household Income Across Stops

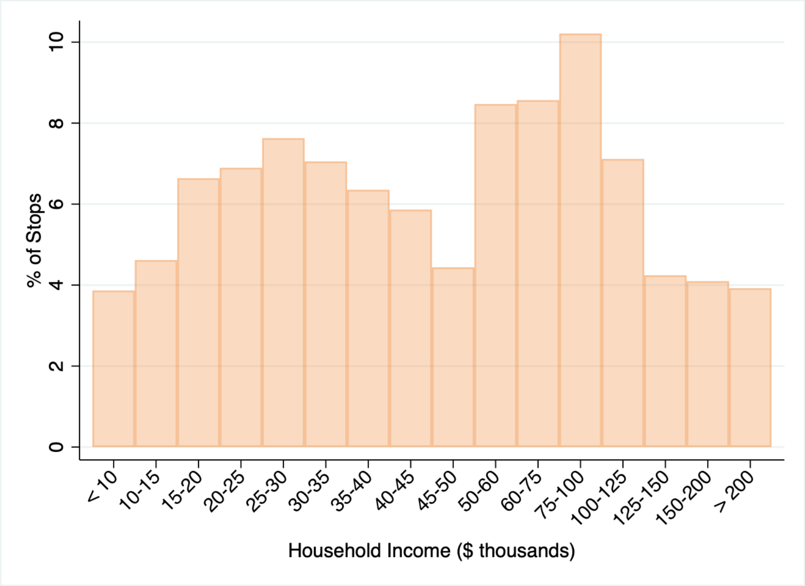

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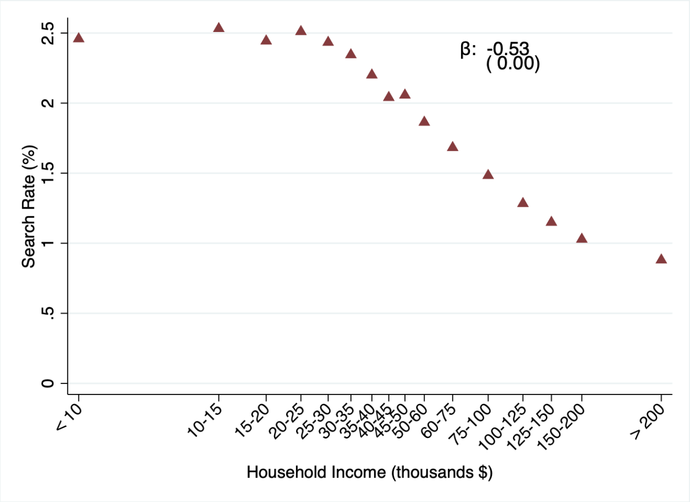
Figure: Search Rates are Decreasing in Motorist Income



- Motorists in top (bottom) income quintile searched in 1.1% (2.5%) of stops; for comparison, Black and Hispanic motorists are searched 150% and 60% more often than White motorists

Do Class Disparities Reflect Other Contextual Differences?

- These disparities may reflect differences in stop context, including the location and time, or other motorist demographics
  - We estimate regression models of the form:

$$Y_{it} = \alpha_{\ell_{i,t}\tau(t)y(t)} + \beta \text{log(income)}_{it} + X_{it}\Gamma + \epsilon_{it} \tag{1}$$

  - $\alpha_{\ell_{i,t}\tau(t)y(t)}$ are fixed effects for combination of trooper patrol area (“sergeant area”), time of week (quarter of day, weekday or weekend), and year
  - X_{it} is a vector of motorist demographic characteristics, including race and gender

    Separately by Race

- Could also reflect differences in violations associated with stops
  - Qualitatively similar findings if we limit to speeding stops

    Speeding Only Descriptives | Speeding Only Results

Table: Search Rates by Motorist Income

Outcome:	Search ($\times$100)		
	(1)	(2)	(3)
log Household Income	-0.53	-0.54	-0.48
	(0.00)	(0.00)	(0.00)
Sgt. Area $\times$ Time of Week $\times$ Year FEs		✓	✓
Motorist Demographics			✓
Mean of DV		1.92	
Observations		11,022,012	

How Do Hit Rates Vary with Motorist Income?

- Low-income motorists are more likely to be searched
- One potential explanation: low-income motorists are more likely to carry contraband
- We measure contraband yield ("hit rates") by motorist income
  - No evidence of differences by income in contraband type Contraband Type

Figure: Hit Rates Are Increasing in Motorist Income

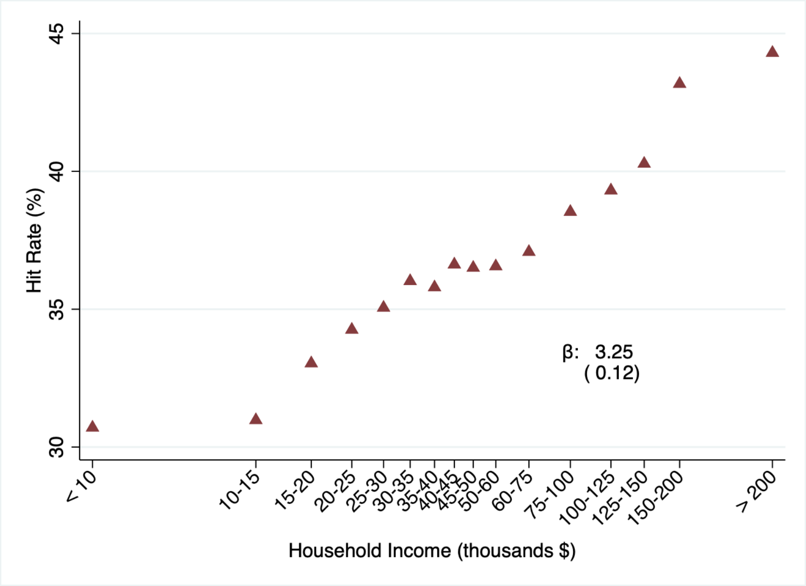


Table: Hit Rates by Motorist Income

Outcome:	Contraband Recovery ($\times$100)		
	(1)	(2)	(3)
log Household Income	3.25	1.56	1.36
	(0.12)	(0.12)	(0.12)
Sgt. Area $\times$ Year FEs		✓	✓
Motorist Demographics			✓
Mean of DV	35.88		
Observations	211,546		

