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ABSTRACT

Does the economic model of optimal punishment explain the variation in the sentencing of murderers? As the model predicts, we find that murderers with a high expected probability of recidivism receive longer sentences. Sentences are longest in murder types where apprehension rates are low, and where deterrence elasticities appear to be high. However, sentences respond to victim characteristics in a way that is hard to reconcile with optimal punishment. In particular, victim characteristics are important determinants of sentencing among vehicular homicides, where victims are basically random and where the optimal punishment model predicts that victim characteristics should be ignored. Among vehicular homicides, drivers who kill women get 56 percent longer sentences. Drivers who kill blacks get 53 percent shorter sentences.

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I. Introduction

The economic approach to punishment pioneered by Bentham (1823) and Becker (1968) is normative. Their work, and the literature that has followed, analyzes "how many resources and how much punishment should be used to enforce different kinds of legislation?" (Becker, 1968). But is this normative theory of optimal deterrence also a good positive theory of punishment? Are prison sentences meted out in a way that corresponds with the implications of Becker's model? Can we explain the differences in sentence lengths with a theory where punishment is meant only to incapacitate and deter, or do we need a theory that also incorporates a taste for vengeance?[1]

This paper examines the determinants of punishment by examining the sentences given out to murderers in the U.S. Using Bureau of Justice Statistics data on murders, we test the basic implications of the economic model. Becker (1968) argues that sentences should be longer when apprehension rates are lower. Indeed, across murder types, we find that sentences are highest when the expected apprehension rate for murderers is lowest.

An optimal deterrence model also suggests that punishments should be stiffer in crimes where the deterrence elasticities are greater. We do not have direct measures of deterrence elasticities across types of homicide, but it is likely that inelastically supplied crimes will have less variance across cities (see Appendix 1). For inelastically supplied crimes, cross-city differences in probabilities of arrest or returns to crimes will cause less variation. As such, we use cross-city crime variances as a proxy for deterrence elasticities and we find that sentences are stiffer from murder types that appear to be less elastic.

A third implication of optimal punishment is that criminals with higher recidivism rates should be incarcerated for longer periods. Using data from the Bureau of Justice Statistics "Recidivism of Felons on Probation 1986-1989," we predict the probability of recidivism for each murderer. This probability is based on the murderer's past record, demographic characteristics and type of crime. We then correlate predicted recidivism with sentence length and find that murderers with

[1] Bentham asserts that the only function of punishment is to reduce crime through deterrence and incapacitation. He views the taste for vengeance as illegitimate. Becker does not incorporate a taste for vengeance into the model, but he does not argue against catering to that taste.

higher recidivism rates receive stiffer penalties. Thus, in these three tests, the optimal punishment model appears to actually predict the variation in sentence lengths

However, in a fourth test of the optimal punishment model, it becomes clear that there is more to sentencing murderers than optimal deterrence and incapacitation. The optimal punishment model suggests that victim characteristics will not matter when the victim is determined at random. Using two data sets on vehicular homicides, we look for the importance of victim characteristics. In the Bureau of Justice Statistics national data set, we find that victim race, age and criminal record still determine sentence length even when the victim was killed in a vehicular homicide. Drivers who kill black victims get substantially shorter sentences. Drivers who kill women get substantially longer sentences. Indeed, there is no difference in the magnitude of victim effects (when using the logarithm of sentence length) between vehicular homicides and other types of murder. In a data set on vehicular homicides in Alabama, we still find that there is a substantial victim gender effect. There is no statistically discernable victim race effect in these data.

One proposed explanation for the above findings is that sentence lengths are driven, in part, by a taste for vengeance. Since this taste may operate at a subconscious level, it would not be surprising if victim characteristics still motivate this taste, even when the victim is random. The presence of victim effects in vehicular homicides suggests to us that the taste for vengeance is an important determinant of actual sentence lengths. However, one should not ignore the fact that the basic optimal punishment model has a great deal of explanatory power. Both optimal punishment and a taste for vengeance appear to drive sentencing in homicides.

II. The Determinants of Punishment

In this section, we summarize the predictions of a version of the basic Becker framework. The general formula for optimal punishment begins with the behavior of murderers. We assume there is a supply of murders, denoted M(.), which is a function of the probability of apprehension, denoted P, times the severity of punishment, denoted S. To satisfy second order conditions, we assume that this function is declining and convex. We will treat the probability of apprehension as exogenous and solve for the optimal severity of punishment.[2]

The social loss from the death of a victim is denoted V. This loss is meant to include the loss to the victim and to the rest of society. The social cost of imposing a sentence of severity S on a criminal of type T is C times S. This cost is meant to be high for individuals who produce much for society at large. The social cost of prison will be low for people with high recidivism rates who are likely to commit socially damaging crimes if they are released. The social planner then would choose the level of severity to minimize M(PS)[V+PCS]. Optimization produces the formula $S = \frac{M}{PC} * \frac{\varepsilon_{PS}^{M}}{\left(1 - \varepsilon_{PS}^{M}\right)}$, where $\varepsilon_{PS}^{M} = -\frac{PSM'(PS)}{M(PS)}$, the elasticity of the murder rate with respect to the quantity of punishment.

If this elasticity is treated as a constant parameter, then this equation yields four comparative statics that are at the core of the normative implications of economic approach to punishment. Severity (i.e. sentence length) should be higher when the deterrence elasticity is higher. Severity should be higher when the victim is valued more by society, or when the recidivism rate is high. Increases in deterrence elasticity should increase sentence length. As the probability of apprehension rises, the sentence length should fall. We will test all of these hypotheses.

One thing that the optimal deterrence model does not predict is that random features of the crime should be part of the punishment. Punishing criminals on the basis of the random characteristics of criminals just introduces extra randomness into sentencing and serves no purpose according to this model.[3] Randomness in punishment is undesirable for many reasons. For example, it may be that costs of punishment to the victim rise more slowly with randomness than the costs of punishment to the state (see Polinksy and Shavell, 1984, for a discussion).[4]

III. Data Description

[2] Our basic set-up builds upon that of several authors including Becker (1968), Posner (1981), Polinsky and Shavell, (1984).

[3] If the conditions that make random punishment undesirable are not met, then this just means that we should see random punishment, not punishment based on the random characteristics of victims.

[4] Note that many features of the criminal justice system, such as sentencing guidelines, are designed to reduce randomness in punishment. See for example published reports from the Massachusetts Commission for Sentencing Guidelines.

