Do Private Prisons Distort Justice? Evidence on Time Served and Recidivism*

Anita Mukherjee†

March 15, 2015

Abstract

I contribute new evidence on the impact of private prisons on prisoner time served and recidivism by exploiting the staggered entry and exit of private prisons in Mississippi between 1996 and 2004. Little is known about this topic, even though burgeoning prison populations and an effort to cut costs have caused a substantial level of private contracting since the 1980s. The empirical challenge is that prison assignment may be based on traits unobservable to the researcher, such as body tattoos indicating a proclivity for violent behavior. My first result is that private prisons increase a prisoner's fraction of sentence served by an average of 4 to 7 percent, which equals 60 to 90 days; this distortion directly erodes the cost savings offered by privatization. My second result is that prisoners in private facilities are 15 percent more likely to receive an infraction (conduct violation) over the course of their sentences, revealing a key mechanism by which private prisons delay release. Conditional on receiving an infraction, prisoners in private prison receive twice as many. My final result is that there is no reduction in recidivism for prisoners in private prison despite the additional time they serve, suggesting that either the marginal returns to incarceration are low, or private prisons increase recidivism risk. These results are consistent with a model in which the private prison operator chooses whether to distort release policies, i.e., extend prisoner time served beyond the public norm, based on the typical government contract that pays a diem for each occupied bed and is imperfectly enforced.

*I am indebted to my dissertation advisers David S. Abrams, Fernando Ferreira, Olivia S. Mitchell, and Jeremy Tobacman for their guidance and support. I thank Rachel Barkow, Kerwin Charles, John DiIulio, Mark Duggan, Clayton Featherstone, David Garland, Jean-François Houde, Robert Jensen, Judd Kessler, John MacDonald, Emily Owens, Jesse Shapiro, and participants of the Wharton Applied Economics Workshop and Conference on Empirical Legal Studies in 2013, especially my discussant Eric Helland, for helpful comments. I also thank Audrey MacAfee, Lynn Mullen, and Jeff Giles at the Mississippi Department of Corrections (MDOC) for providing the raw extracts of the prisoner data and for their hospitality during my visit to Mississippi. I gratefully acknowledge financial assistance from the Pension Research Council and the Population Studies Center at the University of Pennsylvania. This paper does not reflect the opinions of the MDOC or any of the funding organizations. All errors are my own.

†Wisconsin School of Business, University of Wisconsin-Madison, 5273 Grainger Hall, 975 University Avenue, Madison, WI, 53706. E-mail: amukherjee@bus.wisc.edu.

1 Introduction

The United States contains 5 percent of the world's population but 25 percent of its prisoners (Golinelli and Carson 2013). The country's prison population has increased more than sixfold since 1980, creating concerns about excessive costs and prison overcrowding that have fueled a trend toward private contracting. The phenomenon is also global: while the United States houses 10 percent of its prisoners in private facilities, countries like the United Kingdom, Australia, and New Zealand house even larger fractions of their prisoner populations in private facilities (McDonald 1994). Individuals, advocacy groups, and state governments have voiced numerous concerns about this $5 billion industry ranging from human rights violations to the lack of cost savings, but there has been little retrospective analysis to either verify or dispel these concerns. The underlying tension is that private prisons are typically paid a diem for each occupied bed with few other conditions, creating a potentially perverse incentive for them to maximize the number of occupied beds (Sigler 2010; Dolovich 2005; DiIulio Jr. 1988). In a recent case that highlights the extent to which these incentives can distort justice, a private prison operator in Pennsylvania paid two judges over $2.6 million to inflate offender sentences and assign them to its juvenile facility (Chen 2009).

In this paper, I estimate the impact of private prisons on two important prisoner outcomes, time served and recidivism, in an effort to evaluate whether and how states should continue private prison contracting.[1] Time served in prison is the primary punishment that society imposes on all prisoners. This punishment is carried out unfairly, however, if it depends on quasi-random prison assignment (Kyle 2013; Dolovich 2005). Beyond the fairness aspect, the number of days a prisoner is incarcerated directly contributes to costs, threatening the main appeal of private contracting (Pratt and Maahs 1999). I also study recidivism, which is the rate at which a prisoner re-offends with a new felony. Analysis on this outcome is necessary because it permits welfare calculations if society is willing to trade incarceration costs or an unfair penal system for reduced crime. Moreover, recidivism offers a measure of prison performance, especially because private prisons claim to lower the rate of prisoner re-offending via high-quality and innovative rehabilitation programs (Spivak and Damphousse 2006; Bales et al. 2005; Bayer and Pozen 2005).

The lack of existing empirical work on private prisons is attributable to the difficulty of obtaining the necessary micro-data, along with a concern about selection in prison assignment. If prison assignment is based on characteristics unobserved to the researcher,

[1] Throughout this paper, I consider only for-profit private prisons. I ignore the few non-profit private prisons, especially since there are none in Mississippi, the state I study.

such as body tattoos indicating a proclivity for violent behavior, a credible research strategy requires a source of experimental or quasi-experimental randomization to draw valid conclusions about the effect of private prisons on prisoner outcomes. Perhaps owing to the difficulty of finding such variation, the existing research has ignored selection effects and instead conducted simple analyses comparing prisoner outcomes in public and private prisons. In particular, researchers have studied recidivism using data from Florida and Oklahoma (Spivak and Sharp 2008; Bales et al. 2005; Bayer and Pozen 2005; Lanza-Kaduce, Parker and Thomas 1999), but the results from these studies are conflicting.[2] To the best of my knowledge, no previous research has compared differences in prisoner time served between public and private prisons.

I address the problem of unobservable selection in prison assignment by exploiting the staggered entry and exit of private prisons in Mississippi between 1996 and 2004. Together with several bed expansions and contractions, these large shocks to private prison bed capacity serve as instruments for prison assignment. My empirical setting in Mississippi also has special significance for studying private prison contracting because the state has a large presence of private prisons—accounting for about 40 percent of all state prison beds in 2012—and the second highest incarceration rate in the United States (Langan and Levin 2013). Figure 1 shows the daily prisoner population across all private facilities in Mississippi: the state appears to have filled each private prison within three months of the openings (or bed capacity expansions), and then operated them at about full capacity. In the case of prison closings or bed capacity contractions, the state appears to have emptied the relevant facility with similar speed. This pattern suggests that the probability with which a prisoner was assigned to private prison is an increasing function of private prison bed capacity, a relationship that persists in a formal regression analysis. I use this finding to implement an instrumental variable analysis in which the identifying assumption is that the sharp shocks to bed capacity did not independently affect prisoner time served or recidivism for prisoners in private prison. I find this assumption plausible given that the rhetoric surrounding privatization only deals with cost-cutting and bed capacity (Price and Riccucci 2005).

I begin the empirical analysis by studying prisoner time served. I estimate the key parameters of interest using ordinary least squares (OLS) regression and matching on both

[2] Bayer and Pozen (2005) use detailed controls and find that juvenile offenders released from private prisons have 5 to 8 percent higher rates of one-year recidivism; they also study the role of non-profit private prisons, which are more prevalent in the juvenile prison system. Bales et al. (2005) and Lanza-Kaduce, Parker and Thomas (1999), however, use similar data and find no effect of private prison assignment on recidivism rates for male, female, or juvenile offenders in Florida. Spivak and Sharp (2008) estimate a 16 percent greater recidivism rate using data on adult male offenders in Oklahoma.

the full sample and an "event window" sample, the latter of which limits observations to those prisoners admitted to prison in the months surrounding the bed capacity shocks. I then conduct an instrumental variable analysis using the capacity-based instrument, which measures the change in private prison bed capacity over a prisoner's sentence.[3] I show that ignoring unobservable selection implies that private prisons extend prisoner time served by about 7 percent, but addressing unobservable selection suggests that the estimate is closer to 4 percent. These results withstand many robustness checks. Despite the nearly 50 percent reduction in the event window and instrumental variable estimates, they are not significantly different from the OLS estimates. For this reason, I interpret these results to be suggestive, but not confirmatory, of negative selection of prisoners into private prison.

I then explore several mechanisms that could be driving the observed difference in prisoner time served between public and private prisons. I establish that the widespread use of infractions, or prison conduct violations, by private prisons is a key mechanism by which they distort release policies: baseline infraction rates between public and private prisons are 18 and 47 percent, respectively. Even after controlling for all covariates, a prisoner in private prison is 15 percent more likely to be cited with an infraction over the course of his sentence.[4] I also estimate a panel regression with fixed effects for each prisoner, where the analysis is at the prisoner-month level and controls for any unobserved prisoner characteristics. Using this method, I find that these additional infractions result directly from time spent in private prison. In other words, it is not the case that the difference in infraction rates results from prisoners with high levels of infractions in the public prison system being transferred to private prison. The difference in infraction rates could be due to a variety of factors, including worse prison conditions or higher reporting rates, and I discuss these hypotheses in detail. I also rule out certain other mechanisms that could explain the difference in prisoner time served, including particular features of the contract structure and the amount of time elapsed since a prison's opening.

The final step in the empirical analysis examines recidivism. I apply the same empirical strategies for studying prisoner time served to this analysis, and I additionally employ hazard models in keeping with the literature. Using the prisoner's probability of re-offending with a new felony three years post-release as my main outcome measure, I find that private prisons do not significantly affect recidivism risk. The confidence interval on my IV estimate is wide,

[3]I also use a second instrument, "leave-one-out", which equals the fraction of prisoners assigned to private prison in the same admission month and year of a given prisoner.

[4]The infractions data is only available post-2000. Due to the lack of private prison capacity shocks in this more recent time period, I am unable to implement an instrumental variable analysis for this analysis.

however: I cannot rule out effects between -10 and 6 percent, which represent meaningful effect sizes relative to the base of 24 percent. This result independently contributes to an unresolved question regarding the relationship between incarceration length and recidivism. Abstracting away from all the other differences between public and private prisons, my estimate suggests that additional time served in the order of 60 to 90 days has no effect on recidivism risk.[5] Understanding the relationship between prisoner time served and recidivism is paramount in view of recent policies that promote changes in sentence lengths and parole guidelines.

Having established three empirical results related to prisoner time served, infractions and recidivism, I use insights from the literature to construct a model that can explain these findings. As aforementioned, the standard private prison contract pays a diem per bed occupied with limited additional contingencies, creating an incentive for private operators to maximize the number of days served by each prisoner; similar contracts are pervasive in health care (overview in Hurst 1991). The theoretical prediction given this type of contract is that private operators may *increase* prisoner recidivism because they ignore the benefits of non-contractible quality, for example, in the form of rehabilitation programs (Hart, Shleifer and Vishny 1997). In my model, the private operator chooses whether to distort release decisions based on the marginal profit and the level of government monitoring. I posit that private prison operators respond to government monitoring because they fear contract termination and lawsuits, both of which can damage long-term profit. My model also yields implications for recidivism based on the assumption that recidivism risk declines with time since offense, and I explore further implications when this assumption is relaxed.

This research also contributes to the broad literature on privatization, especially within criminal justice. The degree to which the government can successfully contract public services has been studied in a multitude of contexts including health, education, and social security (overviews in Domberger and Jensen 1997; Vickers and Yarrow 1991; examples include Ballou 2001; Duggan 2000; Mitchell and Zeldes 1996). There is a growing level of privatization within many areas of criminal justice such as police forces (Spitzer and Scull 1977), probation services (Lucken 1997), and bail bondsmen (Helland and Tabarrok 2004), but the full impacts of private contracting in these settings are unknown.

[5]The main challenge in studying this relationship is that the mechanisms that induce variation in time served may exert an independent effect on recidivism risk. For example, current studies leverage idiosyncratic judge behavior in assigned sentence length (Abrams 2010), state-wide release policy changes (Kuziemko 2013) and mass releases (Kuziemko 2013; Maurin and Ouss 2009), to name a few. The results from these papers are mixed, however: they find negative, zero and positive effects of time served on recidivism.

The data I obtained also afford an opportunity to explore the role of prisoner race on time served and recidivism. One-third of Mississippi's population is African American, yet this group makes up two-thirds of the state's prison population. In my instrumental variable analysis, I find that compared to all other prisoners, African American prisoners serve about 1.4 percent larger fractions of their sentences and are 2.5 percent more likely to be cited with an infraction. The experience of incarceration on this demographic is large—in fact, Neal and Rick (2013) estimate that the practice has left many young, male African Americans no better off than they were in the late 1960s. The level of incarceration also has spillover effects on other population groups. For example, Charles and Luoh (2010) find that rising male incarceration has a large impact on women via the marriage market.

The remainder of this paper is organized as follows. Section 2 provides institutional background on private prison contracting and the parole system in Mississippi; Section 3 provides a model on release policy; Section 4 describes the data; Section 5 details the empirical strategy; Section 6 discusses the results on time served; Section 7 revisits the model and discusses the results on recidivism; Section 8 investigates mechanisms, with a focus on infractions; Section 9 provides robustness checks; and Section 10 concludes.

2 Institutional Background

The main correctional facilities in Mississippi include four private prisons, three state prisons, and about 50 county jails approved for holding long-term inmates.[6] As of October 1, 2013, private prisons operated about 40 percent of all prison beds in the state. The county jails provide a large number of medium-security beds that are direct substitutes for prison beds, and many of the prisoners that go to private prison at the time of the capacity shocks are drawn from these jails. For the purposes of my analysis, I group all state prisons and county jails into "public prison" and group all the private prisons into "private prison."

The private prisons in Mississippi are comparable to the public prisons on most dimensions: both types of facilities primarily supply medium-security beds with similar cell types ("dormitory-style" or "pod-style"), offer a variety of programs including general education development courses and drug rehabilitation courses, and are accredited by the American

[6]Figure B.2 shows the locations of the public and private prisons. I consider only approved jails as part of the state's bed space, since state law mandates that prisoners cannot serve more than 30 days in unapproved jails. There are about 60 unapproved jails in Mississippi. There are also several community correctional centers which hold low-security inmates to help them reconnect with their families and obtain pre-release social services.

Correctional Association. The main difference is the operating structure, and private operators are granted control over a wide range of management decisions—from meal choices to employee hiring—as long as they meet coarse guidelines specified in the contract. Since 80 percent of a prison's operating costs are related to labor (McDonald et al. 1998), the main way in which private prisons are able to earn profit is by hiring lower-wage guards and programming staff. Private prison guards in Mississippi earn about $15,000 less per year ($50,000 versus $35,000) and have access to fewer benefits like health insurance and matched pension contributions (Mississippi Department of Corrections 2012). This difference is stark given that public employees may be underpaid since they are not unionized.

2.1 Private Prison Contracts

States typically contract with private operators to save costs and expand bed capacity. A quote from former MDOC Commissioner S.W. Pickett to the State of Mississippi's Governor and Legislature dated January 4, 1996, illustrates these core goals (1996 was also the year that Mississippi began private prison contracting):

> "The end of the Fiscal Year 1995 was essentially the middle of the largest expansion program in the Mississippi Department of Corrections' history. Included in this expansion was the initiation of institutional privatization. This approach will minimize construction expenditure obligated by the state to relieve overcrowding, and must show at least a 10 percent cost savings in operational expenses. Our current expansion program will help ensure that Mississippi has an adequate number of prison beds to house those offenders sentenced to the Agency (Mississippi Department of Corrections 1996)."

To choose a contractor, the state solicits proposals to provide private prison beds for specific capacity needs, e.g., medium-security adult male beds. In Mississippi, and in many states, the private prison beds—also called "per diem" beds—are required to provide a cost savings of at least 10 percent compared to the public prison.[7] The contractual diem payments only depend on prisoner classification (e.g., medium-security), although separate transfers are sometimes made to compensate for prisoner health expenses.[8] All four private prisons

[7]The Mississippi Senate Bill # 2005 states: "No contract for private incarceration shall be entered into unless the cost of the private operation, including the state's cost for monitoring the private operators, offers a cost savings of at least 10 percent to the Department of Corrections for at least the same level and quality of service offered by the Department of Corrections."