- Group differences in hit rates indicate troopers could increase contraband yield by reallocating searches (Feigenberg and Miller, 2022)

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2. Search and Hit Rates by Income
3. Class Differences in Pretext Stops
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Class Differences in Pretext Stops

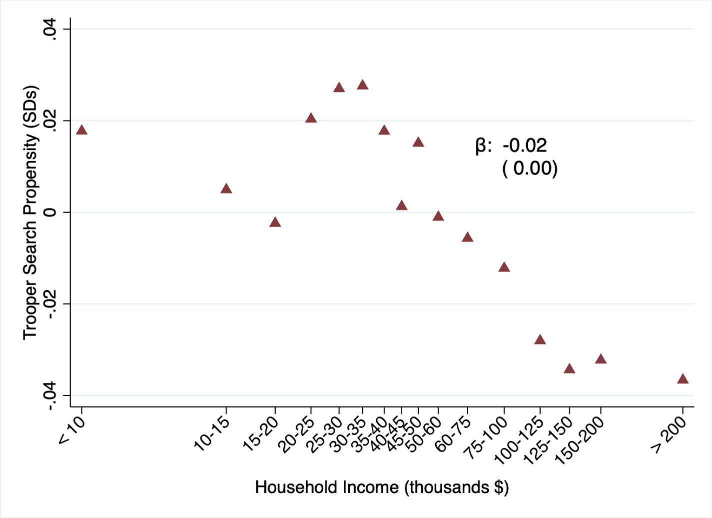
- Some stops are “pretextual”—based on minor infractions with goal of identifying a more serious crime (via search)
- Given that low-income motorists are more likely to be searched, we posit that low-income motorists are also at higher risk of pretext stops
- Problem: generally difficult to study how troopers make stop decisions because of the “benchmarking problem” (Grogger and Ridgeway, 2006)
- We develop test based on simple model of trooper stop and search behavior Model
  - Stop decision depends on infraction severity and option value of search
  - Key prediction: *search-intensive troopers* are more likely to conduct pretext stops

Measuring Trooper Search Propensities

- We measure trooper search propensities in three ways
  1. Trooper's leave-out search rate ($\sigma = 2.3pp$)
  2. Partial out motorist income and location by time fixed effects ($\sigma = 2.0pp$)
  3. Partial out both motorist and location by time fixed effects ($\sigma = 1.1pp$)

- We standardize each measure to have mean zero, standard deviation one

Figure: Low-Income Motorists are Stopped by Search-Intensive Troopers



Speeding Only

Table: Trooper Search Propensities by Motorist Income

	Outcome: Trooper Search Propensity (SDs)					
	(1)	(2)	(3)	(4)	(5)	(6)
log Household Income	-0.017 (0.000)	-0.020 (0.000)	-0.021 (0.000)	-0.019 (0.000)	-0.011 (0.000)	-0.012 (0.000)
Sgt. Area × Time of Week × Year FEs		✓		✓		✓
Propensity Measure	Baseline		Controls		Motorist FEs	
Observations	11,021,893					

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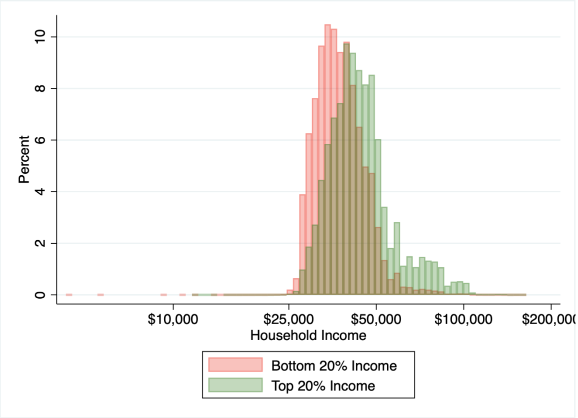
Is This Class Discrimination?

- Troopers may *discriminate* on the basis of perceived class; or they may target searches based on other motorist characteristics that are *correlated* with perceived class
- A central challenge to investigating disparities is distinguishing between the two (Charles and Guryan, 2011)
- Ideal experiment: Vary the *perceived* class of a motorist, holding behavior fixed
- Our strategy: look at the *same* motorist stopped in *different* vehicles
  - Assumption: other than motorist's perceived class, motorist characteristics are fixed, or variation is uncorrelated with variation in vehicle
  - Plausible given trip to trip variation in vehicle (many motorists have access to multiple vehicles, new purchases infrequent)
  - 60% of stops involve motorists that are stopped multiple times; in pairs of consecutive stops, over half involve different vehicles

Figure: Distribution of Vehicle Status by Income



- We measure vehicle status as predicted log household income based on vehicle make, type (passenger car, pick-up truck, or SUV), and age (SD: 22 log points)

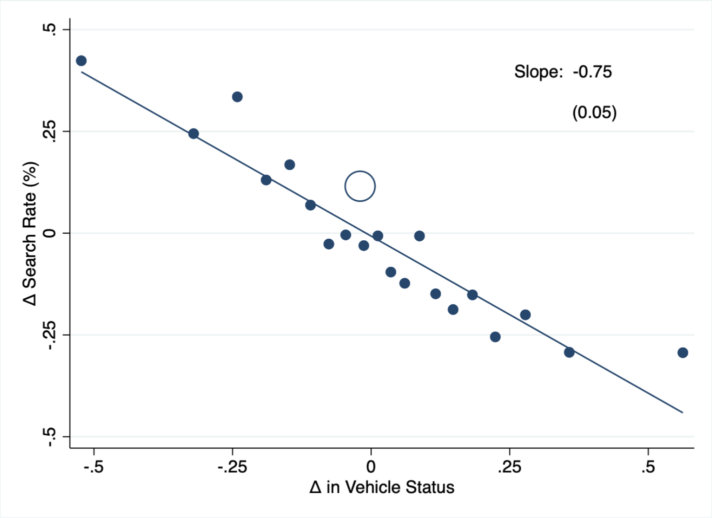
NHTS Correlations

Table: Search Rates, Hit Rates, and Trooper Search Propensities by Vehicle Status

