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

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Abstract

In the U.S., every year roughly 600,000 people are released from prison, two-thirds of whom without having served their full sentence behind bars. Yet little is known about 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 custodial and noncustodial sanctions affect recidivism. Specifically, I study the effects of time in prison and time on parole on recidivism. 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 a 1.12 percentage points decrease in the probability that an individual will reoffend while on parole, but it appears to have no effect on overall reoffending.

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1 Introduction

Over 600,000 people are released from the U.S. prison system every year. More than three-fourths of these individuals are released before they fully serve their judge-determined prison sentence, subject to a period of parole supervision in the community (Carson, 2018).[1] In 2016, the U.S. adult correctional systems supervised more than 6.6 million people, of which 4.5 million were under some type of community supervision (Kaeble, 2018; Kaeble and Cowhig, 2016).[2] Federal, state, and local expenditures on corrections—totaling $83 billion—consume a growing portion of the nearly $273 billion spent annually on public safety (Bronson, 2018). 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 activity. The purpose of this paper is to investigate how both time served in prison and time on parole affect recidivism, and thus to provide an estimate of the effect of a total prison sentence.

Nagin et al. (2009) suggest that studying the effect of both custodial and noncustodial sanctions on recidivism to be a fruitful research direction. This paper tries to fill this gap in the literature by disentangling the effect of custodial (prison) and noncustodial (parole) sanctions on recidivism and by contrasting the effect of time outside of prison under parole supervision versus under no custodial supervision at all. There have been recent policy efforts to reduce the incarcerated population through not only "front-end" sentencing and admission policies, such as diversion, but also through "back-end" release and re-entry policies, such as expanding the role of parole boards (Raphael and Stoll, 2014). Hence quantifying the effect of community supervision, such as parole, is especially important for policy makers.

I contribute to the existing literature in two ways. First, I estimate the causal effect of parole time and quantify the impact of total correctional punishment on the offending choices

[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, all parolees have to agree and meet to a set of standard conditions of parole–avoiding injurious habits, obeying the law, etc.–as well as any individual specific conditions, such as substance abuse or mental counseling. Failure to comply with any of the conditions can result in a parole revocation and a return to prison.

[2] People on parole comprised about 19 percent of all adults under community supervision (Kaeble, 2018).

of convicts. For most convicts in the U.S., punishment consists of both prison and parole time. These two types of supervision differ in the severity of the sanctions, and therefore provide different incentives for criminals to reoffend. Estimating these two effects simultaneously is not a trivial exercise because it requires exogenous variation in both prison time and sentence length. 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 both are 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 ordinary least squares estimation of the relationship between the size of the sentence reduction and recidivism will be biased upward. One of the key contributions of this paper is to provide causal estimates of prison and parole time on recidivism using observational data. Two peculiarities of the Georgia criminal and prison systems allow me to construct two instrumental variables. 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 to instrument for sentence length. I use the variation generated by the formulaic calculation of recommended time to serve in prison by the Georgia Parole Board to address the endogeneity of actual time served behind bars. Although these two instruments have been used before in the literature, neither of them has been used to evaluate the effect of parole time or total correctional punishment. Second, prior work that uses two-stage least squares regressions to estimate the effect of prison time on recidivism do not account for time on parole. Unless offenders serve their whole sentence in prison, this omission could possibly confound the direct effect of time in prison on recidivism.

Using the likelihood of returning 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 statistically significant effect on recidivism. In addition, the estimated effect of parole time is relatively small–in some specifications it is almost five times smaller than that on prison time. This is important for policy purposes for two reasons. First, the use of community supervision, such as post-release supervision, has expanded over the last three decades resulting in approximately 1 in 55 adults in the U.S. being under community supervision in 2016 (Kaeble, 2018). Second, 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 based on sentencing guidelines as well as the prisoner's institutional behavior.[3]

My estimate of the effect of prison time on overall probability of return to prison within three years of release is half that of Kuziemko (2013) and insignificant.[4] However, I find that one extra month served in prison confinement reduces the likelihood of recidivism while on parole by 1.04 percentage points, which is comparable to the findings of Kuziemko (2013).[5] Supported by additional data from the GDC, my study complements Kuziemko (2013) by estimating the treatment effect of parole time in addition to that of prison time. I also document a potential bias in the estimation of the effect of prison time on recidivism. This bias is caused by split decision-making in Georgia, and many other jurisdictions, where judges sentence and parole boards then decide how much of a sentence is served behind bars and how much in the "community" under the supervision of a parole officer. My results provide little evidence that not accounting for parole time distorts the estimation of prison time using data from Georgia. Specifically, accounting for parole time increases, by a little, the magnitude of the estimated effect and decreases its significance.

For the most part, my findings of the treatment effect of parole and prison time on recidivism carry 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 U.S. correctional system. I do find heterogeneous effects by race and type of offense if reoffending occurs while under parole supervision. I find that the significant effect of time in prison on

[3]In 2016, twenty three states have used discretionary parole as their primary prison release mechanism (Kaeble, 2018). 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 ex-prisoners. The only difference is whether or not states allow for discretion in the prison release decisions.

[4]A plausible explanation for this might be that my estimation sample consist of people who are serving much shorter sentences, and potentially are serving much less time on parole. A detailed discussion on how my sample differs from that of (Kuziemko, 2013) is outlined in the Appendix A.

[5]It is worth noting that the way I measure recidivism is slightly different from Kuziemko (2013). I account for the timing of the reoffending event relative to one's sentence expiration date and distinguish between recidivism that occurs on parole or off parole. However, it appears that I cannot reject the hypothesis that my estimate of the effect of prison time on recidivism *while on parole* is statistically different from Kuziemko (2013)'s effect of prison time on recidivism, regardless whether it occurred on or off parole, of 1.3 percentage points.

recidivism while on parole is driven by white offenders.

Related Literature There have been a few papers, predominantly in criminology, that examine noncustodial sanctions such as probation and parole.[6] Although these studies control for selection on observables, they do not properly account for selection on unobservables. In addition, they focus primarily on determining whether prison sanctions are more effective than parole, and do not attempt to evaluate the two types of supervision together as separate parts of total punishment. Estimating the joint effect of imprisonment and parole supervision is also important for policy makers. In 2016, there were 641,027 prisoners released, from whom 426,755 were conditionally released on probation or parole before their full sentence had expired (Carson, 2018).[7] 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 actually decreases recidivism rates, and thus helps ex-prisoners stay out of trouble. 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 more cost-effective for the government to reduce incarceration while utilizing longer periods of parole. This paper also relates to the relatively new literature that examines how parole can serve as an incentive for good behavior (Kuziemko, 2013), and how "front-end" (Mueller-Smith and Schnepel, 2018) and "back-end" alternatives to incarceration (Di Tella and Schargrodsky, 2013) affect recidivism.[8]

[6] Refer to Nagin et al. (2009) for an exhaustive list.

[7] Probation supervision is part of an 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 two types of noncustodial sanctions, offenders under both kinds of supervision are required to adhere to similar conditions. Failure to comply with these conditions can result in incarceration. Given the similarities between these two noncustodial supervisions, understanding the effect of parole on recidivism might inform policy makers about the impact of other types of post-prison supervision, such as probation.

[8] Like the current study, the study of Di Tella and Schargrodsky (2013) examines how community supervision after prison affects recidivism. Though the Di Tella and Schargrodsky (2013) results can be informative about the effect of electronic monitoring when used as a substitute for pre-trial incarceration, their generalizability to the US and other types of noncustodial supervision such as parole is unknown. My data and empirical strategy allow me to quantify not only the effect for a general U.S. adult prison population, a group that actually makes up a large fraction of the total world's incarcerated population, but also to separate the

This paper also contributes to the existing work which estimates the effect of prison time on future criminal behavior and which can be separated into two major groups.[9] The first group uses mostly 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). These studies find a wide range of plausible magnitudes–one additional criminal in prison decreases the crime rate by 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; Maurin and Ouss, 2009; McCrary and Lee, 2009; Kuziemko, 2013; Nagin and Snodgrass, 2013; Green and Winik, 2010; Gottfredson, 1999; Mueller-Smith, 2015; Mukherjee, 2017). These papers estimate the direct response of individuals to various interventions and find either a small positive or no deterrent effect of imprisonment on future criminal activity.