[8]For example, private prison operators in Mississippi are only responsible for providing the first 72 hours of medical care. After that period, the state pays for all medical bills even though the private prisons use

in Mississippi were paid per bed occupied until May 2001. At that time, the state passed a bill stipulating that two of the these private prisons would receive a guaranteed payment for 90 percent of the beds. I examine the effect of this contract change on prisoner outcomes in Section 8, but in practice, this guarantee is not binding since the private prisons typically operate above 90 percent occupancy.

2.2 Parole Process

Parole is the process by which prisoners may be released prior to the completion of the full sentence. On average, prisoners serve about 70 percent of their sentences, indicating the large degree of judgment involved in granting early release. In Mississippi, the Parole Board consists of five state employees that serve on a rotating basis. For each prisoner, the chief considerations for early release are the amount of time already served, severity of the main offense, the number of other offenses committed, community support or opposition, prior misdemeanor or felony convictions, history of drug or alcohol violence, crimes committed while incarcerated, behavior in prison, and participation in rehabilitative programs. Prisoners convicted of murder, manslaughter, sex crimes, and kidnapping became ineligible for parole in Mississippi as of June 30, 1995. In practice, however, these criminals can still be released long before the sentence end date under a special type of parole called "earned supervised release." I include indicator variables for all the parole-ineligible crimes in the empirical analysis, but most of them are excluded from the sample due to restrictions on sentence length and classification.

Generally, to be parole eligible, the prisoner must serve the greater of either 25 percent of the sentence or the following statutory minimums.[9] Although there are new minimum guidelines for the amount of time served in prison, in practice, the 25 percent rule is the guiding principle since the minimum time requirements can be circumvented with earned supervised release. The MDOC has slowly reversed much of the truth-in-sentencing legislation starting in 2005, though these reversals do not affect my empirical work since the most recent prison admission date I study is in 2004. I control flexibly for prisoner admission date, and its interaction with sentence length, to deal with any release policies that may be

separate medical networks from the state prisons.

[9]These statutory minimums are: if the sentence is from one to two years he must serve at least nine months; if the sentence is two to five years he must serve at least ten months; if the sentence is more than five years but less than thirty years he must serve at least one year; if the sentence is thirty years or more he must serve at least 10 years. Although I do not study prisoners sentenced before June 30, 1995, the rule for these offenders was simply that they had to serve at least 25 percent of their sentences.

changing at this level of observation.

A nice feature of the Mississippi parole system is that the primary determinant of parole, apart from observed admission factors, is the prisoner's behavior in prison. This behavior is measured via infractions, or rule violation reports given for violations ranging from being too loud or possessing contraband (e.g., cell phones). The availability of the infractions data allows me to uncover the mechanism by which parole outcomes differ for prisoners in private versus public prison. Previous research, including Kuziemko (2013) and Bernhardt, Mongrain and Roberts (2012), have studied how in-prison behavior is affected by other institutional structures such as discretionary parole.

3 A Model of Prisoner Release Decisions

I develop a model of prisoner release decisions to illustrate the distortion that can result from private contracting. The model is based on Kuziemko (2013), who studied the costs and benefits of discretionary parole regimes. The basic setup is also constructed to incorporate an important aspect of the incomplete contracting model in Hart, Shleifer and Vishny (1997), which argues that private prison operators may undertake excessive cost cutting because they ignore the impact of these cost reductions on non-contractible quality.[10] In my model, changes in release policies that occur systematically in private prisons represent distortions of justice because they differ from the public norm.

3.1 Baseline Model without Private Contracting

I posit that a state chooses an optimal release policy based on the trade-off between incarceration costs and the cost of severity-weighted recidivism risk. As in Kuziemko (2013), incarcerating a prisoner for an additional day costs some amount C, but society benefits from a reduction in crime due to both an incapacitation effect (i.e., the prisoner cannot commit crime while incarcerated), and an aging or specific deterrence effect (i.e., a prisoner's recidivism risk may decline with time since the original offense).[11]

[10]Specifically, Hart, Shleifer and Vishny (1997) outline a model in which the manager of the prison (public or private) produces a "modified good", $B = B_0 - b(e) + \beta(i)$, with cost structure $C = C_0 - c(e)$. The private operator chooses effort levels e^* and i^*, which are the effort provisions for innovating on cost reduction and quality improvement, respectively. The broad implication is that the private operator over-invests in cost reduction, e^*, and under-invests in quality innovation, i^*, because the operator profits from cost innovations but is not compensated for quality innovations.

[11]There may also be a general deterrence effect in which criminals decide to engage in less crime because of an increase in the expected incarceration length. This effect follows directly from the models in Becker

Let prisoner i pose a severity-weighted cost of recidivism r_i that is a function of his individual-specific risk, R_i, and a parameter β that captures the rate at which his recidivism risk changes with the number of days since his offense:

$$r_i(t) = R_i - \beta_i t. \tag{1}$$

If the daily cost of incarceration to the state is C, the state's cost minimization problem is given by:

$$\min_{s_i} \quad \overbrace{Cs_i}^{\text{Incarceration costs}} \quad + \overbrace{\int_{s_i}^{\infty} r_i(t)\,dt}^{\text{Recidivism costs}} . \tag{2}$$

In this cost minimization problem, the first order condition is $C - r_i(s_i^*) = 0$, and the optimal policy for the state is to release prisoner i at s_i^*, which is the point at which the prisoner's expected risk r_i, or marginal social benefit, equals C, the marginal social cost.[12] Rewriting and rearranging this equality in terms of the components of r_i yields:

$$s_i^* = \frac{R_i - C}{\beta_i}. \tag{3}$$

Accordingly, the optimal time served in prison is an increasing function of the prisoner's initial risk R_i and a decreasing function of the rehabilitation rate β_i. Figure 2 shows the recidivism cost and daily incarceration curves.[13] The optimal number of days served, s_i^*, has a natural upper bound at the court-ordered sentence. This framework can also be used to study optimal release policies measured by fractions of sentences that served, in which case $s_i \in [0, 1]$ has a natural upper bound at 1. By law, as described in Section 2, the state holds prisoners for a minimum of 25 percent of the court-ordered sentence. In this setup, the state pays Cs_i^* in incarceration costs in exchange for social benefit $\int_0^{s_i^*} r_i(t)dt$ from incapacitation. At this optimum, the state still faces an expected cost of $\int_{s_i^*}^{\infty} r_i(t)dt$ in severity-weighted potential recidivism resulting from prisoner i's release.

(1968) and Ehrlich (1973), where the rational criminal bases his decision to commit crime based on the probability of punishment and the size of the punishment. This paper ignores the general deterrence effect because the analysis only concerns prisoner outcomes *conditional* on court-ordered sentences. An important paper on this topic is Levitt (1996), which argues that the cost of incarceration is small compared the effect on incapacitation and general deterrence.

[12] The marginal social cost C abstracts from the prisoner's own value of freedom, but I incorporate this cost in the next section.

[13] Kuziemko (2013) provides robustness of these results to several modeling assumptions.

3.2 Distortion of the Release Decision by the Private Operator

As established in Section 2, private prison operators must provide cost savings to obtain the contract. Let the private operator charge $C' < C$ for each bed occupied. Friction arises in this setting because the private contractor treats C' as its marginal revenue; it does not care about minimizing the risk of recidivism. Since C' is the negotiated payment made by the state to the private prison operator for each bed occupied, the private operator must incur marginal cost $C'' < C'$, else it would not generate profit. The private operator's marginal cost, C'', need not be constant, although it is useful (without loss of generality) to think of C' as a fixed marginal cost saving at least until the private contractor holds the prisoner for s_i^* number of days.[14]

When a private operator holds a prisoner beyond the number of days expected by the state, it must exert effort to profit from this distortion. This effort could take the form of citing excessive infractions, which are prison conduct violations that delay a prisoner's release. Formally, let the marginal cost of the private prison be:

$$C_i'(t) = \begin{cases} C' & \text{if } \hat{d}_i \leq 0 \\ M\hat{d}_i^{\,2} & \text{if } \hat{d}_i > 0 \end{cases}$$

where M is a scalar capturing the intensity with which the state monitors the private operator. Observe that if $M = \infty$, then $s_i = s_i^*$; in other words, if monitoring is perfect, then private operators have no scope to extend prisoner time served. For any $M < \infty$, however, distortion occurs although its magnitude can be mitigated by high levels of monitoring or lower marginal incentives (C'). This distortion allows the private prison operator to realize profit on each prisoner i in the amount:

$$\int_0^{s_i^*+\hat{d}_i} C' - C'' dt. \tag{4}$$

This model assumes that the government is watchful for positive distortions, i.e., distortions that increase a prisoner's time served in prison; relatively simple extensions can be carried out for other monitoring policies. For example, the state may also be watchful for distortions that decrease time served for prisoners in private prison that are expensive or dangerous to incarcerate. Figure 2 illustrates how equation (3.2) affects the equilibrium outcomes in the

[14]The case where the private firm faces marginal cost C" but seeks to reduce recidivism risk as its objective describes non-profit prisons, which are studied in (Bayer and Pozen, 2005).

broader framework.

The cost function in equation (3.2) can easily be endogenized. Consider that the private operator faces profit function:

$$(C' - \eta_i)(s_i^* + \hat{d}_i) - \frac{1}{M}\hat{d}_i^{\,2}P, \tag{5}$$

where η is a flat marginal daily cost of incarceration for the private operator, $\hat{d}_i$ is the number of days—positive or negative—that the private operator keeps prisoner i different from the public norm s_i^*, M is the level of government monitoring (probability of getting "caught"), and P is a punishment for "getting caught" with distortion. The private operator decides on the optimal level of distortion, $\hat{d}_i$, based on the first order condition:

$$\hat{d}_i = \frac{2(C' - \eta_i)P}{M} + s_i^*, \tag{6}$$

which, as expected, is increasing in the punishment P and decreasing in the level of government monitoring M. In this case, the distortion in the number of prisoner days served is always positive as long as the marginal revenue, C', exceeds the daily cost to the private operator, η.

3.3 Assessing Welfare

Distortion of the release decision has direct implications regarding the fairness of the criminal justice system: conditional on all available information, the state, acting as the social planner, does not seek differential punishment of prisoners by assigning them to private or public facilities. This will occur, however, if prison assignment is based on extraneous factors such as prison capacity. The primary welfare loss from release policy distortion is due to injustice, but society may also care about the eroded cost savings and the prisoner's value of freedom.

Quantifying the value of prisoner freedom is difficult. Using experimental evidence on bail setting in Philadelphia, Abrams and Rohlfs (2011) offer an estimate of about \$1,000 (\$1,270 in today's dollars) for 90 days of freedom, but their estimates are noisy and may not be relevant for prisoners who have already served a substantial number of days in prison. If the daily value of a prisoner i's freedom is constant at F_i, then distortions in release policy induces a welfare loss to prisoners of the amount:

$$\sum_{i \in I} \hat{d}_i F_i, \tag{7}$$

where $\hat{d}_i$ represents the distortion (in number of days) that a prisoner is kept beyond his expected number of days in prison, s_i^*.

The erosion in cost saving is important for social welfare. The state pays an extra $\hat{d}_i C'$ in incarceration costs for each prisoner i, and loses all the expected cost savings from private contracting if $\hat{d}_i C' > (C - C')s_i^*$. If the cost savings offered by private operators is $(1-\gamma)$ percent per occupied bed (by Mississippi state law, $(1-\gamma) \geq 10$ percent), then the inequality becomes $\hat{d}_i \gamma C > (1-\gamma) C s_i^*$, which simplifies to:

$$\frac{\hat{d}_i}{\hat{d}_i + s_i^*} > 1 - \gamma. \tag{8}$$

When the distortion is viewed in percentages of fraction served, equation (8) implies that the private operator directly erodes cost savings by one percent for each percent of distortion.

An extension to this model that allows for the state to re-optimize release policies is provided in Section A.3. The intuition is that if the state views private prison contracting as a technology that reduces the marginal cost of daily incarceration, then it may re-optimize release decisions accordingly. However, distortion may still occur because the state and the private operator maximize different objective functions: while the state seeks to minimize the risk of severity-weighted recidivism, the private operator only cares about its profit.

4 Mississippi Felony Data and Sample Definition

To evaluate the extent to which release policies are distorted by private prisons, I study Mississippi felonies from May 1, 1996 to July 31, 2013. This state's prison data are rich, and several private prison bed expansions and contractions provide useful quasi-experimental sources of variation in prison assignment. Administrative records were obtained directly from the Mississippi Department of Corrections (MDOC). The MDOC manages an "inmate data file" that covers every inmate who served time in a state prison since 1981, although some variables, such as the timing of transfers between facilities, are available only from May 1, 1996. The felony-level files contain standard criminal justice data on the offender's demographics, offense, infractions, and release type. A special feature of this data is that I am able to observe the movement of prisoners between facilities over the course of their sentences—this allows me to determine the amount of time that a prisoner spent in private prison, as opposed to several existing studies that only look at whether the releasing facility was a private prison.

The demographic variables in the MDOC dataset include the offender's age, gender, race, county of conviction, and prior felonies. Classification data include information on the offender's bed security level (ranging from minimum to maximum), medical score (ranging from values A, healthy, to E, extremely sick) and the "level of care" score (ranging from 1, indicating a prisoner who is normally functioning and able to work, to 5, indicating a prisoner who is severely physically or mentally constrained). The dataset also includes information on the crime committed, court-ordered sentence length, and the number of days served while the case was under trial. Using these data, I construct three variables of interest: whether a prisoner was ever assigned to private prison (the main independent variable in my analyses), whether the prisoner had a prior incarceration in the five years prior to the admission date, and whether the prisoner recidivated within three years of release with a new sentence.[15]

My primary sample consists of felonies that occurred in Mississippi between May 1, 1996 and July 31, 2004. Each observation is a prisoner-sentence; on average, there are 1.1 sentences per offender. There were initially 34,571 prisoners contributing 40,195 observations between May 1, 1996 and July 31, 2004. I omit sentences that occur after July 31, 2004 to allow for a three-year recidivism window for the 85 percent of sentences that are less than or equal to six years. Between August 1, 2004 and August 1, 2013, I observe an additional 39,059 sentences for 34,620 prisoners, from which I calculate whether a prisoner returns to prison in the three years following release. My sample is further restricted to adult inmates (age $\geq$ 18) because the juvenile correctional system is wholly different from the adult correctional system.[16]

Table 1 shows summary statistics for prisoners by whether they are assigned to public or private prison, for the full sample as well as an "event window" sample; the latter group limits observations to those prisoners admitted in the few months surrounding the bed capacity shocks. Specifically, I include only prisoners with admission dates at least 30 days before a capacity shock who have release dates at least 90 days following the capacity shock. This

[15] I only observe recidivism if the new felony occurs in Mississippi. This is a common censoring problem, but the problem is ameliorated by the observation that most recidivating cases tend to occur in the same state (Beck and Shipley 2013; Langan and Levin 2013).

[16] A few other inconsequential restrictions are imposed to reduce the noise in the final sample. I omit a few sentences that are shorter than one year because the MDOC states that all felonies must carry a minimum sentence of one year. In rare cases, however, the judge may award up-front meritorious time to reduce the sentence. The sample also excludes prisoners with life or death penalty sentences because the prisoner outcomes I study are not relevant in the context of life or death penalty sentences—the sentence length restriction of 1 to 6 years is enough to exclude these prisoners. Finally, I limit the sample to those offenders who serve at least 25 percent of their sentences, since this is the minimum required by the Mississippi law and exceptions are only made under exceptional circumstances.

sampling choice is discussed further in Section 5. My full analysis sample therefore consists of 26,593 prisoners, about 19 percent of whom go to private prison over the time period examined. The event window sample consists of 13,282 prisoners—for this sample, I define the prisoner as being assigned to private prison only for the 1,054 prisoners that are sent to a private prison *within the first six months* of the prison opening or bed expansion.[17] The purpose of this categorization is to leverage the quasi-random variation in prison assignment induced by the capacity shocks on the event window sample in the empirical analysis.

