Building Criminal Capital vs Specific Deterrence: The Effect of Incarceration Length on Recidivism

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Abstract

In attempting to understand the efficacy of a criminal justice system that makes use of incarceration, a vital relationship to understand is that between incarceration and recidivism. Because almost all previous empirical attempts to estimate this relationship suffer from omitted variables bias, even the sign is unknown. In this paper, I build on previous work identifying substantial heterogeneity in attorney ability in public defender office with random case assignment. I make use of this variation to address the omitted variables problem by instrumenting for sentence length using the randomly assigned public defender. I then use this instrument to estimate the causal impact of sentence length on recidivism using several different measures for recidivism. In the IV specification I find a negative impact of sentence length on recidivism, although one that is not statistically significant. Using a non-parametric approach, I find the relationship to be complex and non-monotonic. For the lowest sentences, the relationship is negative; it becomes positive for an intermediate sentence length, and then negative for the longest sentences. This evidence is consistent both with theories of criminal capital formation and with specific deterrence.

JEL Classifications: J24, K14, K42

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I. Introduction

The growth in the incarceration rate in the United States in the last several decades of the 20th century and early 21st century is well known. Much has been written about the efficacy, justice, and efficiency of this approach to crime for a myriad of methodological perspectives.[1] In this paper I attempt to understand one piece of the incarceration puzzle: the impact of sentence length on recidivism, often called specific deterrence.

This relationship between recidivism and deterrence is important to understand from an economic perspective, as it is one important component of the welfare calculation regarding the efficiency of incarceration. This is part of a larger agenda to try to determine the costs and benefits of various aspects of the criminal justice system.[2] The end goal is to answer the question: In what situations incarceration is welfare-enhancing? This project may be thought of as a large cost-benefit calculus, in which the costs include the capital expenditures on incarceration, the value of freedom, and potential criminogenic effects of imprisonment. Benefits from incarceration include crime reduction due to incapacitation, general deterrence, and specific deterrence.[3]

This paper focuses on the last of these relationships, incarceration and specific deterrence. The reduced form version of the question is "How much does recidivism

[1] Cite several background papers here.
[2] Other papers include Abrams and Rohlfs (2009) on optimal bail-setting and the value of freedom; Abrams (2009) on general deterrence; Abrams, Bertrand and Mullainathan (2008) on defendant race and sentencing.
[3] One may also include retribution and rehabilitation in the calculus, although these are much harder values to estimate.

change in response to a one month increase in incarceration?"[4] While simple to state, there is substantial complexity in the question, and as I show in this paper, in the answer.

First, defining recidivism is a hard enough problem that substantial amount of work has been devoted just to this topic (Maltz, 2001). I sidestep much of the complexity of this interesting problem in this paper, by using several different measures of recidivism, each of which is simply a binary variable. I find that the results are largely consistent for each of these measures.[5]

Second, and perhaps most confounding in much of the previous research on the topic, is the fact that there are almost certainly unobservable variables that are correlated to both sentence length and recidivism. Because defendants who are relatively "bad" are more likely to both get longer sentences and recommit offenses, an inability to control for "badness" will yield upward-biased estimates of the effect of sentence length. In previous work (eg Spohn and Halleran, 2002; Gottfredson, 1999) they attempt to control for it through synthetic control groups, covariate balancing, and other matching techniques based on observables. But there is substantial literature in economics and elsewhere that illustrates the difficulties in using even the most sophisticated matching techniques (Lalonde, 1986; Dehejia and Wahba, 1998; Deheji, 2000).

A third challenge posed by the simple question is that it may presume a simple answer, as in a single coefficient on the sentence length from an OLS or probit regression. I estimate both reduced form and IV regressions in this paper, and find a negative

[4] I will sometimes refer to the derivative of recidivism with respect to sentence length as the magnitude of specific deterrence or simply specific deterrence.

[5] In future work I hope to introduce more complexity into the measure of recidivism, accounting for time to reoffense, number of offenses, and severity.

relationship between recidivism and sentence length. But the relationship between the variables turns out to be non-monotonic and complex, and is better explored through non-parametric techniques.

Using locally weighted regressions of the recidivism residuals, I find a relationship between sentence length and recidivism that can be characterized as having three separate regions: low sentence, intermediate sentence and high sentence. In the low sentence regime, increasing sentence length reduces recidivism. This is true even though most defendants in this region are not sentenced to incarceration, and those that are receive very short terms. This finding may be explained by the fact that in this region, besides the intensive effect of increased length of sentence, there is substantial variation along the extensive margin (incarceration or not), as well. Thus an increase in expected sentence may deter more through its concomitant increase in likelihood of incarceration than the actual duration of stay.

In the second, intermediate region of sentence length increases in sentence length cause and *increase* in recidivism. While potentially surprising, this is a phenomenon that may be explained by theories of criminal capital. The notion that criminals learn skills and gain information while incarcerated is not a new one [add cite]. The evidence found here for the positive relationship is also consistent with Spohn and Holleran's (2002) findings. Another explanation for this type of relationship is the fact that any non-criminal skills that offenders have may atrophy while incarcerated, thus making it harder to find employment at the end of their term. Kling (2004) explores this theory using a dataset of offenders from

Florida but finds little evidence to support the notion that longer duration sentences lead to worse labor outcomes.

In the region of longest sentence lengths , there is a negative relationship between sentence length and recidivism. This is exactly the sort of effect that theories of specific deterrence predict, that individuals become less likely to recidivate, the more severely they are punished. One concern may be that this result is driven by the well-established empirical regularity that criminality decreases with age. I use several techniques to address this concern: controlling for age at offense, proxying for age at release, and renormalizing the data to explicitly account for the age-criminality profile. The main results are robust to all of these controls.

This paper builds on a large and important literature in economics and criminology. Chen and Shapiro (2007) use a regression discontinuity approach to investigate a related topic, the effect of a harsher prison environment on recidivism. They find weak evidence that harsher conditions may in fact make offenders more likely to recidivate. The closest papers to this one are Loeffler (2005) and Turner (2009). Loeffler also recognizes the omitted variables problem and addresses it by using interjudge variation in sentencing as an instrument for incarceration. He finds no significant effect of incarceration on recidivism (his paper focuses exclusively on the extensive margin).

The remainder of the paper is organized as follows. In Section II, I provide some background information on the Public Defender's office in Clark County and describe the data set. Specification choices? In Section III I present the empirical specifications and the main results, which I then discuss and attempt to interpret in Section IV. Section V concludes.

II. Background and Data Description

The data for this paper comes from two sources, both in Nevada.[6] The first data source is the Clark County Public Defender (CCPD)[7] and includes data on defendants represented by the CCPD's office from 2001 – 2008. The initial data set was collected in order to investigate the impact that attorneys have on case outcomes (Abrams & Yoon, 2007; Abrams & Yoon, 2009). The key feature of the CCPD is that the office uses random assignment of cases to public defenders for almost all cases[8]. In this paper, I exploit this random assignment and the substantial variation in public defender skill to instrument for sentence length.

The CCPD is in the minority of public defender offices in that it uses random case assignment and also makes use of vertical representation. This ensures that a single public defender handles almost all cases from beginning to end. The office uses random assignment partly as a recruiting tool, to entice ambitious young attorneys with the prospect of handling interesting cases much more quickly than in other offices. The system is also seen as being more equitable than the hierarchical one used in most offices. For this

[6] The Nevada DOC data is still being collected.
[7] Las Vegas contains the vast majority of the population of Clark County.
[8] There are several classes of exceptions, including public defenders in their first year, certain sex crimes, and capital murder cases. For further detail see Abrams and Yoon (2007).

paper, what is important is its consistent application. In Abrams and Yoon (2007 & 2009) it was empirically verified that observable case characteristics appear to be randomly assigned across public defenders.

The second data set comes from the Nevada Department of Corrections (NDOC) and contains data on prisoners held in Nevada from January, 2006 – October, 2009. The offender information includes demographic information and may include beginning and end dates of the prison term.

