

ABSTRACT

Title of thesis: COUNTY EFFECTS ON WHITE-COLLAR
SENTENCING IN MARYLAND CIRCUIT COURTS

Justin Pascal Bernstein, Master of Arts, 2015

Thesis directed by: Professor Sally S. Simpson
Department of Criminology and Criminal Justice

Research on local contexts has been a major development within sentencing literature in recent years. White-collar sentencing, however, is an area that has not received much attention from local contexts research. The current study addresses that gap, estimating geographical effects on sentencing outcomes for a group of white-collar offenders in Maryland's circuit courts using data from the Maryland State Commission on Criminal Sentencing Policy. The results show, consistent with local contexts research focused on conventional offenders, that the jurisdiction sentencing a white-collar defendant affects outcomes after controlling for a variety of individual-level case characteristics. The county effects this study finds, however, are not entirely consistent with what the local contexts of sentencing literature would predict for general offender sentencing. These findings, though limited, suggest that somewhat different dynamics may apply in the white-collar sentencing context, highlighting the need for further research in this area.

COUNTY EFFECTS ON WHITE-COLLAR SENTENCING IN MARYLAND
CIRCUIT COURTS

by

Justin Pascal Bernstein

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Master of Arts
2015

Advisory Committee:

Professor Sally S. Simpson, Chair
Professor Brian D. Johnson
Professor Raymond Paternoster

©Copyright by

Justin Pascal Bernstein

2015

Table of Contents

Chapter 1: Introduction	1
Chapter 2: Literature Review	10
Chapter 3: Data	28
a. The Maryland Sentencing Guidelines Database	28
b. White-Collar Crime in the Maryland Sentencing Guidelines Database.	31
c. Geographical Variables.....	39
d. Dependent Variables.....	43
e. Control Variables.....	46
f. Analytic Strategy	50
Chapter 4: Results and Discussion.....	52
a. Placement.....	52
b. Departures	57
c. ABA Pleas.....	59
d. Summary and Conclusion	61
Conclusion	65
Tables and Figure.....	68
Appendices.....	83
Appendix I: Maryland Sentencing Guidelines Offense Table Excerpt.....	84
Appendix II: Robustness Checks.....	87
Appendix III: Other Modeling Approaches for Departures and Disposition	90
References.....	92

List of Tables and Figure

Table 1a: Distribution of Cases by County (and Region) and Offense Type.....	69
Table 1b: Distribution of Outcomes by County (and Region).....	70
Table 2: Descriptive Statistics.....	71
Table 3a: Logistic Regression of Any Incarceration.....	73
Table 3b: Varying the Reference Category in Model 5 of Table 3a.....	74
Table 4a: Logistic Regression of Incarceration After Sentencing.....	75
Table 4b: Varying the Reference Category in Model 5 of Table 4a.....	76
Table 5a: Logistic Regression of Downward Departures.....	77
Table 5b: Varying the Reference Category in Model 5 of Table 5a.....	78
Table 6a: Logistic Regression of ABA Pleas, Relative to Non-ABA Pleas.....	79
Table 6b: Varying the Reference Category in Model 4 of Table 6a.....	80
Table 7: Summary of Results.....	81
Figure 1: Mean Predicted Probabilities for Each Outcome.....	82

CHAPTER 1: INTRODUCTION

Real and perceived differences in criminal justice outcomes unrelated to case merits were an animating concern underlying the modern sentencing reform movement beginning in the 1970s (*see, e.g.*, Frankel, 1972). These included disparities based on the defendants' social status characteristics, as well as idiosyncratic differences between judges or courts.

A group of seminal studies during the early years of the sentencing reform era focused on differences relating to social status and white-collar sentencing. At that time data from those studies were among the few quantitative sources on prereform sentencing practices. These data were powerful and influential, as large sentencing datasets, though now commonplace, generally did not exist before the establishment of the sentencing commissions collecting them. At least in part because of this, the data have played a role in sentencing research more broadly, not merely with respect to white-collar crime. The traditional and widespread understanding of sentencing as a two-stage process involving distinct placement and length decisions, for example, derives from the early white-collar sentencing literature (*see* Bushway, Johnson, & Slocum, 2007: 166-167 & n.24; Johnson, 2006: 273-274).

As with much of the sentencing reform movement, an emphasis on disparities characterizes a lot of this early white-collar sentencing research. But while concerns regarding race-, ethnicity-, and gender-based disparities have largely dominated most general sentencing literature, this early research on white-collar sentencing tended to explore differential treatment based on white-collar status (Hagan, Nagel, & Albonetti, 1980; Wheeler, Weisburd, & Bode, 1982), along with the effect of political scandal (e.g.,

Watergate) on sentencing outcomes (*see* Benson & Walker, 1988; Wheeler, Weisburd, & Bode, 1982).

Studies reached conflicting results concerning white-collar status effects (*see* Simpson, 2013). A relatively consistent finding from this research though was that place mattered. Sentencing outcomes prior to the Federal Sentencing Guidelines varied for white-collar offenders sentenced in different districts across the federal judicial system for violating the same laws.

Compared to race, a patently unwarranted basis for any differences in outcomes, differences associated with geography are more nuanced. Where a crime occurs (or a court sits) is arguably as irrelevant and arbitrary a basis for differences in case processing as is skin color. But reasonable people might disagree, as location-based differences among otherwise similarly situated cases arguably reflect legitimately differing priorities, values, politics, and resources inherent in systems with high degrees of local control. As Ulmer and Johnson (2004: 137) state:

If the sentence one receives and the grounds for that sentence depend on location, then the notions of equal justice that underlie most Western legal systems may be undermined. On the other hand, local autonomy and decentralized government are also valued features of American democratic philosophy, and are certainly central features of American criminal justice
.....

While local autonomy characterizes much of the criminal justice system, geographical variation is ultimately problematic. We do not, generally speaking, devolve criminal legislative powers to local authorities. Geographical variation in sentencing outcomes has this effect though, and does not provide the benefit of notice through positive law. Although geographical variation raises troubling equal justice issues,

subsequent white-collar sentencing research has not paid much attention to the role of place.

Pre-Guidelines white-collar sentencing research concerning geographical disparities represents a precursor to the appreciation of the importance of and focus on macro-level social contexts that has become a major development within contemporary sentencing research. Described by a leading sentencing scholar as “perhaps one of the most prominent developments in sentencing theory and research” of the early 21st century, research on social contexts shows that “local variation permeates many aspects of sentencing” (Ulmer, 2012: 13, 14). Although individual case level factors generally explain most of the variation in sentencing (*e.g.*, Ulmer & Johnson, 2004: 165-166), contextual research “suggests that various elements of the courtroom social context matter” (Johnson, 2005: 763). Going beyond the finding that sentencing outcomes vary by locale, research on local contexts demonstrates that not only “what kind of sentence one gets” but also “the factors that predict why one gets it, in significant part depends on where one is sentenced” (Ulmer, 2012: 14 (emphasis omitted)).

A “burst” of studies on local context occurred in the 2000s (Ulmer, 2012: 13). These studies have investigated a wide variety of outcomes, predictors, and crime types in different jurisdictions. White-collar sentencing, however, is an area that has received less attention from local context researchers.¹

¹ White-collar crime in general remains relatively less studied and understood compared to many areas within the criminological mainstream; Simpson (2013: 310) asserts “white-collar crime may be the least understood but most consequential crime type.”

General sentencing studies often do not separate white-collar offenders out from the far more numerous conventional offenders (and when they do the researchers typically focus on the latter). Research suggests that additional factors or concerns not present in sentencing of conventional criminals might come into play with white-collar sentencing. The special sensitivity hypothesis, for example, posits that white-collar defendants' privileged backgrounds make them especially ill-suited for incarceration. Incarceration may be particularly iatrogenic for these offenders, and seen as less appropriate. Though this proposition might not be true empirically (*see* Stadler, Benson, & Cullen, 2013), if judges believe it they may sentence accordingly. We should therefore exercise caution when assuming that general-sentencing findings necessarily apply fully to white-collar sentencing as well (though neither should one automatically assume that general-sentencing findings are entirely inapposite).

The relatively fewer white-collar crimes in official data quickly become overshadowed in analyses of large datasets.² Although obtaining reliable estimates of white-collar crime's incidence and prevalence is even more challenging than is the case with conventional crime, we do know that white-collar crime is "extensive" (Simpson, 2011: 482-485). Estimates vary, partially as a function of how one defines white-collar crime (discussed below) and methodology. But a recent survey conducted by the Federal Trade Commission (Anderson, 2013) estimates that approximately 25.6 million people were victims in approximately 37.8 million incidents of consumer fraud (which is within

² Low numbers do not necessarily imply infrequency or inconsequentiality. Rather they at least arguably reflect criminal justice actors' "enduring focus" on conventional crime. (*See* Huff, Desilets, and Kane, 2010: 13.)

the Federal Bureau of Investigation’s white-collar crime definition, *see* Barnett, n.d. [2000]) in the United States in 2011.

Despite the small volume of white-collar criminals in most datasets, their harms are likely disproportionate to their numbers. White-collar crime is costly. Estimates again vary, widely, but the total estimated cost of fraud alone—merely one type of white-collar crime—runs into the billions. *See, e.g.*, Deevy and Beals, 2013; Federal Bureau of Investigation, 1989. White-collar crime also inflicts psychological harms, such as depressive episodes and anxiety disorders, (*see* Deevy, Lucich, & Beals, 2012; Ganzini, McFarland, & Bloom, 1990), or feelings of self-blame and complicity, not necessarily present in the conventional property crimes into which researchers frequently fold most white-collar crime. And unlike most crime types, white-collar crime, and a perceived historical leniency towards it (*see* Apuzzo & Protes, 2015), threatens to undermine confidence in the integrity of our economic, legal, and social institutions (*see* Benson & Walker, 1988: 301; Sutherland, 1983 [1949]: 10; *cf.* Owens, 2012: 161 (“[E]conomic contractions that correspond to major scandals in the financial sector are what motivate the largest declines in confidence.”)).

The current study seeks to begin to rejoin the white-collar sentencing and the local contexts of sentencing lines of research by analyzing county³ effects in the sentencing of those convicted of select white-collar crimes in Maryland’s circuit courts.

³ Maryland’s 24 jurisdictions consist of its 23 counties and the City of Baltimore. Baltimore City, as an independent city, has many legal attributes of a county, including its own circuit court and State’s Attorney. For convenience, when referring to Maryland this study uses the words jurisdiction and county interchangeably, both to include Baltimore City.

An existing body of research has demonstrated jurisdictional, i.e. geographical, disparities in the application of the (since-repealed) death penalty in Maryland (*e.g.*, Paternoster et al., 2003; 2004). The current study assesses whether and how place matters in sentencing for one group of crimes in Maryland typically lacking the degree of media exposure, political pressures, and ideological overtones⁴ frequently accompanying the intrinsically extreme case of capital crime, which the existing literature has not prominently featured, and concerning which many traditional criminological theories have little to say. Data limitations, however, preclude a full contextual analysis. The data used (described below) contain few of the higher level observations needed for the multilevel models typically used in these types of analyses and also suffer from relatively few individual observations overall.

While much of the existing research on white-collar sentencing has examined offenders pursued in federal legal settings (*e.g.*, the studies mentioned above; *cf.* Simpson & Yeager, 2015), the current study deliberately relies instead on state sentencing data. Nagel and Hagan (1982: 1440) might very well have been correct that in 1982 “the vast majority of white-collar cases prosecuted and brought to the sentencing stage proceed through the federal district courts,” but they do not cite research or data to support this proposition. Given that state and local criminal justice systems are collectively far larger

⁴ This is, of course, not to suggest that no white-collar crime possesses these qualities. Scandals such as those involving manipulation of foreign exchange markets and benchmark interest rates, resulting in guilty pleas to felonies by several global banks and billions of dollars in fines, certainly make the news (*see* Chon, 2015; Department of Justice, 2015). This study, however, is concerned with more run-of-the-mill white-collar crimes, which may be individually less harmful but more common.

than the federal system (*see, e.g.*, Richman, 2013: 53) the above statement's accuracy is not self-evident, at least in 2015.

Variation across federal district courts is also arguably less interesting than local differences within a state for at least two reasons. Social context research demonstrates that local conditions matter for sentencing, but most federal judicial districts are not particularly local. Most states, including Maryland, have only one federal district covering the entire state. No state has more than four. Even in states with four, the relatively large districts likely mask great heterogeneity (*cf.* Johnson, Ulmer, & Kramer, 2008: 768). The Southern District of New York, for example, combines Wall Street with the South Bronx as part of the same local context. It includes both the highly urban, densely populated, majority of the population racial or ethnic minority, wealthy, and cosmopolitan New York County (Manhattan) with the far more rural, sparsely populated, less wealthy, more politically conservative, and whiter Sullivan County as a single court community. State data from different counties will not eliminate this forced combination of disparate areas entirely, but almost inherently involve smaller geographical units that we can more meaningfully conceptualize as local communities with relevant shared social contexts.

Conflict arises between competing values of equal justice and local control if and when similarly situated defendants receive markedly different sentences for no apparent reason, other than that they happen to be in different locations operating within the same legal regime.⁵ A second reason geographical variation in the federal system is arguably

⁵ Generally enacted at the state level, criminal laws are relatively uniform throughout a state. *See, e.g.*, Criminal Law Article, Annotated Code of Maryland. The same is true within the federal system, *cf.*

less interesting than within states is that the countervailing interest in local control is less salient in the federal criminal justice system. The federal court system, by design, features little local control. As Presidential appointees, United States Attorneys and federal judges neither represent nor are accountable to local communities. How we decide to balance the competing values of equal justice and local control, or otherwise resolve their tension, is ultimately a normative issue (and far beyond the scope of this study). But normative arguments for local control that might justify geographical variation in sentencing outcomes within state courts arguably become far less compelling for the federal courts in the face of equal justice concerns.

We know very little about geographical variation, and even less about local-level geographical effects, in white-collar sentencing. Geographical effects in sentencing undermine equal justice, and to the extent they differ depending on the type of offenders (e.g., white-collar), this raises yet an additional level of concerns. This study addresses

Johnson, Ulmer, and Kramer, 2008: 739 (“Because the federal criminal justice system represents a unified, national system, one might expect punishments to be relatively consistent across districts, especially given organizational pressures for uniformity.”). Interstate (and state-federal) variation in criminal laws and court procedures complicate analysis of jurisdictional variation. Even if perhaps unfair that identical offenders might receive very different sentences for identical actions in different states, few would suggest that such differences are illegitimate, except where they implicate concerns under the Constitution of the United States. But differing definitions, legal requirements, sentencing guidelines formulae, and penalty structures – such as statutory maximum and mandatory minimum penalties or the availability of intermediate sanctions – across legal systems limit the validity and relevance of comparisons between states, even if one assumes their offender populations, courtroom workgroups, and environmental constraints are otherwise comparable (itself often a strong assumption).

whether and the extent to which the county-level differences previous research finds concerning the death penalty in Maryland reflects a wider and more broadly applicable phenomenon, as suggested by a broader local contexts of sentencing literature that has yet to devote much attention to white-collar crime, or might be related to the unusual attributes of death penalty cases. This will increase understanding not only of white-collar crime, but also of sentencing practices (in Maryland) more broadly.

CHAPTER 2: LITERATURE REVIEW

Social contexts of sentencing research has flourished in the early twenty-first century, but the court community perspective laid the initial theoretical groundwork for these studies in the late 1970s (*see* Eisenstein & Jacob, 1977). Eisenstein and Jacob assert that court actors “operate in a common task environment, which provides common resources and imposes common constraints on their actions” (1977:10). Common goals motivate court actors sharing their task environment, who develop relationships “cemented by exchanges of inducements” (Eisenstein & Jacob, 1977: 10).

The nature of the relationships between court actors (collectively the courtroom workgroup) shape court outcomes. The court community perspective places particular emphasis on the stability and familiarity of relationships in the courtroom workgroup. Those relationships are subject to organizational and environmental (the latter including other criminal justice actors, the media, and the larger political climate) incentives and pressures (*see* Eisenstein & Jacob, 1977).

While a formal rationalist (*see* Savelsberg, 1992) or legal formalist might be surprised to learn of geographical effects on sentencing outcomes, the court community perspective “predicts significant interjurisdictional variation in sentencing” (Ulmer & Johnson, 2004: 140). Where relationships are strong, courtroom workgroups can efficiently dispose of their cases and reduce the uncertainty inherent to trials, while maintaining group cohesiveness, through plea bargains (Eisenstein & Jacob, 1977). Through their relationships courtroom workgroups therefore establish “locally distinctive, informal and ever-evolving case processing and sentencing norms, or ‘going rates’” (*see* Ulmer & Johnson, 2004: 140 (citing Eisenstein, Flemming, & Nardulli, 1988;

Ulmer, 1997)). Going rates can provide workgroup members with standard terms and sentences as a basis for plea bargaining (Ulmer & Johnson, 2004).

In general, the court community literature predicts that courts in large urban court communities will sentence less severely than small courts (*see, e.g.*, Johnson, Ulmer, & Kramer, 2008; Ulmer & Johnson, 2004). Larger court communities, the perspective asserts, will have more autonomy from outside pressures. Because of the court community size, routine cases will receive less public and media scrutiny. Increased bureaucratization of sponsoring agencies in larger court communities should also tend to increase sentencing leniency (*see* Johnson, Ulmer, & Kramer, 2008). And the “amount and diversity of social deviance in general” purportedly typically being greater in larger and more urban areas, greater tolerance and leniency towards deviants results (Ulmer & Johnson, 2004: 141).

Complementary to the court community perspective, the focal concerns perspective posits that court actors’ perceptions of a defendant’s blameworthiness, the need to protect the community, and practical concerns affect sentencing outcomes (*see* Steffensmeier, Ulmer, & Kramer, 1998). Blameworthiness is a function of the extent of the harm caused by and wrongfulness of the defendant’s conduct. Though related, an action might be potentially quite harmful without necessarily being especially wrongful, such as environmental or regulatory crimes with no culpable mental state required, or vice versa, such as embezzling an insubstantial sum. Community protection involves the perceived dangerousness of the defendant (i.e., how bad) and risk of reoffending (i.e., how likely). Practical constraints incorporates many of the environmental pressures from the court community perspective.

Focal concerns is in some respects “an extension of the court community perspective” (Kramer & Ulmer, 2002: 902). This is because “the meaning, relative emphasis and priority, and situational interpretation of [focal concerns] is embedded in local court community culture, organizational contexts, and politics” (Kramer & Ulmer, 2002: 902, 903; *see also* Johnson, 2006: 291; Ulmer & Johnson, 2004: 141). Authors have also used “the focal concerns framework as a heuristic to integrate and organize” the “compatible propositions” from multiple related contemporary theoretical sentencing perspectives (Johnson, Ulmer, & Kramer, 2008; 745 n.4), none of which appear to be “truly competing, mutually exclusive theories of sentencing” (Ulmer, 2012: 8-9 (emphasis omitted)).

