Police Discretion and Racial Disparity in Organized Retail Theft Arrests: Evidence from Texas

Michael Braun *
Cox School of Business
Southern Methodist University
Dallas, TX 75275
braunm@smu.edu

Jeremy Rosenthal and
Kyle Therrian
Rosenthal and Wadas, PLLC
McKinney, TX 75070
j.rosenthal@rosenthalwadas.com

July 17, 2018

Forthcoming in *Journal of Empirical Legal Studies* 15(4), Dec., 2018

Abstract

When definitions of two distinct criminal offenses overlap, power to decide which definition to apply to an arrest devolves to local law enforcement agencies. This discretion can lead to unequal treatment and denial of due process, especially when disadvantaged populations are arrested for nonviolent property crimes. We present a Bayesian analysis of arrests under a vaguely worded statutory scheme for retail theft in Texas, in which a shoplifter who is guilty of property theft is also guilty of organized retail theft. Using arrest data from the Texas Department of Public Safety, we find wide variation across law enforcement agencies in initial charging categories, with black and Hispanic arrestees being charged for the more serious crime more than white arrestees. The racial discrepancy is greater for agencies serving cities with higher per-capita income. These results highlight consequences of ambiguous provisions of criminal codes, and suggest a method for identifying agencies whose policies may have disparate impact across racial and ethnic groups.

Keywords: Shoplifting, racial profiling, "shopping while black," selective enforcement, police discretion, residual clause, retailing, criminal history, pretrial detention, Bayesian models, hierarchical models, logistic regression, overcharging, plea bargaining,

---

*Michael Braun, Ph.D., is an associate professor in the Cox School of Business at Southern Methodist University. Jeremy Rosenthal, J.D., and Kyle Therrian, J.D., are attorneys with Rosenthal and Wadas, PLLC. Professor Braun gratefully acknowledges financial support from the Charles Koch Foundation Program on Criminal Justice and Policing Reform, research assistance from Asha Durgampudi, and helpful comments and suggestions from Greg Allenby, Blake McShane, Glenn Voss, Jonathan Hersh, Bill Dillon, Fred Feinberg, and anonymous reviewers.

I. Overview

The scholarly literature is voluminous on the associations among race and ethnicity, and outcomes of various stages of the criminal justice process (see Spohn 2015 for a review). This research stream includes studies of apparent disparities in arrest rates across racial and ethnic groups, (Smith et al. 1984; Grogger 1992; Golub et al. 2007; Gelman et al. 2007; Lytle 2014; Dobbie et al. 2017b) but has placed less attention on decisions made by the police in the early stages in a pending criminal arrest. Once an arrest is made, police have an initial obligation to decide exactly which section in a state's criminal code has been violated, and the applicable offense category. Law enforcement agencies exercise a great deal of authority when offenses are written ambiguously, overbroadly, or in a manner which overlaps with conduct prohibited by other statutory provisions (what Robinson and Cahill (2005) call the "degrading" of criminal codes). When the offenses are classified differently in terms of potential penalties, inconsistent or incorrect application of the law can have significant adverse effects on the arrestee in ways the legislature may not have intended (Gerstein and Prescott 2015). Such a phenomenon raises constitutional concerns which the United States Supreme Court has addressed time and again: "Men of common intelligence [must] not be forced to guess at the meaning of the criminal law … Where inherently vague statutory language permits such selective law enforcement, there is a denial of due process" (Smith v. Goguen 1974). This article is concerned with the very first legal assessment by a law enforcement officer in the criminal justice process: "for which of these two similarly defined crimes am I making an arrest?" In particular, we are interested in whether that decision is made consistently across law enforcement agencies, and the extent to which agencies accuse white arrestees of the less serious offense more or less often than arrestees of color.

We study this issue in the context of shoplifting arrests in the State of Texas. Organized retail crime (ORC) is a subcategory of shoplifting involving participation in a managed operation to convert stolen merchandise to cash (Finklea 2012). It is a "professional" activity, distinct from "petty" shoplifting motivated by impulse, thrill-seeking, economic necessity, or mental illness (Krasnovsky and Lane 1998). In a typical ORC operation, a "booster" steals a small amount of retail merchandise, and resells it to an upstream "fence" (someone who traffics in stolen goods). The fence aggregates goods from multiple boosters, repackages the goods, and introduces them back into the supply chain through a black market. Flea markets, internet sales, and unscrupulous wholesalers and retailers comprise the downstream stages of the channel. A 2016 survey by the National Retail Federation identifies clothing, handbags, infant formula, laundry detergent, allergy medicine, diabetic test strips, and razors as items most commonly stolen by ORC boosters (National Retail Federation 2016). Estimates of the total cost to U. S. retailers from ORC vary, but tend to be in the tens of billions of dollars (Finklea 2012).

In practice, petty shoplifting is treated as property theft (PT) under the Texas Penal Code (TPC). In 2007, the Texas Legislature defined a new crime, "organized retail theft" (ORT). In this paper, ORC describes the activity of organized retail crime, while ORT is a specific criminal offense. A problem arises because the statutory definition of ORT is worded so *any* shoplifting could qualify as either ORT or PT. At the time, an ORT arrest was subject to a $1,500 minimum value of stolen merchandise, and the penalties for ORT were the same as for PT, so the ORT statute was not used very much. In 2011, the Legislature increased penalties for ORT, but not PT, and removed the $1,500 minimum, but did not change the definition of ORT. This decision created an inadvertent loophole through which local law enforcement agencies could arrest petty shoplifters for the more serious offense of ORT, even when there is no probable cause to prefer an ORT over PT for the arrest charge. Without further guidance from the statute, an inconsistency arose in how ORT is distinguished from PT from agency to agency, and even from arrest to arrest. To be clear, an ORT arrest for petty shoplifting is *technically* legal, in that it is consistent with the exact wording of the statute. The policy issue is that some agencies are inconsistently applying a "residual clause" in the TPC to situations for which the Legislature explicitly did not intend, when an arrest for another, less serious offense would be sufficient.

This paper reveals how overlapping definitions can lead to inconsistent application of the law, when the Legislature implicitly allows agencies to distinguish between two crimes locally. Specifically, we are interested in how the use of the ORT statute for arrests for petty shoplifting (for merchandise valued between $50 and $1,500) varies across agencies, and how many more ORT arrests we can expect of either black or Hispanic arrestees than of white arrestees, given the same number of PT arrests in each group.[1] We quantify this disparity through estimates of posterior distributions of agency-level odds ratios in a Bayesian hierarchical logistic regression. Under the hierarchical structure of the model, these odds ratios are heterogeneous across agencies. In this paper, we consider only arrests for either PT or ORT for amounts less than $1,500, and exclude arrests for certain "listed" ORC-related activities (see Section II). The unmodified term *odds* refers to the odds an arrest is for ORT instead of a PT, among arrests made for either offense. The black and Hispanic *odds ratios* refer to the ratio of odds between either black or Hispanic arrestees, respectively, and white arrestees. We can interpret an odds ratio as a multiple of ORT arrests of either blacks or Hispanics over ORT arrests of whites, given the same number of PT arrests in each group. An odds ratio of one is a "null" result, indicating no disparity. We also estimate associations between these odds ratios and characteristics of the city the agency serves.

Bayesian data analysis is the appropriate tool to use for this study because of our interest in heterogeneity across agencies' propensities for use of the ORT statute, and the methodological

[1]The restriction to arrests of more than $50 arises because PT arrests for less than that amount are Class C misdemeanors, and are not recorded in the Texas criminal history database.

benefits from partially pooling information across agencies, some of which serve sparsely populated areas. By treating the mixture distribution of odds ratios across agencies as a prior for any single agency, the Bayesian approach lets us estimate posterior distributions of odds ratios in a parsimonious way, even when the number of arrests is small. When the sample size for a single agency is large, the estimate of the odds ratio draws primarily on arrest data for that agency. When the sample size is small, the estimate "shrinks" toward the statewide average, but the posterior interval around that estimate may be quite wide. Consequently, Bayesian estimates tend to be more conservative than their frequentist counterparts that do not pool information across heterogeneous units.

We estimate a typical agency will make about twice as many ORT arrests of blacks than whites, and about 20% more of Hispanics than whites, given the same number of PT arrests of whites and the respective nonwhite group. Among female arrestees, the multiple is about 2.6 for blacks and 1.5 for Hispanics. Agencies' prevalence of ORT arrests, and multiples of black or Hispanic to white ORT arrests, vary greatly in both estimated magnitude and statistical significance. For about 30 agencies, the evidence suggests a significantly high probability of a latent propensity for a racial disparity in ORT arrests, especially with regard to black women. Most of the remaining agencies have posterior mean odds ratios greater than one, but their posterior intervals are too wide for us to draw conclusions with confidence. Also, odds ratios are positively associated with the affluence of the city the agency serves. After controlling for the racial composition of the city, we estimate that a 10% increase in per-capita income is associated with a 7.3% increase in the black odds ratio, and with a 5.9% increase in the Hispanic odds ratio. Altogether, the data show the ORT law was applied inconsistently throughout the state during the study period, both across agencies and across racial groups.

We do not attempt to explain why these statistical patterns exist. The results are consistent with a racial disparity in ORT arrests, but they do not address whether an agency is involved in active discrimination against arrestees of color, or in the mathematical equivalent of giving whites an unfair break. Racial disparity is not the same as racism, and there could still be other unobserved factors that lead to fewer ORT arrests among white arrestees than black or Hispanic arrestees. We do not ascribe any motives as to why a petty shoplifter might be booked for ORT instead of PT, even in light of the overlapping definitions and the legislative record.

How police categorize arrests in the presence of ambiguous or redundant statutes is worthy of study because of the frequency with which arrests for many petty offenses occur, the inherent unfairness of inconsistent application of the law, and the consequences for arrestees whose offenses do not match the definitions of the crimes for which they are accused. Even the appearance of a misdemeanor arrest in criminal background reports can narrow both short- and long-term housing and employment options (Blumstein and Nakamura 2009; Bushway et al. 2011; Uggen and Stewart 2014), especially when lay users of the reports do not know how to interpret distinctions between different categories of offenses (Lageson et al. 2015). The effects of criminal background checks can also differ by race (Pager 2003; Bushway 2004; Funk 2004; Decker et al. 2015). Furthermore, magistrates and prosecutors may rely mostly, or solely, on information in the police report without much review (Phillips and Varano 2008; Holleran et al. 2010; Nelson 2013; Nelson 2014). Thus, the category of the arrest charge can affect decisions on pretrial detention and bail, which can lead to punishment before the decision of guilt or innocence takes place (Wald 1964; Frazier et al. 1980; Spohn 2008), and influence the eventual disposition of the case (Myers 1982; Heaton et al. 2017; Leslie and Pope 2016; Dobbie et al. 2017a; Stevenson 2017). Inflating the arrest charge can give a prosecutor an advantage in plea bargaining, and creates incentives for defendants to plead guilty to offenses they did not commit to avoid the possibility of conviction of a more serious crime at trial (Ross 1978; Stuntz 2004; Caldwell 2011; Bushway and Redlich 2012). For example, when a defendant has already spent time in pretrial detention, there is an incentive to accept a guilty plea in exchange for a sentence of "time served" (Bibas 2004; Gerstein and Prescott 2015; Geller 2016). To the extent that racial and ethnic minorities are arrested for more serious offenses, or are more likely to be held pending trial, they face a "cumulative disadvantage" throughout the judicial process (Kutateladze et al. 2014; Johnson 2015; Wooldredge et al. 2015; Chin 2016).

In Section II, we describe how definitions of PT and ORT overlap, and why we should interpret all ORT arrests in our dataset as "overcharges." Section III contains details of the empirical study, including a summary of the data, the specification of the Bayesian hierarchical model, and presentation of statewide and agency-specific results. In Section IV, we discuss the implications and limitations of the results, and propose some policy recommendations.

II. Retail theft laws in Texas

In Texas, ordinary shoplifting is charged as property theft (PT), under §31.03 of the Texas Penal Code (TPC, Texas 2015b). The category of the offense, as defined by the maximum penalty for a conviction, depends on the value of the stolen property. PT of less than $50 is a Class C misdemeanor, with a maximum fine of $500 and no risk of jail time. PT between $50 and $500 is a Class B misdemeanor (maximum penalty of $2,000 and six months in jail), between $500 and $1,500 is a Class A misdemeanor ($4,000 and one year), and between $1,500 and $10,000 is a state jail felony ($10,000 and two years). [2]

[2] In Texas, categories of offenses are defined by the corresponding maximum penalties. These values, categories, and penalties are those that were in effect during the study period (January, 2012 to August, 2015). Texas H.B. 1396 (2015) raised and equalized the steps in the value ladder for both PT and ORT.

In 2007, the Texas Legislature passed House Bill (H. B.) 3584 (Texas Legis. 2007), which added a new offense, Organized Retail Theft (ORT), to the TPC as §31.16. The appendix contains the text of the bill. We are most interested in Section 1(b) [3], which states that a person commits an ORT offense

> if the person intentionally conducts, promotes, or facilitates an activity in which the person receives, possesses, conceals, stores, barters, sells, or disposes of at total value of not less than $1,500 of: (1) stolen retail merchandise; or (2) merchandise explicitly represented to the person as being stolen retail merchandise. (TPC §31.16(b), 2007)

Because shoplifting necessarily involves possessing or concealing stolen merchandise, a strict reading of the 2007 law allows any retail theft arrest over $1,500, to be charged as either PT or ORT, regardless of the motive or tactics of the shoplifter. At the time, this ambiguity was irrelevant in practice; the penalties for ORT were the same as for PT, so even suspected shoplifters of more than $1,500 were rarely arrested for ORT. For petty shoplifters caught stealing less than $1,500, the ORT law did not apply.