Table 1 summarizes the CCPD data set. In addition to the randomly assigned data, a substantial number of additional observations are included in order to calculate recidivism rates. These observations (which bring the initial total to 110,282 observations) often contain missing data, but are taken as indicators of recidivism as long as the defendant is identifiable. Besides the recidivism rates, the data in Table 1 refers only to the randomly assigned cases (n =15,246), which include only the first appearance of an offender in the data set. This implies that the mean sentences used will be lower than the mean of the full data set.

In Nevada, defendants receive a sentence range from the judge, indicating a minimum and maximum. In practice, the vast majority of defendants are incarcerated for a period of time much closer to the minimum sentence length than the mean.[9] For this reason, the principle measure of sentence length I use is the minimum. The mean minimum unconditional sentence length is just over 3 months, although the majority of sentences are zero. The instrument, predicted minimum sentence length, has an identical

[9] In some cases, defendants may be paroled even before serving the minimum sentence length, since a 2007 legislative reform. See Chapter 525, *Statutes of Nevada 2007.*

mean by construction, but substantially lower standard deviation. This is a consequence of the non-normality of the sentencing distribution and in particular its long right tail (Figure 1). The non-normality is to be expected due in part to truncation at zero. One simple potential fix would be to perform a log transformation, as the distribution of log sentence is much closer to normal. However this necessarily discards all of the zero sentences, which make up the majority of the data. This would invalidate the instrument as data would be selected based on the outcome.[10] For most of the specifications, I use the main instrument based on Public Defender identity, and this distribution may be seen in Figure 2.

Due to the large number of zero sentences, conditioning on the sentence[11] being non-zero yields a mean of almost 9 months, substantially higher than the unconditional mean. By comparison the mean unconditional sentence (the average between the minimum and maximum sentencing range) is 5.7 months. Only 35% of the offenders in the data set receive a sentence with some length of incarceration.[12]

Demographically, the defendants resemble those in many other criminal justice populations: heavily male and minority. 77% of the population is male, with 30% Black and 23% Hispanic (these classifications are not mutually exclusive). The average offender age in the data set is almost 33 years old, but there is substantial variation, as can be seen in Figure 3..

[10] One potential way to use this technique may be to find a subset of data for which all defendants receive some sentence, and thus taking the log does not discard any data based on the dependent variable. However, it is likely that the untransformed data will be close to normally distributed for just such a subset, making the transformation unnecessary.

[11] From here forward I use sentence to indicate the minimum sentence, unless otherwise noted.

[12] Probation (or suspended sentences) is counted as a zero sentence length in this data set.

Crime type is broken down into four categories, with Embezzlement, Fraud, and Theft (EFT) the largest category, containing almost half the offenders. Drug crimes make up 30% of the data, and violent crime an additional 21%. Sex crimes make up the remainder, with about 2%.

Recidivism is the primary dependent variable and is defined here as reappearance in the Clark County Public Defender data set within a fixed amount of time from expected release from incarceration. This measure of recidivism is somewhat intermediate between arrest and imprisonment data. It indicates that a prosecution has progressed to the point where a PD has been assigned, but many cases will not result in incarceration or even conviction. The assumption is that this is an unbiased measure of criminal activity. Specifically, the n year recidivism dummy variable is 1 if the offender appears in the data within the n year period immediately following release from incarceration and zero if there is no appearance within this window. Release from incarceration is estimated as the case record data plus the minimum sentence length. In order to avoid truncation effects, recidivism dummies are not calculated for offenders whose sentences end within n years of the end of the data set.

The recidivism rates estimated in this population are in line with those found elsewhere, although the populations and method for computing recidivism vary. The one, two, and three year recidivism rates for the sample are 18.0%, 26.7% and 34.1%, respectively. These rates are similar to those found for federal prisoners in (Chen & Shapiro, 2007) of 16.4%, 27.5% and 37.0%. Another point of comparison is the United States Sentencing Commission FY1992 Recidivism Sample for which the two year recidivism rate is 22.1% (USSC 2003). In the next section I investigate to what extent these recidivism rates are affected by sentence length.

III. The (Complicated) Relationship between Sentence Length and Recidivism

I first investigate the relationship between sentence length and recidivism by running a naïve linear probability model cross-sectional regression (the "reduced form") as in (1):

$$(1)\ recid_{dp} = \alpha + \beta sent_d + X_d + mo_t + \epsilon_d$$

Here *recid* is a dummy variable that is 1 if defendant d recidivates within p years of release from incarceration, zero if the defendant does not recidivate in this window, and not observed otherwise. The independent variable of interest is sentence length to which defendant d was initially sentenced. An array of case and defendant-specific controls, including judge, case type, defendant age, defendant race, defendant sex, as well as monthly time dummies are included as regressors. This is also estimated using a probit specification, where Φ is the cumulative normal distribution.

$$(2)\ p(recid_{dp}) = \Phi(\alpha + \beta sent_d + X_d + mo_t + \epsilon_d)$$

The main problem with this approach is that sentences are not randomly assigned to defendants. In fact it is likely that judges determine sentences based in part on characteristics unobservable to the econometrician that are also correlated with likelihood of recidivism. That is, $E[\varepsilon_d|sent_d] \neq 0$ and is likely > 0. The most likely such characteristic is some underlying criminal propensity, which is orthogonal to all observable control variable, but detectable by the judge and correlated with sentence length. Criminal propensity will also certainly be predictive of recidivism, and thus failure to account for it will result in an upward biased coefficient on sentence length.

The random assignment of Public Defenders to cases in the CCPD constitutes a natural experiment in sentence length assignment. Since PD's vary substantially in individual ability, and assignment is random, defendants effectively face a partial lottery over sentence lengths. I use this lottery to obtain an unbiased estimate of the effect of sentence length on recidivism using an IV regression.

For the first stage regression, I instrument for sentence length using a full set of public defender dummy variables (PD_a) as in (3):

(3) $sent_d = \pi_0 + \pi_a PD_a + X_d + mo_t + \nu_d$

The second state uses the predicted values of sentence length to get exogenous variation in (4), relying on the identifying assumption that $E[\nu_d| PD_a]$ and $E[\varepsilon_d|PD_a] = 0$.

(4) $recid_{dp} = \alpha + \beta \widehat{sent}_d + X_d + mo_t + \epsilon_d$

Table 2 reports results from the reduced form regression as well as the first stage from the IV regression. The first regression reports results from the base linear probability model described in equation 1. There is a statistically significant and negative coefficient on sentence length, indicating that in the cross-section an extra month sentence length is associated with a decreased recidivism rate of about 0.8 percentage points. Off the mean 18% one year recidivism rate found in Table 1, this is a reduction of around 4.4%. Of course, this is likely to suffer from omitted variables bias, as discussed before. Before I attempt to address this concern, I examine the relationship of the control variables and recidivism as well as the other specifications.

The second specification uses a probit model rather than linear probability. The reported marginal effect of -.009 is statistically indistinguishable from the coefficient in the linear probability model. I run probit versions of all of the other models as well and the results are all consistent with the linear probability model, so they are omitted from the tables.

One of the most difficult empirical challenges with determining recidivism rates is how to properly control for age. It is well known[13] that criminality declines over time. In fact one can see trend clearly in this data set, as in Figure 4. But this presents a major challenge to the econometrician. Even if a valid instrument is found for sentence length, the treatment will necessarily imply that those defendants who are represented by worse attorneys (and hence get longer sentences) will be older on average at time of release. This then has a direct negative impact on the magnitude of recidivism.

Thus we now have reasons why the naïve estimate may be upward biased (omitted variables) or downward biased (the criminality age profile, which may also simply be an omitted variable). To address the former concern, I use the IV specification described in equations 3 and 4 above. To address the latter, I take three different approaches: First, I control for age at offense. Since I do not know the exact release date from incarceration in

[13] Reference about criminality-age profile.

the CCPD data set, this is at least likely to be strongly correlated.[14] Second I use the estimated release date, calculated as the initial trial date plus the minimum sentence. Finally, I use the empirical age profile in Figure 4 to normalize the recidivism variable. Thus an observation with recidivism where the offender is 50 will receive substantially more weight than when the offender is 20.