Contextual research drawing broadly on both the court community and focal concerns perspectives has shown that court outcomes vary substantially by local social conditions. Ulmer and Johnson (2004) and Johnson (2006) each study both carceral placement and length of stay in Pennsylvania state courts using hierarchical linear modeling. Among other findings, both studies show that sentencing severity and the effects of predictors vary by county (and in Johnson, 2006, also across judges within counties). They support the proposition that smaller courts are more likely to impose a carceral penalty. Ulmer and Johnson (2004) find that caseload pressure relates negatively to placement, while Johnson (2006) additionally finds that the caseload of violent crimes influences the effect of a violent crime (the heavier the violent caseload, the less punitive judges were towards violent offenders). Ulmer and Johnson (2004) do not find support for more severe sentencing in counties with a higher percentage of people voting Republican in the 1996 presidential election, and little support for the proposition that

minority concentration increases sentencing severity (no support with respect to placement). In summary, this research suggests that smaller courts and courts with lower caseloads sentence more severely than larger courts with larger caseloads, with at best mixed results for the effects of local political and demographic landscapes.

Social contexts research has also examined sentencing guidelines departures as an outcome. As with placement and length, Johnson uses hierarchical linear modeling to show that departures from the Pennsylvania sentencing guidelines varied by local contexts after taking individual-level factors into account, and that the effects of individual-level predictors themselves vary across courts (2005: 780-781). Again consistent with the court community perspective, Johnson (2005: 781) finds court size to be “a powerful predictor of judicial departures decisions.” Large courts in Pennsylvania were more likely and small courts less likely to downwardly depart from the sentencing guidelines than medium-sized courts. Large courts were also less likely to upwardly depart.

In addition to court size, Johnson (2005) finds several court and larger environmental factors affect departures consistent with the court community and focal concerns perspectives. Courts with higher trial rates were more likely to depart upwards, while those with more caseload pressure were more likely to depart downwards. Hispanic defendants in communities with a higher percentage of Hispanics were less likely to receive downward departures and more likely to receive upward departures, but percent voting Republican in the 2000 presidential election and percent unemployed had little effect. Similar to Johnson (2006), a defendant was more likely to receive a downward

departure for a violent crime in communities with a higher violent crime rate (Johnson, 2005).

Kramer and Ulmer (2002) also examine departures, though limited to serious violent offenders in Pennsylvania. Broadly consistent with Johnson (2005) they find downward departures more likely in large urban counties (Kramer & Ulmer, 2002). The five counties accounting for half of all the serious violent crime in the data were all more likely to depart downwards. The counties (not specifically identified in the study) varied widely with respect to their demographic characteristics and violent crime rates, but they did cluster geographically, with two medium-sized suburban counties adjacent to a large urban county on one side of the state, and a third medium-sized suburban county adjacent to the other large urban county on the other side of the state. And four out of the five counties had Democratic majorities or pluralities.

Studying departures in the federal courts, Johnson, Ulmer, and Kramer (2008) also find variation in departures and predictors of departures. Unlike studies with state data, the authors find court size not to affect the likelihood of receiving a departure, which they posit might be due to the size of federal districts (Johnson, Ulmer, & Kramer, 2008: 768). More politically liberal districts were more likely to grant downward departures, as were, similar to the Pennsylvania studies, districts with greater caseload pressure. Judges in socioeconomically disadvantaged areas were less likely to grant downward departures, particularly to black and Hispanic defendants.

Collectively, the social context research on departures indicates that smaller state courts, but not federal courts, are more severe with respect to departures. Larger, more urban courts, and courts with heavier caseloads are more lenient. Larger trial rates and

crime rates also make downward departures more likely. This research also shows mixed effects for political climate, conditional race and ethnicity effects, and a lower probability of a downward departure in socioeconomically disadvantaged areas.

A related group of studies have examined geographical variation specifically with respect to capital punishment. Due to the enhanced procedural safeguards in place in capital cases, one might expect great uniformity in the application of the death penalty. Research consistently shows, however, that even with the death penalty place matters. Poveda (2006), for example, explicitly invokes the court community perspective, as well as other theoretical orientations, in a study on death sentences and executions in Virginia. Based on descriptive discriminant analysis Poveda suggests Virginia's smaller and more rural jurisdictions with more racial homogeneity and larger proportions of homicides involving a prior violent relationship are least likely to be the source of an execution.

Adger and Weiss (2011) use negative binomial regression to study death sentences during the modern era of capital punishment in Alabama. They show that 40% of death sentences have come from four of Alabama's sixty-seven counties. Counties with a higher percentage of black lynching victims between 1880 and 1930 and counties with more residential segregation were responsible for more death sentences.

Pierce and Radelet (2005) use logistic regression to estimate the effects of a small number of county-level characteristics, victim race and ethnicity characteristics, and the presence of aggravating circumstances on death sentencing in California. They show counties with a majority non-Hispanic white population and lower population densities had higher odds of death sentences in the 1990s.

In Illinois between 1988 and 1997, the odds of a death sentence were more than 80% lower in Cook County than in the 74 rural counties not part of a Metropolitan Statistical Area (Pierce and Radelet, 2002). In the five counties bordering Cook County and other urban counties (part of a Metropolitan Statistical Area) the odds were more than 50% lower than in the rural counties, a marginally significant difference.

A study primarily concerned with racial disparities within Harris County, Texas, notes that Harris County has used capital punishment nearly as much during the modern capital punishment era as all other major urban Texan counties combined (Phillips, 2012; *see also* Phillips, 2008). Phillips (2012) notes that Harris County has generated more executions than any state (other than Texas), though as the study analyzes within county disparity, it does not address why this is the case. Even in Texas though, where support for the death penalty is strong (*see, e.g.*, Tuner, 2014), most of the 254 counties have not executed anyone (Gershowitz, 2010).

The current study focuses on Maryland, and geographical variation existed in Maryland's former⁶ capital sentencing system as well. In a study commissioned by then-Governor Glendening, Paternoster et al. "examine the role that race and geography may play at four critical points in the Maryland capital sentencing system while simultaneously considering important features of a case" (2003: 18, *see also* Paternoster et al., 2004). Using a series of logistic regressions Paternoster and colleagues estimate racial and geographical effects, after controlling for numerous other case characteristics,

⁶ Maryland repealed the death penalty in 2013 (2013 Md. Laws Ch. 156 [Senate Bill 276]). The repeal was prospective only, but on his last full day in office Governor O'Malley commuted the sentences of Maryland's four remaining death row inmates to life imprisonment (Wagner, 2015).

on the judge's or jury's decision to sentence a defendant to death, as well as the earlier decisions by the prosecutor to file notice to seek a death sentence, not to withdraw that notice once filed, and to advance a death-eligible case to a penalty trial following a first-degree murder conviction (Paternoster et al., 2003: 5). The researchers find "substantial variation by legal jurisdiction in the decision to seek a death sentence," "*even after controlling for numerous case characteristics*" (Paternoster et al., 2003: 29 (emphasis in first quote omitted)).

From an initial pool of approximately six thousand first- and second-degree murders between 1978 and 1999,⁷ the researchers identified 1,311 death-eligible cases. Death-eligible cases included any in which a state's attorney filed notice of intent to seek the death penalty regardless of whether the state's attorney later withdrew that notice. The research team also classified cases without a notice of intent to seek death as death-eligible where the facts of the case (established by reviewing court transcripts, trial judge reports, state's attorney case files, institutional records from the Maryland Division of Corrections, and death certificates of victims), showed that the state's attorney could have filed notice. In the approximately three hundred cases where the state's attorney did not file notice and the research team found the facts ambiguous, a panel of both prosecutors and defense attorneys with capital experience reviewed case descriptions to determine

⁷ Following *Gregg v. Georgia*, 428 U.S. 153 (1976), and *Woodson v. North Carolina*, 428 U.S. 280 (1976), Maryland's highest court, the Court of Appeals, held Maryland's death penalty unconstitutional, *Blackwell v. State*, 278 Md. 466, 365 A.2d 545 (1976). In response the General Assembly passed a new guided-discretion death penalty statute, which took effect in 1978. Governor Glendening commissioned the study in 2000. See Paternoster et al., 2003: 4, 7-8, 12.

whether a case was death-eligible. The research team added fewer than fifty cases following attorney panel review, Paternoster et al., 2003: 15-17.

Of the (a) 1,311 death-eligible cases, prosecutors filed notice of intent to seek the death penalty in (b) 353 cases. Prosecutors eventually withdrew death notices in 140 of the 353 cases, leaving (c) 213 cases. Out of the 213 cases in which prosecutors did not withdraw notices (d) 180 cases advanced to a penalty trial, with death sentences obtained in 76 cases. Missing data reduced these counts to (a) 1,202, (b) 327, (c) 198, and (d) 169 in the jurisdictional logistic regressions, with less than ten percent missing at each stage.

With access to more than one hundred covariates, the analyses show that “[i]n the Maryland death penalty system, the jurisdiction where the crime occurs and legal prosecution begins is clearly one of the most important factors in determining which death-eligible defendants are ultimately sentenced to death and which are not” (Paternoster et al., 2004: 40-41). Cases in Baltimore County were significantly more likely and cases in Baltimore City and Prince George’s County significantly less likely to result in a death sentence than others⁸ (Paternoster et al., 2003: 29).

By analyzing multiple decision points in the death sentencing system, the researchers conclude that the jurisdictional variation in the final decision to impose a death sentence was due not to case merits, but rather to “the significantly different rate at which prosecutors in the different locations in the state make capital charges and make those capital charges ‘stick’ early in the capital punishment process” (Paternoster et al, 2003: 30). “Although the jurisdictional differences occur early in the process they are

⁸ The “Other Counties” reference category combined cases from the eighteen Maryland counties other than Anne Arundel, Baltimore, Harford, Montgomery, and Prince George’s Counties, and Baltimore City.

propagated to later points and go uncorrected” (Paternoster et al, 2003: 31 (emphasis omitted)). Because of these case processing differences which “cannot be attributed to the kinds of homicides committed” in different counties, “the jurisdiction where the homicide occurs matters and matters a great deal” (Paternoster et al., 2003: 31 (emphasis in first quote omitted)).

In a reanalysis of the data from the Maryland death penalty study, Berk, Li, and Hickman (2005: 386) similarly conclude that “the location in which a case is brought has a very important impact.” Berk, Li, and Hickman (2005) are quite critical of the Paternoster et al. (2003) study. They take issue with the statistical approach used and inferences drawn by Paternoster and his colleagues, particularly with respect to racial effects.⁹ While Berk, Li, and Hickman’s preferred approaches, using random forests modeling and classification and regression trees, find different geographical effects than the earlier research, the substantive conclusion that jurisdiction matters is the same. Berk, Li, and Hickman call for more research into location, deeming county “just a proxy for processes that are not analyzed” (2005: 387), i.e., contextual factors.

The capital sentencing literature on geographical disparities, as with the general social contexts research, suggests that defendants in smaller and more rural jurisdictions are more likely to receive the death penalty, though this result is not uniform across all studies. Local racial composition and idiosyncratic historical factors also seem to matter in some states, but again not consistently in all studies. The Paternoster and colleagues

⁹ For a reply to Berk, Li, and Hickman (2005) *see* Paternoster and Brame (2008). Using propensity scores the authors reaffirm the basic substantive finding from Paternoster et al. (2003) that black killers of white victims fare worse in the death penalty process than other offender-victim racial combinations.

research draws attention to the cumulative influence of local prosecutors' decisions, with Baltimore County's prosecutors particularly punitive, and Baltimore City and Prince George's Counties' prosecutors particularly lenient.

White-collar sentencing research has not benefitted greatly from contemporary emphases on contextual and geographical effects. Existing literature on (primarily federal) white-collar sentencing has largely focused on whether judges sentence white-collar offenders differently from more conventional criminals, with inconsistent results. *See, e.g.*, Benson & Walker, 1988; Hagan, Nagel, & Albonetti, 1980; Nagel & Hagen, 1982; Wheeler, Weisburd, & Bode, 1982.¹⁰ Compared to white-collar or status effects, jurisdictional or contextual variation within federal white-collar sentencing across United States District Courts has received limited attention from researchers. More than 25 years ago Benson and Walker stated "to date, no research has examined the impact of contextual variables, such as urbanization and racial mix, on the sentencing of white-collar offenders" (1988: 301). Unfortunately, research appears to have made little progress in this regard since.

The relative inattention to context and geography in white-collar sentencing scholarship is somewhat surprising, inasmuch as white-collar sentencing research recognized the importance of place decades ago. Hagan, Nagel, and Albonetti analyze sentencing for several thousand white-collar offenders, using an offense-based

¹⁰ The original underlying data from this research is also often quite dated (*see* Simpson, 2013). Much of them predate the Sentencing Reform Act of 1984, which gave rise to the Federal Sentencing Guidelines

definition,¹¹ between 1974 and 1977 in ten districts from large urban areas (1980: 803, 806-807 & nn. 5 & 6; *see also* Nagel & Hagan, 1982.) They find that in “District C”¹² prosecutors took a more proactive approach to white-collar crime than in the other districts in the study. District C prosecutors brought substantially more white-collar cases than prosecutors in other districts.

Perhaps counterintuitively, white-collar criminals received less severe sentences in District C. The researchers interpret this finding as due to prosecutors in District C needing to make larger concessions to defendants because of the greater number of cases prosecutors brought against college educated defendants—cases presumed to be perhaps more complex or large scale and requiring more resources. The researchers speculate that general equity concerns might then diffuse these benefits to white-collar crimes committed by less educated defendants convicted under the same statutes. They conclude that “there may be an inverse relationship between the volume of white-collar convictions and the severity of white-collar sentences.” Hagan, Nagel, and Albonetti, 1980: 818-819; *see also* Nagel & Hagan 1982: 1455 (“Preferential sentencing appears to be the price paid for expanded prosecution of white-collar crime.”).

¹¹ Defining white-collar crime is an ongoing and contentious issue. Definitions generally either focus on characteristics of the offense or characteristics of the offender, with implications for sample composition and results. This study’s definition combines elements of both. Chapter 3 discusses differing definitions of white-collar crime and the rationale for this study’s definition in greater detail.

¹² Although they identify the districts the study involved, the researchers’ data sharing agreement with the Administrative Office of the United States Courts prevented the researchers from specifying which was District C.

Contemporaneous with Hagan, Nagel, and Albonetti (1980), the venerable Yale Studies on White-Collar Crime also find variation in federal white-collar sentencing, again using an offense-based definition, across seven District Courts (six of which overlap with Hagan, Nagel, and Albonetti, 1980), *see* Wheeler, Weisburd, and Bode, 1982. Wheeler and his colleagues also examine whether judges sentence white-collar offenders more leniently than conventional criminals, reaching very different conclusions from Hagan and his colleagues. Wheeler and his colleagues include dummy variables for the district of conviction as “other variables,” in their models.

The researchers find the district “important and highly significant” in the judge’s decision whether to incarcerate, even “more powerful in its effects on length of sentence,” and that the effect of defendant’s sex on the incarceration decision varies by location (Wheeler, Weisburd, and Bode, 1982: 652, 655). In addition to the explanation offered by Hagan, Nagel, and Albonetti (1980), Wheeler, Weisburd, and Bode suggest that the differences may represent variation in local norms (1982: 652). The authors do not seem to find jurisdictional effects troubling, although elsewhere Weisburd, Wheeler, Waring, and Bode (1991) suggest that jurisdictional variation reflects a so-called chaos perspective.¹³

¹³ Weisburd et al. (1991) contrast three perspectives (alternately termed models) of sentencing. The “model of chaos and disarray” posits “judges respond to their own biases and moods, which will vary from judge to judge. The only consistency in sanctioning is the inconsistency of judicial behavior. Punishments will seem arbitrary and bear little relationship to the crime committed” (Weisburd et al., 1991: 132-133). They contrast this with a model of pervasive discrimination and their preferred model based on “common sociolegal norms” rooted in Anglo-American principles of seriousness and blameworthiness, both principles “part of a broader set of normative judgments widely diffused throughout society,” as well as

More recent white-collar sentencing studies have not considered geographical variation to the same extent as the above research. Studies often do not include location in their analyses, *see, e.g.*, Albonetti, 1998a; Eitle, 2000. Others have included measures of geography as control variables, rather than independent variables of substantive interest (with the effect of “controlling for jurisdictional variation rather than [] investigating” it, Johnson, Ulmer, & Kramer, 2008: 741), and omitted them from results reported and discussion, *see, e.g.*, Schanzenbach and Yaeger, 2006; Van Slyke and Bales, 2012. In a study of gender effects on federal white-collar sentencing Albonetti (1998b: 37) also “control[s] for circuit-specific sentencing practices” with dummy variables, consigning most of the circuit results to the appendix without substantive discussion.

The only fairly recent published study of geographical variation in white-collar sentencing concerns regional differences in federal sentencing related to the savings and loan crisis (Jennings & Miller, 2006). Rather than grouping states according to the geographical boundaries of the United States Courts of Appeals, the authors group states into six purported regions, ostensibly based on similar “climate, geography, traditions, culture, and similar divisions in the federal district courts” (Jennings & Miller, 2006: 91). Jennings and Miller use ordinary least squares regression to estimate the effects of region and organizational position on sentence length. The authors find their Southwest region “uniquely more punitive in its handling of white-collar criminals” (Jennings & Miller,

consequences, such as deterrent effects (Weisburd et al., 1991: 133). “[I]f chaos reigns,” they assert, “we should have grave difficulty in predicting sentences at all” (Weisburd et al., 1991: 137).

2006: 96). Their Southwest region (Arizona, New Mexico, Oklahoma, and Texas, spreading across three different Circuits) was both the modal region and most punitive.¹⁴

While geographical variation has not featured prominently in recent white-collar sentencing research, white-collar crime has also been all but absent from research on local contexts and sentencing, *cf.* Ulmer, 2012. Ulmer and his colleagues do use “white collar/fraud” as a reference category in a study of district variation in trial penalties, but they are not entirely clear on what this includes (*compare* Ulmer, Eisenstein, and Johnson, 2010: 570, *with* 576-577). And a recent study of the effect of offender educational attainment on sentencing, purporting to contribute to contextual research, includes white-collar as one of a series of offense-type dummy control variables, but the author provides no indication of what he considers white-collar crime and does not specifically discuss the white-collar offenses (Franklin, 2015).

Existing white-collar sentencing literature therefore provides little guidance on geographical effects. Prioritizing white-collar cases prior to the Federal Sentencing Guidelines seems to have been related to sentencing leniency. But the implications of this finding for white-collar sentencing in state court under a guidelines system are not obvious.

¹⁴ The authors offer three “speculations” (Jennings & Miller, 2006: 97) for the Southwest’s punitiveness. They suggest that the Southwest may have been more punitive because Texas had the largest concentration of thrift insolvencies; Texas was in a severe recession during the time period under examination; and Texas’s, and the other Southwestern states,’ *laissez-faire* business orientation brought on a “heavy-handed response” from the federal government responding “corrupt and unsavory business practices,” and seeking to make an example of the situation (Jennings & Miller, 2006: 97).

