The Effects of Time in Prison and Time on Parole on Recidivism

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Abstract

In the US, every year roughly 600,000 people are released from prison, two-thirds of whom without serving their whole sentence behind bars. Yet little is known how release before full completion of sentence affects recidivism. I exploit the distinction between sentence and actual time served in prison to better understand how imprisonment affects crime. Specifically, I study the effects of time in prison and time on parole on recidivism. The empirical challenge is that time both in prison and on parole are subject to omitted variable bias. Relying on two instrumental variables that provide independent variation in both sentence and time served in prison, I do not find evidence that parole time affects recidivism. However, I find that one month in prison results in 1.12 percentage points decreases in individual's recidivism probability. Further, I explore the interaction between the sentencing authority (judges) and the prison release authority (parole boards) in determining punishment in the criminal justice system.

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†The most recent version is available at https://sites.google.com/site/mzapryanova/research

1 Introduction

Between 600,000 and 700,000 people are released from the US prison system every year. More than three-fourths of these individuals are released before they fully serve their sentence, subject to a period of parole supervision in the community (Carson and Golinelli, 2013).[1] Federal, state, and local expenditures on corrections—totalling $82 billion—consume a growing portion of the nearly $250 billion spent annually on public safety (Kyckelhahn, 2014). Despite the serious monetary burden on the local and federal government budgets, and the skyrocketing number of people under correctional supervision, there exists limited causal evidence of the effect of time served in prison, and especially time served under community supervision such as parole, on future criminal involvement. The purpose of this paper is to investigate how both time served in prison and time on parole affect reoffending.

Existing work focuses mainly on the incapacitation and general deterrent effect of imprisonment time on future criminal behavior and finds a wide range of plausible estimates.[2] I complement these findings by exploring whether time on parole has any additional deterrent effect. I contribute to the literature in three primary aspects. First, prior work[3], which uses two-stage least squares regressions to estimate the effect of prison time on recidivism, do not account for time on parole. This omission invalidates instruments used for time in prison and confounds the direct effect of time in prison on recidivism. The reason is that time on parole is defined as sentence length minus time served in prison, so any instrument for time in prison is trivially correlated with time on parole. It turns out that accounting for parole time does not change the direction of the result, but decreases the magnitude of the estimate. Second, I estimate the impact of total correctional punishment received on the offending choices of convicts. For most convicts in the US, punishment consists of both prison and parole time. If one wants to estimate the effect of total punishment, one needs

[1]People on parole are criminal offenders who are conditionally released from prison to serve the remaining portion of their sentence in the community. In the US, prisoners could be released on parole either by a parole board decision (discretionary parole) or according to provisions of a statute (mandatory parole). All active parolees are required to report regularly to a parole officer. In addition, they are typically expected to meet certain conditions and adhere to specific rules of conduct while in the community. Failure to comply with any of the conditions can result in a parole revocation and a return to prison.

[2]See Levitt (1996), Johnson and Raphael (2012), Buonanno and Raphael (2013), Owens (2009), Drago et al. (2009), McCrary and Lee (2009), Kuziemko (2013), among others. Refer to, Durlauf and Nagin (2011) and Nagin et al. (2009) for a comprehensive review of the existing work.

[3]For instance, Kuziemko (2013).

to separately identify the effect of prison time from that of parole time on recidivism. Moreover, the two types of supervision differ in the severity of the sanctions, and therefore provide different incentives for criminals to reoffend. However, estimating simultaneously these two effects is not trivial because one needs exogenous variation in both convict's sentence length and prison time. Ideally, one would need a two-stage randomized trial. In the first stage of the randomization, individuals should be randomly receive long versus short sentences. In the second stage, they should randomly serve more or less time in prison. However, a quasi-experiment that uses such a randomization does not exist. One of the key contribution of this paper is to provide causal estimates of prison and parole time on recidivism using observational data. I rely on two instrumental variables. First, I use the variation in ideologies across judges along with plausible random assignment of judges to felony cases in Georgia to obtain independent variation in sentence length. The second instrument relies on the discontinuities generated by the formulaic calculation of recommended time to serve in prison by the Georgia parole board, and provides independent variation in time served. Although these two instruments have been used before in the literature, neither of them has been used to evaluate the effect of parole time. Lastly, the richness of the data allows me to explore the interaction between the sentencing authority (judges) and the prison release authority (parole boards) in determining punishment structure in the US.

Estimating the joint effect of imprisonment and parole supervision is also important for policy makers. In 2012, there were 637,411 prisoners released, from whom 408,186 were released on probation or parole before their full sentence has expired (Carson and Golinelli, 2013).[4] Parole is believed to help people released from prison reintegrate back into society (Petersilia, 2002, 2003). Despite its widespread use, remarkably little is known about whether time on parole indeed decreases recidivism rates, and thus helps ex-prisoners stay out of

[4]Probation supervision is part of offender's initial sentence, and it is handed down by the judge at the trial in combination with some prison time. In contrast, parole is determined while the defendant is serving time in prison, and it is granted by parole boards or in accordance with mandatory release laws. Besides the procedural differences between the the two types of noncustodial sanctions, offenders under both kinds of supervision are required to adhere to similar conditions while in the community (e.g., payment of fines, participation in treatment, and reporting regularly to a probation/parole officer). For both probationers and parolees, failure to comply with any of these conditions can result in incarceration. If a defendant is accused of violating the terms of probation (parole), the judge (parole board) decides whether his probation (parole) should be revoked, and, if so, the punishment for the violation. Given the similarities between these two noncustodial supervisions, understanding the effect of parole on recidivism might inform policy makers about the impact of other post prison supervision types such as probation.

trouble.[5] Additionally, within three years of release, 67.8 percent of released prisoners are rearrested and 49.7 percent return to prison (Durose et al., 2014). Lastly, the annual cost of parole supervision is estimated to be $2,800 per parolee (Schmitt et al., 2010). Given that prison is almost ten times more expensive than parole, and if parole supervision reduces recidivism, it might be cost effective for the government to keep incarceration spells shorter and parole spells longer.

The main empirical challenge controlling for both sentence length—which is decided by the judge—and time served in prison—which is determined by the prison release authority, such as a parole board—is that they are both subject to an unobservable variable bias. In particular, offenders who receive shorter sentences or are released early on parole, are less likely to recidivate than those who receive longer sentences and serve most or all of it behind bars. Since the difference between sentence length and actual time served is presumably negatively correlated with the underlying individual criminal propensity, a simple OLS estimation of the relationship between the size of the sentence reduction and recidivism will be biased upward. Two peculiarities of the Georgia criminal and prison system allow to address this empirical hurdle. First, I rely on the heterogeneity in sentencing practices among judges with different punishment tendencies combined with a plausible random assignment of felony cases to judges as a source of exogenous variation in sentence length. Second, I use the variation generated by the formulaic calculation of recommended time to serve in prison by the Georgia parole board to deal with the endogeneity of actual time served behind bars.

Using the likelihood of retuning to prison in three years after release as a proxy for reoffending, my results offer no evidence that time on parole—defined as the difference between actual sentence length and time served in prison—has any effect on recidivism. Time served in prison, however, has a statistically significant negative effect on reoffending. One extra month served in prison confinement reduces the likelihood that an inmate returns to prison within three years of release by 1.12 percentage points.[6] For the most part, this

[5]There have been a few studies, mostly in criminology, that try to understand the deterrent effects of various noncustodial sanctions, including parole (see Nagin et al. (2009) for a comprehensive review). However, most of these studies have been descriptive and have not addressed the potential omitted variable bias between parole and reoffending.

[6]The estimated effect is lower than that of Kuziemko (2013), who finds that prison time decreases the chance of recidivating by 1.3 percentage points. This is not surprising since Kuziemko (2013) does not control for parole time, which is definitely negatively correlated with time in prison. The correlation between the instrument Kuziemko (2013) uses and time on parole, which she does not control for in her regressions,

finding carries over to subgroups by race and type of offense. Results for minorities are of special interest given the historical trends of over-representation of minorities in the US correctional system. I find that time in prison statistically decreases recidivism only for property and White offenders, while it has no statistically significant effect for other types of offenders.

This study also seeks to understand the interaction between the two agents in the criminal justice system who jointly determine the punishment structure. In many states, including Georgia, criminal punishment is indeterminate. This means that once a judge determines the sentence, the parole board decides the duration of imprisonment, which might be less than the judge-determined sentence. Suppose both the judge and the parole, decide sanctions based on their beliefs about the rehabilitation of the criminal. When determining punishment, a judge relies only on his prior beliefs about the time a convict needs to serve. The parole board members, however, can use the institutional behavior of the convict to update their beliefs about the time the convict needs to be incarcerated. By using behavior in prison, I find evidence that the parole board takes into account the judge's harshness only when a prisoner with a disciplinary record is released. In other words, for prisoners who are more likely to succeed on parole, the sentence determined by the judge is not binding for the parole board release decisions. For prisoners who have behavior problems in prison, and the board wants to keep them in prison longer, the actual sentence handed down by the judge matters. I observe that for misbehaving prisoners, the judges harshness has a small statistically significant effect on time spent in prison—as the judges harshness increases by one month, time served in prison increases by 0.02 months.[7] This is important for policy purposes as many states have moved away from discretionary parole policy and moved toward mandatory release policies, in which the prison sentence is mostly determined by the discretion of the judge interacted with some sentencing guideline minimums and the prisoner's institutional behavior.[8]

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makes her estimate of the direct effect of prison time questionable and an overestimate.