In 2011, the Legislature amended TPC §31.16 in four ways (Texas Legis. 2011, see the appendix for text):

1. Penalties for ORT were increased to one category higher than for PT for merchandise of the same value. ORT became a Class B misdemeanor for goods valued less than $50, a Class A misdemeanor for items valued between $50 and $500, and a state jail felony for items valued between $500 and $1,500.

2. Penalties for specific fencing activities were increased one additional category.

3. Penalties were increased by one category for engaging in specific listed activities thought to be used by ORC boosters to remove large amounts of merchandise from a store: activating an alarm after using a fire exit, attempting to disable a fire alarm or theft detection device; or evading a theft detection device by, for example, using a foil-lined "booster bag" to block electronic sensors.

4. The $1,500 minimum value for an ORT charge was removed.

The definition of ORT in §31.16(b) became a residual clause, and removing the $1,500 minimum opened a path for petty shoplifters with no ORC connection to be arrested for ORT instead of PT. Except for the activities listed in Item 3 above, there is no objective criterion an arresting officer,

[3] Other sections of H. B. 3584 (2007) addressed jurisdictional issues to make it easier to arrest fences, and increased penalties for fencing activities.

responding to a complaint by a retailer, could use to tell the difference between PT and ORT. For example, stealing items commonly associated with ORC does not indicate involvement in ORC. A common characteristic of many items sold through ORC-supplied black markets is that they are necessities of daily living that may not be otherwise affordable to disadvantaged populations (Gustafson 2013). Although a suspected booster might be supplying these goods to an ORC network, he or she might also be stealing those items for personal use. Furthermore, it is highly unlikely that police would target known boosters, but not be able to collect evidence with a total aggregated value of more than $1,500.[4] Working in collaboration with others, intending to resell the goods, or even sparking suspicion of being associated with known ORC fences, is not sufficient probable cause for an ORT arrest. A prosecutor could upgrade a PT arrest to ORT later if additional evidence were to surface, but it is generally not appropriate for an arresting officer to presume the more serious offense in the absence of that evidence.

At the same step in the value ladder, PT and ORT are different categories of crimes, so the overlapping definitions create a situation in which two arrestees, accused of engaging in nearly identical activities, could face different outcomes from the criminal justice process. For example, under §17 of the Texas Code of Criminal Procedure (Texas 2015a, henceforth, TCCP), the amount of bail is set by a magistrate within 48 hours of arrest, and depends on many factors, including the category of the specific offense cited by the arresting officer (TCCP §17.15). If the arrestee cannot provide bail, or a bond through which a third party guarantees the financial commitment of bail terms, he or she may remain in jail until trial. Additionally, Texas limits the amount of time an arrestee can be held before formal charges are filed. When this time expires, he or she must be released on a personal bond that requires no financial commitment. This time limit is 15 days for a Class B misdemeanor, 30 days for a Class A misdemeanor, and 90 days for a felony (TCCP §17.151). Some jurisdictions give discretion to jail staff to release an arrestee for a minor offense on a personal bond. Rules for this kind of pretrial release are set in advance by local judges, and also depend on the category of the arrest charge. Thus, the likelihood and duration of pretrial detention depends in part on the category of the offense at the time of arrest, before the charge is reviewed by a prosecutor or judge.

As a matter of law, the residual clause in the ORT statute is impermissibly vague, in that it fails to provide "fair notice" regarding the penalties for specific activities (Connally v. General Constr. Co. 1926; Johnson v. U.S.. 2015; Sessions v. Dimaya 2018). The U. S. Supreme Court has addressed the "void-for-vagueness" doctrine in terms of a legislature's responsibility for defining the scope of defined offenses, and the necessary limits that responsibility places on law enforcement.

[4] TPC §31.09 states that "[w]hen amounts are obtained in violation of this chapter pursuant to one scheme or continuing course of conduct, whether from the same or several sources, the conduct may be considered as one offense and the amounts aggregated in determining the grade of the offense."

> …the void-for-vagueness doctrine requires that a penal statute define the criminal offense with sufficient definiteness that ordinary people can understand what conduct is prohibited and in a manner that does not encourage arbitrary and discriminatory enforcement. Although the doctrine focuses both on actual notice to citizens and arbitrary enforcement, we have recognized recently that the more important aspect of the vagueness doctrine "is not actual notice, but the other principal element of the doctrine — the requirement that a legislature establish minimal guidelines to govern law enforcement." Where the legislature fails to provide such minimal guidelines, a criminal statute may permit "a standardless sweep [that] allows policemen, prosecutors, and juries to pursue their personal predilections." (Kolender v. Lawson 1983, quoting Smith v. Goguen 1974)

The variation and inconsistency in how a statute is applied is not only a denial of due process, but a violation of separation of powers as well.

> Nor is the worry only that vague laws risk allowing judges to assume legislative power. Vague laws also threaten to transfer legislative power to police and prosecutors, leaving to them the job of shaping a vague statute's contours through their enforcement decisions. (Sessions v. Dimaya 2018, Gorsuch, J., concurring)

In light of the overlap in statutory definitions of PT and ORT, the differential impact of the arrest charge on the arrestee, and the inconsistency in application of the law we describe in Section III, the question arises as to whether any ORT arrest made under §31.16(b) is appropriate, or should be considered an "overcharge." Considering ORT arrests as violations of equal protection and due process might lead us to that conclusion. We can also rely on the intent of the Legislature. "Legislative intent" is the appropriate legal standard for resolving disputes involving ambiguous statutes (Radin 1930; Breyer 1991; Nourse 2014). How offenses are defined and categorized is inherently a legislative role, because delegation of that responsibility to local officials detracts from uniform application of the law (Robinson et al. 2010). Legislative intent does not typically guide the day-to-day decisions of police, but it does act as a "tie breaker" when determining which section of a statute should be used in particular circumstances.

This intent is revealed through documentation of the legislative history, such as committee reports, public testimony, and statements by key legislators (Davis 2007, as cited in Graham 2014, note 22). The appendix contains information about the legislative history of both the 2007 and 2011 bills. An analysis report on the 2007 bill for the Texas House of Representatives Committee on Criminal Jurisprudence describes the purpose of the bill as a tool to target fences, not petty shoplifters (Texas House bill analysis 2007). This justification of the bill was confirmed in public hearings by the committee chairman and sponsor of the bill, as well as representatives of two retailers (Texas comm. testimony 2007). In a report on the 2011 bill, the committee writes that the bill's purpose is to increase penalties for the specific, listed activities as a tool to prosecute gangs and terrorist groups that use ORC activity as a source of funds (Texas House bill analysis 2011). There is no mention of otherwise expanding the scope of ORT to include petty shoplifters. In fact, the committee considered, and ultimately rejected doing just that. The "first reading" of the bill (the version of the bill that was initially submitted to the House, and referred to committee) contains a definition of "boost" that includes all retail theft, but sets boundaries around ORT to limit its application (Texas Legis. 2011, as introduced). This language was removed in committee, signaling the intent for the ORT statute to be used only against fences, and boosters engaging in the listed activities. Retailers' testimony during public committee hearings focused on how the listed activities are believed to be consistent with ORC, and the need for greater deterrence for *high-value* boosters (Texas comm. testimony 2011).

Therefore, it is reasonable to interpret ORT arrests for petty shoplifting of less than $1,500, and made under the residual clause in §31.16 (i.e., not one of the ORC-related activities considered by the Legislature), to be overcharges — arrests for an offense that is inconsistent with, and more serious than, the activity that led to the arrest (Alschuler 1968; Graham 2014). The question of whether the ORT arrests we consider in our empirical analysis should be treated as overcharges is relevant only for deciding how strong the causal interpretation of the odds ratio should be. Without any additional assumptions regarding the appropriateness of ORT arrests, an odds ratio different from one still indicates a disparity in ORT arrests across agencies and racial groups. However, the proportion of ORT arrests that were preceded by true ORC activity could be a confounding variable. To assign a causal interpretation to the odds ratio, that proportion should be the same between black or Hispanic and white arrestees. Although we cannot directly observe the activities that led to an arrest, the legislative record and case law allow us to claim no ORT arrests for less than $1,500 can reasonably considered to be consistent with the intent of the Legislature. If we accept this identifying assumption, the rates of ORC activity in the scope of our empirical study are zero for all groups, and we can interpret an odds ratio as an indicator of a causal effect of race on an agency's propensity to arrest for ORT instead of PT.

III. Empirical study

Our primary data source is the Computerized Criminal History (CCH) system managed by the Texas Department of Public Safety (DPS) Criminal Records Service (CRS) to track criminal arrests, charges and case outcomes in the state. We requested the data under §411.083(a)(4)(B) of the Texas Government Code, which allows for "dissemination of criminal history record information" to "a person working on a research or statistical project" that meets certain Federal requirements on protection of personally identifiable information.

The request was for data on all arrests made under TPC sections §31.03(e)(2)(Ai), §31.03(e)(3), §31.16(c)(2), and §31.16(c)(3), between January 1, 2012 and August 31, 2015. The first two sections categorize PT for items valued from \$50 to \$500, and \$500 to \$1,500, respectively. The second two sections do the same for ORT. After extensive data clean-up (e.g., standardizing characters, stripping white space, joining tables), we removed all arrests involving juveniles; arrests coexisting with other offenses that would either indicate the incident was not related to retail theft, or would otherwise make the case "complicated" (e.g., drug possession, burglary, robbery, assault, fraud, or prostitution); and arrests made by agencies other than municipal police departments (e.g., sheriff's offices, corrections and probation officers, and agencies serving special jurisdictions like universities and airports). Arrests for the listed ORC activities described in Section II are made under their own sections of the TPC, so they are not included in the dataset. The offense is determined at the time of the initial processing of the arrestee, and may be different from charges later filed by a prosecutor.

The CCH database contains fields for the race and ethnicity of the arrestee, which we use to classify arrestees as either black, Hispanic, or white. The U.S. Census Bureau defines "white" and "black" as races, and "Hispanic" and "non-Hispanic" as ethnicities. We collapse the race and ethnicity dimensions into a single race factor, in which "white" refers to non-Hispanic white arrestees. Where possible, we inferred missing ethnicities from arrestees' countries of residence and birth. A small number of arrests (1,036) were dropped from the analysis because the arrestees could not be categorized as one of those three groups, either because the arrestee was of a different race (e.g., Asian or native American), or we could not reliably infer race from the available data.

We also collected demographic information on the cities served by each arresting agency. Specifically, these data come from the 2014 U.S. Census Bureau American Community Survey five-year span: Table B19301 for per-capita income, and Table B03002 for the percent of the local population that is either white, Hispanic, or black (Glenn 2016; United States Census Bureau 2014a; United States Census Bureau 2014b). We will use these data to estimate the marginal effects of local affluence and racial composition on the odds ratio.

A. Data summary and model-free estimates

The dataset contains records for 110,084 arrests, of 97,740 distinct individuals, made by the 669 agencies that made at least one qualifying PT or ORT arrest in the \$50 to \$1,500 range during the study period. Table 1 summarizes arrest counts by race and sex of the arrestee, and the step of the value ladder for the allegedly stolen items (\$50 to \$500, or \$500 to \$1,500).

In Table 2, we display "model-free" estimates for a common odds ratio across agencies, computed directly from the observed data using two methods. The "aggregate" estimates are computed using the arrest counts from Table 1, combining arrests from all agencies into a single pool. For black, female arrestees in the \$500-\$1,500 step of the value ladder, this estimate is significantly greater than

Table 1: Classification of all 110,084 PT and ORT arrests under consideration.

		Black			Hispanic			White			
Value	ORT	Female	Male	**Total**	Female	Male	**Total**	Female	Male	**Total**	**Total**
$50-$500	No	11,978	12,244	**24,222**	16,174	17,558	**33,732**	19,515	16,598	**36,113**	**94,067**
$500-$1,500	No	1,477	2,343	**3,820**	1,860	3,148	**5,008**	2,202	2,884	**5,086**	**13,914**
Total	No	13,455	14,587	**28,042**	18,034	20,706	**38,740**	21,717	19,482	**41,199**	**107,981**
$50-$500	Yes	217	164	**381**	167	137	**304**	535	404	**939**	**1,624**
$500-$1,500	Yes	106	70	**176**	54	54	**108**	82	113	**195**	**479**
Total	Yes	323	234	**557**	221	191	**412**	617	517	**1,134**	**2,103**
Total	Total	13,778	14,821	**28,599**	18,255	20,897	**39,152**	22,334	19,999	**42,333**	**110,084**

Table 2: Model-free Odds Ratio Estimates.

			Aggregate			Mantel-Haenszel				
Value	Sex	Race	OR	X_1^2	*p*-value	OR	X_1^2	*p*-value	95% CI	
\$50-\$500	Female	Black	0.661	25.9	$< 10^{-4}$	1.73	23.7	$< 10^{-4}$	1.39	2.15
		Hisp	0.377	128.1	$< 10^{-4}$	1.40	6.7	0.0095	1.09	1.79
	Male	Black	0.550	41.6	$< 10^{-4}$	1.24	2.9	0.0864	0.98	1.57
		Hisp	0.321	143.9	$< 10^{-4}$	1.13	0.7	0.4127	0.86	1.48
\$500-\$1,500	Female	Black	1.927	18.8	$< 10^{-4}$	3.43	33.6	$< 10^{-4}$	2.22	5.30
		Hisp	0.780	1.7	0.1889	2.12	6.4	0.0112	1.24	3.63
	Male	Black	0.763	2.8	0.0924	1.30	1.6	0.2128	0.88	1.93
		Hisp	0.438	24.9	$< 10^{-4}$	1.06	0.0	0.8423	0.71	1.60
(all)	Female	Black	0.845	5.7	0.0168	2.14	62.2	$< 10^{-4}$	1.77	2.59
		Hisp	0.431	118.9	$< 10^{-4}$	1.51	12.7	0.0004	1.21	1.88
	Male	Black	0.604	40.4	$< 10^{-4}$	1.27	5.5	0.0191	1.04	1.56
		Hisp	0.348	166.8	$< 10^{-4}$	1.12	0.9	0.3301	0.90	1.40
	(all)	Black	0.722	39.2	$< 10^{-4}$	1.68	55.9	$< 10^{-4}$	1.46	1.93
		Hisp	0.386	289.1	$< 10^{-4}$	1.30	10.5	0.0012	1.11	1.52

Note: Hypothesis tests are $H_0 : OR = 1$ against $H_A : OR \neq 1$. The aggregate estimate uses the total arrest counts from Table 1.

one. In the remaining groups, the estimates are less than one, and mostly significantly so, implying possible preferential treatment for non-white arrestees over whites.