In the cross-section, adding the age controls do increase the coefficient on sentence length, but only very slightly. The point estimates are somewhat larger in absolute magnitude for the 2 and 3 year measures of recidivism, but as a fraction of base recidivism rates they are even smaller, although still statistically significant. For the 3 year measure the cross-sectional regression indicates an approximate 3% decline in recidivism for a month increase in expected minimum sentence. Since the sentencing distribution is very skewed, the standard deviation is not necessarily very informative. Still using the value of 10.3 months translates to a substantial 31% decline in recidivism associated with a one standard deviation increase in sentence length. An examination of the control variables indicates little consistency that is statistically significant across most specifications, except that Black and male offenders tend to have higher recidivism rates.

Table 3 presents the main regression results from the IV strategy, although as I will discuss shortly, linear regression tells a very incomplete story in this context. The results from the first stage are in column one are unsurprising: male defendants tend to receive longer sentences as do those who commit violent crimes, EFT[15] crimes, and sex offenses.

[14] In future work incorporating Nevada DOC data I will know the exact date of release.
[15] EFT stands for embezzlement, fraud, theft.

Weak instrument tests strongly reject the null (p<.001). I also perform tests of the overidentifying restrictions and cannot reject the null of valid instruments.

The main reason that IV is important in this context is to avoid the unobserved variables problem. I argued above that the unobserved criminal propensity is likely to bias the coefficient on sentence upward in this context. In column 2 we find evidence for this argument, as the coefficient on sentence is about 25% more negative than in the reduced form. This pattern holds when comparing the coefficients for all of the 1 year and 3 year specifications, although not for the two year specifications. In addition, none of the coefficients on sentencing in the IV specifications are statistically significant at the 5% level.

Adding age controls, as in columns 3-5, increases the coefficient, as it did in the cross section. The effect of age controls is substantially diminished when using the 2 and 3 year specifications and thus those regression results are omitted. The magnitude of the IV coefficient varies somewhat depending on controls and measure of recidivism. The 3 year rate shows the largest effect in magnitude, but smallest relative to the baseline recidivism rate. We may get a sense of the magnitude of the effect, using the column 4 specification as an example: controlling for age at release and using the 1 year recidivism measure. The coefficient of -.87% predicts to a 4.8% decline in recidivism in response to an 1 month increase in expected minimum sentence. As mentioned above, though not particularly informative in this context, a one standard deviation increase in sentence length would lead to an expected drop in recidivism of almost 50%.

As in the reduced form, offender age is significantly negatively related to recidivism. Black and male offenders have higher recidivism rates as well, which was also seen in the reduced form.

While the IV approach is key to getting an unbiased measure of specific deterrence, the coefficients are not meaningful if the relationship between deterrence is not linear, as has been assumed thus far. Rather than attempting a more complicated parametric or semi-parametric approach, I take a completely non-parametric approach here. In order to control for various case and defendant characteristics, I regress the recidivism rate on these controls and predict the residuals. Since the residuals are still close to binary, and a figure of two horizontal lines is rarely illuminating, I use locally weighted regressions to produce a local approximation of the recidivism rate residuals. This is then plotted against the predicted sentence length, based on the public defender instrument, as in Figure 5, which uses 1 year recidivism rates.

The figure shows a complicated relationship between recidivism and sentence length, one that is not well-captured in a monotonic regression as reported in Tables 2 and 3. Age controls do little to change the general picture of the relationship. Figure 6 reports residuals from the 1 year recidivism data renormalized to correct for the recidivism-age profile. Figures 7 and 8 are the corresponding figures using 2 and 3 year recidivism measures, respectively.[16]

[16] One slightly unusual aspect of all figures is that predicted sentence can be negative. This is a consequence of the model assumptions used in the first stage. In future work I will make use of a negative binomial in the first stage to better match the empirical distribution.

While the figures look rather distinct on first glance, they all share several patterns. First, there is a negative relationship between recidivism and sentence length for low values of sentence length. There is then an increasing relationship between the two variables from around 0 to 1.5 or 2 months, depending on which version of the dependent variable is used. Each figure then has a dip, that is, a relatively short range with a relatively strong negative and then positive relationship. Then, beginning with about two months expected sentence, the relationship is mostly negative, but for a small dip. I discuss possible interpretations of this pattern in the following section.

IV. Discussion

In trying to interpret the data displayed in figure 6-8, it may be helpful to simplify the overall pattern of the relationship between recidivism and sentence length. There are 3 major regions of the data. The first has a negative relationship, from about -2 months to 0. In the second, the relationship is positive, from about 0 to 2. In the third region, from 2 to 5, the relationship is once again negative.

The first region, which contains about 13% of the data, exhibits a negative relationship between recidivism and sentence length. In this region of the data, only 28 defendants actually receive any length of incarceration at all[17]. Those who are incarcerated

[17] This value is for the 1 year recidivism data set. The numbers are 23 and 2 for the 2 and 3 year recidivism measures, respectively.

receive a median sentence of 45 days. Even though these jail stints are short and uncommon, they appear to have a deterrent effect. Why the decrease in recidivism?

Since independent variable here is expected sentence length, it combines both the extensive margin of entering jail at all, and the intensive margin of receiving a longer sentence length. This is true for all 3 regions, but is most salient in the first one, where the incarceration rates are lowest. The reduction in recidivism may be a response more to the experience of incarceration altogether, rather than an increase in its duration.

The second region, from 0 to 2 months expected minimum sentence, contains 37% of the offenders many more of whom do receive incarceration. In this region there is a positive relationship between sentence length and recidivism. This may be best explained by the theory that one may enhance "criminal capital" while incarcerated.[18] Petty criminals may actually benefit by short periods in jail by learning about new techniques to avoid police, new tools for burglary, emerging drug markets, etc. Further, 95% of offenders in this category receives a sentence below 1 year, meaning they will be serving time in a local jail, rather than a potentially more remote and severe prison facility.

Chen and Shapiro (2007) investigate a related question, regarding the security of the prison, and find greater recidivism among former inmates held in more secure prisons. However their study only examines federal prisons and did not include local jails which are likely to be substantially different. In this second region of the figures, it may be that any increase in specific deterrence, due to a longer sentence, is outweighed by the enhanced

[18] Citation to come

criminal skills and knowledge gained while incarcerated. Thus we see a positive relationship between recidivism and deterrence in this region.

Region 3 contains about half of the offenders, the vast majority of those incarcerated, and all of those with sentences beyond 2.5 years. The general trend in this region is for recidivism to decrease with increased sentence length. It is important to note that this is not simply an artifact of the recidivism-age profile discussed earlier. While those offenders with longer sentences will be released at more advanced ages, the age-related reduction in recidivism has already been netted out. The simplest story that remains is of specific deterrence. In an economic framework, it must be the case that individuals who have personal experience with incarceration increase the expected cost of recidivism, due to the likelihood of further incarceration. This change in cost may be explained by imperfect information or perhaps by behavioral biases (salience, etc).

V. Conclusion

Seen together, the data tells a complicated story, but one that helps explain the divergence of previous findings. Loeffler (2005) reports that of the handful of papers that have previously tried to address the omitted variables concern, 6 reported no deterrent effect and 4 reported a positive effect. Depending on which part of the distribution one focuses on, this paper could find a positive, negative, or no effect.

By instrumenting for sentence length using randomly assigned public defenders, I am able to obtain a causal estimate of the impact of sentence length on recidivism. But this causal relationship is complex. There appears to be three regions where the direction of the relationship switches. For the lowest sentences, an increase in sentence length leads to a reduction in recidivism. For an intermediate range, recidivism rises with sentence length, and for the longest sentences, recidivism again decreases with sentence length. This complex relationship lends at least some support both to theories of specific deterrence and criminal capital. These complexity of these findings are intriguing and should spur further theoretical and empirical work with an eye ultimately toward potentially significant policy implications.