The descriptive statistics in columns (1) to (3) of Table 1 foreshadow the main results. First, prisoners in public prison serve 70 percent of their sentences on average, but prisoners that go to private prison serve 73 percent of their sentences. Much of this difference is attributable to prisoners who serve exactly 100 percent of their sentences: whereas 11 percent of prisoners in public prison serve the maximum number of days in prison, about 17 percent of their counterparts in private prison do so. Recidivism rates are similar for the two groups (25 versus 26 percent), and are very close to the national average of 24 percent (Langan and Levin 2013). The higher average sentence length among privately incarcerated prisoners reflects both the state's preferences in prison assignment, and the fact that prisoners with longer sentences experience more private prison openings and bed expansions.

Figure 3 shows the cumulative distribution function (CDF) plots of the fraction of sentence served by offense category, and Figure 4 shows the same plots by bins of sentence length. For both variables, the CDFs of fraction of sentence served for prisoners that go to private prison stochastically dominates the CDFs for those prisoners in public prison almost every instance. The CDFs also show peaks at the 50, 85 and 100 percent, which are common release points. Together, these figures suggest that release policies differ systematically between public and private prison, without heterogeneity by offense category or sentence length.

Table 1 also reveals a considerable degree of difference along observed characteristics between those in public versus private prison. Echoing the anecdotal evidence provided in Spivak and Sharp (2008) and Avio (1991), I find that prisoners in private prison are more likely to be black (71 versus 67 percent), single (67 versus 55 percent), young (mean age of 28 versus 32) and less educated (56 versus 53 percent are high school dropouts).[18] Figure 5

[17]The reason I do not observe more prisoners going to private prison during the capacity shocks is because many of them are still in prison. Additionally, many of these prisoners were admitted to the system before 1996, and are excluded from the sample because their movement data are unavailable.

[18]Spivak and Sharp (2008) also find evidence of this type of selection in Oklahoma: "Private prison inmates tended to be younger, had fewer years in prison, were often minority and drug offenders who were reputed to be associated with gangs, and often appeared to be seeking social status through violent confrontations with

shows the CDFs of some of these variables divided by whether the prisoner was assigned to private prison; interestingly, variables such as age and sentence length are different across the two groups for the entire distribution, not just at the mean. This degree of observable selection raises concerns about unobservable selection, suggesting an instrumental variable approach is required to obtain an unbiased estimate of the impact of private prisons on prisoner outcomes.

The other variables shown in Table 1 relate to the prisoner movements, offenses and release types. I observe that the typical path for a prisoner is to serve "court days" while his case is deliberated and then, if he is found guilty, he is transferred to the corrections system. Prisoners who are found guilty are given full credit for days served while in court. At that point, the prisoner is classified at a public facility and then assigned to long-term placement in either a public or private prison, though he can be moved several times again afterward. The classification process is lengthy: on average, column (1) reveals that it takes 8.4 months. There are some differences by offense category in the types of prisoners that are assigned to private prison; for example, fewer have drug possession and felony DUI charges, and more have robbery and assault charges. Prisoner release types also differ slightly between the two types of facilities, with more prisoners in private prison released under "earned supervised release", which is a type of release granted to prisoners who have served large fractions of their sentences. The descriptive statistics for the event window sample, in columns (4) to (6) of Table 1, largely mirror those in the overall sample. The main differences in the summary statistics between the full sample and the event window sample are due to time trends—the full sample includes observations from 2000 to 2004, which the event window analysis does not.[19]

5 Empirical Strategy

Next, I offer four sets of estimates relating prisoner time served to private prison assignment. The first two sets of estimates use ordinary least squares (OLS) on the full and event window samples to characterize the underlying relationships in the data. A third set of estimates is generated by an instrumental variable analysis that exploits capacity shocks to private

other inmates and by adverse interactions with security and management staff....These offenders may have differed qualitatively from inmates less troublesome to staff (and thus less likely to be transferred) in ways that would enhance their hazard of recidivism but not be adequately captured by the control variables."

[19] I also provide the prison-by-prison summary statistics in Table B.1, but present the pooled analysis in the main text since the prison-by-prison analysis does not provide additional insights.

prison bed capacity to obtain quasi-random assignment of prisoners to private prison. The fourth approach employs a "leave-one-out" instrumental variable that equals, for each prisoner, the number of *other* prisoners admitted in the same month-year that are assigned to private prison. Robustness analyses, including matching and a control function approach, are provided in Section 9. I leave the recidivism analysis for Section 7.

5.1 Benchmark: OLS Using the Full Sample

The first OLS regression that links the effect of private prison assignment on prisoner outcome Y_i as follows:

$$Y_i = \beta Private_i + \theta X_i + \epsilon_i, \tag{9}$$

where $Private_i$ is a binary variable indicating whether the prisoner serves any time in private prison. I measure time served as either the fraction of sentence served, or the number of days served. The vector X_i captures demographic, classification, offense, admission time and crime-related information. Demographic information includes prisoner age at admission date, race, citizenship, marital status, and education level. I also use the prisoner's county of conviction, which is typically identical to the prisoner's county of residence (Thomas and Torrone 2008). For crime-related information, I control for sentence length, offense type, and criminal history. For admission time, I include both linear and quadratic terms, and interact each of these terms with sentence length.[20]

The parameter of most interest, β, measures the effect of private prison assignment on outcome Y_i. The two outcomes I study have natural interpretations in the face of selection. If there is negative selection, I expect that prisoners that would typically (1) serve a larger fraction of his sentence and (2) recidivate at a higher rate would be systematically assigned to private prison. The opposite is true in the presence of positive selection, i.e., the world in which unobservedly "better" prisoners are assigned to private prison.[21] Based on my conversations with MDOC officials, I expect that those prisoners assigned to private prison are more likely to re-offend even in the absence of treatment, i.e., the "worse" prisoners are assigned to private prison. Several papers have also suggested that negative selection on unobservables is probable in private prison assignment (Avio 1991; Gaes 2012; Spivak and

[20]Admission time is calculated as days since January 1, 1990. Hence, if a prisoner begins his sentence on January 1, 1999, his value of admission time is $9 * 365 = 3,285$.

[21]Mathematically, β will be biased if private prison assignment is correlated with the error term ϵ_i due to omitted variables bias. If "better" prisoners are systematically more likely to be assigned to private prison, then β will be biased downward. If systematically "worse" prisoners are assigned to private prison, then β will be biased upward.

Sharp 2008).

5.2 OLS Using the Event Window Sample

If the capacity shocks to private prison bed capacity exogenously shift the probability of private prison assignment, then the OLS analysis on the full sample can be improved by constructing a better control group for the prisoners that go to private prison. I implement an event window research design to achieve this goal and isolate the effect of private prison assignment on prisoner outcomes using variation only from the prisoners who are induced to private prison assignment by the private prison capacity shocks.

The event window design I use addresses one of the key challenges in leveraging the capacity shocks to private prison capacity as an instrument for private prison assignment: new prisoners are rarely assigned to private prison. In fact, the average time served in jail or public prison prior to private prison assignment is just over eight months (see Table 1)—due to this institutional feature, it is not possible to conduct a conventional "before and after" analysis. Instead, I limit the sample to prisoners that have an admission date at least 30 days prior to the date of the capacity shock, and a release date at least 90 days after the capacity shock.[22] Within this sample, for each capacity shock, the variable *Private* equals one if the prisoner is assigned specifically to the prison with the capacity shock ("ramp up") within the time period.

5.3 Instrumental Variable Analysis Using Bed Capacity Shocks

To extend the event window analysis, I adopt an instrumental variable approach in which prisoners are assigned to private prison depending on a measure of private prison capacity. This method extends the event window analysis in two ways. First, I am able to use prison closings as an additional source of variation in private prison bed capacity. Second, this analysis measures the "intensity" with which a prisoner is exposed to private prison openings and closings and hence uses variation in sentence length.

Estimating the first stage equation requires care because the endogenous variable, whether the prisoner is assigned to private prison, is binary and has a low mean.[23] To instrument for a prisoner's likelihood of private prison assignment, I operationalize the bed capacity shocks

[22] The reason I use the 30 and 90 day cutoffs is because the MDOC states that these are rough guidelines.

[23] A linear probability model for private prison assignment predicts a large number of negative values. Using the variables in my preferred specifications shown in Table B.5, I find that a linear probability model predicts negative values for whether a prisoner is assigned to private prison in 15 percent of the cases.

illustrated in Figure 1 using the following formula:

$$RAMP_i = \sum_{j=1}^{J} ramp_{ij}, \tag{10}$$

where J is the number of capacity shocks and $ramp_{ij}$ is defined as:

$$ramp_{ij} = \begin{cases} C_j & \text{if } \ a_i \leq t_j - 30 \text{ and } v_i \geq t_j + 90, \\ 0 & \text{otherwise,} \end{cases} \tag{11}$$

where a_i is the prisoner's admission date, v_i is his maximum release date (i.e., the prisoner's admission date plus his court-ordered sentence), t_j is the date of the private prison bed capacity shock, C_j is the number of beds opening or closing. Variation in the instrument is induced by differences in prisoner admission date and sentence length.

I also adopt a conventional leave-one-out instrument that equals the fraction of *other* prisoners with the same admission month and year who go to private prison. For prisoner i admitted in month m of year y, the instrument is defined as:

$$\textit{Leave-one-out}_{imy} = \frac{\sum_{i=1}^{N_{my}} Private_{my} - 1}{N_{my} - 1}.$$

Figures 6 and 7 show scatter plots of these two instruments by prisoner admission date. The two instruments that I use differ from each other in important ways. The capacity shock instrument is a function of both the prisoner's admission date and sentence length. The leave-one-out instrument is a only a function of the prisoner's admission date.

To address the nonlinearity of the first stage, I adopt the probit correction outlined in Wooldridge (2002). This method leverages the probit model to capture the nonlinearity of the first stage, and the predicted probabilities from this model are used as instruments in a standard two-stage least squares (2SLS) framework. An advantage of this method is that it is robust to misspecification of the probit model (one of the drawbacks of a control function approach), and the standard errors are the same as the usual 2SLS standard errors. The probit model is given by $P_i = \Phi(\kappa Z_i + \beta X_i)$, where X_i is the same as in the OLS specification and Z_i refers to the instrument. The first stage equation is given by:

$$Private_i = \alpha_S + \beta_S \hat{P}_i + \delta_S X_i + \eta_i \tag{12}$$

The second stage equation uses as an instrument the predicted probability, $\widehat{Private}$:

$$Y_i = \alpha_{IV} + \beta_{IV}\widehat{Private}_i + \delta_{IV}X_i + \epsilon_i. \tag{13}$$

Identification requires three assumptions. First, the instrument Z_i must be a good predictor of prison assignment, and I show this in the regression analysis. Second, there should be monotonicity: the instrument should affect private prison assignment in the expected direction. In other words, expansions should *increase* the probability of private prison assignment, while contractions should *decrease* the probability of private prison assignment. Finally, the exclusion restriction should be satisfied—the instrument should be otherwise unrelated to prisoner outcomes. A threat to my identification strategy would have to predict differential outcomes for prisoners in private versus public prison, which seems unlikely given that the rhetoric surrounding privatization only deals with cost-cutting and bed capacity.[24] Formally, the exclusion restriction requires that η_i, the first stage regression error, is independent of ϵ_i, the second stage regression error.

6 Results on Time Served

This section presents the estimates of the effect of private prison assignment on prisoner time served. I find suggestive evidence of negative selection of prisoners to private prison because the event window and instrumental variable (IV) estimates are smaller, though not statistically significantly different from, the benchmark OLS estimates (4 versus 7 percent, or 60 versus 90 "extra" days).

Table 2 presents the OLS and event window results—in particular, columns (3) and (6) report the saturated regression estimates with all the controls discussed in Section 5. These results show that prisoners in private prison appear to serve 6 to 7 percent larger fractions of their sentences than prisoners in public prison. The coefficient of 6 to 7 percent is remarkably stable: moving from column (1) which only controls for offense, admission time trends, and county of conviction, to column (3) which includes all the demographic and classification information, does not change the point estimate. Since the mean sentence length for prisoners in private prison is 3.68 years, an increase of 6.8% in the fraction of sentence served translates to 91.3 additional days.[25] Given that the mean fraction served is

[24]Even if the state re-optimizes release decisions simultaneously with capacity shocks, I show in Section A.3 that the theoretical predictions about release policy distortion are still relevant.

[25]Table B.2 presents estimates using days served as the dependent variable. The estimate from this

about 70 percent, my OLS estimate translates to an effect size of about 10 percent.

The other covariates in columns (1) to (6) of Table 2 have the expected sign: prisoners with larger sentences serve smaller fractions of their sentences, and the number of prior incarcerations increases the fraction of sentence served by about one percent. Even after controlling for all covariates, I find that single, black and older prisoners each serve significantly larger fractions of their sentences. The estimates in column (3) suggest that single prisoners serve 2.4 percent and black prisoners serve 1.4 percent larger fractions of their sentences. Some of these differences may be due to in-prison behavior, which I discuss further in Section 8. I find no effect of education level, as measured by whether the prisoner completed high school, on the release decision.

Table 3 shows the instrumental variable estimates of private prison assignment on the fraction of sentence served. The two instrumental variables are the capacity-based instrument, shown in columns (2) to (4), and the leave-one-out instrument, shown in columns (5) to (7). Columns (3) and (6) report the first stage regressions: the F-statistic is 37 for *Ramp* and above 100 for *Leave-one-out*. Both sets of instrumental variable estimate reveal a much smaller relationship between private prison assignment and fraction of sentence served than that indicated by the OLS and event window estimates, but the standard errors on the IV estimates are large and cannot rule out the earlier estimates. According the to IV analysis, the true effect of private prison on prisoner time served is closer to 4 percent, which equals about 60 additional days.[26]

7 Recidivism Analysis

7.1 Assessing Welfare Impacts Considering Recidivism

I return to the model in Section 3 and discuss the welfare impacts of private prisons considering recidivism as an outcome. The empirical work thus far has established that private prisons cause a distortion in a prisoner's time served. If the additional days in prison decrease recidivism, then the distortion may not be harmful from a social welfare perspective. In this section, I relax the implicit assumption that distortions to time served are necessarily welfare-decreasing for society. Specifically, I allow for reductions in recidivism to outweigh the increased incarceration cost, and derive a new set of welfare calculations to assess the

regression is 93.2 additional days for prisoners assigned to private prison.

[26]This result is corroborated by the specification in which the dependent variable is measured as days served instead of fraction of sentence served, shown in Table B.3.

impact of private prisons.

The time elapsed since a prisoner's offense may affect his risk of recidivism, as shown in equation (2). Therefore, while it is unfair for prisoners in private prison to receive differential punishment, society may benefit from the distortion if it is willing to trade incarceration costs and unfair punishment for reduced crime.[27] Figure 8 depicts this trade-off: distortions to time served are beneficial as long as they are sufficiently small and the recidivism risk curve is sufficiently flat. The total social cost of incarcerating an individual without private prison contracting is given by:

$$(C - R_i)s_i^* + \frac{\beta}{2}(s_i^*)^2 + \Delta, \tag{14}$$

where the parameters C, R_i, β, and s_i^* are the same as in equation (2), and $\Delta = R_i t - \frac{\beta}{2}t^2\Big|_{t=\infty}$.