However, the aggregate odds ratio is not the correct estimate to use in our case of sparse, unbalanced data across agencies. Agencies vary in the number of arrests made, and in how the arrests break down by race and offense. If a large city has a high proportion of nonwhites, but the police in that city do not make any ORT arrests, aggregated statewide statistics would hide indications that nonwhites are disproportionally arrested for ORT. Therefore, in Table 2 we also report the Mantel-Haenszel estimate of the common odds ratio across agencies, which effectively groups arrests by the agency that makes them (see Agresti 2013, Section 6.4). Unlike the aggregate odds ratio estimate, the Mantel-Haenszel estimates are all greater than one, with estimates for female arrestees and black arrestees being the most significant. This result is consistent with a story of "within agency" racial disparity in ORT arrests in favor of whites, relative to female and black arrestees.

The extent to which the ORT statute is used at all varies substantially across agencies. Table 3 summarizes the distribution of arrests across agencies by characteristics of the arrest and arrestee. Most of the arrests are concentrated in a small number of agencies, and 80% of agencies did not make any ORT arrests at all. Table 4 presents the number of PT and ORT arrests for the 15 agencies with the highest numbers of arrests, and percentages of ORT arrests, as well as the racial composition (percent of population identified as black or Hispanic), and per-capita income for the city the agency serves. The largest cities in Texas (e.g., Houston, San Antonio, Dallas and Austin) make the largest number of total arrests, but not the most ORT arrests. Agencies in several smaller communities, like Gainesville, Marble Falls, and Liberty, appear to charge for ORT for a majority of

Table 3: Distribution of Number of Arrests by Agency

			Quantiles							
Arrest Type	Mean	SD	Min	10%	25%	50%	75%	90%	Max	Prop =0
ORT	3.1	17.6	0	0	0	0	0	3	249	0.800
PT	161.4	737.5	0	2	3	11	66	254	11,351	0.004
Black	42.7	274.1	0	0	0	1	11	58	5,461	0.371
Hisp	58.5	324.3	0	0	0	2	15	70	4,658	0.306
White	63.3	268.5	0	1	1	5	34	140	5,428	0.100
Total	164.6	740.2	1	2	3	11	70	261	11,361	0.000

Note: Prop =0 refers to the proportion of agencies with no arrests of the type for that row.

Table 4: ORT and PT Arrests for Top 15 Agencies, by Total Arrests and Percentage of ORT Arrests.

(a) Top 15 Agencies by Total Arrests

	Arrest count			Arrest %			Population			Income
Agency	ORT	PT	Total	ORT	Black	Hisp	Total	% Black	% Hisp	($)
San Antonio	10	11,351	11,361	0.09	11.2	41.0	1,385,438	6.8	63.0	22,784
Houston	21	9,186	9,207	0.23	59.3	24.0	2,167,988	23.3	43.4	27,938
Dallas	28	7,129	7,157	0.39	47.6	24.5	1,240,985	24.6	41.5	27,917
Austin	19	4,751	4,770	0.40	26.1	34.0	864,218	7.8	34.5	32,672
El Paso	0	4,321	4,321	0.00	5.3	81.7	669,771	3.6	79.3	20,050
Laredo	5	4,089	4,094	0.12	0.6	97.0	245,048	0.4	95.2	15,127
Fort Worth	94	3,821	3,915	2.40	42.8	18.1	778,573	18.9	34.0	24,726
McAllen	0	2,363	2,363	0.00	0.4	95.7	135,048	0.8	84.6	21,410
Tyler	1	1,472	1,473	0.07	35.5	11.2	99,344	24.1	22.4	26,132
Beaumont	6	1,412	1,418	0.42	58.1	4.5	117,543	48.0	13.6	23,925
Garland	1	1,397	1,398	0.07	36.3	24.8	232,305	13.1	39.8	21,661
Plano	43	1,350	1,393	3.09	24.3	19.9	271,166	7.5	14.5	41,902
Waco	0	1,358	1,358	0.00	35.2	20.8	127,796	20.9	31.4	18,623
Brownsville	13	1,318	1,331	0.98	0.5	94.9	179,834	0.3	93.5	14,124
Arlington	8	1,283	1,291	0.62	38.3	18.5	375,305	19.8	28.2	25,236

(b) Top 15 Agencies by Percentage of ORT Arrests (total arrests ≥ 50)

	Arrest count			Arrest %			Population			Income
Agency	ORT	PT	Total	ORT	Black	Hisp	Total	% Black	% Hisp	($)
Gainesville	249	12	261	95.4	12.3	14.2	16,040	5.3	29.2	20,623
Marble Falls	195	23	218	89.4	6.4	19.3	6,137	5.5	32.9	22,975
Liberty	69	20	89	77.5	20.2	7.9	8,696	17.5	21.1	20,607
Schertz	86	58	144	59.7	6.2	38.9	35,093	9.5	25.9	30,578
Marshall	73	64	137	53.3	48.2	5.8	24,424	40.1	18.6	20,025
Jacksonville	91	105	196	46.4	26.5	8.7	14,654	22.2	36.6	16,732
Mineola	19	35	54	35.2	7.4	3.7	4,514	16.5	14.2	17,365
Allen	78	149	227	34.4	34.8	18.9	89,845	8.0	10.6	40,741
Weatherford	56	190	246	22.8	5.7	12.2	26,490	3.3	16.8	25,637
Kaufman	11	39	50	22.0	16.0	4.0	6,837	10.1	27.9	17,993
Terrell	36	131	167	21.6	31.7	6.6	16,146	24.0	28.2	21,124
Lewisville	175	704	879	19.9	23.8	20.6	99,039	9.0	29.8	28,630
Alvin	26	123	149	17.4	11.4	26.2	24,938	4.4	34.5	20,855
Conroe	167	845	1,012	16.5	20.3	14.9	61,268	10.2	37.4	23,362
Commerce	14	76	90	15.6	41.1	6.7	8,348	22.5	14.1	12,981

Note: Income is the mean per-capita income of the city.

arrests, while those in population centers like El Paso, McAllen, and Waco made no ORT arrests at all.

B. Model specification

We propose a model-based approach for inferring odds ratios for each agency, and the distribution of these odds ratios across agencies. The model is a Bayesian hierarchical logistic regression, in which the log odds of an ORT arrest is a linear function of covariates, and the coefficients are heterogeneous across agencies.[5]. The Bayesian paradigm offers important benefits. Arrest decisions made by the same agency are likely subject to similar policies, tendencies and external contexts. Thus, we cannot treat arrests as independent outcomes. A hierarchical model is a parsimonious and intuitive way to induce dependence across arrests made by the same agency. Bayesian inference partially pools information across agencies, so we can compute consistent estimates of posterior moments and quantiles of agency-level parameters, and functions of those parameters, even for agencies with few observed arrests. The posterior means for agencies with few arrests are substantially "shrunk" toward the statewide mean, but have diffuse posterior distributions over their odds ratios. The posterior distributions for agencies making many arrests will be narrower, with less influence from other agencies (i.e., those estimated posterior means will shrunk less toward the statewide mean than those for agencies with few arrests). Even for agencies with small samples, the agency-level posterior moments and quantiles are exact (up to Monte Carlo error), rather than asymptotic, and are directly interpretable as probability distributions over unobserved parameters.

1. Arrest-level models

Let p_i be the probability that an arrest is for ORT (rather than PT), let i index arrests, and let j index agencies. Define dummy variables b_i and h_i as indicators for whether an arrestee is black or Hispanic, respectively. Under this model, the log odds of an ORT arrest is

$$\text{logit}\left(p_i\right) = \beta_{0j} + \beta_{1j} b_i + \beta_{2j} h_i \tag{1}$$

The coefficients β_{1j} and β_{2j} are the log odds ratios. That is, $\exp(\beta_{1j})$ and $\exp(\beta_{2j})$ are the multiples of ORT arrests for black and Hispanic arrestees, respectively, relative to white arrestees, given the same number of PT arrests for whites and for the corresponding other group. By including an additional dummy variable for the sex of the arrestee, and interactions with the dummy variables for race, we can estimate odds ratios separately for female and male arrestees. Similarly, we can include dummy variables and interactions for whether the value of stolen merchandise is between \$50 and \$500, or between \$500 and \$1,500. Thus, we consider four different arrest-level models, in which arrests

[5] For a reference on Bayesian approaches to hierarchical modeling, see Gelman and Hill (2006)

are either pooled, or separated by sex, value, or both. In the interest of brevity we do not explicitly specify the interaction models here. We define β_j as the agency-specific vector of coefficients on the race, sex and value dummies, and the corresponding interaction terms.

2. Agency-level models

To capture heterogeneity in the odds and odds ratios across agencies, we specify a multivariate normal mixing distribution across β_j, with mean $\mathrm{E}\left(\beta_j\right) = \Delta z_j$ and covariance Σ. The covariate vector z_j describes characteristics of agency j, and Δ is a matrix of coefficients. We consider four different agency-level models, which differ in which covariates are included in z_j. All models include a constant term for an intercept. The Constant model includes no other covariates, so the β_j have a common prior mean. For the Income model, z_j includes log per-capita income (standardized with the center at the mean income across agencies). The Race model includes two covariates: the proportions of the population in the agency's city that are black and Hispanic, centered at their statewide proportions. The Race+Income model includes both race and income covariates.

We can infer from Δ the income elasticities of the odds ratio. For example, let's consider the pooled arrest-level model from Equation 1, and define $\beta_{1\bullet}$ as the vector of log odds ratios for blacks, relative to whites, for all agencies. Under the Income agency-level model, $z_{\bullet 1}$ is the vector of standardized log per-capita incomes for all agencies, Δ_{10} is an intercept, and Δ_{11} is the corresponding coefficient on $z_{\bullet 1}$, so

$$\mathrm{E}\left(\beta_{1\bullet}\right) = \Delta_{10} + \Delta_{11} z_{\bullet 1}, \quad \text{where } z_j = \frac{\log(\text{income}) - \mu}{\omega} \tag{2}$$

In Equation 2, μ and ω are centering and scaling parameters. For our dataset, we chose $\mu = 10.066$ (the log of the arithmetic mean income of \$23,533), and $\omega = 0.369$ (the standard deviation of log income).

Taking differentials of both sides of Equation 2,

$$\frac{\mathbf{d}\,\mathrm{E}\left(\beta_{1\bullet}\right)}{\beta_{1\bullet}} = \left(\frac{\Delta_{11}}{\omega}\right) \frac{\mathbf{d}\,\text{income}}{\text{income}}. \tag{3}$$

Thus, Δ_{11}/ω is the percent change in the expected odds ratio for blacks that is associated with a 1% increase in per-capita income.

Likewise, we can estimate the marginal effect of the racial composition of the jurisdiction on the odds ratio. The approach is similar, except that the proportions are not on a logarithmic scale, and we do not need to scale them. We do center them at the Texas statewide proportions of 0.099 for blacks and 0.328 for Hispanics. The corresponding coefficients in the Δ matrix are interpreted as the percent change in the expected odds ratio that is associated with a one percentage *point* increase in the black or Hispanic population.

3. Estimation

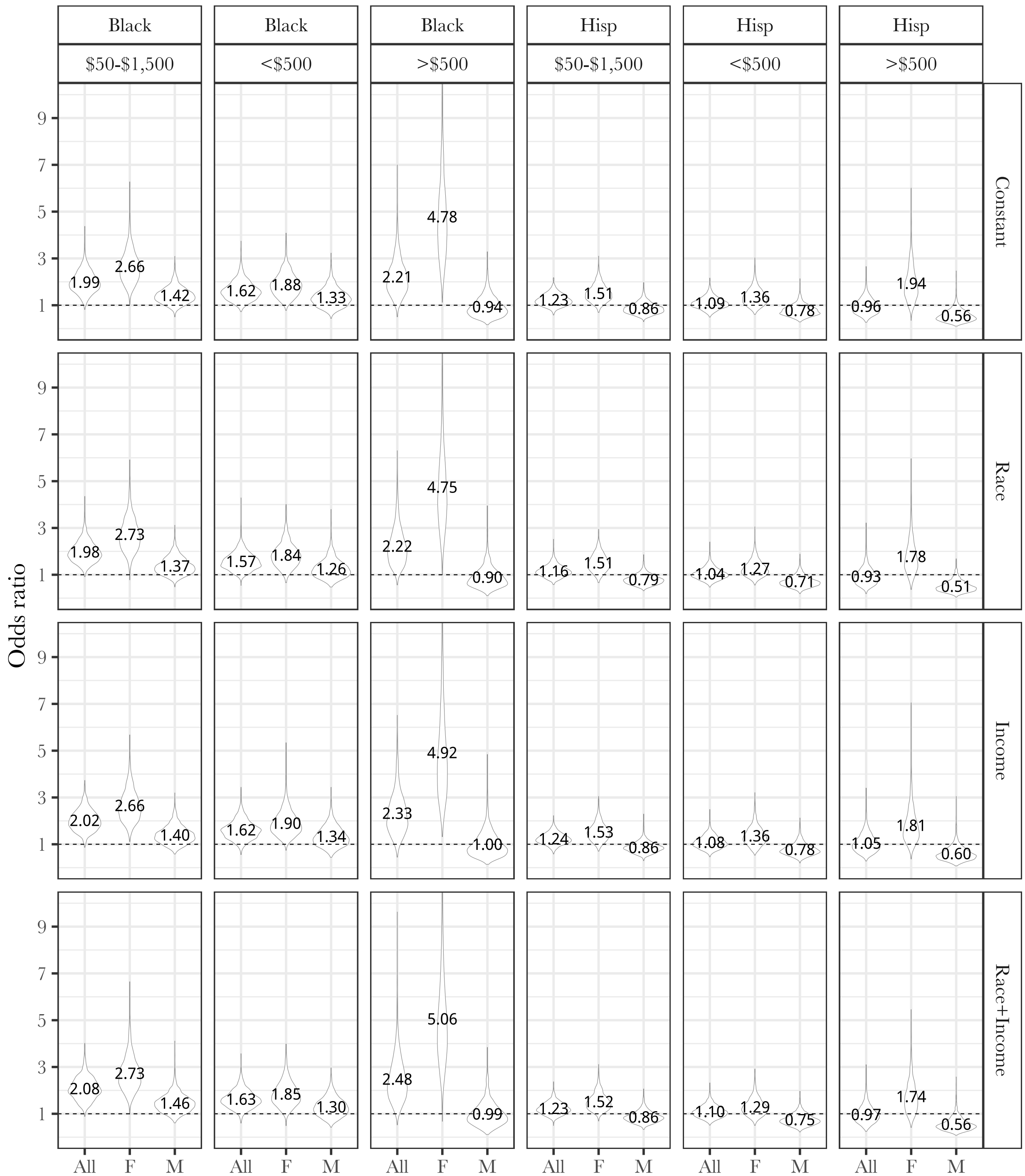
The hyperprior on each element of Δ is a t-distribution with 7 degrees of freedom. The 95% interval of a t_7 distribution is ± 2.36, implying a 0.95 prior belief the baseline (white, female, \$50-\$500) ORT arrest probability is between 0.086 and 0.914, and either odds ratio is between 0.094 and 10.64. This weakly informative prior is conservative in that it induces slight shrinkage of parameter estimates toward the null values (an ORT arrest probability of 0.5 and an odds ratio of 1), but is otherwise overwhelmed by the large dataset. The hyperprior on Σ is an inverse Wishart distribution with an identity scale matrix, and degrees of freedom of four more than the number of elements in β_j. These hyperparameters represent prior independence of β_j across agencies, and allow for weak shrinkage of agency-level β_j toward statewide means.