[7] Judge's harshness is defined as the average incarceration sentence a judge gives over a 13-year period. For more details, refer to Section 3.1. The interpretation of this results should be careful for two reasons. First, the estimates are relatively small. And second, an F-test reveals I cannot reject the null hypothesis that the coefficient of the judge's harshness index is the same for prisoners with or without a disciplinary record.

[8] In 2012, eighteen states have used discretionary parole as their primary prison release mechanism (Maruschak and Bonczar, 2013). The remaining states have either abolished parole entirely or have greatly limited the scope and practice of parole release. It is worth noting that even though only a few states use discretionary parole, most states do use post-release supervision as a way to integrate and look after

The remainder of the paper proceeds as follows. Section 2 reviews the existing literature. Section 3 describes the court and parole board procedures in Georgia and provides an overview of the empirical methodology used in the analysis. Section 4 introduces the data. Section 5 presents the main findings and results. Section 6 summarizes my conclusions.

2 Previous Literature

Both criminologists and economists have extensively studied the determinants of recidivism.[9] Although there has been a lot of research in this area, estimating the true effect of imprisonment has proven difficult, and most of the previous work has not dealt with the inherent omitted variable bias problem that arises due to the fact that individuals who get harsher punishments tend to be the ones that are more likely to recidivate. Past work that has addressed this identification problem can be separated into two major groups. The first group of papers uses aggregate crime and prison data to estimate both the incapacitation and deterrent effect of prison (Levitt, 1996; Johnson and Raphael, 2012; Buonanno and Raphael, 2013; Owens, 2009).[10] These studies find a wide range of plausible magnitudes for the effect of interest and suggest that one additional criminal in prison decreases aggregate crime rate anywhere between 2.8 and 30 crimes per year. The second strand of literature consists of quasi-experimental studies that estimate the so called specific deterrent effect of prison using individual level data (Drago et al., 2009; McCrary and Lee, 2009; Kuziemko, 2013; Nagin and Snodgrass, 2013; Green and Winik, 2010). These papers estimate the direct response of individuals to various interventions and find zero to a small positive deterrent effect of imprisonment on future criminal involvement. There has been very few papers, predominantly in criminology that look at noncustodial sanctions such as probation and parole (see Nagin et al. (2009)) for an exhaustive list). Although these studies control for selection on observables, they do not properly account for selection on unobservables. These studies also

ex-prisoners. The only difference is whether or not states allow for discretion in the prison release decisions.

[9] For a comprehensive review of the literature, see Nagin et al. (2009) and Durlauf and Nagin (2011). Nagin et al. (2009) also suggest that studying the effect of both custodial and noncustodial sanctions on recidivism might be a fruitful future research direction. Thus, this paper attempts to disentangle the effect of different sanction regimes on recidivism.

[10] Note that Owens (2009) does not use aggregate crime data. Rather, she relies on individual data and sentence enhancements targeting young offenders in Maryland. However, I have included her work in this type of studies since she examines both the deterrent and incapacitation effect of prison.

focus on determining if prison sanctions are more effective than parole, and do not attempt to evaluate the two mechanisms together as separate parts of the total punishment.

In terms of the data and empirical methods used, the current paper is related to studies that use random assignment of criminal cases and parole guidelines to estimate the effect of incarceration on future criminal involvement. Kuziemko (2013) uses the same data and the parole board practices as an instrument for time served to evaluate discretionary release policies and quantify the deterrent effect of prison. Unlike Kuziemko (2013), this study seeks to untangle the effect of cumulative punishment, which includes both time spent in prison and under parole supervision. Moreover, by not controlling for parole time, the estimated effect of prison time in Kuziemko (2013) is confounded. Specifically, her instrument for time served in prison, namely the discontinuities in the parole evaluation process, does not meet the exclusion restriction because it is trivially correlated with parole time. To address this concern, I use two sources of independent variation to estimate the true effect of time served in prison on recidivism. In addition to the proposed instrument by Kuziemko (2013) and supported by additional data from the Georgia Department of Corrections (GDC), I try to properly deal with the mechanical relationship between incarceration and parole time by using a second instrument—namely, random assignment of felony cases to judges.

A few recent studies use random assignment of defendants in criminal courts to evaluate the effect of incarceration on various crime outcomes (Kling, 2006; Aizer and Doyle Jr, 2011; Di Tella and Schargrodsky, 2013; Nagin and Snodgrass, 2013; Green and Winik, 2010).[11] Although these studies use court random assignment of cases as an instrument for incarceration sentence, they do not examine whether time on parole has any deterrent effect beyond that of time served behind bars with the exception of Di Tella and Schargrodsky (2013). Using data from Argentina, they compare the effect of prison to that of an alternative form of incapacitating sanction, namely electronic monitoring and find that the rate of recidivism for the latter is almost fifty percent lower. Though the Di Tella and Schargrodsky (2013) study can be informative about the effect of electronic monitoring, its generalizability to the US and other types of noncustodial supervision such as parole is questionable. My data and empirical strategy, however, allows me not only to quantify the effect for a general adult

[11] Random assignment research design has been employed to study the impacts not only of incarceration, but also of disability insurance (Maestas et al., 2013; French and Song, 2014; Dahl et al., forthcoming), foster care placement (Doyle Jr, 2007), and bankruptcy protection (Dobbie and Song, forthcoming) on various economic outcomes.

U.S. state prison population, a group that actually represents a large portion of the world's incarcerated population, but also separate the effect of prison and parole sanctions. Nagin and Snodgrass (2013) andGreen and Winik (2010) both use random assignment of judges to estimate the effect of prison on reoffending. These studies face an identification problem as they use sentence as a proxy for time in prison. This is problematic as both studies use data from states that have discretionary parole (Pennsylvania in the case of Nagin and Snodgrass (2013) and Washington D.C. in the case of Green and Winik (2010)) and most of the prisoners do not serve their full sentence behind bars. If prisoners do not serve their full sentence behind bars, then sentence is not a good proxy for time served in prison. Thus, random assignment of felony cases to judges gives independent variation only in sentence length, which identifies the effect of sentence (as opposed to time in prison) on recidivism.

The closest papers in spirit to the current study are Maurin and Ouss (2009) and Drago et al. (2009) who use collective pardons in France and Italy, respectively, to examine the specific and general deterrence effect of sentence reduction. Using the 1996 Bastille Day pardon in France as a natural experiment, Maurin and Ouss (2009) find that greater sentence reduction via pardon leads to an increase in future recidivism. Drago et al. (2009) study the effect of the collective pardon in Italy in 2006, which not only set free most inmates with three years or less remaining on their sentence, but also established a sentence enhancements for those who reoffend. In particular, people who are released via the pardon and reoffend within five years of release would face the new sentence they received plus the remainder of their unserved time. The authors find that those inmates who faced a longer sentence enhancement were 1.3 percent less likely to reoffend after being released through the collective pardon. The main difference between the current study and the above mentioned papers is in the different incentives produced by collective pardon and parole. The former, since it is not based on individual behavior, might convince prisoners that the time they serve in prison is not correlated with their behavior while in prison. In contrast, good behavior is central in determining release under parole. Furthermore, collective pardons are rare in the US, and sentence enhancement is not used.

3 Empirical Strategy

To estimate the effect of parole time and to deal with the confounding effect of parole time on the estimation of the direct effect of time in prison on recidivism, I adopt an instrumental variable approach. In the sections that follow I describe the institutional factors that help me construct the instruments. I also discuss the empirical framework as well as the identification of the objects of interests—namely, parole and prison time.

3.1 Instruments and First Stage Estimation

Once a felon is convicted under a certain penal code citation, it is typically the judge who determines the sentence. In Georgia, the judge has full discretion over the sentence length without being restricted by specific rules of a uniform sentencing policy. The absence of established rules for sentencing does not mean that judges in Georgia can hand down any sentence they wish. In determining sentence length, a judge is restricted to giving a sentence that is between the minimum and maximum punishment, as described in the Official Code of Georgia Annotated (O.C.G.A.). For instance, O.C.G.A. requires that a sentence for robbery should not be shorter than one year and not longer than 20 years.

Most importantly for my analysis, felony cases are assigned randomly to judges within a specific court, whose judicial calendar is predetermined at the beginning of the year.[12] Since judges vary in their sentencing ideologies and the assignment of cases is random, defendants effectively face a partial lottery over sentence lengths. I use the variation in this lottery to provide independent variation in convict's sentence length and to instrument for parole time. A major advantage of the random assignment of cases to judges is that disparities in judges' harshness should not be attributable to case characteristics, because each case has an equal chance of being assigned to a given judge. If the initial assignment of judges is truly random, as I assume, this requirement will be satisfied and the IV estimates will be unbiased.