Our first data set is the Bureau of Justice Statistics "Murder Cases in 33 Large Urban Counties." This is a random sample of homicide cases drawn from prosecutors' files. The data set includes information on offender characteristics, victim characteristics and trial outcomes for 2800 murders. The 75 largest counties account for more than half of the murders in the U.S. each year. This data set brings together information on the crime, the offender, the victim, and the sentence. Such information cannot all be linked in other larger data sets such as the Uniform Crime Reporting (UCR) Data or the National Crime Victimization Survey (NCVS). Most crime data sets are institutionally based, so that the Department of Corrections can tell us about the number of prisoners moving in and out of the prison system, or the FBI can give us numbers on complaints and arrests. But such data sets do not allow us to follow an offender and victim from the commission of the crime, through arrest, the judicial system and sentencing.

When we compare the circumstances of the murders in our data set with the data in the much larger Uniform Crime Reports Supplementary Homicide Reports, the distribution across homicide types (circumstances) is similar. Appendix Table 1 gives a complete set of means and standard deviations for our primary data set. While we have solid data on the prior criminal history of both the criminal and the victim, we have only limited other demographic information on each individual. We know age, gender and race and for a subsample of the data we have hand coded occupational information. We use the mean income in the occupation as a proxy for true income.[5]

All of these cases are ones in which a homicide related charge was filed. In our data, 76 percent of the cases led to a conviction. Table 2 presents an overview of conviction rates by types of homicides. Of these cases, less than 1 percent of offenders receive the death penalty and 9 percent receive life in prison. As we will generally attempt to work with a single attribute "sentence length," there is an issue as to how we treat life sentences. We will generally treat a life sentence as a 50 year sentence, but our results are robust to alternate treatments of life sentences.

Table 1 also presents an overview of sentence lengths and conviction rates by types of murder. The harshest penalties appear to be levied against arsonists (50 years), although there are only 5 convicted arsonists in the sample, so this is surely measured with considerable error. Given the possibility that arson can create truly horrendous social costs, it seems reasonable that this crime is particularly singled out for a severe penalty. Among the other crime categories, murders that are done by professional criminals in the course of other crimes receive harsh penalties (close to 30 years in many cases). Murders that are the result of arguments that are not part of other crimes, appear to receive much shorter sentences, around 15 years. In general, murderers serve approximately 50 percent of the length of the sentence to which they are convicted.[6]

One testable explanation for these findings is that they provide support for the marginal deterrence hypothesis (Stigler, 1970). According to this hypothesis, because criminals are already receiving severe penalties for their first crimes, to deter murder, tougher sentences must occur for combining the crimes. To check for this possibility, we examine the correlation between sentence length in crimes without murder and sentence lengths, for the same crimes, when there is a murder.[7] Across crime categories there is no relationship between the non-murder sentence (which should be interpreted as the sentence for the crime if murder had not occurred) and the murder sentence (which should be interpreted as the cumulative sentence for both the murder and the other crime). This casts some doubt on whether America is generally following a policy of marginal deterrence.

The Alabama Data: To construct a second micro-data set on vehicular homicide cases, we obtained data from the Alabama Administrative Office of Courts and a number of Alabama State offices. We merged data on offenders from court records with data on victims from the FBI Supplementary Homicide Reports, death records from the Alabama Office of Health Statistics, and accident records of the Alabama Department of Public Safety. For each victim, we know age, sex, and race. The conviction rates and sentence lengths are comparable to those found in our main BJS data set.

IV. Optimal Punishment

In this section, we describe the construction of variables relating to the role of deterrence, incapacitation and sympathy for either the victim or the perpetrator. We then test for the importance of these variables.

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[5] A non-trivial number of occupations were in the illegal sector (e.g. prostitute, mafia bodyguard). In those cases, we used the closest legal occupation.

[6] See the *Sourcebook of Criminal Justice Statistics* or various BJS Publications.

Deterrence Elasticities: To test the importance of deterrence, we want to see whether types of murder that have higher deterrence elasticities receive stiffer penalties. Ideally, one would use exogenous sources of variation in the level of punishment over space and test whether different types of crime respond differentially to these different punishment levels. However, the studies that use exogenous variation in arrest rates (e.g. Levitt, 1998) do not distinguish between types of homicides.

An alternative approach, which is sketched in Appendix 1, is to rely on the variation of murder rates for different types of murder over space. As the appendix illustrates, differences in the coefficient of variation across different types of crime are a function of the deterrence elasticity of the crime rate and other differences over space in the attractiveness of particular types of crime. The intuition of this effect is that if regions differ in their level of deterrence, then the murder types with high deterrence elasticities will have big variation in their levels of space. The murder types with low deterrence elasticities will have less variation over space. Unquestionably, this is a noisy measure of the deterrence elasticity, but it is the best available to us.

Figure 1 shows the relationship between this measure of deterrence elasticity and sentence lengths across types of crimes. In general there is a positive relationship and the relationship is significant. Murders resulting from lover's quarrels and other arguments have the least variation (and probably the lowest deterrence elasticities) and the lowest punishment.

Probability of Apprehension: The next prediction of the Becker framework is that crimes where probabilities of apprehension are low will be punished more severely. The Supplementary Homicide Reports can be used to determine whether or not the police consider the case cleared by arrest. While this is not exactly the apprehension rate, it is a good proxy.

Figure 2 shows the relationship between this apprehension rate variable and the average sentence length. The relationship is negative, as predicted. The correlation across homicide types between sentence and apprehension rates is –38 percent. Lover's quarrels, arguments and brawls under alcohol have the highest probabilities of apprehension and the lowest sentence lengths.

[7] Available upon request. In the interest of space, we did not include these results.

Arson has a particularly low probability of apprehension and the highest average sentence length. Of course, long prison sentences for arsonists may have more to do with the great potential for social damage created by arson.

Incapacitation: We are particularly interested in measuring the propensity of various murderers to commit further crimes. As high recidivism rates will lead to high elasticities of crime quantity with respect to sentence lengths and as high recidivism rates reduce the average social cost of putting someone in prison, individuals with a high propensity for recidivism will be more likely to receive stiffer sentences. Our approach is to create a predicted recidivism measure for each offender and to include that as a variable that might explain sentence length.

We use data from the Bureau of Justice Statistics "Recidivism of Felons on Probation 1986-1989" data set. In Appendix Table 2, we show the result of a probit where the dependent variable is "committing a violent crime while on parole." In this regression, we find that crime characteristics tend to be quite important. Individuals who are guilty of robbery are very likely recidivists. Gender, race and number of priors also matter. Our recidivism measure is essentially an index that is higher for men, blacks, criminals with more prior arrests and individuals who are guilty of robbery and assault.