To estimate posterior distributions of the parameters of interest, we generate random samples using the "No U-Turn" (NUTS) Monte Carlo method in the Stan sampling engine (Hoffman and Gelman 2014). The details of this sampler and the specific implementation are beyond the scope of this paper; the interested reader can find them at Carpenter et al. (2017) and Stan Development Team (2016). For each model variation, we initialized 18 independent chains at random starting values, ran the algorithm for 3,000 iterations, and retained every 10th observation after the first 2,000, leaving 1,800 total samples for inference. Posterior means and quantiles for each quantity of interest are computed from the empirical distributions of the samples.

C. Statewide averages and marginal effects

We first consider the posterior distribution of odds ratios across agencies or, equivalently, the prior distribution for a randomly selected agency for which we have no agency-specific data. Figure 1 presents the estimated posterior distributions over the statewide mean black and Hispanic odds ratios, considering male and female arrestees both separately and together, and value ranges above and below \$500 separately and together, under the four agency-level models. These distributions are qualitatively consistent across agency-level specifications, so we will discuss results for only the Constant model (first row of panels) here. For black arrestees, and especially black female arrestees, nearly all of the posterior probability mass is greater than one, for all three value ranges. Using the posterior mean as a point estimate for the odds ratio, for the full \$50-\$1,500 value range we expect 1.99 times as many ORT arrests of blacks than whites, given the same number of PT arrests among arrestees in each group. We expect that multiple for female arrestees to be 2.66. The estimates are quite a bit higher for values above \$500 than below, but the \$50-\$500 estimates are significant nonetheless. A possible explanation for the difference between value ranges is that police might be

Figure 1: Estimated posterior densities over average odds ratios across agencies, by sex of arrestee and value of merchandise, annotated with posterior means



Note: Panel columns indicate whether the odds ratio is for black or Hispanic arrestees (relative to white arrestees), and the value of ranges of merchandise. Panel rows correspond to variables in the agency-level model. The x-axis indicates whether the estimate is for all arrestees, or only female or male arrestees.

more likely to overcharge blacks, relative to whites, when value of goods is high. However, this does not mean the activities leading to the higher-value arrests are more likely to be related to ORC. The posterior distributions of odds ratios for black males, and for Hispanic males and females, place too much probability on either side of one for us to make strong statements about whether there is truly a racial disparity either in favor of, or against, whites.

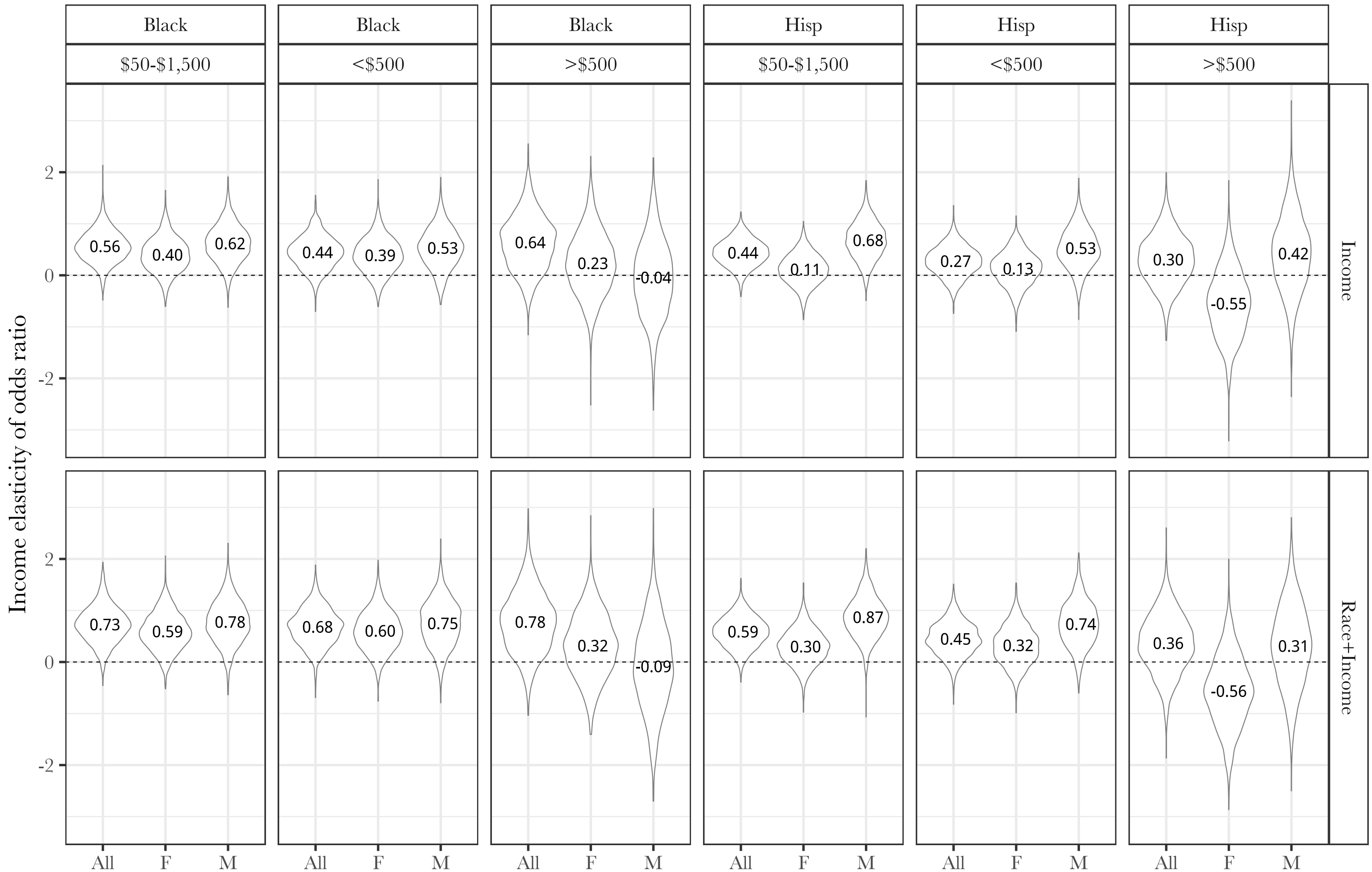
Figure 2 displays posterior distributions over the income elasticities of the odds ratios. This elasticity is the percent change in the multiple of black or Hispanic ORT arrests over white ORT arrests, given the same number of PT arrests, associated with a one percent increase in the per-capita income in the city served by the arresting agency. The Race+Income model controls for the local racial composition, using both the proportion of blacks, and of Hispanics, in the local population. In most cases, the estimates from the Race+Income model are higher and more significant than the estimates from the Income model. Under that model, we estimate a 7.3% increase in the odds ratio for black arrestees, and a 5.9% increase for Hispanic arrestees, per 10% increase in per-capita income. Thus, we infer that agencies serving wealthier communities exhibit more disparity in ORT arrests. This sensitivity of the odds ratio to community affluence is more likely to be positive when the arrest is for less than \$500. That is, agencies in wealthier areas appear more likely to charge black or Hispanic arrestees for ORT, given the same number of PT charges for white arrestees, when the merchandise value is low.

We also estimate the marginal effects of race on odds ratios, with and without controls for income. The posterior distributions in Figure 3 are over the percentage change in the odds ratios associated with a one percentage point increase in the proportion of blacks or Hispanics in the local population. Nearly all of these distributions straddle zero, so we cannot infer an effect of racial demographics on the ORT odds ratios. Altogether, it appears that affluence of the local community, rather than racial composition, is associated with variation in odds ratios across agencies.

D. Agency-level estimates

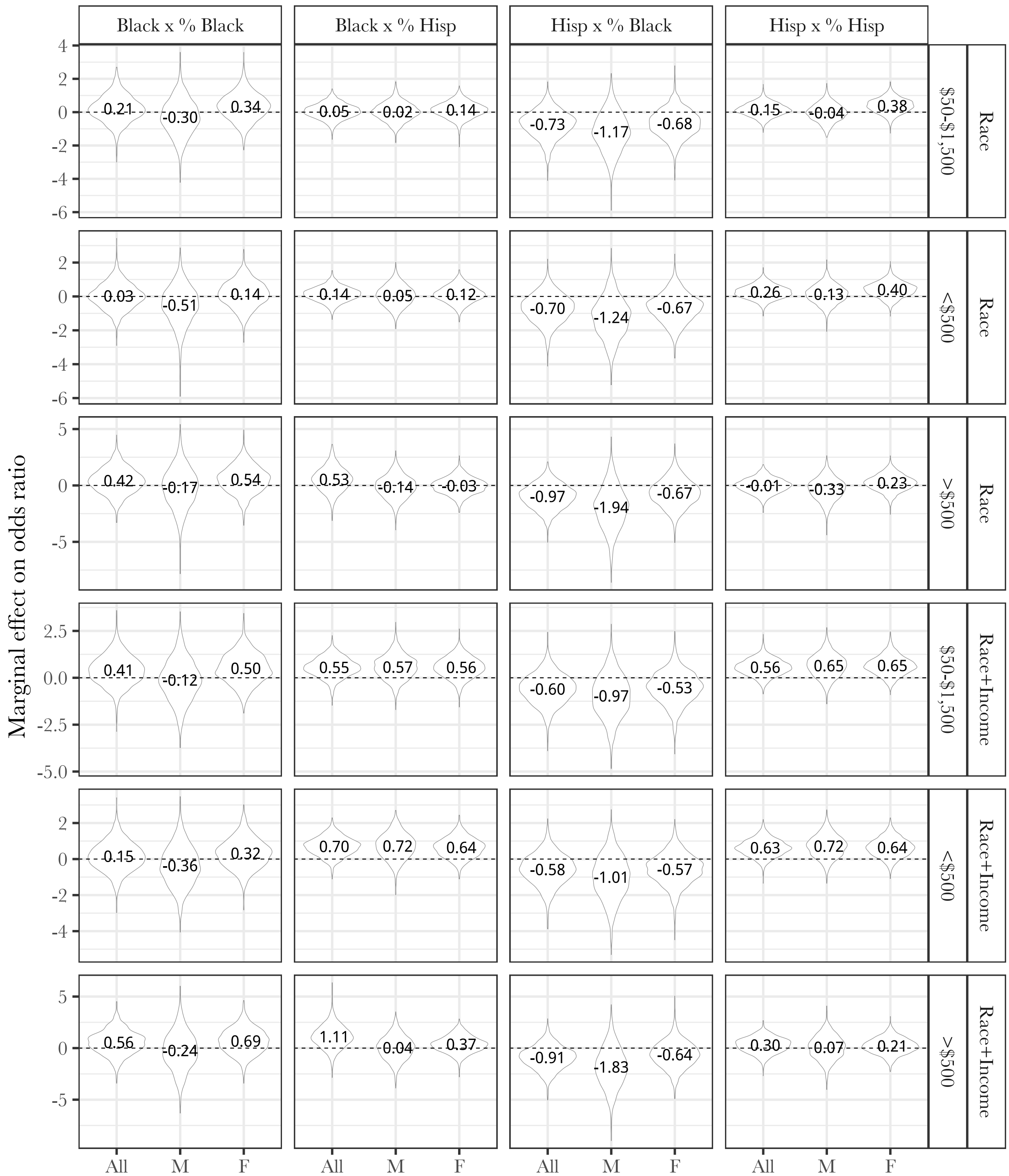
Figure 4 summarizes posterior distributions over odds ratios for individual agencies for black, female arrestees (no agencies have odds ratios significantly different from one for other groups of arrestees). Each panel corresponds to a range of values of the stolen merchandise. The agencies in Figure 4 are those on which we place a high posterior probability the odds ratio is different from one. An agency is included in a panel if it made more than 10 ORT arrests in that value range, or if the posterior probability the odds ratio is greater than one ($P > 1$) is either more than .975 or less than .025. The $P > 1$ probability quantifies significance in a Bayesian sense, analogous to the probability of not erroneously inferring the incorrect sign of a parameter (Gelman and Tuerlinckx 2000; Gelman and Carlin 2014). This criterion excludes agencies whose ORT arrest counts are too low for the Bayesian

Figure 2: Estimated posterior distributions over income elasticities of odds ratios, annotated with posterior means



Note: Panel columns indicate whether the odds ratio is for black or Hispanic arrestees (with respect to white arrestees), and the value ranges of merchandise. Panel rows correspond to whether the agency-level model controls for racial composition (Race+Income), or not (Income). The x-axis indicates whether the elasticity estimate is for all arrestees, or only female or male arrestees.

