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

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Abstract

In the United States, every year roughly 600,000 people are released from prison, two-thirds of them 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 time served in prison to better understand how custodial and noncustodial sanctions affect recidivism. In particular, I study the effects of time in prison and time on parole on recidivism. Relying on two instrumental variables that provide independent variation in sentence and time served in prison, I do not find evidence that parole time affects recidivism. However, I find that a month in prison results in a 1.12-percentage-point decrease in the probability that an individual will reoffend while on parole, but it appears to have no effect on overall reoffending.

1. Introduction

Over 600,000 people are released from the US prison system every year. More than three-fourths of these individuals are released before they fully serve their judge-determined prison sentence, subject to a period of parole supervision in the community (Carson 2018).[1] In 2016, the US adult correctional systems super-

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[1] People on parole are criminal offenders who are conditionally released from prison to serve the remaining portion of their sentences in the community. In the United States, 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 to and meet a set of standard conditions of parole—avoiding injurious habits, obeying the law, and so forth—and any individual-specific conditions, such as

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vised 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 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 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, Cullen, and Jonson (2009) suggest that studying the effect of custodial and noncustodial sanctions on recidivism is 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 prison under parole supervision versus under no custodial supervision at all. Recent policy efforts to reduce the incarcerated population include not only front-end sentencing and admission policies, such as diversion, but also back-end release and reentry 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 of convicts. For most convicts in the United States, 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 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 time served is presumably negatively correlated with the individual's underlying criminal propensity, a simple ordinary least squares (OLS) 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 al-

substance abuse or mental health counseling. Failure to comply with any of the conditions can result in a parole revocation and a return to prison.

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

low me to construct two instrumental variables (IVs). 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 prison time by the Georgia Parole Board to address the endogeneity of time served behind bars. Although these two instruments have been used before in the literature, neither 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 does not account for time on parole. Unless offenders serve their whole sentence in prison, this omission could confound the direct effect of time in prison on recidivism.

Using the likelihood of returning to prison within 3 years of release as a proxy for reoffending, I find no evidence that time on parole—defined as the difference between sentence length and time served in prison—has a 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 the effect of prison time. This is important for policy purposes for two reasons. First, the use of community supervision, such as postrelease supervision, has expanded over the last 3 decades, which resulted in approximately one in 55 adults in the United States being under community supervision in 2016 (Kaeble 2018). Second, many states have moved away from discretionary parole policy and toward mandatory-release policies in which the prison sentence is mostly determined by the discretion of the judge on the basis of sentencing guidelines and the prisoner's institutional behavior.[3]

My estimate of the effect of prison time on overall probability of return to prison within 3 years of release is half that of Kuziemko (2013) and insignificant.[4] However, I find that an extra month served in prison reduces the likelihood of recidivism while on parole by 1.04 percentage points, which is comparable to the findings in Kuziemko (2013).[5] Supported by additional data from the Georgia Department of Corrections (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

[3] In 2016, 23 states 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 use postrelease supervision as a way to integrate and look after ex-prisoners. The only difference is whether states allow for discretion in prison release decisions.

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

[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 the 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 the effect of prison time on recidivism in Kuziemko (2013), 1.3 percentage points, regardless of whether it occurred on or off parole.

jurisdictions, where judges sentence and parole boards then decide how much of a sentence is served behind bars and how much is served in the community under the supervision of a parole officer. Using the data from Georgia, I find little evidence that not accounting for parole time distorts the estimation of prison time. In particular, accounting for parole time increases, by a little, the magnitude of the estimated effect and decreases its significance.

For the most part, my findings for 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 overrepresentation of minorities in the US 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 recidivism while on parole is driven by white offenders.

There have been a few papers, predominantly in criminology, that examine noncustodial sanctions such as probation and parole (for an exhaustive list, see Nagin, Cullen, and Johnson 2009). Although these studies control for selection on observable characteristics, they do not properly account for selection on unobservable characteristics. 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 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, of whom 426,755 were conditionally released on probation or parole before their full sentence had expired (Carson 2018).[6] Parole is believed to help people released from prison reintegrate into society (Petersilia 2002, 2003). Despite its widespread use, remarkably little is known about whether time on parole decreases recidivism rates and thus helps ex-prisoners stay out of trouble. In addition, within 3 years of release, 67.8 percent of released prisoners are rearrested, and 49.7 percent return to prison (Durose, Cooper, and Snyder 2014). Finally, the annual cost of parole supervision is estimated to be $2,800 per parolee (Schmitt, Warner, and Gupta 2010). Given that prison is almost 10 times more expensive than parole, and if parole 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

[6] Probation 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 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, understanding the effect of parole on recidivism might inform policy makers about the impact of other types of post-prison supervision, such as probation.

and Schnepel 2018) and back-end alternatives to incarceration (Di Tella and Schargrodsky 2013) affect recidivism.[7]

This paper also contributes to the existing work that estimates the effect of prison time on future criminal behavior and that can be separated into two major groups (for a comprehensive review, see Nagin, Cullen, and Jonson 2009; Durlauf and Nagin 2011). The first group uses mostly aggregate crime and prison data to estimate the incapacitation and deterrent effects of prison (Levitt 1996; Johnson and Raphael 2012; Buonanno and Raphael 2013; Owens 2009). Those 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, Galbiati, and Vertova 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). Those 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 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 United States is a combination of prison and parole time, and to estimate the treatment effect of parole time. Maurin and Ouss (2009) and Drago, Galbiati, and Vertova (2009) use collective pardons 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 collective pardons are not based on individuals' behavior while in prison, while good behavior is central in determining release under parole. Furthermore, collective pardons are rare in the United States, and sentence enhancement is not generally used.