Kuziemko (2013) also uses data from the Georgia Department of Corrections (GDC) and the procedures of the Georgia Parole Board to evaluate the effect of discretionary release policies on in-prison behavior and to quantify the effect of prison time on recidivism. Unlike Kuziemko (2013), this study seeks to untangle the effect of cumulative punishment, which for the majority of prisoners in the U.S. is a combination of prison and parole time, and to estimate the treatment effect of parole time. Maurin and Ouss (2009) and Drago et al. (2009) who use collective pardon in France and sentence enhancements after a collective pardon in Italy, respectively, to examine the specific and general deterrence effect of sentence reduction. Collective pardon or parole might provide different incentives to released prisoners since pardons are not based on individual behavior while in prison while good behavior is central in determining release under parole. Furthermore, collective pardons are rare in the U.S., and sentence enhancement is not generally used.

In terms of the data and empirical methods used, the current paper is related to studies that use random assignment of criminal cases to estimate the effect of incarceration on future criminal behavior. A few recent studies use random assignment of defendants in criminal courts to evaluate the effect of incarceration (Kling, 2006; Aizer and Doyle Jr, 2015; Di Tella and Schargrodsky, 2013; Nagin and Snodgrass, 2013; Green and Winik, 2010; Mueller-Smith, 2015) and pretrial detention (Heaton et al., 2017; Dobbie et al., 2018) on various outcomes,

effects of prison and parole sanctions.

[9]For a comprehensive review of the literature, see Nagin et al. (2009) and Durlauf and Nagin (2011).

including future criminal involvement.[10] Although these studies use random court assignment of cases as an instrument for a prison sentence, they do not examine whether time on parole has any effect beyond that of time served behind bars. In addition, Nagin and Snodgrass (2013) and Green and Winik (2010) both use random assignment of judges to estimate the effect of sentence as a proxy for prison time on reoffending. Given that their analysis relies on data from Pennsylvania and Washington, D.C., two regions that use discretionary parole, sentence will be a noisy proxy for prison time because the Parole Boards ultimately decide prison time. Given that, their analysis will provide an estimate of the total correctional supervision, instead of just prison time, and their instrument could potentially be weak.

The remainder of the paper proceeds as follows. Section 2 introduces the data. Section 3 describes the court and Parole Board procedures in Georgia and provides an overview of the empirical methodology, including the construction of the two instrumental variables, used in the analysis. Section 4 presents the main findings and results. Section 5 summarizes my conclusions.

2 Data

I use two administrative databases from the Georgia Department of Corrections to estimate the differential effect of time served in prison and on parole on recidivism.[11] First, the GDC provides administrative records of all people released from the Georgia prison system from 1980 to 2008 (henceforth, Prison Data). These records contain rich information about socio-demographics, criminal history, parole, and current conviction for each person admitted to state 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

[10] 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., 2014), foster care placement (Doyle Jr, 2007), and bankruptcy protection (Dobbie and Song, 2015) on various economic outcomes.

[11] For more information about the data and the sample construction, please refer to Appendix A

in Georgia. I use this data only for the construction of my instrument for sentence length as it represents the sentencing patters of the universe of judges in Georgia and describe it in more detail in Appendix A.[12] Because of the necessary data restrictions outlined below, I am unable to make use of the full data set. Thus, the sample for the main analysis is restricted to people sentenced to prison after January 2001 and released from prison before October 2005.[13]

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.[14] 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.[15] I further 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 primarily 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 if their parole officers are relatively lenient. However, all new crime commitments are sent to prison and their sentence is determined by a randomly assigned judge. The Prison Data contains the success score and severity levels that the Georgia Parole Board uses as guidelines for determining prison time. Since the parole guidelines seem to be

[12]Note that the Conviction Data contains information specifically on convicts and excludes people who were charged with a crime but were never convicted. 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 there are individuals who are arrested for committing a serious crime but consequently charged with a less serious crime or even a misdemeanor. Relying on the random assignment of felony cases assumption, I do not expect that certain judges will systematically receive such cases more than other judges.

[13]That means that my analysis is restricted to people who spent between 7 and 56 months in prison, and thus the results in this paper should be interpreted for people who spend a relatively short time behind bars.

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

[15]In the Appendix A, I do not find any evidence that this could introduce additional bias or threaten the validity of the judge harshness instrument.

the strongest predictor of time served for crimes with a severity level less than five, I drop all individuals imprisoned for more serious crimes.[16] Note that the Parole Board is not required to follow the parole guidelines and can adjust the recommendation up and down. In Figure OA3 I present histograms of the difference between the parole-established temporary release month (TPM) and the Parole Guidelines-recommended TPM by crime severity level. It is worth noting that the Parole Board adheres to the Guidelines recommendation more than 30 percent of the time for crimes with a severity level less than five, and the Board decision is within four months of the recommendation almost 70 percent of the time. However, the Board exerts more discretion for crimes with a severity level higher than five, and follows the guidelines less than 20 percent of the time in those instances.

I use the Conviction Data to construct my instrument for sentence length. I limit the Conviction Data to felons convicted between 2001 and 2013 because the GDC started recording the name of the sentencing judge after 2001. The judge harshness index, described in Section 3.3, is determined based on the sentencing patterns of a judge over 13 years. It is calculated from the judge's full caseload without excluding any sentences.[17] The final Conviction Data sample has more than 700,000 observations, and it is used only for the construction of the judge harshness index.

Table 1 shows summary statistics for the sample used in the main analysis, which consists of convicts sentenced after 2001 and released from prison before 2005. Individuals in the sample are predominantly male and black, with an average age at release from prison around 34.8. The average prisoner has 2.8 prior convictions and the two most common crimes for which a prisoner has been incarcerated are property (41 percent) and drug-related (38 percent). Because I exclude crimes with severity levels above five from the estimation sample, it is not surprising that only 6 percent of prisoners are charged with a violent offense. The mean sentence length is just above four years, while the mean prison time served is about 22 months. The average prisoner serves only 52 percent of his sentence behind bars, and the rest on parole, which highlights the importance of evaluating the impact of non-custodial time on recidivism.

In the analysis, parole time is measured as the portion of the prison sentence not served behind bars. The average parole supervision time is 26.5 months. However, there are two

[16] My instrument for time served becomes very weak if I include people convicted to serious crimes.
[17] Please refer to Appendix A for more details on how I handle life sentences.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
Prison and parole		
Returned to prison (RTP)	0.32	0.47
RTP on parole	0.23	0.42
RTP off parole	0.09	0.29
Prison time	22.07	8.74
Sentence length	48.60	21.08
Percent of sentence served	51.92	24.74
Parole time	26.54	20.54
Demographic and criminal background		
Black	0.60	0.49
Female	0.13	0.34
Age at admission	34.77	9.92
Prior convictions	2.76	2.89
Current offense		
Drug	0.38	0.49
Other	0.16	0.36
Property	0.41	0.49
Violent	0.06	0.23
Parole and judge		
Judge harshness index	64.12	20.62
Guidelines-recommended prison time	18.58	5.77
Success score	10.86	4.06
Severity level I	0.37	0.48
Severity level II	0.35	0.48
Severity level III	0.21	0.40
Severity level IV	0.08	0.27

Note: The table shows summary statistics of the estimation sample (N=8,402). Return to prison (RTP) is the probability that an individual returns to prison in the state of Georgia within 3 years of release. Prison time, parole time, sentence length are measured in months. Judge harshness index is a leave-out mean sentence (in month) given by a judge between 2001 and 2013. Guidelines-recommended prison time is the recommend months to serve in prison as shown in Table 2. Severity level measures are defined in Table OA2 and the success score is calculated based on the factors listed in Table OA1.
Data source: Georgia Prison and Conviction Data.

main reasons why this might not be the actual length of parole supervision. First, the Official Code of Georgia Annotated (O.C.G.A.) §42-9-52 grants the Board the authority to discharge a person from parole prior to the expiration of the judge-determined sentence. Second, if a parolee absconds, the Parole Board can stop his parole supervision time until he is found and then keep him on parole after the sentence expiration date to make up for the time. In the Prison Data, I observe the last date of discharge for the incarceration episode of each inmate. It will be problematic for the identification of parole time if these exceptions are very prevalent in the data because the Parole Board can decide not only how long a person should serve behind bars, but also has the power to either increase or decrease the judge-determined sentence. To explore whether the additive relationship between shorter prison time and longer parole time is preserved in my estimation sample, I further restrict my attention to people who have completed their prison sentence by October 2008, the end of the Prison Data, and therefore have a recorded parole discharge date. I plot the difference in months between the sentence expiration date and the parole discharge date in Figure OA4. About 60 percent of parolees are discharged from parole supervision within 3 months of their sentence expiration date and only 617 people are discharged from parole past the sentence expiration date determined by the judge. So, the additive relationship between shorter prison time and longer parole time is preserved for a majority of the observations.