Figure 3: Estimated posterior distributions over marginal effects of local racial composition on odds ratios, annotated with posterior means



Note: Panels columns indicate the odds ratio and the racial composition of the agency. For example, the Black x % Hisp panels refer to the effect of a one percentage point increase in the proportion in the Hispanic population on the black odds ratio. Panel rows correspond to value ranges of merchandise, and whether local per-capital income is included in the agency-level model.

estimate to be informative (i.e., the posterior distributions are too diffuse), but allows for including other agencies whose odds ratios could be close to, or even below one. The vertical line in each plot (other than vertical axis at one) is the posterior estimate of the statewide odds ratio (i.e., the posterior mean for the Constant model in Figure 1). The box plots depict quantiles of the Bayesian posterior distribution over the odds ratio, and indicate ranges of odds ratios that are most likely for each agency. Agencies are sorted in descending order by $P > 1$. There are no agencies for which $P > 1$ is less than 0.025 (the lowest is 0.173 for any sex-race-value group), so we do not infer from the data that any agency has a propensity to treat either blacks or Hispanics more favorably than whites.

An attractive feature of Bayesian agency-level estimates is that they are "conservative", in that they are shrunk toward the statewide mean. Our interest is less on precisely estimating the odds ratio of any single agency, and more on identifying those agencies for whom there is high probability of an odds ratio being greater than one. By using the statewide distribution as a prior for each individual agency, we reduce the chance of incorrectly flagging some agencies for tendencies of racial disparity in ORT arrests. The Bayesian approach tempers estimates that would otherwise be computed from finite samples during a limited observation period, and might otherwise appear to be unreasonably extreme.

Agencies with high odds ratios are not necessary those that make a high proportion of ORT arrests. Comparing data in Table 4 with estimates in Figure 4, some agencies like Marble Falls and Gainesville have high ORT arrest rates and low estimated odds ratios. These agencies might be overcharging ORT for everyone, regardless of race. Conversely, cities like Conroe make a fewer proportion of ORT arrests overall, but exhibit significant disparity in the arrest charges for black female arrestees.

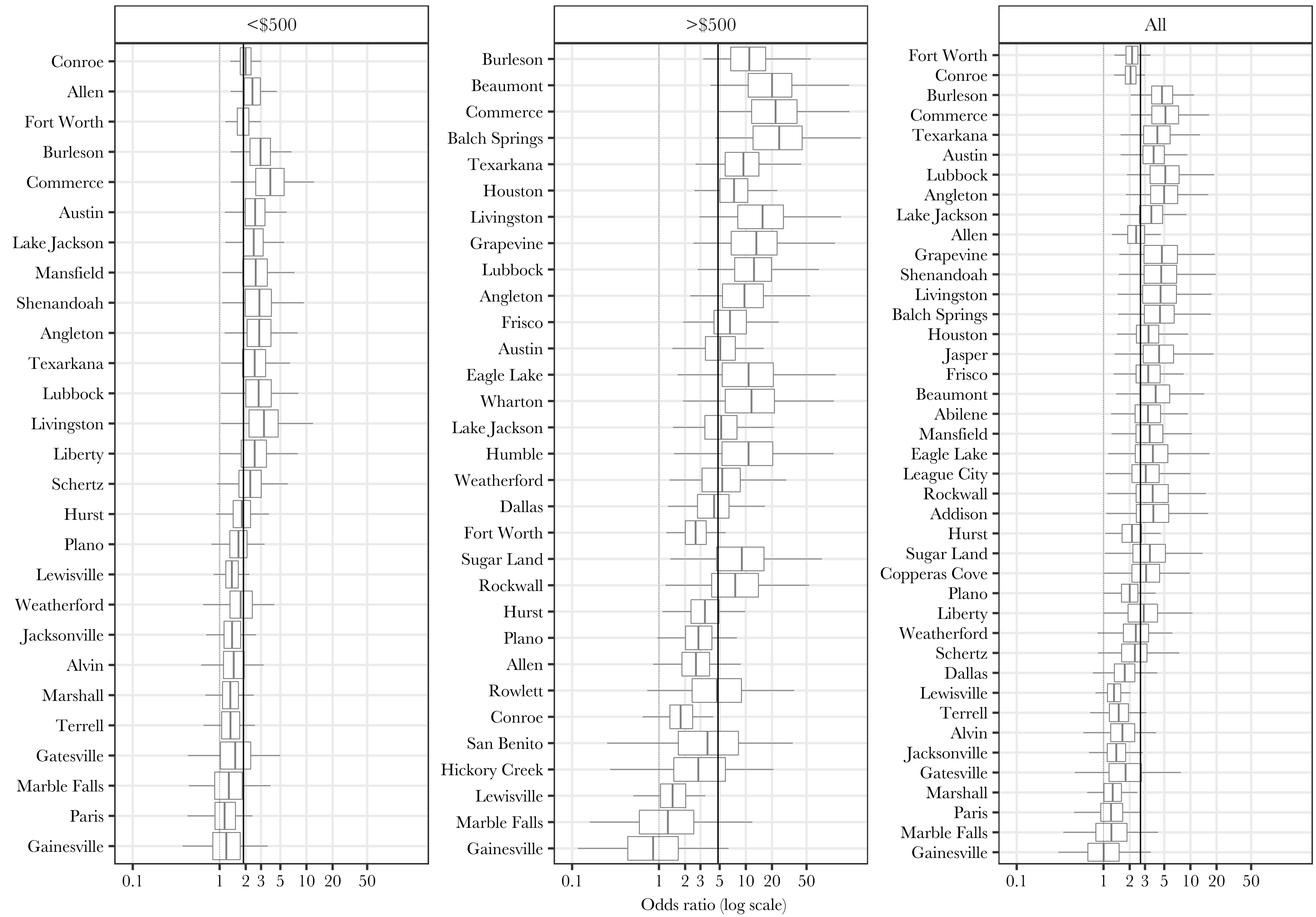
In summary, the results of the statistical analysis indicate that on average, agencies arrest blacks more often than whites for ORT, given the same number of PT arrests in each group. The effect is greatest for black women. However, this odds ratio varies across agencies, with some of that heterogeneity being explained by variation in the affluence of agencies' cities.

E. Reviewing arrest charges

The odds ratio does not directly reveal whether the ORT arrests made under the residual clause of the statute are somehow incorrect or inappropriate. However, if the proportions of arrestees under the residual clause in the TPC who are engaged in ORC activities *according to criteria revealed during the legislative process* are the same across groups, the odds ratio reflects a difference in overcharge rates.[6] This condition holds in our study because arrests for the ORC-related activities specifically

[6]Define p^* as the probability that the activity for which an ORT arrest is made is legally appropriate, and define γ be an "overcharge parameter," such that $\text{logit}(p) = \text{logit}(p^*) + \gamma$. Rewriting Equation 1, $\beta_{1j} = \text{logit}(p^*_B) - \text{logit}(p^*_W) + \gamma_B - \gamma_W$.

Figure 4: Estimated posterior intervals of agency-level odds ratios for black, female arrestees



Note: Odds ratios on the x-axis are on a logarithmic scale. Box plots describe the posterior distributions of odds ratios, estimated from MCMC samples (the end points are the 2.5% and 97.5% quantiles). Vertical lines are at one, and the statewide mean.

considered by the Legislature are made under their own sections of the TPC, not the residual clause, so they are not included in our dataset. Therefore, the underlying participation rates are equally zero for all groups of arrestees, all of the ORT arrests in our dataset are effectively overcharges, and we can assign a causal interpretation to the odds ratio. An ORT arrest under the residual clause would not be an overcharge if the activity leading to the arrest were contemplated by the Legislature as something different enough from PT to warrant a more serious penalty. For low-value arrests, this is highly unlikely. Police would have to accumulate evidence to have probable cause a shoplifter is a known ORC participant (either as a booster or fence), and the aggregate value of that evidence would almost certainly be more than $1,500.

Nevertheless, we still wanted some confirmation that the ORT arrests made under the residual clause were not, generally speaking, for activities the Legislature intended to be treated as ORT. We take two approaches: reviewing arrest report narratives (written descriptions of activities and evidence that led to the arrest, such as those found in police reports), and counting charge adjustments made by prosecutors. The results in this section are consistent with evidence of ORT overcharges, but not conclusive. We include them because they add interesting perspectives regarding events surrounding ORT arrests, and may form a basis for future research.

Arrest narratives could help us evaluate whether ORT arrests made under the residual clause in §31.16(b) are consistent with the intent of the Legislature, as well as the requirements of due process and equal protection. Unfortunately, each local agency has its own policies, procedures, and costs for assembling and releasing arrest reports, and there is no statewide standard in how these reports are compiled and formatted. Examining narratives for all arrests was not feasible. However, we did obtain 376 narratives of ORT arrests from 17 agencies. These agencies were selected primarily out of convenience, as some were more responsive to public information requests than others. Within an agency, we selected arrests randomly, although agencies with a small number of ORT arrests received requests for all of them. Agencies were not told the purpose of the request, so there was no reason for them to withhold specific reports, but we do not want to give the impression this set of narratives constitutes a random sample.

Some narratives include a justification of the ORT arrest. For example, in at least one case, the arresting officer charged for ORT because two or more people were working together. Although one might colloquially describe that activity as "organized", that criterion could also include groups of wayward youths, or couples stealing for personal use. Occasionally, a narrative would describe facts that might be consistent with ORC boosting, such as shoplifting goods commonly sold through ORC channels (e.g., laundry detergent), or stealing from multiple stores in a short period of time,

If the "true" ORT probabilities among arrestees are the same across groups, the log odds ratio is the difference in the overcharge parameters.

but non-ORC explanations (e.g., personal use) are at least as likely. It is possible a high odds ratio could be an artifact of, for example, black, female petty shoplifters being more likely to shoplift in groups than white, female petty shoplifters. These activities do not constitute probable cause for on ORT arrest over a PT arrest.

We also looked at charges for which the arrestee is eventually prosecuted. This approach is similar to what Graham (2014) did to "point toward those U.S. Attorney's offices that merit further study either as possible hotbeds of overcharging or as offices that tend to avoid this practice" (p. 2014). Ideally, an ORT overcharge will be downgraded to PT when the prosecutor reviews the case (Stanko 1981). The filing of the charge as submitted by the police (i.e., when an ORT arrest is eventually prosecuted as ORT) does not prove the absence of an arrest overcharge, but a prosecutor's decision to downgrade *might* indicate the presence of one. Table 5 summarizes the ORT arrests in the dataset by the charge that is eventually filed by the prosecution. A "no charge" indicates that either the case is pending and has not yet advanced to the prosecution stage, or that the prosecutor decided to not proceed with the case. In total, 27.8% of all ORT arrests, and 31.9% of the ORT arrests for which there is a prosecution charge, were downgraded to PT.

Table 6 tallies the number of PT and ORT arrests, and the number of prosecutorial downgrades of the ORT arrests, for agencies that made more than 10 ORT arrests, and had at least one downgrade. There are, of course, many reasons an ORT arrest might be downgraded to PT. One possibility is that the prosecutor is acting as a check on police overreach. Another is that the police could be coordinating with the prosecutor, and overcharging to give the prosecutor more power in plea negotiations. More study is needed to ascertain if either explanation is correct.

The collateral consequences of an arrest overcharge do not go away if the prosecutor downgrades the offense. During the time between arrest and the prosecutor's review of the case, the arrestee may have already been subject to pre-trial incarceration for a longer period, or bail may have been set at a higher amount, than would have been the case has the arrest been charged correctly. During that time, employment and housing opportunities can be threatened, and the stress of a potential felony conviction already felt. The arrest charge can also influence the eventual disposition of the case. For example, the downgrade could have been the outcome of plea bargaining, with the starting point of negotiations set at the higher charge. Even though the number of ORT arrests is small relative to PT arrests, and even after some charges are downgraded, damage is already done to those arrested for ORT overcharges.

Prosecutors also have the option of upgrading PT arrests to ORT. This happens rarely: only 60 of the 107,981 PT arrests in our dataset were prosecuted as ORT. More than half of these were in the city of Copperas Cove, the largest city in Coryell County. The police department in Copperas Cove made 281 total arrests, of which only 5 were for ORT. However, 31 of the 276 PT arrests were

Table 5: Prosecution Status of ORT Arrests

	Arrests	Prosecution charge			Pct. downgraded	
group	Total ORT	PT	ORT	No charge	All ORT	With charge
Black	222	59	127	36	26.6	31.7
Hisp	191	63	99	29	33.0	38.9
White	517	137	328	52	26.5	29.5
(all)	930	259	554	117	27.8	31.9

Note: Pct. downgraded is the number of PT arrests, divided by the total number of ORT arrests ("All ORT"), or the number of ORT arrests for which a prosecution charge is recorded ("with charge"). "No charge" indicates that either the case is pending and has not yet advanced to the prosecution stage, or that the prosecutor refused to proceed with the case.

prosecuted as ORT. We do not yet have an explanation for why so many Copperas Cove PT arrests were upgraded to ORT. One possible reason could be that there is a significant ORC ring that is operating in the city, and post-arrest investigations are leading prosecutors to upgrade PT arrests to ORT. Another could be that the political climate in Coryell County could create incentives for prosecuting crimes at the highest possible charge. Interestingly, the police department in Gatesville, which is also in Coryell County, made 18 ORT arrests out of 21 total arrests. This high ORT arrest rate would be consistent with a hypothesis that a county-wide initiative exists to push for ORT arrests. We reserve testing of this hypothesis for future research.