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

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

on various outcomes, including future criminal involvement.[8] 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) 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 the District of Columbia, 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 provides an estimate of total correctional supervision instead of just prison time, and their instrument could be weak.

The remainder of this 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 IVs 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 GDC to estimate the differential effect of time served in prison and on parole on recidivism (for details about the data and the construction of the sample, see the Appendix). First, the GDC provides administrative records of all people released from the Georgia prison system from 1980 to 2008 (henceforth, the prison data). These records contain rich information about sociodemographics, criminal history, parole, and current conviction for each person admitted to state prison in Georgia. Second, I take advantage of a database that contains all felony prison and probation sentences from the Georgia Superior Courts from 1980 to 2013 (hereafter, the conviction data). These data are from court dockets and contain the name of the sentencing judge, sentence length, offense, circuit court, and some basic demographic characteristics of each offender convicted of a felony in one of the 49 circuit courts in Georgia. I use these data only for the construction of my instrument for sentence length, as they indicate the sentencing patterns of the universe of judges in Georgia. I describe these data in more detail in the Appendix.[9] Because of the necessary restrictions outlined below, I am unable to make use of the full data set.

[8] Random-assignment research design has been employed to study the impacts of various economic outcomes, such as incarceration and disability insurance (Maestas, Mullen, and Strand 2013; French and Song 2014; Dahl, Kostøl, and Mogstad 2014), foster care placement (Doyle 2007), and bankruptcy protection (Dobbie and Song 2015).

[9] Note that the conviction data contain information about convicts and exclude people who were charged with a crime but were not convicted. Another shortcoming of the conviction data is that I observe only the final sentence a person receives. Thus, my results might be 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 assumption of the random assignment of felony cases, I do not expect that certain judges will systematically receive such cases more than other judges.

Thus, the sample for the main analysis is restricted to people sentenced to prison after January 2001 and released from prison before October 2005.[10]

The main outcome of interest, recidivism, is defined as an indicator equal to one if the offender returns to prison within 3 years of release.[11] Since the prison data are composed of all prison releases in Georgia through October 2008, and I want to allow at least 3 years for each criminal to potentially recidivate, I restrict the sample to individuals released no later than October 2005. I further restrict the sample to individuals admitted to prison for conviction of a new crime rather than a parole violation. The justification of 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 when 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 individuals who commit a new crime are sent to prison, and their sentences are determined by a randomly assigned judge. The prison data contain the success scores and severity levels that the Georgia Parole Board uses as inputs in its guidelines for determining prison time (see Tables OA1 and OA2 in the Online Appendix). Since the parole guidelines seem to be the strongest predictor of time served for crimes with a severity level less than 5, I exclude individuals imprisoned for more serious crimes. Note that the parole board is not required to follow the parole guidelines and can adjust the recommendation up and down. Figure OA1 in the Online Appendix presents histograms of the difference between the parole-established tentative release month and the parole-guidelines-recommended tentative release month by severity level of the crime. 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 5, and the board's decision is within 4 months of the recommendation almost 70 percent of the time. However, the board exerts more discretion for crimes with a severity level higher than 5 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 sample 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 by the sentencing patterns of a judge over 13 years. It is calculated from the judge's full caseload without exclud-

[10] 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.

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

Table 1
Summary Statistics

	Mean	SD
Prison and parole:		
Recidivism	.32	.47
Recidivism on parole	.23	.42
Recidivism off parole	.09	.29
Prison time (months)	22.07	8.74
Sentence length (months)	48.60	21.08
Sentence served (months)	51.92	24.74
Parole time (months)	26.54	20.54
Background:		
Black	.60	.49
Female	.13	.34
Age at admission	34.77	9.92
Prior convictions	2.76	2.89
Current offense:		
Drug	.38	.49
Other	.16	.36
Property	.41	.49
Violent	.06	.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 1	.37	.48
Severity level 2	.35	.48
Severity level 3	.21	.40
Severity level 4	.08	.27

Note. Recidivism is the probability that an individual returns to prison in Georgia within 3 years of release. The judge harshness index is a judge's leave-out mean sentence (in months), 2001–13. $N = 8{,}402$.

ing any sentences.[12] 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. Because I exclude crimes with severity levels above 5 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 48 months, while the mean prison time served is about 22 months. The average prisoner serves only 52 percent of his sentence behind bars and serves the rest on parole, which highlights the importance of evaluating the impact of noncustodial time on recidivism.

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

[12] Please refer to the Appendix for more details on how I handle life sentences.

are two main reasons why this might not be the actual length of parole supervision. First, section 42-9-52 of the Official Code of Georgia Annotated 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 prevalent in the data because the parole board not only can decide 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 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 expiration date of the sentence and the parole discharge date in Figure OA3. 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 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.

Approximately 32 percent of the individuals in the sample return to prison, with or without a new sentence, within 3 years of release. I construct two additional recidivism measures depending on the timing of the recidivating event, and I find that 23 percent of those who return to prison do so while on parole. One drawback of the data is that recidivism is observed only in the state of Georgia, so I cannot distinguish an individual who reoffends in a different state from an individual who does not reoffend in Georgia.[13]

3. Empirical Strategy

To estimate the joint effect of prison and parole time on recidivism, I adopt an IV approach. In the sections that follow, I explain how the institutional setup 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 parole and prison time.