	Search ($\times$100)			Contraband Recovery ($\times$100)			Trooper Search Propensity (SDs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vehicle status	-3.71	-3.23	-2.95	2.69	2.63	1.80	-0.18	-0.18
	(0.02)	(0.02)	(0.02)	(0.56)	(0.56)	(0.57)	(0.00)	(0.00)
log household income			-0.33			1.30		-0.01
			(0.00)			(0.13)		(0.00)
Sgt. Area $\times$ Time of Week $\times$ Year FEs	✓	✓	✓				✓	✓
Sgt. Area $\times$ Year FEs				✓	✓	✓		
Motorist Demographics		✓	✓		✓	✓		
Observations	11,022,012			211,546			11,021,893	

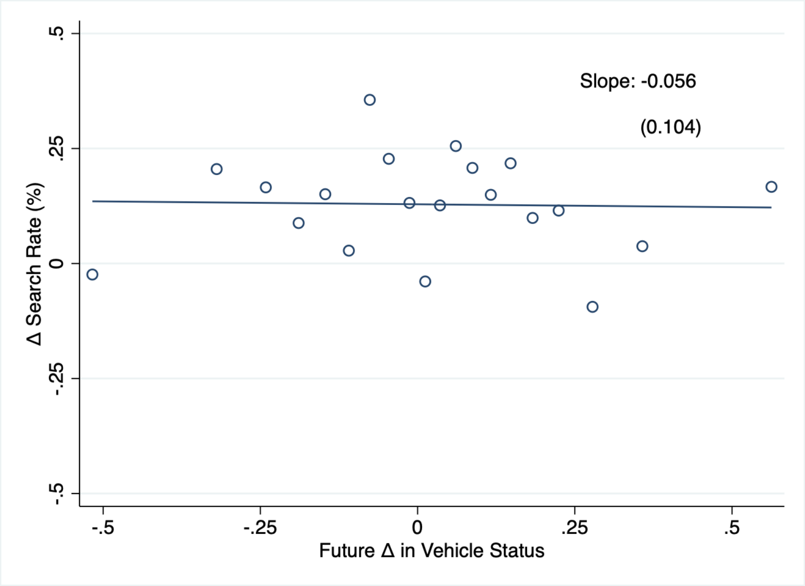
- Results consistent with greater salience of vehicle status
- We next relate first differences in search rates to first differences in vehicle status
  - Average (absolute) change in vehicle status is 19 log points

Figure: Troopers Profile Motorists at the Search Margin



- Within-motorist magnitude about $1/4$ of overall relationship Descriptive Statistics Speeding Only

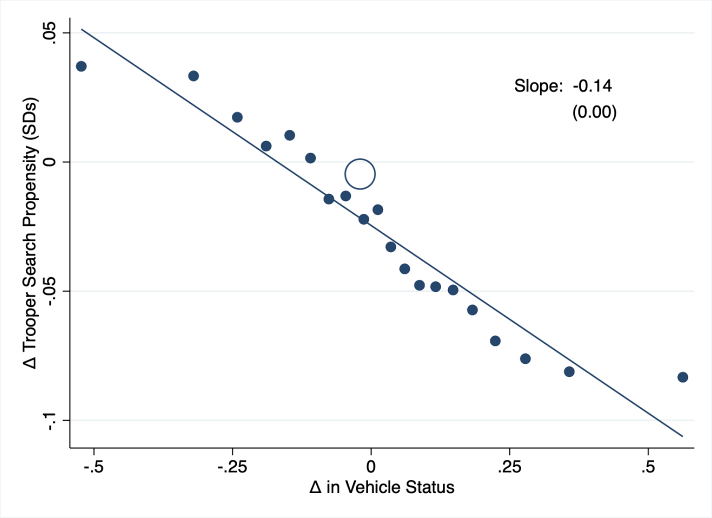
Figure: No Change in Search Rates Prior to Vehicle Switch



Robustness Checks

- To provide additional evidence that the profiling pattern we document does not reflect some contemporaneous common shock to the motorist, we show:
  - Same pattern among consecutive stops with less time between stops Time Between Stops
  - Same pattern for motorists that are later stopped again in original vehicle Alternating Vehicles
  - No meaningful change in address-based income measure Motorist Income

Figure: Troopers Profile Motorists at the Stop Margin



- Within-motorist magnitude about 80% of overall relationship Robustness

Table: Marginal Hit Rate is Increasing in Motorist Income

Outcome:	Δ Search (×100)		Δ Contraband Recovery (×100)			
	Bottom Tercile	Top Tercile	Bottom Tercile	Top Tercile	Bottom Tercile	Top Tercile
Δ Vehicle Status	-0.64	-0.75	-0.09	-0.27		
	(0.10)	(0.07)	(0.05)	(0.04)		
Δ Search					0.15	0.36
					(0.08)	(0.05)
Model	OLS	OLS	OLS	OLS	2SLS	2SLS
Observations	897,801	659,249	897,801	659,249	897,801	659,249

- We estimate 2SLS models within top and bottom income terciles, instrumenting for search using vehicle status
- We find that reallocating marginal searches to high-income motorists would increase contraband yield

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Why Are Troopers Targeting Low Status Motorists?

- Puzzle: Troopers search high status motorists *less* often yet achieve *higher* hit rate
- We posit that troopers may respond to anticipated "hassle costs" associated with adjudication process following contraband discovery and arrest
  - In Texas, as elsewhere, troopers may be required to testify in court proceedings
  - Evidence from Dallas of officer aversion to overtime (Chalfin and Goncalves, 2020)
  - Court appearances particularly disruptive and stressful (Newell et al., 2022; Boyce, 2006)
- Evidence that attorneys assigned to indigent defendants perform poorly in Texas (Agan et al., 2021; Cohen, 2014)
  - Fewer pre-trial motions and hearings, fewer hours dedicated to case, higher guilty/no contest plea rate when compared to privately-retained attorneys
- We next relate motorist income to courts-based measures that proxy for hassle costs

Figure: Guilty/No Contest Plea Rates Are Decreasing in Motorist Income (DPS Searches)

