To Serve and Collect: The Fiscal and Racial Determinants of Law Enforcement

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ABSTRACT

We exploit local deficits and state-level differences in police revenue retention from civil asset forfeitures to estimate how incentives to raise revenue influence policing. In a national sample, we find that local fine and forfeiture revenue increases faster with drug arrests than arrests for violent crimes. Revenues also increase faster with arrests of blacks and Hispanics than with whites' drug arrests. Concomitant with higher rates of revenue generation, we find that arrests of blacks and Hispanics for drugs, driving under the influence, and prostitution, and associated property seizures, increase with local deficits when institutions allow officials to more easily retain revenues from forfeited property. Whites' drug and driving under the influence arrests are insensitive to these institutions. We do, however, observe comparable increases in whites' prostitution arrests. Our results show that revenue-driven law enforcement can distort police behavior and decision-making, altering the quantity, type, and racial composition of arrests.

1. INTRODUCTION

Law enforcement has become a significant source of revenue for many local governments (Baicker and Jacobson 2007). Traditionally, local law enforcement was funded from tax revenues. However, US police departments increasingly use fine and forfeiture revenues to supplement their budgets. For a minority of municipalities, the local police department is a net positive source of revenue.

In the classic economic model of law enforcement, Becker (1968) shows that fines are preferable to jail time for many criminal offenses.

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Fine and forfeiture revenue, however, may provide law enforcement with incentives to pursue crimes and targets that increase revenue more than—or even at the expense of—social welfare (Friedman 1999; American Civil Liberties Union 2010). Revenue-driven law enforcement may also disparately impact minorities because the logic of revenue maximization can systematically encourage police to focus their efforts on vulnerable groups.

The 2015 US Department of Justice report on the Ferguson, Missouri, police department illustrates many of these issues. The report notes that the municipal government used law enforcement to support the city budget and that their efforts changed law enforcement objectives and resulted in a disparate racial impact:

> City officials routinely urge Chief Jackson to generate more revenue through enforcement. . . . The importance of focusing on revenue generation is communicated to FPD officers. Ferguson police officers from all ranks told us that revenue generation is stressed heavily within the police department, and that the message comes from City leadership. . . . FPD appears to bring certain offenses almost exclusively against African Americans. For example, from 2011 to 2013, African Americans accounted for 95% of Manner of Walking in Roadway charges, and 94% of all Failure to Comply charges. . . . Our investigation indicates that this disproportionate burden on African Americans cannot be explained by any difference in the rate at which people of different races violate the law. (US Department of Justice 2015, pp. 2–5)

We focus on one source of revenues from policing: civil asset forfeiture. Civil asset forfeiture is a doctrine whereby police can seize and keep property on the mere suspicion that it is connected to a crime (Williams et al. 2010; Holcomb, Kovandzic, and Williams 2011). Once property has been seized, prosecutors move against the property in a civil case. As the cases are against the property rather than the owner, they often have names such as *U.S. v. One 2003 Mercedes Benz CL500*.

Reversing the traditional burden of proof, owners of seized property are often considered guilty until proven innocent, which implies that they must sue to recover their property. Moreover, since the civil asset forfeiture is against the property rather than the owner, the owner has no right to counsel and must bear any costs of recovery. In some states, a property owner who challenges seizures may be subject to further costs. In Illinois, for example, a property owner who challenges a seizure must (with some exceptions) post a bond of $100 or 10 percent of the value of the property, whichever is greater. If owners win the case, they lose the bond payment. If owners lose their case, they lose the entire value of the bond and must pay the government's legal fees. Not surprisingly, once property has been seized, few people sue to repossess it.

In a few states, such as Maine, seized cash and receipts from the sale of seized property are allocated to the state's general fund. In a majority of states, however, the police can keep 100 percent of the value of any seized cash or property, especially if they allege a connection to drugs (Holcomb, Kovandzic, and Williams 2011). Police officers value funds from seizures because they can be allocated with little oversight. For example, Kenneth Burton, the chief of police for Columbia, Missouri, illustrates his discretion with respect to allocation of the funds arising from forfeitures: "It's usually based on a need—well, I take that back. There's some limitations on it. . . . Actually, there's not really on the forfeiture stuff. We just usually base it on something that would be nice to have that we can't get in the budget, for instance. We try not to use it for things that we need to depend on because we need to have those purchased. It's kind of like pennies from heaven—it gets you a toy or something that you need is the way that we typically look at it to be perfectly honest" (Institute of Justice 2015, p. 15).

We use data from a sample of 36 states to study the fiscal determinants of arrest patterns, including arrests by race. We hypothesize that police departments that can keep seized assets are more likely to make the kinds of arrests that lead to seized assets, especially when department budgets are tight. In our empirical work, we consider states in which the police department is able to use seized assets to supplement its budget and compare their arrest patterns to the subset of states in which police are not allowed to retain the value of any seized property.[1]

1. Even when state law requires seized funds to go into a general or earmarked state fund, this is not always done because seized assets are not well monitored. Seized funds often stay where they are generated (a flypaper effect). In addition, state law can be circumvented through federal equitable sharing. Under the equitable sharing program, when a local and federal law enforcement department cooperate in seizing property, the federal government may share the proceeds with the local department according to federal law rather than state law. Holcomb, Kovandzic, and Williams (2011) find that federal equitable sharing increases as state laws on civil asset forfeiture become stricter. Thus, even in states where state law dictates that no funds be retained, some funds can still be locally retained. Federal equitable sharing, however, is not without cost (the federal entity takes a share), nor is it always available. For our purposes, we need only that a department's incentive to seize property is higher in states where state law allows it to keep 50 percent or more of the property compared with other states.

1.1. Revenue-Driven Policing and Types of Arrests

A frequently adopted model of crime derives rules for deterrence by optimizing a social welfare function (Becker 1968; Shavell 2004). This model can be viewed as an application of optimal tax theory to public bads. Our conceptual framework does not focus on conditions for optimal law enforcement actions but on revenue-driven objectives by those who enforce the law. Therefore, our model draws from public choice and positive political economy (Persson and Tabellini 2000; Mueller 2003).