For the case where the government contracts with private prisons, the total social cost of incarcerating an individual depends on the amount of distortion $\hat{d}_i$, and the extent to which C' is less than C. The total social cost is given by:

$$(C' - R_i)\left(s_i^* + \hat{d}_i\right) + \frac{\beta}{2}\left(s_i^* + \hat{d}_i\right)^2 + \Delta. \tag{15}$$

Total social welfare improves under private prison contracting if the following is true:

$$\left[(C - R_i)s_i^* + \frac{\beta}{2}(s_i^*)^2\right] - \left[(C' - R_i)\left(s_i^* + \hat{d}_i\right) + \frac{\beta}{2}\left(s_i^* + \hat{d}_i\right)^2\right] \geq 0, \tag{16}$$

or, equivalently, if:

$$(C - C')s_i^* - (C' - R_i)\hat{d}_i - \beta\hat{d}_i s_i^* - \frac{\beta}{2}\hat{d}_i^{\,2} \geq 0, \tag{17}$$

where, from equation (3), $s_i^* = \frac{R_i - C}{\beta_i}$.

Before showing the conditions under which equation (17) is positive, a few observations are in order. First, absent distortion (i.e., $\hat{d}_i = 0$), social welfare is guaranteed to improve under private contracting, and this improvement is equal to $(C - C')s_i^*$, which is the cost saving offered by private prisons. Indeed, policy discussions surrounding private prison contracting strongly suggest that this is the overarching goal of privatization. Second, if

[27] Of course, the prisoner's own value of daily freedom F_i, as discussed in Abrams and Rohlfs (2011), remains as a potentially important part of the calculation.

recidivism risk does not respond to time elapsed since offense (i.e., $\beta = 0$), the increase in social welfare from private prison contracting is $(C - C')s_i^* - (C' - R_i)\hat{d}_i$. In this case, social welfare is actually an *increasing* function of distortions, as long as the criminal justice system chooses to incarcerate individuals with recidivism risk greater than the marginal cost of incarceration.

Returning to equation (17), I find that social welfare increases if:

$$\hat{d}_i \leq \frac{(C - C')^2 + \sqrt{(C - C')^2 + 2(C - C')(R_i - C)}}{\beta}. \tag{18}$$

The intuition from equation (18) is as follows. If the amount of distortion from private prison contracting is sufficiently low, then there is a gain in social welfare. If $\beta = 0$, the condition requires only that $\hat{d}_i < \infty$, which is always the case since the private prison cannot hold a prisoner beyond his court-ordered sentence length. If private prisons offer no cost saving, i.e., if $C = C'$, then equation (18) shows that social welfare is unchanged only if there is no distortion.

Two testable implications emerge from this framework. First, if recidivism risk is truly falling in time since offense, and if private prisons have no other impact on recidivism risk, then recidivism risk should be lower for prisoners who go to private prison. Using prisoner data from Georgia and an instrumental variable analysis based on parole guidelines, along with the same definition of recidivism used in this paper, Kuziemko (2013) estimates that each additional month in prison is associated with a 1.4 percent reduction in recidivism. If this estimate applies to Mississippi, I would expect a 2.8 to 4.2 reduction in recidivism rates for prisoners who go to private prison.

This is ultimately an empirical question, since prior studies argue that time in prison can either reduce or increase recidivism rates. If I do not find any reduction in recidivism for prisoners that go to private prisons, the null result could serve as evidence for two hypotheses. First, the marginal social benefit of incarceration, β, may be close to zero (Abrams 2007; Hirschi and Gottfredson 1983). Second, as illustrated in Panel B of Figure 8, private prisons may affect the slope of the recidivism risk curve: this could occur if private prisons serve as a "school of crime", meaning that prisoners learn how to commit more crime during their incarceration (Cook et al. 2013; Bayer, Hjalmarsson and Pozen 2009).

7.2 Recidivism Results

None of the methods I employ reveal significant effects of private prison assignment on recidivism rates. The OLS result of the effect of private prison assignment on recidivism in Table 4 suggests that private prison assignment has no discernible effect on recidivism. The point estimates from the benchmark and event window regressions in columns (3) and (6) are 0.007 and 0.005, respectively. Neither effect is significant, though several results on the covariates corroborate findings from the literature: First, prisoners with a felony history recidivate at greater rates, and each prior incarceration within the five years before the admission date is associated with a 5.5 percent increase in recidivism. Second, older prisoners are associated with lower recidivism risk, and each additional year in a prisoner's age at time of admission causes a 3 percent decline in recidivism risk (the estimate in Ganong (2012) is 5 percent). Third, unmarried prisoners recidivate at 7 percent higher rates than married prisoners. Finally, prisoners with less than high school education appear to recidivate at a 1 percent *lower* rate.[28]

Table 5 shows the instrumental variable results, and I continue to find no effect of private prison assignment on recidivism. Interestingly, the point estimate from the IV analyses in columns (2) and (3) are both about -2 percent, which is consistent with the 1 percent reduction in recidivism for each 1 additional month in time served found in (Kuziemko, 2013). Additionally, moving from OLS to IV, the reduction in the point estimate is consistent with the results of the time served analysis. The point estimates on the other covariates are similar to the OLS estimates.[29]

Keeping with the recidivism literature, I also implement a hazard model that allows for censoring and counts the number of days until re-offense. The hazard regression estimates are provided in Table B.4; the point estimate on *Private* is -0.027 for the full sample and -0.013 for the event window sample, but the confidence intervals are wide in each case. Figure B.3 shows the cumulative hazard estimate of prisoners by whether they went to private prison, and also by buckets of sentence length. Panel A shows that there is no discernible difference in recidivism rates between prisoners that go to public versus private prisons. Panel B shows that recidivism rates are increasing with sentence length—this result is not surprising

[28] I also estimate a probit model, shown in Table B.7, where I find similar results.

[29] Table B.6 shows the instrumental variable estimates of recidivism employing the standard 2SLS framework without the first stage correction for nonlinearity. Both sets of estimates have wide standard errors and cannot preclude reasonably large effects of private prison exposure on recidivism. Section B discusses the welfare consequences for a range of possible recidivism values, considering the incarceration costs, the prisoner's value of freedom, and the social cost of crime.

because offenders with short sentences tend to be "habitual offenders", while prisoners with longer sentences tend to be "one-off" criminals. One drawback of hazard models that limits the scope of further analysis, however, is that they are not compatible with instrumental variable methods.

8 How Can Private Prisons Distort Release Policy?

Having established that private prison exposure causes a 4 to 7 percent increase in the fraction of sentence served with no discernible effect on recidivism, I now explore mechanisms that could explain these results. The backdrop for several of the candidate mechanisms is that private prisons are paid per bed occupied, and the incompleteness of the contract allows them to manipulate prisoner outcomes.

8.1 Infractions

Based on Table 1, a leading explanation for why prisoners serve larger fractions of their sentences in private prison is via differences in infraction rates: 47 percent of prisoners in private prison are cited with an infraction, versus 18 percent in public prisons. Infractions are an important outcome to study because the parole board ties them to release decisions (Flanagan 1983). However, they are imperfect measures of behavior because they can also result from harsher prison conditions in private prisons or better monitoring. Harsher prison conditions may cause prisoners to misbehave in prison, resulting in greater infractions (Drago, Galbiati and Vertova 2011; Dolovich 2009; Chen and Shapiro 2007). Private prisons may also have a better technology for monitoring infractions, or they might be more likely to report infractions accurately out of fear of government monitoring.[30]

I provide a more detailed breakdown of infractions by prisoners assigned to public or private prison, continuing with the definition of whether a prisoner is ever assigned to private prison over the course of his sentence, in Table 6. The summary statistics suggest that infractions are widespread in private prison. Prisoners in every demographic, offense and sentence length category appear to accumulate more infractions if they are assigned to private prison. Table 6 could also suggest that there is negative selection to private prison the basis of infractions, and I explore this hypothesis formally in a fixed effect regression analysis described later in this section. The reason I cannot implement an instrumental variable

[30] Figure B.4 shows that at the least the type of infraction cited does not vary significantly between public and private prison, although the overall probabilities of citation are much higher in private prison.

analysis measuring infractions as an outcome is because the data is only available post-2000, which is after the period in which most of the private prison bed capacity shocks occur.

Table 7 shows the difference in the probability of receiving an infraction by whether a prisoner is assigned to public or private prison after controlling for the available covariates, using both probit and linear probability specifications. The estimating equation used to generate columns (1) to (3) of Table 7 is:

$$Infractions_i = \Phi(\beta Private_i + \delta X_i), \tag{19}$$

where $Infractions_i$ is a binary variable indicating whether the prisoner received any infractions over the course of his sentence. The estimating equation used to generate columns (4) to (6) is given by:

$$Infractions_i = \beta Private_i + \delta X_i + \epsilon_i. \tag{20}$$

Estimates of the saturated models are provided in columns (3) and (6). Both the probit and linear probability model estimates suggest that a prisoner is 15 percent more likely to obtain an infraction over the course of his sentence in private prison than in public prison. In both specifications, prisoners with longer sentences, more prior incarcerations and less education are more likely to obtain in infraction. In addition, prisoners that are young, black or single all have higher rates of receiving an infraction.

I also estimate a fixed effects regression model in which each observation represents one month during which a prisoner is incarcerated. The estimating equation for prisoner i in month number m of his sentence is given by:

$$Infractions_{im} = \beta InPrivate_{im} + \delta X_i + \gamma_i + \xi_{im}, \tag{21}$$

where $InPrivate_{im}$ is a dummy variable indicating whether the prisoner was housed in a private prison for that month, and γ represents the fixed effect for each prisoner (technically, each prisoner-sentence). The month number m takes values from 1 to 72, since the maximum sentence length in the sample is six years. The dependent variable is the number of infractions received in that month. The results from these regressions are provided in Table 8: I show results for the entire sample, and also by bins of sentence length. I find that in a given month, a prisoner in private prison receives 0.015 more infractions than if he is in public prison. For the average prisoner in private prison with a sentence length of 3.7 years, this translates to 0.7 more infractions over the course of a sentence. This result is significant for all prisoners except those with a sentence length closest to 5 years.

Finally, Figure B.4 shows the types of infractions that are conferred by private versus public prisons. Using detailed incident-level data for each infraction, the types of infractions are broken down by whether they deal with assault (typically on another prisoner), contraband (e.g., illegal possession of drugs or other property behind bars), loud behavior, refusing staff orders, refusing work orders, or engaging in prohibited sexual activity. Interestingly, there do not appear to be any systematic differences in the breakdown of infractions received by prisoners in private prison—the main difference is only that the overall probability of receving each one is higher.

8.2 Potential Confounds: Per-Diem Contracts and Prison Age

One conclusion from Figure 1 is that private prisons obtain no marginal benefit from distorting release policies because they always operate at full capacity. Yet, this may be inaccurate for two important reasons. First, the private prisons are not exactly 100 percent full each day, so there is still some margin on which the private operator can profit from additional time served due to per-diem contracts. Second, the private prison industry is highly concentrated, so it can obtain more profit when the total number of prisoners increases.[31]

In my data, all the private prisons are paid per bed occupied prior to May 2001. At that time, the contracts for two out of the four prisons (each with capacity of 1,000 beds) provided guaranteed payments for 90 percent of the beds. Table 14 reports results from an OLS regression in which I interact private prison exposure with contract type. I find that the effect of private prison on prisoner time served and recidivism does not change with the contract structure; the effect on time served is about 6 percent for either contract type, and the effect on recidivism is not significant. This result is not surprising since these prisons with the new contract structure still operate at greater than 90 percent occupancy, which renders the guarantees inoperative. Accordingly, there remain marginal incentives for the

[31]The second point is illustrated by Little's Law, a core concept from the marketing and operations literature. Little's Law is used to study retail as it provides a formula that relates total inventory, L, to a waiting period for the next customer, W, and an arrival rate of new customers, λ. This formula illustrates the incentives faced by private prison operators, who are in the business of selling "prisoner-days": if they can increase the waiting period, W, by even 5 percent by manipulating parole decisions, then the overall inventory of prisoners also increases by 5 percent holding λ constant. For example, lobbying efforts that increase conviction rates affect λ. This figure can represent up to a 5 percent increase in profits in a fixed-cost industry, which for the private prison sector amounts to about $150 million annually. Another reason that private prisons may seek to manipulate parole decisions is that they may seek approval for bed expansions or new prison construction. In fact, in the 10-K statements for these private prisons, they explicitly state that one of the largest risk factors is the potential for a decrease in the stock of prisoners. In Mississippi, four of the five private prisons were operated by the same firm; as of October 1, 2013, all five private prisons are run by the same firm.

private prison to manipulate parole decisions.

One feature of the data worth noting is that much of the effect of private prison on the prisoner's fraction of sentence served is caused by the larger portion of prisoners that serve the full 100 percent of their sentences in private prison. While it could be that private prisons actively distort release policies, it could also be that the reason so many more prisoners serve full sentences in private prison is because it takes effort on part of the employees to recommend prisoners for earlier release. In particular, case managers are prison employees that oversee all aspects of the prisoner's file, and there is one case manager assigned to each prisoner at each prison where the prisoner is transferred. Case managers in private prison tend to have higher workload than case managers in public prison (the MDOC provided an estimate of 150 versus 50 cases).

One mechanism that could be driving my results is *new* prisons. For example, if new prisons typically hire newly trained guards that may be over-eager to cite prisoners with infractions. To investigate this possibility, I estimate the OLS regressions for fraction of sentence served, days served and recidivism for each sentence length bucket; the results are in Table 13. I find that the effect of private prison exposure on fraction of sentence served is lower for prisoners admitted in 2004, for example, than prisoners admitted in 1996: The difference is 4 percent versus 8 percent. This decreasing trend can reflect either the lack of ability for the MDOC to select "worse" prisoners to private prison, or a decreasing effect size by the amount of time elapsed since the prison's opening.

9 Robustness

9.1 Alternative Estimation Strategies

I implement nearest neighbor matching on the event window sample described in Section 5. An advantage of this method is that it provides fully non-parametric estimates of the effect of private prison exposure on prisoner outcomes around the observation windows where I believe that there is less unobservable selection of prisoners to private prison. To implement the matching approach, I match each prisoner that was assigned to private prison to a prisoner that was never assigned to private prison. I also force exact matches on prisoner race, sentence length (rounded to the nearest year), and admission year, to control for covariates that are particularly important in determining release.

Table 10 shows the results from matching on prisoner fraction served. The estimates are slightly smaller than the OLS and event window estimates: the predicted effect of private prison exposure on prisoner fraction of sentence served is a reported 5.4 percent (column (6) of Table 10). Correcting for the fraction of prisoners in the control group that eventually go to private prison, the estimate is about 6.5 percent. This estimate is close to the OLS estimates presented in Section 6. Table 11 shows the results from matching on recidivism. The point estimate in column (6) is positive and suggests that prisoners who served time in private prison recidivate at a 4 to 5 percent (after correcting for the fact that 17 percent of the comparison groups eventually goes to private prison) higher rate than prisoners in public prison, but this estimate is imprecise. The lack of a significant effect of private prison exposure on recidivism matches the overall finding from the OLS and event window results.

I also supplement the instrumental variable approach outlined in section 5 by employing a control function approach—this empirical strategy is known as the treatment effects model. Since the basic treatment effects model is identified by functional form, which is not a preferred source of identification, I use instrumental variables to obtain quasi-random variation in the probability of private prison assignment. Specifically, I use a two-equation model where the first stage models whether the prisoner is assigned to private prison using a probit regression, and the second stage is a linear model for the two prisoner outcomes: time served and recidivism. The control function approach differs from the standard 2SLS framework because the first stage is modeled by a probit regression and the error terms in the selection and outcome equations are jointly normally distributed with correlation coefficient ρ.

Let P_i^* denote the latent index that measures the treatment propensity for prisoner i:

$$P_i^* = \beta_1 X_i + \beta_2 Z_i + \epsilon_i, \tag{22}$$

where the instrument Z_i equals either the capacity shock or the leave-one-out variable. The probability of treatment is also assumed to depend on a random error component ϵ_i that is uncorrelated with X_i and Z_i. The variable $Private_i$ in the second stage equation is then an indicator for whether individual i was ever assigned to private prison; it equals one if and only if the latent index P_i^* exceeds zero. The second-stage equation is given by:

$$Y_i = \gamma Private_i + \theta X_i + \xi_i, \tag{23}$$

where Y_i is the outcome of interest. The parameter γ measures the casual effect of private prison exposure prisoner outcome under the assumption that the error ϵ_i is jointly normally distributed with each ξ_i with correlation coefficients ρ.