One problem with this data set is that we have a data set on recidivism for all criminals and we are considering the punishment of murderers only. (There are no sizeable data sets on the recidivism of murderers.) Certainly, this is problematic but we have no reason to believe that the same characteristics that predict recidivism among standard felons do not predict recidivism among murderers as well.

In Figure 3, we show the relationship between recidivism and sentence length. Recidivism also predicts sentence length. Lover's quarrel murders are again at the low end of the recidivism scale and the low end of sentence length. Robberies are at the high end of the recidivism scale. The fact that arguments and lovers' quarrels have low sentence lengths and are low on deterrence, and recidivism and high on apprehension suggests that several theories exist to explain sentence lengths for many crimes.

Table 2: In Table 2, we explore these variables in a simple regression setting. In this case, the unit of observation is the murder. In the cases of the elasticity measure and the apprehension

rate, there is only variation across type of homicide. The recidivism measure differs also by offender characteristics. In all cases, the standard errors have been corrected to address the fact that we do not have meaningful heterogeneity across all of the observations in the regression.

In the first regression, we examine all three variables without any other controls. All three variables are both quantitatively and statistically significant. A one-standard deviation increase in the recidivism measure increases the sentence length by 12 percent (which is .1 standard deviations). Sentence length rises with the elasticity measure and falls sharply with the apprehension rate. As the apprehension rate increases by 10 percent, the sentence length falls by almost the same amount. This quite remarkable result is the exact prediction of some versions of the optimal deterrence model where expected punishment should be kept constant across types of crimes. If anything we would expect the endogeneity of apprehension rates to mean that this parameter is underestimated, because more effort may be put into apprehending more dangerous murderers who are then given stiffer sentencing.

The second regression includes controls for conviction type. Much of the variation in sentencing depends on whether the murderer is convicted of first degree murder, second degree murder or manslaughter. The jury ultimately decides the conviction type. The judge, who is subject in many cases to sentencing guidelines, determines the sentence after conviction.[8] We find that controlling for conviction type makes no difference to the recidivism variable. Apparently, the connection between recidivism and sentence length works through sentencing, post conviction, not through the actions of juries. Most of the effect of the elasticity measure disappears when we control for conviction type. Forty percent of the apprehension rate effect disappears when we include conviction type dummies.

The third regression includes controls for victim and offender characteristics. Our results on the recidivism, variation and apprehension rates are not altered by these controls. There are very striking effects of victim characteristics. Murderers who kill black victims receive 26.8 percent shorter sentences.[9] Murderers who kill male victims receive 40.6 percent shorter sentences. It also appears to be true that when the victim is older the sentence is longer. The income variable is positive—richer victims appear to lead to longer sentences—but it is not significant.

[8] All of our results are robust to including state and county fixed effects

One interpretation of our race, gender and age effects is that society values women, whites and the elderly more and therefore optimal punishment calls for stiffer sentences of murderers who kill these victims. However, there is little evidence that suggests that our society values women more than men. Lichtenberg (1998) shows we generally spend slightly less researching diseases the afflict women. In civil cases where there are value of life judgements, male lives are generally attributed a higher value. Many people believe that society discriminates against women, not for them. The racial effects on sentencing may be despicable, but are still readily explained under racist preferences and optimal punishment given those preferences. The gender effect is more of a puzzle, which we will return to at the end of the paper.

Table 3 shows the results of regressing sentence length on characteristics of the victim and perpetrator. In the first regression we regress the log (sentence years) for convicted murderers as a function of victim characteristics, murderer characteristics and circumstance dummies.[10] In general, characteristics of both the victim and the offender tend to be quite important. A male offender receives on average a .47 log point increase in his sentence relative to a female offender. Offender age is insignificant. African-American offenders appear to receive slightly longer sentences but this effect is not statistically significant. Hispanic offenders do not receive longer sentences.

Offenders with more violent prior convictions receive much stiffer sentences. Controlling for this variable is the crucial step towards eliminating the impact of offender race on sentence. One interpretation of this fact is that there is no offender race effect on sentencing. Alternatively, past discrimination may have lead to more violent prior convictions prior to this current crime, so controlling for this variable could cause an erroneous conclusion of no racial prejudice towards black offenders.

The victim characteristics are also quite significant. Offenders who kill male victims receive much shorter sentences. One interpretation is that male victims are more likely to have initiated the conflict. We have been able to partially reject this interpretation by examining only murders where the offender was the aggressor, and in those cases the victim's gender is still quite important.

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[9] Throughout the paper, we adopt the convention of referring to log point differences as percent differences.

The race of the victim is also quite important. Perpetrators who kill blacks and hispanics are much less likely to receive stiff sentences than perpetrators who kill whites. There is no real cross effect between the race of the offender and the race of the perpetrator. When victims are gang members, sentences appear to be shorter by a sizable margin, but this effect is not statistically significant. Note from Appendix Table 1 that only 5% of the victims are gang members. It is also true that when there are more victims, the sentences are stiffer. Killing a victim with a past criminal record yields a shorter sentence.

Victims over the age of 65 are associated with much stiffer sentences. Young victims (less than 12 years old) are associated with lower sentences. This latter effect reflects the fact that younger victims are often in child abuse cases for which sentences are lower on average. When the victims are unemployed or prostitutes, sentences are shorter. We find that the female gender effect is significantly reduced when the victim is a prostitute. One interpretation of this finding is that society values these people less. An alternative view is that the taste for vengeance is closely tied to the innocence of the victim.

The impact of offender race and gender is not new. For example, Baldus et al. (1988) show that death sentences are much rarer when the victim is black. Gross and Mauro (1998) show that death sentences are more common when African-Americans kill whites. Spohn (1994) shows the impact of victim race in sexual assault cases. While in a sense, we are only confirming a well known race of victim effect, given the general nature of our data set, we think that finding this effect in a national homicide sample is particularly important.

We also include a wide range of crime circumstance dummies. These are always significant and they always take the predicted signs. For example, it is always true that when the victim "provoked" the attack, the sentences are much shorter. Sentences are longer when the murder took place in the context of a professional crime. Vehicular homicide offenders get by far the shortest sentences.