Modeling law enforcement activities as revenue driven generates different predictions from the welfare-maximization model (Garoupa and Klerman 2002).[2] Some types of offenses generate more revenue, potentially incentivizing a divergence from welfare-maximizing rates of enforcement. Assaults, for example, involve no financial transactions and tend not to provide law enforcers with an opportunity to seize assets. Drug traffickers and users, in contrast, tend to use cash for illegal transactions, which makes these offenses lower-cost targets for police interested in asset forfeitures. Further, nonviolent crimes are, on balance, more likely to be punished with fines, while violent crimes are more likely to be punished via jail or a prison sentence. The revenue-driven model predicts that police will pursue the enforcement of laws that provide greater opportunities to generate fine and forfeiture revenue.

Even if every crime created equal opportunity for revenue, we would still expect to observe systematic effects of revenue-driven law enforcement, because the elasticity of arrests with respect to police efforts differs across crimes. Homicide arrests, for example, are constrained by the number of homicides, which are relatively accurately counted. Drug arrests, in contrast, are more responsive to police effort because drug use likely far exceeds drug arrests.[3]

Crimes such as homicide, robbery, and burglary are on the police log because victims, or those related to victims, notify the police. The police are asked to solve these crimes and are, in turn, judged on the basis

2. The hypothesis that revenue generating is one of the objectives of law enforcement activities has been investigated in the context of speeding tickets (Garrett and Wagner 2009; Makowsky and Stratmann 2009, 2011). A common finding in this literature is that revenue-driven law enforcement increases in jurisdictions where the local governments face budget deficits.

3. For example, nearly 10 percent of the US population used an illicit drug in the last month. See National Survey on Drug Use and Health, Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings and Detailed Tables (https://www.samhsa.gov/data/report/results-2013-national-survey-drug-use-and-health-summary-national-findings-and-detailed).

of their clearance rates. In contrast, for victimless crimes, such as drug possession and prostitution, or for public-order crimes, such as improper window tinting or jaywalking, the crime rate is not tallied by citizens' reports or notifications but by arrests. Police officers are not judged by the ratio of drug arrests to drug usage or violation but rather by the number of arrests. Therefore, victim-reported crimes can be understood as being subject to constraints, while victimless crimes can be understood more as police choice variables.

Incentives are more important when enforcement effort is a choice. Thus, a revenue-driven model of enforcement predicts that police will focus on crimes that are more responsive to police effort and, of those crimes, those that are more productive of revenue.[4] Our model also predicts that revenue-driven law enforcement will increase when revenue demands become more salient relative to other demands and when revenue control accrues to agents who influence law enforcement choices.

In particular, we predict that revenue-driven law enforcement will increase when municipalities run deficits. Deficits reduce bureaucratic slack and threaten jobs, so a municipality that is running a deficit is more likely to pressure the police department to raise revenue, all else equal. Since deficits are not necessarily randomly allocated in our empirical estimations, we focus on interactions of deficits with legal variables that govern how easily police departments can retain revenues. Holding deficits constant, we expect departments that can retain revenues to engage in more revenue-driven policing.

1.2. Fines, Fees, and Forfeitures as a Significant Source of Police Funding

Civil asset forfeiture is a significant and growing source of revenues generated through law enforcement (Benson, Rasmussen, and Sollars 1995; Baicker and Jacobson 2007). Arrests, regardless of associated property, are also a potential source of revenue, because fines and fees are a common feature of the justice system. A random sample of felony defendants in Washington State in 2004, for example, found that 66 percent of pris-

4. Garoupa and Klerman (2002) show that, compared with a social-welfare-maximizing government, a rent-seeking government is more likely to prosecute minor crimes and less likely to prosecute major crimes. Prosecuting minor crimes, such as jaywalking, generates revenue, which incentivizes a rent-seeking government but not a social-welfare-maximizing government. Prosecuting major crimes (if such crimes generate revenue) deters them, and a rent-seeking government does not want to "kill the goose that lays the golden eggs," even if the goose is a social menace.

oners and 84 percent of felony defendants had been assessed criminal justice fees with a mean total assessment per offense of $2,540 (Harris, Evans, and Beckett 2010). Common fees include a DNA database fee ($100), a clerk's fee ($200), or a crime lab analysis fee ($100).

In some cases, defendants also have to pay a fee for public counsel. In *Gideon v. Wainwright* (372 U.S. 335 [1963]) the Supreme Court acknowledged a constitutional right to counsel similar to the Miranda warnings—"If you cannot afford an attorney, one will be appointed to you"—but not a right to free counsel. As a result, every state and the federal government have recoupment statutes that impose fees or posttrial liens on defendants who use their constitutional right to an attorney (Holly 1998). Fees may also be assessed for time spent in jail and services rendered in jail (American Civil Liberties Union 2010; Bannon, Nagrecha, and Diller 2010; Harris et al. 2010).[5] Fees increased in the 1990s and have increased further following the 2008–9 recession (Bannon, Nagrecha, and Diller 2010; Diller 2010).

Overall, fees and forfeitures serve as funding for the criminal justice system and are a significant share of police operating budgets (Baicker and Jacobson 2007). In 2012, for example, fines and forfeitures were equal to 15 percent of operating expenses on average. In 10 percent of departments, fees and forfeitures equaled nearly one-third (32 percent) of operating expenses, and in 1 percent of departments, fees and forfeitures were more than 90 percent of operating expenses. Occasionally, revenues from fees and forfeitures exceed a department's annual budget.[6]

2. RACIAL BIAS AND REVENUE-DRIVEN POLICING

The Department of Justice report on the events in Ferguson expresses the concern that the enforcement of law differs across racial groups (Shaw

5. The Criminal District Court in Orleans Parish in Louisiana imposes fees for its judicial expense fund from which the court pays for courtroom improvements such as carpeting and supplemental health insurance for judges. When questioned as to the propriety of such a fund, the judges insisted that the judicial expense fund is "self-generated money," not public funds. The fees are notorious and under investigation (Simerman 2012).