The current inquiry's goal is to establish whether and how court outcomes for white-collar criminals in Maryland differ based on where the case transpires, "after controlling for numerous case characteristics" (*cf.* Paternoster et al., 2003: 29 (emphasis omitted)). Focal concerns predicts local court communities distinctively interpreting, prioritizing, and emphasizing the ideas of blameworthiness, community protection, and practical concerns in the context of their courtroom workgroups. The existing literature shows that local contexts affect a variety of case outcomes for a variety of crime types, in both state and federal courts. Whether a violent criminal goes to jail or not, whether a racial or ethnic minority defendant receives a sentencing departure or not, and whether a murderer receives the death penalty or not, all appear to turn partially on the seemingly innocuous matter of court location. White-collar defendants, however, represent a gap in this literature. The gap is particularly large in the state courts handling the bulk of routine criminal prosecutions.

This study addresses that gap. The most consistent finding from the literatures summarized above is that courts in larger, more urban, more politically liberal communities tend to sentence more leniently in terms of placement, length, or departures than smaller, more rural, politically conservative court communities. For white-collar crime, however, this plausibly might not be the case. Business-related white-collar crimes might be a more salient concern, and perceived as posing more of the threat to the community in larger and more urban court communities. Smaller and more politically conservative communities might be more skeptical of nontraditional or business-related economic crimes, and perceive offenders as less blameworthy. White-collar criminals also include many organizational offenders, which might also alter typical patterns.

One might therefore expect, and this study predicts, geographical results for white-collar sentencing that differ from general offender findings. I expect that outcomes will vary by jurisdiction, and that larger court communities will sentence more severely, and smaller courts more leniently, than we would usually anticipate. Given the inchoate state of the literature on geographical differences in white-collar sentencing, limitations of the data, and the current study's essentially exploratory nature,¹⁵ this study does not, however, attempt to test which county-level factors predict variation in white-collar sentencing.

Simpson's warning that "many traditional criminological theories may be irrelevant" (2013: 318) with respect to white-collar crime concerns theories of offending. But to the extent sentencing reflects why and how judges believe people offend or experience punishment, we should exercise caution in applying general sentencing research and theory in the white-collar sentencing context as well. The mere existence of the special sensitivity hypothesis, for example, whether or not it is empirically accurate (*see* Stadler, Benson, & Cullen, 2013), suggests considerations in white-collar sentencing may differ from conventional crimes. Whether we observe geographical effects in Maryland's white-collar sentencing, similar to those under its former capital sentencing system and contextual research more broadly, is therefore a threshold question with

¹⁵ Babbie (2013) characterizes as exploratory research intended to familiarize the researcher in a relatively new subject of inquiry. Among other things exploratory research may yield "approximate answers," point the way towards "more extensive study," and serve as "a source of grounded theory" (Babbie, 2013: 90-91).

respect to how processing theories explaining sentencing of conventional crime apply to the white-collar area.

CHAPTER 3: DATA

This chapter begins by describing the Maryland Sentencing Guidelines Database (the “Database”), the source of the data used in this study. It then discusses how this study operationalizes white-collar crime from the Database extract. The chapter then describes the variables that the data analyses use.

a. The Maryland Sentencing Guidelines Database

The Maryland State Commission on Criminal Justice Policy (the “Commission” or “MSCCSP”) oversees Maryland’s voluntary sentencing guidelines and monitors Maryland circuit court sentencing practices.¹⁶ Towards that end the Commission collects sentencing guidelines worksheets from cases sentenced in circuit courts. Information from the worksheets forms the basis for the Database. The data this study uses are an extract of the Database.

In addition to the sentencing guidelines worksheets, the Maryland Judiciary is a second supplemental data source for the Database and this study. The person calculating sentencing guidelines typically fills the sentencing guidelines worksheet out by hand, though the Commission and local jurisdictions are in the process of automating

¹⁶ Circuit courts are the “trial courts of general jurisdiction” in Maryland (Maryland Judiciary, 2015), unlike the Courts of Appeals for the 13 federal circuits, which exercise appellate jurisdiction over the United States District Courts. Slightly muddling matters, Maryland’s circuit courts also hear appeals from the District Court of Maryland, and the latter has concurrent jurisdiction over some criminal cases, although circuit courts “generally handle the . . . more serious criminal matters” (Maryland Judiciary, 2015). Maryland’s sentencing guidelines only apply in circuit courts. The Database therefore only reflects cases sentenced in circuit courts.

guidelines calculation and worksheet submission. As a result of this manual process, worksheet entries are occasionally incomplete or ambiguous, sometimes for no other reason than difficult handwriting or someone not pressing hard enough with a pen for writing to transfer across copies. When information on a worksheet is missing or unclear the Commission augments the data from the worksheets with the Maryland Judiciary Case Search website (<http://casesearch.courts.state.md.us/>). This website allows anyone, searching by name or case number, to retrieve a wealth of information on individual cases.

The Database extract includes people sentenced in a Maryland circuit court between January 01, 1999, and June 30, 2014, for whom Commission received sentencing information.¹⁷ The full dataset includes approximately 180,000 sentencing events, in which a judge sentenced a defendant for one or more crimes. A sentencing event may involve multiple charges, so the approximately 180,000 sentencing events include over 240,000 offenses. Defendants who recidivated within the fifteen years covered, if sentenced in a circuit court for the new offense(s), will appear in the data more than once. Since 2007 sentencing guideline worksheets have collected State

¹⁷ Although essentially all incarcerable violations of Maryland state law originally prosecuted in circuit court are subject to the sentencing guidelines and require a sentencing guidelines worksheet (*see* MSCCSP, 2015b), compliance with this requirement is not universal. In 2014 the Commission and Judicial Information Systems (a division of the Maryland Judiciary's Administrative Office of the Courts) developed an indicator in the courts' case management system to identify guidelines-eligible cases requiring a worksheet (MSCCSP, 2015a: 12). The number of cases from prior years which should have had a sentencing guidelines worksheet prepared but did not is unknown.

Identification Numbers, which should permit one to identify a defendant appearing subsequent times in the Database, but in practice this field is frequently missing.

This study focuses on data from a small subset of cases with defendants sentenced only for a single count that was a white-collar crime (operationally defined below) or where the white-collar offense was the controlling (i.e., the most serious) offense¹⁸ ($n=381$), also spanning from 1999 to 2014. As in other court systems, most people sentenced in Maryland circuit courts receive sentences for conventional crimes. Comparisons in sentencing between white-collar and conventional criminals have generated a substantial literature, but this being a study on geographical variation in white-collar sentencing, comparing sentences of more common crimes has little relevance, and the primary analyses only consider the white-collar defendants.¹⁹

The Database and Case Search have several notable limitations. Other than indicating the circuit court that sentenced the defendant neither source contains court- or county-level information, such as court caseloads or county population characteristics. The Database does not identify sentencing judges (Case Search rarely does so) or prosecutors, or include their characteristics. The Database also does not include predisposition outcomes, such as charge reductions or pretrial release. Because the

¹⁸ For one defendant sentenced for two identical white-collar counts with each labeled controlling I recoded one count to not controlling to avoid having the sentencing event appear twice in the data.

¹⁹ Insofar as the volume of (predominantly nonwhite-collar) cases sentenced reflects court size or caseload pressures, court context factors such as these likely affect sentencing outcomes for all defendants. Although potentially a topic for future research, contextual or multilevel analysis incorporating court-level variables would be beyond the scope of the present inquiry.

Commission removes defendant names before issuing the data to requesters, Case Search is not be available if the case number is missing. And not all cases are retrievable on Case Search.

b. White-Collar Crime in the Maryland Sentencing Guidelines Database.

No universally agreed-upon definition of white-collar crime exists. The term does not, generally speaking, refer to a specific statutorily enumerated offense or class of offenses. *See, e.g.*, Podgor, 2007: 24. *But see* 42 U.S.C. § 3791(a)(18) (defining white-collar crime for purposes of Chapter 46 of Title 42 of the United States Code); 42 U.S.C. § 3722(c)(2)(F) (the sole section using § 3791’s definition of white-collar crime, and the only section in the entire United States Code other than § 3971 using the term, authorizing the National Institute of Justice to conduct or authorize research and development concerning white-collar crime). As a result competing definitions abound, *cf.* Green, 2004, along with much debate, which has been “a distraction to moving the field forward” (Simpson, 2013: 313).

Broadly speaking, despite lack of consensus, white-collar crime definitions typically fall within one of two intellectual and research traditions. Sutherland (1940) first articulated the concept and identified the problem of white-collar crime. Sutherland offers an offender-based understanding of white-collar crime, defining it “approximately as a crime committed by a person of respectability and high social status in the course of his occupation” (Sutherland, 1983 [1949]: 7). A competing tradition, following Edelhertz (1970), has used offense-based definitions. Considering Sutherland’s approach too narrow, Edelhertz defines white-collar crime as “an illegal act or series of illegal acts committed by nonphysical means and by concealment or guile, to obtain money or

property, to avoid the payment or loss of money or property, or to obtain business or personal advantage” (1970: 3).

Definitional disagreements frequently coalesce along disciplinary lines. Literature favoring Sutherland’s offender-based definition and its progeny has typically come from social scientists. *E.g.*, Simpson, 2013. Law enforcement agencies and lawyers, on the other hand, have tended towards offense-based definitions descended from Edelhertz. *See, e.g.*, Barnett, n.d. [2000]; Federal Bureau of Investigation, 1989; *see also* Green, 2004.²⁰ Legal actors and scholars are hardly the only people to rely on offense-based definitions though, *see, e.g.*, Stadler, Benson, and Cullen, 2013, if for no other reason than because most administrative or other readily accessible existing datasets typically lack good measures, or sometimes any measures, of social status, actions taken in the course of one’s occupation, or both.

The choice of how one defines white-collar crime is not trivial. As Simpson (2013: 312) explains “research that adopts one approach over the other tends to generate a different portrait of the white-collar offender.” An offense-based definition will, for example, likely result in predominantly middle class offenders, with unusually large numbers, in relative terms, of females. *See* Simpson, 2013; Weisburd, Waring, and Chayet, 2001.

A status-neutral definition might possess certain *prima facie* appeal on fairness grounds, *see, e.g.*, Podgor, 2007: 737, based on the idea that we generally define crimes based on the act and not the actor. An offense-based sample may, however, bear little

²⁰ Offender- and offense-based definitions are not mutually exclusive options. The Bureau of Justice Statistics (1982), for example, has defined white-collar crime by drawing on both perspectives.

resemblance to the particular problem of the modern robber barons with whom Sutherland was concerned (1983 [1949]: 7-8). Offender-based conceptualizations also likely have greater resonance with and are closer to the construct of white-collar crime as understood by the general public (*cf.* Simpson and Yeager, 2015: 46), especially in the wake of the global financial crisis and recent (if unrelated) sensational cases.

Using sentencing data in research tends to widen the gap between offense- and offender-based definitions. Although, for example, Sutherland's "approximate[]" definition refers only to "crime," Sutherland's idea of white-collar crime deliberately embraces civil and regulatory offenses (1983 [1949]: 6-7). Sutherland suggests that people with respectability and high social status avoid criminal sanctions in part due to influence over the criminal law itself, rather than meaningfully different behavior or harm.

The underlying illegal behavior in civil or regulatory proceedings can be indistinguishable from crime. That behavior is frequently subject to any of criminal, civil, and administrative penalties. Holder (2012), for example, notes "[t]he potential for parallel proceedings arises in many of the Department [of Justice]'s white collar enforcement priorities, and it is essential that an effective and successful response involve an evaluation of criminal, civil, regulatory, and administrative remedies. Crooks et al. (2014: 1054) similarly state "[m]ost of the [nine principal environmental] statutes . . . contain overlapping civil, criminal, and administrative penalty provisions."

The language in Edelhertz's (1970) definition of white-collar crime similarly does not preclude noncriminal violations of law. But sentencing datasets, and other

administrative and official data, typically do not include information on civil²¹ or regulatory proceedings, effectively limiting much sentencing research to criminal-offense-based definitions of white-collar crime. Doing so omits much of the theoretically critical behavior contemplated by Sutherland's (and other) offender-based definitions. And even if sentencing datasets were to include civil judgments or administrative penalties, an offender-based understanding of white-collar crime would likely expect that data limited to offenders pleading or found guilty, or reaching analogous noncriminal dispositions, will systematically select out white-collar offenders, who presumably have access to better (or simply more) legal resources. This is not inherently a problem for offense-based definitions, but will result in a very different offender profile.

This study attempts to address white-collar crimes that are consistent with Sutherland's definition. Offender-based definitions of white-collar crime have greater construct validity than offense-based definitions; Edelhertz's definition, for example includes such crimes as welfare fraud as white-collar crime, which seems dubious. As with many sentencing datasets (*see, e.g.*, Kramer & Ulmer, 2002: 908), however, the Database does not have a good measure of high social status. Type of defense attorney is the only available proxy, albeit crude, available for high social status.²² The Database

²¹ The Federal Justice Statistics Program, which includes civil case files from the Executive Office for United States Attorneys and the Administrative Office of the United States Courts, is a notable exception. The civil case series is relatively recent, and while certainly an advance and promising is still developing and has several limitations. *See* Simpson and Yeager, 2015.

²² The Database has a separate measure of low social status, relating to whether the court waived imposing \$45 in court costs upon finding that the defendant is unlikely to be able to pay any significant part of the

also does not have a direct measure of crimes committed in the course of one's occupation.

Due to these limitations, for this study I reviewed the list of crimes present within the Database extract and selected four types of offenses that facially seem most consistent with Sutherland's offender-based definition. These are crimes that by their nature appear, admittedly only intuitively, to be more likely to have occurred in the course of the defendant's occupation, and can include crimes committed by business entities. And these offenses also seem almost to require the defendant to have, if not a high social status, at least a higher social status than is generally the case in a sample of criminally sentenced people.²³

costs within the following twelve years. Aside from indicating low, rather than high, social status, this field is missing more than two thirds of the time, effectively eliminating any potential usefulness.

²³ Though by no means a test, the proportion of defendants with a private defense attorney was far higher for those convicted of crimes designated below as white-collar crimes than among defendants overall in the Database extract. Approximately one third of defendants whose controlling (or sole) conviction count was not a white-collar crime had a private defense attorney, whereas a more than 50% larger share of defendants whose controlling (or sole) conviction count was white collar had a private defense attorney (approximately 54%). Similarly the proportion of defendants represented by the Office of the Public Defender was more than 50% larger for defendants whose controlling (or sole) conviction count was not a white-collar crime than for defendants whose controlling (or sole) conviction count was white-collar (approximately 43% vs. approximately 27%). These percentages are prior to data cleaning, so that the percentages for white-collar and conventional cases are comparable. In the main analyses below, limited to white-collar defendants, following data cleaning an even greater percentage of white-collar defendants had private representation.

The Commission has categorized a group of offenses as “Commercial Fraud, Other” (there is no general “Commercial Fraud” category). These offenses are COMAR# 80 to 98-4 in the Guidelines Offense Table appended to the Maryland Sentencing Guidelines Manual (MSCCSP, 2015b; *see also* Md. Code Regs. [COMAR] 14.22.02.02), though offenses listed in the Guidelines Offense Table are not necessarily all present in the data.²⁴ Crimes in this category include false statements with the intent to deceive a person authorized to examine the affairs of the bank (COMAR# 80), willful failure to obtain and maintain a corporate surety bond or to hold sums of money in an escrow account (COMAR# 84), and pyramid schemes (COMAR# 95), among various other frauds.

The Commission has also categorized a group of actions as violations of “Consumer Protection Laws” (COMAR# 99), for violating provisions of the Credit Card Number Protection Act. This crime involves the unauthorized use or disclosure of a credit card number, other payment device or the holder’s signature (Criminal Law Article, § 8-214). The provision “aim[s] at persons who came into possession of a credit card number(s) with a fraudulent intent or who came into possession of the number(s) lawfully, but thereafter formed a fraudulent intent.” *Clark v. State*, 188 Md. App. 185, 199-200, 981 A.2d 710 (2009). Simply stealing a credit card and using it does not violate this section. *Id.*

²⁴ Appendix I is an excerpt of the Offense Table detailing the offenses in the Database extract that this study designates white-collar crimes. The full Offense Table is available at <http://www.msccsp.org/Files/Guidelines/offensetable.pdf>.

The Commission's "Public Health and Safety, Crimes Against" heading contains, among other things, several environmental crimes (COMAR# 331 to 338-1). I have included as white-collar crimes those environmental offenses that appear to be pursuing violations in the course of an occupation or a business. These include unlawfully dumping for commercial purposes (any amount) or of more than five hundred pounds or two hundred sixteen cubic feet of litter (COMAR# 333) and failing to meet the regulatory requirements for generators (COMAR # 334). Within this heading, however, I have excluded improperly disposing of more than 100 but less than five hundred pounds or more than 27 but less than 216 cubic feet of litter not for commercial gain (COMAR# 338) as too general to be plausibly targeting violations in the course of an occupation or a business.

Lastly, the Commission's "Theft, Crimes Involving" heading contains several general theft offenses, but also the more specific embezzlement by fiduciaries (COMAR# 387). This study categorizes the latter as white-collar crime. Under Maryland law, this crime involves a fiduciary's appropriation of entrusted money or property for some use other than intended. *See State v. Burroughs*, 333 Md. 614, 622, 636 A.2d 1009 (1994). A fiduciary is one transacting business or handling money or property for the benefit of another person, where the two have a relationship "implying and necessitating great confidence and trust" in one and "a high degree of good faith" from the other. *Schwartz v. State*, 103 Md. App. 378, 386, 653 A.2d 958 (1995) (internal citations omitted). As one example, by no means necessarily representative, the president of a savings and loan is a fiduciary of the corporation, *Stathes v. State*, 29 Md. App. 474, 481, 349 A.2d 254 (1975).