In the second, third and fourth regressions, we examine the role that sentencing and conviction play in determining the length of sentence. Regression (2) reports marginal effects from a probit regression where the dependent variable is whether the prosecutor brought a charge of first

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[10] All regressions are robust to including county fixed effects.

degree murder against the defendant. Murder one was actually charged in a majority of our cases. There is a substantial race effect in which black victims are associated with fewer murder one charges. Circumstance factors are also important. The gender of the victim is not correlated with charging murder one. Other than past offenses, perpetrator characteristics are uncorrelated with being charged with first degree murder.

In the third regression, we look at the probability of being convicted in a first degree murder case. Here the gender effect appears strongly. Cases where women are victims are much more likely to result in murder one convictions than other cases. Again, the race of the victim also matters and when the victim is white, a murder one conviction is much more likely. The priors of the victim are also very important. Since the victim effects really appear to matter at the conviction stage, we suspect that it is a taste for vengeance among juries and prosecutors that really matters.

The fourth regression looks at sentencing, controlling for conviction type. The gender effects are weaker than without conviction type dummies but they are still quite significant. The coefficient on victim male drops from -.415 to -.260, but remains quite significant. One way to interpret this change is that forty percent of the gender effect is being determined by differential conviction rate and sixty percent by post-conviction sentencing. Victim income and age also matters in this stage. The dummies for type of conviction are naturally incredibly strong for predicting the sentence length.

Tables 4a-4d present evidence on sentence rates as a function of the race and gender of the murderer and the victim.[11] These tables help us to think about whether there are interactions between the race of the offender and the race of the victim. They also present our results in a simple fashion. In Table 4a, we show the mean sentence length by the race of the murderer and the victim. Without including any other controls, we find that white murderers receive a 3.7 year shorter sentence if they kill a black person relative to a white person and black murderers receive a 5 year shorter sentence if they kill a black person. Without including other controls, it also appears that black offenders get longer sentences. If the victim is white, then black offenders appear to get a 3.3 year stiffer sentence and if the victim is black then black offenders appear to receive a 2 year longer sentence.

Table 4b shows that the gender effects are even more striking. Male offenders receive a 6.2 year longer sentence than female offenders if the victim is female and a 6.9 year longer sentence if the victim is male. Killing a woman also results in a substantially longer sentence. For male offenders, killing a woman increases the sentence length by 4.2 years. For female offenders, killing a woman results in a 4.9 year longer sentence. In the Alabama data set we find a significant victim gender effect with female perpetrators, but not with male perpetrators.

One issue with these results is that gender and race may be correlated with attributes of the murder that are not observable. To try and address this issue, and to further test the optimal punishment hypothesis, we now turn to a narrow class of murders: vehicular homicides.

V. Vehicular Homicides

Vehicular homicides have the advantage that they are a relatively homogenous crime category. Overwhelmingly, they involve substance abuse and reckless driving. To a first approximation, it seems most likely that conditional upon the characteristics of the offender, the victim is random. As such, optimal punishment clearly suggests that victim characteristics should not matter, or at the very least should matter much less than in other homicides. Unfortunately, we have relatively few vehicular homicides in the Bureau of Justice Statistics (142). We cast a wide net going state-by-state to try and accumulate more records. Only in Alabama were we able to accumulate more cases (another 46).

Tables 4c and 4d show the basic results on vehicular homicides. The gender effects remain and seem to be about as strong as in the case of murders overall. In the Bureau of Justice Statistics data, the gap for male offenders between male victims and female victims is 5.1 years. The gap for overall homicides was 5 years. In the Alabama data, the gap is smaller: 2.77 years. The BJS data also appear to show strong offender gender effects.

Table 5 shows our results in a regression setting. In the first regression we include all of our vehicular homicides. Forty-eight of these observations involve victims who are pedestrians or people in other cars. The remaining cases involve people in the offender's car. Since these are

[11] These are raw means include all people charged. The raw differences (in terms of years) are similar when we

less likely to be random, in the second regression we include only cases where the victim is a pedestrian or driving in another car. In both regressions, there are substantial victim gender effects. Victim race remains quantitatively large in the second regression, but becomes statistically insignificant. The past criminal history of the victim is quite important in both regressions. It seems that drunken drivers who are "lucky" enough to run over males with a criminal history face shorter sentences than drivers who run over innocent women. The third regression gives results for the Alabama data set. Again, there is a substantial gender effect. There is no race effect in the Alabama data set.

Overall, we believe that there are substantial victim effects that are strong even when the victim is random. Indeed, even if the victim is not purely random in the case of vehicular homicides, there can be no doubt that there is substantially more randomness for vehicular homicides than there is for other types of murders. At the very least, therefore, we would expect the effect of victim characteristics to diminish for these types of homicide. However, the victim effects are just as large as in cases where the murderer clearly selects the victim. These findings are difficult to reconcile with the view that sentences reflect optimal punishment.

VI. Explaining the Results: The Taste for Vengeance

One alternative to the classical economic model of optimal punishment is that punishment responds to tastes for vengeance among judges, juries and the citizenry as a whole. A rich set of experimental results seems to confirm that human beings are often willing to sacrifice material benefits to punish others; Romer (1995) develops an elegant model, which explains an evolutionarily dominant taste for punishment. This taste for vengeance seems close to the "outrage" model advanced in Sunstein (2000).

If punishment is based on the taste for vengeance of judges and juries, then the emotional apparatus that determines the taste for vengeance may operate at a subconscious level and therefore may not respond perfectly to unusual circumstances of the crime. For example, the emotional response to victim characteristics will probably not be altered all that much even if we know that the victim was essentially random. Because the taste for vengeance is not the outcome of rational thought, the knowledge that the murderer did not select the victim may not alter the

condition upon conviction. The regressions that follow condition upon sentence >0.

demand for vengeance. According to this view, there is likely to be a much stronger visceral response to a drunk driver who accidentally kills an eight year old girl than to a drunk driver who accidentally kills a 22 year old gang member. Thus, a taste for vengeance based view of punishment may help us to understand our results on vehicular homicides.

Past social scientists have connected the taste for vengeance with the innocence of the victim. Adam Smith (1759) in *Theory of Moral Sentiments* connected the taste for retribution to "our sympathy with the unavoidable distress of the innocent sufferers." Smith emphasizes the extent to which the victims are innocent as a determinant of the thirst for revenge.[12] If women are thought to be more innocent than men, then this may explain the pervasive gender effects. Our results on victim criminal records and victims who are prostitutes are also easy to understand using this idea. Anecdotally, we believe that the public is particularly anxious to punish men who allegedly kill women (e.g. O.J. Simpson, Jack the Ripper, Klaus von Bulow, Sam Shepard), or men who allegedly kill children (the Lindbergh baby kidnappers, Richard III).