6. In 2003, for example, the Refugio police department in Texas had civil forfeitures more than three times greater than their annual budget. Initially, we assumed that this was a coding error in the Law Enforcement Management and Administrative Statistics database, but the numbers were verified by newspaper accounts. Refugio is a small, rural department. However, its jurisdiction includes a highway, and in 2002, one of the department's police officers seized $2.8 million dollars in cash during a highway stop. In 2012, the police chief during that period was sentenced to 3 years imprisonment for recklessly spending the money (Romo 2012).

and US Department of Justice 2015). Black Americans are arrested and imprisoned at higher rates than their population share. While this racial differential is attributable in part to higher levels of crime for blacks (Tonry 2011; Rehavi and Starr 2014), there remains evidence of racial bias in sentencing and the processing of appeals (Everett and Wojtkiewicz 2002; Alesina and La Ferrara 2014), traffic searches (Knowles, Persico, and Todd 2001), prosecutors' choices of charges (Rehavi and Starr 2014), and bail decisions (Arnold, Dobbie, and Yang 2018). In particular, racial bias appears to play a significant role in crimes involving drugs (see, for example, Tonry 2011; Alexander 2012). There is some evidence that African Americans are more likely to be arrested, imprisoned, and given long sentences for drug crimes even though they are no more likely to use or sell drugs than non-Hispanic whites (Tonry 2011). Donohue and Levitt (2001) find that police officers are less likely to arrest members of their own race, which also suggests the potential for a variety of biases, especially against minorities.

Our empirical approach uses variation in the incentives that police departments have to raise revenues to identify and understand the consequences of revenue-driven policing. We are less able to identify when policing is driven by racial animus. Our model, however, does predict that revenue-driven law enforcement will lead to unequal arrest rates across racial groups if the elasticity of revenue with respect to enforcement effort differs systematically across those groups.

White and black drug sellers, for example, do not sell to the same types of customers. White drug sellers are more likely to sell powder cocaine within networks of family, friends, and associates, while black drug sellers are more likely to sell crack cocaine in open-air street markets. Thus, detection costs are higher for whites, since police officers seeking to make arrests can more easily observe street sellers than sellers in private homes. In this case, the marginal cost of making an additional arrest of a black drug seller is lower than an additional arrest of a white drug seller (Beckett, Nyrop, and Pfingst 2006; Tonry 2011), which generates the prediction of higher drug arrest rates for African Americans, even in the context of equal drug use.

Differential effects may arise out of seemingly neutral policies. In Washington State, for example, the party demanding a jury in a civil trial must pay $125 for a six-person jury and $250 for a 12-person jury (Wash. Rev. Code, sec. 36.18.016). Minorities, however, benefit from larger juries because a minority is more likely to be a member of the jury pool if the jury is larger, and this has a significant effect on outcomes

(Anwar, Bayer, and Hjalmarsson 2012). Thus, something as simple as higher fees for larger juries can systematically bias results against minorities. Any factor that increases the costs of due process while reducing the prospects of fines or retaining forfeited property changes the revenue elasticity of arrests. Wealthier arrestees, for example, are more likely to retain private counsel, which corresponds to higher rates of case dismissal and deferred adjudication, lower rates of conviction, and smaller fines paid (Agan, Freedman, and Owens 2017).

The costs of enforcement to the police may also differ because groups have different amounts of power to influence the police in the political marketplace, be it through racial animus, wealth, or institutional history. Suppose, for example, that police officers have the choice to increase drug arrests by targeting either a predominantly African American neighborhood or a neighborhood with considerable student housing near a university campus. Arrests in the university neighborhood are more likely to arouse significant political opposition from taxpayers and university officials fearful of upsetting tuition-paying parents, perhaps more so than arrests in the African American neighborhood. All else equal, police are less likely to focus their attention on groups with countervailing power. Federal judge David Hamilton noted, "For governments under fiscal pressure, the temptation may be strong to raise money with . . . fees on a group unlikely to have political clout" (*Markadonatos v. Village of Woodridge*, 739 F. 3d 984, 1001 [7th Cir. 2014]). Thus, enforcement of violations that are subject to police discretion, such as loitering, vagrancy, or jaywalking, may occur more frequently for African Americans because, on average, members of African American communities may have fewer resources to contest improper policing. For all of the reasons enumerated above, we also investigate whether the consequences of revenue-driven policing differ by race.

3. DATA

Our primary measure of fiscal distress, local budget deficits and outstanding debt, comes from the 2002, 2007, and 2012 Census of Governments.[7] Table 1 summarizes these data at the county level, as well as the county demographic data used in our analysis. These county-level data on fiscal

7. US Census Bureau, Census of Governments, State and Local Government Finance Historical Tables (https://www.census.gov/programs-surveys/cog.html).

Table 1. Summary Statistics: County Budgets and Demographics

	N	Mean	SD	Min	Max
County budgets and rules:					
Deficit, % of revenue	3,774	1.03	8.62	−83.6	77.3
Fine and forfeiture revenue ($1,000s)	2,633	2,167.28	9,693.79	1.0	185,770
Fines and forfeitures per capita	2,633	.02	.02	.0	.4
Fines and forfeitures, % of revenue	2,633	.42	.49	.0	6.5
Police operations ($1,000s)	3,773	17,230.56	60,133.01	10.0	1,152,713
Police operations per capita	3,773	.16	.10	.0	1.7
Police operations, % of total expenditures	3,773	.04	.02	.0	.3
Debt, % of revenue	3,431	62.04	78.96	.0	1,353.6
Demographics:					
White (%)	10,697	89.01	13.70	19.2	99.4
Black (%)	10,697	7.28	12.62	.0	78.8
Hispanic (%)	10,697	5.30	7.80	.1	81.3
Population (1,000s)	10,697	86.73	213.82	.558	3,400.58
Population ages 15–24 (%)	10,697	13.89	4.27	7.87	50.95
Median household income ($1,000s)	10,697	42.95	10.66	20.48	114.20
Unemployment rate (%)	10,697	6.58	2.95	1.1	25.1

Note. Data for county budgets and rules are from Census of Governments (2002, 2007, 2012). A positive number indicates a deficit. Demographic data are from Census Bureau (2000–2012). Unemployment rates are from Bureau of Labor Statistics (2000–2012).

distress are the sum of all budget deficit and debt measures of governments within the geographic area of a county, including municipalities, townships, special district governments, and independent school district governments.