I suffer from no misconception that all offenders sentenced for the above crimes would satisfy a purely offender-based definition (nor that no defendants sentenced for crimes in excluded categories would fit Sutherland's definition). Someone can certainly commit insurance fraud or illegally disclose a credit card number, for example, outside the scope of an occupation and without being high status. The data also almost certainly include those involved in illicit businesses, deviating from Sutherland's emphasis on activity related to legitimate business entities. Within the limitations of the data, however, the selected offenses are the best available option. They likely select an offender pool that on average has higher social status than in the Database extract more broadly (though in these data that is an untestable assumption) and at least avoid crimes such as public benefits frauds (e.g., COMAR# 326, 327), which fit within Edelhertz's offense-based definition but seem a far cry from what Sutherland or the general public would realistically view as white-collar crime.²⁵

Limiting this study to and defining white-collar crime as convictions for one of four types of offenses introduces biases. As with other studies limited to criminally convicted defendants selection is likely. More skillful offenders, or more skillfully

²⁵ The Commission (2015b: 5; *see also* Md. Code Regs. [COMAR] 14.22.01.02B(22)) has defined "white collar offense," for purposes of the Maryland sentencing guidelines in terms nearly identical to Edelhertz (1970). Other than in defining the term, the only use of white collar offense in the Maryland sentencing guidelines is as one of nine common reasons for upward departures from the recommended sentencing range (*see* MSCCSP, 2015b: 59; Md. Code Regs. [COMAR] 14.22.01.05C(5)). Upward departures are uncommon, and in cases with upward departures the reason field is frequently blank (*see, e.g.,* MSCCSP, 2015a: 41, 48). Judges have used the white collar offense departure code at only eighty-nine sentencing events, mostly with defendants convicted under general theft provisions.

represented offenders, are less likely to appear among the convicted. White-collar offenders, particularly elite offenders and business entities, may successfully have their matters diverted to civil or administrative proceedings that are simply unavailable for conventional criminals. Despite selecting offenses believed to be most consistent with Sutherland's offender-based definition, the presumable inclusion of offenders not possessing respectability or high social status, or not committing their crimes in the course of legitimate occupations, will limit the relevance of any geographical effects detected beyond the selected crimes. One must therefore exercise caution regarding generalizability to offenders convicted of other arguably white-collar offenses, nonconvicted offenders, or offender-based conceptions of white-collar crime more generally.

c. Geographical Variables

Because this is a study of local effects on sentencing, the main independent variable of interest is the location of sentence. Dummy variables indicate county. The analyses consider five counties with at least thirty white-collar observations individually: Anne Arundel County ($n=97$, 25.46%), Montgomery County ($n=70$, 18.37%), Baltimore County ($n=51$, 13.39%), Baltimore City ($n=50$, 13.12%), and Prince George's County ($n=30$, 8.40%).

Due to smaller numbers of observations, I group the remaining counties for the analyses. The groups derive from the regions used in the Maryland Uniform Crime Reporting Program (*see* Maryland Department of State Police, 2014). They also largely correspond to the regions in the Maryland Statistical Handbook (*see* Maryland Department of Planning, 2015). Table 1a shows the distribution of counties and regions

by white-collar offense type in the Database extract, Table 1b shows the distribution of counties and regions by outcome, and Table 2 shows descriptive statistics for all variables used.

[Table 1 and 2 about here.]

Though the counties in each region are by no means identical, they tend to share various similarities. The court community and focal concerns literatures emphasize court community size, likely the most consistently important characteristic related to variation in outcomes. A common way to measure court size has been with respect to the number of judgeships in a jurisdiction, which are generally similar within the regions. The number of judges in a jurisdiction is related to other community attributes with some, though less consistent, support in existing research, that also tend to be similar within regions. Larger, more urban, and more densely populated counties, which are also often more heavily Democratic with a higher percentage minority population, tend to have more judgeships, as do jurisdictions (often disadvantaged) with more violent crime.

The Maryland UCR Program's Region I - Eastern Shore ($n=21$, 5.51%), includes Cecil, Dorchester, Queen Anne's, Somerset, Talbot, and Wicomico Counties (*see* Maryland Department of State Police, 2014).²⁶ These are small court communities. The circuit courts for four of these six counties have only one judgeship each, though two courts each have four judgeships (Courts and Judicial Proceedings Article, § 1-503.). Not

²⁶ Region I also includes Caroline, Kent, and Worcester Counties, but these had no cases in which the controlling or sole conviction offense was a white-collar crime. They therefore do not appear in the analyses. The Maryland Statistical Handbook splits the Eastern Shore into separate Upper Eastern Shore and Lower Eastern Shore Regions (*see* Maryland Department of Planning, 2015).

surprisingly, the counties in this region have relatively small populations (four had less than 50,000 people in 2014, the others around 100,000 people) and low population densities (the four smallest, and six of the seven smallest of counties in the white-collar data). These are largely rural areas, several with fairly high 2013 poverty rates, and 2013 median household incomes mostly lower than the state median. The 2013 violent crime rate for these counties ranges between 1.9 and 5.0 per 1,000 people, which is similar to most other counties, though with wider a range (the Eastern Shore includes at least twice as many counties as the other regions, so the wider range is not surprising). (*See* Maryland Department of Planning, 2012; 2015). While neither major political party systematically dominates voter registration among these counties, about 64% to 79% voted for Larry Hogan (R) in the 2014 gubernatorial election, compared to about 51% statewide (*see* Maryland State Board of Elections, 2014a; 2014b).

Region II - Southern Maryland ($n=26$, 6.82%) in the Maryland UCR Program includes Calvert, Charles, and Saint Mary's Counties (*see* Maryland Department of State Police, 2014). They generally comprise slightly larger court communities, with three or four judgeships per county circuit court (Courts and Judicial Proceedings Article, § 1-503). These counties are generally more populated (about 90,000 to 150,000 people in 2014), and more densely populated, than the Eastern Shore Counties. Though still largely rural the Southern Maryland counties are more urban than most of the Eastern Shore, with generally less poverty and higher household incomes (all three are above the 2013 state median), and their violent crime rates ranged from 1.2 to 3.8 per 1,000 in 2013. (*See* Maryland Department of Planning, 2012; 2015). In Calvert and Saint Mary's Counties, with roughly equal numbers of registered Democrats and Republicans, Hogan

received about 69% and 73% of the 2014 vote (respectively), though in Charles County, where Democrats outnumber Republicans nearly two and a half to one, Anthony Brown received a majority (52%) (Maryland State Board of Elections, 2014a; 2014b).

The Maryland UCR Program's Region III - Western Maryland ($n=19$, 4.99%) includes Allegany, Frederick, and Washington Counties (*see* Maryland Department of State Police, 2014).²⁷ Frederick and Washington Counties have slightly still larger court communities, with five judgeships each, while Allegany County has two, i.e., more than most of the Eastern Shore but less than any of the Southern Maryland counties (Courts and Judicial Proceedings Article, § 1-503). Allegany County's 2014 population was greater than four of the six Eastern Shore counties, but less than the Southern Maryland counties, while Frederick and Washington Counties had similar (Washington) and higher (Frederick) populations than the Southern Maryland Counties in 2014, and roughly comparable population densities. Allegany County is very rural, while Frederick and Washington Counties had urban levels similar to two of the three Southern Maryland counties. Allegany and Washington Counties had 2013 poverty rates above the statewide level (though Washington is within the statewide margin of error), and median household incomes below. The 2013 violent crime rate ranged between 2.5 and 3.4 for these counties. (*See* Maryland Department of Planning, 2012, 2015). Republicans outnumber

²⁷ Region III also include Carroll and Garrett counties, but these had no cases in which the controlling or sole conviction was a white-collar crime, and they therefore do not appear in the analyses. The Maryland Statistical Handbook does not include Frederick County (or Carroll County) in its Western Maryland Region (*see* Maryland Department of Planning, 2015).

Democrats by 10% to 30%, and Hogan received 63% to 75% of the gubernatorial vote in the Western Maryland counties (Maryland State Board of Elections, 2014a; 2014b).

This study analyzes the Maryland UCR Program's two Washington Metropolitan (Region IV) counties (Montgomery and Prince George's Counties) (*see* Maryland Department of State Police, 2014) individually, as well as three of the five Baltimore Metropolitan (Region V) counties (Anne Arundel and Baltimore Counties, and Baltimore City). This study combines the remaining two Baltimore Metropolitan region counties (Harford and Howard) as Other Counties ($n=15$, 3.94%).

Harford and Howard Counties each have five judgeships, the same as Frederick and Washington Counties, and more than the other grouped counties, but fewer than the individual counties (*see* Courts and Judicial Proceedings Article, § 1-503). They have larger populations, more densely arranged, than the counties in the other three regions (though fewer and less densely populated than in the individually considered counties). Harford and Howard are both more urban than the other grouped counties (though Howard is nearly twice as urban as Harford), and their 2013 violent crime rates were 2.7 and 2.1 per 1,000, respectively. Both had 2013 poverty rates below the statewide level and 2013 median household incomes above it. (*See* Maryland Department of Planning, 2012; 2015).

d. Dependent Variables.

This study models three outcomes captured by the Database—(1) placement, with two measures for this outcome; (2) departures below the guidelines recommended sentencing range; and (3) disposition type (ABA pleas, defined below). As previously noted the Database does not include predisposition outcomes, such as charge reductions

or pretrial release. While it includes sentence length this field is highly skewed. More than 60% of white-collar defendants received no incarceration (a plurality of the remainder received one month or less). This study thus does not model sentence length.

As described above a variety of court community features predict placement, a common indication of sentence severity. The placement decision being binary, this study uses a binary logistical regression model for it, the equation for which is

$$P(\textit{placement}) = \frac{e^{x\beta}}{1 + e^{x\beta}} \quad (1)$$

where x is a vector of explanatory variables, and β the logit coefficients. This study models two measures of the placement outcome separately—any incarceration and postsentencing incarceration. Approximately 30% ($n=115$) of the defendants received a jail or prison term after their sentencing. Also including those held before sentencing, such as on bail, increases this number by 21% ($n=139$, 36.48%).²⁸

The existing literature shows that court community features also affect departures, an additional indication of severity. Though judges mostly sentenced white-collar defendants in these data within the recommended guidelines range ($n=281$, 73.75%), a substantial minority received sentences below the recommended sentencing guidelines range ($n=69$, 18.11%). A smaller proportion received sentences above the recommended

²⁸ Coding a defendant who the judge sentences to one month incarceration, but who was held on bail for a month (or more) during the pendency of the case as not receiving any carceral penalty would improperly equate such a defendant with one held on bail for a month, and then sentenced to probation only. The 139 referred to above should include only the former.

guidelines range ($n=25$, 6.56%).²⁹ Because of the very small percentage of upward departures, this study uses a dummy variable for downward departures as the outcome, modeled with binary logit.³⁰

A particular strength of the Maryland data is the granularity of the disposition field with respect to pleas. Some sentencing research distinguishes only between pleas and trials. Some studies separate pleas with agreements from pleas without agreements. The Maryland data further differentiate between what the Database refers to as ABA plea agreements and non-ABA plea agreements.

An ABA plea agreement is a “plea agreement that a court has approved relating to a particular sentence, disposition, or other judicial action” (MSCCSP, 2015b: 2; *see also* Md. Code Regs. [COMAR] 14.22.01.02B(2)). Pursuant to Maryland Rule 4-243(c), ABA plea agreements bind the court. Other plea agreements, i.e. those which a judge has not approved, are non-ABA plea agreements and do not bind the court.

An ABA plea agreement can therefore reduce uncertainty for court actors beyond the reduction achieved through ordinary plea agreements. It indicates consensus among all key members of the courtroom workgroup concerning an appropriate outcome for a particular defendant given his, her, or its crime. An ABA plea is hence different in kind from non-ABA plea agreements (or pleas without agreement).

²⁹ This study used a slightly different definition of departures than the MSCCSP uses in analyzing guidelines compliance rates.

³⁰ If there had been more departures, particularly more upward departures, an ordinal or a multinomial logit model might have been more informative than a binary logit model of downward departures. As discussed further in Appendix III, these approaches were not practical.

Disposition type may vary by jurisdiction as a function of court community features. All else being equal, courtroom workgroups with more familiar and stable relationships should, for example, converge on more ABA pleas than jurisdictions with weaker workgroup relationships, as ABA pleas require greater agreement. To estimate geographical effects for this greater degree of agreement, this study uses binary logit, limited to those white-collar defendants reaching some form of plea agreement.³¹

The vast majority of white-collar defendants in the Database extract pleaded guilty, either with an ABA plea agreement ($n=113$, 29.66%), a non-ABA plea agreement ($n=153$, 40.16%), or a plea without agreement ($n=33$, 8.66%). As is typical, few jury ($n=15$, 3.94%) and bench trials ($n=5$, 1.31%) occurred. These numbers include defendants for whom the disposition was originally missing in the Database extract, but was available from Case Search. For some cases though Case Search only indicated that the defendant pleaded guilty or went to trial, and not the specific type of plea or trial. Because these are still more informative than leaving the field missing, I recoded these defendants to guilty plea of unknown type ($n=48$, 12.60%) or trial of unknown type ($n=3$, .79%).

e. Control Variables.

The data contain a number of other individual case-level measures used as controls. These include defendant demographic characteristics such as the defendant's

³¹ Although one could use a multinomial logit model to estimate geographical effects for all disposition types, this approach was not practical as discussed in Appendix III. ABA pleas are the outcome with the greatest theoretical interest (as compared to non-ABA plea agreements), so binary logit is sufficient.

age at sentence (average age was 40.76 years old), sex (approximately 40% female) and race ($n=209$ (54.86%) black, 149 (39.11%) white, 17 (4.46%) other or unidentifiable).³²

The data have four criminal history measures including: (1) whether the defendant had a current relationship with the criminal justice system³³ at the time of the offense ($n=36$, 9.45%); a summary criminal conviction measure ranging from 0 to 5 (the average score was 1.00); whether the defendant had any prior parole or probation violations as an adult ($n=37$, 9.71%). The sum of these measures (and a delinquency score, which the Commission strips from the publicly available data) is the offender score, which can range from 0 to 9 (average score was 1.20). The primary analyses below rely on the total offender score, and use the components in robustness checks.

Within the four categories of white-collar crimes considered in this study, most defendants received sentences for commercial frauds ($n=232$, 60.89%), followed by embezzlement ($n=88$, 23.10%), consumer protection law violations ($n=40$, 10.50%), and environmental crimes ($n=21$, 5.51%). Most of the convictions were for felonies ($n=244$, 64.04%) as opposed to misdemeanors.³⁴ The average statutory maximum carceral penalty was 127.50 months.

³² The defendant in at least one of the cases missing all the demographic variables was a company.

³³ Defined as “on parole, on probation, incarcerated, on work release, on mandatory supervision, an escapee, or had a comparable status” (MSCCSP, 2015b: 23).

³⁴ In Maryland, however, the distinction between misdemeanors and felonies is not the same as in much of the United States. In many places, crimes punishable by up to one year of incarceration are misdemeanors, while those punishable with more than one year of incarceration are felonies. Maryland has statutory misdemeanors punishable with ten years of more in prison, and at least one felony with a one year statutory

The Commission has classified all the conviction offenses used in the analyses as seriousness category V ($n=327$, 85.83%), VI ($n=12$, 3.15%), or VII ($n=42$, 11.02%). seriousness category VII is the least serious, and for the analyses I rescaled the seriousness categories from one to three, with three the most serious.³⁵ The average rescaled seriousness category was 2.75.

When assigning seriousness categories, the Commission considers the already established serious categories of offenses with comparable statutory maximum penalties, felony or misdemeanor levels, and substance. The primary analyses below rely on the seriousness category, and use the variables reflecting the Commission's considerations in determining seriousness categories in robustness checks.

The offender score and seriousness category together determine the recommended sentencing guidelines range. Taking the midpoint of the range, the average recommended sentence was 15.27 months. The primary analyses below rely on the offender score and seriousness category, and use the guidelines midpoint in robustness checks.

The data include several additional case processing variables which could conceivably affect outcomes. They indicate the defendant's representation type—Public Defender, private attorney, court appointed or self. The analyses use a dummy variable

maximum (*see* MSCCSP 2015b). Robustness checks, described in Appendix II controlled for this quirk in Maryland law, using felony classification and statutory maximum penalties.

³⁵ Given the few category VI and very few category VII offenses, combining categories VI and VII or just using a dummy variable for category V could have been another potential approach. I rescaled and kept the categories separate to preserve the original ordered character and maintain the admittedly limited variation.

for private defense attorney ($n=248$, 65.09%).³⁶ Most defendants had a single conviction count ($n=321$, 84.25%), but some had two or more ($n=60$, 17.75%). A dummy variable for multiple offences controls for the effects of having additional conviction counts. As noted above the Commission is in the process of automating guidelines calculation. To control for possible instrumentation effects due to this change a dummy variable indicated whether the worksheet used was electronic ($n=18$, 4.72%).

Sentencing practices change over time. This might be the result of changing general societal views on incarceration. Or it could be in response to a particular event (such as a financial crisis or a particularly high profile individual case) that might make white-collar crime a more salient issue. Alternately budgets change from year to year, imposing different practical constraints on criminal justice processes. The year of sentence therefore controls for period effects. Beginning with Fiscal Year 1999 coded as 1, the mean fiscal year of sentence was 9.33. The primary analyses below rely on the fiscal year (as this more accurately reflects practical concerns such as available resources), and use calendar year (beginning with 1999 coded as 1, the mean calendar year was 8.86) as a robustness check.

³⁶ This field was originally missing for approximately sixty white-collar defendants (about 15%). Using the Case Search website I identified an attorney for all but seven cases (about 2%). Although Case Search does not indicate whether the defendant has retained or the court has appointed private counsel, because less than one percent of cases in the Database extract (white-collar defendants and in general) indicate court-appointed representation, for data-cleaning purposes I assumed the defendant had retained any private attorneys listed. Omitting these cases from the regressions affected the magnitudes and significance levels of several of the geographical variables.

Assuming that the case disposition is separate from and prior to the placement and departure decisions (rather than, for example, the parties simultaneously negotiating a guilty plea with an agreed sentence), conviction type also likely predicts placement and departures. Models for placement and departures therefore also include controls for conviction type with a series of dummy variables.

This study demonstrates how geography affects placement, downward departures, and ABA pleas in white-collar cases in Maryland's circuit courts. Doing so shows whether white-collar sentencing follows patterns observed in other contexts and consistent with theoretical predictions. This provides insight into the wider applicability of the earlier findings and theoretical perspectives, and raises potential equal justice concerns.

f. Analytic Strategy

Because the primary independent variable is a multicategory nominal variable, the choice of reference category matters a great deal. For each dependent variable's final model, I therefore report three sets of results below, alternating the reference category between Baltimore City, the Eastern Shore counties, and Anne Arundel County. These counties differ considerably with respect to relevant features of their court communities.

Baltimore City has by far the largest circuit court in Maryland, with thirty-three judgeships. This court has a large criminal caseload, and the city has high levels of violent crime. It is the most urbanized jurisdiction in Maryland, and is heavily Democratic.

The Eastern Shore counties' court communities are in some ways the opposite of Baltimore City. These are generally very small courts—four of the six Eastern Shore

counties in the data have only one judge each. The counties are largely rural and sparsely populated. The circuit courts have relatively light caseloads, and the communities are politically more conservative than Baltimore City.

Anne Arundel County is somewhat in the middle. Of the five large counties it has the smallest court (twelve judgeships currently, though fewer prior to 2009). It has a smaller population and it is less densely populated than the other large counties, though greater population than any of the small court communities. And Anne Arundel is less urbanized than some of the other large counties.

The court community perspective predicts that Baltimore City's courts will sentence (conventional offenders) less severely (i.e., less likely to incarcerate, more likely to depart downwards) than other courts.³⁷ The court community perspective would typically expect small courts in rural jurisdictions, as on the Eastern Shore, to sentence more severely than others. And for Anne Arundel County, we would generally expect to see a split between the other large courts sentencing less severely and the smaller courts sentencing more severely. But with white-collar offenders, the expected patterns for conventional sentencing data may not hold, and could plausibly be the opposite in some circumstances. For the ABA plea outcome, I expect courts that sentence less severely will be able to reach a greater level of agreement, and all else being equal will have more ABA pleas.