As before, it is useful to think of the correlations between the selection and outcome equations as unobserved "dangerousness". I estimate the two treatment effect models via maximum likelihood.[32] Table 12 shows the treatment effect model results for both fraction of sentence served and recidivism. Columns (1) and (4) show the results when no instrument is used; these results are informative about the extent to which identification is driven by functional form. For fraction of sentence served, I find that the instrumented estimates of 5 and 6 percent in columns (2) and (3) are similar to the OLS, event window and instrumental variable estimates in Section 6.

The correlation ρ indicates the relationship between the error terms in the selection equation and the outcome equation; the positive value of 0.16 implies that a prisoner with a positive shock to private facility assignment also has a positive shock to the outcome. The coefficient λ (the inverse Mill's ratio) is estimated to equal 0.028 and is the loading factor on unobserved heterogeneity ;he positive sign of this coefficient implies positive correlation between the errors of the selection and outcome equations. As expected, I only find evidence of selection in the models without instrumental variables, which are shown in columns (1) and (4).

9.2 Alternative Definitions and Sampling Strategies

Thus far, I have treated private prison exposure as binary. I also estimate equations in which the treatment variable is defined as the fraction of sentence served in private prison.[33] Table 9 shows the regression results with fraction private as the main independent variable, using both the capacity-based and leave-one-out instruments. I find that the coefficient on $FractionPrivate$ is 0.22 in the OLS specification, 0.18 in the IV with the capacity based instrument, and 0.14 in the IV with the leave-one-out instrument. Since the mean fraction of sentence served in private prison is about 30 percent, these estimates corroborate the main results, which are roughly one-third the size of these estimates. This result suggests that the amount of release policy distortion increases with a prisoner's time spent in private prison.

I also examine robustness to the sampling time period. The analysis in this paper has been limited to prisoners who committed felonies between May 1, 1996 and July 31, 2004,

[32]I use the command "etregress" in STATA version 13.0 and cluster the errors by both admission year and dummies for the number of sentenced years. The maximum likelihood estimator for the treatment effects model is derived in Maddala (1983).

[33]Figure B.5 shows a histogram of this variable in Panel A; Panel B shows the histogram of the variable if days served, not sentence days, is in the denominator of the definition. I do not use this latter definition in the empirical analysis because days served is endogenous to private prison assignment, but the relatively uniform distribution is interesting.

with sentence lengths between one and six years. The reason that this sampling frame is chosen is to maximize the number of observations in the sample while still observing release decisions and three-year recidivism rates. The trade-off between these sentence length and calendar time restrictions are shown in Figure 9. The estimated coefficient is positive and relatively stable for the samples that include prisoners with sentence length of three or more years.

9.3 Placebo Tests

Two groups of offenders are not eligible for placement in any private prison in Mississippi: women and juveniles, i.e., those under the age of 18. Across the United States, private prisons tend to house only male adults, likely because female and juvenile offenders—about 10 and 25 percent of the prisoner populations in Mississippi, and in the nation—tend to enroll in more programs and are hence more expensive. Juvenile populations are especially costly because of their intensive education needs. One way to leverage my data on these two groups of prisoners is to use them as placebo groups.

I estimate the reduced form regression of prisoner time served and recidivism on these prisoner groups using the capacity-based and leave-one-out instruments. Table 15 shows the results for fraction of sentence served: columns (1) and (4) show the reduced form estimate for the primary sample of male adults, columns (2) and (5) repeat the exercise for female offenders, and columns (3) and (6) repeat the exercise for juvenile offenders. The instrument is only significant for the primary sample, which suggests that the timing of the capacity shocks did not affect prisoner time served for female and juvenile offenders. The test may be under-powered, although the point estimates of 0.02 for the female and juvenile offenders is smaller than the point estimate of 0.05 for the male adult offenders. Table 16 provides results for recidivism. The instruments are not significant in any regression for any prisoner group, although the point estimates are always negative.

10 Conclusion

Private contracting of prison services has increased dramatically since the 1980s, and it is expected to grow further in the next decade. Recent experiences in the United States with prison overcrowding and concerns about excessive costs have contributed to the rise of private prison use. For example, the state of California recently approved two new private prison contracts in October 2013 in response to a Supreme Court order to alleviate prison overcrowding (Huffington Post 2013). The federal government is the largest purchaser of private prison services, and currently over half of all immigration detainees, the fastest growing segment of the domestic prison population, are held in private facilities. Despite the increased demand for privatized prisons, there has been little research on whether private prisons impact outcomes such as prisoner time served and recidivism, or whether they actually provide cost savings. This paper provides the first set of unbiased estimates on this question.

Evaluating private prisons is challenging because prison assignment may occur on unobservable prisoner traits. I address this problem by leveraging prison capacity shocks to generate quasi-random assignment. Using this identification strategy, I find that prisoners in private prison serve about 4 to 7 percent larger fractions of their sentences, or 60 to 90 extra days for the average prisoner. Yet, the additional incarceration time does not contribute to reduced recidivism rates. Since the state does not seek to punish prisoners randomly based on private prison assignment, systematic differences in release policies constitute a distortion of justice. Moreover, because private prisons are typically 10 percent cheaper than public prisons (by state law), my finding suggests that this expected cost saving is directly eroded by distortions in the release policy. An additional 5 percent of fraction served, or 60 days in prison, leads to an additional cost per prisoner-sentence of about $3,000, since the contractual payments average $50 for each bed occupied. This difference erodes about half the projected cost saving offered by private prisons. Because there does not appear to be a reduction in recidivism either via innovation in the private prison system or via the additional days served, private prisons may not be as attractive a choice as claimed.

I further show that the mechanism by which private prisons distort release policies is by conferring infractions, or prison conduct violations, at higher rates than public prisons. Infractions are used by the state parole board to assess whether a prisoner should be granted early release, and prisoners in private prison are 15 percent more likely to receive an infraction over the course of their sentences. This finding suggests that the government could reduce the distortion in release policy by increasing monitoring efforts. For example, the state can appoint a committee to evaluate in greater detail whether infractions are correctly granted—currently, virtually all reported infractions are recorded as "guilty". The state could also invest in establishing more rigid guidelines regarding the citing of infractions to address the widespread differences between public and private prisons.

My findings raise several questions for future work. Most private prison contracts today specify per-diem payments with few restrictions, but other forms of contracting may better align incentives between the private operator and the state. The federal government in the

United Kingdom, for example, recently experimented with "pay for performance" contracts (akin to those used in health care) in prison services, and it realized large decreases in recidivism for prisoners assigned to these prisons (British Broadcasting Corporation 2013). One concern that remains, however, is that state agencies may ultimately lack the resources to write and monitor effective contracts for private prison services (Donahue 1988). I also do not explore the political environment surrounding private prison contracting in this paper, but there is enormous scope to study the effects of public labor unions and corporate lobbying on prisoner outcomes.

References

Abrams, David S. 2007. "More Time, Less Crime? Estimating the Deterrent Effect of Incarceration Using Sentencing Enhancements." *University of Pennsylvania Law School Working Paper.*

Abrams, David S. 2010. "Building Criminal Capital vs. Specific Deterrence: The Effect of Incarceration Length on Recidivism." *University of Pennsylvania Law School Working Paper.*

Abrams, David S., and Chris Rohlfs. 2011. "Optimal Bail and The Value of Freedom: Evidence From the Philadelphia Bail Experiment." *Economic Inquiry*, 49(3): 750–770.

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. 1996. "Identification of Causal Effects Using Instrumental Variables." *Journal of the American Statistical Association*, 91(434): 444–455.

Avio, Kenneth L. 1991. "On Private Prisons: An Economic Analysis of the Model Contract and Model Statute for Private Incarceration." *New England Journal on Criminal and Civil Confinement*, 17: 265.

Bales, William D., Laura E. Bedard, Susan T. Quinn, David T. Ensley, and Glen P. Holley. 2005. "Recidivism of Public and Private State Prison Inmates in Florida." *Criminology and Public Policy*, 4(1): 57–82.

Ballou, Dale. 2001. "Pay for Performance in Public and Private Schools." *Economics of Education Review*, 20(1): 51–61.

Bayer, Patrick, and David E Pozen. 2005. "The Effectiveness of Juvenile Correctional Facilities: Public versus Private Management." *Journal of Law and Economics*, 48(2): 549–589.

Bayer, Patrick, Randi Hjalmarsson, and David Pozen. 2009. “Building Criminal Capital Behind Bars: Peer Effects in Juvenile Corrections.” *The Quarterly Journal of Economics*, 124(1): 105–147.

Beck, Allen J., and Bernanrd E. Shipley. 2013. *Recidivism of Prisoners Released in 1983.*

Becker, Gary S. 1968. “Crime and Punishment: An Economic Approach.” *The Journal of Political Economy*, 76(2): 169–217.

Bernhardt, Dan, Steeve Mongrain, and Joanne Roberts. 2012. “Rehabilitated or Not: An Informational Theory of Parole Decisions.” *Journal of Law, Economics, and Organization*, 28(2): 186–210.

British Broadcasting Corporation. 2013. “Prison Payment-by-Results Schemes See Reoffending Cut.” 13 June 2013, http://www.bbc.co.uk/news/uk-22886395.

Charles, Kerwin Kofi, and Ming Ching Luoh. 2010. “Male Incarceration, The Marriage Market, and Female Outcomes.” *The Review of Economics and Statistics*, 92(3): 614–627.

Chen, Keith, and Jesse Shapiro. 2007. “Do Harsher Prison Conditions Reduce Recidivism? A Discontinuity-Based Approach.” *American Law and Economics Review*, 9(1): 1–29.

Chen, Stephanie. 2009. “Pennsylvania Rocked by Jailing Kids for Cash Scandal.” 23 February 2009, http://www.cnn.com/2009/CRIME/02/23/pennsylvania.corrupt.judges.

Cook, Philip J., Stephen Machin, Olivier Marie, and Giovanni Mastrobuoni. 2013. *Lessons from the Economics of Crime: What Reduces Offending?* MIT Press.

DiIulio Jr., John J. 1988. “What’s Wrong with Private Prisons.” *Public Interest*, 92: 66–83.

Dolovich, Sharon. 2005. “State Punishment and Private Prisons.” *Duke Law Journal*, 437–546.

Dolovich, Sharon. 2009. “Cruelty, Prison Conditions, and the Eighth Amendment.” *New York University Law Review*, 84: 881.

Domberger, Simon, and Paul Jensen. 1997. “Contracting Out by the Public Sector: Theory, Evidence, Prospects.” *Oxford Review of Economic Policy*, 13(4): 67–78.

Donahue, John D. 1988. *Prisons for Profit: Public Justice, Private Interests.* Economic Policy Institute Washington, DC.

Drago, Francesco, Roberto Galbiati, and Pietro Vertova. 2011. “Prison Conditions and Recidivism.” *American Law and Economics Review*, 13(1): 103–130.

Duggan, Mark G. 2000. "Hospital Ownership and Public Medical Spending." *The Quarterly Journal of Economics*, 115(4): 1343–1373.

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *The Journal of Political Economy*, 521–565.

Flanagan, Timothy J. 1983. "Correlates of Institutional Misconduct Among State Prisoners." *Criminology*, 21(1): 29–40.

Gaes, Gerald G. 2012. "The Current Status of Prison Privatization Research on American Prisons." *Working Paper.*

Ganong, Peter N. 2012. "Criminal Rehabilitation, Incapacitation, and Aging." *American Law and Economics Review*, 14(2): 391–424.

Golinelli, Daniela, and Ann E. Carson. 2013. "Prisoners in 2012: Advance Counts." *Washington, DC: Bureau of Justice Statistics.*

Hart, Oliver, Andrei Shleifer, and Robert W. Vishny. 1997. "The Proper Scope of Government: Theory and an Application to Prisons." *The Quarterly Journal of Economics*, 112(4): 1127–1161.

Heckman, James J., and Richard Robb. 1985. "Alternative Methods for Evaluating the Impact of Interventions: An Overview." *Journal of Econometrics*, 30(1): 239–267.

Helland, Eric, and Alexander Tabarrok. 2004. "The Fugitive: Evidence on Public versus Private Law Enforcement from Bail Jumping." *Journal of Law and Economics*, 47(1): 93–122.

Hirschi, Travis, and Michael Gottfredson. 1983. "Age and the Explanation of Crime." *American Journal of Sociology*, 552–584.

Huffington Post. 2013. "For-Profit Prisons Are Big Winners Of California's Overcrowding Crisis." 25 October 2013, http://www.huffingtonpost.com/2013/10/25/californiaprivateprison415.

Hurst, Jeremy W. 1991. "Reforming Health Care in Seven European Nations." *Health Affairs*, 10(3): 7–21.

Kuziemko, Ilyana. 2013. "How Should Inmates be Released from Prison? An Assessment of Parole versus Fixed-Sentence Regimes." *The Quarterly Journal of Economics*, 128(1): 371–424.

Kyle, Peter H. 2013. "Contracting for Performance: Restructuring the Private Prison Market." *William and Mary Law Review*, 54: 2087–2087.

Langan, Patrick A., and David J. Levin. 2013. "Recidivism of Prisoners Released in 1994." *Washington, DC: Bureau of Justice Statistics.*

Lanza-Kaduce, Lonn, Karen F. Parker, and Charles W. Thomas. 1999. "A Comparative Recidivism Analysis of Releasees from Private and Public Prisons." *Crime and Delinquency*, 45(1): 28–47.

Levitt, Steven D. 1996. "The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation." *The Quarterly Journal of Economics*, 111(2): 319–351.

Lucken, Karol. 1997. "Privatizing Discretion: "Rehabilitating" Treatment in Community Corrections." *Crime and Delinquency*, 43(3): 243–259.

Maddala, Gangadharrao S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge University Press.

Maurin, Eric, and Aurelie Ouss. 2009. "Sentence Reductions and Recidivism: Lessons from the Bastille Day Quasi Experiment." IZA discussion papers.

McDonald, Douglas C. 1994. "Public Imprisonment by Private Means-The Re-Emergence of Private Prisons and Jails in the United States, the United Kingdom, and Australia." *British Journal of Criminology*, 34: 29.

McDonald, Douglas, Elizabeth Fournier, Malcolm Russell-Einhorn, and Stephen Crawford. 1998. *Private Prisons in the United States: An Assessment of Current Practice.* Abt Associates.

Mississippi Department of Corrections. 1996. "Fiscal Year 1995 Annual Report." http://www.mdoc.state.ms.us/Annual%20Report%20PDF/1996.pdf.

Mississippi Department of Corrections. 2012. "Fiscal Year 2011 Annual Report." http://www.mdoc.state.ms.us/Annual%20Report%20PDF/2012_Annual_report.pdf.

Mitchell, Olivia S, and Stephen P Zeldes. 1996. "Social Security Privatization: A Structure for Analysis." *American Economic Review*, 86(2): 363–67.

Neal, Derek, and Armin Rick. 2013. "The Prison Boom and the Lack of Black Progress Since Smith and Welch." University of Chicago Working Paper.

Pratt, Travis C., and Jeff Maahs. 1999. "Are Private Prisons More Cost-Effective than Public Prisons? A Meta-Analysis of Evaluation Research Studies." *Crime and Delinquency*, 45(3): 358–371.

Price, Byron E., and Norma M. Riccucci. 2005. "Exploring the Determinants of Decisions to Privatize State Prisons." *The American Review of Public Administration*, 35(3): 223–235.

Sigler, Mary. 2010. "Private Prisons, Public Functions, and the Meaning of Punishment." *Floridate State Univeristy Law Review*, 38: 149.