Almost 32 percent of the sample return to prison, with or without a new sentence, within three years of release. I construct two additional recidivism measures depending on the timing of the recidivating event, and I find that 23 percent of the people who return to prison do so while on parole supervision. One drawback of the data is that recidivism is observed only within the state of Georgia, so in the data I cannot distinguish an individual who reoffends in a different state from an individual who does not reoffends in the state of Georgia.[18]

[18]The majority of my sample consists of adults released before their sentence expiration date. Given that one condition of parole is often that the parolee stays within the state after release, it is unlikely that reoffending in a different state is prevalent. Additionally, using data on prison releases from 30 states in 2005, Durose et al. (2014) estimate that only about 7% of released prisoners were arrested out of state within 3 years of release. So while out of state migration could potentially be an issue, I believe it will not have large effects on my results.

3 Empirical Strategy

To estimate the joint effect of prison and parole time on recidivism, I adopt an instrumental variable (IV) approach. In the subsections that follow I explain how the institutional set-up in Georgia allows me to construct two instruments needed for the estimation of total prison sentence on reoffending. I also discuss the empirical framework and the identification of both parole and prison time.

3.1 Institutional Details

The O.C.G.A. defines criminal conduct and has established high maximum sentences. Once a felon is convicted under a certain penal code citation, it is typically the judge who determines the sentence.[19] In Georgia, judges have complete discretion to impose any sentence within the very wide statutory bounds set by O.C.G.A. For instance, while O.C.G.A. requires that a sentence for robbery should not be shorter than one year and not longer than 20 years, the judge has full discretion to impose any sentence up to the statutory maximum. Most importantly for my analysis, within a specific court, felony cases in Georgia are assigned randomly to judges, whose judicial calendar is predetermined at the beginning of the year.[20]

The Georgia Parole Board starts preparing an individual's parole file immediately upon receiving individual's sentencing sheet from the Clerk of Courts. The sentencing sheet contains the individual's sentence length, maximum release date, and, if applicable, the parole eligibility date determined by state law. Once the convict is transferred to one of the GDC diagnostic prisons, the Parole Board starts its pre-parole investigation. This investigation includes interviewing the prisoner to obtain information about family, education, job history, criminal record, health, and any other personal information. All court records pertaining to

[19]In Georgia, there are no sentencing guidelines that structure the sentencing process or limits judicial discretion by requiring judges to reference or adhere to a specific sentencing recommendations that are typically established by a state sentencing commission.

[20]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 main analysis to only new court convictions.

the prisoner are also included, such the circumstances of the current offenses, prior convictions, arrests, etc.

Table 2: Georgia Parole Board Guidelines

Crime Severity Level	Success Group (Score)		
	Excellent (14-20)	Average (9-13)	Poor (0-8)
I	10	16	22
	(18.61)	(20.71)	(24.64)
II	12	18	24
	(17.88)	(20.53)	(25.21)
III	14	20	26
	(21.93)	(23.08)	(26.29)
IV	16	22	28
	(25.93)	(24.82)	(26.77)

Note: This table shows the recommended prison time (in months) based on the crime severity level and success scores outlines by of the Georgia Parole Board Guidelines. Total success scores are grouped in three groups: excellent (14 to 20 success points), average (9 to 13 success points), and poor (less than 8 success points). For more information about the Parole Guidelines refer to `https://pap.georgia.gov/parole-consideration/parole-consideration-eligibility-guidelines`T. The numbers in parenthesis correspond to the mean actual prison time (in months) based on the estimation sample (N=8,402).

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 Board has developed Parole Guidelines. In Georgia, every parole-eligible inmate is evaluated using the Guidelines 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 it.[21] The columns of Table OA1 correspond to the parole success score that reflects age, prior offense record, and other pre-incarceration prisoner's characteristics. Table OA1 shows all the components used in this calculation along with their corresponding success score points. Every inmate receives success points on each of eight success factors

[21] 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.

based on the past and current criminal and personal background. The inmate's total success score is a summation of the points received on each factor.[22] The parole success score is bracketed into three categories: poor (0–8 points), average (9–13), and excellent (14–20). The cells of Table OA1 contain recommended lengths of prison time based on the success score and crime severity level, in months. The Parole hearing examiner determines the tentative parole month (TPM) based on the recommended prison time using the Parole Guidelines shown in Table 2. The Guidelines' recommended prison time and TPM are then included in the summary of the contents of the parole file.

In contrast to parole under mandatory supervision (also known as "good time" release), parole in Georgia is granted or denied at the absolute discretion of a five-member panel. The Parole Board does not meet as a group to review the parole files, but rather each member reviews them and votes independently to set a tentative parole month, a reconsideration date, or neither a reconsideration date nor a tentative parole month. The Board members are not bound by the recommended prison time and the tentative parole month based on the Guidelines when casting their vote. When determining the actual tentative parole month, the voting members can take into account their general impression of the inmate as well as other factors such as statements from the victim, prosecutor, police officers, and most importantly for the purpose of this paper, the judge. The parole decision is set once the first three Board members vote the same way (O.C.G.A. §42-9-42). If the Board decides to set neither a reconsideration date nor a tentative parole month, the prisoner serves its maximum sentence set by the judge. If the Board has set a reconsideration date, then the Board will make a decision whether to set a tentative parole month on that date. Note that the tentative parole month is not a guaranteed release date, but it is a tentative decision to grant parole on that date. A few months before the tentative parole month, the Board members review all new materials added to the parole file or any new disciplinary records and decide to grant or deny parole.

It is worth noting that the Parole Guidelines and the calculation of the success score during my study period do not explicitly include the judge's sentence.[23] The heterogeneity

[22] To illustrate the process, suppose that an inmate was previously incarcerated at the age of 17, then 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.

[23] Since 2008, which is outside of my estimation period, the statewide-average length of prison sentences imposed by Georgia Superior Court judges have been included in the Parole Guidelines. For more information

of the sentencing judge does not directly affect prison time but it can affect, indirectly, the release decisions of the Parole Board because statements of the sentencing judge might be included in the inmate's parole file.[24] In the case of Georgia, there are two additional channels through which the judge can indirectly affect prison time. First, inmates are eligible to be considered for parole and have the Board decide on their parole file on the parole eligibility date (PED), which is usually set at around one-third of their prison sentence. Although the Parole Board could release a prisoner before his parole eligibility date, it has to inform the sentencing judge in writing about its decision and the judge has the option to express his or her opinion. Second, the judge's decision might affect the Parole Board in determining the length of imprisonment period given that a prisoner can be incarcerated for more time than his original sentence in some rare instances.[25]

3.2 Identification of Time in Prison and Time on Parole

Figure 1: Timeline of How a Sentence is Carried Out

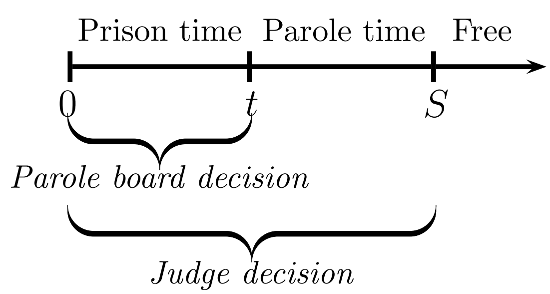


Figure 1 represents a simple graphical depiction of how a sentence is carried out in the state of Georgia. At time 0 a convict is sentenced by a judge and receives a sentence of length S. Shortly after that, the Parole hearing examiner prepares the parole file of the convict and

about this, please refer to `https://pap.georgia.gov/parole-consideration-eligibility-guidelines`. None of the prisoners in my sample was graded after this particular policy change.