IV. Discussion

Our empirical results show variation across both agencies and racial groups in the odds a petty shoplifter, once arrested, will be arrested for ORT instead of PT. This disparity is felt more strongly by black women than white women. Estimates of a disparity between black and white men, and between Hispanics and whites of both sexes, are less conclusive. The magnitude and significance of the odds ratio vary greatly across agencies, with a positive association between the odds ratio and the affluence of the city the agency serves. We cannot conclude there is an association with the racial composition of the city.

A. Limitations and extensions

These statistical patterns do not reveal motives of arresting officers, and we are careful to avoid interpreting a high odds ratio as evidence of wrongdoing by a law enforcement agency. Nevertheless, the posterior distributions over odds ratios do form a sort of statistical profile of each agency's

Table 6: Downgrades of ORT Arrests by Agency

	Arrests		White			Black			Hisp			All		
Agency	Total	% ORT	ORT	Down	%	ORT	Down	%	ORT	Down	%	ORT	Down	%
Schertz	144	59.7	22	17	77.3	4	4	100.0	15	8	53.3	86	29	33.7
Lewisville	879	19.9	36	27	75.0	27	16	59.3	22	16	72.7	175	59	33.7
Fort Worth	3,915	2.4	18	15	83.3	12	10	83.3	10	6	60.0	94	31	33.0
Alvin	149	17.4	7	5	71.4	0	0		3	3	100.0	26	8	30.8
Allen	227	34.4	11	9	81.8	14	9	64.3	14	5	35.7	78	23	29.5
Plano	1,393	3.1	13	8	61.5	5	1	20.0	7	3	42.9	43	12	27.9
Frisco	501	2.4	3	2	66.7	1	0	0.0	1	1	100.0	12	3	25.0
Hurst	1,163	2.5	2	2	100.0	2	1	50.0	5	4	80.0	29	7	24.1
Burleson	369	7.0	5	4	80.0	3	1	33.3	0	0		26	5	19.2
Paris	194	10.8	6	1	16.7	2	2	100.0	2	0	0.0	21	3	14.3
Cleburne	296	5.1	6	2	33.3	0	0		0	0		15	2	13.3
Lake Jackson	422	3.8	1	1	100.0	1	1	100.0	0	0		16	2	12.5
Terrell	167	21.6	9	2	22.2	5	2	40.0	1	0	0.0	36	4	11.1
Weatherford	246	22.8	26	5	19.2	6	0	0.0	1	1	100.0	56	6	10.7
Austin	4,770	0.4	1	1	100.0	4	1	25.0	2	0	0.0	19	2	10.5
Liberty	89	77.5	16	4	25.0	6	0	0.0	5	3	60.0	69	7	10.1
Marshall	137	53.3	16	5	31.2	10	2	20.0	0	0		73	7	9.6
Cleveland	243	8.6	7	2	28.6	4	0	0.0	1	0	0.0	21	2	9.5
Kaufman	50	22.0	3	1	33.3	0	0		0	0		11	1	9.1
Brownsville	1,331	1.0	0	0		1	0	0.0	4	1	25.0	13	1	7.7
Denton	937	1.4	5	1	20.0	1	0	0.0	0	0		13	1	7.7
Commerce	90	15.6	1	0	0.0	2	1	50.0	0	0		14	1	7.1
Mineral Wells	180	8.9	7	1	14.3	0	0		2	0	0.0	16	1	6.2
Jacksonville	196	46.4	24	5	20.8	16	0	0.0	3	0	0.0	91	5	5.5
Odessa	970	2.0	3	0	0.0	1	0	0.0	8	1	12.5	19	1	5.3
Gainesville	261	95.4	86	1	1.2	11	0	0.0	21	0	0.0	249	1	0.4

Note: Percentages of downgrades are with respect to total arrests. Minimum ORT arrests: 10.

latent propensity for disparate application of the ORT statute. Some agencies may merit further attention because their arrest patterns are at least consistent with selective enforcement of ORT by race. Whether further investigation would reveal that ORT arrests are justified more for some groups than others (e.g., perhaps there really are ORC fences limiting their involvement to $1,500 in merchandise), or that more nefarious motives or incentives are at work, are interesting paths for follow-up research.

We acknowledge our analysis is limited to instances of theft that result in an arrest for either PT or ORT. Ideally, we would also observe when an officer decides not to make an arrest at all. Some racial groups may be more likely to engage in shoplifting, get caught, be referred to police for arrest, or be targeted or profiled by retailers. There is an established stream of research concerned with the "shopping while black" issue (e.g., Harris et al. 2005; Dabney et al. 2006) that falls outside the scope of our study. We do not observe potential arrests that are not made, so we are careful to not interpret the odds ratio as a broad indicator of an agency's propensity for racial bias (i.e., an agency might be less likely to arrest blacks than whites, but more likely to charge for ORT than PT if that arrest is made). However, in our context it is unlikely an arresting officer would exercise the discretion not to arrest. In most cases, the matter is referred to the police by the retailer, who already has evidence of a theft. The most salient decision remaining for the officer is whether the arrest is PT or ORT. And since low-value ORT arrests are likely overcharges anyway, our results still form a statistical profile of agencies with regard to their propensities to arrest for ORT instead of PT.

Some agencies may be distinguishing ORT from PT using their own, seemingly objective criteria that are unrelated to ORC. For example, an agency might, on its own initiative, apply the ORT statute to an arrestee working with an accomplice, stealing a moderate quantity of goods that frequently appear in the black market, or possessing a criminal record. These are not sufficient justifications for the ORT arrest. Due process requires arrests under ambiguous statutes should be resolved in favor of the defendant, so these arrests can just as easily be made under the PT statute. More research is needed to determine if some agencies are, in essence, creating their own definitions of ORT different from what the Legislature intended. If these local policies disparately impact arrestees of one race more than another, they might explain the mechanism behind the high odds ratios we estimate in this paper. Yet, even if there were no racial disparity in ORT enforcement, anyone being arrested for a crime whose definition does not fit the alleged activity is harmed.

Any model can be made arbitrarily complex by adding additional covariates or relaxing modeling assumptions. Data constraints limit our options for enhancing the arrest-level model. Gathering information about locations of arrests requires sorting through individual police reports and narratives which, as we explain in Section III.E, cannot be done at scale. Other than basic demographic data, we do not have access to personal information about arrestees. A more fruitful extension of our research would involve collecting, and testing the effects of, even more agency-level characteristics on the odds ratios. We have already excluded the size of the retail sector in an agency's county as a significant agency-level covariate, but there may be other covariates that are predictive. For example, perhaps the overall crime rate in an agency's jurisdiction influences ORT arrest decisions. We defer these questions to future research.

B. Policy implications

This research shines light on the consequences of one instance of overlapping or ambiguous statutes, but the quality of criminal codes is a more general concern (Robinson and Cahill 2005; Robinson 2015). Robinson (2009) reviews dozens of examples of inconsistencies and ambiguities offenses in the Pennsylvania Consolidated Statutes. For example, "unauthorized administration of an intoxicant with the intent to rape is a specific instance of the offense of attempted rape. Yet the former is punishable by up to 7 years, while the latter carries a maximum sentence of 20 years — nearly three times the maximum penalty" (Robinson 2009, p. 49). Robinson et al. (2010) presents an empirical study that reveals how activities, offenses, and categories are mismatched to the perceptions and values of the public. Stacy (2008) describes Kansas cases in which case outcomes were affected by imprecise definitions of offenses, such as whether "compounding" is either manufacture or distribution of an illegal drug, or whether a precursor of a drug also qualifies as drug paraphernalia. Cooke (2017) expresses similar concerns regarding a North Carolina statute targeting "revenge porn."

It is therefore worthwhile to consider how the Legislature could amend §31.16 to better distinguish between PT and ORT, and to narrow the scope of ORT residual clause so it excludes non-ORC activities. The problem at hand is that the power to distinguish the professional ORC booster from those who shoplift because of thrill-seeking, mental illness, or economic necessity, is effectively delegated to local authorities. Clarification of the statute could reduce the prevalence of legal mistakes by the police, which themselves raise concerns about due process (Logan 2011). How a legislature constructs its ORT statute depends in part on the extent to which it considers shoplifting on behalf of a booster to be different from shoplifting for other reasons.

A review of state statutes found 18 states with "residual" definitions of ORC that excluded listed activities like evading theft detection systems or using fire exits. In general, these definitions still require an intent to reintroduce the merchandise into commerce; a minimum value for stolen goods (either a monetary value, or "exceeding amounts required for personal use"); and/or a continuing pattern of theft or course of conduct of retail theft. Three instructive examples are from the criminal codes of Maine, Delaware, and Massachusetts, in which a person is guilty of organized retail crime if the person…

Table 7: Selected Options for Amending the Definition of ORT in the Texas Penal Code

Policy option	Arguments in favor	Arguments against
Reinstate minimum value of stolen merchandise	• Excludes low-value incidents from scope of ORT. • Aggregating values across multiple incidents allows for prosecution of repeat ORC boosters at higher value levels.	• Boosters can strategically keep value just below the minimum. • Goods may still enter ORC supply chain.
Require evidence of intent to resell, or reintroduce goods into commerce	• Consistent with definition of ORC, which also requires intent. • Excludes other reasons for petty shoplifting.	• Criterion is subjective.
Require quantities that exceed those normally needed for personal use.	• Consistent with patterns of ORC activities. • Excludes other reasons for petty shoplifting.	• Subjective judgment about what the appropriate quantity should be.
Define ORT as at least two people working together.	• Prevents solo, non-ORC shoplifters from being arrested for ORT. • Agencies commonly (but incorrectly) use this criterion to distinguish between PT and ORT now.	• Groups of shoplifters are not necessarily professional boosters. • Excludes solo ORC boosters.
Require continuing pattern of behavior	• Consistent with repeated activity of ORC boosters.	• Statute already increases penalties for those with multiple convictions. • Criterion is subjective.

> …commits two or more thefts of retail merchandise …either as a principal or an accomplice, pursuant to a scheme or course of conduct engaged in by two or more persons involving thefts from two or more retail stores for the purpose of selling the stolen merchandise or conducting fraudulent returns of the stolen merchandise (Maine Revised Statutes, Title 17A, §363).

> …takes, exercises control over, or obtains retail merchandise of another person …in quantities that would not normally be purchased for personal use or consumption, with the intent to appropriate or to resell or reenter the merchandise into commerce (Delaware Code, Title 11, §841B).

> …acting in concert with 2 or more persons, and within a 180-day period steals, embezzles or obtains by fraud, false pretense or other illegal means retail merchandise valued at more than $2,500 to resell or otherwise reenter such retail merchandise into commerce… (Massachusetts General Laws, Ch. 266, §30D).

In these cases, there is a sharper distinction than in Texas between which activities constitute organized retail crime, rather than petty shoplifting. Table 7 summarizes various policy options, with arguments for and against, that the Legislature might consider.

References

Agresti, A. (2013). *Categorical Data Analysis*. 3rd edition. Hoboken, N. J.: John Wiley & Sons.

Alschuler, A. W. (1968). "The Prosecutor's Role in Plea Bargaining." *University of Chicago Law Review*, 36(1):50–112. JSTOR:1598832.

Bibas, S. (2004). "Plea Bargaining Outside the Shadow of Trial." *Harvard Law Review*, 117(8):2463–2547. JSTOR:4093404.

Blumstein, A. and K. Nakamura (2009). "Redemption in the Presence of Widespread Criminal Background Checks." *Criminology*, 47(2):327–359. DOI:10/fvxbsv.

Breyer, S. (1991). "On the Uses of Legislative History in Interpreting Statutes." *Southern California Law Review*, 65:845–874.

Bushway, S. D. (2004). "Labor Market Effects of Permitting Employer Access to Criminal History Records." *Journal of Contemporary Criminal Justice*, 20(3):276–291. DOI:10/cmw3hf.

Bushway, S. D., P. Nieuwbeerta, and A. Blokland (2011). "The Predictive Validity of Criminal Background Checks: Do Age and Criminal History Affect Time to Redemption?" *Criminology*, 49(1):27–60. DOI:10/c7mmfg.

Bushway, S. D. and A. D. Redlich (2012). "Is Plea Bargaining in the 'Shadow of the Trial' a Mirage?" *Journal of Quantitative Criminology*, 28(3):437–454. DOI:10/bgdpq2.

Caldwell, H. M. (2011). "Coercive Plea Bargaining: the Unrecognized Scourge of the Justice System." *Catholic University Law Review*, 61(1):63–96.

Carpenter, B., A. Gelman, M. D. Hoffman, D. Lee, B. Goodrich, M. Betancourt, M. A. Brubaker, J. Guo, P. Li, and A. Riddell (2017). "Stan: A Probabilistic Programming Language." *Journal of Statistical Software*, 76(1). DOI:10/b2pm.

Chin, W. Y. (2016). “Racial Cumulative Disadvantage: The Cumulative Effects of Racial Bias at Multiple Decision Points in the Criminal Justice System.” *Wake Forest Journal of Law and Policy*, 6:441–458.

Connally v. General Constr. Co. (1926). 269 U. S. 385.

Cooke, A. (2017). “The Right to Post: How North Carolina’s Revenge Porn Statute Can Escape Running Afoul of the First Amendment Post-Bishop.” *First Amendment Law Review*, 15:472–496.

Dabney, D. A., L. Dugan, V. Topalli, and R. C. Hollinger (2006). “The Impact of Implicit Stereotyping on Offender Profiling: Unexpected Results from an Observational Study of Shoplifting.” *Criminal Justice and Behavior*, 33(5):646–674. DOI:10/fft6wc.