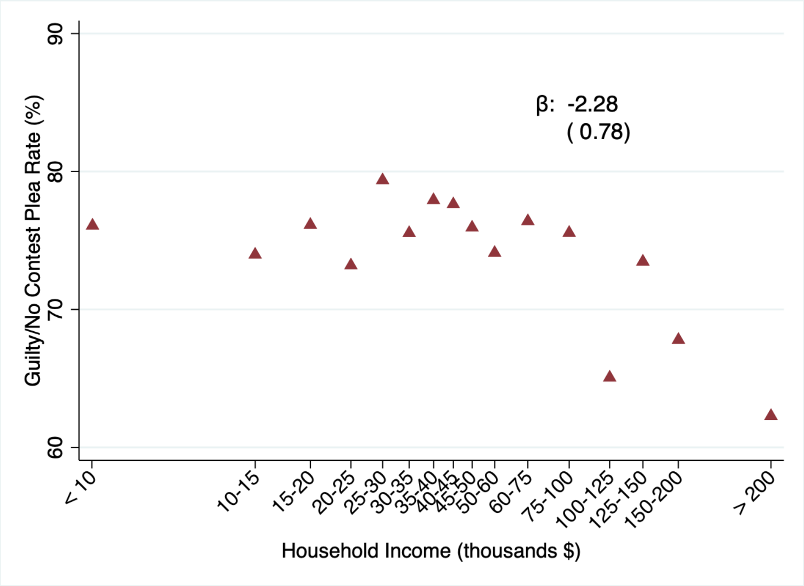
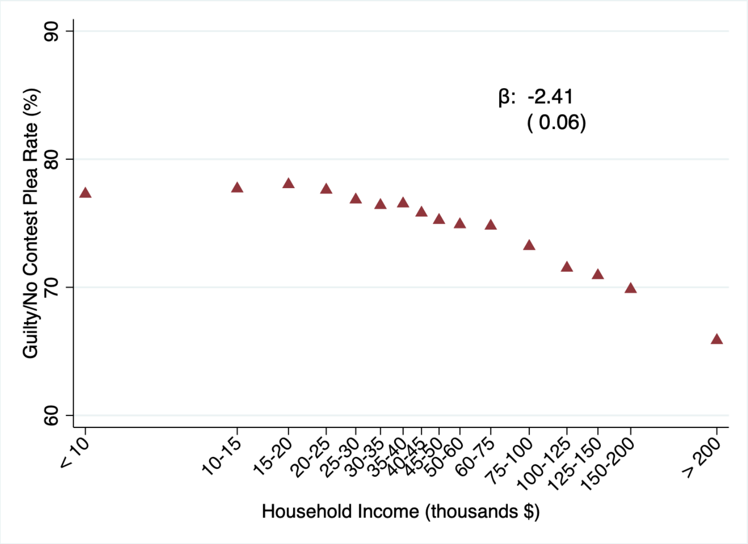


Figure: Guilty/No Contest Plea Rates Are Decreasing in Motorist Income (All Drug Arrests)



Dismissals/Acquittals

County-level Search Rates and Hassle Costs

- If troopers respond to anticipated hassle costs, search rates should be falling in expected hassle costs, all else equal

- To test, we leverage cross-county variation in courts-based outcomes after conditioning on charge and defendant characteristics (Feigenberg and Miller, 2021):

$$Y_{ict} = \alpha_{cth(i,t)} + X_i\Gamma^x + Z_{it}\Gamma^z + \Theta_{j(i,c,t)} + \epsilon_{ict}. \tag{2}$$

  - $\alpha_{cth(i,t)}$ are specific charge by defendant criminal history by year fixed effects
  - X_i represents race, ethnicity and gender; Z_{it} represents defendant age and age squared
  - $\Theta_{j(i,c,t)}$ is the set of county fixed effects

- We relate these county FEs to residual search rates constructed as follows:

$$Y_{ict} = \alpha_{\tau(t)y(t)} + X_i\Gamma^x + \Theta_{j(i,c,t)} + \epsilon_{ict}. \tag{3}$$

  - $\alpha_{\tau(t)y(t)}$ are year-by-stop time (quarter of day, weekday or weekend) fixed effects

Table: County-level Search Rates and Hassle Costs

	Outcome: County-level Residual Search Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
County-level Residual	0.016	0.014	0.014			
Guilty/No Contest Plea Rate	(0.005)	(0.004)	(0.004)			
County-level Residual				-0.017	-0.017	-0.016
Dismissal/Acquittal Rate				(0.005)	(0.004)	(0.004)
Residualized on Motorist FEs		✓	✓		✓	✓
Residualized on Defendant FEs			✓			✓
Dependent Variable Mean	0.019	0.020	0.020	0.019	0.020	0.020
Observations	225					

- Results consistent with trooper search decisions responding to anticipated hassle costs

Discussion

- We document large class disparities in search rates and pretext stops
- Low-income motorists are more likely to be searched and found with contraband despite being less likely to be found with contraband conditional on being searched
- Class disparities at least in part reflect class discrimination
- Finding have important implications for fairness and equity, exposure to criminal sanctions
- We present suggestive evidence that trooper behavior is at least in part explained by anticipated downstream hassle costs

Table: Traffic Stop Descriptive Statistics

	All Stops			All Searches		
	Below Median	Above Median	All	Below Median	Above Median	All
Black	10.14	8.685	9.462	16.79	15.04	16.18
Hispanic	37.70	24.63	31.60	39.39	29.72	36.01
White	49.84	63.18	56.07	42.00	52.61	45.71
Female	35.10	34.55	34.84	19.81	18.96	19.51
Log Household Income	9.938	11.34	10.59	9.908	11.23	10.37
	(0.606)	(0.489)	(0.891)	(0.608)	(0.445)	(0.842)
Search Rate	2.341	1.438	1.919	100	100	100
Unconditional Hit Rate	0.819	0.562	0.699	34.44	38.56	35.88
Moving	67.89	73.83	70.67	59.80	62.19	60.64
Driving while intoxicated	2.261	1.328	1.825	22.11	21.57	21.93
Speeding	55.38	63.43	59.14	28.27	32.94	29.90
Equipment	4.170	2.873	3.564	4.830	4.282	4.638
Regulatory	42.99	36.05	39.75	42.46	37.16	40.60
Observations	5,874,428	5,147,584	11,022,012	137,517	74,029	211,546