[13] The majority of my sample consists of adults released before the sentence expiration date. Given that one condition of parole is often that the parolee stay in the state after release, it is unlikely that reoffending in a different state is prevalent. In addition, using data on prison releases from 30 states in 2005, Durose, Cooper, and Snyder (2014) estimate that only about 7 percent of released prisoners were arrested in another state within 3 years of release. So while out-of-state migration could be an issue, I believe that does not have large effects on my results.

3.1. Institutional Details

The Official Code of Georgia Annotated defines criminal conduct and establishes the maximum sentences. Upon verdict or plea of guilty, it is the judge who determines the sentence.[14] In Georgia, judges have complete discretion to impose any sentence within the very wide statutory bounds set by law. For instance, while the Official Code of Georgia Annotated requires that a sentence for robbery should not be shorter than 1 year and not longer than 20 years, the judge has full discretion to impose any sentence up to the statutory maximum. Most important for my analysis, within a court, felony cases in Georgia are assigned randomly to judges, whose judicial calendar is predetermined at the beginning of the year.[15]

The Georgia Parole Board starts preparing an individual's parole file immediately on receiving a 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 preparole 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 the prisoner are also included, such as the circumstances of the current offenses, prior convictions, arrests, and so forth.

The parole board in Georgia is required by law to make decisions on the basis of the risk a person may pose to public safety if released on parole (Ga. Code Ann., sec. 42-9-40) using its parole guidelines to determine the risk. In Georgia, every parole-eligible inmate is evaluated using the guidelines and receives a success score that determines whether he is a risk to the public safety and whether he is likely to succeed on parole if granted it.[16] Table OA1 in the Online Appendix shows parole success scores that reflect age, prior offense record, and prisoners' other preincarceration characteristics. Every inmate receives points for each of eight success factors according to past and current criminal and personal backgrounds, with the success score a sum of the points received.[17] The parole success score is bracketed into three categories: poor (0–8 points), average (9–13 points),

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

[15] The process is described in Superior Courts of the State of Georgia, Uniform Rules, Rule 3: Assignment of Cases and Actions (https://www.gasupreme.us/wp-content/uploads/2020/07/UNIFORM-SUPERIOR-COURT-RULES-2020_07_02.pdf). In general, for all probation revocation cases, new charges would be assigned to the court that handed down the initial sentence. This is not an issue for the analysis, since the conviction data consist only of new felony convictions as opposed to probation violations. Moreover, I restrict the main analysis to new convictions.

[16] In Georgia, all inmates are automatically considered for parole, except 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; and those convicted of a fourth felony.

[17] To illustrate the process, suppose that an inmate was previously incarcerated at the age of 17; he would receive 0 success points in the age category as compared with an inmate who was previously incarcerated at 26 and thus receives 5 success points.

Table 2
Georgia Parole Board Guidelines Recommended Prison Time by Crime Severity Level and Success Score

Severity Level	Excellent	Average	Poor
1	10	16	22
	(18.61)	(20.71)	(24.64)
2	12	18	24
	(17.88)	(20.53)	(25.21)
3	14	20	26
	(21.93)	(23.08)	(26.29)
4	16	22	28
	(25.93)	(24.82)	(26.77)

Note. Recommended prison time is in months. Values in parentheses are the mean prison times (in months) based on the estimation sample ($N = 8{,}402$).

and excellent (14–20 points). Table 2 contains 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 on the basis of the recommended prison time in the parole guidelines. The guidelines-recommended prison time and tentative parole month 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. The board members are not bound by the recommended prison time and the tentative parole month based on the guidelines when casting votes. When determining the tentative parole month, the voting members can take into account their general impression of the inmate and other factors such as statements from the victim, prosecutor, police officers, and, most important for the purpose of this paper, the judge. The parole decision is set once the first three board members vote the same way (Ga. Code Ann., sec. 42-9-42). If the board decides to set neither a reconsideration date nor a tentative parole month, the prisoner serves the maximum sentence set by the judge. If the board sets 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 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.[18] The heterogeneity 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.[19] In 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 status on the parole eligibility date, which is usually set at around one-third of the 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 given that a prisoner can be incarcerated for more time than his original sentence in some rare instances.[20]

3.2. Identification of Time in Prison and Time on Parole

Figure 1 shows how a sentence is carried out in 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 convict's parole file and calculates the recommended prison time using the parole guidelines. The parole board then reviews the file and the guidelines recommendation, determines the tentative 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, $S - t$, under parole supervision.

Causal estimation of the effect of prison time on recidivism requires random variation in t. However, such variation on its own is not sufficient to identify parole time $S - t$, because identification of parole time requires random variation in both prison time and sentence. I construct two IVs that offer quasi-experimental variation in 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 is not sufficient to identify parole time given that the parole board ultimately decides 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 them separately.[21] Second, if I instrument for prison time, I can identify only the

[18] Since 2008, which is after my estimation period, the statewide average length of prison sentences imposed by Georgia Superior Court judges have been included in the parole guidelines (see State Board of Pardons and Paroles, Parole Consideration, Eligibility and Guidelines [https://pap.georgia.gov/parole-consideration-eligibility-guidelines]). No prisoner in my sample was graded after this policy change.

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

[20] If a prisoner absconds supervision, which means that the parolee misses an appointment and/or his whereabouts are unknown, then the parole board will increase his sentence by the number of days for which he is unaccounted. Only 25 individuals, or .3 percent of the estimation sample, served more time behind bars than their sentences.