[24]Unfortunately, I do not observe the content of each parole file and whether it contains any statements from the judge in the data.

[25]If a prisoner absconds supervision, meaning that the parolee missed an appointment and/or his or her whereabouts were unknown, then the Parole Board will increase his sentence by the number of days the prisoner is unaccounted for. Only 25 individuals, or 0.3 percent of the estimation sample, served more time behind bards than their sentence.

calculates the recommended prison time based on the Parole Guidelines. The Parole Board then reviews the file and the Guidelines-recommendation, determines the temporary parole month, and ultimately, releases the prisoner at time t. Thus, the convict serves time t in prison and completes the rest of his sentence, $S - t$, on parole supervision.

Causal estimation of the effect of prison time on recidivism requires random variation in t. However, such variation on its own will not be sufficient to identify parole time, $S-t$, because identification of parole time requires random variation in both prison time and sentence. I construct two instrumental variables that offer quasi-experimental variation in both t and S, and allow me to estimate the causal effect of parole time on reoffending. It is worth noting that each of these instruments on its own will not be sufficient to identify parole time given that the Parole Board is the ultimate decider of prison time in Georgia. First, if I instrument only for sentence length, I can identify the combination of time in prison and time on parole and I cannot identify either one separately.[26] Second, if I instrument for prison time, I could identify only the effect of time in prison. However, in states that have discretionary release and $t < S$, any such instrument could potentially be correlated with parole time simply due to the mechanical relationship that parole time is the sentence minus time served in prison.[27]

Since early releases from prison in Georgia are based solely on the discretion of the Parole Board, it is the Board members that ultimately decide t. The main quasi-experimental variation in prison time is therefore derived from the formula-calculated recommended prison time based on Parole Guidelines Table 2. Each cell of these Guidelines contain recommended lengths of prison stay, which I use as an instrument. Once I control for success points and severity level, the remaining variation of the Guidelines-recommended prison time should be uncorrelated with individual's propensity to recidivate. The identification thus takes advantage of the difference in the recommended prison time between adjacent cells of the Parole Guidelines. I test the relevance of my instrument empirically in the first stage and the relationship between the Parole Guidelines-recommended time and actual prison time goes in the expected direction.

[26] This argument is particularly harmful to studies that have used sentence length as a proxy for prison time and random assignment of judges in states with a discretionary parole (Green and Winik, 2010).

[27] Kuziemko (2013) uses the same data over a different time period and same instrument for prison time as the one used in my analysis. Her estimate of the effect of prison time on recidivism, however, could potentially be confounded and most likely overstates the true effect. In her regressions, she does not include parole time but she does include sentence fixed effects, which might have attenuated the omitted variable problem.

I measure judge stringency as the average sentence length in other cases a judge has handled. This serves as an instrument for sentence length since it is highly predictive of the judges decision in the current case, but as I document in the next section, uncorrelated with observable case characteristics. Random assignment of cases to judges is sufficient for a causal interpretation of the reduced form impact of being assigned to a stricter judge and receiving a longer sentence and addresses concerns over correlated unobservables.[28] Figure OA1 shows the relationship between prison time, parole time, and judge harshness index. The ultimate decider of prison time is the Parole Board and the prisoner's initial sentence is not directly accounted for in the Parole Guidelines. It is therefore not surprising that a judge's heterogeneity provides minimal variation in prison time in Georgia, but it does provide significant variation in parole time through its effect on S. A judge's stringency measure, through its effect on S, and the Parole Guidelines-recommended prison time, through its effect on t, are the two instrumental variables that allow me to identify the causal effect of parole time, $S - t$, on reoffending. My empirical results suggest that the latter instrument has a larger effect on parole time than the former.

While random assignment of judges can be useful to address concerns over correlated unobservables, there remain issues that could bias the estimated effect of prison time on recidivism. In particular, in contexts where the parole board is the true decider of prison time, random assignment of judges can be a very weak instrument for prison time, which may lead to severe bias in the two-stage least squares estimates.[29]

3.3 Construction of the Instruments and First Stage Estimation

Since judges vary in their sentencing ideologies and the assignment of cases is random, defendants in Georgia 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

[28] I test the validity of the random assignment assumption in the section 3.3.

[29] In 2016, 49.5% of the total adults entering parole supervision were due to a parole board decision, and 23 states including Texas, Pennsylvania, Missouri, among others, used discretionary parole as their main method of parole release (Kaeble, 2018).

assignment of judges is truly random, as I assume, this requirement will be satisfied and the two-stage least squares estimates will be unbiased.

Following Aizer and Doyle Jr (2015), for defendant i's judge, I construct a judge harshness index, $Judge_i$, and use it to instrument for i's actual sentence length.[30] Using an exhaustive set of sentences a judge hands down can produce a bias, which results from the mechanical correlation between an 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 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. Adult felony offenders in Georgia may be sentenced to serve time either in prison or in prison to be followed by a period of time on probation (split sentence). I include only the number of years sentenced to prison and ignore the probation part of the sentence for split sentences when I calculate the judge's harshness index. 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. Ignoring the probation part of a split sentence should not be problematic and should not underestimate the judge harshness index if lenient judges are more likely to give split sentences.[31]

Although it is impossible to verify directly whether judges are indeed assigned to defendants at random, one can examine the validity of this assumption using the available data.[32] In particular, if defendants are randomly assigned to judges, I would expect those

[30] Aizer and Doyle Jr (2015) 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 or not.

[31] Such an assumption seems to be plausible as Gottfredson (1999) argues that judges take into consideration their own prediction and judgment of whether the offender will recidivate when imposing a split sentence. This means that if a judge believes that an offender is less likely to recidivate, she/he might be more likely to order less prison time and more probation time.

[32] According to discussions with Mike Cuccaro, random assignment of cases is a priority of each circuit

Table 3: Random Assignment Test

Characteristic	(1) Lenient ($Judge_i < Median$) Unconditional mean	(2) Harsh ($Judge_i \geq Median$) Conditional mean	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

Notes: I define harsh judges to be those whose harshness index, as defined by Equation 1, is greater or equal to the median in the whole Conviction Data; and lenient, otherwise. Col.(1) reports the unconditional means of the observable defendant characteristics. Col.(2) reports the predicted means from OLS regressions of each characteristics on an indicator if the sentencing judge is harsh. 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 equals 1 if the judge harshness index, which is leave-out mean sentence given by the judge over the sample period, is greater or equal to the median. The judge harshness index is measured in years. Circuit court and year of sentence fixed effects are included in each regression and standard errors are clustered by circuit court.
Data source: Georgia Conviction Data (N=701,562).

appearing in front of lenient judges to be similar on observables to defendants assigned to harsher judges. Following Aizer and Doyle Jr (2015), 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:

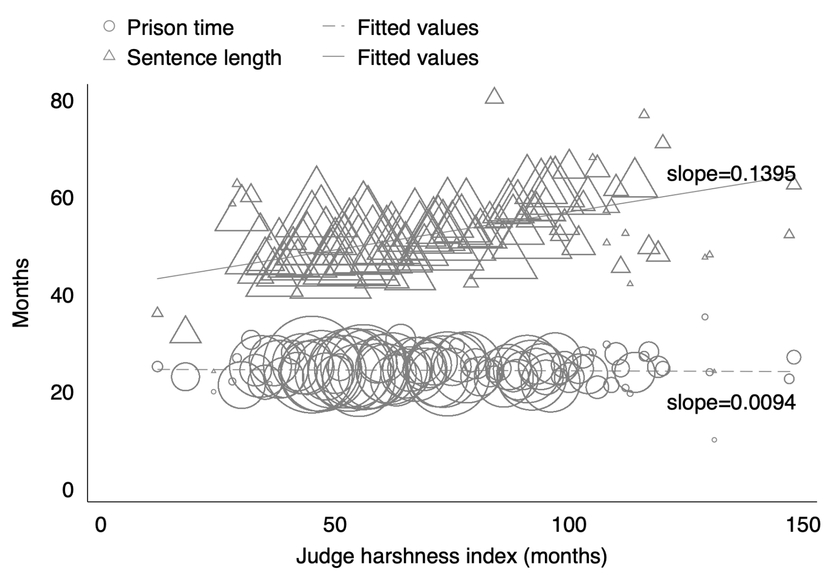
$$Char_i = \phi_0 + \phi_1 \mathbb{I}[Judge_i \geq Median] + \kappa_c + \tau_y + \epsilon \tag{2}$$

where $\mathbb{I}[Judge_i \geq Median]$ is an indicator that equals to 1 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 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 3. 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 3 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 a statistically significant predictor of any of the defendants' characteristics.