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Figure 1

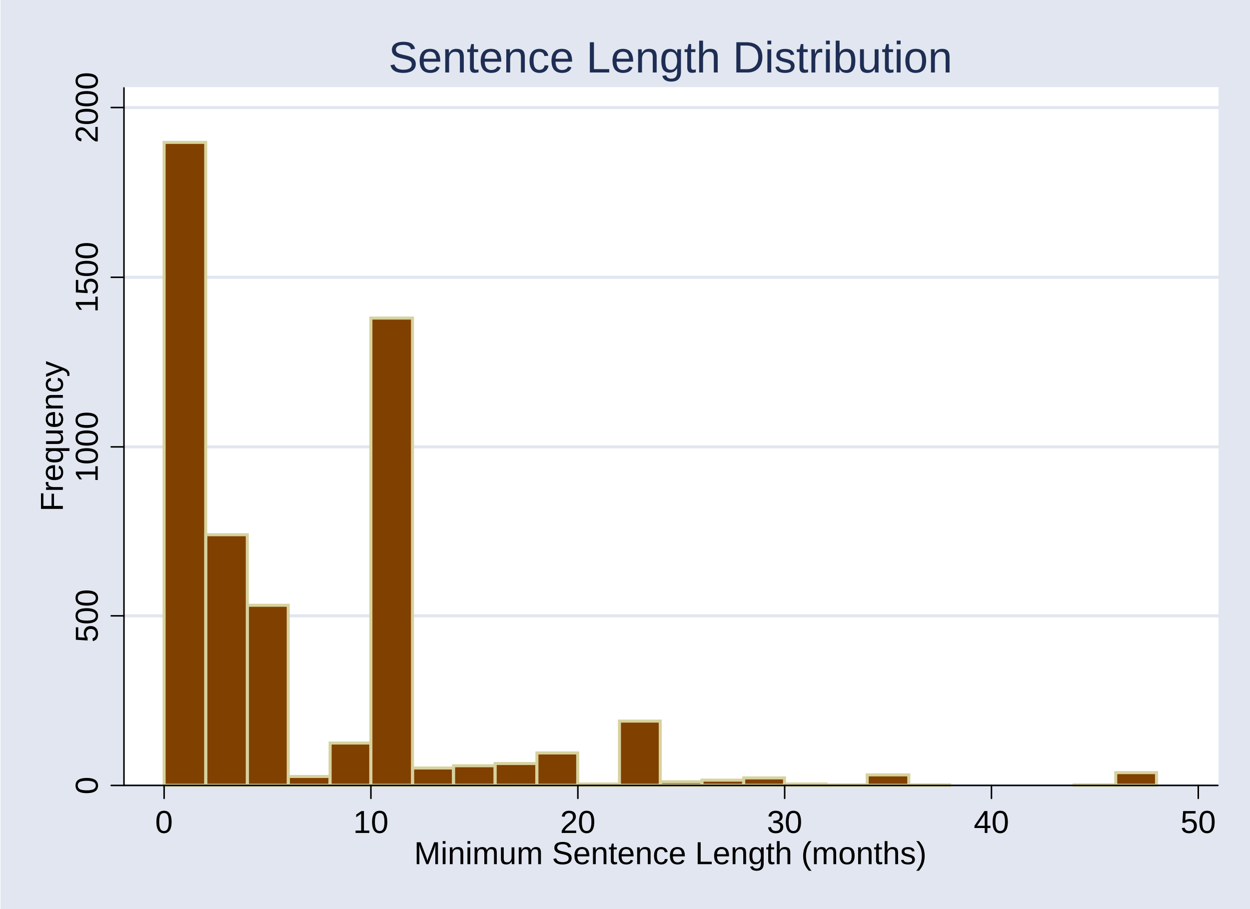

Sentence Length Distribution
Frequency
0
500
1000
1500
2000
0
10
20
30
40
50
Minimum Sentence Length (months)

Figure 2

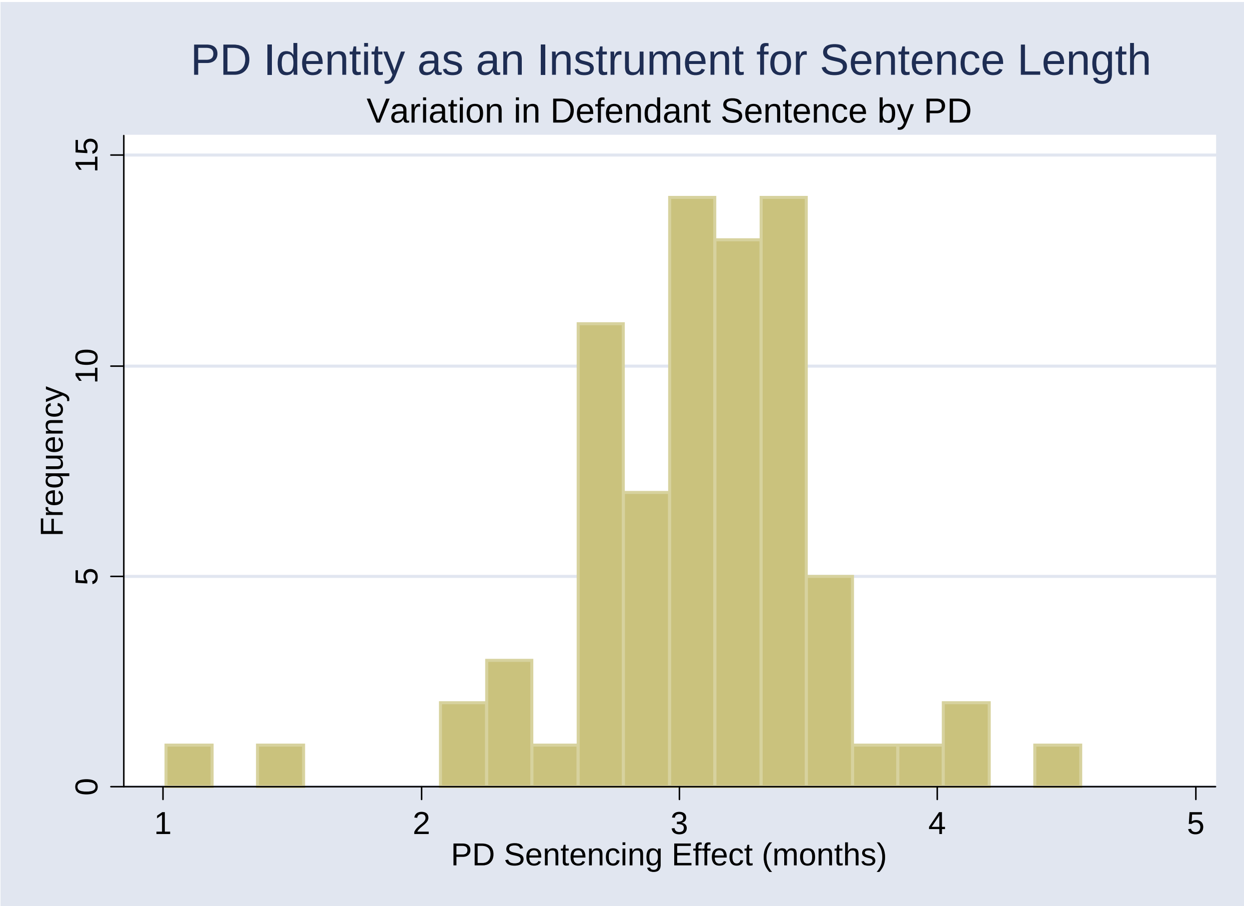
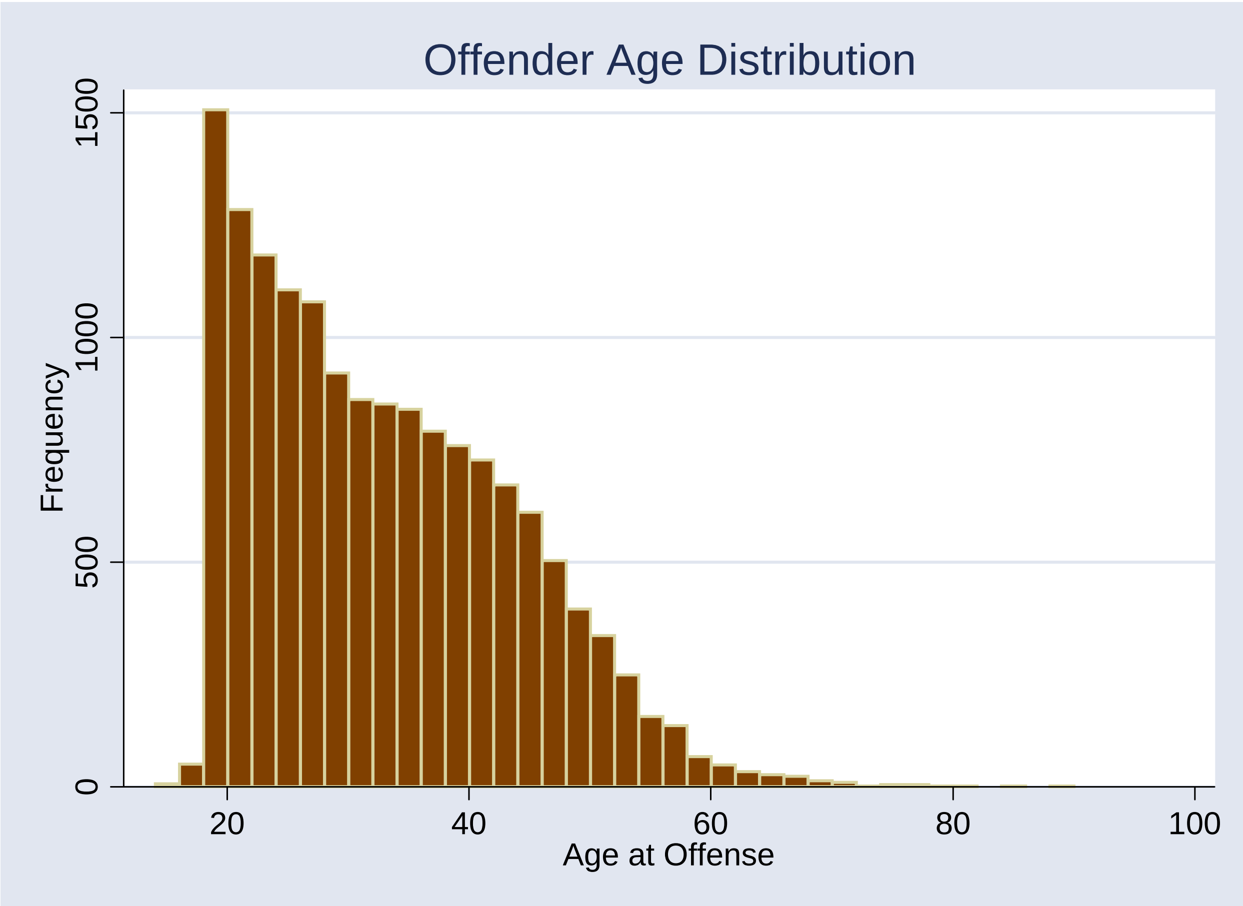