Wile we have little evidence on these issues, as yet. Our suspicion is that the emotional responses of juries are based upon (1) the degree to which they are able to identify with the victim, and (2) the degree to which the victim is thought to morally pure. Kerr (1978) documents the importance of victim innocence (as well as victim attractiveness) in mock jury trials.

VI. Conclusion

We have presented evidence on the determinants of punishment for murderers in the United States. We find the characteristics of the victim, the offender and the crime all generally matter. Much of these effects can be understood as implications of an "optimal" punishment model where punishments are higher when there is a greater value to incapacitation or a greater deterrence elasticity. Some of our results can be understood as the outcome of a greater desire of society to protect particular types of people.

[12] Smith also emphasizes that "our heart rises up against the detestable sentiments which influenced [villain's] conduct." This suggests the importance of intent and the state of mind of the perpetrator and might explain the rules concerning first degree murder.

However, we find the victim characteristics are also very important in vehicular homicides and even in those vehicular homicides where the victim is a pedestrian. Optimal punishment theory generally predicts that random aspects of the victim should not be important determinants of punishment. But they are and this tends to supports a taste for vengeance view of the determinants of punishment.

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Appendix 1: Using the Variance of Crime Rates to Measure Relative Deterrence

We treat each subcategory of crime separately. In each location there is a distribution of private net benefits of crimes. Within these net benefits we include the full range of psychic and financial benefits from crime as well as the opportunity cost of time. The only component that is specifically excluded is the costs of legal deterrence. We separate out these benefits into a space-specific mean level of net benefits (denoted B) and a remainder "b." We assume that the distribution of b is constant across space with cumulative distribution F(b) and density f(b). There is also an expected level of deterrence, incorporating all of the expected punishment from crime, which is denoted D, and which is assumed to differ over space but to be constant within each location.

The quantity of criminals in each location are those for whom the benefits of crime B+b are greater than the expected deterrence costs, D. There will be a marginal criminal, denoted b* for whom b*=D-B. The total quantity of crime in each location will equal 1-F(b*)=1-F(D-B). The elasticity of crime with respect to deterrence is -Df(b*)/(1-F(b*)).

We let $\underline{D}$ and $\underline{B}$ reflect the mean levels of D and B across the entire U.S. and let $\underline{b}=\underline{D}-\underline{B}$. If we take a Taylor series approximation for F(.) so that

$$\text{(A1)} \qquad Quantity\ of\ Crime\ per\ Capita = 1 - F(b^*) \cong 1 - F(\underline{b}) - f(\underline{b})\left(D - B - \underline{D} + \underline{B}\right).$$

Which means that elasticity of crime with respect to deterrence is -Df(b*)/(1-F(b*)). Then taking variances gives us that:

$$\text{(A2)} \qquad Variance\ of\ Crime\ Rates = f(\underline{b})^2\, Var\left(D - B\right),$$

or that:

$$\text{(A3)} \qquad Log\left(\frac{\sigma_{crime}}{\mu_{crime}}\right) = Log\left(\frac{\underline{D}f(\underline{b})}{1-F(\underline{b})}\right) + Log\left(\frac{\sigma_{D-B}}{\underline{D}}\right),$$

which means that the logarithm of the coefficient of variation of this crime equals the elasticity (approximately) plus an error term relating primarily to the variance of the deterrence and net benefits over space. If this variance is constant across crimes there will be no extra bias. If this variance differs, then there will be a question that the elasticity is measured with error and typically the coefficient on the elasticity will fall below the true elasticity value.

Table 1
Prison Sentences By BJS Circumstance of Murder

Circumstances	Mean Sentence (years)	Standard Deviation of Sentence	Mean Conviction Rate	Number Of Obs.
Robbery	32.3	17.9	.79	350
Burglary	32.1	17.5	.82	33
Sexual assault	36.3	17.9	.87	30
Arson	50.0	0.0	.83	6
Larceny	33.4	22.8	.71	7
Auto theft	33.5	19.2	.92	25
Romantic triangle	14.7	12.5	.83	58
Property/money	17.1	16.5	.78	263
Redress of insult/personal honor	14.9	15.2	.77	256
Matters of opinion	18.2	17.3	.81	134
Lover/spouse quarrel	18.0	16.6	.81	305
Barroom dispute/brawl	13.2	14.7	.69	67
Street fight	12.5	15.2	.84	32
Punishment for stealing drugs/money	20.0	16.7	.84	25
Bad deal/bad drugs	15.8	12.5	.87	39
Money owed	22.6	17.2	.61	72
Stealing drugs/drug money	24.6	18.8	.71	73
Dispute over drugs	20.1	16.3	.80	113
Other gang fight between rival gang	10.7	7.2	.88	24
Contract killing/Hit for money	30.9	18.6	.70	53
Total	27.6	19.8	.76	3086

Notes: These figures include life sentence and adjust it to be a 50 year sentence. Mean sentence is the mean *conditional upon conviction*. Sample size includes convictions and non-convictions. Standard deviations of conviction rates are p(1-p)^.5 and are not shown.

Table 2: The Determinants of Sentence Length

	(1)	(2)	(3)
Dependent Variable:	**Log(Sentence Length)**		
Probability of Recidivism	1.327 (2.936)	1.328 (3.878)	2.000 (3.439)
Variance of Crime Rates (elasticity measure)	0.031 (1.979)	0.012 (1.466)	0.034 (2.651)
Apprehension Rate	-0.934 (-2.890)	-0.554 (-2.888)	-1.085 (-3.259)
Victim black			-0.268 (-3.111)
Victim male			-0.406 (-3.767)
Victim age			0.005 (2.010)
log(victim income)			0.141 (1.325)
Victim income missing			1.262 (1.218)
Constant	2.826 (8.770)	1.885 (9.840)	1.819 (1.704)
Conviction type dummies*	no	yes	no
N	1772	1772	1772
R squared	.02	.44	.07

T statistics in parentheses. Standard errors corrected for clustering at the crime type level. *Dummies for murder 1,2, manslaughter 1.