Figure 2 plots the average time served in prison and the average sentence length by the harshness of the judge. Each circle or triangle corresponds to the average time in prison and sentence length, respectively. 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. A one month increase in the harshness of the judge leads to an expected 0.13 month increase in defendant's sentence. It is worth noting that the judge harshness index provides

court in Georgia.

Figure 2: Sentence Length and Time Served in Prison by Judge Harshness Index



almost no variation in time served.[33] Second, the difference between the fitted values for sentence length and those for time served in prison represents the parole time. Graphically, it is apparent that if one wants to estimate the effect of parole time, one needs another source of independent variation. In what follows, I describe the second instrument that will 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 the offender gets released from prison. To instrument for the actual prison time served, I rely on the institutional peculiarities of the release policy in Georgia, and in particular the Georgia Parole Board's Guidelines-recommended prison time. Controlling for severity and success score points fixed effects, I use the suggested months to serve from the Guidelines, outlined in Table 2, as an instrument for actual time served.[34] The identification thus takes

[33]This result can have implications for studies, such as (Green and Winik, 2010), that use random assignment of judges in states that use discretionary parole as their main prison release mechanism and sentence length as a proxy for prison time and random assignment of judges as an instrument for prison time.

[34]See Angrist and Lavy (1999) for details about this methodology.

advantage of the difference in the recommended prison time between adjacent cells of the Parole Guidelines. In Table 2, I observe that conditional on severity level lower success scores are associated with more time in prison on average. Similar pattern is observed if we condition on success group–namely, higher severity levels are on average associated with more prison time. The relationship between the success score, time in prison, and time on parole is depicted in Figure OA2, where the lines represent the mean time served in prison and on parole. The patterns in the graph match what I observe in Table 2—namely, the higher the success score, the lower the average time served in prison and the higher the average time on parole.

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. Time on parole supervision is defined as the difference between the individual's sentence and time served in prison. One can think of time on parole as the portion of the criminal sentence a prisoner served under correctional supervision, but not behind bars. $Recom_i$ is the recommended time to serve from the parole guidelines for prisoner i. In Georgia, recommended prison time is determined by a known deterministic function of two variables—parole success points (criminal background) and severity level (current crime type). Given that I control for both these two variables,the guidelines-recommended 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.[35]

$Judge_i$ is the average sentence based on sentencing patterns 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

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

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 a predetermined yearly schedule, I include year of sentence fixed effects to account for any year-to-year variation in the availability 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.

3.4 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 ordinary least squares is that neither time served in prison nor time spent 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.[36] 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.[37] By construction, the time on parole is calculated as the sentence minus the number of months served in prison. An implication

[36] 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.

[37] 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.

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 effect of an additional month served behind bars and of a month less served on parole. This joint effect estimates the full impact of criminal punishment for reoffending.

The sign of the effect of parole time on recidivism, captured by the coefficient estimate β_2, is ambiguous a priori. Offenders who receive a large reduction in their sentence might get the impression that the criminal justice system is generally more forgiving and they might 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 reoffend and have to return to prison to serve the rest of their sentence behind bars suggesting that β_2 could be positive.

4 Results

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

The first stage results are given in Table 4. I follow Sanderson and Windmeijer (2016) to perform a multivariate F-test for weak instruments, which is a refinement of the Angrist Pischke multivariate F-test. The Sanderson and Windmeijer (2016)'s conditional first stage F statistic measure of instrument strength, shown at the bottom of Table 4, is high enough indicating that both instruments are predictive of time served in prison 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 quarter of a month less time on parole, while a one month increase in the judge harshness index leads to 0.06 more months spent under community supervision of parole. Although the judge harshness index has a small effect, perhaps due to the fact that parole supervision can rarely exceed judge-determined sentence length, the Parole Guidelines recommendations have the most predictive power for time served in prison. As seen in Table 4 Col. (2), a one month increase in the Guidelines-recommended months to be incarcerated results in almost a half month increase in the actual time served in prison. Given that the Parole

Table 4: First Stage Estimates

	(1) Parole time	(2) Prison time
Guidelines-recommended prison time	-0.248***	0.447***
	(0.0707)	(0.0496)
Judge harshness index	0.0614***	0.0122*
	(0.0181)	(0.00699)
Black	2.788***	-0.0470
	(0.470)	(0.191)
Female	1.223**	-2.628***
	(0.568)	(0.233)
Age at prison release	-0.0440*	0.0585***
	(0.0231)	(0.00989)
Prior convictions	-0.273**	0.303***
	(0.111)	(0.0462)
Constant	41.22***	5.838**
	(8.666)	(2.894)
Observations	8,402	8,402
F-stat	17.36	
R-squared	0.151	0.229

Notes: Heteroskedasticity-robust standard errors in parentheses. Estimates in Col. (1) and (2) are obtained by OLS. The dependent variables, parole time and prison time, are measured in months. Besides the variables reported, all regressions control for crime type (violent, property, drug, other), year of sentence, circuit court. Dummy variables for success points and severity level are also included in Col.(1) and (2). The listed F-stat corresponds to Sanderson and Windmeijer (2016)'s "conditional first stage F-stat" measure of the instrument strength under multiple endogenous variables. *** p<0.01, ** p<0.05, * p<0.1

Board has full discretion on early releases in Georgia, it is not surprising that the coefficient estimate on Parole Guidelines is much bigger in magnitude than the judge harshness index. Although the true decider of prison time in Georgia is the parole board, there are three possible explanations how the judge can still influence time served in prison, which might explain the small significant coefficient on the judge harshness index in Table 4 Col. (2). 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.[38] Second, statements from the judge could potentially be included in the prisoner's parole file that could have an effect on the prison release decision by the Parole Board. Finally, the judge's decision might affect the Board in determining the length of imprisonment period because a prisoner can rarely be incarcerated for more time than his original sentence.

Table 5 presents the regression results from the second stage for the effect of prison and parole time on whether the released prisoner returns to prison within three years of release. Note that both columns report estimates from a linear probability model and Col. (1) shows the OLS estimates, which do not take into account the endogeneity of time served in prison or on parole and the propensity to reoffend. The OLS results for time on parole suggest that parole has a significant but small criminogenic effect. These estimates are most probably biased upwards or towards zero because of selection. In particular, those sentenced to longer terms probably spent more time on parole and are more likely to reoffend. Once I control for selection on unobservables, Col. (2) suggests that both time on parole and time in prison have a deterrent effect, but these effects are not statistically significant. A possible explanation for the divergence between the OLS estimates and the IV estimates is that the OLS estimates suffer from selection bias due to correlated unobservables. In particular, people with higher risk of reoffending might be assigned more prison time by the Parole Board and might receive longer sentence from a judge. If this is the case, one could conclude that the high rates of recidivism among ex-convicts is due to selection, and not a consequence of the experience of being under correctional supervision. The negative effect of parole could simply be due to the nature of how behavior is monitored on parole, as individuals under parole supervision will be monitored more closely by a parole officer, and

[38] 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 my sample, only five percent of inmates are released before the PED. Moreover, the results are robust to excluding these individuals.