Following Aizer and Doyle Jr (2011), for defendant i's judge, I construct a judge harshness

[12] Refer to the official Uniform Rules of the Superior Court found on `https://www.georgiacourts.gov/index.php/court-rules`. The so called companion or related actions cases do not undergo random assignment. In general, for all probation revocation cases any new charges would be assigned to the specific court, which handed down the initial sentence. This is not an issue for the analysis, since the Conviction data consists only of new felony convictions as opposed to probation violations. Moreover, I restrict the analysis to only new court convictions in the Prison Data.

index, $Judge_i$, and use it to instrument for i's actual sentence length.[13] Using an exhaustive set of sentences a judge hands down can produce a bias, which results from the mechanical correlation between offender's own outcomes and the constructed instrument. To deal with this issue, I exclude the offender's own incarceration spell when calculating judge's harshness index. One can think of the instrument as the average incarceration sentence length for judge j based on all cases except prisoner i himself. In particular, for each prisoner i sentenced by judge j, I calculate the instrument as the following leave-out mean:

$$Judge_i = \frac{\sum_{k \neq i}^{N_j} S_k}{N_j - 1} \tag{1}$$

where N_j is the total number of felony cases judge j has had from 2001 to 2013 while S_k is the length of the prison sentence for the convict k. For a criminal with a split sentence, I use only the number of years sentenced to prison and ignore the probation part of the sentence.[14] For instance, if a judge hands down a split sentence of seven years that consists of two years in prison followed by five years of probation, then S_k for this felon would be equal to two.

Although it is impossible to verify directly whether judges are indeed assigned randomly to defendants, one can examine the validity of this assumption using the available data.[15] In particular, if defendants are randomly assigned to judges, I would expect those appearing in front of lenient judges to be similar on observables to defendants assigned to harsher judges. Following Aizer and Doyle Jr (2011), I classify a judge to be harsh if he assigns a prison sentence length above the median in the Conviction Data sample and to be lenient, otherwise. For each observable characteristics of defendant i, $Char_i$, I run the following OLS regression:

$$Char_i = \phi_0 + \phi_1 \mathbb{I}[Judge_i \geq Median] + \kappa_c + \tau_y + \epsilon \tag{2}$$

where $\mathbb{I}[Judge_i \geq Median]$ is an indicator if defendant i has been sentenced by a harsh judge; κ_c and τ_y are circuit court and year of sentence fixed effects. Including these fixed

[13] Aizer and Doyle Jr (2011) use judge incarceration propensity to instrument for juvenile incarceration. This instrument is not suitable in my context since I am interested in the intensive margin effect of sentence length on recidivism as opposed to just the extensive margin effect of being incarcerated.

[14] A split sentence is when the sentence is separated in two parts—the first part is served by incarceration and the second, by probation.

[15] According to discussions with Mike Cuccaro, random assignment of cases is a priority of each circuit court in Georgia.

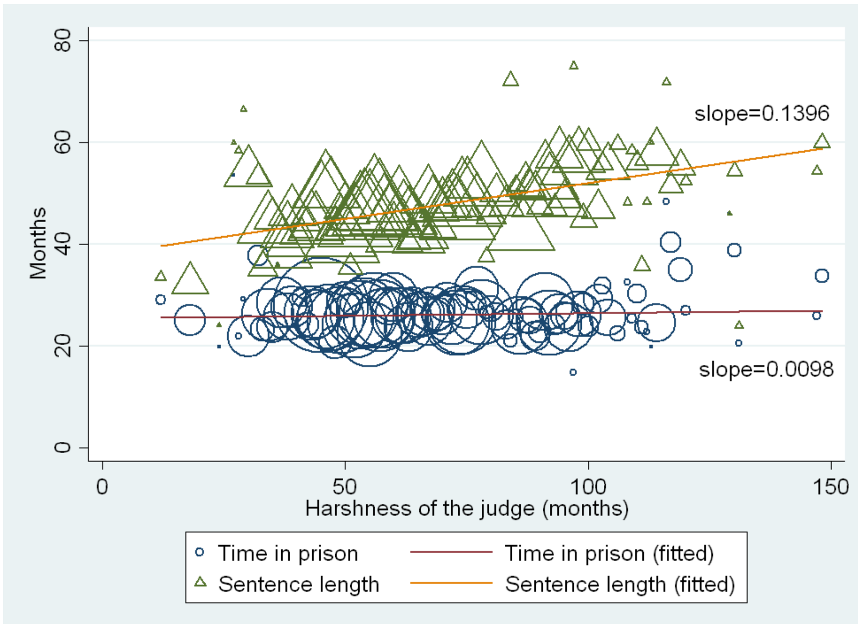
Table 1: Random Assignment Test

Characteristic	Unconditional mean $Judge_i < Median$	Conditional mean $Judge_i \geq Median$	p-value
Instrument			
Judge harshness index, $Judge_i$	3.73	5.16	0.000542
Demographics			
Age	32.34	32.17	0.185
Female	0.2055	0.1985	0.615
Black	0.5126	0.5367	0.429
Crime Characteristics			
Drug possession	0.2970	0.2797	0.112
Drug sale	0.0492	0.0606	0.0982
DUI	0.0125	0.0149	0.580
Non violent	0.0034	0.0030	0.839
Property	0.3827	0.3709	0.284
Sex offense	0.0314	0.0346	0.125
Violent	0.1430	0.1547	0.161
Other	0.0807	0.0815	0.359

The results presented here use only the Conviction data sample (N=701,562), described in more detail in Section 4. I define harsh judges as judges, whose harshness index, as defined by Equation 1, is greater or equal to the median in the whole Conviction data. Col.(1) reports the unconditional means, while Col.(2) reports the predicted means from an OLS regression of the characteristics on an indicator if the sentencing judge is harsh, controlling for court and year of sentence fixed effects. The p-value corresponds to that of coefficient ϕ_1 in Equation 2. Specifically, it is calculated from a separate regression of each characteristic on an indicator that the judge's average sentence length was greater or equal to the median. Circuit court and year of sentence fixed effects also included.

effects accounts for the fact that randomization occurs within a circuit court as well as for any unobservable year-to-year changes in the judge's calendars or court practices. The p-values of the coefficient of judges' harshness, $\mathbb{I}[Judge_i \geq Median]$, are presented in the last column of Table 1. To test the validity of the assumption of random assignment of judges, I compare the unconditional means of the observable characteristics of defendants sentenced by lenient judges to the conditional means of those sentenced by harsh judges. The results in Table 1 show that lenient and harsh judges are assigned comparable defendants in terms of age, gender, race, and type of offense. The results indicate that cases do not seem to be assigned to judges based on defendant observable characteristics as all the p-values produced by this test indicate that judge harshness is not statistically significant predictor of any of the defendants' characteristics.

Figure 1: Sentence Length and Time Served in Prison by Judge Harshness Index



Includes inmates who meet the sampling restriction described in Section 4 and Table 2. The triangles and circles represent the average time served in prison and sentence length, respectively, by judge harshness index. The size of each circle or triangle corresponds to the number of convicts sentenced by a judge with a particular value of harshness index. The lines are fitted values for time in prison and time on parole by judge harshness index.

In Figure 1, I plot the the average time served in prison and the average sentence length by the harshness of the judge. Each circle and triangle corresponds to the average time in prison and sentence length, respectively, associated with each value of the judge harshness index. The size of each circle or triangle matches the number of convicts sentenced by a judge with a specific harshness index. For instance, the bigger the triangle, the more people have been sentenced by a judge with the particular harshness. The lines are fitted values for time in prison and sentence length. There are two main takeaways from this graph. First, the judge harshness index provides independent variation in the sentence length. In particular, the harsher a judge is on defendant i, the longer sentence i receives. In particular, a one month increase in the harshness of the judge leads to an expected 0.13

month increase in defendant's own incarceration sentence. It is worth noting that there is a minimal variation in time served in prison with respect to the judge harshness index. Green and Winik (2010) use random assignment of judges in Washington D.C. as an instrument for sentence length to estimate the effect of prison on various outcomes. This might lead to a significant identification problem of their estimates given how little variation the judge harshness index provides for actual time served in prison and the fact that Washington D.C. uses discretionary parole as their main prisoner release mechanism. Second, the difference between the fitted values for sentence length and those for time served in prison represents the parole time. If one wants to estimate the effect of parole time on outcomes, one needs another source of independent variation. In what follows I describe the second instrument that would provide this independent variation.