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

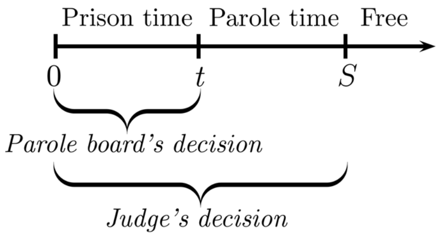

Figure 1. Sentence timeline

effect of time in prison. However, in states that have discretionary release and $t < S$, any such instrument could be correlated with parole time simply because of the mechanical relationship that parole time is the sentence minus time served in prison.[22]

Since early releases from prison in Georgia are based solely on the discretion of the parole board, it is the board members who ultimately decide *t*. The main quasi-experimental variation in prison time is therefore derived from the formula-calculated recommended prison time based on the parole guidelines shown in Table 2. I use those recommended lengths of prison stay 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 an 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 guidelines-recommended time and prison time goes in the expected direction.

I measure judges' stringency as the average sentence length in other cases the judge has handled. This serves as an instrument for sentence length since it is highly predictive of the judge's decision in the current case but, as I document in Section 3.3, uncorrelated with observable characteristics of a case. 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 about correlated unobservable characteristics.[23] Figure OA3 in the Online Appendix shows the relationship between prison time, parole time, and the judge harshness index. The parole board ultimately decides prison time, 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

[22] Kuziemko (2013) uses the same data over a different time period and the same instrument for prison time as the one used in my analysis. Her estimate of the effect of prison time on recidivism, however, could 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 attenuate the omitted-variable problem.

[23] I test the validity of the random-assignment assumption in Section 3.3.

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 IVs 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 about correlated unobservable characteristics, issues remain 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.[24]

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 convicts' sentence lengths 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 cases' characteristics, because each case has an equal chance of being assigned to a given judge. If the initial assignment of judges is truly random, as I assume, this requirement will be satisfied, and the two-stage least squares estimates will be unbiased.

Following Aizer and Doyle (2015), for defendant i's judge, I construct a judge harshness index Judge_i and use it to instrument for i's sentence length.[25] Using an exhaustive set of sentences a judge hands down can produce a bias that results from the mechanical correlation between an offender's outcomes and the constructed instrument. To deal with this issue, I exclude the offender's incarceration spell when calculating a 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. In particular, for each prisoner i sentenced by judge j, I calculate the instrument as the following leave-out mean:

$$\text{Judge}_i = \frac{\sum_{k \neq i}^{N_j} S_k}{N_j - 1}, \tag{1}$$

where N_j is the number of felony cases judge j had from 2001 to 2013 and S_k is the length of the prison sentence for the convict k. Adult felony offenders in Georgia

[24] In 2016, 49.5 percent of the adults entered parole supervision after a parole board decision, and 23 states, including Texas, Pennsylvania, and Missouri, used discretionary parole as their main method of parole release (Kaeble 2018).

[25] Aizer and Doyle (2015) use judges' 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.

may be sentenced to serve time either in prison or in prison followed by probation (a split sentence). I include only the number of years sentenced to prison and ignore the probation for split sentences when I calculate the judge harshness index. For instance, if a judge hands down a split sentence of 7 years that consists of 2 years in prison followed by 5 years of probation, then S_k for that felon would be equal to 2. 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.[26]

Although it is impossible to verify directly whether judges are indeed assigned to defendants at random, I can examine the validity of this assumption using the available data.[27] In particular, if defendants are randomly assigned to judges, I would expect those appearing in front of lenient judges to be similar on observable characteristics to those assigned to harsher judges. Following Aizer and Doyle (2015), I classify a judge as harsh if he assigns a prison sentence longer than the median in the conviction data sample and as lenient otherwise. For each observable characteristic of defendant i, Characteristic_i, I estimate the OLS regression

$$\text{Characteristic}_i = \phi_0 + \phi_1 \mathbb{I}[\text{Judge}_i \geq \text{Median}] + \kappa_c + \tau_y + \varepsilon, \tag{2}$$

where $\mathbb{I}[\text{Judge}_i \geq \text{Median}]$ is an indicator that equals one if defendant i is sentenced by a harsh judge and κ_c and τ_y are fixed effects for circuit court and year of sentence. Including these fixed effects accounts for the fact that randomization occurs within a circuit court and for any unobservable year-to-year changes in the judge's calendar or court practices. The p-values of the coefficients of judges' harshness, $\mathbb{I}[\text{Judge}_i \geq \text{Median}]$, are presented in 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 with 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. Cases do not seem to be assigned to judges on the basis of defendants' observable characteristics, as the p-values produced by this test indicate that judges' 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. The size of each circle or triangle indicates the number of convicts sentenced by a judge with a specific harshness index. There are two main takeaways from Figure 2. First, the judge harshness index provides independent variation in the sentence length: the harsher a judge is toward defendant i, the longer sentence i receives. A 1-month increase in the harshness of

[26] 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, he or she might be more likely to order less prison time and more probation time.

[27] According to discussions with Mike Cuccaro, assistant director of the Administrative Office of the Courts of Georgia, random assignment of cases is a priority of circuit courts in Georgia.