Spitzer, Steven, and Andrew T. Scull. 1977. "Privatization and Capitalist Development: The Case of the Private Police." *Social Problems*, 18–29.

Spivak, Andrew L., and Kelly R. Damphousse. 2006. "Who Returns to Prison? A Survival Analysis of Recidivism Among Adult Offenders Released in Oklahoma, 1985-2004." *Justice Research and Policy*, 8(2): 57–88.

Spivak, Andrew L., and Susan F. Sharp. 2008. "Inmate Recidivism as a Measure of Private Prison Performance." *Crime and Delinquency*, 54(3): 482–508.

Thomas, James C., and Elizabeth Torrone. 2008. "Incarceration as Forced Migration: Effects on Selected Community Health Outcomes." *American Journal of Public Health*, 98: S181–S184.

Vickers, John, and George Yarrow. 1991. "Economic Perspectives on Privatization." *The Journal of Economic Perspectives*, 5(2): 111–132.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data.* The MIT Press.

Figure 1: Daily Prison Population by Facility, 1996-2012

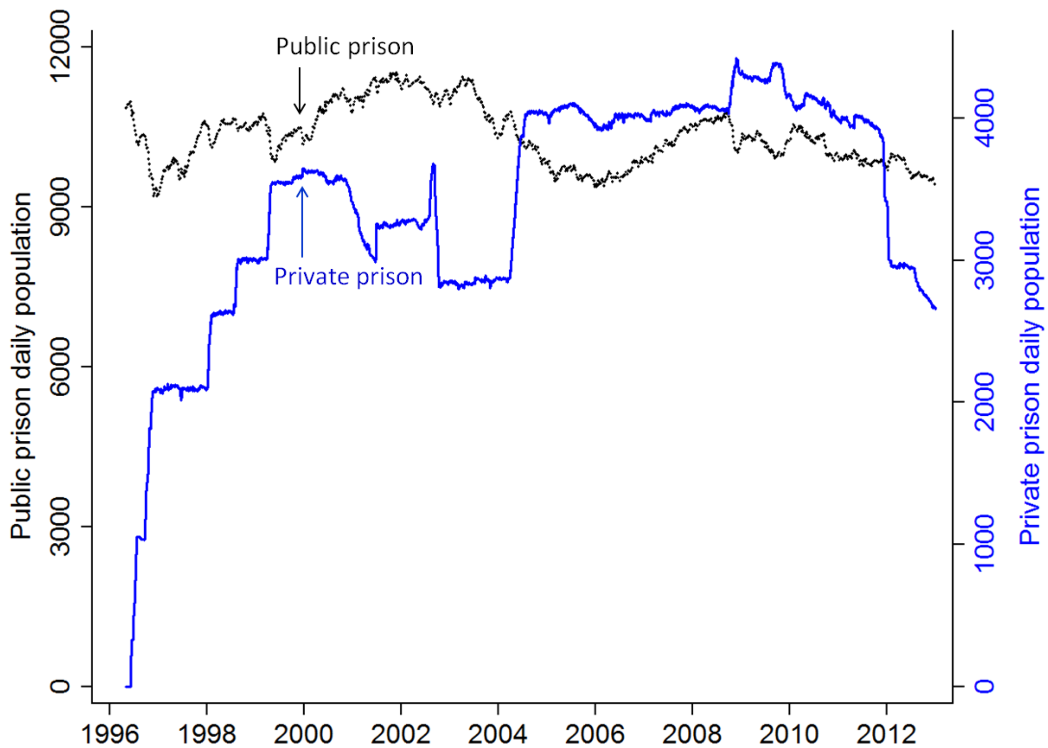


Figure shows the daily prisoner population by facility type for prisoners admitted between May 1, 1996 and May 1, 2012. The spikes in the daily population of the private prison population correspond to shocks in the private prison capacity either through private prison entry, closure or bed expansion. Public prison includes the three state prisons and all county jails; private includes the five private prisons, excluding one juvenile facility. The dip in the private prison population in March 2001 corresponds to the opening of a juvenile private prison facility (see Figure B.1), where many 18 to 20 year old prisoners were transferred upon its opening.

Figure 2: Basic Theoretical Framework

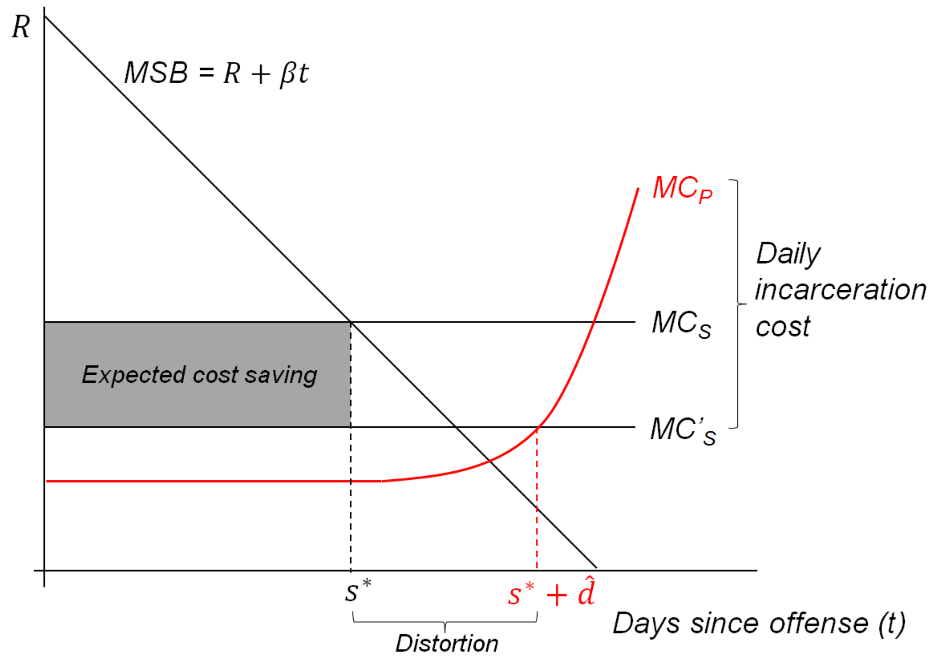


Figure shows the distortion in release policy arising from differences in objective between the state and private operator. The state minimizes severity-weighted recidivism (MSB) subject to cost MC_s, but the private operator maximizes profit given its marginal revenue MC_s' and marginal cost MC_P. The parameter R_i represents prisoner i's recidivism risk, and β is the rate at which recidivism risk declines with days since offense. The state chooses to operate at s^* and the private prison chooses to extend the prisoner's sentence by $\hat{d}$ days.

Figure 3: CDF Plots of Fraction of Sentence Served by Offense

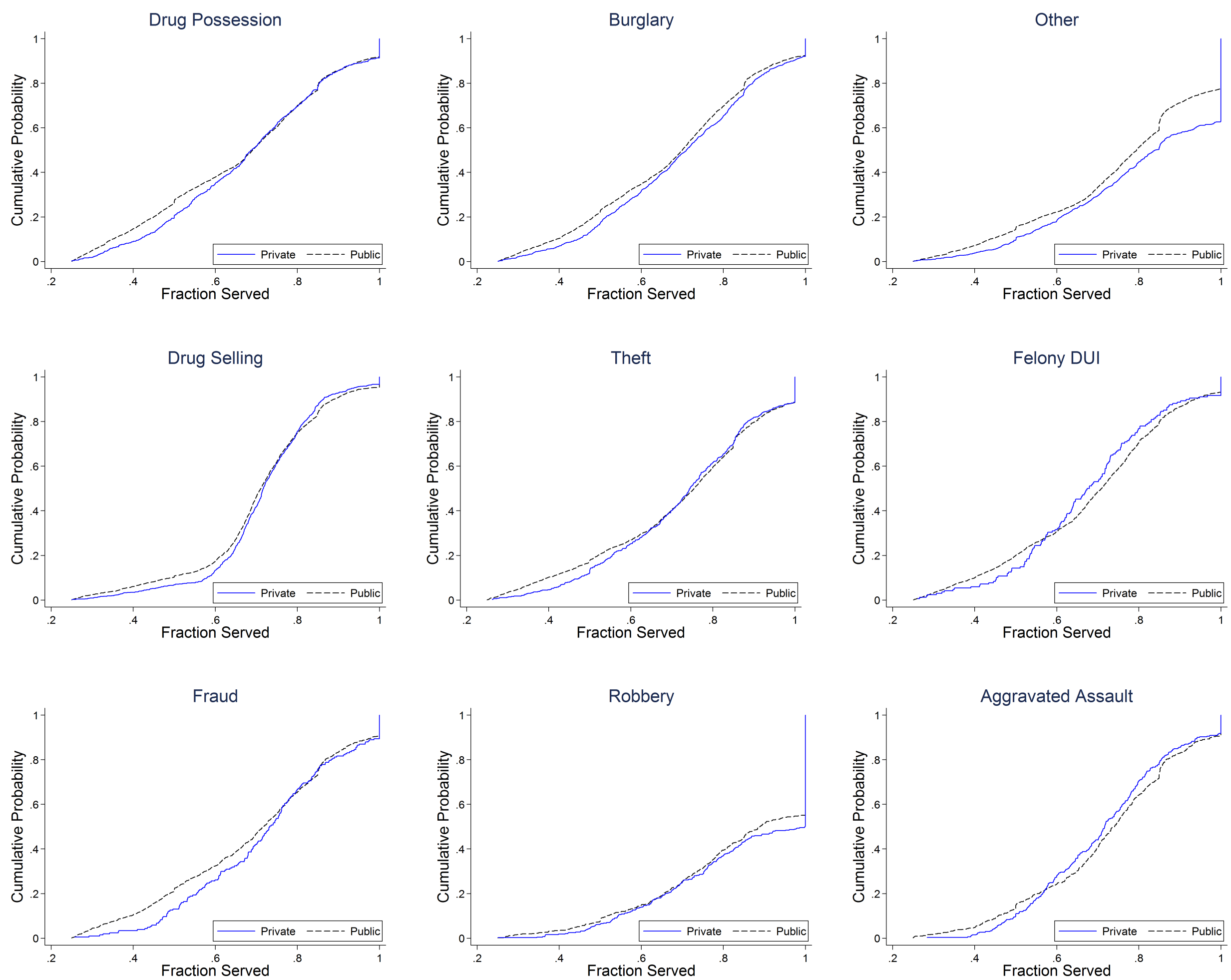


Figure shows the cumulative density function plots of fraction of sentence served by whether the prisoner ever went to private prison during his sentence; there appears to be a bunching at 100 percent of the fraction served for prisoners in private prison. Offenses are ordered left-right, top-bottom, in the order of frequency with which they appear in the data: drug possession (20 percent), burglary (18 percent), other (16 percent), drug selling (14 percent), theft (10 percent), felony DUI (8 percent), fraud (6 percent), robbery (4 percent) and aggravated assault (4 percent).

Figure 4: CDF Plots of Fraction of Sentence Served by Sentence Length

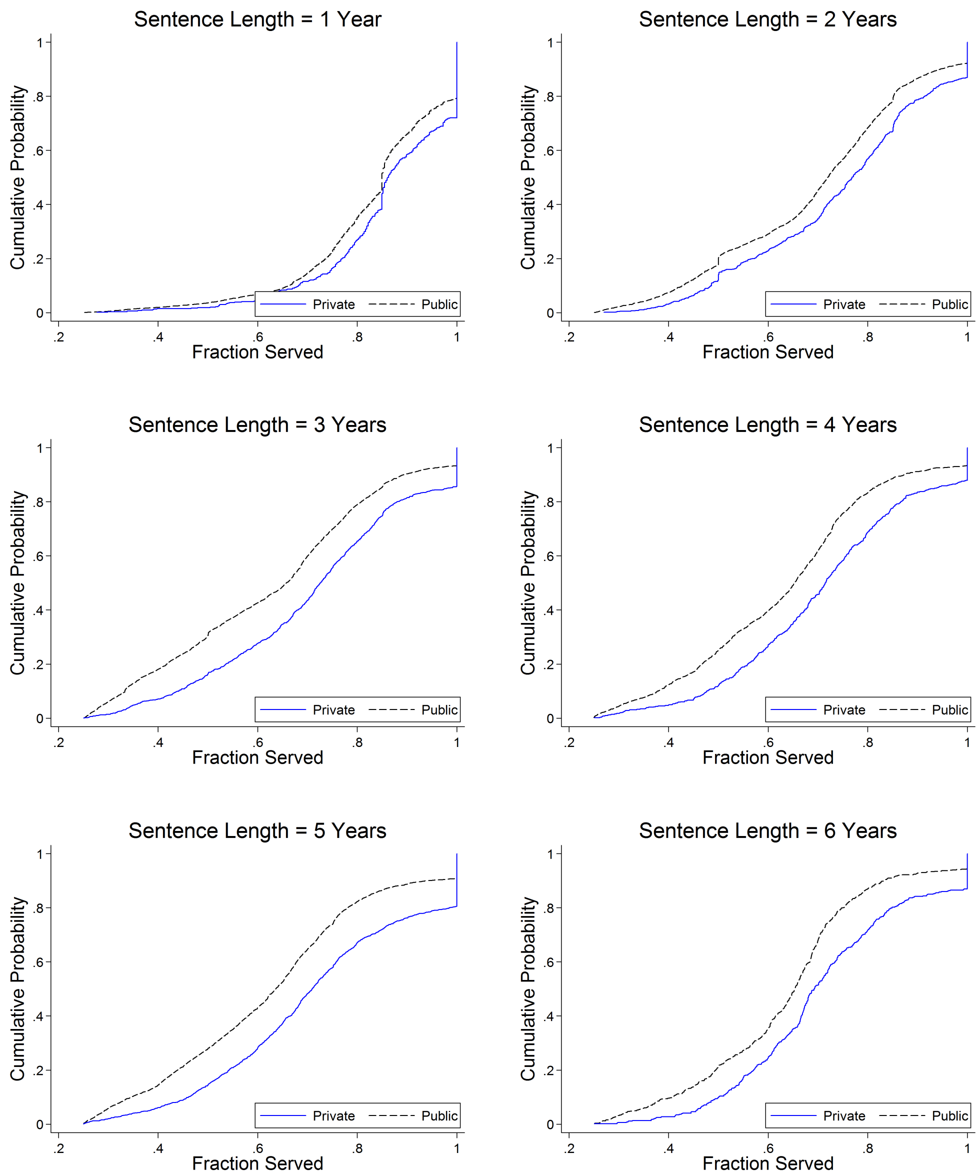


Figure shows the cumulative density function plots of fraction of sentence served by whether the prisoner ever went to private prison during his sentence; there appears to be a bunching at 100 percent of the fraction served for prisoners in private prisons.

Figure 5: Variable CDF Plots by Private Prison Exposure

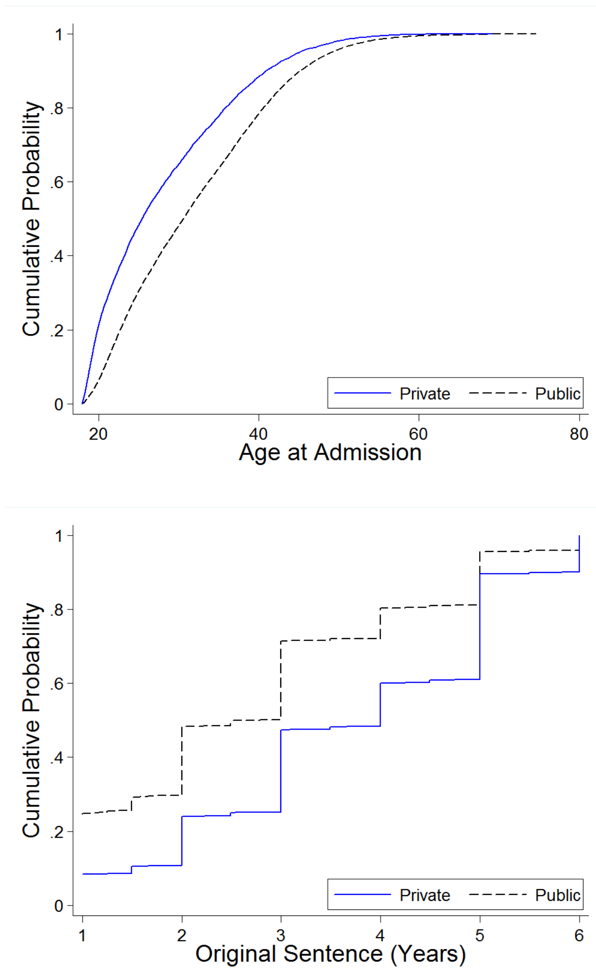


Figure shows the cumulative density function plots of age and original sentence by whether the prisoner ever went to private prison during his sentence. The jumps in the CDF for original sentence are due to the discrete nature of most sentence lengths, which frequently occur in steps of 6 or 12 months. The median sentence length for the sample is 3 years.