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Table: Sample Selection

Sample step	Observations Dropped	Observations Remaining
1. All stops conducted by Texas Highway Patrol between 2009 and 2015		15,761,299
2. Drop stops with missing trooper ID or stop outcomes	2,114	15,759,185
3. Retain stops of motorists with Texas addresses	1,872,413	13,886,772
4. Retain stops of motorists with valid addresses	1,958,380	11,928,392
5. Retain stops of valid passenger cars, pick-up trucks, and SUVs	577,141	11,351,251
6. Drop stops with missing location information	329,239	11,022,012

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Figure: Search Rates are Decreasing in Motorist Income (Separately by Race)

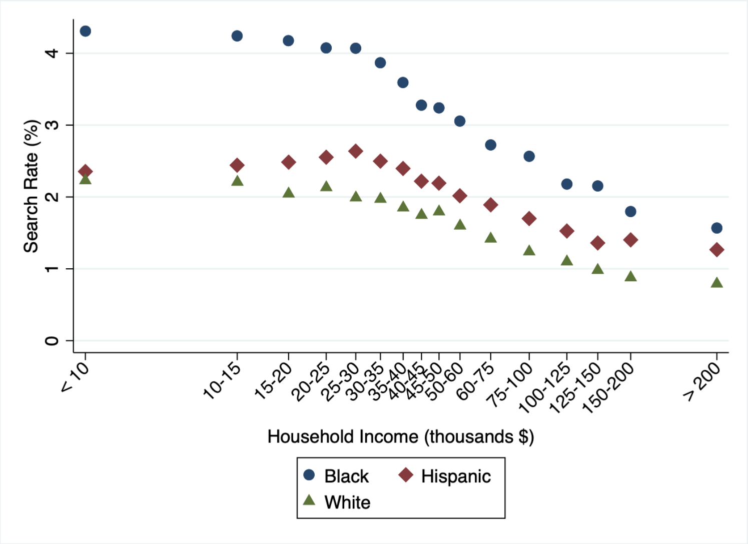

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Table: National Household Travel Survey (NHTS) Correlational Analysis

	Outcome: Log HH Income		Outcome: Years of Schooling			
	(1)	(2)	(3)	(4)	(4)	(6)
Log Average Income by Vehicle Group	0.810 (0.023)	0.792 (0.023)	1.472 (0.056)	0.784 (0.056)		
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			

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Table: Traffic Stop Descriptive Statistics, Non-DWI Speeding Stops

	All Stops			All Searches		
	Below Median	Above Median	All	Below Median	Above Median	All
Black	9.627	7.801	8.865	19.69	16.79	18.81
Hispanic	33.10	20.71	27.93	37.78	26.71	34.42
White	54.71	67.81	60.18	40.50	53.39	44.41
Female	37.62	36.00	36.94	18.61	17.02	18.13
Log Household Income	10.08	11.48	10.67	10.02	11.41	10.44
	(0.617)	(0.457)	(0.888)	(0.626)	(0.428)	(0.856)
Search Rate	0.964	0.586	0.806	100	100	100
Unconditional Hit Rate	0.259	0.194	0.232	26.60	32.85	28.49
Moving	100	100	100	100	100	100
Driving while intoxicated	0	0	0	0	0	0
Speeding	100	100	100	100	100	100
Equipment	1.062	0.732	0.924	2.091	1.951	2.048
Regulatory	24.86	18.76	22.31	42.29	31.98	39.16
Observations	3,772,069	2,703,131	6,475,200	36,352	15,834	52,186

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Figure: Search Rates Are Decreasing in Motorist Income, Non-DWI Speeding Stops

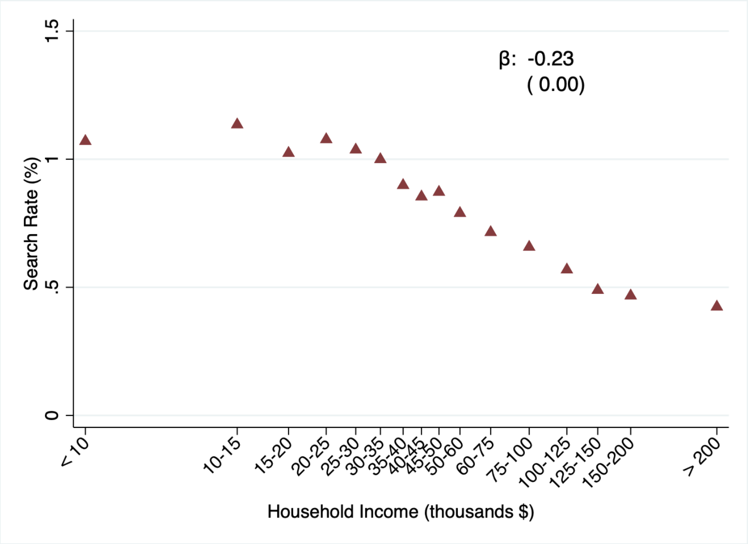

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Table: Contraband Type by Motorist Income

	Log Income Quintile				
	Q1	Q2	Q3	Q4	Q5
Contraband Type (%)					
Currency	0.7	0.4	0.4	0.4	0.3
Drugs	51.6	51.6	52.3	52.3	53.5
Weapon	44.0	44.1	43.7	43.6	42.7
Other	3.6	4.0	3.6	3.7	3.5
Observations	19,901	19,508	15,111	12,581	9,941

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A Simple Model of Trooper Behavior: Search Margin

- Expands on Anwar and Fang (2006)
- For each stopped motorist, trooper observes noisy signal (θ) for likelihood that motorist is carrying contraband, given by $P(G|\theta)$
- Normalized cost of search is τ
- At search margin, trooper's utility given by

$$U(\theta, \tau) = \max\{P(G|\theta) - \tau; 0\}$$

- Trooper conducts search when $P(G|\theta) \geq \tau$; sets some threshold θ^*
- Note that trooper's utility is decreasing in τ