Table 3

Defendants' Characteristics: Random-Assignment Test

	Lenient	Harsh	p-Value
Judge harshness index	3.73	5.16	.000542
Demographic:			
Age	32.34	32.17	.185
Female	.2055	.1985	.615
Black	.5126	.5367	.429
Offense:			
Drug possession	.2970	.2797	.112
Drug sale	.0492	.0606	.098
Driving under the influence	.0125	.0149	.580
Nonviolent	.0034	.0030	.839
Property	.3827	.3709	.284
Sex	.0314	.0346	.125
Violent	.1430	.1547	.161
Other	.0807	.0815	.359

Note. Harsh judges have a harshness index greater than or equal to the median in the conviction data ($N = 701{,}562$); all other judges are considered lenient. Results for lenient judges are unconditional means; results for harsh judges are predicted conditional means from ordinary least squares regressions. The p-value is for the estimated ϕ_1 in equation (2). All regressions include circuit court and year-of-sentence fixed effects.

the judge leads to an expected .13-month increase in the defendant's sentence. It is worth noting that the judge harshness index provides almost no variation in time served.[28] Second, the difference between the fitted values for sentence length and those for time served in prison represents the parole time. 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 provides it.

There might exist characteristics of offenders that are unobservable to the econometrician but are correlated with how long the offender serves in prison and his decision to commit a crime after he is released. To instrument for 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 crime severity and success score points, I use the suggested months to serve from the guidelines, outlined in Table 2, as an instrument for actual time served (for methodological details, see Angrist and Lavy 1999). The identification thus takes advantage of the difference in the recommended prison time between adjacent cells of the parole guidelines. In Table 2, I observe that, conditional on crime severity level, lower success scores are associated with more

[28] 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, sentence length as a proxy for prison time, or random assignment of judges as an instrument for prison time.

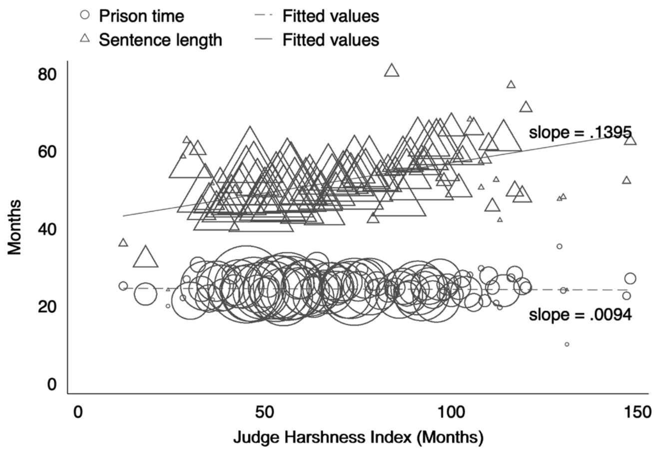

Figure 2. Sentence length and time served by judge harshness index

time in prison on average. A similar pattern is observed if I 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 shown in Figure OA4 in the Online Appendix. The patterns in Figure OA4 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:

$$\begin{aligned}\text{Prison}_i = \alpha_0 + \alpha_1 \boldsymbol{X}_i + \alpha_2 \text{Recommendation}_i + \alpha_3 \text{Judge}_i \\ + \pi_p + \sigma_s + \kappa_c + \tau_y + \varepsilon\end{aligned} \tag{3}$$

and

$$\begin{aligned}\text{Parole}_i = \gamma_0 + \gamma_1 \boldsymbol{X}_i + \gamma_2 \text{Recommendation}_i + \gamma_3 \text{Judge}_i \\ + \pi_p + \sigma_s + \kappa_c + \tau_y + \varepsilon.\end{aligned} \tag{4}$$

The dependent variables Prison_i and Parole_i are months served in prison confinement and months served under parole supervision, respectively. Time on parole is defined as the difference between the individual's sentence and time served in prison, or the portion of the criminal sentence a prisoner served under correctional supervision but not behind bars. The variable Recommendation_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 crime severity level (current crime type). Given that I control for both 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.[29]

The variable Judge_i is the average sentence based on sentencing patterns of the judge who sentenced prisoner *i;* π_p and σ_s are fixed effects for crime severity levels and success points, respectively; κ_c and τ_y are again court and year-of-sentence fixed effects, respectively. Including court fixed effects not only controls for the fact that random assignment of judges occurs in 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 according to 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 and other changes in judicial policies or practices across all felony cases in a year. The vector $\boldsymbol{X}_i$ 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:

$$\text{Recidivism}_i = \beta_0 + \beta_1 \text{Prison}_i + \beta_2 \text{Parole}_i + \beta_3 \boldsymbol{X}_i + \varepsilon_i. \tag{5}$$

The main problem in estimating the above model using an OLS analysis is that neither time served in prison nor time spent under community supervision is randomly assigned to offenders. In fact, it is very likely that judges and parole boards determine sentences and time to serve in part on the basis of characteristics unobservable to the econometrician, which are also correlated with the propensity to recidivate. In other words, one would expect that $\mathbb{E}(\varepsilon_i | \text{Prison}_i) \neq 0$ and $\mathbb{E}(\varepsilon_i | \text{Parole}_i) \neq 0$. 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.[30] The second-stage regression becomes

$$\text{Recidivism}_i = \beta_0 + \beta_1 \widehat{\text{Prison}_i} + \beta_2 \widehat{\text{Parole}_i} + \beta_3 \boldsymbol{X}_i + \varepsilon_i. \tag{6}$$

The main coefficients of interest, β_1 and β_2, represent the effect of time in prison and time under parole supervision, respectively.[31] By construction, the time on parole is calculated as the sentence minus the number of months served in prison. An implication of this is that time served, time on parole, and original

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

[30] See Angrist, Imbens, and Rubin (1996) for a discussion of the estimation methodology. Angrist (2006) provides an overview of the use of instrumental variables in criminology research.