Table 5: Second Stage Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Dependent Variable	Recidivism		Recidivism on parole		Recidivism off parole	
Prison time	0.000404	-0.00583	-0.000226	-0.0104***	0.000705*	0.00456
	(0.000617)	(0.00476)	(0.000527)	(0.00376)	(0.000378)	(0.00324)
Parole time	0.00474***	-0.00479	0.00857***	-0.000227	-0.00380***	-0.00351
	(0.000254)	(0.00625)	(0.000217)	(0.00504)	(0.000155)	(0.00391)
Black	0.00974	0.0359*	-0.0109	0.0129	0.0216***	0.0211*
	(0.0111)	(0.0207)	(0.00949)	(0.0171)	(0.00680)	(0.0126)
Female	-0.0545***	-0.0591***	-0.0320**	-0.0477***	-0.0243***	-0.0146
	(0.0148)	(0.0174)	(0.0126)	(0.0150)	(0.00903)	(0.00998)
Age at release	-0.00574***	-0.00580***	-0.00414***	-0.00396***	-0.00145***	-0.00165***
	(0.000542)	(0.000597)	(0.000462)	(0.000510)	(0.000331)	(0.000358)
Prior convictions	0.00730***	0.00657**	0.00409*	0.00477*	0.00250	0.00140
	(0.00258)	(0.00319)	(0.00221)	(0.00274)	(0.00158)	(0.00188)
Constant	0.344	0.703**	0.199	0.648**	0.147	0.0254
	(0.234)	(0.331)	(0.200)	(0.297)	(0.143)	(0.167)

Notes: Heteroskedasticity-robust standard errors in parentheses. The odd columns report estimates from an OLS model while the even columns report estimates from an IV model. Besides the variables reported, all regressions control for crime type (violent, property, drug, other), year of sentence, circuit court. The IV regressions also include success points and severity level fixed effects. In Col. (1)-(2), the dependent variable is an indicator that equals to one if the inmate returned to prison within three years of his release and zero otherwise. In Col. (3)-(4), the dependent variable is an indicator that equals to one if the inmate returned to prison within three years of his release while under parole supervision and zero otherwise. In Col. (5)-(6), the dependent variable is an indicator that equals to one if the inmate returned to prison within three years of his release while not under parole supervision and zero otherwise. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

therefore might encounter fewer criminal opportunities or be afraid of being caught easily. To better understand the role of parole supervision Table 5 presents IV estimates of the effect of parole and prison time on recidivism occurring while under parole supervision and not. Yet I find no statistically significant effect of the duration of non-custodial sanctions.[39]

In the case of collective pardon in Italy, Drago et al. (2009) find a big deterrent effect of the unserved portion of the sentence. 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 his new sentence. Though the fact that reoffending while on parole might be an aggravating factor when the judge determines sentence, it is not necessarily true that the previously unserved time would be fully reflected in the new sentence. Moreover, because the pardon in Italy manipulated both past time served and prospective time served, this enhanced punishment could result in unusual cognitive salience that could explain the large deterrent effect that the authors find.

I build upon Kuziemko (2013) by quantifying the effect of total correctional punishment and estimating the treatment effect of parole time. In contrast to Kuziemko (2013), I find that time behind bars does not have any statistically significant effect on overall recidivism rate. Besides losing its significance, the estimated effect is almost half of Kuziemko (2013). A plausible explanation might be the way I restrict the sample because of the missing judges' names. In particular I focus on people who serve a maximum of five years in prison, while (Kuziemko, 2013) includes people who serve a maximum of ten years. To investigate further, I run the second stage accounting for the timing of recidivism. I find that a one month increase in time spent in prison leads to a 1.04 percentage point (approximately 4.5 percent) decrease in the likelihood of returning to prison within three years after release if the recidivating event occurs under parole supervision. The estimate flips sign and becomes insignificant

[39]The estimated effect of parole time on recidivism is modest in magnitude, suggesting that one month on parole is associated from 0.1 percent to 3.9 percent decrease in individual's probability of returning to prison withing 3 years of release. Although the effect of parole time seems modest at the individual level, it could potentially be sizable given that more that 4.5 million are under some type of community supervision.

if the recidivism occurs after parole supervision. A possible reason why I see this effect only when the recidivism occurs under parole supervision might be due to how behavior is monitored while on parole. Being monitored by a parole officer might make it much more costly to be involved in criminal activities because there is a higher chance of being caught under non-custodial supervision. Although prisoners in my sample serve just less than 3 months in prison than those in (Kuziemko, 2013), they might be on parole for a much shorter period of time, which might explain why I do not observe significant effect of prison time on overall recidivism, but do observe a negative effect once I take into account the timing of the recidivating event.[40]

To investigate the degree to which not including parole time confounds the estimation of prison time, Table OA5 presents the second stage estimates with and without controlling for parole time. In the case of Georgia and using the Georgia's Parole Guidelines as an instrument for time in prison, I do not find evidence that excluding parole biases the effect of prison time by a lot. It appears that not accounting for parole time does not distort the estimated effect of prison time.

The other covariates have the expected signs. For instance, the probability to recidivate is 5.45 percentage points lower for females, and decreases by almost half of a percentage point with each additional year of age—consistent with the fact that criminality declines with age (Bushway and Piehl, 2007). Prior criminal history has a robust negative statistically significant effect on the probability of recidivism.

4.2 Heterogeneous Effects of Time Served in Prison and on Parole

Motivated in part by the overrepresentation of minorities in the U.S. criminal justice system, in this section, I investigate whether the deterrent effect of prison and parole varies across inmate characteristics. The second stage estimates by race and type of offense, reported in Tables 6 and 7, are in line with the full-sample findings for the lack of a significant effect of time spent on parole on recidivism. Nevertheless, the full-sample results of the deterrent effect of time in prison appears to be driven primarily by the sample of white prisoners. 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

[40]Unfortunately, (Kuziemko, 2013) does not report the average sentence length for her sample and thus I cannot verify that the prisoners in her sample spent much less time on parole than those in my sample.

Table 6: Heterogeneous Effects of Time Served in Prison and on Parole on Recidivism

	By Race		By Crime Type			
	White	Minority	Drug	Violent	Property	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Prison time	-0.0123*	-0.00518	0.0121	0.0221	-0.0186	-0.00630
	(0.00678)	(0.00368)	(0.0146)	(0.0509)	(0.0114)	(0.00855)
Parole time	-0.0240	0.00452	0.000609	0.0194	-0.0154	0.00375
	(0.0155)	(0.00756)	(0.00744)	(0.0303)	(0.0157)	(0.0139)
Black			0.0366	-0.0726	0.0167	0.00606
			(0.0403)	(0.170)	(0.0267)	(0.0262)
Female	-0.0132	-0.103***	0.00287	-0.0401	-0.0571	-0.0172
	(0.0350)	(0.0243)	(0.0404)	(0.135)	(0.0450)	(0.0871)
Age at release	-0.00709***	-0.00508***	-0.00650***	-0.00872**	-0.00310**	-0.00708***
	(0.00139)	(0.000782)	(0.00145)	(0.00425)	(0.00149)	(0.00146)
Prior convictions	0.0106	0.0122**	0.000896	0.0267	0.00455	0.0166*
	(0.00717)	(0.00508)	(0.00701)	(0.0217)	(0.00580)	(0.00960)
Constant	1.593***	-0.229	0.0743	-1.466	1.258**	0.778
	(0.552)	(0.533)	(0.440)	(2.991)	(0.633)	(0.482)
Observations	3,329	5,073	3,185	464	3,438	1,315

Notes: Heteroskedasticity-robust standard errors in parentheses. The estimates reported are from an IV estimation and each column is estimated on the sample of individual indicated by the column header. Besides the variables reported, all regressions control for crime type (violent, property, drug, other), year of sentence, circuit court, success points and severity level fixed effects. The dependent variable is an indicator that equals to one if the inmate returned to prison within three years of his release and zero otherwise. *** p<0.01, ** p<0.05, * p<0.1

blacks.[41]