Davis, A. J. (2007). *Arbitrary Justice: The Power of the American Prosecutor*. New York: Oxford University Press.

Decker, S. H., N. Ortiz, C. Spohn, and E. Hedberg (2015). “Criminal Stigma, Race and Ethnicity: The Consequences of Imprisonment for Employment.” *Journal of Criminal Justice*, 43(2):108–121. DOI:10/b38b.

Dobbie, W., J. Goldin, and C. S. Yang (2017a). “The Effects of Pre-Trial Detention on Conviction, Future Crime and Employment: Evidence from Randomly Assigned Judges”. NBER:22511.

Dobbie, W., C. S. Yang, and D. Arnold (2017b). “Racial Bias in Bail Decisions”. Working paper. National Bureau of Economic Research. NBER:23421.

Finklea, K. M. (2012). “Organized Retail Crime”. R41118. Congressional Research Service.

Frazier, C. E., E. W. Bock, and J. C. Henretta (1980). “Pretrial Release and Bail Decisions.” *Criminology*, 18(2):162–181. DOI:10/dr7j2w.

Funk, P. (2004). “On the Effective Use of Stigma as a Crime Deterrent.” *European Economic Review*, 48:715–728. DOI:10/dhc3fz.

Geller, A. (2016). “The Process is Still the Punishment: Low-level Arrests in the Broken Windows Era.” *Cardozo Law Review*, 37:1025–1058.

Gelman, A. and J. Carlin (2014). “Beyond Power Calculations: Type S (Sign) and Type M (Magnitude) Errors.” *Perspectives on Psychological Science*, 9(6):641–651. DOI:10.1177/1745691614551642.

Gelman, A., J. Fagan, and A. Kiss (2007). “An Analysis of the New York City Police Department’s ’Stop-and-Frisk’ Policy in the Context of Claims of Racial Bias.” *Journal of the American Statistical Association*, 102(479):813–823. DOI:10.1198/016214506000001040.

Gelman, A. and J. Hill (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York: Cambridge University Press.

Gelman, A. and F. Tuerlinckx (2000). “Type S Error Rates for Classical and Bayesian Single and Multiple Comparison Problems.” *Computational Statistics*, 15(3):373–390. DOI:10.1007/s001800000040.

Gerstein, C. and J. J. Prescott (2015). “Process Costs and Police Discretion.” *Harvard Law Review Forum*, 128:268–288. SSRN:2543945.

Glenn, E. H. (2016). *acs: Download, Manipulate and Present American Community Survey and Decennial Data from the U. S. Census*. R package. Version 2.0. URL: https://CRAN.R-project.org/package=acs.

Golub, A., B. D. Johnson, and E. Dunlap (2007). "The Race/Ethnicity Disparity in Misdemeanor Marijuana Arrests in New York City." *Criminology and Public Policy*, 6(1):131–164. DOI:10/fm6pw5.

Graham, K. (2014). "Overcharging." *Ohio State Journal of Criminal Law*, 11(2):701–724. SSRN:2227193.

Grogger, J. (1992). "Arrests, Persistent Youth Joblessness, and Black/White Employment Differentials." *The Review of Economics and Statistics*, 74(1):100–106. JSTOR:2109547.

Gustafson, K. (2013). "Degradation Ceremonies and the Criminalization of Low Income Women." *UC Irvine Law Review*, 3(2):101–160. SSRN:2254054.

Harris, A.-M. G., G. Henderson, and J. D. Williams (2005). "Courting Customers: Assessing Consumer Racial Profiling and Other Marketplace Discrimination." *Journal of Public Policy and Marketing*, 24(1):163–171. JSTOR:30000577.

Heaton, P., S. Mayson, and M. Stevenson (2017). "The Downstream Consequences of Misdemeanor Pretrial Detention." *Stanford Law Review*, 69(3):711–794.

Hoffman, M. D. and A. Gelman (2014). "The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo." *Journal of Machine Learning Research*, 15:1593–1623.

Holleran, D., D. Beichner, and C. Spohn (2010). "Examining Charging Agreement Between Police and Prosecutors in Rape Cases." *Crime and Delinquency*, 56(3):385–413. DOI:10/fpw8qj.

Johnson v. U.S.. (2015). 135 U.S. 2551.

Johnson, B. D. (2015). "Examining the 'Life Course' of Criminal Cases." *Criminology and Public Policy*, 14(2):183–186. DOI:10/b38c.

Kolender v. Lawson (1983). 461 U. S. 352.

Krasnovsky, T. and R. C. Lane (1998). "Shoplifting: A Review of the Literature." *Aggression and Violent Behavior*, 3(3):219–235. DOI:10/fsm69s.

Kutateladze, B. L., N. R. Andiloro, B. D. Johnson, and C. C. Spohn (2014). "Cumulative Disadvantage: Examining Racial and Ethnic Disparity in Prosecution and Sentencing." *Criminology*, 52(3):514–551. DOI:10/f6f3j8.

Lageson, S. E., M. Vuolo, and C. Uggen (2015). "Legal Ambiguity in Managerial Assessments of Criminal Records." *Law and Social Inquiry*, 40(1):175–204. DOI:10/f64fkz.

Leslie, E. and N. G. Pope (2016). "The Unintended Impact of Pretrial Detention on Case Outcomes: Evidence from NYC Arraignments". Working paper. University of Chicago. URL: http://home.uchicago.edu/~npope/pretrial_paper.pdf.

Logan, W. A. (2011). "Police Mistakes of Law." *Emory Law Journal*, 61(1):69–110. URL: http://ir.law.fsu.edu/articles/172.

Lytle, D. J. (2014). "The Effects of Suspect Characteristics on Arrest: A Meta-analysis." *Journal of Criminal Justice*, 42(6):589–597. DOI:10/f6q33r.

Myers, M. A. (1982). "Common Law in Action: the Prosecution of Felonies and Misdemeanors." *Sociological Inquiry*, 52(1):1–15. DOI:10/b8nhgr.

National Retail Federation (2016). "Organized Retail Crime Survey". Report. URL: https://tinyurl.com/ORTreport2016 (visited on 01/10/2017).

Nelson, E. L. (2013). "The Relationship Between Individual Police Officer Work Habits and the Stated Reasons Prosecutors Reject Their Domestic Violence Investigations." *SAGE Open*, 3(4):1–11. DOI:10/b2s4.

Nelson, E. L. (2014). "If You Want to Convict a Domestic Violence Batterer, List Multiple Charges in the Police Report." *SAGE Open*, 4(1):1–12. DOI:10/b38d.

Nourse, V. F. (2014). "Elementary Statutory Interpretation: Rethinking Legislative Intent and History." *Boston College Law Review*, 55:1613–1658. SSRN:2561598.

Pager, D. (2003). "The Mark of a Criminal Record." *American Journal of Sociology*, 108(5):937–975. DOI:10/dpvv3f.

Phillips, S. W. and S. P. Varano (2008). "Police Criminal Charging Decisions: An Examination of Post-arrest Decision-making." *Journal of Criminal Justice*, 36(4):307–315. DOI:10/dtwgm7.

Radin, M. (1930). "Statutory Interpretation." *Harvard Law Review*, 43(6):863–885. JSTOR:1330769.

Robinson, P. H. (2009). "Report on Offense Grading in Pennsylvania". Faculty Scholarship Paper 295. University of Pennsylvania Law School. URL: http://scholarship.law.upenn.edu/faculty_scholarship/295.

Robinson, P. H. (2015). "The Rise and Fall and Resurrection of American Criminal Codes." *University of Louisville Law Review*, 53(2):173–191.

Robinson, P. H. and M. T. Cahill (2005). "The Accelerating Degradation of American Criminal Codes." *Hastings Law Journal*, 56:633–655. SSRN:784524.

Robinson, P. H., T. Gaeta, M. Majarian, M. Schultz, and D. M. Weck (2010). "The Modern Irrationalities of American Criminal Codes: An Empirical Study of Offense Grading." *The Journal of Criminal Law and Criminology*, 100(3):709–764. JSTOR:25766108.

Ross, S. F. (1978). "Bordenkircher v. Hayes: Ignoring Prosecutorial Abuses in Plea Bargaining." *California Law Review*, 66(4):875–883. JSTOR:3479971.

Sessions v. Dimaya (2018). 138 U. S. 1204.

Smith v. Goguen (1974). 415 U. S. 566.

Smith, D. A., C. A. Visher, and L. A. Davidson (1984). "Equity and Discretionary Justice: The Influence of Race on Police Arrest Decisions." *The Journal of Criminal Law and Criminology*, 75(1):234–249. JSTOR:1143211.

Spohn, C. (2008). "Race, Sex, and Pretrial Detention in Federal Court: Indirect Effects and Cumulative Disadvantage." *University of Kansas Law Review*, 57:879–901. URL: https://tinyurl.com/Spohn2008.

Spohn, C. (2015). "Race, Crime, and Punishment in the Twentieth and Twenty-first Centuries." *Crime and Justice*, 44(1):49–97. DOI:10/b38j.

Stacy, T. (2008). "Relating Kansas Offenses." *Kansas Law Review*, 56(4):831–869.

Stan Development Team (2016). *RStan: the R Interface to Stan*. R package. Version 2.10.1. URL: https://cran.r-project.org/package=rstan.

Stanko, E. A. (1981). "The Arrest Versus the Case: Some Observations on Police/District Attorney Interaction." *Journal of Contemporary Ethnography*, 9(4):395–414. DOI:10/fnjm3w.

Stevenson, M. (2017). "Distortion of Justice: How the Inability to Pay Bail Affects Case Outcomes". Working paper. George Mason University. SSRN:2777615.

Stuntz, W. J. (2004). "Plea Bargaining and Criminal Law's Disappearing Shadow." *Harvard Law Review*, 117(8):2548–2569. JSTOR:4093405.

Texas (2015a). *Texas Code of Criminal Procedure*. URL: https://tinyurl.com/TexCrimProc.

Texas (2015b). *Texas Penal Code*. URL: https://tinyurl.com/TexPenalCode.

Texas. Legislature. House of Representatives (2007). "An Act Relating to the Prosecution and Punishment of Certain Theft Offenses". H. B. 3584. 80th Legislative Session. URL: https://tinyurl.com/HB3584-2007.

Texas. Legislature. House of Representatives (2011a). "A Bill to be Entitled 'An Act Relating to the Offense of Organized Retail Theft'". First reading H.B. 2482. 82nd Legislative Session. URL: https://tinyurl.com/HB2482-2011-first.

Texas. Legislature. House of Representatives (2011b). "An Act Relating to the Prosecution of and Punishment for Certain Offenses Involving Theft". HB 2482. 82nd Legislative Session. URL: https://tinyurl.com/HB2482-2011.

Texas. Legislature. House of Representatives. Committee on Criminal Jurisprudence (2007a). "Bill Analysis". CSHB 3584. 80th Legislative Session. House Committee Report. URL: https://tinyurl.com/HB3584-2007-report.

Texas. Legislature. House of Representatives. Committee on Criminal Jurisprudence (2007b). "Committee testimony". video. URL: https://tinyurl.com/HB3584-testimony. April 3, 2007. Start time 2:25:50.

Texas. Legislature. House of Representatives. Committee on Criminal Jurisprudence (2011). "Committee testimony". video. URL: https://tinyurl.com/HB2482-testimony. March 22, 2011. Start time 34:20.

Texas. Legislature. House of Representatives. House Research Organization (2011). "Bill Analysis". CSHB 2482. 82th Legislative Session. URL: https://tinyurl.com/CSHB2482-report.

Uggen, C. and R. Stewart (2014). "Piling On: Collateral Consequence and Community Supervision." *Minnesota Law Review*, 99:1871–1910.

United States Census Bureau (2014a). "Table B03002: Hispanic or Latino Origin by Race". 2010-2014 American Community Survey.

United States Census Bureau (2014b). "Table B19301: Per-capita Income in the Last 12 Months in 2014 Inflation-adjusted Dollars". 2010-2014 American Community Survey.

Wald, P. (1964). "Pretrial Detention and Ultimate Freedom: A Statistical Study." *New York University Law Review*, 39:631–640.

Wooldredge, J., J. Frank, N. Goulette, and L. Travis (2015). "Is the Impact of Cumulative Disadvantage on Sentencing Greater for Black Defendants?" *Criminology and Public Policy*, 14(2):187–223. DOI:10/b38f.

Appendix

In this appendix we provide the texts of H. B. 3584 (2007) (Texas Legis. 2007) and H. B. 2482 (2011) (Texas Legis. 2011), along with relevant committee reports and excerpts from transcripts of testimony in public hearings.

H. B. 3584 (2007)

H. B. 3584 (2007) reads as follows:

AN ACT relating to the prosecution and punishment of certain theft offenses. Be it enacted by the Legislature of the State of Texas:

Section 1. Chapter 31, Penal Code, is amended by adding Section 31.16 to read as follows:

SEC. 31.16. ORGANIZED RETAIL THEFT

(a) In this section, "retail merchandise" means one or more items of tangible personal property displayed, held, stored, or offered for sale in a retail establishment.

(b) A person commits an offense if the person intentionally conducts, promotes, or facilitates an activity in which the person receives, possesses, conceals, stores, barters, sells, or disposes of a total value of not less than $1,500 of:

(1) stolen retail merchandise; or

(2) merchandise explicitly represented to the person as being stolen retail merchandise.

(c) An offense under this section is:

(1) a state jail felony if the total value of the merchandise involved in the activity is $1,500 or more but less than $20,000;

(2)-(4) [categories and levels for higher steps in the value ladder]

(d) An offense described for purposes of punishment by Subsections (c)(1)-(3) is increased to the next higher category of offense if it is shown on the trial of the offense that the person organized, supervised, financed, or managed one or more other persons engaged in an activity described by Subsection (b).