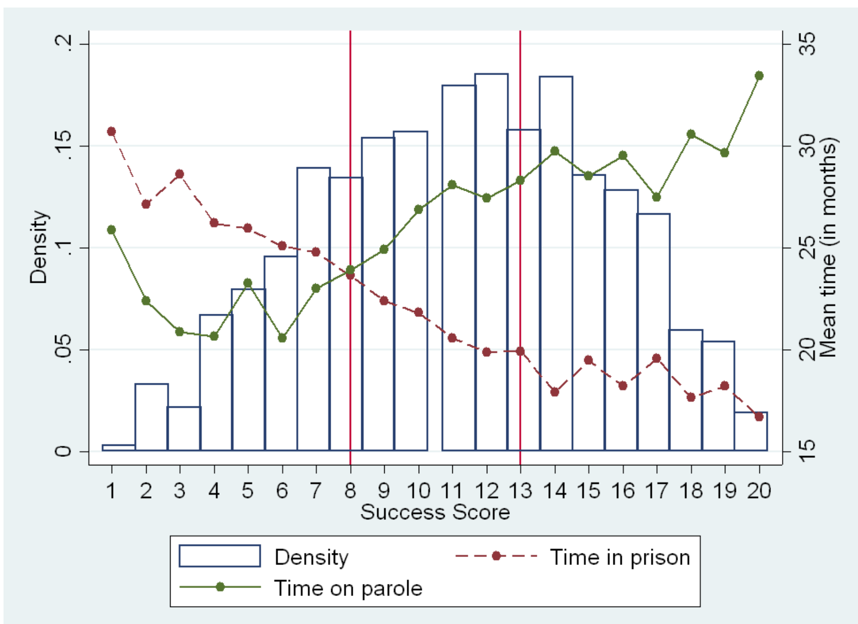
There might exist offender characteristics unobservable to the econometrician that are both correlated with how long he serves in prison and his decision to commit a crime after he gets released from prison. To instrument for the actual time served, I rely on the institutional peculiarities of the release policy in Georgia. In contrast to parole under mandatory supervision or "good time" release policies, parole in Georgia is granted or denied at the absolute discretion of a five-member panel. The parole board in Georgia is required by law to make parole decisions based on the risk a person may pose to public safety if he or she were released on parole (O.C.G.A.§42-9-40). To determine that risk, the parole board has developed Parole Decisions Guidelines. In Georgia, every parole-eligible[16] inmate is evaluated and receives a "success score," which determines whether he is a risk to the public safety and whether he is likely to succeed on parole, if he is granted one. The success score is calculated on the basis of the inmate's personal and criminal background.[17] It is worth noting that the board does not use the exact success points, but instead categorizes each inmate into three groups depending on the likelihood of the inmate to be succeed on parole—excellent (14 to

[16]In Georgia, all inmates are automatically considered for parole, except the following individuals: those sentenced to life without parole; those serving sentences for a serious violent felony such as rape, aggravated sodomy, aggravated child molestation, aggravated sexual battery, armed robbery, or kidnapping; those convicted of a fourth felony.

[17]Table A2 shows the scale used in this calculation along with their corresponding success score points. Every inmate receives success points on each of the eight success factors. To illustrate the process, suppose that an inmate was previously incarcerated at the age of 17, the this inmate would receive zero success points in that category as compared to an inmate who was previously incarcerated at 26 and thus, receives five success points. The total success score of an inmate is the summation of the success points he receives from all eight factors.

20 success points), average (9 to 13 success points), and poor (1 to 8 success points). As seen in Table A1, a combination of a calculated parole success score and the type of current offense generates a recommended time to serve.[18] For instance, suppose two inmates, A and B, have committed a crime of severity level I. Suppose that after the parole board evaluation process, inmate A receives 14 success points, and thus is categorized as having excellent chance to succeed on parole, while inmate B receives 13 success points, and thus considered to have an average chance to succeed on parole. Given the parole guidelines, inmate A will be recommended to serve 10 months behind bars, while inmate B will be recommended 16 months (or 6 months more than A).

Figure 2: Time Served in Prison by Success Points



Includes inmates who meet the sampling restriction described in Section 4 and Table 2. The dashed red line represents mean time served in prison, while the solid green line represents mean time served on parole. The histogram shows the distribution of people by success score. The two vertical lines represent the cutoffs for the success score groups—excellent (14 to 20 success points), average (9 to 13 success points), and poor (1 to 8 success points).

The relationship between the success score, time in prison, and time on parole is depicted

[18]Table A3 shows the crime classification that the parole board in Georgia has adopted in 1994 and uses to determine the crime severity levels.

in Figure 2, where the lines represent the mean time served in prison and on parole by success score. Since the parole board uses the success score to evaluate the risks that a person will recidivate, higher success scores should be associated with lower probabilities that an inmate will pose risk to public safety if he were granted parole. The patterns in the graph match this as I observe that the higher the success score, the lower the average time served in prison and the higher the mean time on parole. Around the cutoffs that determine the parole success groups, marked with the vertical red lines on Figure 2, a drop in the mean time served that can be distinguish from the general negative trend of time served and success score is observed. The average inmate who receives a success score of nine and is categorized as having an average chance to succeed on parole serves three months less than his counterpart, who scores eight points and thus, has a poor chance to succeed on parole. Similar pattern is observed for inmates that score 13 versus 14 success points. Controlling for severity and success score points fixed effects, I use the suggested months to serve from the guidelines, outlines in Table A1, as an instrument for actual time served.[19]

Turning back to a regression framework, I estimate the following first stage equations:

$$Prison_i = \alpha_0 + \alpha_1 X_i + \alpha_2 Recom_i + \alpha_3 Judge_i + \pi_p + \sigma_s + \kappa_c + \tau_y + \epsilon \tag{3}$$

$$Parole_i = \gamma_0 + \gamma_1 X_i + \gamma_2 Recom_i + \gamma_3 Judge_i + \pi_p + \sigma_s + \kappa_c + \tau_y + \epsilon \tag{4}$$

The dependent variables, $Prison_i$ and $Parole_i$, are months served in prison confinement and months served under parole supervision, respectively. Note that time on parole is simply the difference between the individual's sentence and time served in prison. One can think of time on parole as the portion of the prisoner's sentence that is not served behind bars. $Recom_i$ is the recommended time to serve from the parole guidelines for prisoner i. Since recommended time to serve is determined by a known deterministic function of two variables—parole success points (previous criminal background) and severity level (current crime seriousness)—if one controls for both components, then guidelines recommended

[19]See Angrist and Lavy (1999) for details about this methodology. The identification comes from how the success score and the crime severity level interact. In particular, once I control for variation in the criminal background (success score) and seriousness of the current offense (severity level), all the remaining variation of the guidelines recommendation should be uncorrelated with the individual's propensity to recidivate and should provide independent variation in time served both in prison and on parole.

months to serve are almost certainly related to actual time served in prison for reasons other than the effect of changing the success score and/or the crime severity level.[20]

$Judge_i$ is the average incarceration sentence based on the entire sentencing history of the judge who sentenced prisoner i; π_p and σ_s are crime severity levels and success points fixed effects, respectively; κ_c include court fixed effects while τ_y include year of sentence dummies. Including court fixed effects not only controls for the fact that random assignment of judges occurs within a particular circuit court, but also allows me to interpret the within-court variation of the instrument as variation in the prison sentence that a randomly assigned judge gives to a felon relative to other felony cases in the same circuit court. Since judges are assigned randomly to cases based on already predetermined yearly schedule, I include year of sentence fixed effects to account for any year-to-year variation in the size of the judicial calendar as well other changes in judicial policies or practices across all felony cases in a particular year. The vector X_i represents demographic controls, widely used in the criminology literature, such as age at prison release, gender, race, current crime type, and prior convictions.

3.2 Second Stage Estimation

The main outcome of interest, recidivism, can be written as a function of the following regressors:

$$Recid_i = \beta_0 + \beta_1 Prison_i + \beta_2 Parole_i + \beta_3 X_i + \epsilon_i \tag{5}$$

The main problem in estimating the above model using OLS is that neither time served in prison nor time under community supervision are randomly assigned to offenders. In fact, it is very likely that judges and parole boards determine sentences and time to serve in part based on characteristics unobservable to the econometrician, which are also correlated with the propensity to recidivate. In other words, one would expect that $\mathbb{E}(\epsilon_i|Prison_i) \neq 0$ and $\mathbb{E}(\epsilon_i|Parole_i) \neq 0$. To overcome this problem, I estimate the second stage by using the predicted values of $Prison_i$ and $Parole_i$ from the first stage equations—Equations 3 and

[20]Controlling for the interaction between success points and severity levels leads to similar estimates. For simplicity I present the results without any interaction terms.

4.[21] The second stage regression, becomes

$$Recid_i = \beta_0 + \beta_1 \widehat{Prison}_i + \beta_2 \widehat{Parole}_i + \beta_3 X_i + \epsilon_i \tag{6}$$

The main coefficients of interests, β_1 and β_2, represent the specific effect of time in prison and time under parole supervision, respectively.[22] By construction, the time on parole is calculated as the sentence minus the number of months served in prison. An implication of this is that time served, time on parole, and original sentence are collinear. Thus, the estimated effects on recidivism should be interpreted as the joint deterrent effect of an additional month served behind bars and of a month less served on parole. One can interpret the effects as the full impact of criminal punishment on reoffending.

If the parole board correctly assesses the recidivism risk of prisoners, then β_2 should not be statistically significant. However, if the parole board fails to correctly predict recidivism risk, then β_2 should be statistically significant; its sign, however, is ambiguous. Offenders who receive a large reduction in their sentence might get the impression that the criminal justice system is generally more forgiving and be less deterred in the future (Bushway and Owens, 2013). For this group of offenders, β_2 will be positive. Alternatively, offenders who have been released on parole before their sentence expiration date might be extra careful not to recidivate and have to return to prison to serve the rest of their sentence behind bars.