Table 7: Heterogeneous Effects of Time Served in Prison and on Parole on Recidivism while on Parole

	By Race		By Crime Type			
	White	Minority	Drug	Violent	Property	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Prison time	-0.0118**	-0.00936***	0.0150	-0.00641	-0.0196**	-0.0142*
	(0.00508)	(0.00305)	(0.0153)	(0.0168)	(0.00970)	(0.00750)
Parole time	-0.0127	0.00463	8.26e-05	0.0104	-0.00946	0.0211
	(0.0118)	(0.00619)	(0.00697)	(0.0101)	(0.0136)	(0.0129)
Black			0.0271	0.00933	0.00520	0.00399
			(0.0373)	(0.0626)	(0.0236)	(0.0257)
Female	-0.00853	0.106*	0.0458	-0.102	-0.0592	-0.0709
	(0.0273)	(0.0627)	(0.0423)	(0.0629)	(0.0380)	(0.0846)
Age at release	-0.00515***	-0.0745***	-0.00551***	-0.000674	-0.00236*	-0.00530***
	(0.00107)	(0.0211)	(0.00141)	(0.00177)	(0.00129)	(0.00146)
Prior convictions	0.00823	-0.00340***	-0.00120	0.00975	0.00422	0.0130
	(0.00568)	(0.000662)	(0.00681)	(0.0104)	(0.00503)	(0.00870)
Constant	1.299***	-0.0528	0.139	-0.500	1.173**	0.437
	(0.435)	(0.442)	(0.422)	(1.012)	(0.571)	(0.342)
Observations	3,329	5,073	3,185	464	3,438	1,315

Notes: Heteroskedasticity-robust standard errors in parentheses. The estimates reported are from IV and each column is estimated on the sample of individual indicated by the column header. Besides the variables reported, all regressions control for crime type (violent, property, drug, other), year of sentence, circuit court, success points and severity level fixed effects. The dependent variable is an indicator that equals to one if the inmate returned to prison within three years of his release while under parole supervision and zero otherwise. *** p<0.01, ** p<0.05, * p<0.1

I do not find any heterogeneous effects with respect to type of crime. These results, however, do change once I separately examine recidivism on and off parole as a dependent variable. I find heterogeneous effects of time in prison in both type of crime and race for

[41]It is worth pointing out that the differences in the effects of prison time and parole time in Table 6 are not statistically different across race. Testing whether the effect of prison time is different for white and minority prisoners is yields a p-value of 0.3034 while testing whether parole time is different across race results in a of 0.4207.

individuals who recidivate while on parole. I find that prison time decreases the probability of recidivism while on parole for both White and minority convicts, though the effect for minorities is half of that for white inmates. A similar effect is observed for property offenders. The point estimates for property offenders suggest that an additional month behind bars results in a 1.96 percentage point decrease in the probability that they will return back to prison within three years of release.

5 Conclusions

This paper investigates how release before full completion of a criminal sentence affects recidivism. The causal effect of prison and parole time on recidivism is 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 1.04 percentage points only if a prisoner recidivates while on parole. With respect to the previous literature, this study makes two important contributions. First, it quantifies the effect of time on parole, and in tern the effect of total correctional supervision, on recidivism. My estimate on prison time is small and insignificant. The insignificance of this effect might be rationalized by the fact that the Parole Board is assessing the recidivism risk of prisoners accurately.[42] The insignificance of this effect might be rationalized by the fact that the Parole Board is assessing the recidivism risk of prisoners accurately. 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-evaluate policies that limit parole discretion. The declining use of parole discretion may explain why recidivism rates have been so high. 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.

State and federal governments 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 on recidivism rates, more research is needed

[42] This is in line with 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.

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 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.

References

Aizer, Anna and Joseph J Doyle Jr, "Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges," *The Quarterly Journal of Economics*, 2015, *130* (2), 759–803.

Angrist, Joshua D, "Instrumental variables methods in experimental criminological research: what, why and how," *Journal of Experimental Criminology*, 2006, *2* (1), 23–44.

Angrist, Joshua D. and Victor Lavy, "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," *The Quarterly Journal of Economics*, 1999, *114* (2), 533–575.

Angrist, Joshua D, Guido W Imbens, and Donald B Rubin, "Identification of causal effects using instrumental variables," *Journal of the American statistical Association*, 1996, *91* (434), 444–455.

Bronson, Jennifer, "Justice Expenditure And Employment Extracts, 2013 - Final," *Bureau of Justice Statistics. Washington, DC: US Department of Justice*, 2018.

Buonanno, Paolo and Steven Raphael, "Incarceration and Incapacitation: Evidence from the 2006 Italian Collective Pardon," *The American Economic Review*, 2013, *103* (6), 2437–2465.

Bushway, Shawn D and Anne Morrison Piehl, "The inextricable link between age and criminal history in sentencing," *Crime & Delinquency*, 2007, *53* (1), 156–183.

_ **and Emily G Owens**, "Framing Punishment: Incarceration, Recommended Sentences, and Recidivism," *Journal of Law and Economics*, 2013, *56* (2), 301–331.

Carson, E Ann, "Prisoners in 2016," *Bureau of Justice Statistics, December*, 2018.

Dahl, Gordon B, Andreas Ravndal Kostøl, and Magne Mogstad, "Family welfare cultures," *The Quarterly Journal of Economics*, 2014, *129* (4), 1711–1752.

Dobbie, Will and Jae Song, "Debt relief and debtor outcomes: Measuring the effects of consumer bankruptcy protection," *American Economic Review*, 2015, *105* (3), 1272–1311.

_ **, Jacob Goldin, and Crystal S Yang**, "The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges," *American Economic Review*, 2018, *108* (2), 201–40.

Drago, Francesco, Roberto Galbiati, and Pietro Vertova, "The deterrent effects of prison: Evidence from a natural experiment," *Journal of Political Economy*, 2009, *117* (2), 257–280.

Durlauf, Steven N and Daniel S Nagin, "Imprisonment and crime," *Criminology & Public Policy*, 2011, *10* (1), 13–54.

Durose, Matthew R, Alexia D Cooper, and Howard N Snyder, "Recidivism of Prisoners Released in 30 States in 2005: Patterns from 2005 to 2010," *Bureau of Justice Statistics*, 2014.

French, Eric and Jae Song, "The effect of disability insurance receipt on labor supply," *American Economic Journal: Economic Policy*, 2014, *6* (2), 291–337.

Gottfredson, Don M, *Effects of judges' sentencing decisions on criminal careers*, US Department of Justice, Office of Justice Programs, National Institute of Justice, 1999.

Green, Donald P and Daniel Winik, "Using Random Judge Assignments to Estimate the Effects of Incarceration and Probation on Recidivism Among Drug Offenders," *Criminology*, 2010, *48* (2), 357–387.

Heaton, Paul, Sandra Mayson, and Megan Stevenson, "The downstream consequences of misdemeanor pretrial detention," *Stan. L. Rev.*, 2017, *69*, 711.

Johnson, Rucker and Steven Raphael, "How Much Crime Reduction Does the Marginal Prisoner Buy?," *Journal of Law and Economics*, 2012, *55* (2), 275–310.

Jr, Joseph J Doyle, "Child protection and child outcomes: Measuring the effects of foster care," *The American Economic Review*, 2007, pp. 1583–1610.

Kaeble, Danielle, "Probation and parole in the United States, 2016," *Washington, DC: Bureau of Justice Statistics, US Department of Justice*, 2018.

_ **and Mary Cowhig**, "Correctional populations in the United States, 2016," 2016.

Kling, Jeffrey R., "Incarceration Length, Employment, and Earnings," *American Economic Review*, 2006, *96* (3), 863–876.

Kuziemko, Ilyana, "How should inmates be released from prison? An assessment of parole versus fixed-sentence regimes," *The Quarterly Journal of Economics*, 2013, *128* (1), 371–424.