PD Identity as an Instrument for Sentence Length
Variation in Defendant Sentence by PD
Frequency
0
5
10
15
1
2
3
4
5
PD Sentencing Effect (months)

Figure 3



Offender Age Distribution
Frequency
0
500
1000
1500
20
40
60
80
100
Age at Offense

Figure 4

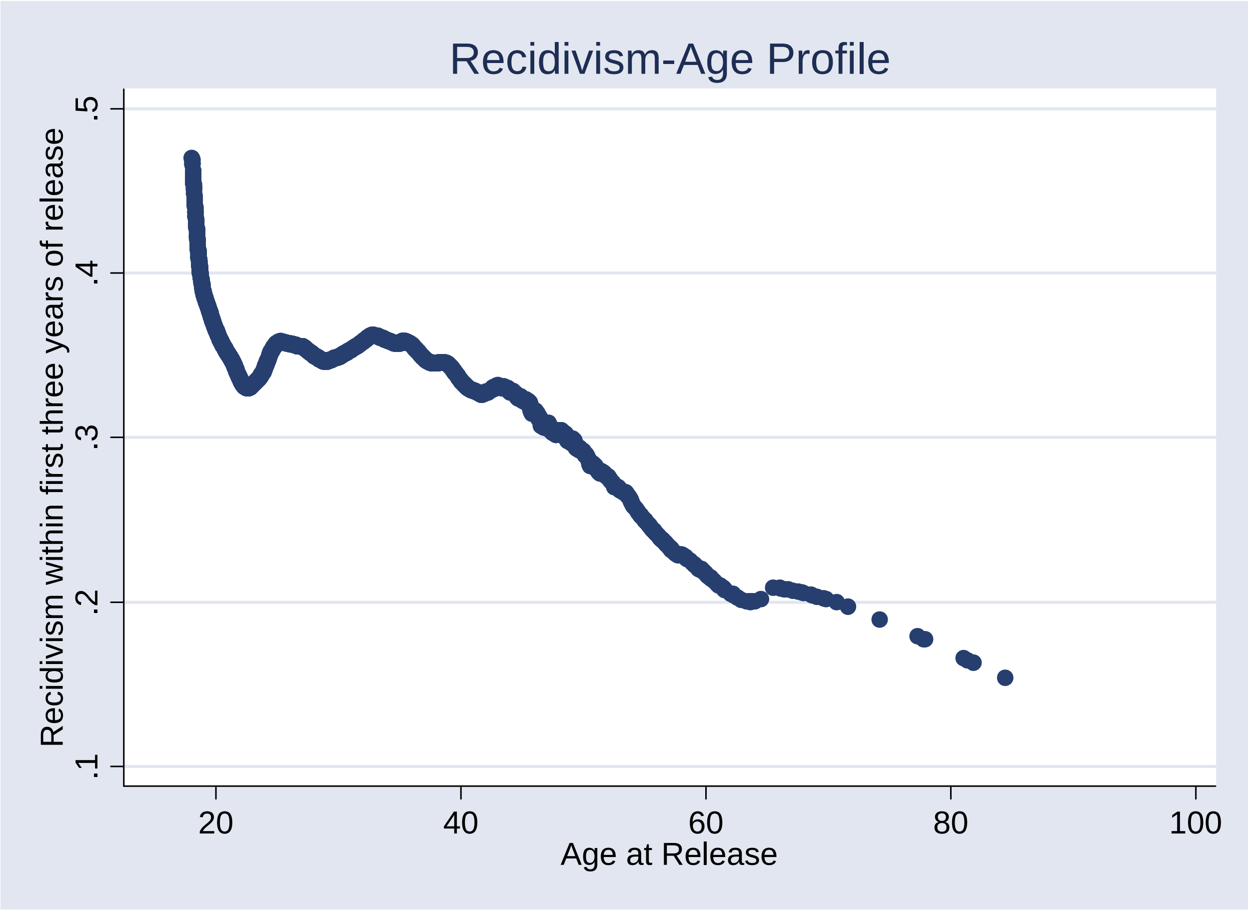

Recidivism-Age Profile
Recidivism within first three years of release
.1
.2
.3
.4
.5
20
40
60
80
100
Age at Release