Table 3
Victim Effects in BJS Data:
Overall, During Arrest, During Conviction, During Sentencing

	(1) Log(Sentence Length)	(2) Probability of Murder 1 being charged at arrest	(3) Probability of Murder 1 conviction	(4) Log(Sentence Length) with conviction dummies
Method of Estimation	OLS	Probit	Probit	OLS
Offender Male	0.470	-0.068	0.061	0.364
	(4.835)	(-2.000)	(1.710)	(4.971)
Offender Black	0.077	0.002	-0.016	0.066
	(1.139)	(0.040)	(-0.430)	(1.262)
Offender Age	-0.002	0.001	0.002	-0.003
	(-0.555)	(1.070)	(1.540)	(-1.123)
Victim Male	-0.415	0.010	-0.095	-0.260
	(-5.048)	(0.400)	(-2.470)	(-4.618)
Victim Black	-0.274	-0.098	-0.091	-0.126
	(-3.843)	(-2.690)	(-3.200)	(-2.158)
Victim Age	0.004	-0.001	0.000	0.002
	(1.372)	(-0.750)	(0.040)	(1.277)
Offender number of violent priors	0.068	0.018	0.009	0.060
	(4.622)	(2.070)	(0.900)	(5.271)
Victim gang member	-0.296	0.238	0.019	-0.246
	(-1.051)	(3.420)	(0.390)	(-0.969)
Victim # violent priors	-0.084	-0.005	-0.053	-0.060
	(-1.860)	(-0.180)	(-2.150)	(-2.076)
Victim unemployed	-0.286	-0.041	-0.080	-0.103
	(-2.582)	(-0.370)	(-1.460)	(-1.179)
Victim prostitute	-0.625	-0.020	-0.104	-0.153
	(-2.230)	(-0.100)	(-0.820)	(-0.936)
Victim less than 12 years of age	0.002	-0.052	-0.006	0.010
	(0.017)	(-1.170)	(-0.100)	(0.112)
Victim greater than 65 years of age	-0.049	0.020	-0.069	0.084
	(-0.268)	(0.190)	(-0.890)	(0.634)
Constant	0.045			-1.279
	(0.037)			(-1.485)
N	1772	1772	1772	1772
R squared	.16	.03	.07	.48

T statistics in parentheses. Standard errors corrected for clustering at the county level. All regressions include controls for victim income and homicide circumstance dummies (robbery, burglary, arson, kidnapping, child abuse, vehicular manslaughter, family dispute, romantic dispute). Conviction dummies in regression 4 are for first and second degree murder and first degree manslaughter .

Table 4a
Prison Sentences by Race of Offender and Victim

Mean Sentence (years)
Standard Deviation(sentence)
Number of Observations

		Offender Black		
Victim Black		0	1	Total
	0	18.7	22.0	19.5
		13.7	14.6	14.0
		801	246	1047
	1	15.0	17.0	16.9
		12.9	14.0	13.9
		73	1006	1079
Total		18.4	18.0	18.2
		13.7	14.3	14.0
		874	1252	2126

Table 4b
Prison Sentences by Gender of Offender and Victim

		Offender Male		
Victim Male		0	1	Total
	0	10.6	16.8	16.0
		13.9	15.3	15.2
		83	546	629
	1	5.7	12.6	11.8
		10.4	14.2	14.0
		266	2204	2470
Total		6.9	13.4	12.7
		11.5	14.5	14.4
		349	2750	3099

Table 4c
Prison Sentences by Gender of Offender and Victim
Vehicular Homicides: BJS Data

Mean Sentence (years)
Standard Deviation(sentence)
Number of Observations

		Offender Male		
Victim Male		0	1	Total
	0	4.1	10.1	9.3
		2.6	11.7	11.1
		4	25	29
	1	3.1	5	4.7
		3	4.3	4.2
		21	92	113
Total		3.2	6.1	5.6
		2.9	6.9	6.5
		25	117	142

Table 4d
Prison Sentences by Gender of Offender and Victim
Vehicular Homicides: Alabama Data

		Offender Male		
Victim Male		0	1	Total
	0	10	5.5	5.8
		.	5.61	5.53
		1	14	15
	1	2.46	2.73	2.65
		3.22	2.93	2.96
		9	22	31
Total		3.22	3.81	3.68
		3.86	4.32	4.19
		10	36	46

Table 5
Victim Effects in Vehicular Homicides

Dependent Variable: Log(Sentence Length)	(1) All Vehicular Homicides, BJS	(2) Victim is pedestrian or other driver, BJS	(3) Victim is pedestrian or other driver, Alabama
Offender male	0.392 (1.316)		-0.094 (-0.176)
Offender black	0.260 (1.323)	0.363 (1.214)	0.321 (0.425)
Offender age	-0.017 (-1.649)	0.042 (2.514)	
Victim male	-0.561 (-2.377)	-1.261 (-2.653)	-0.905 (-2.038)
Victim black	-0.526 (-2.021)	-0.179 (-0.386)	0.129 (0.153)
Victim race missing			-0.127 (-0.243)
Victim age	0.006 (0.937)	0.006 (0.380)	
Victim # violent priors	-0.160 (-1.753)	-0.448 (-2.162)	
Number of victims	0.351 (2.311)	-0.008 (-0.046)	
Constant	-3.530 (-1.128)	8.230 (1.530)	1.214 (1.930)
N	134	48	46
R squared	.21	.40	.11

T statistics in parentheses. Standard errors corrected for clustering at the county level.

Regressions 1-2 also include controls for victim and offender income, offender number of violent priors, victim gang member.