To measure arrests, we use data from the National Incident-Based Reporting System (NIBRS) that cover 31 million arrests from 4,874 police departments, which span 36 states and 1,447 counties, from 2002 to 2012. The NIBRS covers less of the United States than the Federal Bureau of Investigation's (FBI's) Uniform Crime Reports (UCR). However, agencies that report to NIBRS provide more information than they report to the FBI. Table 2 shows the summary statistics for the NIBRS arrest data used in our analysis. We use data from Holcomb, Kovandzic, and Williams (2011) on the percentage of forfeitures that are retained by local law enforcement.

4. EXPLORATORY DATA ANALYSIS

Using the Census of Governments, we collect data on local government fine and forfeiture revenue from 2007 and 2012.[8] Before analyzing whether fiscal stress increases revenue-generating arrests, we establish some basic correlations between fine and forfeiture revenue by county and county racial demographics and between fine and forfeiture revenue and arrests.

Figure 1 includes fines and forfeitures per capita for 189 counties in 2007 and 2012 over the percentage of county population that is black.[9] The binned scatterplots show that fine and forfeiture revenues per capita

8. Unlike overall revenues and expenditures, there are insufficient fine and forfeiture data reported for 2002.

9. The Census of Governments classification manual (US Census Bureau 2000, code U30) requires that revenues reported as fines and forfeits should include "[r]eceipts from penalties imposed for violations of law; civil penalties (e.g., for violating court orders); court fees if levied upon conviction of a crime or violation; court-ordered restitutions to crime victims where government actually collects the monies; and forfeits of deposits held for performance guarantees or against loss or damage (such as forfeited bail and collateral)" and should exclude "[p]enalties relating to tax delinquency . . . library fines . . . and sale of confiscated property." In practice, revenues from confiscated property sales are likely spread across three categories: fines and forfeitures and two separate miscellaneous revenue categories. As such, while reporting governments are told to omit the value of seized property from the fines and forfeitures category, we can confidently assume that fines and forfeitures underestimate a local government's total revenues from law enforcement, which serves the purpose of our exploratory analysis.

Table 2. Summary Statistics: Agencies and Arrests per Year, 2002–12

	Mean	SD	Min	Max
Arrests (N = 37,331):				
Violent crime	6.14	9.72	0	979.59
Black	1.29	5.31	0	551.02
Hispanic	6.33	18.72	0	1,068.87
White	4.67	5.94	0	428.57
Drugs	4.44	11.70	0	857.14
Black	.86	4.17	0	408.16
Hispanic	3.54	20.33	0	1,930.50
White	3.48	9.13	0	800.00
Driving under the influence	4.65	9.22	0	530.61
Black	.31	2.06	0	183.67
Hispanic	7.20	24.54	0	1,526.95
White	4.16	7.70	0	441.44
Prostitution	.03	.33	0	37.93
Black	.01	.11	0	12.56
Hispanic	.04	.69	0	60.22
White	.02	.23	0	25.37
Arrestees:				
Male	518.45	1,593	0	53,009
Black	188.19	1,137	0	43,479
Hispanic	57.65	318	0	13,109
White	495.99	1,226	0	36,238
SeizureRetain$_s$	.89		0	1
Population density (per 1,000 miles^2)	1.11	1.31	<.01	18.37
Law enforcement agency:				
Municipal police	.73		0	1
Sheriff's department	.27		0	1
County police	.0039		0	1
State agency	.0002		0	1
Special police	.0003		0	1
Tribal	.0002		0	1
Regional police	.0002		0	1

Note. The unit of observation is a police jurisdiction in the 36 states (1,447 counties) included in the National Incident-Based Reporting System. Values for arrests are per 1,000 adults in the census. SeizureRetain$_s$ equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise.

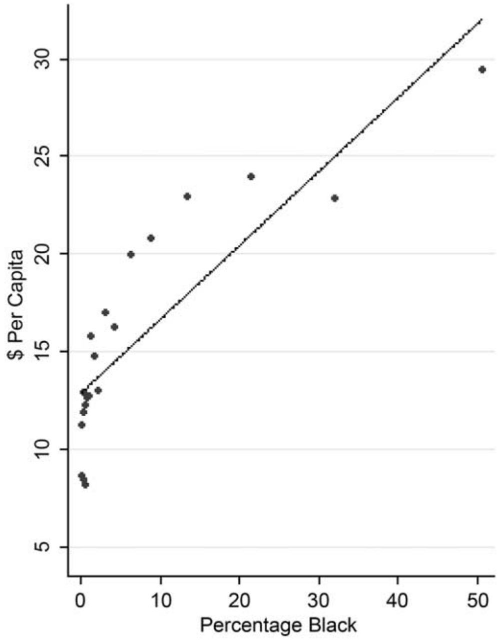

Figure 1. Fines and forfeitures per capita by race

are increasing in the black population and decreasing in the white population in the county.[10] The analysis is consistent with revenue-driven policing but is only correlational. Using a similar sample, Sances and You (2017) show that the relationship between fine and forfeiture revenue and black population is diminished by black representation on city councils.

The relationship between fine and forfeiture revenues and the percentage of the population that is black is likely mediated by arrests. Extending this simple exploratory analysis, we model the relationship between revenues and arrests in a county-year panel:

$$\text{F\&F}_{ct} = \beta_0 + \beta_1 \text{Arrests}_{ct} + \text{County}_c + \text{Year}_t + \varepsilon_{ct}, \tag{1}$$

where $\text{F\&F}_{ct}$ is logged revenue from fines and forfeitures per capita in county c during year t and Arrests_{ct} is a vector of logged arrest rates per

10. Binned scatterplots provide a nonparametric estimate of the conditional expectations function. To generate a binned scatterplot, the x-axis variable is divided into equal-sized bins. The mean of the x-axis and y-axis variable in each bin are then plotted to create a scatterplot along with the regression line using the full population of observations. See Chetty, Friedman, and Rockoff (2014) and Stepner (2013) for more on binned scatterplots.