[31] 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. I account for this bias in all the estimations.

sentence are collinear. Thus, the estimated effects on recidivism should be interpreted as the joint effect of an additional month served behind bars and a month less served on parole. This joint effect estimates the full impact of the punishment for reoffending.

The sign of the effect of parole time on recidivism, captured by the coefficient estimate β_2, is a priori ambiguous. Offenders who receive a large reduction in their sentences 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's expiration date might be extra careful not to reoffend and have to return to prison to serve the rest of their sentence behind bars, which suggests 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) conditional first-stage *F*-statistic of 17.36 is high enough to indicate that both instruments are predictive of time served in prison and on parole. Observe that in the estimates for parole time (equation [4]) a 1-month increase in the guidelines recommendations leads to a quarter of a month less time on parole, while a 1-month increase in the judge harshness index leads to .06 more of a month spent under parole. Although the judge harshness index has a small effect, perhaps due to the fact that parole can rarely exceed the judge-determined sentence length, the parole guidelines have the most predictive power for time served in prison. As seen in the estimates for prison time in Table 4, a 1-month increase in the guidelines-recommended months to be incarcerated results in almost a half-month increase in the time served in prison. Given that the parole board has full discretion regarding 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 for how the judge can influence time served in prison, which might account for the small significant coefficient on the judge harshness index in Table 4. First, inmates in Georgia are eligible to be considered for parole on their parole eligibility date, which is usually set at around one-third of the prison sentence.[32] Second, the prisoner's parole file may include statements from the judge and could have an effect on the prison release decision by the parole board. Finally, the judge's decision might affect the

[32] The parole board is not constrained by the parole eligibility date (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 opinion. In my sample, only 5 percent of inmates are released before the PED. Moreover, the results are robust to excluding those individuals.

Table 4

First-Stage Estimates

	Parole Time	Prison Time
Guidelines-recommended prison time	−.248**	.447**
	(.0707)	(.0496)
Judge harshness index	.0614**	.0122+
	(.0181)	(.00699)
Black	2.788**	−.0470
	(.470)	(.191)
Female	1.223*	−2.628**
	(.568)	(.233)
Age at prison release	−.0440+	.0585**
	(.0231)	(.00989)
Prior convictions	−.273*	.303**
	(.111)	(.0462)
Constant	41.22**	5.838*
	(8.666)	(2.894)
R^2	.151	.229

Note. Estimates are from ordinary least squares regressions, with heteroskedasticity-robust standard errors in parentheses. Parole time and prison time are in months. All regressions control for crime type (violent, property, drug, and other), year of sentence, and circuit court and include dummy variables for success points and severity level. Sanderson-Windmeijer F-statistic = 17.36. N = 8,402.

+ $p < .1$.
* $p < .05$.
** $p < .01$.

board in determining the length of imprisonment because a prisoner can rarely be incarcerated for longer 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 3 years. Estimates are from a linear probability model; the OLS estimates do not take into account the endogeneity of time served in prison or on parole and the propensity to reoffend. The results in column 1 for time on parole suggest that parole has a significant but small criminogenic effect. These estimates are most probably biased upward or toward 0 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 unobservable characteristics, column 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 unobservable characteristics. In particular, people with a higher risk of reoffending might be assigned more prison time by the parole board and might receive longer sentences from a judge. If this is the case, one could conclude that the high rates of recidivism among

Table 5
Second-Stage Estimates

	Recidivism		Recidivism on Parole		Recidivism off Parole	
	(1)	(2)	(3)	(4)	(5)	(6)
Prison time	.000404	−.00583	−.000226	−.0104**	.000705+	.00456
	(.000617)	(.00476)	(.000527)	(.00376)	(.000378)	(.00324)
Parole time	.00474**	−.00479	.00857**	−.000227	−.00380**	−.00351
	(.000254)	(.00625)	(.000217)	(.00504)	(.000155)	(.00391)
Black	.00974	.0359+	−.0109	.0129	.0216**	.0211+
	(.0111)	(.0207)	(.00949)	(.0171)	(.00680)	(.0126)
Female	−.0545**	−.0591**	−.0320*	−.0477**	−.0243**	−.0146
	(.0148)	(.0174)	(.0126)	(.0150)	(.00903)	(.00998)
Age at release	−.00574**	−.00580**	−.00414**	−.00396**	−.00145**	−.00165**
	(.000542)	(.000597)	(.000462)	(.000510)	(.000331)	(.000358)
Prior convictions	.00730**	.00657*	.00409+	.00477+	.00250	.00140
	(.00258)	(.00319)	(.00221)	(.00274)	(.00158)	(.00188)
Constant	.344	.703*	.199	.648*	.147	.0254
	(.234)	(.331)	(.200)	(.297)	(.143)	(.167)
Model	OLS	IV	OLS	IV	OLS	IV

Note. Heteroskedasticity-robust standard errors are in parentheses. All regressions control for crime type (violent, property, drug, and other), year of sentence, and circuit court; instrumental variables (IV) regressions include success-point and crime-severity-level fixed effects. Recidivism equals one if the inmate returned to prison within 3 years of release and zero otherwise. Recidivism on Parole equals one if the inmate returned to prison within 3 years of release while on parole and zero otherwise. Recidivism off Parole equals one if the inmate returned to prison within 3 years of release while not on parole and zero otherwise. OLS = ordinary least squares.

+ $p < .1$.
* $p < .05$.
** $p < .01$.