3.3 Identification of the Time in Prison and Time on Parole

Figure 3: Timeline for the decisions of judges and the parole boards

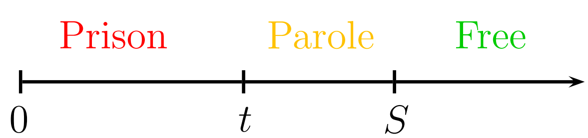


Figure 3 represents a graphical depiction of the timing of the decisions of a judge and a

[21]See Angrist et al. (1996) for a discussion of the estimation methodology.Angrist (2006) provides an overview of the use of instrumental variables in criminology research.

[22]Since the second stage estimation is based on generated regressors from the first stage, the second-stage standard errors are biased downward without accounting for estimation errors from the first stage. In all the estimations, I have accounted for this bias.

parole board. Suppose that a convict, i, is sentenced by a judge at time 0 and receives a sentence of length S. Then, the parole board decides to release convict i any time between 0 and S. Note that the parole board cannot legally keep a convict in prison past his sentence expiration date. Suppose that the parole board releases i at time t. Thus, convict i serves time t in prison and completes the rest of his sentence, $S - t$, on parole supervision. Once the whole sentence is served in prison and parole, the convict is no longer under correctional supervision and he is set free.

Note that in order to be able to estimate the effect of time on parole, one needs random variation in both sentence length, S, and time served, t. The two instruments described in Section 3.1 provide independent variation in both time served in prison and on parole. The estimated β_1 and β_2 in Equation 6 should be interpreted as the causal effect of prison time and parole time, respectively, on recidivism since the variation, provided by the parole board guidelines and the random assignment of cases to judges, constitutes a quasi experiment that provides independent variation in time served behind bars and sentence length.

Note that each one of these instruments on its own is not sufficient to identify time served if the parole board determines t. First, if judge harshness is used as an instrument for sentence length, one can identify a combination of the effect of time in prison and time on parole and cannot identify neither one separately.[23] Second, if only the parole guidelines is used as an instrument, one could identify only the effect of time in prison. However, in states that have discretionary release and $t < S$, any instrument that is used to identify t would be correlated with parole time, $S - t$, simply due to the mechanical relationship that parole time is the sentence minus time served in prison.[24]

[23] This argument is particularly harmful to studies that have used random assignment of judges in states with a discretionary parole to instrument for sentence length, which in terms is used to study the effect of time in prison on recidivism (Green and Winik, 2010)

[24] Kuziemko (2013) uses the parole guidelines as an instrument but does not account for parole time $(S - t)$. Her estimate of the direct effect of prison time on recidivism is confounded and most probably overestimates the true effect since the parole guidelines affect both t and $S - t$. However, at the time she conducted her analysis she did not have access to the data that allow me to construct the judge harshness index.

4 Data

I use two administrative databases from the Georgia Department of Corrections (GDC) to estimate the differential effect of time served in prison and on parole on recidivism. First, the GDC provides administrative records of all people released from the Georgia prison system from 1980 to 2008 (henceforth, Prison Data). This dataset offers rich socio-demographic, criminal history, parole, and current conviction information of each person admitted to prison in Georgia. Second, I take advantage of a database, which contains all felony prison and probation sentences from the Georgia Superior Courts from 1980 to 2013 (hereafter, Conviction Data). This database comes from court dockets and contains the name of the sentencing judge, sentence length, offense, circuit court, and some basic demographic characteristics of each offender convicted of a felony in one of the 49 circuit courts in Georgia. I use these data only for the construction of my instrument for sentence length as it contains the sentencing history of each judge in Georgia. Note that the Conviction Data contains information specifically on convicts and excludes people who just get charged with a crime but never get convicted.[25]

I decided to focus on Georgia because of the detailed nature of the GDC data. Comparing Georgia's prison population summary statistics to the national is reassuring since inmates in Georgia appear to be representative of those nationwide in many key ways. Table A4 presents data on how individuals sentenced in the state of Georgia compare to those sentenced nationwide.[26] The two populations are similar in most fundamental measures—sentence length, average age at sentencing, and type of crime. In 2002, 32.4 percent (29.9 percent) of the national (Georgia) felony population were convicted of a drug crime, 18.8 percent (18.9 percent) of a violent crime, and 30.9 percent (35 percent) of a property offense. People sentenced nationwide and in Georgia not only were convicted for similar types of offenses, but also receive similar sentence lengths and the average convict's age at sentencing was

[25] Another shortcoming of the Conviction Data is that I only observe the final sentence a person receives. Thus, my results might be potentially affected if we have individuals who get arrested for committing a serious crime, but consequently get charged with a less serious crime or even misdemeanor. Relying on the random assignment of felony cases assumption, I do not expect that certain judges will receive systematically such cases as defendants (and their lawyers) cannot simply "shop for" a judge.

[26] The statistics for Georgia are based on the raw Prison Data with no sampling restrictions described later in Section 4. The only restriction applied to the Prison Data is the exclusion of sentences to death or to life in prison in order for the statistics to match the ones produced by the Bureau of justice Statistics.

identical. However, the sentenced population in Georgia seems somewhat different from that nationwide in terms of race and to some extent, gender.[27] In 2002, Black offenders comprised 45 percent (60 percent), and male offenders comprised 83 percent (88 percent), of the total number of individuals sentenced nationally (in Georgia).

The main outcome of interest, recidivism, is defined as an indicator equal to one if the offender returns to prison within three years of release.[28] Since the Prison Data is comprised of all prison releases in Georgia through October 2008 and I want to allow at least three years for each criminal to potentially recidivate, I restrict the sample to individuals released no later than October 2005. A possible worry about this necessary data cut is that prisoners who are released before 2005 (early) have different observable characteristics than those released after 2005 (late). If this is the case, the results of this paper will be generally biased downward if we assume criminals who are generally less likely to reoffend get released earlier. To address this concern, I compare the characteristics of people released before and after October 2005 in Table A5. Overall, I do not observe that prisoners released before 2005 are much different in terms of observables than those released after 2005. Early releases have comparable time spent on parole and serve almost the same percentage of their initial sentence compared to their counterparts that get released later. In terms of demographics and parole success scores, the two samples seem to be comparable with the exception that early releases tend to be more likely to be Black on average. Not surprisingly, people released before 2005 have shorter sentences and have served less time in prison. Note that because of this difference, we observe that early releases are more likely to commit a less severe crime (such as a drug possession) than a more serious violent crime. A bigger concern with regard to the validity of the judge harshness index is if the instrument is correlated with the timing of prison releases. I do not find any sizeable differences in the instrument for the people releases before and those released after 2005. Referring again to Table A5, the mean value of the judge harshness index is 64.03 months for prisoners released before 2005 and 63.99 months for those released after.

Since the parole guidelines seem to be the strongest predictor of time served for crimes

[27]The discrepancies with respect to race are mostly due to the different categorization Hispanics receive in my data and that of the Bureau of Justice statistics

[28]Note that return to prison would be a proxy for serious reoffending and will not capture people, who are rather only arrested or sentenced to probation or some other form of noncustodial sanction.

with a severity level less than five, I drop all individuals imprisoned for more serious crimes.[29] Moreover, the parole board adheres to the guidelines recommendation 35 percent of the time for crimes with severity less than five, and it is within four months of the recommendation almost 70 percent of the time. However, the board exerts more discretion for crimes with severity higher than five, and follows the guidelines less than 20 percent of the time. I also restrict the sample to individuals admitted to prison for a new crime conviction rather than a parole violation. The justification behind this restriction is twofold. First, the assignment of judges to parole violators is not random. Rather, each parole violator is sent to the sentencing judge who handed down his initial sentence. Given this institutional detail, the instrument for sentence would not be valid since it would not provide random variation in the average sentence length a parole violator receives. Second, not all parole violators are sent directly to prison once they violate the terms of parole. Instead, the decision depends mostly on the leniency of the parole officer. This could create some selection bias as the parole violators, who are sent back to prison, might be the worst offenders. However, all new crime commitments are sent to prison and their sentence is determined by a randomly assigned judge.

To construct the judge harshness index, $Judge_i$, I rely solely on the Conviction Data provided by the GDC. I limit the Conviction Data to felons convicted between 2001 and 2013. I impose this restriction since by mid-2000, the GDC started collecting more complete information from the court dockets including the actual name of the sentencing judge. The judge harshness index, described in Section 3.1, is determined based on the sentencing patterns of a judge over 13 years, and it is calculated only using sentences between one and eighty years.[30] I exclude sentences shorter than one year since they are most usually served in local jails rather than prisons and including them would underestimate the harshness of a judge. Similarly, longer sentences or life sentences would not only overestimate a judge's harshness, but would also be hard to quantify.[31] The final Conviction Data sample has more than 700,000 observations, and it is used only for the construction of the judge harshness

[29] My instrument for time served becomes very weak if I include people convicted to serious crimes.

[30] Note that criminals convicted before 2013, the judge harshness index is based on both the historical and the future sentences he/she gives. For instance, if a convict is sentenced on January 1, 2002, the judge harshness index for this convict will be determined by the sentences his/her judge has given before and after January 1, 2002.