Table 3. County Fine and Forfeiture Revenue: Drug Arrests by Race

	(1)	(2)	(3)	(4)
Black	.246**			.221**
	(.022)			(.022)
Hispanic		.400**		.269**
		(.072)		(.075)
White			.088**	.049**
			(.011)	(.012)
Constant	1.952**	2.073**	1.906**	1.797**
	(.042)	(.041)	(.049)	(.049)
R^2	.08	.05	.06	.10

Note. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year and county fixed effects. $N = 2{,}623$.
** $p < .01$.

capita by race (black, Hispanic, or white). Each specification includes county and year fixed effects, with standard errors clustered by county.[11]

In Table 3 we model the relationship between $F\&F_{ct}$ and drug arrests. We find that revenues are increasing with drug arrests of blacks, Hispanics, and whites per capita ($p < .01$), although the increase associated with whites is much smaller. When all three arrest rates are included as right-hand-side variables in the model, the same relationships hold.

In Table 4 we model the relationship between $F\&F_{ct}$ and violent-crime arrests. We find that revenues are increasing with violent-crime arrests of blacks, Hispanics, and whites per capita. The observed coefficients are between 30 and 60 percent smaller than those observed with drug arrests, and again the increase associated with arrests of whites is much smaller. When all three violent-crime arrest rates are included as determinants, the same relationships hold. However, when drug arrest rates are included as well, Hispanics' and whites' violent-crime arrest rates drop out of significance and the coefficient on blacks' arrests shrinks by nearly 50 percent.

While the data do not allow the separation of arrest-related revenue from other police actions, such as traffic citations and parking fines, these basic results confirm that fine and forfeiture revenues are increasing in a meaningful way with drug arrests. Increases associated with arrests for violent crimes are much smaller and appear to be largely driven by parallel increases in drug arrests. These results support the assumptions un-

11. The inclusion of county and year fixed effects precludes the inclusion of most standard demographic control variables at the county level.

Table 4. County Fine and Forfeiture Revenue: Violent-Crime Arrests by Race

	(1)	(2)	(3)	(4)	(5)
Violent crime:					
Black	.176**			.166**	.107**
	(.016)			(.016)	(.028)
Hispanic		.163**		.099*	.000
		(.041)		(.042)	(.067)
White			.059**	.035**	.000
			(.010)	(.011)	(.015)
Drugs:					
Black					.099*
					(.039)
Hispanic					.266*
					(.119)
White					.055**
					(.016)
Constant	1.948**	2.087**	1.912**	1.794**	1.756**
	(.042)	(.041)	(.055)	(.055)	(.055)
R^2	.08	.04	.05	.09	.10

Note. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year and county fixed effects. $N = 2{,}623$.
* $p < .05$.
** $p < .01$.

derpinning our model that there exists at least an incentive for revenue-motivated discretion in law enforcement and that these incentives are heterogeneous across arrest types.

5. EMPIRICAL STRATEGY

Our model predicts that policing will be influenced by both the opportunity and incentive to generate revenues. We use variation in state laws governing property seizures to identify the ability to generate revenue through policing. The term SeizureRetain_s is an indicator variable for whether the arrest occurred in a state where the police department is able to retain seized property (and, when relevant, its subsequent auction value).[12] Arrests in the 31 states where local police can retain forfeited property account for 89 percent of our sample. See Appendix Table A1 for the value of SeizureRetain_s for each state.

12. There is some variation in the percentage the department retains. Twenty-nine states allow for greater than 75 percent retention of seized property by local police. Two states, Colorado and Wisconsin, allow for departments to retain 50 percent of the value.

Table 5. County Characteristics by Seizure Laws and Budget Deficits

	Seizure Laws		Deficit	
	No Retention	Retention	Low	High
Black (%)	5.556	8.431	8.224	9.441
	(7.741)	(12.709)	(13.638)	(12.918)
Hispanic (%)	1.985	5.477	5.161	5.268
	(1.669)	(6.876)	(6.901)	(6.628)
Incidents reported per capita	.045	.056	.055	.057
	(.037)	(.073)	(.109)	(.072)
Unemployment	6.863	6.819	6.674	6.634
	(2.803)	(2.863)	(3.041)	(2.687)
Log population	11.203	10.997	10.208	11.265
	(1.492)	(1.576)	(1.383)	(1.623)
Log median household income	10.691	10.676	10.656	10.691
	(.162)	(.256)	(.251)	(.253)
N	3,984	33,347	3,728	9,339

Note. Deficits are characterized as low if they are below the 25th percentile in the sample and high if above the 75th percentile. Black, Hispanic, unemployment, log population, and log median income are county-level measures. Incidents reported is estimated at the police jurisdiction (originating agency identifier) level.

A naïve strategy might compare policing in states with and without strong seizure retention laws. But, as Table 5 shows, seizure retention laws are not randomly assigned. Thus, a more careful approach is required to better isolate causal effects.

In addition to opportunity, revenue-driven policing is motivated by incentives. As the example of Ferguson, Missouri, illustrates, police departments face greater pressure from their superiors and elected officials to increase revenues when the budget situation is tight. When a local government is in fiscal distress, our model predicts an increase in arrests for offenses that carry fines or the opportunity to forfeit assets. Table 5 shows that, in comparison with seizure retention laws, deficits are considerably more randomly distributed with respect to county characteristics.

The relationship between deficits and arrests, however, may be difficult to disentangle because of reverse causality: in addition to increasing the demand for arrests, deficits may cause a reduction in police resources, which works to reduce arrests. To test for the presence of revenue-driven policing, therefore, we do not analyze seizure retention laws or deficits directly. Instead, we interact deficits with SeizureRetain. Our main test is whether deficits exert a bigger influence on arrests in states where police departments retain a large share of fines (SeizureRetain equals one). If deficits increase arrests more in places where the police can more easily retain a greater share of fines, this suggests revenue-driven policing. Note that our strategy does not require that SeizureRetain_s be randomly assigned, nor does it require an absence of reverse causality from deficits to arrest—our strategy requires only that deficits are random with respect to SeizureRetain_s.