Figure 5

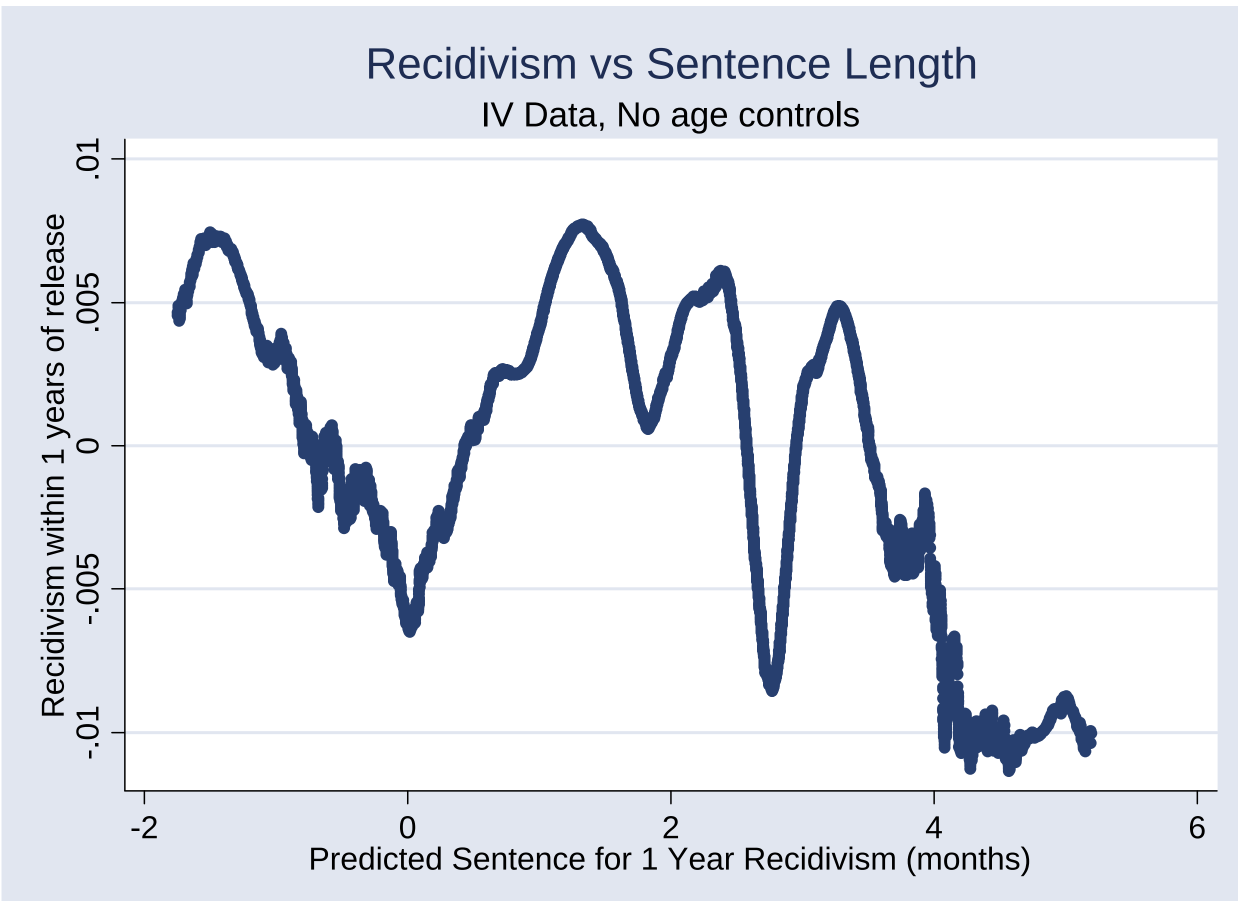

Recidivism vs Sentence Length
IV Data, No age controls
Recidivism within 1 years of release
.01
.005
0
-.005
-.01
-2
0
2
4
6
Predicted Sentence for 1 Year Recidivism (months)

Figure 6

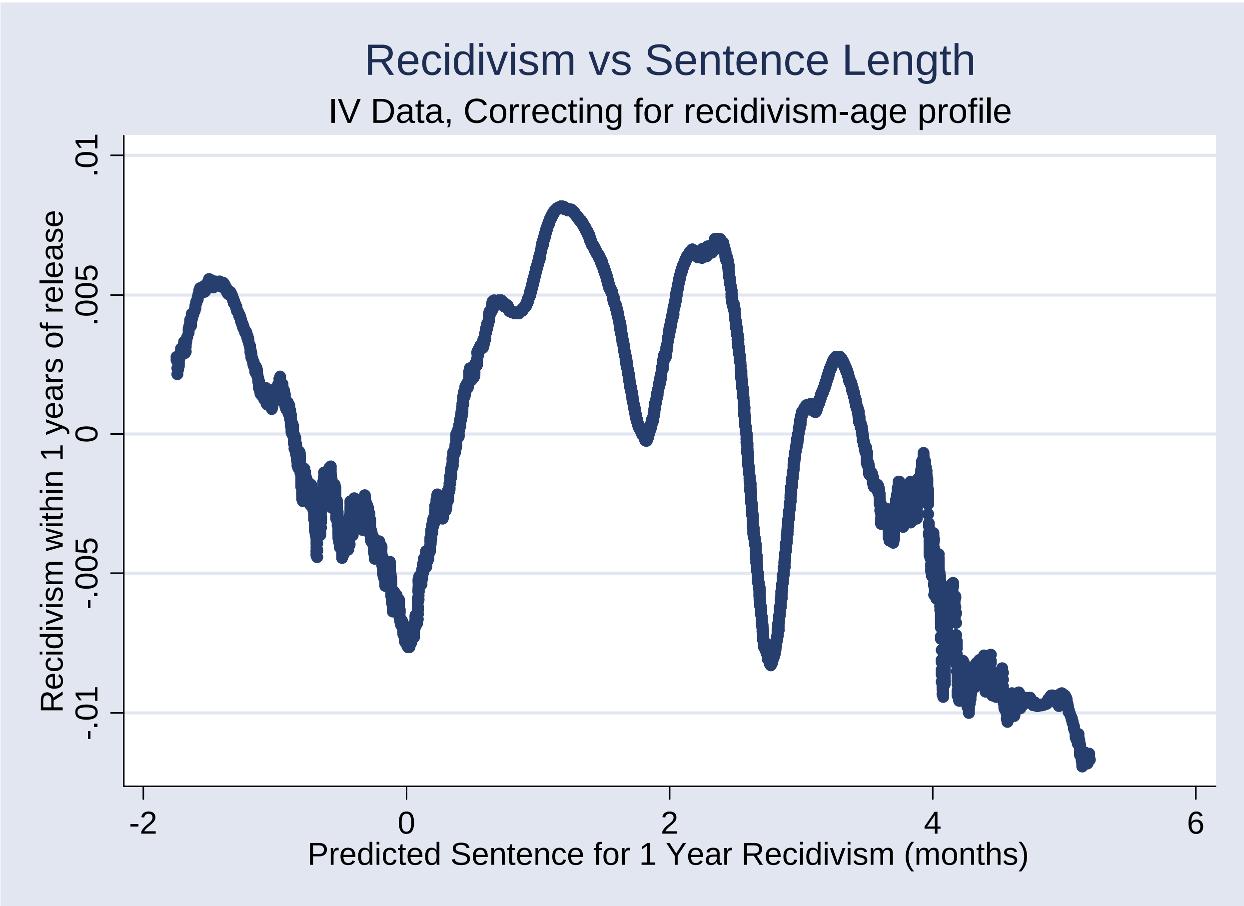
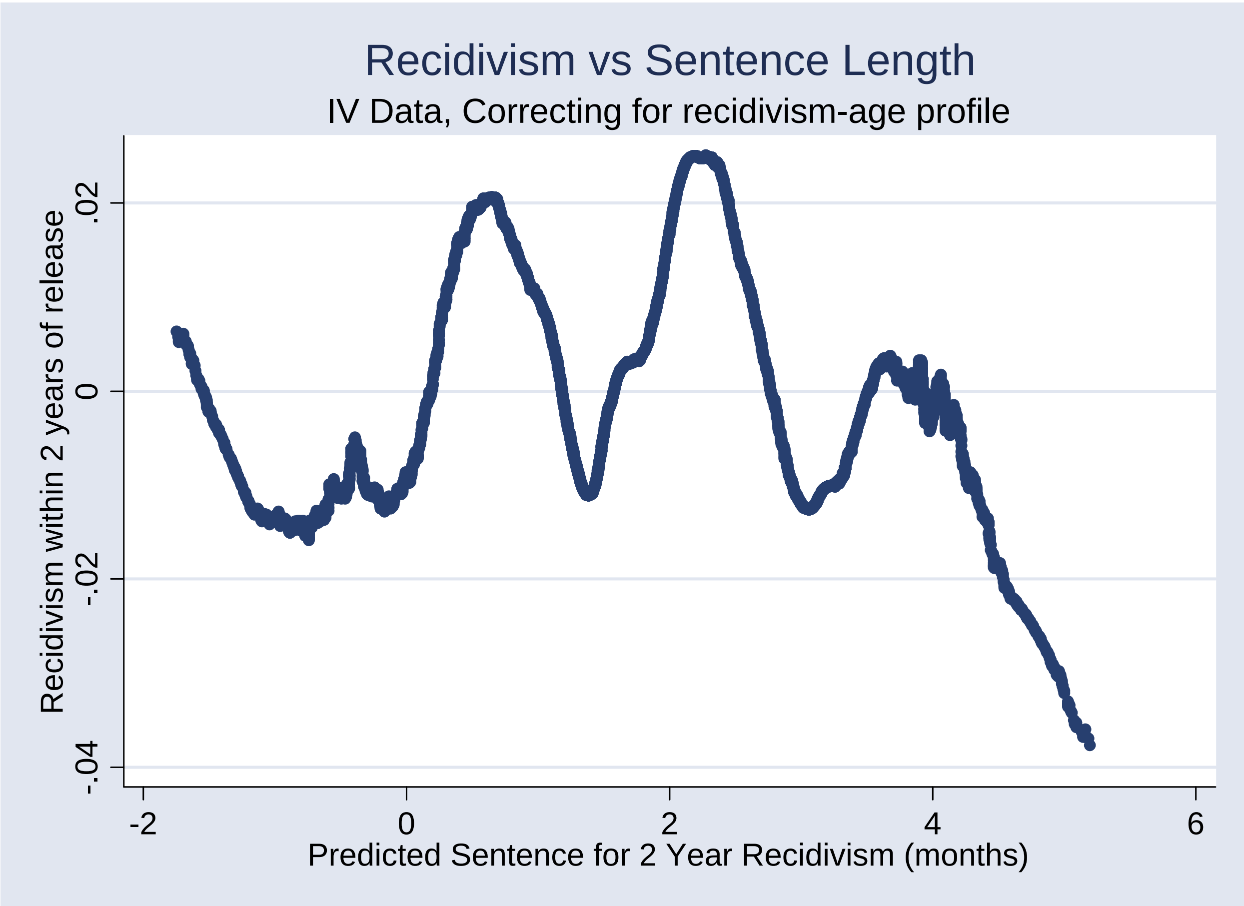