³⁷ Baltimore City does have a high percentage minority population and high poverty levels, which theory predicts result in more severe outcomes. But the empirical literature has not consistently supported this prediction, and where it has often only conditionally so.

CHAPTER 4: RESULTS AND DISCUSSION

a. Placement

Table 3a displays the results of the logistic regression³⁸ of any incarceration on the county and control variables (with Anne Arundel County as the reference category) for white-collar offenders. Model 1 shows the results with only the geographic variables as regressors. Model 2 controls for legitimate bases for differences in placement, the defendant's criminal justice history (i.e., offender score) and the offense seriousness category. Model 3 adds controls for potential illegitimate influences on placement, the defendant's demographic characteristics with sex (female=1), race (black=1), and age in years (along with age-squared). Model 4 includes the additional case processing characteristics as controls. The final model (Model 5) assumes case disposition is a distinct event from, and precedes, the placement decision, and hence controls for conviction type (the reference category is ABA plea).

Model 5 shows the odds of a white-collar defendant receiving any carceral sentence are significantly higher in Prince George's County (*odds ratio* \approx 4.36), the Eastern Shore counties (*odds ratio* \approx 8.07), the Southern Maryland counties (*odds ratio* \approx 8.46), and in the Other Counties (*odds ratio* \approx 6.06), than in Anne Arundel County.

[Table 3a about here.]

Those results are generally robust to alternate specifications of criminal justice history, crime seriousness, and year (Appendix II outlines robustness checks used). If one does

³⁸ All regressions used Stata 14. All tables report the logit coefficients exponentiated into more easily interpretable odds ratios.

not accept Model 5's assumption that conviction type precedes the placement decision, Model 4 shows that except in Montgomery County, controlling for disposition type has little effect on the geographic variables' odds ratios. Without controlling for disposition Montgomery County also has marginally higher odds of placement (*odds ratio* \approx 2.36), whereas it is not significant when controlling for disposition type.

Table 3b shows how the odds ratios for the geographic variables differ for Model 5 of Table 3a depending on the reference category. (The first column, with Anne Arundel as the reference category, simply repeats the results from Model 5)

[Table 3b about here.].

The odds ratios are significantly lower in Baltimore City (center column of Table 3b) than everywhere except Anne Arundel County and the Western Maryland counties (Baltimore County is marginal). With Baltimore City as the reference category, the odds ratios for white-collar defendants are approximately equal to 3.07 for Baltimore County, 3.38 for Montgomery County, 9.64 for Prince George's County, 17.85 for the Eastern Shore, 18.7 for Southern Maryland counties, and 13.39 for the Other Counties.

The Eastern Shore counties have significantly higher odds of incarceration than Anne Arundel County (*odds ratio* \approx .124), Baltimore City (*odds ratio* \approx .056), Baltimore County (*odds ratio* \approx .172), Montgomery County (*odds ratio* \approx .189), and the Western Maryland Counties (*odds ratio* \approx .103).

Several of the control variables in Model 5 (and Table 3b) also have significant results, generally in the directions one would anticipate. Higher offender scores and offense seriousness categories significantly increase the odds of placement, which is both reassuring and unsurprising. Age slightly increases the likelihood of incarceration, but at

a marginally declining rate. White-collar defendants with a private defense attorney are significantly less likely to receive a carceral sentence. This could be a status effect, but might simply be a function of having a lawyer with more time to devote to one's case. Those with more than one count at conviction are significantly more likely to receive placement, which is expected given that these are likely more serious cases. Over time there is a slight decrease in the odds of incarceration.

Unexpectedly, women convicted of a white-collar crime are marginally more likely to receive a carceral sentence than men. Daly (1989), using the Wheeler, Weisburd, and Bode (1982) data, assesses gender differences in white-collar crime (with an offense-based definition). Daly shows that female white-collar criminals in the Yale data generally had lower a socioeconomic status than males. They were more likely to be clerical workers (as opposed to managerial or professional workers), black, and unconnected to the labor force, as well as less likely to have completed a four-year college degree. If white-collar female offenders in the Maryland data extract similarly had lower socioeconomic status than male white-collar offenders, their higher odds of incarceration may reflect less resources or power to secure release.

White-collar defendants receiving a non-ABA plea agreement have significantly lower odds of incarceration than defendants with an ABA plea. This is an additional unexpected result, without an obvious explanation.

Table 4a displays the same models as Table 3a, using incarceration subsequent to sentencing, rather than any carceral sentence, as the measure of placement. The results from the final modal (Model 5) are largely similar to the results from Table 3a with respect to significance and direction (i.e., less than one or greater than one) of the

geographic variables. The magnitudes are sometimes somewhat larger, however, and Baltimore City is now significantly different from Anne Arundel County.

[Table 4a about here.]

The geographical results for Model 5 of Table 4a are also generally robust to alternate specifications (*see* Appendix II), as was the case for any incarceration, particularly with respect to significance and direction, though less so as for magnitude.

Table 4b, as with Table 3b, again shows how the odds ratios for the geographic variables differ depending on the reference category. With Anne Arundel as the reference category (Model 5 of Table 4a and the first column of Table 4b), the odds of a white-collar defendant receiving placement after sentencing were significantly lower in Baltimore City (*odds ratio* $\approx .25$), higher in Prince George's County (*odds ratio* ≈ 3.65), the Eastern Shore counties (*odds ratio* ≈ 12.19), the Southern Maryland counties (*odds ratio* ≈ 11.62), and in the Other Counties (*odds ratio* ≈ 8.01).

The odds ratios are significantly lower in Baltimore City (the middle column of Table 4b) than everywhere else (Western Maryland is marginal). Compared to Baltimore City, the odds ratios are approximately equal to 3.99 for Anne Arundel County, .474 for Baltimore County, 4.69 for Montgomery County, 14.58 for Prince George's County, 48.7 for the Eastern Shore, 4.96 for Western Maryland, 46.4 for Southern Maryland, and 32.01 for the Other Counties.

The Eastern Shore counties have significantly higher odds of incarceration after sentencing than Anne Arundel County (*odds ratio* $\approx .08$), Baltimore City (*odds ratio* $\approx .02$), and Baltimore, Montgomery, and the Western Maryland Counties (*odds ratio* $\approx .1$).

Some of the control variables in Table 4b (and Model 5 of Table 4a) once again have significant results for postsentencing placement. These were generally the same as in Table 3b, except that none of the demographic variables had a significant effect.

Collectively, the results for the two measures of the placement outcome are, contrary to my prediction, fairly similar, for white-collar defendants to what one would expect in data on conventional sentencing. The Eastern Shore was more likely to incarcerate white-collar defendants than most other courts, while Baltimore City was least likely to do so. And many of the significant odds ratios were substantively quite large in magnitude.

The pre-Guidelines research on federal white-collar sentencing associated prioritization of white-collar cases with sentencing leniency (*see* Hagan, Nagel, & Albonetti, 1980). Anne Arundel was the modal county in the current analyses, accounting for approximately one quarter of white-collar cases. While Anne Arundel had lower odds of placement than several others, we should not read too much into this as a prioritization effect, as characterizing ninety-seven cases out of thousands (over a fifteen year period) as prioritizing white-collar crime would be rather dubious. Even if one views Anne Arundel County as analogous to District C, Anne Arundel County had significantly higher odds of postsentencing placement than Baltimore City. So Anne Arundel County was not even strictly the most lenient.

But examining the results more closely, they were not uniformly consistent with what the court community perspective would predict for conventional crime. Across both measures of placement, the odds ratios for Prince George's County, the second largest court community, showed a significantly higher likelihood of placement compared to

Anne Arundel County, and were not significantly different from the small court communities on the Eastern Shore. This is also different from what one would predict based on Paternoster et al. (2003; 2004), where Prince George's County was more lenient (i.e., less likely to impose the death penalty) than others. For Anne Arundel County the odds did not differ significantly from some of the larger counties (including Baltimore City for the any placement measure) or for the fairly small Western Maryland court communities (which also did not differ from Baltimore City for any placement). Granted Prince George's and Anne Arundel are only two counties, but with only nine geographic categories in these data two are not obviously trivial.

b. Departures

While the results for placement of white-collar offenders did not differ drastically from a conventional sentencing story, the results for downward departure are quite different, and much more consistent with my predictions. Table 5a shows the binary logistic regression for downward departures. Model 5 indicates that controlling for the defendant's criminal justice history, offense seriousness, demographic characteristics, case processing variables, and disposition,³⁹ Baltimore City has significantly lower odds of a downward departure (*odds ratio* $\approx .04$) than Anne Arundel County, the reference category.

[Table 5a about here.]

³⁹ The models for placement control for each of jury trials, bench trials, and trials of unknown type. Including these as separate terms in the model for downward departures results in eighteen observations perfectly predicted and not used. To avoid losing observations the model for downward departures combined all trials into a single category.

When varying the reference category for the geographic variables, Baltimore City is the only jurisdiction with significantly different odds of a downward departure for white-collar defendants than the others.⁴⁰ Baltimore City has significantly lower odds of a downward departure than everywhere else except Prince George's County, the Eastern Shore counties, and the Other Counties (Table 5b, center column). The odds of a downward departure are significantly higher in Anne Arundel County (*odds ratio* \approx 23.99), Baltimore County (*odds ratio* \approx 15.61), Montgomery County (*odds ratio* \approx 15.04), the Western Maryland counties (*odds ratio* \approx 29.38), and the Southern Maryland counties (*odds ratio* \approx 11.49) than in Baltimore City.

[Table 5b about here.]

These results are less robust to different specifications than placement (*see* Appendix II). Magnitudes of the odds ratios vary a lot under some specifications. With only approximately 20% of defendants in these data receiving downward departures, sensitivity is to be expected, and bespeaks the need for caution in interpreting the results. But the substantive conclusion that a white-collar defendant has multiple times better odds of a downward departure nearly anywhere in Maryland compared to the largest court community in Baltimore City is, however, generally consistent,⁴¹ and is the

⁴⁰ Additional analyses, not shown but available upon request, rotated each geographic unit as the reference category. Across all specifications only Baltimore City differed significantly from any of the other categories.

⁴¹ The null results for Prince George's County, the second largest court community, are still generally consistent with the overall narrative of larger courts sentencing more severely. The Eastern Shore counties are not consistent with this narrative, but they were only just below marginally significant, with $p \approx .11$, using a two-tailed test to be conservative.

opposite of what the court community perspective would predict for conventional offenders.⁴²

With respect to control variables, defendants with more extensive criminal justice histories have significantly higher odds ratios of a downward departure. This might seem counterintuitive, but because the guidelines increase nonlinearly (*see* Bushway & Piehl, 2011), towards the upper end a one unit increase in an offender score can greatly increase the recommendation, which might induce more departures as a substantively rational local correction to the guidelines (*see* Kramer & Ulmer, 2002). The other control variables are generally unsurprising. The odds of a downward departure have increased over time for white-collar defendants, consistent with overall patterns of slightly increasing departures in Maryland's circuit courts. Defendants sentenced for more than one count have significantly lower odds of a downward departure, and the odds ratio for defendants convicted by trial are marginally lower, but with a large magnitude.

c. ABA Pleas

Table 6a shows, given reaching a plea agreement, the odds ratios of a white-collar defendant obtaining an ABA plea, relative to a non-ABA plea. Model 4 indicates that, controlling for offender score, offense seriousness, demographic characteristics, and case processing variables, the odds of an ABA plea are significantly higher in Baltimore City (*odds ratio* \approx 253.21), Montgomery County (*odds ratio* \approx 33.24), Prince George's County (*odds ratio* \approx 101.26), the Southern Maryland counties (*odds ratio* \approx 21.4), and the Other Counties (*odds ratio* \approx 29.62) than in Anne Arundel County.

⁴² It is also different from what one would expect based on Paternoster et al. (2003; 2004), in which Baltimore City was less likely than the other jurisdictions to impose the death penalty.

Robustness checks (*see* Appendix II) produced similar results in terms of significance and direction, but the magnitudes of some odds ratios became much larger under some alternate specifications. And as with the other outcomes discussed above, the reference county matters for the odds of an ABA plea relative to a non-ABA plea, as shown in Table 6b.

[*Tables 6a and 6b about here.*]

The odds of an ABA plea relative to a non-ABA plea agreement are significantly higher for Baltimore City than everywhere else, except Prince George's County. Compared to Baltimore City, the odds ratios are approximately equal to .004 for Anne Arundel County, .003 for Baltimore County, .13 for Montgomery County, .004 for the Eastern Shore counties, .01 for the Western Maryland counties, .09 for the Southern Maryland counties, and .12 for the Other Counties.

Compared to the Eastern Shore counties, most other jurisdictions had significantly higher odds of an ABA plea (relative to a non-ABA plea). The odds were higher for Baltimore City (*odds ratio* ≈ 246.11), Montgomery County (*odds ratio* ≈ 32.31), Prince George's County (*odds ratio* ≈ 98.42), the Southern Maryland Counties (*odds ratio* ≈ 20.8), and the Other Counties (*odds ratio* ≈ 28.79).

With respect to control variables, neither offender score nor offense seriousness significantly affected the odds of receiving an ABA plea relative to a non-ABA plea; there is not necessarily a reason why they should have. Black defendants were significantly less likely, and female defendants marginally less likely, to receive an ABA plea than nonblack or male defendants. If white-collar crime committed by black or female offenders is less of a "normal crime" (Sudnow, 1965), which seems plausible,

there may be less of a consensus or no going rate, making ABA pleas more difficult for these defendants. More than one sentencing count at sentencing significantly decreased the odds of achieving an ABA plea. This makes sense as these are more complex cases, likely requiring more negotiation. Use of an electronic sentencing guidelines worksheet also decreased the odds of an ABA plea.

Whether these results support the prediction that courts that sentence white-collar offenders less severely will be more likely to reach ABA plea agreement depends on the measure of severity used. For the departure outcome, these results do not support the prediction. Baltimore City, the jurisdiction least likely to grant a downward departure, was more likely than almost any other to reach an ABA plea, with some rather extreme odds ratios. For the Eastern Shore counties though, which was more severe than most in terms of placement, several other courts that were less likely to give a white-collar defendant a carceral sentence were more likely to reach an ABA plea. These were not consistently the larger or smaller court communities. The counties significantly different from Anne Arundel in terms of the odds of an ABA plea do not seem systemically related to those with which it differed on odds of placement.

d. Summary and Conclusion

The results provide inconsistent and mixed support for the predictions based on the focal concerns and court community literatures. Some of the findings are very similar to what one would expect for a general offender sentencing sample. But others suggest that, in some instances, different dynamics may be in play with white-collar sentencing in Maryland. Table 7 summarizes the main findings, while Figure 1 presents the mean predicted probability by county (or region) for each outcome measure.

[Table 7 and Figure 1 about here.]

Figure 1 shows that while the several of the small jurisdictions have the highest mean predicted probabilities of placement of white-collar defendants, the second largest court community in Prince George's County is not far behind, particularly on the any placement measure. As suggested above, the small Western Maryland court communities' mean predicted probability of placement is more similar to some of the larger court communities, and Anne Arundel's (the smallest of the large court communities) mean predicted probability is slightly lower than some of the other large counties.

The mean predicted probabilities for downward departures show less variation. But interestingly the largest court community, which the logistic regression results showed as significantly less likely than others to depart downwards for white-collar offenders (Baltimore City) does not have the lowest predicted probability.⁴³ The regression results for downward departures concerning Baltimore City are substantively noteworthy, because they identify an area in which white-collar sentencing appears to have the exact opposite pattern from local contexts research on conventional sentencing. The low mean predicted probability for Montgomery County, not reflected in significant regression results, might be a function of its caseload composition; unlike in the other

⁴³ Note, however, that the mean predicted probability depends not only on court-specific practices, but also on case composition. If all else being equal a court sentences leniently but sentences many white-collar defendants with more than one conviction count or has a larger number of trials, for example, the predicted probabilities of a downward departure reflect both, rather than being a pure county effect.

jurisdictions, a large majority of the cases in Montgomery County involved embezzlement.⁴⁴

As to the probability of an ABA plea, the very high mean predict probabilities for Baltimore City and Prince George's County stand out (along with their improbably large regression coefficients⁴⁵). It is intriguing that the largest court community was most likely to reach an ABA plea and seemed least likely to depart downwards for white-collar defendants, while the second largest court community was next most likely to reach an ABA plea and was one of the only not significantly more likely than Baltimore City to depart downwards. Although contrary to my initial expectation concerning lenient sentencing and ABA pleas, in retrospect the connection between ABA pleas and departures perhaps should not have been surprising—if there is greater consensus and firmly established going rates, there may be less need to depart.

Baltimore City and Prince George's County are the two largest court communities. They also have the highest percentage of the population minority. In both jurisdictions Democrats vastly outnumber Republicans (approximately 10:1). For Baltimore City the poverty level is also quite high. (*See* Maryland Department of

⁴⁴ This raises the troubling possibility that these and other apparent results might actually be artifacts of nonsubstantive charging behavior or other administrative or recordkeeping practices. Some State's Attorneys, for example, might be charging identical conduct under other provisions, such as general theft statutes rather than embezzlement, or vice versa.

⁴⁵ One need not necessarily believe the exact magnitudes of the numbers to accept that they indicate that a white-collar defendant in Baltimore City or Prince George's County is much more likely, all else being equal, to reach an ABA plea agreement, relative to a non-ABA plea agreement, than a white-collar defendant in Anne Arundel County or the Eastern Shore.

Planning, 2012; Maryland State Board of Elections, 2014a.) Although the general local contexts literature has found little effect for political and demographic factors of a community, it is possible that the similarities between these two jurisdictions reflects not only larger courts perceiving white-collar offenders as more of a threat to the community, but also something of a backlash against relatively privileged offenders committing crimes of greed rather than crimes of need. At this point, though, that is speculation.

CONCLUSION

Local effects for white-collar defendants, and local effects that are unanticipated based on the general sentencing literature, are not as much results as they are questions. This exploratory effort has of necessity focused on establishing *whether* and *what*. But the more meaningful, important, and substantively interesting question is *why*. Why does a white-collar offenders' likelihood of receiving a downward departure, and to a lesser extent a carceral sentence, not only vary depending on which (Maryland circuit) court sentences that defendant, but seems to vary differently from conventional offenders? Although I have offered some speculation, what is driving the results is unclear. Dummy variables for localities are a fairly blunt instrument, and readily available information may be unable to explain the differences. This underscores the need for further research in this area

This study has several substantial limitations. It used highly selected cross-sectional data, with a relatively low numbers observations, and little variation for several key fields. Robustness checks showed sensitivity of the magnitudes of some of the results. As with many sentencing datasets, the Database extract lacks predispositional outcomes and good measures of theoretically important constructs.

Notwithstanding and subject to those weaknesses, this study showed that outcomes in white-collar sentencing in Maryland's circuit courts vary significantly across location, even when controlling for a variety of case characteristics. Where the local contexts of sentencing literature has so far largely overlooked white-collar crime, these are meaningful findings that begin to fill gaps and connect the white-collar sentencing and local contexts of sentencing literatures.