[31] Lastly, I drop outlier judges with fewer than 100 cases over the 13 year time period. This results in dropping less than 15 judges or only 0.02 percent of the total Conviction Data sample.

index.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.
Returned to prison within 3 years of release	0.29	0.45
Time served in prison (months)	25.98	12.24
Sentence length (months)	47.08	20.51
Percent of sentence served	62.12	29.11
Time on parole (months)	21.11	21.03
Demographic and criminal background		
Black	0.60	0.49
Female	0.12	0.33
Age at release	34.51	10.18
Prior convictions	2.49	2.82
Current offense		
Number of disciplinary infractions	2.09	2.11
Drug	0.32	0.47
Other	0.16	0.36
Property	0.35	0.48
Violent	0.17	0.38
Parole and judge		
Judge harshness index, $Judge_i$	64.03	20.91
Guidelines recommendations, $Recom_i$	24.58	11.19
Success score	11.25	4.21

The sample (N=11,607) comes from the Georgia Prison Data.

Table 2 shows summary statistics for the sample used in the analysis. Individuals in the sample are predominantly male and Black, with average age at release from prison around 34.5. The average prisoner has 2.5 prior convictions and the two most common crimes that the prisoners in the sample have been incarcerated for are property (35 percent) and drug related (37 percent). Since I exclude crimes with severity level above five from the estimation sample, it is not surprising to see that there are only 17 percent of prisoners charged with a violent offense. The mean sentence length is just below four years, while the mean time served is about 26 months in prison. Moreover, the average prisoner serves only 62 percent of his sentence behind bars, and the rest on parole. Almost 30 percent of the sample return to prison, with or without a new sentence, within three years of release. One drawback of the data is that recidivism is observed only within the state of Georgia. If an inmate moves away to another state, I do not observe his recidivism likelihood. Thus, my recidivism measure is potentially underestimated if criminals who are more likely to recidivate move away from Georgia and reoffend elsewhere.[32]

5 Results

5.1 The Effects of Time in Prison and on Parole on Recidivism

The first stage results are given in Table 3. The F-statistics of all first stage regressions are above 50, and the instruments are highly predictive of time served in custody and on parole. I include controls widely used in the literature such as race, age at release, and number of past convictions. In all regressions, I also include crime type, year of sentence, circuit court, success points, and severity level fixed effects. Observe that in Col.(1), which estimates Equation 4, a one month increase in the parole guidelines recommendations leads to a half a month less time on parole, while a one month increase in the judge harshness index leads to a 0.03 more months spent under community supervision of parole. Although the judge harshness index has a small effect, the parole guidelines recommendations have the most predictive power for time served in prison. As seen in Table 3 Col. (2), a one month increase in the guidelines recommended months to be incarcerated results in a half month increase in the actual time served in prison. There are two possible explanations how the judge can influence time served in prison. First, in the state of Georgia, inmates are eligible to be considered for parole on the parole eligibility date (PED), which is usually set at around one-third of their prison sentence.[33] Second, the judge's decision might affect the parole board in determining the length of imprisonment period since a prisoner cannot be

[32]Durose et al. (2014) estimate that about ten percent of released prisoners in one of the 30 states they have sampled were rearrested in a state other than the one that released them. This suggests that the majority of released prisoners nationwide recidivate in the state they were released in and thus, making the potential underestimation of the recidivism measure less problematic.

[33]The parole board is not constrained by the PED. Rather, if the board wants to release a prisoner on parole before the PED, it needs to inform the judge in writing and the judge has the option to express his or her opinion. In the sample, only five percent of inmates are released before the PED. Moreover, the results are robust to excluding these individuals.

Table 3: First Stage Estimates

Variables	(1) Time on parole	(2) Time in prison
Guidelines recommendations, $Recom_i$	-0.521***	0.505***
	(0.0186)	(0.00993)
Judge harshness index, $Judge_i$	0.0335***	0.0158**
	(0.0130)	(0.00692)
Black	2.340***	0.0519
	(0.387)	(0.206)
Female	1.734***	-2.888***
	(0.525)	(0.280)
Age at prison release	-0.0182	0.0798***
	(0.0183)	(0.00978)
Prior convictions	-0.119	0.229***
	(0.0938)	(0.0500)
Constant	7.424***	9.465***
	(2.161)	(2.769)
Observations	11,607	11,607
F-stat	55.63	92.15
R-squared	0.284	0.396

Standard errors in parentheses. Time served in prison (and on parole) is measured in months. Crime type, year of sentence, circuit court, grid points, and severity level fixed effects included. *** p<0.01, ** p<0.05, * p<0.1

kept in prison past his sentence expiration date. Since the main objective of the parole board is to release potentially rehabilitated prisoners who are less likely to recidivate, the board would like to keep prisoners who are less likely to be rehabilitated for as long as possible. Given that a prisoner cannot be incarcerated for more time than his original sentence, the board decision of how long to keep a prisoner is restricted by the sentence given by the judge. Later in the paper, I test this hypothesis by examining the heterogeneous effects of the behavior in prison.

Table 4 presents the regression results from the second stage. Note that both columns report estimates from a linear probability model. Col. (1) shows the naïve OLS estimates, which do not take into account the endogeneity of time served in prison or on parole and

Table 4: Second Stage Estimates

Variables	(1) OLS	(2) 2SLS
Time in prison	-0.000206	-0.0112*
	(0.000384)	(0.00665)
Time on parole	0.00447***	-0.00239
	(0.000220)	(0.00642)
Black	0.0342***	0.0263
	(0.00911)	(0.0181)
Female	-0.0706***	-0.0662***
	(0.0125)	(0.0149)
Age at prison release	-0.00691***	-0.00489***
	(0.000422)	(0.000588)
Number of prior convictions	0.0306***	0.00997***
	(0.00158)	(0.00261)
Constant	0.253***	0.637**
	(0.0734)	(0.322)
Observations	11,607	11,607

Standard errors in parentheses. Time served in prison (and on parole) is measured in months. Crime type, year of sentence, circuit court fixed effects included in both the OLS and 2SLS. Grid points and severity level fixed effects included as well in the 2SLS. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

the propensity to reoffend. The results indicate that time behind bars does not have any statistically significant effect on the probability to return to prison. The OLS results for time on parole suggest that parole has a significant but small criminogenic effect. However, this estimate is biased upwards because of omitted variables bias. Once I control for the endogeneity problems, Col. (2) suggests that both time on parole and time in prison have a deterrent effect. While I find no statistically significant effect of the duration of parole sanctions, a one month increase in time spent in prison leads to a 1.12 percentage points (approximately 4 percent) decrease in the likelihood to return back to prison within three years after release. The other covariates have the expected signs. For instance, the probability to recidivate is 6.62 percentage points lower for females, and decreases by almost one percentage point with each additional year of age—consistent with the fact that criminality declines over time (Bushway and Piehl, 2007).

In the case of collective pardon in Italy, Drago et al. (2009) find a big deterrent effect of the unserved portion of the sentence. However, using data from the state of Georgia I do not find any significant effect of time spent on parole on future criminal involvement. One possible explanation for this is that, in contrast to the Italian pardon, for which the remaining sentence was attached to any new sentence, US sentences are not cumulative. In particular, offenders who are arrested for committing a new crime while on parole are detained in prison under a parole board warrant until their new charges have been settled. Once the new charges are determined and a new conviction is made, the convict is sent to prison to serve their new sentence. Though the fact that reoffending while on parole might influence the judge to give a harsher punishment, it is not necessarily true that the previously unserved time would be fully reflected in the new sentence.

5.2 Heterogeneous Effects of Time Served in Prison and on Parole

Motivated in part by the overrepresentation of minorities in the US criminal justice system, in this section, I investigate whether the deterrent effect of prison and parole varies across inmates characteristics. The second stage estimates by race and type of offense, reported in Table 5, are in line with the full-sample findings for the lack of effect of time on parole on recidivism. Nevertheless, the full-sample results of the deterrent effect of time in prison appear to be driven primarily by the sample of White prisoners and people whose major offense is property related. One explanation of these heterogeneous effects is that property offenses tend to be more opportunity driven in contrast to drug and violent crimes which are usually crimes of addiction or passion. The point estimates for property offenders suggest that an additional month behind bars results in a 2.9 percentage points decrease in the probability that they will return back to prison within three years of release. Ignoring potential nonlinear effects of time in prison, if the average property offender enters prison with a seventy percent probability of recidivating, then after spending one year in prison this recidivating risk decreases to around 35 percent. The heterogeneous effects by race could be rationalized if for White offenders prison is a more unpleasant experience than for Blacks or if Whites have a better outside option than Blacks.