Thus, we test our hypothesis that fiscal conditions encourage revenue-driven arrests rates by estimating

$$\begin{aligned} \text{Arrests}_{jcst} = {} & \beta_0 + \beta_1 \text{SeizureRetain}_s + \beta_2 \text{Deficit}_{cst} \\ & + \beta_3 \text{SeizureRetain}_s \times \text{Deficit}_{cst} + \beta_4 \boldsymbol{X}_{jcst} \\ & + \text{State}_s + \text{Year}_t + \varepsilon_{jcst}, \end{aligned} \tag{2}$$

where Arrests_{jcst}, depending on the specification, indicates one of the following types of arrests: drug-related crimes, driving under the influence (DUI), prostitution, and violent crimes. The term Arrests_{jcst} also include property seizures, including seizures of currency, automobiles, or other nonnarcotic items. We measure all arrest variables per 1,000 residents in police jurisdiction j in county c, in state s, in year t. We calculate separate measures of arrests and seizures for black, Hispanic, and white arrestees. Note that Deficit_{cst} measures the county's aggregate local government deficit as a percentage of its aggregate current expenditures. For counties with budget surpluses, Deficit_{ct} has negative values.

In some model specifications, we add a vector of control variables, $\boldsymbol{X}_{jcst}$. Control variables include county-level measures of aggregated outstanding local government debt; the unemployment rate; the percentages of the population that self-identifies as black, Hispanic, or white in the census; the percentage of the population between the ages of 15 and 24; logged county population; and logged median household income.[13] At the police jurisdiction level, we include as control variables the population per square mile of the jurisdiction.

All models include year fixed effects, and some models include state fixed effects. However, SeizureRetain_s does not vary within a state in our sample period. Thus, when we include state fixed effects, we do not in-

13. Demographic controls are from the US Census Bureau. Unemployment data are from the Bureau of Labor Statistics. Demographic and deficit data between censuses are carried forward between census years. Results are similar when we include only Census of Governments years (2002, 2007, and 2012) in the sample of analysis.

clude SeizureRetain$_s$ but only the aforementioned interaction term. In all model specifications, we cluster errors at the county level.

We also include indicator variables for the different types of law enforcement agencies that may operate in a jurisdiction, most notably sheriffs and municipal police. Municipal police chiefs are usually appointed. Sheriffs are often elected, although some municipalities also contract police services to sheriffs, blurring the distinction between sheriffs and appointed police chiefs.[14]

6. RESULTS

6.1. Revenue Retention and Nonviolent Crimes

Table 6 presents regression results from our core model of log drug arrests per capita with the main variables of interest: seizure retention laws, deficits, and the interaction of the two. Some specifications include state fixed effects, while all include indicators for local police department type and year fixed effects.

The stand-alone seizure retention indicator for drug arrests is positive and significant ($p < .01$), while the coefficient on SeizureRetain$_s$ $\times$ Deficit$_{cst}$ is not. When state fixed effects are included in the model, however, our stand-alone indicator for SeizureRetain is perfectly collinear with these fixed effects and drops out, and the estimate on the interaction term is small and statistically insignificant.

While the coefficient on Seizure$_s$ is positive and statistically significant for arrests of blacks, Hispanics, and whites when state fixed effects are excluded, the coefficient on SeizureRetain$_s$ $\times$ Deficit$_{cst}$ is positive only for blacks' and Hispanics' arrests ($p < .05$). Further, only the coefficient on blacks' drug arrests is positive and significant when state fixed effects are included ($p < .01$).[15]

In Table 7 we add the vector of control variables while retaining year and state fixed effects. These regressions constitute our full specifications and are mirrored in all subsequent tables. The coefficient on SeizureRetain$_s$ $\times$ Deficit$_{cst}$ remains statistically significant for drug arrests for blacks ($p <$

14. We investigated whether our results are moderated by whether a municipality employs a chief of police or a sheriff but did not find statistically significant effects.

15. Using a seemingly unrelated estimation comparison of the specifications, we find that the difference in coefficients on SeizureRetain$_s$ $\times$ Deficit$_{cst}$ for arrest rates of blacks and whites is statistically significant ($p < .05$).

Table 6. Drug Arrests by Jurisdiction and Year: Annual Data for 2002–12

	All		Black		Hispanic		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SeizureRetain$_s$	.437**		.378**		.625**		.377**	
	(.079)		(.090)		(.086)		(.074)	
Deficit	−.537	.066	−1.591**	−1.361**	−2.659**	−.986$^+$	−.543	.139
	(.592)	(.620)	(.467)	(.428)	(.674)	(.549)	(.571)	(.590)
SeizureRetain$_s$ × Deficit	.417	.086	1.404*	1.437**	1.650*	.655	.373	−.020
	(.658)	(.642)	(.592)	(.466)	(.748)	(.584)	(.634)	(.614)
Constant	−.016	.100**	−1.824**	−1.756**	−2.588**	−2.279**	−.141$^+$	−.066$^+$
	(.079)	(.036)	(.084)	(.032)	(.084)	(.031)	(.075)	(.036)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	.09	.28	.11	.44	.14	.34	.08	.25

Note. Arrests are per 1,000 adults in the census. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year and agency fixed effects. SeizureRetain$_s$ equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise. $N = 37{,}331$.

$^+$ $p < .10$.

* $p < .05$.

** $p < .01$.

Table 7. Drug Arrests by Jurisdiction and Year, with State Fixed Effects: Annual Data for 2002–12

	All	Black	Hispanic	White
Deficit	−.087	−1.240**	−.840*	−.140
	(.609)	(.414)	(.423)	(.604)
$\text{SeizureRetain}_s \times$ Deficit	.033	1.287**	.988*	.141
	(.636)	(.457)	(.449)	(.627)
Debt	.056*	.039+	.063**	.067**
	(.026)	(.021)	(.018)	(.026)
Density	.038*	.039+	−.067*	.003
	(.016)	(.020)	(.027)	(.015)
Unemployment	.005	−.036**	−.007	.007
	(.009)	(.009)	(.007)	(.009)
% Age 15–24	−.050	−.876*	−1.335**	−.202
	(.417)	(.415)	(.397)	(.402)
Log median household income	−.057	.062	−.154	−.133
	(.115)	(.121)	(.102)	(.113)
Black (%)	.003	.030**	−.007*	−.005
	(.004)	(.004)	(.003)	(.004)
Hispanic (%)	−.000	.000	.046**	.001
	(.004)	(.003)	(.003)	(.004)
White (%)	.005	−.005	−.002	.014**
	(.004)	(.003)	(.002)	(.003)
Log population	.099**	−.117**	−.259**	.125**
	(.020)	(.023)	(.018)	(.020)
Constant	−.813	−.705	2.245*	−1.215
	(1.189)*	(1.216)	(1.022)	(1.153)
R^2	.30	.49	.44	.28

Note. Arrests are per 1,000 adults in the census. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year and agency fixed effects. SeizureRetain_s equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise. $N = 33{,}499$.