Appendix Table 1: BJS Murder Data Set-- Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
sentence: life in prison	3836.00	0.09	0.28	0.00	1.00
sentence: death penalty	3836.00	0.01	0.09	0.00	1.00
sentence: in days include life sent	3124.00	7433.89	11765.46	0.00	18250.00
log (sentence)	2168.00	2.85	1.16	-5.21	3.91
sentence: years	2752.00	20.75	20.92	0.00	50.00
convicted (0,1)	3086.00	0.76	0.43	0.00	1.00
offender male	3122.00	0.89	0.32	0.00	1.00
offender black	3102.00	0.60	0.49	0.00	1.00
offender hispanic	3103.00	0.18	0.39	0.00	1.00
offender age	3060.00	29.82	10.76	15.00	88.00
offender < 18	3836.00	0.03	0.17	0.00	1.00
offender violent priors	3124.00	0.61	1.69	0.00	51.00
offender is dealer	3124.00	0.13	0.34	0.00	1.00
offender gang member	3124.00	0.05	0.21	0.00	1.00
prior relation w/ victim	2946.00	0.79	0.44	0.00	1.00
family relationship w/ victim	3836.00	0.03	0.17	0.00	1.00
romantic relationship	3836.00	0.08	0.27	0.00	1.00
victim family or friend	3836.00	0.26	0.44	0.00	1.00
victim stranger	3836.00	0.25	0.43	0.00	1.00
circumstance: robbery	3836.00	0.09	0.29	0.00	1.00
circumstance: sexual assault	3836.00	0.01	0.09	0.00	1.00
circumstance: burglary	3836.00	0.01	0.09	0.00	1.00
circumstance: vehicular	3836.00	0.05	0.21	0.00	1.00
charge: first degree	3836.00	0.58	0.49	0.00	1.00
charge: second degree	3836.00	0.18	0.39	0.00	1.00
victim age	2925.00	32.97	15.46	1.00	87.00
victim male	3099.00	0.80	0.40	0.00	1.00
victim black	3055.00	0.52	0.50	0.00	1.00
victim hispanic	3836.00	0.15	0.36	0.00	1.00
alcohol in victim	1980.00	0.47	0.50	0.00	1.00
drugs in victim	1793.00	0.29	0.46	0.00	1.00
victim provoked attack	2647.00	0.18	0.38	0.00	1.00
victim prior convictions	3039.00	0.21	1.46	0.00	51.00
victim is gang member	3111.00	0.02	0.14	0.00	1.00
victim prior arrests	3111.00	0.76	4.51	0.00	51.00
plea bargain	3098.00	0.40	0.49	0.00	1.00
jury trial (versus bench)	1307.00	0.71	0.45	0.00	1.00
northeast	3030.00	0.26	0.44	0.00	1.00
south	3030.00	0.32	0.47	0.00	1.00
central	3030.00	0.18	0.39	0.00	1.00
west	3030.00	0.24	0.43	0.00	1.00
victim local	3836.00	0.76	0.43	0.00	1.00
number of victims	3120.00	1.05	0.27	1.00	5.00
offender prior arrests	3124.00	2.72	5.54	0.00	103.00
black offender on white vic	3041.00	0.10	0.30	0.00	1.00
offender 20-39	3836.00	0.57	0.50	0.00	1.00
offender 40+	3836.00	0.13	0.34	0.00	1.00
victim 20-39	3836.00	0.48	0.50	0.00	1.00
victim 40+	3836.00	0.19	0.39	0.00	1.00

Source: BJS Murder Cases in 33 Counties

Note: Sentences truncated at 50 years; life and death penalty counted as 50 years

Appendix Table 2:
Probits of Recidivism on Offender Characteristics
DATA: Recidivism of Felons on Probation; BJS

Offender Characteristics	**Δ Probability of Receding to Violent Crime (dF/dx from Probit)**
Rapist	0.010 (0.012)
Robber	0.156 (0.015)
Assault	0.060 (0.012)
Burglar	0.021 (0.009)
Male	0.035 (0.006)
Black	0.055 (0.006)
number of priors	0.009 (0.004)
N	9,449

Standard errors in parentheses.
Source: Recidivism of Felons on Probation 1986-1989, Bureau of Justice Statistics, US Dept of Justice