Figure 6: Scatter Plot of "Ramp" and Admission Date

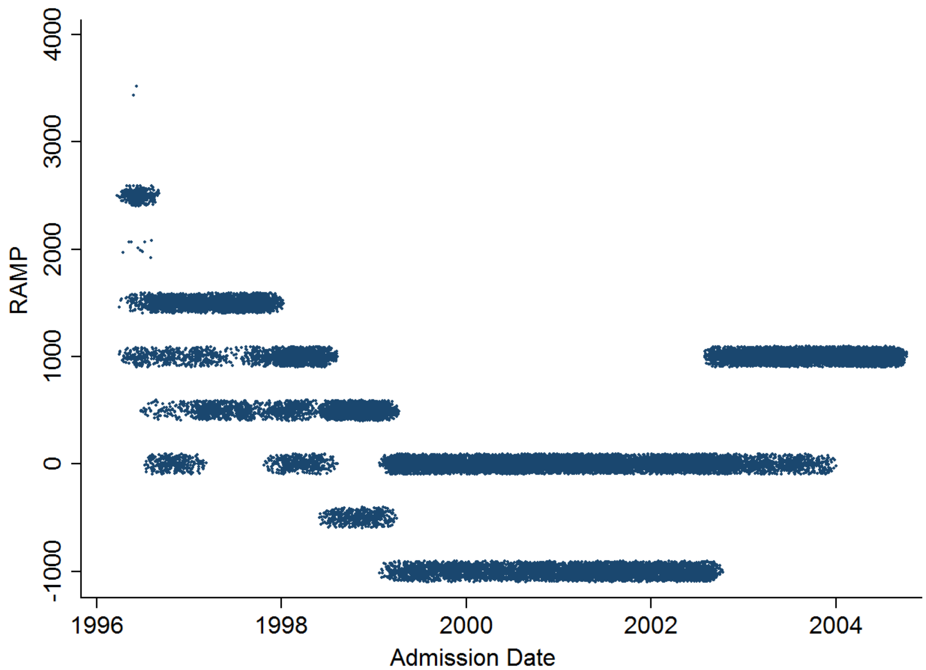


Figure shows the scatter plot of the instrumental variable ramp versus prisoner admission date. The instrumental variable is defined as the change in private prison bed capacity over the course of the prisoner's court-ordered sentence. The negative values result from private prison closings, i.e., drops in private prison bed capacity. For each admission date, variation in the level of the instrument is solely a function of the prisoner's assigned sentence length. The figure is jittered slightly to show the density of observations at each level of the instrumental variable.

Figure 7: Scatter Plot of "Leave-One-Out" and Admission Date

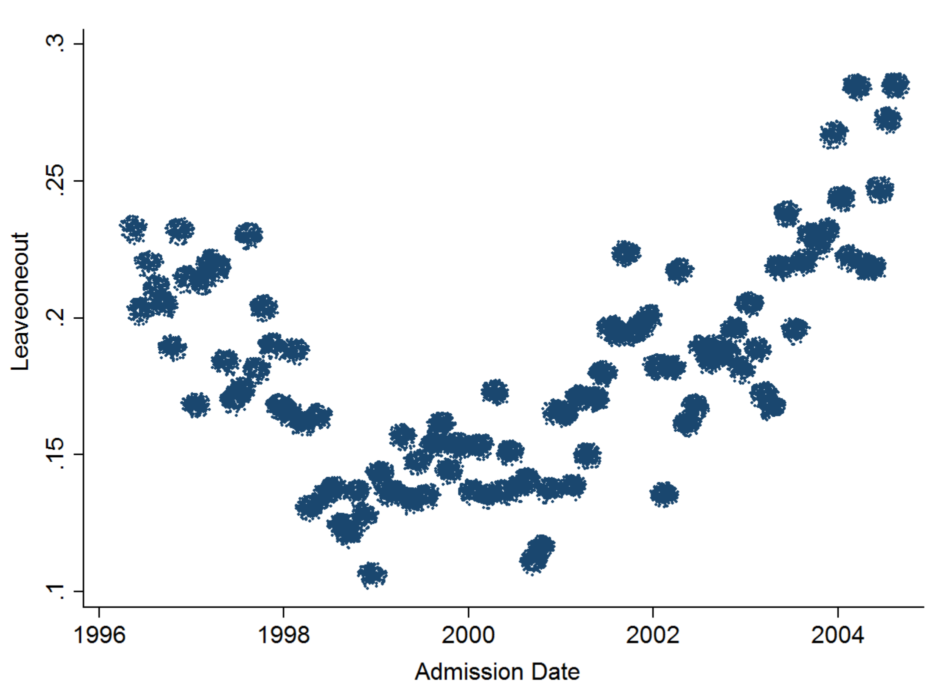
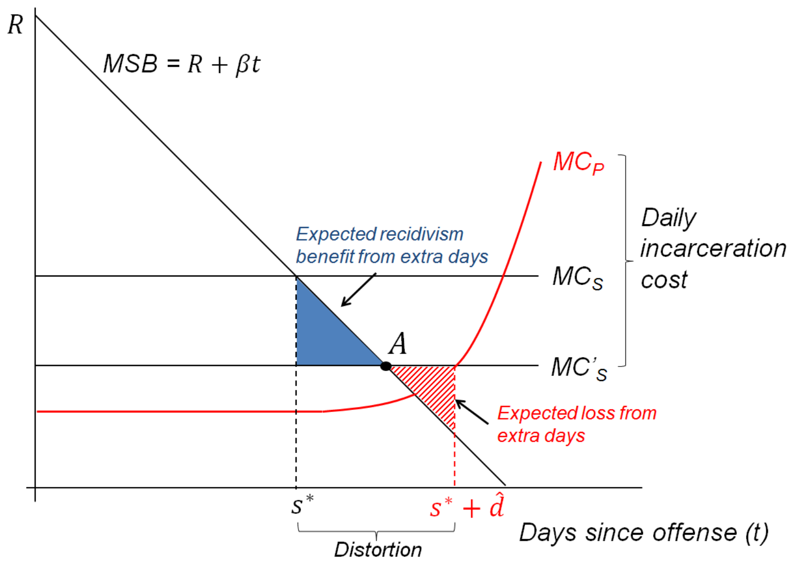


Figure shows the scatter plot of the leave-one-out instrumental variable versus prisoner admission date. The leave-one-out variable is constructed to equal the fraction of *other* prisoners assigned to private prison in the same month and year of a prisoner's admission date. The figure is jittered slightly to show the density of observations at each month-year of admission.

Figure 8: Basic Theoretical Framework with Recidivism

Panel A



Panel B

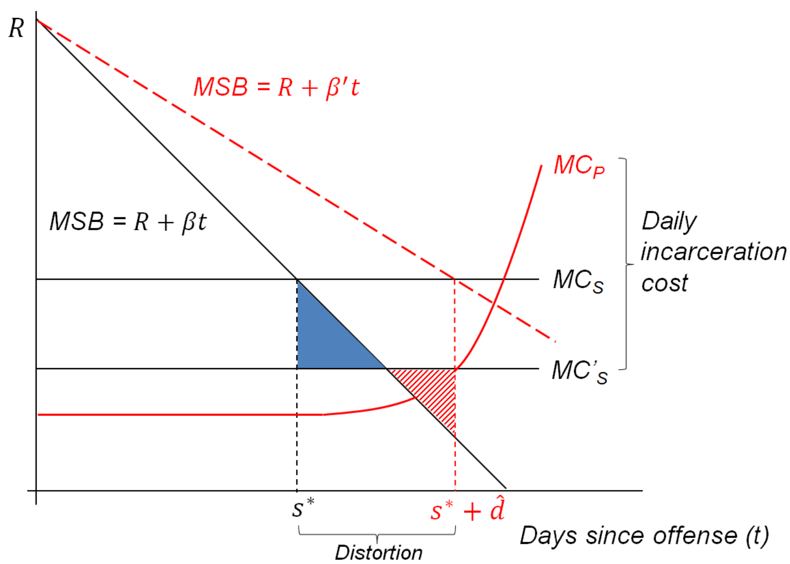


Figure 9: Estimates of β by Sentence Length Cutoff

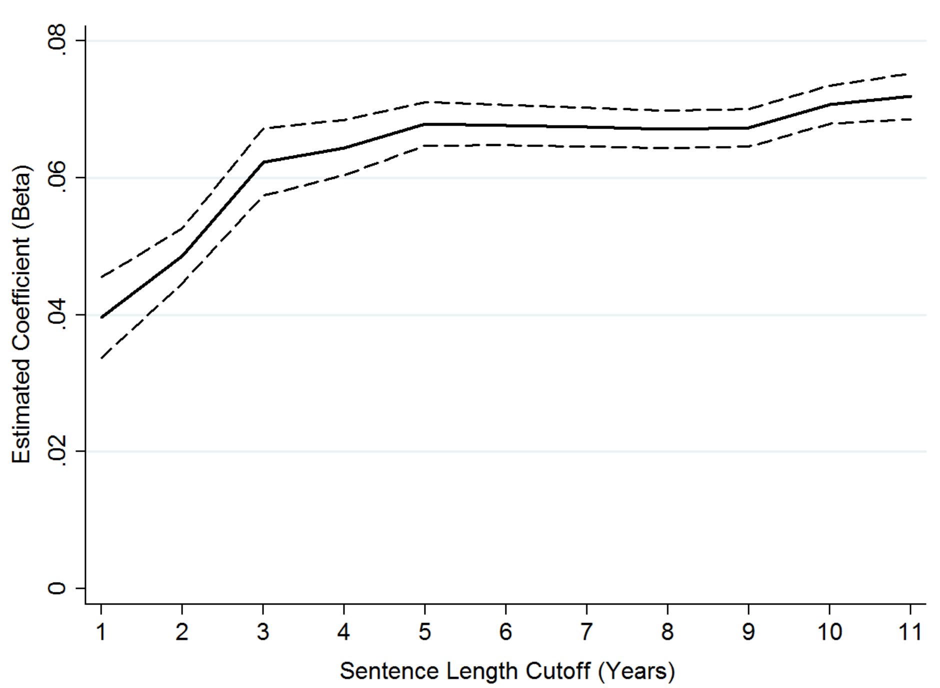


Figure shows the estimated β from an OLS regression of fraction of sentence served on private prison exposure, by different samples of sentenced days and calendar year. The estimate for each cutoff reports a result from a different regression. The main estimates in this paper are from a sentence length cutoff of 6 years.

Table 1: Summary Statistics

	Full Sample			Event Window Sample		
	All (1)	Public (2)	Private (3)	All (4)	Public (5)	Private (6)
Outcomes						
Fraction of Sentence Served	0.71	0.70	0.73	0.72	0.72	0.78
Exactly 100 percent Served	0.12	0.11	0.17	0.14	0.13	0.20
Recidivism (36-month)	0.25	0.25	0.26	0.25	0.25	0.25
Years served	1.98	1.82	2.65	2.42	2.37	3.02
Sentence Length	2.93	2.75	3.68	3.46	3.42	3.93
Infractions*	0.24	0.18	0.47	0.25	0.23	0.56
Movement Variables						
Years in private prison	0.23	0.00	1.19	0.34	0.24	1.54
Years in jail	0.46	0.49	0.34	0.51	0.53	0.37
Years in court	0.15	0.15	0.14	0.17	0.17	0.12
Years until prison transfer	0.71	0.72	0.69	0.80	0.81	0.70
Demographics						
Black	0.68	0.67	0.71	0.70	0.70	0.72
Age $\div$ 100	0.31	0.32	0.28	0.31	0.31	0.30
Single	0.57	0.55	0.67	0.61	0.61	0.65
Education $<$ HS	0.54	0.53	0.56	0.51	0.51	0.56
Offenses (percent)						
Aggravated Assault	0.04	0.03	0.07	0.05	0.04	0.07
Burglary	0.18	0.17	0.21	0.20	0.20	0.22
Drug Possession	0.20	0.22	0.14	0.18	0.18	0.12
Drug Selling	0.14	0.13	0.15	0.14	0.14	0.14
Felony DUI	0.09	0.10	0.03	0.05	0.05	0.02
Fraud	0.06	0.06	0.04	0.05	0.05	0.04
Other	0.16	0.16	0.18	0.18	0.18	0.19
Robbery	0.04	0.03	0.09	0.06	0.05	0.09
Theft	0.10	0.10	0.10	0.10	0.10	0.11
Release type (percent)						
House arrest	0.01	0.01	0.01	0.01	0.01	0.00
Term expiration	0.45	0.45	0.46	0.48	0.48	0.56
Probation	0.36	0.36	0.33	0.33	0.33	0.27
Parole	0.02	0.02	0.02	0.01	0.01	0.01
Earned supervised release	0.15	0.14	0.18	0.15	0.15	0.15
Observations	26,593	21,449	5,144	13,282	12,228	1,054

Each observation is a prisoner-sentence between May 1, 1996 and July 31, 2004. The sample consists of male prisoners with original sentences of 1 to 6 years that serve at least 25 percent of their sentences; see Section 4 in the text for further details. Columns (1) to (3) report summary statistics for the full sample and columns (4) to (6) report summary statistics for the subsample of prisoners that comprise the event window analysis.
$*$ Infractions data are only available post-2000. Hence, N = 15,754 in column (1) (with 3,203 in private prison) and 6,004 in column (4) (with 390 in private prison).