$^{+}$ $p < .10$.

* $p < .05$.

** $p < .01$.

.01) and Hispanics ($p < .05$). None of the coefficients on county deficits and their interactions with SeizureRetain_s are statistically significant for drug arrests of whites, and their magnitudes remain comparatively much smaller. Drug arrests of whites are insensitive to property seizure laws and fiscal distress.

Considered together, Tables 6 and 7 indicate that drug arrests increase in counties where local governments are running deficits but only in states that allow police departments to retain seizure revenues. These increases, however, are observed only for drug arrests of blacks and Hispanics; drug arrests of whites remain unchanged.

Table 8. Driving under the Influence and Prostitution Arrests by Jurisdiction and Year: Annual Data for 2002–12

	Black	Hispanic	White
Driving under the influence:			
Deficit	−1.593**	−1.351**	−.776
	(.410)	(.439)	(.765)
SeizureRetain$_s$ × Deficit	1.546**	1.372**	.660
	(.445)	(.471)	(.775)
Prostitution:			
Deficit	−1.169**	−1.124**	−1.192**
	(.392)	(.387)	(.403)
SeizureRetain$_s$ × Deficit	1.066*	.984*	1.158**
	(.422)	(.420)	(.435)

Note. Arrests are per 1,000 adults in the census. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year, state, and agency fixed effects. Controls for county debt, population density, unemployment, percentage of the population between the ages of 15 and 24, log median household income, log county population, and the percentages of black, Hispanic, and white adults in the census are not included. SeizureRetain$_s$ equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise. $N = 33{,}499$.
* $p < .05$.
** $p < .01$.

In Table 8, DUI and prostitution arrest[16] rates are modeled as in Table 7. We observe that DUI arrest rates for both blacks and Hispanics are increasing with deficits and seizure laws ($p < .01$), while DUI arrests for whites are not. Similarly, the coefficients on SeizureRetain$_s$ × Deficit$_{cst}$ for prostitution arrests are positive and statistically significant. It is notable, however, that for drug and DUI arrests, the observed statistically significant increases are not limited to prostitution arrest rates for blacks and Hispanics but include prostitution arrest rates for whites as well.

We similarly model the determinants of property seizures from arrests by property type and the race and ethnicity of the arrestee. In Table 9, we report that the seizure of nonnarcotic property from black and Hispanic

16. Arrests for driving under the influence and prostitution often involves fees, fines, and forfeitures. In Chicago, for example, a drunk driver whose car is impounded must pay a towing fee, a daily storage fee, and an administrative fee of $2,000 to retrieve the car from the city lot (Goldman & Associates, Retrieving a Car Impounded after a DUI Arrest [https://www.criminallawyer-chicago.com/practice-areas/chicago-dui-lawyers/retrieving-car-impounded-dui-arrest/]; Ciaramella 2018). Automobiles of johns can also be impounded when men are charged with soliciting a prostitute, and 41 states allow for asset forfeiture of assets involved in commercial sex offenses (Brown 2015).

Table 9. Seizures by Jurisdiction and Year: Annual Data for 2002–12

	Black	Hispanic	White
All nondrug property:			
Deficit	−1.267**	−.977**	−.688
	(.352)	(.374)	(.432)
$\text{SeizureRetain}_s \times$ Deficit	1.061**	.922*	.491
	(.405)	(.404)	(.480)
Cash:			
Deficit	−1.242**	−1.063**	−.921**
	(.339)	(.377)	(.311)
$\text{SeizureRetain}_s \times$ Deficit	1.000*	.943*	$.691^{+}$
	(.394)	(.408)	(.359)
Automobiles:			
Deficit	−1.075**	−1.145**	−.949*
	(.386)	(.385)	(.380)
$\text{SeizureRetain}_s \times$ Deficit	.952*	1.060*	$.809^{+}$
	(.421)	(.418)	(.416)

Note. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year, state, and agency fixed effects. Controls for county debt, population density, unemployment, percentage of the population between the ages of 15 and 24, log median household income, log county population, and the percentages of black, Hispanic, and white adults in the census are not included. SeizureRetain_s equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise. $N = 33{,}499$.

$^{+}$ $p < .1$.

* $p < .05$.

** $p < .01$.

arrestees increases with the size of the deficit in states where police departments can retain revenue from seized property. The comparable coefficient for property seizures from white arrestees is positive but smaller and not statistically significant. When we separately model seizures of currency and automobiles, the coefficients on $\text{SeizureRetain}_s \times \text{Deficit}_{cst}$ remain of similar size for black and Hispanic arrestees, while increasing in size for seizures of cash ($p < .05$) and automobiles ($p < .10$) from white arrestees.

6.2. Revenue Retention and Violent Crimes

We hypothesize that violent crimes are less likely to generate increases in fine and forfeiture revenue, since the penalties for those crimes are typically jail and prison sentences. This prediction is supported by our exploratory analysis of county fine and forfeiture revenue (column 5 of Table 4).