White-collar sentencing research has not (recently) paid much heed to the role of place, particularly in state courts. Local contexts of sentencing research has directed little attention specifically to white-collar crime. This study showed that not only did white-collar placement and departures vary in Maryland state courts according to place, they do so in ways not entirely anticipated by existing theoretical perspectives and social contexts research focusing on conventional criminal cases. In Maryland, larger and more urban court communities are not uniformly more lenient when it comes to white-collar sentencing than smaller and more rural court communities, in apparent contradiction to what seems to be the most consistent finding from more general social contexts research

Given the limitations of the data, and what are rather modest results, future research is necessary to expand upon this study. Research using white-collar data from other states, ideally with more observations, greater variation, and better measures of white-collar crime, should establish whether this study's results are peculiar to Maryland, the selected offenses, or both. If data permit, multilevel analyses should formally test the relationships between court- or county-level characteristics and individual level outcomes, including cross-level interactions, for white-collar offenders.

Future research should also dig deeper into this study's findings as concerns Maryland. This study posited that ABA pleas have special theoretical significance, indicating stronger courtroom workgroup relationships. The results concerning ABA pleas were, however, somewhat unclear. Qualitative research could investigate what is truly happening in ABA pleas, which might provide insight into the extremely large odds ratios estimated.

We know earlier case decisions can affect later outcomes, as reflected in the Paternoster and colleagues research. But the Database extract used in this study cannot be used to address these earlier decisions. As quantitative data on these early outcomes are unavailable, qualitative research might also be able to examine how these processes, particularly charging decisions, vary across jurisdictions and ultimately affect outcomes for white-collar offenders.

TABLES AND FIGURE

Table 1a: Distribution of Cases by County (and Region) and Offense Type						
County	UCR Region	Commercial Fraud	Consumer Protection	Environmental	Embezzlement	Total
Anne Arundel		83	5	3	6	97
Baltimore City		46	0	3	1	50
Baltimore County		30	13	4	4	51
Montgomery		16	4	0	50	70
Prince George's		18	1	3	10	32
Cecil	Region I - Eastern Shore	1	0	0	2	3
Dorchester		2	0	0	2	4
Queen Anne's		0	0	0	3	3
Somerset		0	0	1	0	1
Talbot		0	0	1	1	2
Wicomico		4	0	4	0	8
Calvert	Region II - Southern Maryland	4	0	0	0	4
Charles		14	3	1	2	20
Saint Mary's		1	0	0	1	2
Allegany	Region III - Western Maryland	0	0	0	1	1
Frederick		3	8	0	1	12
Washington		5	1	0	0	6
Harford	Other (Region V) Counties	1	1	0	1	3
Howard		4	4	1	3	12
Total		232	40	21	88	381

	<u>Placement Postsentencing</u>		<u>Any Placement</u>		<u>Downward Departure</u>		<u>ABA Plea (vs. Non-ABA Plea Agreement)</u>	
	No	Yes	No	Yes	No	Yes	No	Yes
Anne Arundel	81	16	75	22	78	19	62	6
Baltimore City	41	7	35	13	39	9	5	37
Baltimore County	38	12	35	15	38	12	31	3
Montgomery	48	21	43	26	61	8	18	28
Prince George's	15	15	12	18	25	5	2	16
Eastern Shore	8	13	8	13	17	4	12	2
Southern MD	10	16	9	17	20	6	7	11
Western MD	13	6	13	6	15	4	12	3
Other Counties	6	9	6	9	13	2	4	7
Total	260	115	236	139	306	69	153	113

Table 2: Descriptive Statistics (N=381, Except as Noted)						
<u>Variable</u>	<u>Obs</u>	<u>%</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min.</u>	<u>Max.</u>
County or Region						
Anne Arundel	97	25.46%				
Baltimore City	50	13.12%				
Baltimore County	51	13.39%				
Montgomery	70	18.37%				
Prince George's	32	8.40%				
Eastern Shore	21	5.51%				
Southern MD	26	6.82%				
Western MD	19	4.99%				
Other (Central MD)	15	3.94%				
Any Placement						
No	236	61.94%				
Yes	139	36.48%				
Missing	6	1.57%				
Postsentencing Placement						
No	260	68.24%				
Yes	115	30.18%				
Missing	6	1.57%				
Departures						
Downward	69	18.11%				
Within Guidelines	281	73.75%				
Upward	25	6.56%				
Missing	6	1.57%				
Disposition						
ABA Plea	113	29.66%				
Non-ABA Plea Agreement	153	40.16%				
Plea, No Agreement	33	8.66%				
Guilty Plea Unknown Type	48	12.60%				
Bench Trial	5	1.31%				
Jury Trial	15	3.94%				
Trial Unknown Type	3	0.79%				
Missing	11	2.89%				
Offender Score			1.20	1.97	0	7
Offense Seriousness Category			2.75	0.64	1	3
Guidelines Midpoint (Months)			15.27	30.65	0	330
Current Criminal Justice Relationship						
No	343	90.03%				
Yes	36	9.45%				
Missing	2	.52%				
Prior Adult Criminal Record (n=379)			1.00	1.66	0	5

Table 2: Descriptive Statistics (Continued) (N=381, Except as Noted)						
<u>Variable</u>	<u>Obs</u>	<u>%</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min.</u>	<u>Max.</u>
Prior Parole/Probation Violation						
No	342	89.76%				
Yes	37	9.71%				
Missing	2	0.52%				
Offense Type						
Commercial Fraud	232	60.89%				
Consumer Protection	40	10.50%				
Environmental	21	5.51%				
Embezzlement	88	23.10%				
Offense Level						
Misdemeanor	137	35.96%				
Felony	244	64.04%				
Statutory Maximum Carceral Penalty (Months)			127.50	65.77	12	180
Sex						
Male	229	60.10%				
Female	151	39.63%				
Missing	1	0.26%				
Race						
Black	209	54.86%				
White	149	39.11%				
Other or Unidentifiable	17	4.46%				
Missing	6	1.57%				
Age at Sentencing (n=377)			40.76	11.93	18.31	83.92
Private Attorney						
No	126	33.07%				
Yes	248	65.09%				
Missing	7	1.84%				
Counts at Sentencing						
Single Count	321	84.25%				
>1 Count	60	15.75%				
Worksheet Type						
Paper	363	95.28%				
Electronic	18	4.72%				
Fiscal Year Sentenced (FY 99=1)			9.33	4.17	1	16
Calendar Year Sentenced (CY 99=1)			8.86	4.20	1	16

Table 3a: Logistic Regression of Any Incarceration

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)
Baltimore City	1.266	(0.513)	0.832	(0.369)	0.842	(0.379)	0.734	(0.346)	0.452	(0.255)
Baltimore County	1.461	(0.573)	1.106	(0.476)	1.229	(0.539)	1.427	(0.660)	1.389	(0.700)
Montgomery	2.061*	(0.716)	2.050 [†]	(0.765)	2.072 [†]	(0.807)	2.358 [†]	(1.034)	1.528	(0.725)
Prince George's	5.114**	(2.274)	5.397**	(2.589)	4.364**	(2.228)	5.828**	(3.191)	4.361*	(2.566)
Eastern Shore	5.540**	(2.829)	5.855**	(3.165)	7.962**	(4.910)	7.521**	(4.774)	8.074**	(5.451)
Western MD	1.573	(0.865)	1.187	(0.701)	1.300	(0.788)	0.812	(0.522)	0.828	(0.553)
Southern MD	6.439**	(3.080)	6.828**	(3.511)	6.518**	(3.374)	8.810**	(4.806)	8.461**	(5.034)
Other Counties	5.114**	(2.967)	5.297**	(3.341)	6.241**	(4.044)	6.923**	(4.653)	6.059*	(4.306)
Offender Score			1.442**	(0.092)	1.446**	(0.097)	1.460**	(0.106)	1.520**	(0.118)
Offense Seriousness			2.123**	(0.525)	1.967**	(0.491)	1.825*	(0.479)	2.025*	(0.599)
Female					1.303	(0.348)	1.448	(0.408)	1.632 [†]	(0.481)
Black					0.840	(0.224)	0.739	(0.208)	0.810	(0.239)
Age (years)					1.146*	(0.074)	1.143*	(0.077)	1.147 [†]	(0.083)
Age ²					0.999*	(0.001)	0.999 [†]	(0.001)	0.999 [†]	(0.001)
Private Attorney							0.435**	(0.128)	0.373**	(0.116)
>1 Count							2.575**	(0.900)	2.698**	(1.021)
MAGS case							0.422	(0.337)	0.711	(0.584)
Fiscal Year							0.946	(0.033)	0.937 [†]	(0.035)
Non-ABA Plea									0.382*	(0.152)
Plea, No Agreement									1.127	(0.596)
Plea, Type Unknown									0.802	(0.362)
Bench Trial									0.475	(0.512)
Jury Trial									2.871	(2.121)
Trial, Type Unknown									2.103	(3.032)
Constant	0.293	(0.071)	0.024	(0.018)	0.002	(0.003)	0.005	(0.008)	0.005	(0.009)
Observations	375		375		366		360		355	

[†]p<.1 *p<.05 **p<.01

Table 3b: Varying the Reference Category in Model 5 of Table 3a (N=355)

	Reference=Anne Arundel		Reference=Baltimore City		Reference=Eastern Shore	
†p<.1 *p<.05 **p<.01	Odds Ratio	SE	Odds Ratio	SE	Odds Ratio	SE
Anne Arundel	-	-	2.211	1.246	0.124**	0.084
Baltimore City	0.452	0.255	-	-	0.056**	0.045
Baltimore County	1.389	0.7	3.070†	1.959	0.172*	0.127
Montgomery	1.528	0.725	3.377*	1.892	0.189*	0.136
Prince George's	4.361*	2.566	9.639**	6.346	0.54	0.428
Eastern Shore	8.074**	5.451	17.849**	14.436	-	-
Western MD	0.828	0.553	1.831	1.397	0.103**	0.088
Southern MD	8.461**	5.034	18.703**	12.521	1.048	0.838
Other Counties	6.059*	4.306	13.394**	10.323	0.75	0.657
Offender Score	1.520**	0.118	1.520**	0.118	1.520**	0.118
Offense Seriousness	2.025*	0.599	2.025*	0.599	2.025*	0.599
Female	1.632†	0.481	1.632†	0.481	1.632†	0.481
Black	0.81	0.239	0.81	0.239	0.81	0.239
Age (years)	1.147†	0.083	1.147†	0.083	1.147†	0.083
Age ²	0.999†	0.001	0.999†	0.001	0.999†	0.001
Private Attorney	0.373**	0.116	0.373**	0.116	0.373**	0.116
>1 Count	2.698**	1.021	2.698**	1.021	2.698**	1.021
MAGS case	0.711	0.584	0.711	0.584	0.711	0.584
Fiscal Year	0.937†	0.035	0.937†	0.035	0.937†	0.035
NonABA Plea	0.382*	0.152	0.382*	0.152	0.382*	0.152
Plea, No Agreement	1.127	0.596	1.127	0.596	1.127	0.596
Plea, Type Unknown	0.802	0.362	0.802	0.362	0.802	0.362
Bench Trial	0.475	0.512	0.475	0.512	0.475	0.512
Jury Trial	2.871	2.121	2.871	2.121	2.871	2.121
Trial, Type Unknown	2.103	3.032	2.103	3.032	2.103	3.032
Constant	0.005	0.009	0.002	0.004	0.04	0.072

Table 4a: Logistic Regression of Incarceration After Sentencing

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)
Baltimore City	0.864	(0.425)	0.537	(0.284)	0.530	(0.284)	0.393 [†]	(0.222)	0.250*	(0.165)
Baltimore County	1.599	(0.687)	1.214	(0.566)	1.266	(0.594)	1.289	(0.644)	1.187	(0.654)
Montgomery	2.215*	(0.838)	2.241*	(0.910)	2.298*	(0.963)	1.835	(0.861)	1.173	(0.597)
Prince George's	5.063**	(2.310)	5.373**	(2.656)	4.066**	(2.149)	4.919**	(2.833)	3.650*	(2.281)
Eastern Shore	8.227**	(4.328)	9.627**	(5.420)	11.025**	(6.892)	10.358**	(6.730)	12.192**	(8.446)
Western MD	2.337	(1.319)	1.874	(1.130)	1.939	(1.205)	1.133	(0.746)	1.241	(0.855)
Southern MD	8.100**	(3.946)	8.914**	(4.689)	8.514**	(4.497)	11.648**	(6.559)	11.617**	(7.085)
Other Counties	7.594**	(4.509)	8.378**	(5.437)	8.662**	(5.752)	8.445**	(5.987)	8.014**	(6.069)
Offender Score			1.424**	(0.092)	1.421**	(0.095)	1.453**	(0.107)	1.523**	(0.121)
Offense Seriousness			2.337**	(0.648)	2.160**	(0.603)	2.112*	(0.637)	2.528**	(0.878)
Female					0.903	(0.255)	0.946	(0.283)	1.020	(0.320)
Black					0.835	(0.233)	0.715	(0.215)	0.797	(0.251)
Age (years)					1.068	(0.068)	1.063	(0.071)	1.055	(0.075)
Age ²					0.999	(0.001)	0.999	(0.001)	1.000	(0.001)
Private Attorney							0.529*	(0.165)	0.454*	(0.152)
>1 Count							4.326**	(1.585)	4.721**	(1.878)
MAGS case							1.173	(0.954)	2.267	(1.929)
Fiscal Year							0.925*	(0.035)	0.919*	(0.038)
Non-ABA Plea									0.374*	(0.161)
Plea, No Agreement									1.255	(0.685)
Plea, Type Unknown									1.102	(0.526)
Bench Trial									0.575	(0.654)
Jury Trial									2.733	(2.023)
Trial, Type Unknown									2.587	(3.764)
Constant	0.198	(0.054)	0.012	(0.010)	0.004	(0.007)	0.012	(0.021)	0.011	(0.022)
Observations	375		375		366		360		355	

[†]p<.1 *p<.05 **p<.01

Table 4b: Varying the Reference Category in Model 5 of Table 4a (N=355)

	Reference=Anne Arundel		Reference=Baltimore City		Reference=Eastern Shore	
[†] p<.1 *p<.05 **p<.01	Odds Ratio	SE	Odds Ratio	SE	Odds Ratio	SE
Anne Arundel	-	-	3.994*	2.63	0.082**	0.057
Baltimore City	0.250*	0.165	-	-	0.021**	0.018
Baltimore County	1.187	0.654	4.742*	3.414	0.097**	0.074
Montgomery	1.173	0.597	4.687*	3.015	0.096**	0.072
Prince George's	3.650*	2.281	14.579**	10.998	0.299	0.243
Eastern Shore	12.192**	8.446	48.700**	42.574	-	-
Western MD	1.241	0.855	4.958 [†]	4.075	0.102**	0.087
Southern MD	11.617**	7.085	46.404**	34.512	0.953	0.757
Other Counties	8.014**	6.069	32.011**	27.556	0.657	0.589
Offender Score	1.523**	0.121	1.523**	0.121	1.523**	0.121
Offense Seriousness	2.528**	0.878	2.528**	0.878	2.528**	0.878
Female	1.02	0.32	1.02	0.32	1.02	0.32
Black	0.797	0.251	0.797	0.251	0.797	0.251
Age (years)	1.055	0.075	1.055	0.075	1.055	0.075
Age ²	1	0.001	1	0.001	1	0.001
Private Attorney	0.454*	0.152	0.454*	0.152	0.454*	0.152
>1 Count	4.721**	1.878	4.721**	1.878	4.721**	1.878
MAGS case	2.267	1.929	2.267	1.929	2.267	1.929
Fiscal Year	0.919*	0.038	0.919*	0.038	0.919*	0.038
NonABA Plea	0.374*	0.161	0.374*	0.161	0.374*	0.161
Plea, No Agreement	1.255	0.685	1.255	0.685	1.255	0.685
Plea, Type Unknown	1.102	0.526	1.102	0.526	1.102	0.526
Bench Trial	0.575	0.654	0.575	0.654	0.575	0.654
Jury Trial	2.733	2.023	2.733	2.023	2.733	2.023
Trial, Type Unknown	2.587	3.764	2.587	3.764	2.587	3.764
Constant	0.011	0.022	0.003	0.006	0.139	0.255

Table 5a: Logistic Regression of Downward Departures

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)
Anne Arundel	-	-	-	-	-	-	-	-	-	-
Baltimore City	0.947	(0.426)	0.246 [†]	(0.185)	0.219*	(0.168)	0.230 [†]	(0.193)	0.042**	(0.047)
Baltimore County	1.296	(0.542)	0.738	(0.473)	0.839	(0.542)	0.748	(0.512)	0.650	(0.505)
Montgomery	0.538	(0.245)	0.454	(0.319)	0.490	(0.354)	0.968	(0.800)	0.627	(0.586)
Prince George's	0.821	(0.454)	0.287	(0.255)	0.275	(0.252)	0.200	(0.205)	0.171	(0.189)
Eastern Shore	0.966	(0.591)	0.322	(0.294)	0.242	(0.247)	0.361	(0.383)	0.465	(0.572)
Western MD	1.095	(0.677)	0.447	(0.416)	0.631	(0.605)	1.327	(1.344)	1.224	(1.314)
Southern MD	1.232	(0.654)	0.914	(0.735)	0.942	(0.746)	0.745	(0.656)	0.479	(0.475)
Other Counties	0.632	(0.506)	0.139	(0.201)	0.173	(0.265)	0.155	(0.221)	0.121	(0.177)
Offender Score			2.822**	(0.313)	2.712**	(0.306)	3.134**	(0.436)	3.549**	(0.583)
Offense Seriousness			1.059	(0.363)	1.089	(0.394)	1.051	(0.391)	1.119	(0.466)
Female					0.532	(0.263)	0.533	(0.280)	0.618	(0.350)
Black					0.863	(0.384)	1.079	(0.514)	1.380	(0.715)
Age (years)					1.216	(0.177)	1.267	(0.209)	1.324	(0.242)
Age ²					0.998	(0.002)	0.997	(0.002)	0.997	(0.002)
Private Attorney							3.121*	(1.690)	2.734 [†]	(1.604)
>1 Count							0.133**	(0.099)	0.124*	(0.105)
MAGS case							0.048	(0.114)	0.027	(0.079)
Fiscal Year							1.142*	(0.073)	1.181*	(0.087)
Non-ABA Plea									0.345	(0.255)
Plea, No Agreement									0.232	(0.212)
Plea, Type Unknown									0.337	(0.314)
Any Trial									0.064 [†]	(0.097)
Constant	0.244	(0.062)	0.043	(0.043)	0.001	(0.003)	0.000	(0.000)	0.000	(0.000)
Observations	375		375		366		360		355	

[†]p<.1 *p<.05 **p<.01

Table 5b: Varying the Reference Category in Model 5 of Table 5a (N=355)