A Simple Model of Trooper Behavior: Stop Margin

- Trooper observes the severity of violation; ν is direct benefit of stop given violation
- Trooper also observes ω, a noisy signal for θ
  - ω is *even noisier* signal for likelihood that motorist is carrying contraband
- Let c denote cost of stop; trooper will conduct a stop if

$$\nu + E[U(\theta, \tau)|\omega] \geq c$$

- *Pretext stop* defined as stop where

$$\nu < c \leq \nu + E[U(\theta, \tau)|\omega]$$

Testing for Class Disparities in Pretext Stops

- Key prediction: lower search costs $\tau \Rightarrow$ more pretext stops
- We test whether lower-income motorists are stopped by troopers with lower search costs
- We infer trooper search costs using their search propensities, holding motorist characteristics fixed

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Table: Descriptive Statistics for Sequential Stops

	Single Stop	Multiple Stops	
		Same Vehicle	Different Vehicle
Black	10.67	8.446	8.364
Hispanic	30.73	30.43	35.23
White	54.68	58.95	54.40
Female	40.98	33.65	25.83
Log Household Income	10.62	10.56	10.55
	(0.874)	(0.906)	(0.908)
Search Rate	2.022	1.808	1.925
Unconditional Hit Rate	0.749	0.684	0.684
Change in Vehicle Status	.	-0.0199	0.0197
	(.)	(0.0294)	(0.245)
Change in Vehicle Age	.	0.694	-0.461
	(.)	(0.924)	(6.510)
Months between Stops	.	8.683	16.69
	(.)	(10.37)	(15.26)
Absolute Change in Vehicle Status	.	0.0199	0.187
	(.)	(0.0294)	(0.160)
Absolute Change in Vehicle Age	.	0.694	4.865
	(.)	(0.924)	(4.350)
Observations	4,398,158	2,102,948	2,323,337

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Figure: Troopers Profile Motorists at the Search Margin, Non-DWI Speeding Stops

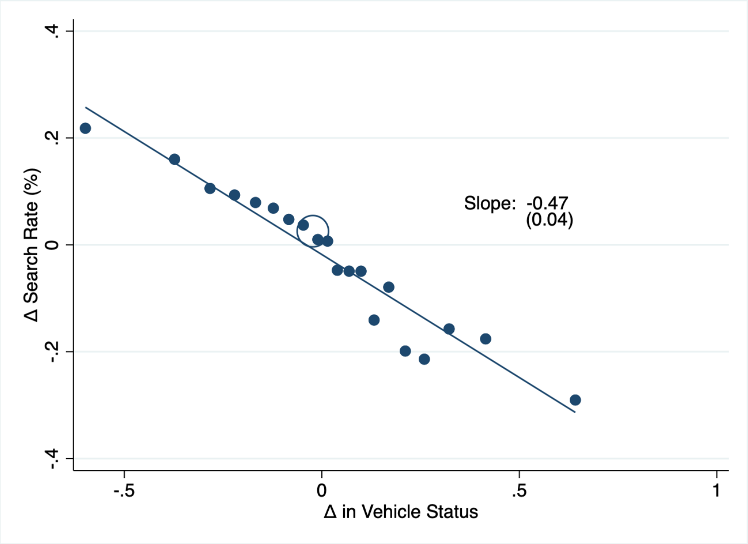

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Figure: Low-Income Motorists are Stopped by Search-Intensive Troopers, Non-DWI Speeding Stops

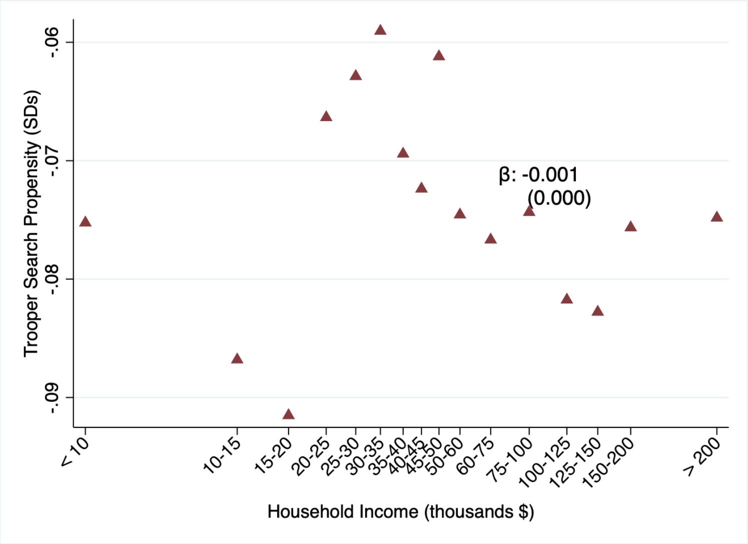

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Figure: Same Pattern for Motorists that Switch Back to Original Vehicle (Contemporaneous Change)

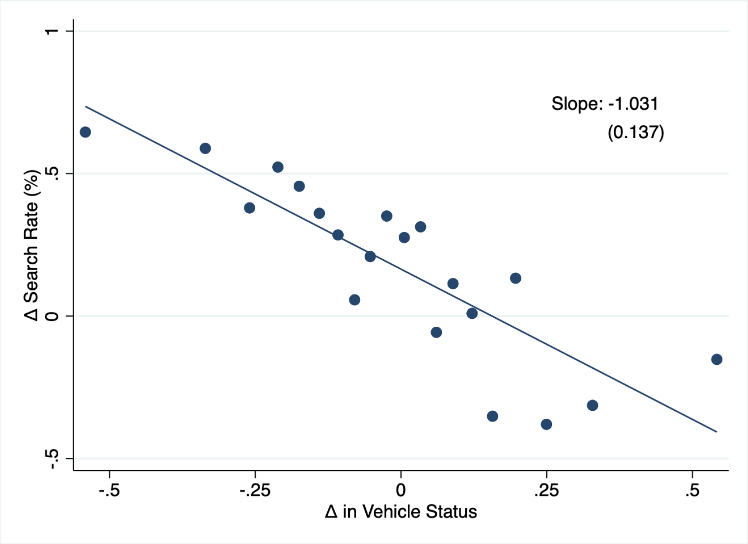

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Figure: Same Pattern for Motorists that Switch Back to Original Vehicle (Placebo)