Table 10. Violent-Crime Arrests by Jurisdiction and Year: Annual Data for 2002–12

	Black			Hispanic			White		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SeizureRetain_s	.217**	.084*		.553**	.307**		.309**	.141**	
	(.061)	(.037)		(.057)	(.023)		(.060)	(.042)	
Deficit	−.546	.106	.022	−1.616**	−.552**	−.355*	.521	.666	.271
	(.462)	(.278)	(.279)	(.453)	(.177)	(.171)	(.588)	(.458)	(.411)
$\text{SeizureRetain}_s \times$ Deficit	.456	−.218	−.032	1.411**	.398+	.373+	−.908	−1.045*	−.421
	(.594)	(.323)	(.296)	(.531)	(.221)	(.195)	(.635)	(.477)	(.425)
Same-race drug arrests		.697**	.667**		.742**	.720**		.511**	.512**
		(.016)	(.013)		(.012)	(.012)		(.011)	(.011)
State fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
R^2	.44	.73	.74	.43	.76	.77	.12	.46	.50

Note. Arrests are per 1,000 adults in the census. Robust standard errors, clustered at the county level, are in parentheses. All regressions include year and agency fixed effects. Controls for county debt, population density, unemployment, percentage of the population between the ages of 15 and 24, log median household income, log county population, and the percentages of black, Hispanic, and white adults in the census are not included. SeizureRetain_s equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise. $N = 33{,}499$.

$^{+}$ $p < .10$.

* $p < .05$.

** $p < .01$.

To serve, in part, as a comparison for our observed sensitivity of drug, DUI, and prostitution arrests to revenue incentives, we regress violent crime arrests on the identical ordinary least squares model specification (Table 10). Somewhat surprisingly, we still observe a positive coefficient on SeizureRetain_s for all three racial arrest categories. We suspect that most of this is due to an inability to fully separate our drug crime arrests from arrests for violent crimes; that is, many violent crimes occur in the pursuit of drugs and drug profits. We found preliminary evidence for this interpretation in our analysis of fine and forfeiture revenue (column 4 in Table 4), and we find further support for this interpretation in our modeling of violent-crime arrest rates. When we include the same-race drug arrest rates as control variables (columns 2, 5, and 8 in Table 10), the coefficients on SeizureRetain_s drop by roughly 50 percent for black, Hispanic, and white arrest rates. More broadly, when drug arrests and state fixed effects are included, the coefficient on $\text{SeizureRetain}_s \times \text{Deficit}_{cst}$ is not significant for violent-crime arrest rates for either blacks or whites. The estimated coefficient on $\text{SeizureRetain}_s \times \text{Deficit}_{cst}$ remains positive for violent-crime arrests of Hispanics, although the magnitude shrinks considerably and is only marginally significant ($p < .10$). Blacks' violent-crime arrests (column 3 of Table 10) are insensitive to both the deficit and its interaction with seizure laws in comparison with the effects we observe for blacks' drug, DUI, and prostitution arrests.

7. DISCUSSION AND CONCLUSION

In contrast to the optimal deterrence model of law enforcement, we hypothesize and test a model of revenue-driven law enforcement. We find evidence that lends support to this model. In particular, we find increases in the arrest rates of African Americans and Hispanics for drugs, DUI violations, and prostitution during periods of fiscal distress. Comparable effects for whites' arrests are observed only for prostitution. These increases in arrests occur when institutional conditions allow for the retention of revenue from seized property by police departments. The salience of those incentives is further corroborated by similarly observed increases in cash and automobile seizures. Our results serve as evidence that optimal deterrence is not the sole criteria for arrests and that police officers' behavior is influenced by local fiscal conditions. At the same time, our results also raise a number of questions that we hope will motivate future research.

Our identification assumption is that the incentives for revenue-driven policing increase with local deficits when seized revenues can be retained. We should not assume, however, that the conditions we use for identification are the only conditions under which revenue considerations influence policing. Given the limitations of our data and analysis, we identify revenue-driven policing only at the margin, not the total effect. Our measure of deficits, while allowing for comparisons across a national sample, is more aggregated than is ideal, particularly for future research into the explicit personnel economics of policing. Future microdata and event studies that focus on particular police agencies would likely prove fruitful in this regard. Overlapping jurisdictions monitored by separate agencies, falling under different budgets, could provide an opportunity for a superior identification strategy and model of incentives facing individual officers.

The distinction between victim-reported and victimless crimes is often normatively discussed, but placed in the broader context of fiscal and political implications, this distinction offers the possibility of decidedly different incentive structures for law enforcement. What, if anything, serves as oversight for over- or underpolicing of victimless crimes remains an open question. How police choose to exercise their discretion when the number of crimes far exceeds the number of arrests will prove to be an important question for future research.

Without denying the importance of racial bias, our paper also draws attention to how seemingly racially neutral institutional differences can, when combined with revenue-driven policing, generate racially nonneutral outcomes. While our model is agnostic as to the source of differentials in revenue generation, potential explanations include underlying racial animus, differences in the structure of crimes committed by race (for example, indoor versus outdoor drug sales), rates of guilty pleas, sentence bargaining, charge reductions, reliance on public defenders, and the economic and racial determinants of successfully challenging charges at trial. Our results raise questions about the welfare implications of allowing police to generate their own revenues and the broader wisdom of non-revenue-neutral law enforcement. The prospects for justice are dimmed when the probability that an individual is arrested varies not only by the character of his or her transgression but also by the potential windfall he or she presents to the public coffer.

APPENDIX: LOCAL RETENTION OF SEIZED PROPERTY BY STATE

Table A1. Laws Governing Property Seizures

State	SeizureRetain_s	State	SeizureRetain_s
Alabama	1	Montana	1
Alaska	1	Nebraska	1
Arizona	1	Nevada	1
Arkansas	1	New Hampshire	1
California	1	New Jersey	1
Colorado	1	New Mexico	1
Connecticut	1	New York	1
Delaware	1	North Carolina	0
Florida	1	North Dakota	0
Georgia	1	Ohio	0
Hawaii	1	Oklahoma	1
Idaho	1	Oregon	1
Illinois	1	Pennsylvania	1
Indiana	0	Rhode Island	1
Iowa	1	South Carolina	1
Kansas	1	South Dakota	1
Kentucky	1	Tennessee	1
Louisiana	1	Texas	1
Maine	0	Utah	1
Maryland	0	Vermont	0
Massachusetts	1	Virginia	1
Michigan	1	Washington	1
Minnesota	1	West Virginia	1
Mississippi	1	Wisconsin	1
Missouri	0	Wyoming	1

Note. SeizureRetain_s equals one in states where police departments retain greater than half of the proceeds from seized property and zero otherwise.

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