Figure 1
Sentence Length and Cross-City Variation in Crime Rates across

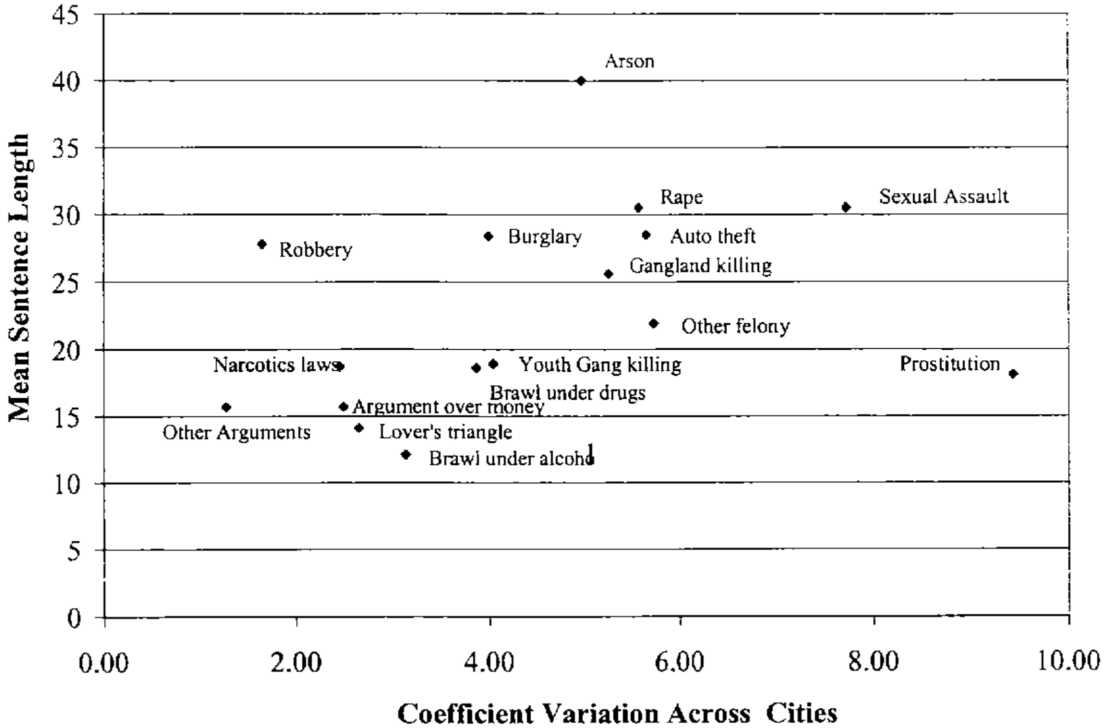
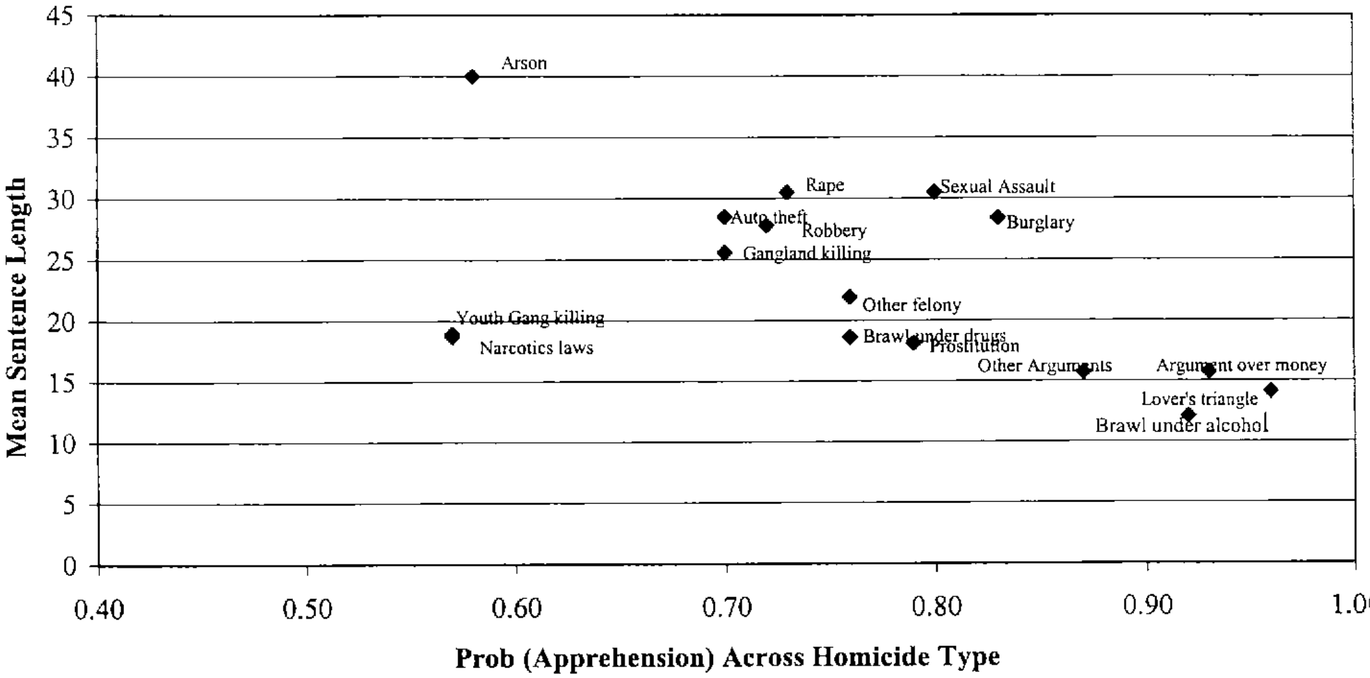
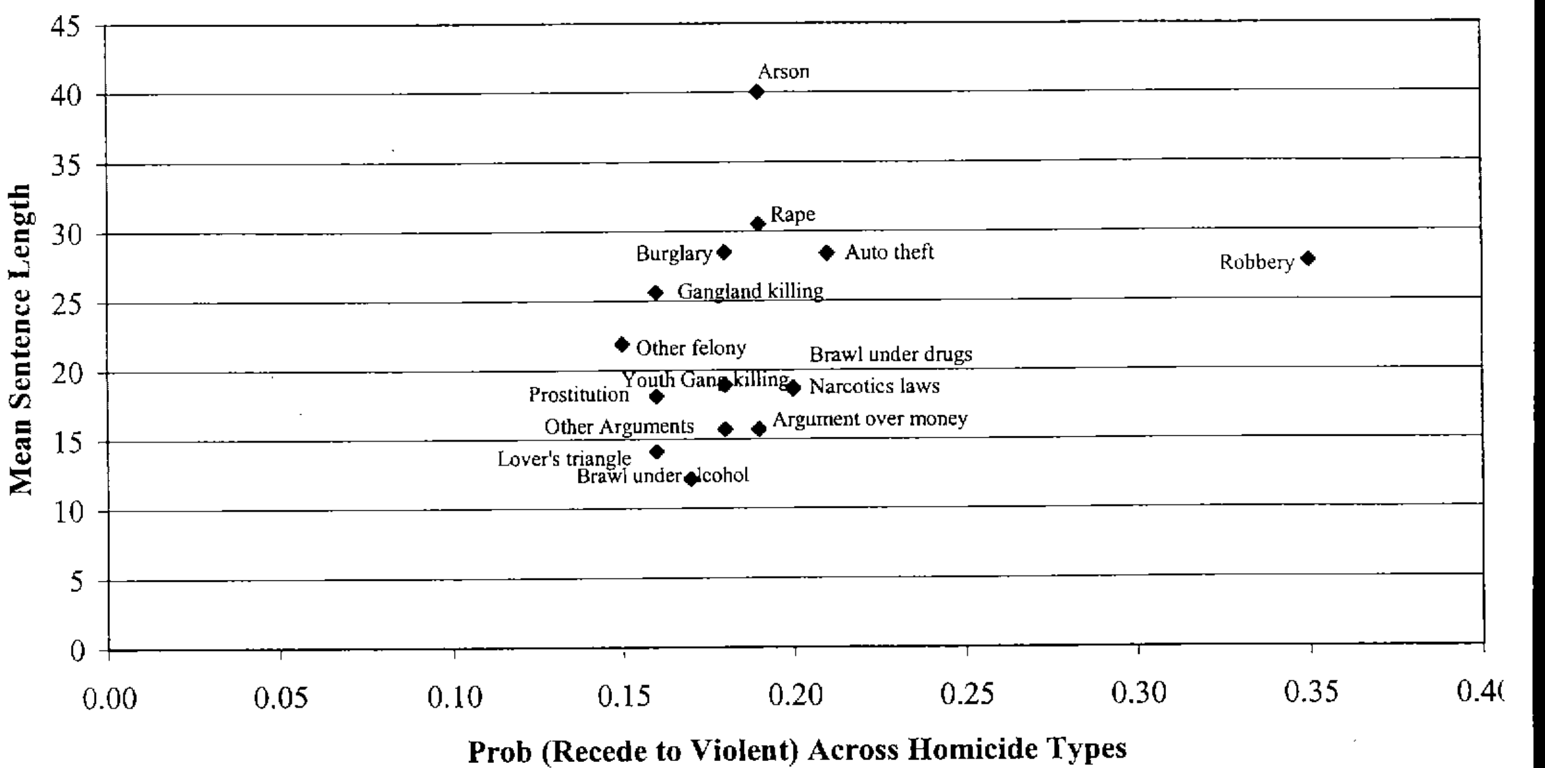


Figure 2
Sentence Length and Apprehension Rates across Homicide Types



Apprenhension rate is measured as fraction of homicides in which police have a charged suspect (i.e. report offender data) in the UCR Supplementary Homicide Reports

Figure 3
Sentence Length and Recidivism Rates across Homicide Types



Recidivism rates are fitted values based on offender characteristics. The coefficients for the fitted values are estimated using the BJS data "Recidivism of Felons on Probation."