Recidivism vs Sentence Length
IV Data, Correcting for recidivism-age profile
Recidivism within 1 years of release
.01
.005
0
-.005
-.01
-2
0
2
4
6
Predicted Sentence for 1 Year Recidivism (months)

Figure 7



Recidivism vs Sentence Length
IV Data, Correcting for recidivism-age profile
Recidivism within 2 years of release
.02
0
-.02
-.04
-2
0
2
4
6
Predicted Sentence for 2 Year Recidivism (months)

Figure 8

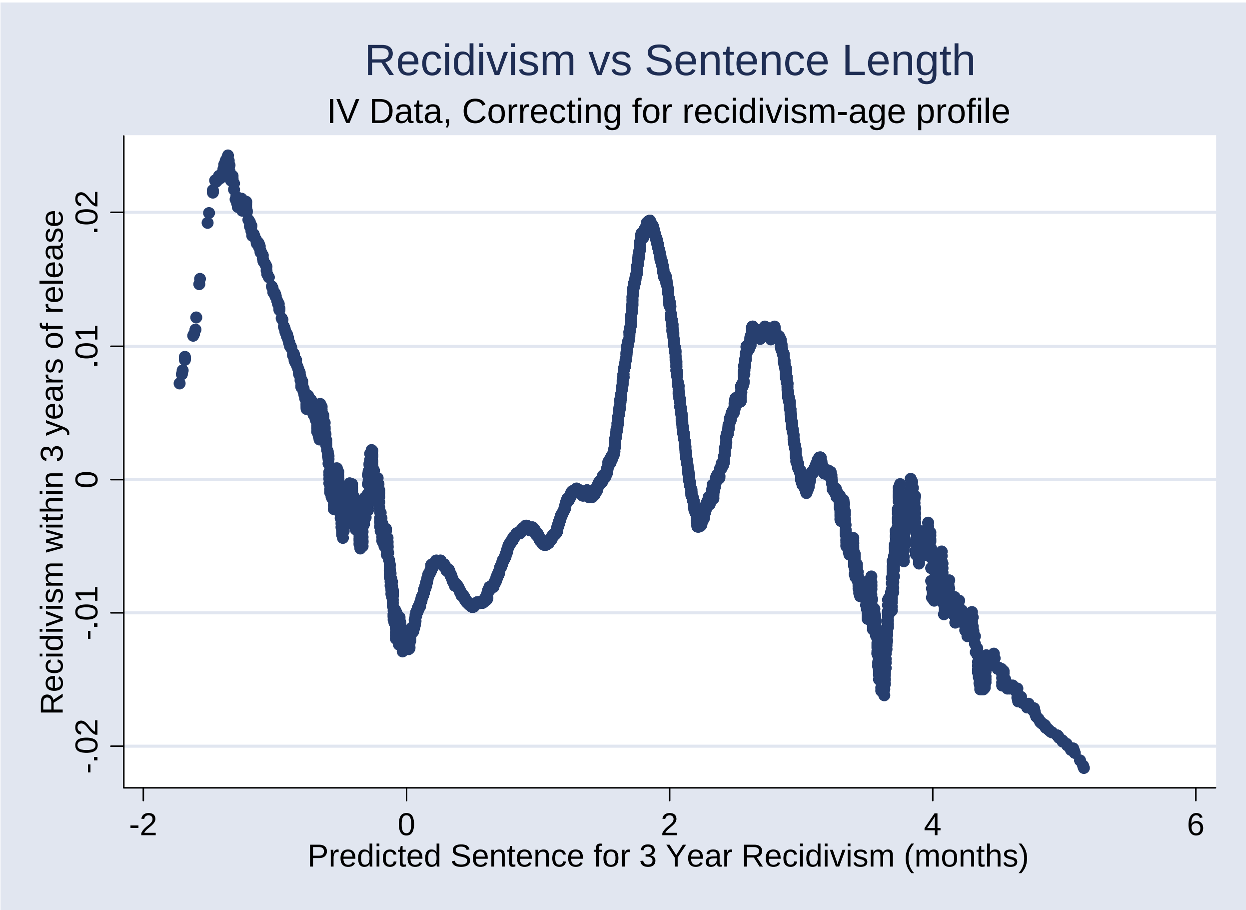

Recidivism vs Sentence Length
IV Data, Correcting for recidivism-age profile
Recidivism within 3 years of release
-.02
-.01
0
.01
.02
-2
0
2
4
6
Predicted Sentence for 3 Year Recidivism (months)

Table 1

Summary Statistics				
Variable	Mean	Median	Std. Dev.	Observations
Sentencing Characteristics				
Minimum Sentence (months)	3.1	0	10.3	15246
Predicted Min Sentence (months)	1.9	2.1	1.7	1225
Mean Sentence (months)	5.7	0	20.7	15246
Min Sentence (non-zero)	8.8	4.8	15.9	5358
Incarceration	0.35	0	0.48	15246
Offender Characteristics				
Age at offense	32.9	31.2	10.9	15246
Black	0.30			15246
Hispanic	0.23			15246
Male	0.77			15246
Offense Characteristics				
Drugs	0.30			15246
Violent Crime	0.21			15246
Sex Crime	0.02			15246
Embezzlement, Fraud, Theft	0.47			15246
Recidivism Rates				
Within one year	0.180			12275
Within two years	0.267			8730
Within three years	0.341			5855
Ever	0.254			15289

Summary Statistics for offender-level data obtained from the Clark County Public Defender for the years 2001 - 2008. Offense characteristics reported for first offense. Data includes 77 Public Defenders, each with a minimum of 50 cases each, and 50 judges. Recidivism is defined as reappearance as a Public Defender client within the indicated time after release from incarceration (if sentenced to incareceration). Predicted Min Sentence includes only observations for which the one year recidivism variable is not missing, and therefore excludes many of the longest sentences.