Table 5: Heterogeneous Effects of Time Served in Prison and on Parole

	By Race		By Crime Type			
	White	Minority	Drug	Violent	Property	Other
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Time in prison	-0.0268*	-0.00466	-0.0113	-0.00672	-0.0290**	0.0126
	(0.0152)	(0.00769)	(0.00854)	(0.0115)	(0.0147)	(0.0141)
Time on parole	-0.0206	0.00581	0.00337	0.00252	-0.0114	0.0117
	(0.0155)	(0.00701)	(0.0115)	(0.00764)	(0.0111)	(0.0138)
Observations	4,597	7,010	3,708	1,974	4,107	1,818

Standard errors in parentheses. Time served in prison (and on parole) is measured in months. Year of sentence, circuit court, grid points, and severity level fixed effects included. Demographic variables (female, age at prison release, prior convictions) included in all regressions. Race is included only in Col. (3)-(6).*** p<0.01, ** p<0.05, * p<0.1

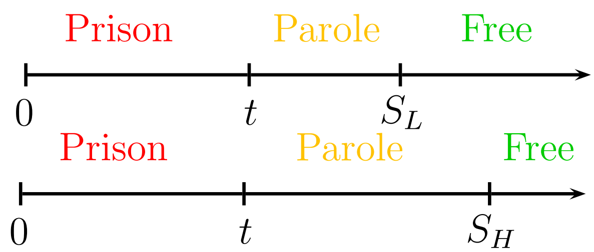
5.3 Parole Board and Judge Interaction

Parole boards can update their beliefs about the likelihood that a prisoner will recidivate when determining the final punishment (time in prison), while judges determine punishment (sentence) only based on their prior beliefs. Suppose that the parole authorities use institutional behavior as a predictor of future reoffending. The parole authorities have prior beliefs about the inmates' likelihood of recidivating, which they update on the basis of behavior observed in prison. The parole board acquires information by observing whether the inmate engages in incidents of bad behavior. Such behavior is likely correlated with recidivating, so an absence of incidents signals likely rehabilitation, and therefore, early release on parole.

As I hinted in Section 5.1, there are two possible channels—the PED and the sentence expiration date—through which the judge harshness index could affect the decisions of the parole board.

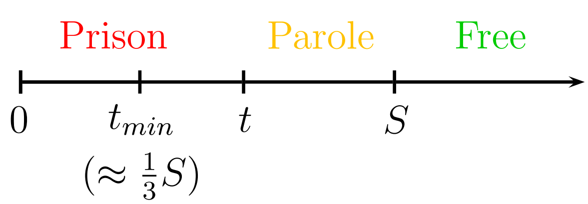
First, consider Figure 4 which illustrates the possible effect of the sentence expiration date on the parole board decisions. Suppose that a prisoner gets sentenced by a harsh judge and thus, receives a much longer sentence, S_H, compared to someone sentenced to S_L by a lenient judge. Moreover, suppose that at time $t < S_L < S_H$ the beliefs of the board is that this prisoner is not ready to be released as he has had disruptive behavior in prison. In this

Figure 4: Timeline for the Decisions of Judges and the Parole Boards by Judge Harshness



instance, the long sentence that this prisoner has received gives the board the opportunity to observe him in prison for $S_H - t$, update his beliefs about the rehabilitation process for the prisoner, and ultimately release him when the parole board believes he is less likely to pose a danger to society . Now, suppose that this same prisoner gets sentenced by a lenient judge and receives a much shorter sentence $S_L < S_H$. In this case, the parole board could keep this prisoner incarcerated for $S_L - t$, which is strictly less than the time they would have enjoyed if the prisoner was sentenced by a harsh judge. Thus, judge harshness would matter for the types of prisoners, for whom the parole board needs to observe in prison for longer in order to make its release decision, judge's harshness would matter.

Figure 5: Timeline for the Decisions of Judges and the Parole Boards with Respect to the PED



Second, Figure 5 depicts how PED could potentially affect the parole board decisions. If the observed effect of judge harshness index in Section 5.1 is due to the PED requirement, one would expect that the judge's harshness would play a bigger role in determining the incarceration length for prisoners without disciplinary infractions. The idea is that a person with a clean record while in prison is much more likely to be released earlier (even before the PED) than a prisoner who has had a disciplinary infraction.

To explore the possible mechanisms of the effect of judge harshness index on time served

Table 6: First Stage Estimates by Behavior in Prison

	(1)	(2)
	Bad Prisoners	Good Prisoners
Variables	Time in prison	
Guidelines Recommendation	0.497***	0.474***
	(0.0131)	(0.0146)
Judge's harshness	0.0165*	0.0134
	(0.00896)	(0.0104)
Black	0.222	-0.638**
	(0.286)	(0.277)
Female	-2.871***	-2.513***
	(0.414)	(0.346)
Age at prison release	0.136***	0.0905***
	(0.0144)	(0.0128)
Prior convictions	0.181***	0.226***
	(0.0644)	(0.0777)
Constant	7.077	4.175
	(6.330)	(3.672)
Observations	7,140	4,467
R-squared	0.378	0.413

Standard errors in parentheses. Time served in prison is measured in months. Bad prisoners refer to prisoners who have at least one disciplinary infraction charge while in prison. Good prisoners are prisoners with no disciplinary infraction charges while incarcerated. Crime type, year of sentence, circuit court, grid points, and severity level fixed effects included. *** p<0.01, ** p<0.05, * p<0.1

in prison, I use a proxy for rehabilitation—prisoner's behavior in prison. The Prison Data contains information on the total number of violent and non-violent disciplinary infractions in prison for the current incarceration episode of each prisoner. I split the sample into two groups–"bad prisoners" are those who have one or more disciplinary infractions in prison and "good prisoners" who have none. Referring to Table A6, good and bad prisoners seem to receive similar initial sentences, which supports the argument that at sentencing, judges do not know whether a convict is rehabilitated or not. In contrast, since the parole board observes the rehabilitation process, it is not surprising to see differences in the incarceration duration, depending on the prisoner's behavior. For instance, a misbehaving criminal serves 28 months on average, almost 6 months more than a well-behaved one. In addition, I reestimate the first stage Equation 3 by prisoner's institutional behavior.[34] Table 6 presents the results. Col. (3) and (4) show that there is no statistically significant effect of the judge harshness index on incarceration length of prisoners with no infraction record, while it has a small positive effect for those with one or more disciplinary infractions. Since the parole board cannot keep a prisoner for longer than his original sentence determined by the judge, the expected annual benefit from releasing a "good prisoner" is not affected by the sentence length. Longer sentences increase the value of information collected from observing an inmate's behavior in prison and it is much more beneficial for "bad prisoners". Thus, it is not surprising to see that the judge harshness index has a statistically significant effect on time served only for bad prisoners, whom the parole board would prefer to observe for longer time, in order to correctly assess their recidivating risk. However, note that I cannot reject that the PED drives the results as I cannot reject the hypothesis that the coefficient on the judge harshness index for bad prisoners is statistically different from that for good prisoners.

One question, motivated by the results in Table 6, concerns the effect of an additional month spent under custodial and noncustodial supervision on recidivism, when the judge-determined sentence length is not binding for the parole board. In other words, if the mechanism through which judge ideological heterogeneity matters is by allowing the parole board to observe bad prisoners for a longer period, do we observe different effects of sanctions for bad and good prisoners? To examine this, Table 7 provides estimates of the second

[34]Referring to Table 2, 37 percent of my sample has one or more disciplinary infractions in prison and the average number of infractions is two.

Table 7: Second Stage Estimates by Behavior in Prison

Variables	(1) Good prisoners	(2) Bad prisoners
Time in prison	-0.00155	-0.0164*
	(0.00828)	(0.00975)
Time on parole	0.00572	-0.00494
	(0.00939)	(0.00861)
Black	-0.0207	0.0470*
	(0.0233)	(0.0263)
Female	-0.0517*	-0.0460**
	(0.0289)	(0.0200)
Age at prison release	-0.00274***	-0.00437***
	(0.000585)	(0.00127)
Prior convictions	0.00543	0.0108***
	(0.00451)	(0.00328)
Constant	0.104	0.932*
	(0.289)	(0.513)
Observations	4,467	7,140
R-squared	0.104	0.120

Standard errors in parentheses. Time served in prison (and on parole) is measured in months. Bad prisoners are prisoners who have at least one disciplinary infraction charge while in prison. Good prisoners are those with no disciplinary infraction charges while in prison. Crime type, year of sentence, circuit court, grid points, and severity level fixed effects included. *** p<0.01, ** p<0.05, * p<0.1

stage regression, separating the sample by inmates' conduct in prison. Interestingly, I find that time behind bars has a deterrent effect only for prisoners, who do not seem to be rehabilitated, i.e. who have at least one misconduct while incarcerated. One additional month in prison for misbehaving prisoners results in a 1.64 percentage point decreases in the probability that they return back to prison in three years after release. I do not observe any statistically significant effect on the probability to recidivate for prisoners, who do not have any disciplinary infractions while in prison. These results should be interpreted with caution as behavior in prison might be potentially endogeneous to the decision to recidivate.

6 Conclusions

This paper investigates how release before full completion of a criminal sentence affects recidivism. The causal effect of time on parole on recidivism are estimated by relying on two instrumental variables—specifically, random assignment of judges to felony cases in Georgia and the variation generated by the formulaic calculation of recommended time to serve in prison by the Georgia parole board. The results suggest that time on parole has no significant effect on recidivism, while time in prison has a negative effect of 1.12 percentage points. With respect to the previous literature, this study makes two important contributions. First, it quantifies the effect of time on parole on recidivism. The insignificance of this effect might be rationalized by the fact that the parole board is assessing the recidivism risk of prisoners accurately. This confirms the finding of Kuziemko (2013), who uses a mass release quasi-experiment in Georgia to conclude that the parole board assigns prison time in an allocatively efficient manner. Second, by using two instruments, this paper provides an estimate of time served in prison on recidivism that is not confounded by time on parole. Many states have abolished discretionary parole completely. However, if parole boards are assessing how dangerous potential offenders truly are, then policymakers may wish to re-evaluated policies that limit parole discretion. The declining use of parole discretion may explain why recidivism rates have been so high.