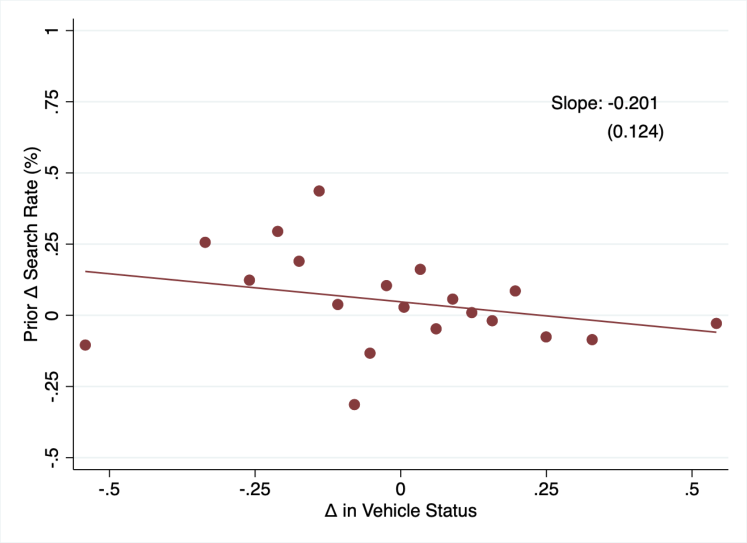

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Figure: Pattern Does Not Vary with Time Between Stops

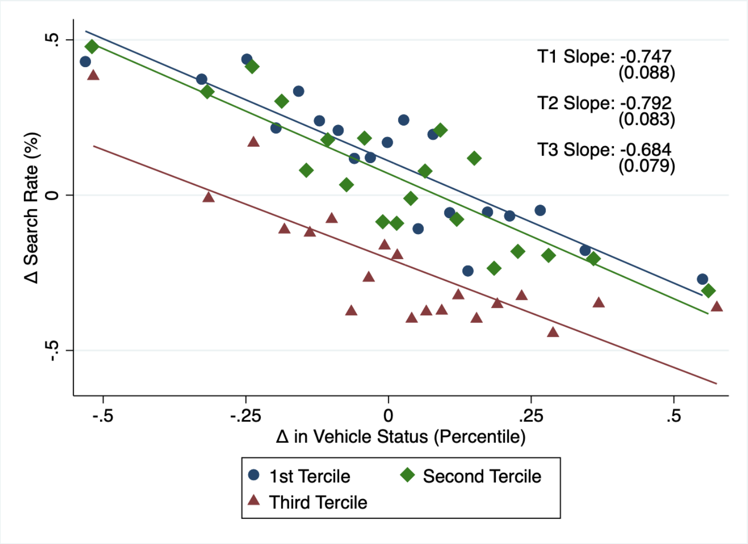

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Figure: No Substantive Change in Motorist Income Between Stops in Within-Motorist Design

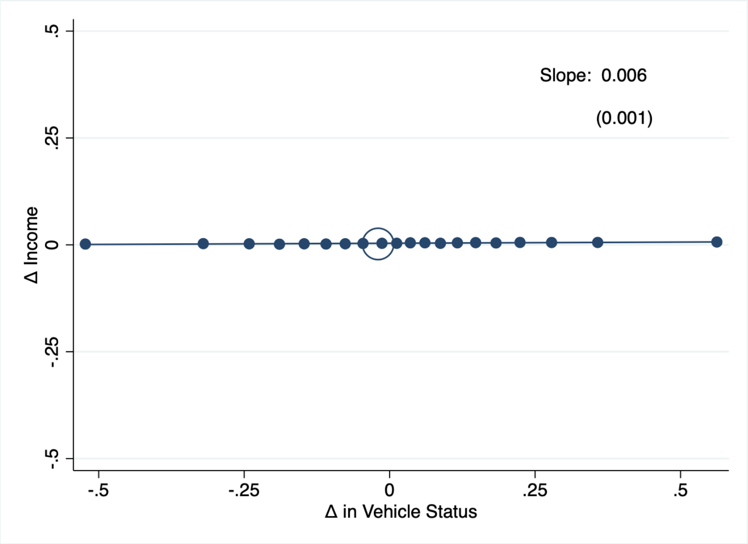

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Figure: No Evidence of Change in Trooper Type Prior to Vehicle Switch

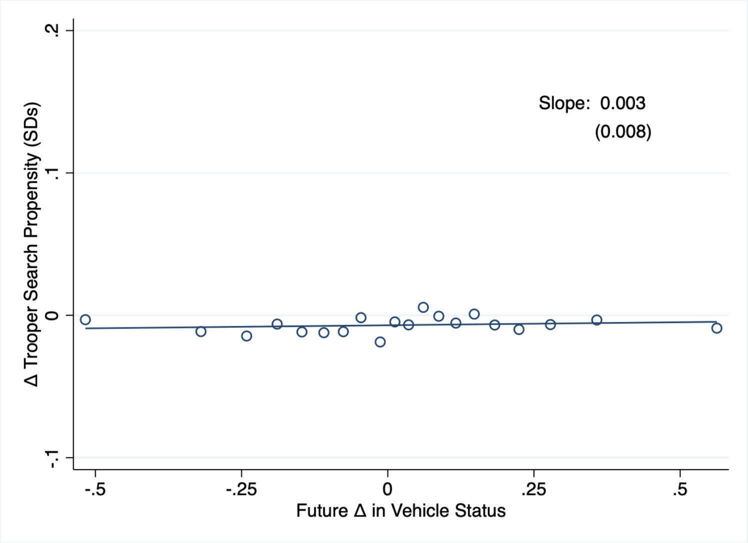

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Figure: Same Trooper Search Propensity Pattern for Motorists that Switch Back to Original Vehicle (Contemporaneous Change)

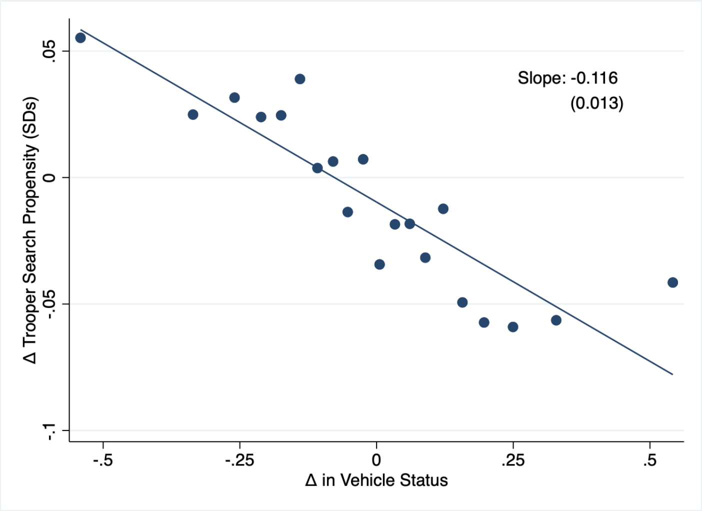

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Figure: Same Trooper Search Propensity Pattern for Motorists that Switch Back to Original Vehicle (Placebo)