Table 2

Cross-sectional regression results									
	1 Year Recidivism					2 Year Recidivism		3 Year Recidivism	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Probit							
VARIABLES	No age control	Marginal Effects	Control for age at offense	Control for age at release	Recidivism-Age Profile Adjustment	Control for age at release	Recidivism-Age Profile Adjustment	Control for age at release	Recidivism-Age Profile Adjustment
Sentence	-0.00793	-0.00908	-0.00788	-0.00775	-0.00773	-0.00942	-0.00942	-0.0103	-0.0104
	(0.000629)**	(0.000989)**	(0.000630)**	(0.000630)**	(0.000644)**	(0.000993)**	(0.00103)**	(0.00146)**	(0.00147)**
Sex (1=male)	0.0571	0.0561	0.0575	0.0575	0.0586	0.0823	0.0839	0.0985	0.100
	(0.00796)**	(0.00758)**	(0.00796)**	(0.00796)**	(0.00802)**	(0.0110)**	(0.0111)**	(0.0145)**	(0.0146)**
Black Offender	0.0338	0.0321	0.0316	0.0316	0.0325	0.0637	0.0651	0.0730	0.0753
	(0.00845)**	(0.00837)**	(0.00846)**	(0.00846)**	(0.00859)**	(0.0115)**	(0.0117)**	(0.0148)**	(0.0149)**
Hispanic Offender	-0.0161	-0.0193	-0.0231	-0.0231	-0.0238	-0.0167	-0.0165	-0.0221	-0.0188
	(0.00863)	(0.00859)*	(0.00874)**	(0.00874)**	(0.00855)**	(0.0122)	(0.0120)	(0.0162)	(0.0160)
Drug Offense	-0.000704	-0.00400	0.000592	0.000590	-0.000304	0.0303	0.0301	0.0673	0.0670
	(0.0102)	(0.00943)	(0.0102)	(0.0102)	(0.0104)	(0.0139)*	(0.0142)*	(0.0187)**	(0.0190)**
Violent Offense	-0.0463	-0.0485	-0.0470	-0.0470	-0.0480	-0.0245	-0.0276	-0.00871	-0.0145
	(0.0111)**	(0.0102)**	(0.0111)**	(0.0111)**	(0.0112)**	(0.0156)	(0.0157)	(0.0207)	(0.0208)
EFT	-0.0111	-0.0105	-0.0132	-0.0132	-0.0153	0.00912	0.00774	0.0261	0.0232
	(0.00924)	(0.00876)	(0.00923)	(0.00923)	(0.00925)	(0.0125)	(0.0126)	(0.0161)	(0.0161)
Sex Offense	-0.0834	-0.0806	-0.0732	-0.0732	-0.0762	-0.0507	-0.0574	0.0514	0.0654
	(0.0253)**	(0.0231)**	(0.0254)**	(0.0254)**	(0.0275)**	(0.0378)	(0.0400)	(0.0513)	(0.0561)
Age at Offense			-0.00150						
			(0.000319)**						
Age at Release				-0.00151		-0.00211		-0.00221	
				(0.000319)**		(0.000439)**		(0.000579)**	
Constant	-0.0708		-0.0166	-0.0165	-0.0703	0.469	0.396	0.957	0.883
	(0.0319)*		(0.0395)	(0.0395)	(0.0328)*	(0.319)	(0.330)	(0.0617)**	(0.0703)**
Observations	12202	12225	12202	12202	12178	8677	8662	5799	5791
Adjusted R-squared	0.023		0.025	0.025	0.023	0.034	0.031	0.044	0.042
** p<0.01, * p<0.05	Robust standard errors in parentheses								

Note: Offender-level data obtained from the Clark County Public Defender Office for the years 2001-2008. Monthly time dummies included to allow for time variation in overall crime rates. Sentence is the minimum sentence measured in months, EFT = embezzlement, fraud, theft. Data includes 78 Public Defenders, each with a minimum of 50 cases and 51 judges. Recidivism is defined as reappearance as a Public Defender client within the indicated time after release from incarceration (if sentenced to incareceration).

Table 3

IV regression results									
		1 Year Recidivism				2 Year Recidivism		3 Year Recidivism	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	First Stage Sentence Length	No age control	Control for age at offense	Control for age at release	Recidivism-Age Profile Adjustment	Control for age at release	Recidivism-Age Profile Adjustment	Control for age at release	Recidivism-Age Profile Adjustment
Sentence		-0.0114	-0.00901	-0.00872	-0.00947	-0.00884	-0.00814	-0.0111	-0.0115
		(0.00595)	(0.00596)	(0.00597)	(0.00595)	(0.00893)	(0.00901)	(0.0108)	(0.0108)
Sex (1=male)	0.734	0.0597	0.0583	0.0582	0.0599	0.0820	0.0829	0.0990	0.101
	(0.0751)**	(0.00909)**	(0.00910)**	(0.00910)**	(0.00916)**	(0.0127)**	(0.0129)**	(0.0158)**	(0.0158)**
Black Offender	0.0755	0.0340	0.0317	0.0315	0.0327	0.0635	0.0651	0.0729	0.0754
	(0.0986)	(0.00848)**	(0.00850)**	(0.00850)**	(0.00862)**	(0.0115)**	(0.0117)**	(0.0148)**	(0.0150)**
Hispanic Offender	-0.0470	-0.0163	-0.0232	-0.0236	-0.0240	-0.0171	-0.0165	-0.0225	-0.0188
	(0.0944)	(0.00869)	(0.00879)**	(0.00879)**	(0.00861)**	(0.0123)	(0.0121)	(0.0163)	(0.0161)
Drug Offense	2.151	0.00643	0.00289	0.00265	0.00325	0.0291	0.0273	0.0689	0.0693
	(0.160)**	(0.0159)	(0.0159)	(0.0159)	(0.0161)	(0.0238)	(0.0241)	(0.0288)*	(0.0291)*
Violent Offense	2.799	-0.0364	-0.0438	-0.0443	-0.0431	-0.0261	-0.0312	-0.00680	-0.0118
	(0.210)**	(0.0203)	(0.0203)*	(0.0203)*	(0.0204)*	(0.0300)	(0.0302)	(0.0325)	(0.0327)
EFT	2.700	-0.00160	-0.0101	-0.0106	-0.0106	0.00750	0.00439	0.0278	0.0257
	(0.139)**	(0.0186)	(0.0187)	(0.0187)	(0.0187)	(0.0262)	(0.0265)	(0.0292)	(0.0293)
Sex Offense	2.642	-0.0741	-0.0702	-0.0700	-0.0716	-0.0512	-0.0603	0.0537	0.0678
	(0.380)**	(0.0298)*	(0.0298)*	(0.0298)*	(0.0317)*	(0.0433)	(0.0454)	(0.0562)	(0.0607)
Age at Offense	0.00444		-0.00150						
	(0.00357)		(0.000321)**						
Age at Release				-0.00160		-0.00222		-0.00231	
				(0.000321)**		(0.000439)**		(0.000581)**	
Constant	-5.024	-0.0862	-0.0218	-0.0175	-0.0780	0.475	0.401	0.958	0.879
	(1.686)**	(0.0507)	(0.0593)	(0.0595)	(0.0520)	(0.302)	(0.314)	(0.0840)**	(0.0926)**
Observations	12202	12202	12202	12202	12178	8677	8662	5799	5791
Adjusted R-squared	0.189	0.017	0.018	0.018	0.017	0.027	0.024	0.038	0.036
** p<0.01, * p<0.05	Robust standard errors in parentheses								

Note: Offender-level data obtained from the Clark County Public Defender Office for the years 2001-2008. Monthly time dummies included to allow for time variation in overall crime rates. Sentence is the minimum sentence measured in months, EFT = embezzlement, fraud, theft. Data includes 78 Public Defenders, each with a minimum of 50 cases and 51 judges. Recidivism is defined as reappearance as a Public Defender client within the indicated time after release from incarceration (if sentenced to incareceration).