	Reference=Anne Arundel		Reference=Baltimore City		Reference=Eastern Shore	
†p<.1 *p<.05 **p<.01	Odds Ratio	SE	Odds Ratio	SE	Odds Ratio	SE
Anne Arundel	-	-	23.994**	26.782	2.151	2.646
Baltimore City	0.042**	0.047	-	-	0.090	0.135
Baltimore County	0.65	0.505	15.606*	17.786	1.399	1.845
Montgomery	0.627	0.586	15.038*	17.546	1.348	1.864
Prince George's	0.171	0.189	4.093	5.124	0.367	0.556
Eastern Shore	0.465	0.572	11.153	16.804	-	-
Western MD	1.224	1.314	29.372*	39.646	2.633	3.910
Southern MD	0.479	0.475	11.492*	13.457	1.030	1.497
Other Counties	0.121	0.177	2.915	4.345	0.261	0.461
Offender Score	3.549**	0.583	3.549**	0.583	3.549**	0.583
Offense Seriousness	1.119	0.466	1.119	0.466	1.119	0.466
Female	0.618	0.35	0.618	0.35	0.618	0.350
Black	1.38	0.715	1.38	0.715	1.380	0.715
Age (years)	1.324	0.242	1.324	0.242	1.324	0.242
Age ²	0.997	0.002	0.997	0.002	0.997	0.002
Private Attorney	2.734†	1.604	2.734†	1.604	2.734†	1.604
>1 Count	0.124*	0.105	0.124*	0.105	0.124*	0.105
MAGS case	0.027	0.079	0.027	0.079	0.027	0.079
Fiscal Year	1.181*	0.087	1.181*	0.087	1.181*	0.087
NonABA Plea	0.345	0.255	0.345	0.255	0.345	0.255
Plea, No Agreement	0.232	0.212	0.232	0.212	0.232	0.212
Plea, Type Unknown	0.337	0.314	0.337	0.314	0.337	0.314
Any Trial	0.064†	0.097	0.064†	0.097	0.064†	0.097
Constant	0	0	0	0	0	0

Table 6a: Logistic Regression of ABA Pleas, Relative to Non-ABA Pleas								
	Model 1		Model 2		Model 3		Model 4	
	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)	Odds Ratio	(SE)
Baltimore City	76.467**	(48.952)	77.509**	(51.513)	128.079**	(92.982)	253.207**	(210.12)
Baltimore County	1.000	(0.741)	0.979	(0.740)	0.986	(0.762)	0.818	(0.643)
Montgomery	16.074**	(8.415)	16.869**	(9.195)	15.733**	(9.257)	33.239**	(23.197)
Prince George's	82.667**	(71.367)	85.177**	(73.940)	108.963**	(99.814)	101.260**	(93.825)
Eastern Shore	1.722	(1.507)	1.597	(1.411)	0.964	(0.917)	1.029	(1.030)
Western MD	2.583	(2.000)	2.637	(2.077)	3.131	(2.587)	3.288	(2.867)
Southern MD	16.238**	(10.48)	16.314**	(10.644)	18.246**	(12.605)	21.402**	(15.404)
Other Counties	18.083**	(13.720)	18.893**	(14.455)	24.479**	(20.933)	29.617**	(26.833)
Offender Score			1.073	(0.096)	1.044	(0.101)	1.107	(0.113)
Offense Seriousness			0.957	(0.257)	0.887	(0.248)	0.942	(0.271)
Female					0.441*	(0.168)	0.495†	(0.203)
Black					0.414*	(0.168)	0.404*	(0.175)
Age (years)					1.125	(0.109)	1.076	(0.102)
Age ²					0.999	(0.001)	0.999	(0.001)
Private Attorney							1.817	(0.852)
>1 Count							0.246*	(0.135)
MAGS case							0.147*	(0.134)
Fiscal Year							0.973	(0.054)
Constant	0.097	0.041	0.099	0.076	0.019	0.042	0.029	(0.069)
Observations	266		266		263		260	

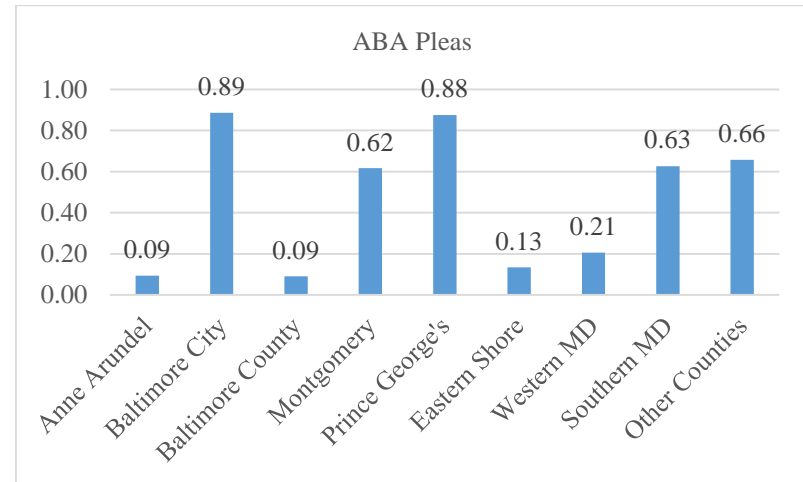
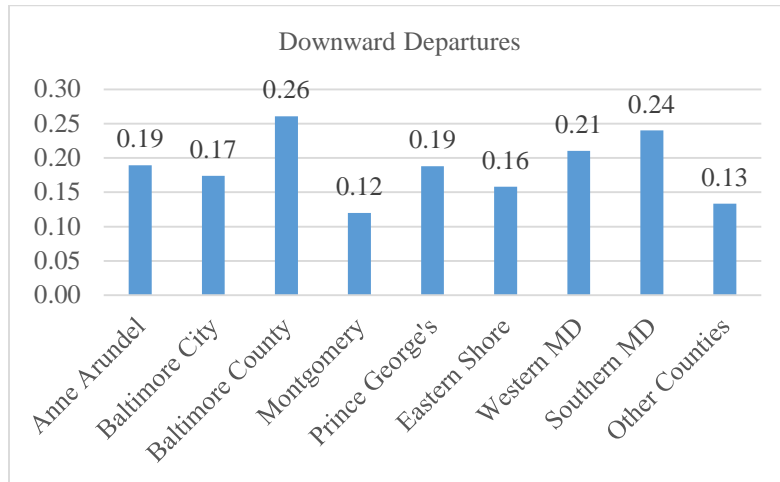
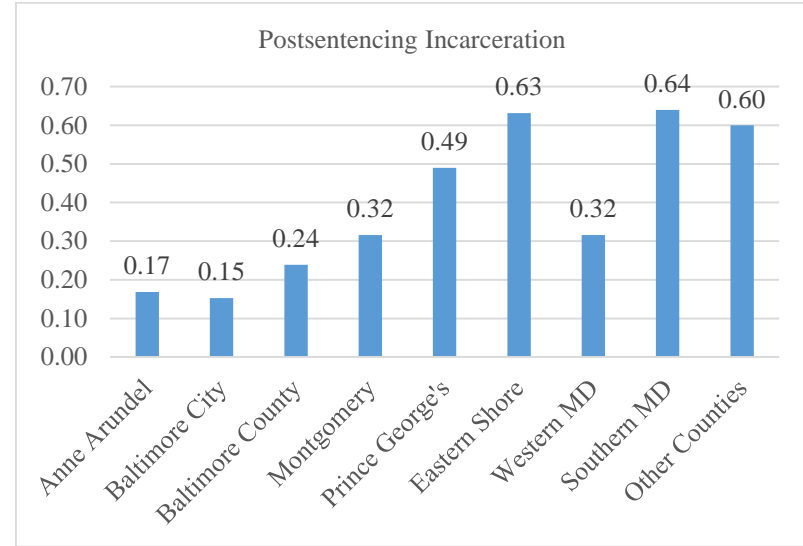
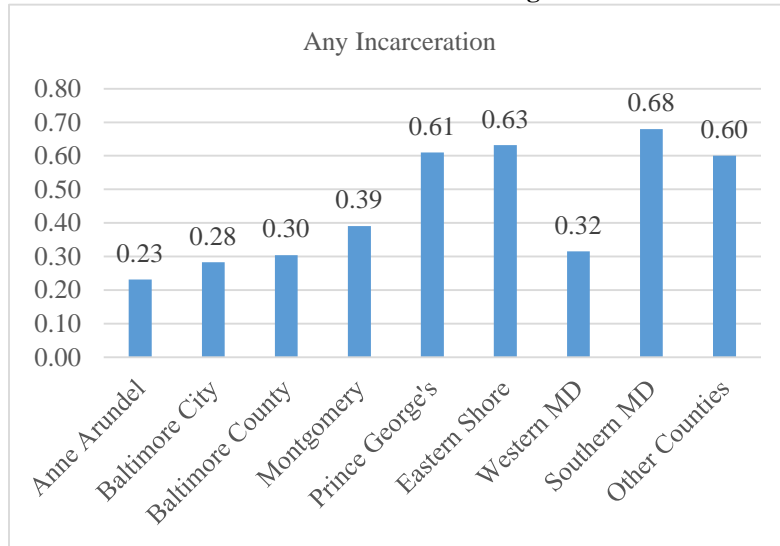
†p<.1 *p<.05 **p<.01

Table 6b: Varying the Reference Category in Model 4 of Table 6a (N=260)

	Reference=Anne Arundel		Reference=Baltimore City		Reference=Eastern Shore	
†p<.1 *p<.05 **p<.01	Odds Ratio	SE	Odds Ratio	SE	Odds Ratio	SE
Anne Arundel	-	-	0.004**	0.003	0.972	0.974
Baltimore City	253.207**	210.12	-	-	246.113**	290.779
Baltimore County	0.818	0.643	0.003**	0.003	0.795	0.875
Montgomery	33.239**	23.197	0.131*	0.106	32.308**	34.348
Prince George's	101.260**	93.825	0.4	0.389	98.423**	123.194
Eastern Shore	1.029	1.03	0.004**	0.005	-	-
Western MD	3.288	2.867	0.013**	0.013	3.195	3.773
Southern MD	21.402**	15.404	0.085**	0.068	20.802**	23.136
Other Counties	29.617**	26.833	0.117*	0.115	28.788**	35.182
Offender Score	1.107	0.113	1.107	0.113	1.107	0.113
Offense Seriousness	0.942	0.271	0.942	0.271	0.942	0.271
Female	0.495†	0.203	0.495†	0.203	0.495†	0.203
Black	0.404*	0.175	0.404*	0.175	0.404*	0.175
Age (years)	1.076	0.102	1.076	0.102	1.076	0.102
Age ²	0.999	0.001	0.999	0.001	0.999	0.001
Private Attorney	1.817	0.852	1.817	0.852	1.817	0.852
>1 Count	0.246*	0.135	0.246*	0.135	0.246*	0.135
MAGS case	0.147*	0.134	0.147*	0.134	0.147*	0.134
Fiscal Year	0.973	0.054	0.973	0.054	0.973	0.054
Constant	0.029	0.069	7.411	18.357	0.03	0.069

Table 7: Summary of Results			
Prediction	Placement	Downward Departures	ABA Pleas
Outcomes for white-collar defendants vary by county	Supported	Supported	Supported
Larger court communities sentence white-collar defendants more severely	Partially supported, but mostly unsupported	Supported	N/A
Courts that sentence white-collar defendants less severely are more likely to reach ABA plea agreements	N/A	N/A	Not supported for downward departures; partially supported for placement, but not clearly related to court community size.

Figure 1: Mean Predicted Probabilities for Each Outcome



APPENDICES

Appendix I: Maryland Sentencing Guidelines Offense Table Excerpt

COMAR#	Offense Literal	Source	Felony or Misd.	Max Term	Min Term	Offense Type	Serious. Category	Fine
80	Commercial Fraud, Other False statement or false entry in records with the intent to deceive a person authorized to examine the affairs of the bank, trust company, or savings bank	FI, § 5-803(b)	Felony	10Y		Property	V	\$5,000
81	Commercial Fraud, Other Misappropriation, fraudulent conversion, or any fraudulent act in the course of engaging in the mortgage lending business	FI, § 11-523(c)	Felony	15Y		Property	V	\$100,000
82	Commercial Fraud, Other Fraudulent Insurance Acts— Violation of § 27-407 or any other provision of §§ 27-403, 27-404, 27-405, 27-406, 27-406.1, 27-407, 27-407.1, or 27-407.2 where the value of the fraud is \$300 or greater	IN, § 27-408(a)(1) (penalty)	Felony	15Y		Property	V	\$10,000
82-1	Commercial Fraud, Other Fraudulent Insurance Acts— Violation of § 27-407 or any other provision of §§ 27-403, 27-404, 27-405, 27-406, 27-406.1, 27-407, 27-407.1, or 27-407.2 where the value of the fraud is less than \$300	IN, § 27-408(a)(2) (penalty)	Misd.	18M		Property	VII	\$10,000
83	Commercial Fraud, Other Fail to obtain and maintain a corporate surety bond or irrevocable letter of credit or to hold sums of money in an escrow account	RP, § 10-305(a)	Felony	15Y		Property	V	\$10,000

COMAR#	Offense Literal	Source	Felony or Misd.	Max Term	Min Term	Offense Type	Serious. Category	Fine
84	Commercial Fraud, Other Sales of property, Custom Home Protection Act-willful failure to obtain and maintain a corporate surety bond or to hold sums of money in escrow account; willful failure to make disclosure; willful commission of a breach of trust provided in § 10-502	RP, § 10-507(b)(2)	Felony	15Y		Property	V	\$10,000
84-1	Commercial Fraud, Other Sales of property, Custom Home Protection Act—any other conduct that fails to comply with RP, Title 10, Subtitle 5	RP, § 10-507(b)(3)	Misd.	1Y		Property	VII	\$1,000
84-5	Commercial Fraud, Other Failure of foreclosure consultant to obtain a real estate broker's license	RP, § 7-318.1(a) RP, § 7-321 (penalty)	Misd.	3Y		Property	VI	\$10,000
88	Commercial Fraud, Other False or misleading statement or omission of material fact in sale of business opportunity	BR, § 14-127(b)	Felony	5Y		Property	VI	\$10,000
91	Commercial Fraud, Other False or misleading statement or omission in prospectus or amendment	BR, § 14-230(b)	Felony	5Y		Property	VI	\$10,000
94*	Commercial Fraud, Other Fraud—false advertising	CL, § 14-2903	Misd.	1Y		Property	VII	\$500
99	Consumer Protection Laws Violation of Title 14 — Miscellaneous Consumer Protection Provisions, Credit Card Number Protection Act	CR, § 8-216	Felony	15Y		Property	V	\$1,000

COMAR#	Offense Literal	Source	Felony or Misd.	Max Term	Min Term	Offense Type	Serious. Category	Fine
332	Public Health and Safety, Crimes Against Hazardous substances—storing, treating, dumping, etc., in other than hazardous substance facility; transporting for treatment, storage, etc. to any place other than hazardous substance facility; falsifying required information; authorizing, directing, etc., any offense listed in this section	EN, § 7-265(a)	Felony	5Y		Person	V	\$100,000
333	Public Health and Safety, Crimes Against Unlawfully cause or unlawfully dump, deposit, throw, etc., litter greater than 500 lbs. in weight or 216 cubic feet in volume or for commercial purposes	CR, § 10-110(f)(2)(iii)	Misd.	5Y		Property	VI	\$30,000
335	Public Health and Safety, Crimes Against Pollutants—dispersing into State waters, 1 st offense	EN, § 9-343(a)(1)(i) (penalty)	Misd.	1Y		Property	VII	\$25,000
387	Theft, Crimes Involving Embezzlement, misappropriation by fiduciaries	CR, § 7-113	Misd.	5Y	1Y	Property	V	

*In 2014 the Commission recategorized this offense under a newly created category heading for “False Advertising and Related Crimes” (COMAR# 145 and 146). The Database extract used includes one person sentenced for this offense in 2000, while the Commission categorized it as a form of commercial fraud.

Appendix II: Robustness Checks

Robustness checks of the final models in Tables 3a, 4a, 5a, and 6a involved: (a) substituting the midpoint of the sentencing guidelines for the offender score and offense seriousness category (together the offender score and offense seriousness category determine the guidelines recommendation); (b) controlling for all three of the offender score, offense seriousness category, and the guidelines midpoint; (c) substituting the relationship to the criminal justice system variable (i.e., currently on parole or probation), prior adult criminal record score, and prior parole or probation violation variable for the offender score (the relationship, adult record, and prior violations variables are three of the four components of the offender score—juvenile delinquency is the fourth and is not available in these data; (d) controlling for both the offender score and its components; (e) substituting the maximum carceral penalty, whether the conviction offense was a felony, and dummy variables for crime type category (consumer protection, environmental, or embezzlement, with commercial fraud the omitted category) for the offense seriousness category—when assigning offense seriousness categories, the MSCCSP considers statutory maximum sentences, felony or misdemeanor classification, and substantive similarity); (f) controlling for both the offense seriousness category and its considerations; (g) using calendar year instead of fiscal year; (h) using dummy variables to control for fiscal year instead of a single term; and (i) using dummy variables to control for calendar year. (Because of few observations in 1999, (h) and (i) combine 1999 with 2000.)

Altering specifications and, in some instances, adding several terms to models that already contain numerous variables, and without very large numbers of observations

will of course affect results. This is particularly the case where, as here, several of the variables have relatively little variation across observations. Nevertheless the results under the various robustness checks were generally similar to the models reported in the Tables. Substantial differences described below.

For the any incarceration outcome, the significant geographic variables in Model 5 of Table 3a were significant in the same direction (i.e., odds ratios greater than one or less than one) under the alternate specifications. Magnitudes of the odds ratios varied under different specifications, but were for the most part similar. (Specification (d) completely determined one success.)

For the postsentencing placement outcome, Baltimore City was no longer significant under (a). Prince George's County's was no longer significant under (g), and its significance became marginal under (e), (f), and (h). For the other geographic variables and under the other robustness checks, the significant geographic variables in Model 5 of Table 4a were significant in the same direction under the alternate specifications. Magnitudes of the odds ratios varied, but were for the most part similar, though some became substantially larger under some specifications. (Specification (d) completely determined one success.)

For the downward departures model the significant geographic variable in Model 5 of Table 5a was significant in the same direction under the alternate specifications. Magnitudes of the odds ratios varied, some substantially, under some specifications. To avoid Stata not using observations, (h) combined fiscal years 1999 through 2002, and (i) combined calendar years 1999 through 2001 for downward departures. (Specification (a) completely determined one success and (i) determined two failures.)

Modeling the odds of reaching an ABA plea, relative to a non-ABA plea, results were generally similar under most of the robustness checks with respect to geographical variables significance, direction, and general magnitude. In specifications (e), (h), and (i) the odds ratios for some of the terms became much larger. For the other geographic variables and under the other robustness checks, the significant geographic variables in Model 4 of Table 8 were significant and in the same direction under the alternate specifications, though the magnitudes of the odds ratios of course varied somewhat. To avoid Stata not using observations, (h) combined fiscal years 1999 through 2001. (Specification (e) completely determines two failures and four successes.)