(e) For the purposes of punishment, an offense under this section or an offense described by Section 31.03(e)(1) or (2) is increased to the next highest category of offense if it is shown at the trial of the offense that the defendant, with the intent that a distraction from the commission of the offense be created, intentionally, knowingly, or recklessly caused an alarm to sound or otherwise become activated during the commission of the offense.

Section 2. Article 13.08, Code of Criminal Procedure, is amended to read as follows:

13.08. THEFT; ORGANIZED RETAIL THEFT

(a) Where property is stolen in one county and removed by the offender to another county, the offender may be prosecuted either in the county where he took the property or in any other county through or into which he may have removed the same.

(b) An offense under Section 31.16, Penal Code, may be prosecuted in any county in which an underlying theft could have been prosecuted as a separate offense.

Section 3. [Text related to the effective date of the act.]

Legislative history

A report on H. B. 3584 (2007) by the Texas House of Representatives Committee on Criminal Jurisprudence, in a section titled "Background and Purpose," recognized PT and ORT as different crimes.

> Organized retail crime is distinct from petty shoplifting in that it involves professional theft rings …to steal large amounts of merchandise. This criminal activity requires many thieves (boosters) organized by a central figure (fence) that pays the boosters pennies on the dollar, then repackages and resells the merchandise through alternate distribution channels to the general public (Texas House bill analysis 2007, Committee on Criminal Jurisprudence).

Committee testimony

Committee hearings on H. B. 3584 were held on April 3, 2007. The chairman of the committee, Rep. Aaron Peña, confirms both legislators and retailers intended to target fences rather than shoplifters.

> This is the request of eBay, and it deletes the misdemeanor language found in the original, as the bill seeks to nab the bigger players, not the petty shoplifters. Shoplifting refers to items stolen for personal use or consumption. Organized retail crime is separate and distinct from petty shoplifting, in that it involves professional theft rings under the direction of a fence who pays pennies on the dollar to the boosters who steal the merchandise. Then the fence resells the stolen goods through alternative distribution channels (Texas comm. testimony 2007, timestamp 2:26:24).

The testimony of Karl Langhorst, Director of Loss Prevention for Randall's and Tom Thumb Food Markets, illustrates the retailers also considered the bill to target the fence, not the booster.

> …this bill is targeted at the fence. The individual that employs what we call the boosters in the store. What you see going on, on a daily basis now, are the boosters getting caught. A fence may employ anywhere from a dozen to several hundred boosters. Those boosters are getting caught. They're the ones law enforcement is having to respond to and fill up our jails and prisons with. However, at the end of the day, the fence is usually not prosecuted. Not even picked up. …What we're asking for, with this legislation, is to target the fence. To get the fence off the street so law enforcement and our court system won't have to be dealing with all these boosters. … This has nothing to do with shoplifting. It has to do with professional rings of thieves (Texas comm. testimony 2007, timestamp 2:33:39).

Mr. Longhorst further described how boosting for a fence is different than stealing with an intent to resell the product.

> They can sell it out of the back of their vehicle, but most boosters don't do that. What they do is they will sell it to a fence, because the fence is the one that moves his product. And this product can go to numerous different locations and does (Texas comm. testimony 2007, timestamp 2:43:02).

Calvin Erves, the Director of Loss Prevention for Albertsons, highlighted a distinction between shoplifters and boosters, and how it is difficult for loss prevention managers to tell them apart.

> Of course, there'll always be shoplifting. We know that, and that's something that, again, as long as there is good and evil, there will be shoplifting. But at the same time, we're giving them an avenue to fence their goods. Not only are we giving them an avenue to fence it, but we're letting them disrupt our business, and your shopping experience, because we have to lock up more and more of these items to prevent as much of this as we can. But as you can see, the list is very broad. Without this list, again, we'll always have somebody stealing a pack of meat, one bottle of aspirin, and I can tell you the first time I ran across a booster, he had a basket full of Tylenol or whatever it could have been, and somebody commented on "he must have had a really bad headache." But no, that's not the case. Because, again, he had no use for that product. So, by eliminating the fences, or increasing the penalty on the fences, basically we will reduce the incidents of theft (Texas comm. testimony 2007, timestamp 2:48:00).

H. B. 2482 (2011)

H. B. 2482 (2011) removed the $1,500 minimum, increased penalties for arrests under TPC §31.16, and listed additional ORC-related offenses to TPC §31.03:

AN ACT relating to the prosecution and punishment of certain theft offenses. Be it enacted by the Legislature of the State of Texas:

Section 1. Section 31.01, Penal Code, is amended by adding Subdivisions (11) through (14) to read as follows:

(11) "Retail merchandise" means one or more items of tangible personal property displayed, held, stored, or offered for sale in a retail establishment.

(12) "Retail theft detector" means an electrical, mechanical, electronic, or magnetic device used to prevent or detect shoplifting and includes any article or component part essential to the proper operation of the device.

(13) "Shielding or deactivation instrument" means any item or tool designed, made, or adapted for the purpose of preventing the detection of stolen merchandise by a retail theft detector. The term includes a metal-lined or foil-lined shopping bag and any item used to remove a security tag affixed to retail merchandise.

(14) "Fire exit alarm" has the meaning assigned by Section 793.001, Health and Safety Code.

Section 2. Section 31.03(f), Penal Code, is amended to read as follows:

(f) An offense described for purposes of punishment by Subsections (e)(1)-(6) is increased to the next higher category of offense if it is shown on the trial of the offense that:

(1)-(4) [Not relevant to this paper.]

(5) during the commission of the offense, the actor intentionally, knowingly, or recklessly:

(A) caused a fire exit alarm to sound or otherwise become activated;

(B) deactivated or otherwise prevented a fire exit alarm or retail theft detector from sounding; or

(C) used a shielding or deactivation instrument to prevent or attempt to prevent detection of the offense by a retail theft detector.

Section 3. Sections 31.16(b), (c), and (d), Penal Code, are amended to read as follows:

(b) [same as above, with the text "a total value of not less than $1,500 of" removed].

(c) An offense under this section is:

(1) a Class B misdemeanor if the total value of the merchandise involved in the activity is less than $50;

(2) a Class A misdemeanor if the total value of the merchandise involved in the activity is $50 or more but less than $500;

(3) a state jail felony if the total value of the merchandize involved in the activity is $500 or more but less than $1,500;

(4)-(6) [categories and levels for higher steps in the value ladder].

(d) An offense described for purposes of punishment by Subsections (c)(1)-(5) is increased to the next higher category of offense if it is shown on the trial of the offense that:

(1) the person organized, supervised, financed, or managed one or more other persons engaged in an activity described by Subsection (b); or

(2) during the commission of the offense, a person engaged in an activity described by Subsection (b) intentionally, knowingly, or recklessly:

(A) caused a fire exit alarm to sound or otherwise become activated;

(B) deactivated or otherwise prevented a fire exit alarm or retail theft detector from sounding; or

(C) used a shielding or deactivation instrument to prevent or attempt to prevent detection of the offense by a retail theft detector.

Section 4. Sections 31.15(a) [definitions of retail theft detector and shielding or deactivation instrument] and 31.16(a) and (e), Penal Code, are repealed.

Legislative history

The report of the Committee on Criminal Jurisprudence describes the "Background and Purpose" of H. B. 2482 (2011).

> Observers note that individuals committing the offense of organized retail theft often deactivate a fire exit alarm or an anti-theft device used to protect retail merchandise, and the observers assert that statutory provisions related to this offense do not adequately address this issue. Interested parties contend that organized criminal enterprises, including gangs and foreign nationals, are often behind organized retail theft crimes and that these crimes have been linked to the funding of domestic and international terrorism, drugs, guns, prostitution, and human smuggling. The

> interested parties believe that Texas must impose stronger punishment and penalties on these large-scale organized retail thefts because they lead to retail business losses and closings, the loss of jobs, and the loss of sales tax revenue, which in turn will have a devastating effect on Texas' economy. (Texas House bill analysis 2011, Committee on Criminal Jurisprudence)

We can also infer the intent of the Legislature by reviewing how versions of the 2011 bill changed at different steps of the legislative process. The version of the bill that was initially submitted to the House, and referred to committee, defined the term "boost" as "to commit an offense under Section 31.03 with respect to retail merchandise." (Texas Legis. 2011, as introduced). It also added a more specific definition of Organized Retail Theft:

> A person commits an offense if the person:
>
> (1) alone or with the aid or assistance of another person, and pursuant to one scheme or continuing course of conduct, boosts:
>
> (A) one or more items of retail merchandise (i) from more than one retail establishment; or (ii) from the same retail establishment on more than one occasion; or
>
> (B) more than one of the same or similar items of retail merchandise from a single retail establishment on a single occasion; or
>
> (2) intentionally conducts, promotes, or facilitates an activity in which the person receives, possesses, conceals, stores, barters, sells or disposes of (A) stolen retail merchandise; or (B) merchandise represented to the person as being stolen retail merchandise.

This version would have defined all retail theft as boosting. However, the committee report explicitly notes the substitute bill (the version referred out of committee)

> omits provisions included in the original defining "boost" and expanding the conditions that constitute the offense of organized retail theft to include boosting one or more items of retail merchandise from a single retail establishment or multiple retail establishments in a certain manner. (Texas House bill analysis 2011, Committee on Criminal Jurisprudence)

Thus, we can infer the committee considered, and rejected, a policy of categorizing all retail theft one level higher than other property theft.

Committee testimony

Committee hearings on this bill were held on March 22, 2011 (Texas comm. testimony 2011). Mike Battles, a regional loss prevention manager for Stage Stores, described retailers' interests in amending the statute, and explains the need for ORT to be a higher category offense than PT.

> Back in 2007, we were very excited when the legislature passed the Organized Retail Theft law and got that put into 31.16 in the penal code. We started working with law enforcements over the years investigating these cases, trying to use that law. We began to realize that there needed

> to be a little bit of some changes could be addressed in the law to make it more effective but separating the law was good because organized retail theft really is a distinct crime separate from petty theft or from shoplifting. The main things that we saw over the years that could be improved of the original bill was the value ladder for prosecution is the same both in the organized retail theft bill and in 31.03, the regular theft. If somebody is apprehended for, say, a state jail felony and it might meet the criteria of organized retail theft, prosecutors were just going with regular theft because in either statute it was a state jail felony. So they were choosing to go with a law that had already been on the books for a good length of time as opposed to being a test subject for the newer law. I think, as of today, there's just a handful of individuals that have been put away for organized retail theft. That's because a lot of the charges end up being filed under regular theft (Texas comm. testimony 2011, timestamp 48:27).

Mr. Battles also explains the connection between ORC and specific activities, such as using fire exits, triggering alarms, and avoiding and disabling theft detection equipment.

> Then one of the other things we learned could use some improvement …is the fire exit thefts, because current law says that they have to have activated the fire exit alarm as an intent to be a distraction from the theft. That's not the case when they're stealing. They'll go to a big box store. They load up thousands of dollars' worth of merchandise near a fire exit at the back of the store. They pull a pickup truck to the back of the store. Once they open that fire exit, they load all that merchandise in the vehicle and take off, and it's a facilitated theft, much easier than if they'd tried to go out the front door. A lot of district attorneys don't end up prosecuting it because that wasn't caused to be a distraction from the crime. That was actually a facilitation of the crime. But that's not the way the law's currently worded.
>
> In my company's opinion, this [bill] makes a lot of necessary changes to help better track and enforce and define organized retail theft. …Then also by getting some of the enhancements in there to the theft will hopefully help deter people from either choosing to engage in organized retail theft or choosing to use the booster bags, the foil lined bags, during their commission of the offense. Part of what the bill would do is instead of having that same value ladder between regular theft and organized retail theft that it currently is, it would be an enhancement. It'd be one level above if it's organized retail theft, so it'd be one step up from 31.03 regular theft.
>
> Then it would also add an enhancement for the use of shielding or deactivation equipment. A lot of these boosters are successful in taking such large quantities of merchandise because they create a bag, whether it's a shopping bag or a purse, and they line it with aluminum foil and duct tape. That stops the signal from the little devices that are on merchandise that detect if it hasn't been paid for and sets off the alarm when it leaves the store. What they do is they just put all this merchandise in a foil-lined bag and walk out of the store with it, and they're able to do those thefts very quickly, take a large amount of merchandise. Currently, it's only the possession of the bag that's an offense. This would make it to where if somebody commits organized retail theft and uses the bag, it would cause an enhancement of the crime.
>
> Then also what was not addressed in current law was any deactivation of equipment. If the pedestal's at the front door, if somebody cuts the wires to them instead of worrying about using a booster bag, that wasn't a crime. Or if somebody deactivated the fire exits to where it wouldn't even make a sound and they'd hopefully be able to get out without anybody knowing anything, the current law only addresses the activation of the alarm. This would allow for is if somebody cut the wires and deactivated the equipment. Then, of course, the last part is the rewording

> of the fire exit to where it's not that it's a distraction from the offense. That it's they set off the alarm during the commission of the offense. It would make it an enhancement. (Texas comm. testimony 2011, timestamp 51.58)

Anthony Sheppard, the National Manager for Organized Retail Crime for CVS/Caremark, described examples of boosters participating in ORC, but at *aggregated* merchandise values much higher than $1,500.

> Recently, we filed a group in the Houston area that left an apartment complex. They targeted four stores in a matter of 40 minutes and had stolen $2,800 worth of product. If we had not been following them and they had been stopped in one location, again, without these changes, they would have been charged with a misdemeanor. We followed another group also out of Houston that traveled to Dallas. They targeted 12 stores and had stolen approximately $12,000 of the product before they were apprehended. Another group that was targeting Houston, it had been boosting for about four hours and had stolen about $10,000 worth of product. In all these cases, it was the product that I mentioned earlier, the over-the-counter product that they were taking. Again, in most cases they are caught often, but they're charged with misdemeanor thefts, and they're back on the street shortly after they've been apprehended (Texas comm. testimony 2011, timestamp 37:57).