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 are monitored more closely by a parole officer and therefore might encounter fewer criminal opportunities or be afraid of being caught easily. To better understand the role of parole, Table 5 also presents IV estimates of the effect of parole and prison time on recidivism occurring while under or not under parole supervision. Yet I find no statistically significant effect of the duration of noncustodial sanctions.[33]

In a study of collective pardon in Italy, Drago, Galbiati, and Vertova (2009) find a big deterrent effect of the unserved portion of the sentence. Using data from 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

[33] The estimated effect of parole time on recidivism is modest in magnitude, which suggests that 1 month on parole is associated with a decrease of from .1 percent to 3.9 percent in an individual's probability of returning to prison within 3 years of release. Although the effect of parole time seems modest at the individual level, it could be sizable given that more than 4.5 million people are under some type of community supervision.

to Italian pardons, for which the remaining sentence is attached to any new sentence, US sentences are not cumulative. In particular, an offender arrested for committing a new crime while on parole is detained in prison under a parole board warrant until 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. Although the fact that reoffending while on parole might be an aggravating factor when the judge determines a sentence, it is not necessarily true that the previously unserved time will be fully reflected in the new sentence. Moreover, because pardons in Italy manipulate 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 on 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 the overall recidivism rate. Besides losing its significance, the estimated effect is almost half of the result in Kuziemko (2013). A plausible explanation might be the way I restrict the sample because of the missing names of judges. In addition, I focus on people who serve a maximum of 5 years in prison, while Kuziemko (2013) includes people who serve a maximum of 10 years. To investigate further, I run the second stage accounting for the timing of recidivism. I find that a 1-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 3 years of release if the recidivating event occurs under parole supervision. The estimate changes signs and becomes insignificant if the recidivism occurs after parole. 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. Although the average prisoner in my sample serves 3 fewer months in prison than the average prisoner in Kuziemko (2013), he might be on parole for a much shorter period of time.[34] This may explain why I do not observe a 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.

To investigate the degree to which not including parole time confounds the estimation of prison time, Table OA3 presents the second-stage estimates with and without controlling for parole time. Using Georgia's parole guidelines as an instrument for time in prison, I do not find evidence that excluding parole time 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 in Table 5 have the expected signs. For instance, the probability of recidivating is 5.45 percentage points lower for females and decreases

[34] 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.

by more than half of a percentage point with each additional year of age—consistent with the fact that criminality declines with age (Bushway and Piehl 2007). Criminal history has a robust positive 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 US criminal justice system, in this section I investigate whether the deterrent effect of prison and parole varies across inmates' characteristics. The second-stage estimates by race and type of offense, reported in 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 appear to be driven primarily by the sample of white prisoners. The heterogeneous effects by race could be rationalized if prison is a more unpleasant experience for white offenders than for black prisoners or if whites have a better outside option than blacks.[35]

I do not find any heterogeneous effects with respect to type of crime. The results, however, change when I separately examine recidivism on and off parole as a dependent variable. I find heterogeneous effects of time in prison on type of crime and race for 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 is much smaller for the latter group. A similar effect on recidivism is observed for property crime offenders. The point estimates for property crime offenders suggest that an additional month behind bars results in a 1.96-percentage-point decrease in the probability that they will return to prison within 3 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 IVs—random assignment of judges to felony cases in Georgia and the variation generated by the formulaic calculation of recommended time 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 turn the effect of total correctional supervision, on recidivism. My estimate for prison time is small and insignificant. The insignificance of this effect might be rationalized by the

[35] 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 yields a p-value of .3034, while testing whether parole time is different across races results in a p-value of .4207.

Table 6
Time Served and Recidivism

	Race		Crime Type			
	White	Minority	Drug	Violent	Property	Other
Prison time	−.0123+	−.00518	.0121	.0221	−.0186	−.00630
	(.00678)	(.00368)	(.0146)	(.0509)	(.0114)	(.00855)
Parole time	−.0240	.00452	.000609	.0194	−.0154	.00375
	(.0155)	(.00756)	(.00744)	(.0303)	(.0157)	(.0139)
Black			.0366	−.0726	.0167	.00606
			(.0403)	(.170)	(.0267)	(.0262)
Female	−.0132	−.103**	.00287	−.0401	−.0571	−.0172
	(.0350)	(.0243)	(.0404)	(.135)	(.0450)	(.0871)
Age at release	−.00709**	−.00508**	−.00650**	−.00872*	−.00310*	−.00708**
	(.00139)	(.000782)	(.00145)	(.00425)	(.00149)	(.00146)
Prior convictions	.0106	.0122*	.000896	.0267	.00455	.0166+
	(.00717)	(.00508)	(.00701)	(.0217)	(.00580)	(.00960)
Constant	1.593**	−.229	.0743	−1.466	1.258*	.778
	(.552)	(.533)	(.440)	(2.991)	(.633)	(.482)
N	3,329	5,073	3,185	464	3,438	1,315

Note. Estimates are from instrumental variables regressions, with heteroskedasticity-robust standard errors in parentheses. The dependent variable is Recidivism. All regressions control for crime type (violent, property, drug, and other), year of sentence, circuit court, success points, and crime severity level.
$^{+}p < .1.$
$^{*}p < .05.$
$^{**}p < .01.$