Appendix III: Other Modeling Approaches for Departures and Disposition

Initially, I attempted to estimate departures using ordinal logit. None of the geographical variables were significant. Null results were not sensitive to the geographical reference category, to alternate specifications of the offender's criminal justice history and offense seriousness, or to using calendar year instead of fiscal year. The only exception was a marginally significant difference for Prince George's County compared to Anne Arundel County when using dummy variables to control for the fiscal year of sentence (but not calendar year). Given the overall robustness of the null results and large number of tests conducted, this seemed likely to have been a Type I error.

Because the ordinal logit model depends on the questionable proportional odds assumption, I also estimated departures with multinomial logit. Baltimore City had marginally lower log odds of a downward departure, compared to a within guidelines sentence, relative to Anne Arundel County when controlling for the offender's criminal justice history, offense seriousness, demographic characteristics, and case processing variables. With controls for disposition type, both Baltimore City and Prince George's County had significantly lower log odds of a downward departure (Prince George's County marginally so), and Baltimore City also had marginally lower log odds of an upward departure, compared to a within guidelines sentence, relative to Anne Arundel County. But controlling for disposition type completely determined three observations, resulting in questionable standard errors.

Results of the multinomial logistic regression for departures were furthermore not very robust. Alternate specifications of the multinomial logit model of departures generated differences with respect to significance, direction, or both, when controlling for

disposition type. And because each of these alternate specifications involved three to five completely determined observations, all the results were questionable. Other differences eventuated using multinomial logit to model departures without controlling for disposition.

Prior research has shown inconsistent and sometimes counterintuitive effects of type of disposition, *e.g.*, King, Soulé, Steen, and Weidner, 2005. Because of that prior research, the current study first attempted to use a multinomial (as opposed to ordinal or binary) logit model of disposition type. Using multinomial logit to estimate geographical effects on seven outcome categories (five if combining all trial types) while varying geographical reference categories quickly became extremely unwieldy, with meaningful interpretations cumbersome and broader assessments of the effect of location on disposition (beyond particular outcome *a* compared to base outcome *b* for County *C* relative to County *D*) impracticable.

Because of null, fragile, and unhelpful results with the more complicated ordinal and multinomial logit models (available upon request), I ultimately used binary logit for downward departures and for ABA plea agreements (ABA pleas were the dispositional outcome with the greatest theoretical interest). The latter was limited to defendants with a plea agreement (a subset comprising approximately 70% of the cases).

REFERENCES

Legislation, Regulations, Court Rules

42 U.S.C. § 3722.

42 U.S.C. § 3791.

2013 Md. Laws Ch. 156 [Senate Bill 276].

Courts and Judicial Proceedings Article, § 1-503, Annotated Code of Maryland

Criminal Law Article, Annotated Code of Maryland.

Md. Code Regs. [COMAR] 14.22.01.02.

Md. Code Regs. [COMAR] 14.22.01.05.

Md. Code Regs. [COMAR] 14.22.02.02.

Maryland Rule 4-243

Cases

Blackwell v. State, 278 Md. 466, 365 A.2d 545 (1976).

State v. Burroughs, 333 Md. 614, 622, 636 A.2d 1009 (1994)

Clark v. State, 188 Md. App. 185, 981 A.2d 710 (2009)

Gregg v. Georgia, 428 U.S. 153, 96 S. Ct. 2909, 49 L. Ed. 2d 859 (1976).

Schwartz v. State, 103 Md. App. 378, 653 A.2d 958 (1995)

Stathes v. State, 29 Md. App. 474, 349 A.2d 254 (1975)

Woodson v. North Carolina, 428 U.S. 280, 96 S. Ct. 2978, 49 L. Ed. 2d 944 (1976).

Literature and Other Sources

Adger, Jennifer, and Christopher Weiss. 2011. Why place matters: Exploring county-level variations in death sentencing in Alabama. *Michigan State Law Review* 2011: 659-704.

Albonetti, Celesta A. 1998a. Direct and indirect effects of case complexity, guilty pleas, and offender characteristics on sentencing for offenders convicted of a white-collar offense prior to sentencing guidelines. *Journal of Quantitative Criminology* 14: 353-378.

- Albonetti, Celesta A. 1998b. The role of gender and departures in the sentencing of defendants convicted of a white collar offense under the federal sentencing guidelines. In *Sociology of Crime, Law, and Deviance*, vol I, ed. Jeffery T. Ulmer. Greenwich, CT: JAI Press Inc.
- Anderson, Keith B. 2013. *Consumer Fraud in the United States, 2011: The Third FTC Survey*. Federal Trade Commission. Available at https://www.ftc.gov/sites/default/files/documents/reports/consumer-fraud-united-states-2011-third-ftc-survey/130419fraudsurvey_0.pdf (last visited November 02, 2015).
- Apuzzo, Matt and Ben Protes. 2015. Justice Dept. sets its sights on executives. *The New York Times* (September 10).
- Babbie, Earl. 2013. *The Practice of Social Research*. 13th ed. Belmont, CA: Cengage Learning.
- Barnett, Cynthia. n.d. [2000]. *The Measurement of White-Collar Crime Using Uniform Crime Reporting (UCR) Data*. United States Department of Justice. Available at http://www.fbi.gov/stats-services/about-us/cjis/ucr/nibrs/nibrs_wcc.pdf (last visited November 02, 2015).
- Benson, Michael L., and Esteban Walker. 1988. Sentencing the white-collar offender. *American Sociological Review* 53: 294-302.
- Berk, Richard, Azusa Li, and Laura J. Hickman. 2005. Statistical difficulties in determining the role of race in capital cases: A re-analysis of data from the state of Maryland. *Journal of Quantitative Criminology* 21: 365-390.
- Bureau of Justice Statistics. 1982. *Dictionary of Criminal Justice Data Terminology*. Washington, DC: United States Department of Justice. Available at <https://www.ncjrs.gov/pdffiles1/Digitization/76939NCJRS.pdf> (last visited November 02, 2015).
- Bushway, Shawn, Brian D. Johnson, and Lee Ann Slocum. 2007. Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology. *Journal of Quantitative Criminology* 23: 151-178.
- Bushway, Shawn D., and Anne Morrison Piehl. 2011. Location, location, location: The impact of guideline grid location on the value of sentencing enhancements. *Journal of Empirical Legal Studies* 8: 222-238.
- Chon, Gina. 2015. Six banks fined \$5.6bn over rigging of foreign exchange markets. *Financial Times*. (May 20).
- Crooks, Ashley, Karri Ridgeway, Wendy Wineholt, and Rosalie Winn. 2014. Environmental crimes. *American Criminal Law Review* 51: 1051-1751.

- Daly, Kathleen. 1989. Gender and varieties of white-collar crime. *Criminology* 27: 769-794.
- Deevy, Martha and Michaela Beals. 2013 [revised 2014]. *The Scope of the Problem: An Overview of Fraud Prevalence Measurement*. Stanford, CA: Financial Fraud Research Center. Available at http://fraudresearchcenter.org/wp-content/uploads/2013/11/Scope-of-the-Problem-FINAL_corrected2.pdf (last visited November 02, 2015).
- Deevy, Martha, Shoshana Lucich, and Michaela Beals. 2012 Scams, Schemes, and Swindles: A Review of Consumer Financial Fraud Research. Stanford, CA: Financial Fraud Research Center. Available at <http://fraudresearchcenter.org/wp-content/uploads/2012/11/Scams-Schemes-Swindles-11.08.12.pdf> (last visited November 02, 2015).
- Department of Justice. 2015. Five Major Banks Agree to Parent-Level Guilty Pleas. Available at <http://www.justice.gov/opa/pr/five-major-banks-agree-parent-level-guilty-pleas> (last visited November 02, 2015).
- Dixon, Jo. 1995. The organizational context of criminal sentencing. *American Journal of Sociology* 100: 1157-1198.
- Edelhertz, Herbert. 1970. *The Nature, Impact and Prosecution of White-Collar Crime*. Washington, DC: United States Department of Justice. Available at <https://www.ncjrs.gov/pdffiles1/Digitization/4415NCJRS.pdf> (last visited November 02, 2015).
- Eisenstein, James, and Herbert Jacob. 1977. *Felony Justice: An Organizational Analysis of Criminal Courts*. Boston: Little Brown.
- Eitle, David J. 2000. Regulatory justice: A re-examination of the influence of class position on the punishment of white-collar crime. *Justice Quarterly* 17: 808-839.
- Federal Bureau of Investigation. 1989. *White-Collar Crime: A Report to the Public*. Washington, DC: United States Department of Justice (on file with author). Available at <http://ter.ps/FBI1989>.
- Frankel, Marvin E. 1972. Lawlessness in sentencing. *University of Cincinnati Law Review* 41:1-54.
- Franklin, Travis W. Sentencing outcomes in U.S. District Courts: Can offenders' educational attainment guard against prevalent criminal stereotypes? *Crime & Delinquency* doi: 10.1177/0011128715570627.
- Ganzini, Linda, Bentson McFarland, and Joseph Bloom, J. 1990. Victims of fraud: Comparing victims of white collar and violent crime. *The Bulletin of the American Academy of Psychiatry and the Law*. 18: 55-63.

- Gershowitz, Adam M. 2010. Statewide capital punishment: The case for eliminating counties' role in the death penalty. *Vanderbilt Law Review* 63: 307-359.
- Green, Stuart P. 2004. The concept of white collar crime in law and legal theory. *Buffalo Criminal Law Review* 8:1-34.
- Hagan, John, Ilene H. Nagel, and Celesta Albonetti. 1980. The differential sentencing of white-collar offenders in ten federal district courts. *American Sociological Review* 45: 802-820.
- Holder, Eric. 2012. Memorandum from Attorney General to All United States Attorneys; Director, Federal Bureau of Investigation; All Assistant United States Attorneys; All Litigating Attorneys; and All Trial Attorneys (Jan. 30, 2012) (on file with author). Available at <https://web.archive.org/web/20150406025341/http://www.nsf.gov/oig/parallelproceedings.pdf> (last visited November 02, 2015).
- Huff, Rodney, Christian Desilets, and John Kane. 2010. *The 2010 National Public Survey on White Collar Crime*. Fairmont, WV: The National White Collar Crime Center. Available at <http://www.nw3c.org/docs/research/2010-national-public-survey-on-white-collar-crime.pdf> (last visited November 02, 2015).
- Jennings, Wesley G., and J. Mitchell Miller. 2006. Examining regional variations in punitiveness for savings and loan industry crime. *Journal of Crime and Justice* 29: 81-100.
- Johnson, Brian D. 2005. Contextual disparities in guidelines departures: Courtroom social contexts, guidelines compliance, and extralegal disparities in criminal sentencing *Criminology* 43: 761-796.
- Johnson, Brian. D. 2006. The multilevel context of criminal sentencing: Integrating judge- and county-level influences. *Criminology* 44: 259-298.
- Johnson, Brian D., Jeffery T. Ulmer, and John H. Kramer. 2008. The social context of guidelines circumvention: The case of federal district courts. *Criminology* 46: 737-783.
- King, Nancy J., David A. Soule, Sara Steen, and Robert R. Weidner. 2005. When process affects punishment: Differences in sentences after guilty plea, bench trial, and jury trial in five guidelines states. *Columbia Law Review* 105: 959-1009.
- Kramer, John H., and Jeffery T. Ulmer. 2002 Downward departures for serious violent offenders: local court corrections to Pennsylvania's sentencing guidelines. *Criminology* 40: 897-931.
- Maryland Department of Planning. 2012. *Maryland Urban and Rural Population by Jurisdiction: 2010, 2000, 1990*. Available at

- http://planning.maryland.gov/msdc/census/cen2010/Urban_rural/PctUrbanRural_County_region_r2.pdf (last visited November 02, 2015).
- Maryland Department of Planning. 2015. 2014 Maryland Statistical Handbook. *Available at* https://planning.maryland.gov/msdc/md_statistical_handbook14.pdf (last visited November 02, 2015).
- Maryland Department of State Police. 2014. *Crime in Maryland: 2013 Uniform Crime Report*. *Available at* http://goccp.maryland.gov/msac/documents/2013_Crime_in_Maryland_UCR.pdf (last visited November 02, 2015).
- Maryland Judiciary. 2015. Maryland's Judiciary System. Annapolis, MD. *Available at* <http://mdcourts.gov/publications/pdfs/mdjudicialsystem.pdf> (last visited November 02, 2015).
- Maryland State Board of Elections. 2014a. Eligible Active Voters on the Precinct Register - By County: 2014 Gubernatorial Primary Election. *Available at* http://www.elections.state.md.us/press_room/2014_stats/PrecinctRegisterCounts_ByCounty.pdf (last visited November 02, 2015).
- Maryland State Board of Election. 2014b. Official 2014 Gubernatorial General Election results for Governor / Lt. Governor, *Available at* http://elections.state.md.us/elections/2014/results/General/gen_results_p2014_2_003-.html (last visited November 02, 2015).
- Maryland State Commission on Criminal Sentencing Policy. 2015a. *2014 Annual Report*. College Park, MD. *Available at* <http://www.msccsp.org/Files/Reports/ar2014.pdf> (last visited November 02, 2015).
- Maryland State Commission on Criminal Sentencing Policy. 2015b. *Maryland Sentencing Guidelines Manual: Version 7.0*. College Park, MD. *Available at* <http://www.msccsp.org/Files/Guidelines/MSGM/Version%207.0.pdf> (last visited November 02, 2015).
- Nagel, Ilene H., and John L. Hagan. 1982. The sentencing of white-collar criminals in federal courts: A socio-legal exploration of disparity. *Michigan Law Review* 80: 1427-1465.
- Owens, Lindsay A. 2012. "The polls—trends confidence in banks, financial institutions, and Wall Street, 1971–2011. *Public Opinion Quarterly* 76: 142-162.
- Paternoster, Raymond, and Robert Brame. 2008. Reassessing Race Disparities in Maryland Capital Cases. *Criminology* 46: 971-1008.
- Paternoster, Raymond, Robert Brame, Sarah Bacon, Andrew Ditchfield, David Biere, Karen Beckman, Deanna Perez, Michael Strauch, Nadine Frederique, Kristin Gawkoski, Daniel Zeigler, and Katheryn Murphy. 2003. *An empirical analysis of*

Maryland's death sentencing system with respect to the influence of race and legal jurisdiction: Final report. College Park, MD: University of Maryland. Available at <http://cdm16064.contentdm.oclc.org/cdm/ref/collection/p266901coll7/id/2227> (last visited November 02, 2015).

- Paternoster, Raymond, Robert Brame, Sarah Bacon, and Andrew Ditchfield. 2004. Justice by geography and race: The administration of the death penalty in Maryland, 1978-1999. *Margins, Maryland's Law Journal on Race, Religion, Gender, and Class* 4: 1-97.
- Phillips, Scott. 2008. Racial disparities in the capital of capital punishment. *Houston Law Review*. 45: 807-840.
- Phillips, Scott. 2012. Continued Racial Disparities in the Capital of Capital Punishment: The Rosenthal Era." *Houston Law Review* 50: 131-155.
- Pierce, Glenn L., and Michael L. Radelet. 2002. Race, region, and death sentencing in Illinois, 1988-1997." *Oregon Law Review* 81: 39-96.
- Pierce, Glenn L., and Michael L. Radelet. 2005. The impact of legally inappropriate factors on death sentencing for California homicides, 1990-1999. *Santa Clara Law Review* 46: 1-47.
- Podgor, Ellen S. 2007. The challenge of white collar sentencing. *The Journal of Criminal Law and Criminology* 97: 731-759.
- Poveda, Tony G. 2006 Geographic location, death sentences and executions in post-Furman Virginia. *Punishment & Society* 8: 423-442.
- Richman, Daniel. 2013. Federal white collar sentencing in the United States: A work in progress. *Law and Contemporary Problems* 76: 53-73.
- Savelsberg, Joachim J. 1992. Law that does not fit society: Sentencing guidelines as a neoclassical reaction to the dilemmas of substantivized law. *American Journal of Sociology* 97: 1346-1381.
- Schanzenbach, Max, and Michael L. Yaeger. 2006. Prison time, fines, and federal white-collar criminals: The anatomy of a racial disparity. *The Journal of Criminal Law and Criminology* 96: 757-793.
- Simpson, Sally S. 2011. Making sense of white-collar crime: Theory and research. *Ohio State Journal of Criminal Law* 8: 481-502.
- Simpson, Sally S. 2013. White-collar crime: A review of recent developments and promising directions for future research. *Annual Review of Sociology* 39: 309-331.

- Simpson, Sally S. and Peter C. Yeager. 2015. *Final Technical Report: Building a Comprehensive White-Collar Violations Data System*. Available at <https://www.ncjrs.gov/pdffiles1/bjs/grants/248667.pdf> (last visited November 02, 2015).
- Stadler, William A., Michael L. Benson, and Francis T. Cullen. 2013. Revisiting the special sensitivity hypothesis: The prison experience of white-collar inmates. *Justice Quarterly* 30: 1090-1114.
- Steffensmeier, Darrell, Jeffery Ulmer, and John Kramer. 1998. The interaction of race, gender, and age in criminal sentencing: The punishment cost of being young, black, and male. *Criminology* 36: 763-798.
- Sudnow, David. 1965 Normal crimes: Sociological features of the penal code in a public defender office. *Social Problems* 12: 255-276.
- Sutherland, Edwin H. 1940. White-collar criminality. *American Sociological Review* 5:1-12.
- Sutherland, Edwin H. 1983 [1949]. *White Collar Crime: The Uncut Version*. New Haven, CT: Yale University Press.
- Turner, Allan. 2014. Texas appeals court judge calls for abolishing the death penalty. *Houston Chronicle*. (November 26).
- Ulmer, Jeffery T. 2012. Recent developments and new directions in sentencing research. *Justice Quarterly* 29: 1-40.
- Ulmer, Jeffery T., James Eisenstein, and Brian D. Johnson. 2010. Trial penalties in federal sentencing: Extra-guidelines factors and district variation. *Justice Quarterly* 27: 560-592.
- Ulmer, Jeffery T., and Brian Johnson. 2004. Sentencing in context: A multilevel analysis. *Criminology* 42: 137-178.
- Van Slyke, Shanna, and William D. Bales. 2012. A contemporary study of the decision to incarcerate white-collar and street property offenders. *Punishment & Society* 14: 217-246.
- Wagner, John. 2015. On last full day, O'Malley issues orders commuting four death-row sentences. *The Washington Post*. (January 20).
- Weisburd, David, Elin Waring, and Ellen F. Chayet. 2001. *White-Collar Crime and Criminal Careers*. New York: Cambridge University Press.

Weisburd, David, Stanton Wheeler, Elin Waring, and Nancy Bode. 1991. *Crimes of the Middle Classes: White-Collar Offenders in the Federal Courts*. New Haven, CT: Yale University Press.

Wheeler, Stanton, David Weisburd, and Nancy Bode. 1982. Sentencing the white-collar offender: Rhetoric and reality. *American Sociological Review* 47: 641-659.