I also explore the interaction between the sentencing authority (judges) and the prison release authority (parole boards) in determining punishment in the criminal justice system. I find that the judge's harshness does not affect the decision of the parole board to release prisoners who have had no disciplinary infractions in prison, while it does for those prisoners with at least one infraction. This study does not conclude that parole cannot work to reduce recidivism. Rather, it finds that the length of parole supervision has no significant deterrent effect. Given that community supervision is costly, it might be optimal for the government to keep the parole spells shorter. These findings, combined with other results in the literature (Drago et al., 2009), might suggest a reform in the US criminal justice system that eliminates parole supervision, but increases new sentence for recidivists by attaching parole time to the new sentence. This policy recommendation should be taken cautiously as it is difficult to generalize results from different contexts, such as the United States and Italy.

States and the federal government are committing significant resources to improving reentry planning and strengthening community supervision. Although this study finds that time under parole does not have any significant effect in decreasing recidivism rates, more research is needed to understand whether this zero effect is driven by the effectiveness of various post-prison supervision policies. I do not have the data to address what types of parole strategies work better than others. Specifically, it would be interesting to see whether parole has any deterrent effect if one accounts for various factors such as type or intensity of supervision, assessment tools, access to rehabilitative programs and treatment. Maximizing the public safety benefits and cost savings of post-release supervision might involve assigning appropriate intensity of supervision, rather than focusing solely on the length of time under parole. Understanding the effect of different parole strategies on recidivism would be a fruitful area for future research.

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A Supplementary Tables and Materials

Table A1: Parole Board Guidelines Recommended Months to Serve in Prison

Crime Severity Level	Success Group (Score)		
	Excellent (14-20)	Average (9-13)	Poor (0-8)
I	10	16	22
II	12	18	24
III	14	20	26
IV	16	22	28
V	34	40	52
VI	52	62	78
VII	72	84	102

Table A2: Parole Board Formula for Calculate Parole Success Score

Success factor		Success points
Age at previous incarceration, if any	26+	5
	22-25	3
	18-21	1
	17-	0
Number of other felony convictions both as a child and an adult	0	3
	1	2
	2-3	1
	4+	0
Times incarcerated for a felony since age of 17	0	2
	1	1
	2	0
Times, if any, of probation or parole revocation	None	4
	Probation only	2
	Parole only	1
	Both	0
Caught with or caught trying to buy heroin, opiate drugs or cocaine	No history	1
	Has history	0
Burglary or forgery current crime	No	2
	Yes	0
Full-time job in the six months before conviction	Yes	1
	No	0
Score on the reading, writing and arithmetic test given by the GDC diagnostic center	Above 8	2
	Below 8	0

Table A3: Parole Board Guidelines Crime Severity Levels

LEVEL I	**LEVEL III**
Bad Checks - under $2,000	Burglary - non-dwelling, 2 to 5 counts, or $2,001 to $5,000
Burglary - non-dwelling, less than $300, one count	Credit Card Fraud - more than 10 counts or $1,000
Credit Card Theft	Criminal Damage - life in danger or over $2,000
Criminal Interference with Government Property	Destroying or Injuring Police Dog or Horse
Escape Custody - no weapon, aiding escape	Forgery I - over 10 counts or $1,000 or more
Forgery II - possession, 10 or fewer counts or less than $1,000	Manufacturing Methamphetamine - 1st offense
Habitual Violator	Obstruction of Officers - Felony
Possession/passing forged prescriptions - 1st offense	Possession/Theft - materials to manufacture illegal drugs, 2nd offense
Possession of tools to commit a crime	Terroristic Threats
Theft - under $1,000	Theft - $5,000 to $10,000
Theft of Vehicle - not to sell; one count, 1st offense	Theft of Vehicle - for sale or 2 to 3 counts without intent to sell or 3rd offense
VGCSA - possession, single offense	VGCSA - sale - 2nd offense or 3rd drug possession
LEVEL II	**LEVEL IV**
Bad Checks - $2,000 or more	Arson II - $2,000
Burglary - non-dwelling, $300 to $2,000, one count	Burglary - non-dwelling, over $5,000 or 6 or more counts
Credit Card Fraud - 10 or fewer counts or less than $1,000	Homicide by Vehicle
Criminal Damage II - $300 to $2,000	Manufacturing Methamphetamine - near a child
Forgery I - 10 or fewer counts or less than $1,000	Serious Injury by Vehicle
Possession of Illegal Firearm or Explosives	Theft of Vehicle - 4 or more counts or 4th or greater offense
Possession/Theft - materials to manufacture illegal drugs, 1st offense	Theft - over $10,000
Reckless Conduct by HIV Infected Persons	VGCSA - sale/distribution/intent to sell Schedule I or II drugs, 2nd offense
Theft - $1,000 to $4,999	
Theft of Vehicle - not for sale, 2nd offense	
VGCSA - possession, 2nd offense	
VGCSA - sale/intent to sell/distribution, 1st offense	

Chart does not include all crimes. To obtain the severity level for unlisted crimes, contact a Board hearing examiner at 404.656.5712. Chart applies to crimes committed from Jan. 1, 1995 to Dec. 31, 2005.

Table A4: Felony Population Nationally and in the State of Georgia by Year of Sentence

	Nationwide			Georgia		
Year	2000	2002	2004	2000	2002	2004
Type of crime						
Violent	18.7	18.8	18.0	19.1	18.9	20.2
Property	28.3	30.9	29.0	34.3	35.0	33.5
Drug	34.6	32.4	34.0	30.6	29.9	30.9
Other	18.4	17.9	20.0	16.1	16.1	15.5
Gender						
Male	83	83	82	89	88	89
Female	17	17	18	11	12	11
Race						
White	35.7	34.2	34.3	37	40	42
Black	46.2	45.1	40.7	63	60	57
Hispanic	16.4	18.1	19.2	-	-	-
Other	1.7	2.6	2.9	0	1	1
Average age	32	32	32	31	31	32
Sentence						
Avg Length (months)	55	53	57	57	56	57
Violent	91	84	92	84	79	80
Property	42	41	45	43	40	41
Drug	47	48	51	54	54	55

National statistics come from the "Felony Sentences in State Courts Series," published bi-annually by the US Bureau of Justice Statistics `http://www.bjs.gov/index.cfm?ty=pbse&sid=28`. The statistics on race come from various issues of "Prisoners" series found at `http://www.bjs.gov/index.cfm?ty=pbse&sid=40`. The statistics for Georgia are based on the raw Prison Data with no sampling restrictions described in Section 4. The only restriction applied to the Prison Data is the exclusion of sentences to death or to life in prison in order for the statistics to match the national ones. The GDC treats Hispanic as ethnicity and thus, I am not reporting summary statistics for Hispanics for the GDC sample.

Table A5: Summary Statistics by Release Date

	Before 2005		After 2005	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Returned to prison within 36 months of release	0.29	0.45	0.13	0.34
Time served in prison	25.98	12.24	35.03	17.75
Sentence length	47.08	20.51	55.40	19.43
Percent of sentence served	62.12	29.11	65.40	26.68
Time on parole	21.11	21.03	20.38	19.23
Demographic and criminal background				
Black	0.60	0.49	0.55	0.50
Female	0.12	0.33	0.11	0.31
Age at release	34.51	10.18	34.87	10.40
Prior convictions	2.49	2.82	2.27	2.83
Current offense				
N of disciplinary infractions	2.09	2.11	2.25	2.12
Drug	0.32	0.47	0.28	0.45
Other	0.16	0.36	0.16	0.36
Property	0.35	0.48	0.33	0.47
Violent	0.17	0.38	0.24	0.42
Parole and judge				
Guidelines recommendations, $Recom_i$	24.58	11.19	27.32	11.67
Judge harshness index, $Judge_i$	64.03	20.91	63.99	20.62
Success score	11.25	4.21	11.92	6.36
N	11,924		10,370	

Source: GDC Prison Data.

Table A6: Summary Statistics by Prisoner Behavior

Variable	Good prisoners		Bad prisoners	
	Mean	Std. Dev.	Mean	Std. Dev.
Returned to prison within 36 months of release	0.21	0.41	0.34	0.47
Time served in prison	22.53	10.54	28.14	12.72
Sentence length	47.65	19.93	46.73	20.86
Percent of sentence served	53.4	26.93	67.58	29.1
Time on parole	25.12	20.43	18.61	21.02
Demographic and criminal background				
Black	0.51	0.5	0.66	0.47
Female	0.16	0.37	0.1	0.3
Age at release	37.03	10.21	32.94	9.84
Prior convictions	1.86	2.36	2.89	3
Current offense				
Drug	0.41	0.49	0.26	0.44
Other	0.16	0.37	0.15	0.36
Property	0.3	0.46	0.38	0.49
Violent	0.12	0.32	0.2	0.4
Parole and judge				
Guidelines recommendation	21.44	10.14	26.54	11.37
Judge harshness	64.28	20.49	63.87	21.17
Success score	12.89	3.78	10.22	4.14
N	4,590		7,334	

See notes of Table 6 for more details on the sample used.