Levitt, Steven D, "The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation," *The Quarterly Journal of Economics*, 1996, pp. 319–351.

Maestas, Nicole, Kathleen J Mullen, and Alexander Strand, "Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt," *The American Economic Review*, 2013, *103* (5), 1797–1829.

Maurin, Eric and Aurelie Ouss, "Sentence reductions and recidivism: Lessons from the Bastille day quasi experiment," *IZA Discussion Paper*, 2009.

McCrary, Justin and David S Lee, "The deterrence effect of prison: Dynamic theory and evidence," *Berkeley Program in Law & Economics, Working Paper Series*, 2009.

Mueller-Smith, Michael, "The criminal and labor market impacts of incarceration," *Working Paper*, 2015.

_ **and Kevin T Schnepel**, "Diversion in the Criminal Justice System," *Working Paper*, 2018.

Mukherjee, Anita, "Impacts of Private Prison Contracting on Inmate Time Served and Recidivism," *Available at SSRN*, 2017. https://ssrn.com/abstract=2523238orhttp://dx.doi.org/10.2139/ssrn.2523238.

Nagin, Daniel S and G Matthew Snodgrass, "The effect of incarceration on re-offending: Evidence from a natural experiment in Pennsylvania," *Journal of Quantitative Criminology*, 2013, *29* (4), 601–642.

_ **, Francis T Cullen, and Cheryl Lero Jonson**, "Imprisonment and reoffending," *Crime and justice*, 2009, *38* (1), 115–200.

Owens, Emily G, "More time, less crime? Estimating the incapacitative effect of sentence enhancements," *Journal of Law and Economics*, 2009, *52* (3), 551–579.

Petersilia, Joan, *Reforming probation and parole in the 21st century*, American Correctional Association Lanham, MD, 2002.

_ , *When prisoners come home: Parole and prisoner reentry*, Oxford University Press, 2003.

Raphael, Steven and Michael A Stoll, *A new approach to reducing incarceration while maintaining low rates of crime*, The Brookings Institution: Hamilton Project, 2014.

Sanderson, Eleanor and Frank Windmeijer, "A weak instrument F-test in linear IV models with multiple endogenous variables," *Journal of Econometrics*, 2016, *190* (2), 212–221.

Schmitt, John, Kris Warner, and Sarika Gupta, "The high budgetary cost of incarceration," *Washington, DC: Center for Economic and Policy Research*, 2010. http://www.cepr.net/documents/publications/incarceration-2010-06.pdf.

Tella, Rafael Di and Ernesto Schargrodsky, "Criminal recidivism after prison and electronic monitoring," *Journal of Political Economy*, 2013, *121* (1), 28–73.

A Appendix

I use data from the state of Georgia collected by the Georgia Department of Corrections (GDC). 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 prisoner population is reassuring because inmates in Georgia appear to be representative of those nationwide in some key ways. Table OA3 presents data on how individuals sentenced in the state of Georgia compare to those sentenced nationwide.[43] In 2000, 34.2 percent (34 percent) of the national (Georgia) felony population were imprisoned because of a property crime, 93.7 percent (89 percent) were male, and 33.3 percent (37.3 percent) were white. People sentenced nationwide and in Georgia also receive similar sentences. However, Georgia's prison population seems somewhat different from that nationwide in terms of its percentage black prisoners and in terms of its percentage of inmates imprisoned because of a violent and drug offense.[44] In 2000, black offenders comprised 46.5 percent (62.2 percent), and prisoners convicted of violent and drug crimes comprised 34.3 and 21.1 percent (25.6 and 30.3 percent), respectively, of the total number of individuals sentenced nationally (in Georgia).

The first dataset, referred to in the text as "Prison Data," contains administrative records of all people released from the Georgia prison system from 1980 to 2008. It provides rich socio-demographic, criminal history, parole, and current conviction information for the universe of people admitted to state prison in Georgia. I use these data to calculate my main recidivism measure, which is an indicator variable that equals 1 if a convicts returns back to prison within three years of release. Following Kuziemko (2013), I restrict the sample to individuals who spent at least seven months of prison time. 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 from prison by October 2005. A possible concern about this necessary data cut is that prisoners

[43]The statistics for Georgia are based on the raw Prison Data with no sampling restrictions described later in Section 2. The only restriction applied to the Prison Data is the exclusion of sentences to death or life in prison and sentences less than one year in order to better match the data from the Bureau of Justice Statistics. For more information, please refer to the notes on Table OA3.

[44]The discrepancies with respect to race are most likely due to how Hispanics are categorized in the GDC data and the Bureau of Justice Statistics analysis. The differences in terms of violent and drug crime types could be a result of the fact that I classify crime type as the major offense committed, while it is unclear whether BJS classifies crime types the same way.

who are released before 2005 have different observable characteristics than those released after 2005. 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 OA4. Overall, I do not observe that prisoners released before 2005 are much different in terms of observables than those released after 2005. Those released before 2005 spent similar time on parole and served almost the same percentage of their initial sentence compared to those released after 2005. In terms of demographics and parole success scores, the two samples seem to be comparable with the exception that early releases are more likely to be black inmates. 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 released before and those released after 2005. Referring again to Table OA4, 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 2005.

The second dataset, referred to in the text as "Conviction Data," contains all felony prison and probation sentences from the Georgia Superior Courts from 1980 to 2013. 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 solely for the calculation of the judge harshness index, $Judge_i$. I limit the Conviction Data to felony sentences handed down between 2001 and 2013 because the GDC incorporated in the Prison Data more complete information from the court dockets, including the actual name of the sentencing judge, by mid-2000. Before 2001, the data simply states "presiding judge" instead of containing the full name of the judge. Note that this necessary restriction results in restricting the Prison Data to individuals sentenced and sent to prison after 2001. I use the Conviction Data exclusively for constructing the judge harshness index, described in Section 3.3. I calculated the judge harshness index based on both the past and future sentences the judge assigned to a particular case has given.[45] I topcoded prison time to 80 years for all

[45]For instance, if a convict is sentenced on January 1, 2002, the judge harshness index for this convict

life sentences and sentences exceeding 80 years in prison in order to use the universe of cases a judge is randomly assigned to preside on between 2001 and 2013. This allows me to use each the universe of sentences of each judge so that I rely on a measure of judge severity defined by his/her full caseload over 13 years. Topcoding should not create any bias in my estimates if cases are randomly assigned to judges, which seems to be true given the tests I run in Section 3.3. I excluded 15 outlier judges who had fewer than 100 cases over the thirteen-year time period. These judges ruled on only 0.02 percent of the total cases in the Conviction Data. The final Conviction Data sample has more than 700,000 observations, and it is used only for the construction of the judge harshness index.

There are several main differences between my sample and that of Kuziemko (2013), which could explain the differences in our sample sizes. First, Kuziemko (2013) samples newly admitted prisoners, serving sentences between 7 months and 10 years, admitted after 1995 and released before 2006. Unlike Kuziemko (2013) who is able to take advantage of most of the GDC Prison Data, I need to restrict my sample to individuals admitted after January 2001 due the fact that GDC collected very sporadically the sentencing judge's name before that. This restriction results in a sample of people who were sentenced between 7 months and 5 years. Thus, Kuziemko (2013) looks at the effect of prison time for people who serve much longer sentences than the prisoners in my sample. Although individuals in both our samples serve similar prison time, prisoners in my sample receive much shorter sentences and thus spend less time on parole. Second, her data terminates in 2011 while mine terminates in 2008 because the GDC provided me with an older extraction of the data. Finally, unlike Kuziemko (2013), I do not restrict my sample based on parole success points. Kuziemko (2013) uses a regression discontinuity relying only on the discontinuity threshold between 8 and 9 success points generated by the Georgia Parole Guidelines. She therefore does not use all success points and restricts her sample to people who receive more than four and less than 13 success points. Similar to Kuziemko (2013) I only focus my analysis to crimes with a severity level less than five because the Parole Board bases parole decisions more on discretion than on the Parole Guidelines, but unlike her I use all success points in my main analysis.

will be determined by the sentences his/her judge has given before and after January 1, 2002.