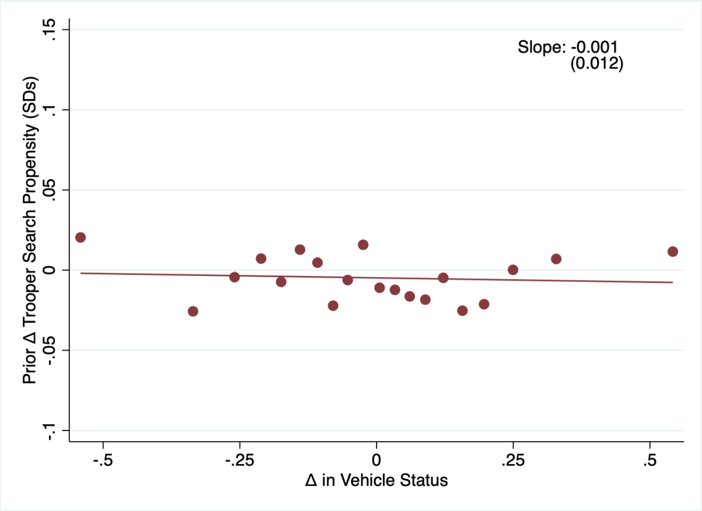

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Figure: Troopers Profile Motorists at the Stop Margin, Non-DWI Speeding Stops

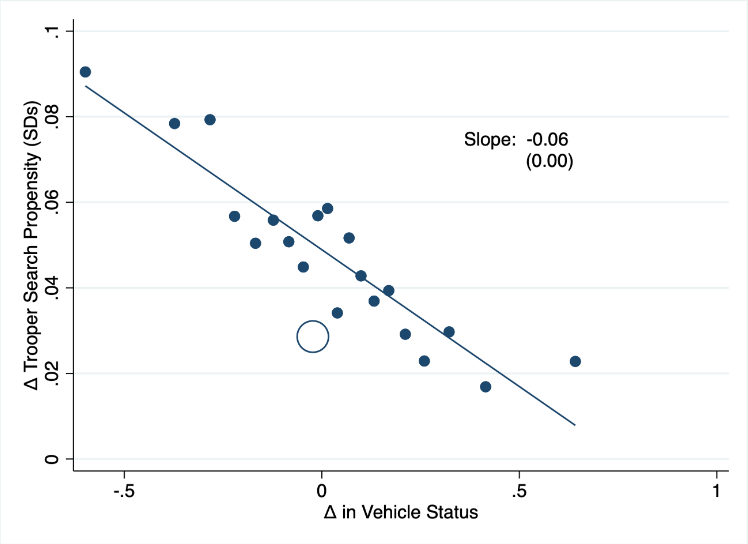

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Figure: Dismissal/Acquittal Rates are Increasing in Motorist Income (DPS Searches)

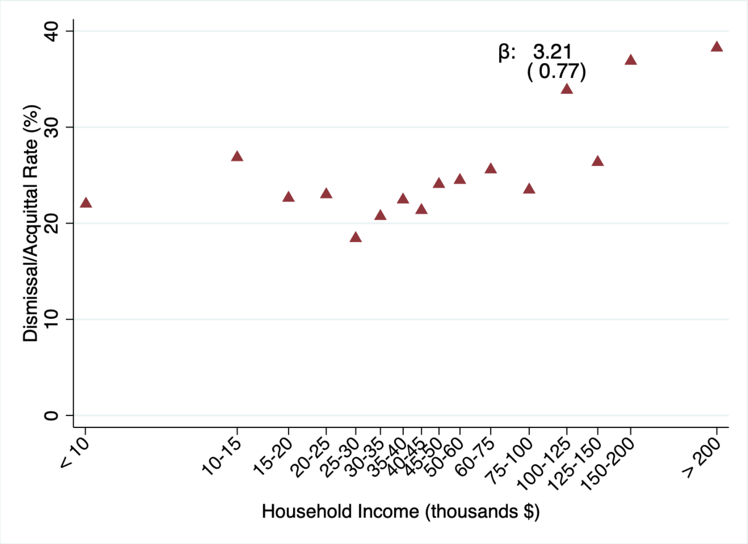

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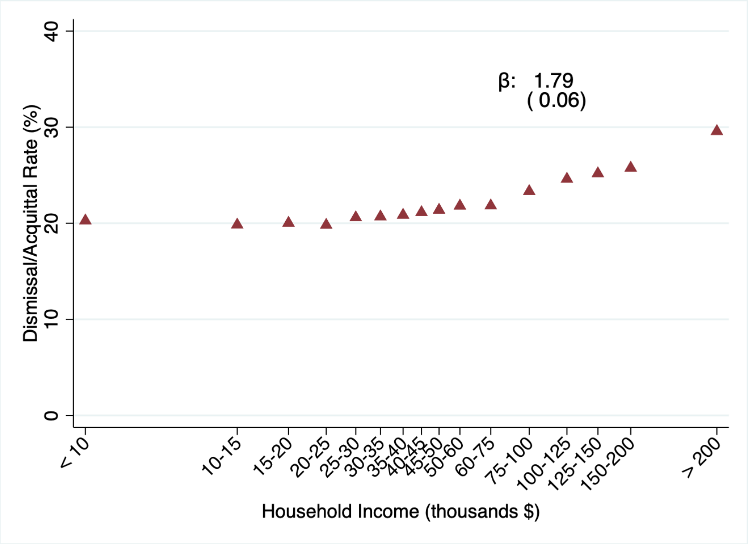
Figure: Dismissal/Acquittal Rates are Increasing in Motorist Income (All Drug Arrests)



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