Table 7
Time Served and Recidivism while on Parole

	Race		Crime Type			
	White	Minority	Drug	Violent	Property	Other
Prison time	−.0118*	−.00936**	.0150	−.00641	−.0196*	−.0142+
	(.00508)	(.00305)	(.0153)	(.0168)	(.00970)	(.00750)
Parole time	−.0127	.00463	8.26e−05	.0104	−.00946	.0211
	(.0118)	(.00619)	(.00697)	(.0101)	(.0136)	(.0129)
Black			.0271	.00933	.00520	.00399
			(.0373)	(.0626)	(.0236)	(.0257)
Female	−.00853	.106+	.0458	−.102	−.0592	−.0709
	(.0273)	(.0627)	(.0423)	(.0629)	(.0380)	(.0846)
Age at release	−.00515**	−.0745**	−.00551**	−.000674	−.00236+	−.00530**
	(.00107)	(.0211)	(.00141)	(.00177)	(.00129)	(.00146)
Prior convictions	.00823	−.00340**	−.00120	.00975	.00422	.0130
	(.00568)	(.000662)	(.00681)	(.0104)	(.00503)	(.00870)
Constant	1.299**	−.0528	.139	−.500	1.173*	.437
	(.435)	(.442)	(.422)	(1.012)	(.571)	(.342)
N	3,329	5,073	3,185	464	3,438	1,315

Note. Estimates are from instrumental variables regressions, with heteroskedasticity-robust standard errors in parentheses. The dependent variable is Recidivism. All regressions control for crime type (violent, property, drug, and other), year of sentence, circuit court, success points, and crime severity level.
$^{+}p < .1.$
$^{*}p < .05.$
$^{**}p < .01.$

fact that the parole board is assessing the recidivism risk of prisoners accurately.[36] Many states have abolished discretionary parole completely. However, if parole boards are assessing how dangerous potential offenders truly are, then policy makers may wish to reevaluate policies that limit their 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 the effect of time served in prison on recidivism that is not confounded by time on parole.

State and federal governments commit significant resources to improving reentry planning and strengthening community supervision. Although this study finds that time on parole does not have any significant effect on recidivism rates, more research is needed to understand whether this 0 effect is driven by the effectiveness of various postprison supervision policies. I do not have the data to address what types of parole strategies work better than others. 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, or access to rehabilitative programs and treatment. Maximizing the public safety benefits and the cost savings of postrelease supervision might involve appropriate intensity of supervision rather than a focus solely on the length of time on parole. Understanding the effect of different parole strategies on recidivism would be a fruitful area for future research.

Appendix

Data

I use data from the state of Georgia collected by the GDC. I focus on Georgia because of the detailed nature of the GDC data. Comparing Georgia's prison population summary statistics with the national prisoner population is reassuring because inmates in Georgia appear to be representative of those nationwide in some key ways. Table OA4 in the Online Appendix presents data on how individuals sentenced in Georgia compare with those sentenced nationwide.[37] 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. Offenders 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 of black prisoners and its percentage of inmates imprisoned because of a violent

[36] 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.

[37] The statistics for Georgia are based on the raw prison data with no sampling restrictions described 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 1 year in order to better match the data from the Bureau of Justice Statistics. For more information, see Table OA4.

offense or drug offense.[38] In 2000, black offenders constituted 46.5 percent (62.2 percent) of the inmates, and prisoners convicted of violent and drug crimes made up 34.3 and 21.1 percent (25.6 and 30.3 percent), respectively, of all individuals sentenced nationally (in Georgia).

The first data set, the prison data, contains administrative records of all people released from the Georgia prison system from 1980 to 2008. It provides rich sociodemographic, 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 one if a convict returns to prison within 3 years of release. Following Kuziemko (2013), I restrict the sample to individuals who spent at least 7 months of prison time. Since the prison data are composed of all prison releases in Georgia through October 2008 and I want to allow at least 3 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 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 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 OA5. Overall, I do not find that prisoners released before 2005 are much different in terms of observable characteristics than those released after 2005. Those released before 2005 spent similar time on parole and served almost the same percentage of their initial sentence as 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, 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. Table OA5 indicates that 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 data set, the 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

[38] The discrepancies with respect to race are most likely due to how Hispanics are categorized in the Georgia Department of Corrections 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 the Bureau of Justice Statistics classifies crime types the same way.

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 name of the sentencing judge, by mid-2000. Before 2001, the data simply indicate “presiding judge” instead of containing the judge’s full name, which 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 calculate the index on the basis of both the past and future sentences the judge assigned to a particular case has given.[39] I top code prison time to 80 years for all life sentences and sentences exceeding 80 years in prison in order to use the universe of cases to which a judge is randomly assigned between 2001 and 2013. This allows me to use the universe of sentences of each judge so that I rely on a measure of judge severity defined by his full caseload over 13 years. Top coding should not create any bias in my estimates if cases are randomly assigned to judges, which seems to be true given the tests discussed in Section 3.3. I exclude 15 outlier judges who had fewer than 100 cases over the 13-year period; those judges ruled on only .02 percent of the cases in the conviction data. The final conviction data sample has more than 700,000 observations.

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 who are admitted after 1995 and released before 2006. Unlike Kuziemko, who takes advantage of most of the GDC prison data, I restrict my sample to individuals admitted after January 2001 because the GDC collected the sentencing judge’s name very sporadically 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 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 on the basis of parole success points. Kuziemko (2013) uses a regression discontinuity design 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 with more than 4 and fewer than 13 success points. Similar to Kuziemko (2013), I focus my analysis on crimes with a severity level less than 5 because the parole board bases its decisions more on discretion than on the parole guidelines, but unlike her I use all success points in my main analysis.

[39] For instance, if an offender is sentenced on January 1, 2002, the judge harshness index for him is determined by the sentences his judge handed down before and after January 1, 2002.

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