Table 2: Private Prison Exposure and Fraction of Sentence Served

	Dep. Var.: Fraction of Sentence Served					
	Full Sample			Event Window Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	0.066***	0.069***	0.068***	0.063***	0.063***	0.057***
	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)
Sentence Length	-0.139***	-0.137***	-0.139***	-0.150***	-0.150***	-0.153***
	(0.034)	(0.035)	(0.035)	(0.052)	(0.052)	(0.051)
Sentence Length Sq.	0.018***	0.018***	0.018***	0.018**	0.018**	0.019**
	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)	(0.008)
Prior incarcerations	0.016***	0.012***	0.012***	0.003	-0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age ÷ 100		0.194***	0.158***		0.115***	0.078***
		(0.019)	(0.018)		(0.021)	(0.022)
Black		0.014***	0.014***		0.014***	0.014***
		(0.003)	(0.003)		(0.003)	(0.003)
Single		0.025***	0.024***		0.019***	0.017***
		(0.004)	(0.004)		(0.004)	(0.004)
Education < HS		-0.000	-0.001		0.005	0.003
		(0.003)	(0.003)		(0.004)	(0.004)
Constant	1.061***	0.977***	0.977***	1.066***	1.007***	1.000***
	(0.040)	(0.042)	(0.042)	(0.065)	(0.066)	(0.065)
R-squared	0.249	0.258	0.262	0.201	0.206	0.211
Observations	26,593	26,593	26,593	13,282	13,282	13,282
Classification	N	N	Y	N	N	Y

All columns control for offense dummies, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and county fixed effects. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3: Instrumental Variable Estimates: Fraction of Sentence Served

	OLS	Probit Eqn	1st Stg.	IV1	Probit Eqn	1st Stg.	IV2
	(1) Fraction Served	(2) Private	(3) Private	(4) Fraction Served	(5) Private	(6) Private	(7) Fraction Served
Private	0.068***			0.043**			0.037*
	(0.003)			(0.020)			(0.019)
Sentence Length	-0.139***	0.459***	-0.006	-0.137***	0.533***	-0.005	-0.137***
	(0.035)	(0.135)	(0.028)	(0.012)	(0.111)	(0.025)	(0.012)
Sentence Length Sq.	0.018***	-0.026	-0.000	0.018***	-0.039**	-0.000	0.018***
	(0.006)	(0.020)	(0.005)	(0.002)	(0.017)	(0.004)	(0.002)
Prior incarcerations	0.012***	-0.008	0.001	0.011***	-0.005	0.001	0.011***
	(0.004)	(0.018)	(0.005)	(0.002)	(0.018)	(0.005)	(0.002)
Age ÷ 100	0.158***	-2.081***	0.066	0.147***	-2.082***	0.050	0.144***
	(0.018)	(0.171)	(0.044)	(0.016)	(0.168)	(0.042)	(0.015)
Black	0.014***	-0.030	0.002	0.014***	-0.029	0.002	0.014***
	(0.003)	(0.025)	(0.006)	(0.003)	(0.025)	(0.006)	(0.003)
Single	0.024***	0.092***	-0.005	0.025***	0.094***	-0.004	0.025***
	(0.004)	(0.022)	(0.005)	(0.002)	(0.022)	(0.005)	(0.002)
Education < HS	-0.001	0.042**	-0.002	-0.001	0.039**	-0.002	-0.001
	(0.003)	(0.020)	(0.005)	(0.002)	(0.020)	(0.005)	(0.002)
Instrument		0.105***			2.622***		
		(0.016)			(0.243)		
Predicted Probit			1.178***			1.143***	
			(0.052)			(0.042)	
Constant	0.977***	-2.478***	-0.009	0.978***	-2.901***	-0.006	0.978***
	(0.042)	(0.285)	(0.048)	(0.020)	(0.229)	(0.044)	(0.020)
R-squared	0.262	-	0.145	0.260	-	0.146	0.259
Observations	26,593	26,593	26,593	26,593	26,593	26,593	26,593

All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. IV1 refers to the capacity-based instrument and IV2 is the leave-one-out instrument. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Private Prison Exposure and Recidivism

	Dep. Var.: Recidivism					
	Full Sample			Event Window Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	0.031***	0.015*	0.007	0.015	0.013	0.005
	(0.008)	(0.008)	(0.008)	(0.014)	(0.014)	(0.014)
Sentence Length	-0.086***	-0.097***	-0.110***	-0.051*	-0.068**	-0.087***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.029)
Sentence Length Sq.	0.006	0.007	0.009*	-0.000	0.002	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Prior incarcerations	0.068***	0.061***	0.055***	0.085***	0.081***	0.077***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)
Age ÷ 100		-0.274***	-0.315***		-0.326***	-0.362***
		(0.031)	(0.030)		(0.041)	(0.044)
Black		0.024***	0.022***		0.036***	0.035***
		(0.007)	(0.006)		(0.008)	(0.008)
Single		0.081***	0.069***		0.050***	0.042***
		(0.010)	(0.009)		(0.010)	(0.011)
Education < HS		-0.012*	-0.013**		-0.014	-0.016*
		(0.006)	(0.006)		(0.008)	(0.008)
Constant	0.447***	0.483***	0.392***	0.462***	0.521***	0.439***
	(0.044)	(0.048)	(0.048)	(0.058)	(0.059)	(0.061)
R-squared	0.047	0.062	0.076	0.053	0.065	0.076
Observations	26,593	26,593	26,593	13,282	13,282	13,282
Classification	N	N	Y	N	N	Y

All columns control for offense dummies, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and county fixed effects. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Instrumental Variable Estimates: Recidivism

	Dep. Var.: Recidivism (36-month)		
	(1) OLS	(2) IV1	(3) IV2
Private	0.007	-0.023	-0.024
	(0.008)	(0.044)	(0.046)
Sentence Length	-0.110***	-0.106***	-0.108***
	(0.031)	(0.028)	(0.028)
Sentence Length Sq.	0.009*	0.009**	0.009**
	(0.005)	(0.004)	(0.004)
Prior incarcerations	0.055***	0.055***	0.055***
	(0.006)	(0.005)	(0.005)
Age ÷ 100	-0.315***	-0.343***	-0.329***
	(0.030)	(0.038)	(0.038)
Black	0.022***	0.021***	0.022***
	(0.006)	(0.006)	(0.006)
Single	0.069***	0.070***	0.069***
	(0.009)	(0.006)	(0.006)
Education < HS	-0.013**	-0.012**	-0.013**
	(0.006)	(0.005)	(0.005)
Constant	0.392***	0.394***	0.393***
	(0.048)	(0.049)	(0.049)
R-squared	0.076	0.073	0.075
Observations	26,593	26,593	26,593

IV1 refers to the capacity-based instrument and IV2 is the leave-one-out instrument. All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Same probit and first stage equations as in Table 3.

Table 6: Summary Statistics on Infractions

	Public (1)	Private (2)
Demographics		
Black	0.19	0.51
White	0.16	0.38
Age 18-24	0.22	0.54
Age 25-34	0.19	0.46
Age 35-49	0.15	0.33
Age 50+	0.11	0.22
Offenses		
Aggravated Assault	0.20	0.45
Burglary	0.25	0.53
Drug Possession	0.14	0.40
Drug Selling	0.22	0.51
Felony DUI	0.09	0.16
Fraud	0.16	0.33
Other	0.19	0.46
Robbery	0.30	0.60
Theft	0.18	0.47
Sentence length		
1	0.05	0.14
2	0.11	0.24
3	0.18	0.37
4	0.31	0.55
5	0.39	0.68
6	0.43	0.76
Overall	0.18	0.46
Observations	3,203	12,551

Summary statistics refer to whether the prisoner received any infraction over the course of his sentence. Sentence length is rounded to nearest year. The sample is restricted to prisoners with admission dates between January 1, 2000 and July 31, 2004, since the infractions data is only available post-2000.

Table 7: Infractions and Private Prison Exposure

	Dep. Var.: Any Infraction?					
	Model: Probit			Model: Linear Probability		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	0.159***	0.130***	0.154***	0.176***	0.156***	0.151***
	(0.015)	(0.014)	(0.013)	(0.021)	(0.018)	(0.018)
Sentence Length	0.100	0.096	0.089	-0.253***	-0.255***	-0.263***
	(0.108)	(0.106)	(0.100)	(0.087)	(0.088)	(0.089)
Sentence Length Sq.	0.030*	0.030*	0.028*	0.049***	0.049***	0.050***
	(0.017)	(0.017)	(0.016)	(0.014)	(0.014)	(0.015)
Prior incarcerations	0.043***	0.040***	0.034***	0.048***	0.044***	0.041***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
Age ÷ 100		-0.376***	-0.419***		-0.362***	-0.423***
		(0.052)	(0.058)		(0.073)	(0.083)
Black		0.022***	0.021***		0.025***	0.025***
		(0.007)	(0.007)		(0.009)	(0.009)
Single		0.040***	0.028***		0.040***	0.032***
		(0.006)	(0.006)		(0.007)	(0.007)
Education < HS		0.014*	0.008		0.018*	0.015*
		(0.007)	(0.007)		(0.009)	(0.008)
Constant				-0.671***	-0.626***	-0.674***
				(0.180)	(0.185)	(0.191)
R-squared	-	-	-	0.287	0.299	0.304
Observations	15,754	15,754	15,754	15,754	15,754	15,754
Classification	N	N	Y	N	N	Y
Time Trends	Y	Y	Y	Y	Y	Y

Infractions data is only available post-2000, hence sample includes prisoner-sentences from January 1, 2000 to July 31, 2004. All columns control for offense dummies and county fixed effects. Time trends are linear and quadratic, each interacted with sentenced days, and dummies for month of prison admission. Marginal effects are reported for the probit model in columns (1) to (3). Robust standard errors in parentheses:
* p<0.10, ** p<0.05, *** p<0.01.

Table 8: Fixed Effect Estimates of Infraction Rates by Private Prison Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:	All	SD = 1	SD = 2	SD = 3	SD = 4	SD = 5	SD = 6
InPrivate	0.015***	0.017**	0.013***	0.016***	0.019***	0.007	0.028***
	(0.003)	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)
Constant	0.036***	0.005***	0.012***	0.024***	0.031***	0.049***	0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	317,701	16,786	33,763	61,362	46,425	113,832	45,533
# Fixed Effects	20,697	4,377	3,809	4,530	2,267	4,342	1,372

Columns (2) to (7) show regression estimates within buckets of judge-assigned sentence length. Each observation represents a month that the prisoner is in prison, and "InPrivate" denotes whether the prisoner was housed in a private facility in a given month. Regressions include a fixed effect for each prisoners, since at least 3 months are observed for every prisoner. In column (1), for example, there are 20,697 fixed effects (one for each prisoner-sentence) for the 317,701 observations—this is an average of 15 months per prisoner. Sample includes all observations starting between May 1, 1996 and July 31, 2004, but since the infractions data is only available post-2000, all observations prior to January 1, 2000 are coded as missing and not part of the regression analysis. The constant term represents the average of the individual fixed effects. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9: OLS and IV Results with Intensity of Private Prison Exposure

		IV: Ramp		IV: Leave One Out	
	OLS	1st Stg.	IV1	1st Stg.	IV2
	(1)	(2)	(3)	(4)	(5)
Fraction Private	0.224***		0.175***		0.144***
	(0.010)		(0.524)		(0.221)
Ramp ÷ 1000		0.007***			
		(0.002)			
Leave One Out				0.218***	
				(0.030)	
Sentence Length	-0.138***	0.011	-0.090***	0.017	-0.111***
	(0.035)	(0.015)	(0.034)	(0.013)	(0.021)
Sentence Length Sq.	0.018***	0.003	0.025***	0.002	0.022***
	(0.006)	(0.003)	(0.005)	(0.002)	(0.003)
Prior incarcerations	0.012***	-0.004**	-0.002	-0.003*	0.004
	(0.003)	(0.002)	(0.007)	(0.002)	(0.004)
Age ÷ 100	0.163***	-0.165***	-0.147***	-0.166***	-0.125***
	(0.018)	(0.017)	(0.028)	(0.017)	(0.043)
Black	0.014***	-0.000	0.012***	-0.000	0.013***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)
Single	0.024***	0.009***	0.055***	0.009***	0.041***
	(0.004)	(0.002)	(0.009)	(0.002)	(0.005)
Education < HS	-0.001	0.004*	0.007	0.003*	0.003
	(0.003)	(0.002)	(0.006)	(0.002)	(0.004)
Constant	0.973***	0.023	0.703***	-0.012	0.724***
	(0.042)	(0.021)	(0.060)	(0.018)	(0.037)
R-squared	0.274	0.104	-	0.105	-
Observations	26,593	26,593	26,593	26,593	26,593

IV1 refers to the capacity-based instrument and IV2 is the leave-one-out instrument. All columns control for offense dummies, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission, county fixed effects and classification. Fraction Private equals the fraction of the prisoner's court-assigned sentence that was served in a private prison. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Matching Estimates: Fraction of Sentence Served

	Dep. Var.: Fraction of Sentence Served					
	(1)	(2)	(3)	(4)	(5)	
ATE	0.045***	0.069***	0.059***	0.057***	0.069**	0.054***
	(0.007)	(0.009)	(0.009)	(0.009)	(0.008)	(0.013)
Observations	1,054	1,054	1,054	1,054	1,054	1,054
Pool of Matches	12,228	12,228	12,228	12,228	12,228	12,228
Offense-Related	Y	Y	Y	Y	Y	Y
Time	N	Y	Y	Y	Y	Y
Classification	N	N	Y	N	Y	Y
Demographics	N	N	N	Y	Y	Y
County	N	N	N	N	N	Y

Each observation is a prisoner-sentence starting between May 1, 1996 and July 31, 2004. Matching implemented using nearest neighbor matching; robust Abadie-Imbens standard errors are reported in parentheses. Offense-Related variables include sentenced days (rounded to the nearest year) and offense category (10 main categories). Time includes year dummies. Classification variables include actual classification (e.g., minimum custody, medium custody) and level of care required (function of health and working ability). Demographics include age, race (indicator for black), marital status and education. County includes dummies for each of the 82 counties. I impose exact matches on classification, race and sentenced days (rounded to the nearest year). The "teffects" command with the "nneighbor" option in STATA 13.0 was used to generate this table. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 11: Matching Estimates: Recidivism

	Dep. Var.: Recidivism					
	(1)	(2)	(3)	(4)	(5)	
ATE	0.009	0.006	-0.008	0.004	-0.007	0.041
	(0.019)	(0.019)	(0.022)	(0.022)	(0.022)	(0.0304)
Observations	1,054	1,054	1,054	1,054	1,054	1,054
Pool of Matches	12,228	12,228	12,228	12,228	12,228	12,228
Offense-Related	Y	Y	Y	Y	Y	Y
Time	N	Y	Y	Y	Y	Y
Classification	N	N	Y	N	Y	Y
Demographics	N	N	N	Y	Y	Y
County	N	N	N	N	N	Y

Each observation is a prisoner-sentence starting between May 1, 1996 and July 31, 2004. Matching implemented using nearest neighbor matching; robust Abadie-Imbens standard errors are reported in parentheses. Offense-Related variables include sentenced days (rounded to the nearest year) and offense category (10 main categories). Time includes year dummies. Classification variables include actual classification (e.g., minimum custody, medium custody) and level of care required (function of health and working ability). Demographics include age, race (indicator for black), marital status and education. County includes dummies for each of the 82 counties. I impose exact matches on classification, race and sentenced days (rounded to the nearest year). The "teffects" command with the "nneighbor" option in STATA 13.0 was used to generate this table. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 12: Control Function Results: Time Served and Recidivism

	Dep. var.: Fraction of Sentence Served			Dep. var.: Recidivism (36-month)		
	(1) No IV	(2) IV1	(3) IV2	(4) No IV	(5) IV1	(6) IV2
Private	0.115***	0.049***	0.057**	0.732***	-0.011	-0.015
	(0.012)	(0.016)	(0.018)	(0.010)	(0.036)	(0.028)
Sentence Length	-0.143***	-0.134***	-0.138***	-0.145***	-0.095***	-0.109***
	(0.012)	(0.012)	(0.011)	(0.033)	(0.028)	(0.028)
Sentence Length Sq.	0.018***	0.018***	0.018***	0.008	0.007	0.009*
	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)
Prior incarcerations	0.016***	0.012***	0.012***	0.070***	0.061***	0.055***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.005)
Age ÷ 100		0.172***	0.153***		-0.286***	-0.325***
		(0.021)	(0.015)		(0.034)	(0.034)
Black		0.013***	0.014***		0.024***	0.022***
		(0.003)	(0.003)		(0.006)	(0.006)
Single		0.027***	0.024***		0.082***	0.069***
		(0.003)	(0.002)		(0.006)	(0.006)
Education < HS		0.000	-0.001		-0.011*	-0.013*
		(0.002)	(0.002)		(0.005)	(0.005)
Constant	1.063***	0.982***	0.977***	0.464***	0.486***	0.392***
	(0.020)	(0.020)	(0.020)	(0.056)	(0.049)	(0.049)
Selection Equation Instruments						
Ramp (÷ 1000)		0.126***			0.126***	
		(0.019)			(0.019)	
Leave One Out			2.710***			2.710***
			(0.275)			(0.275)
Observations	26,593	26,593	26,593	26,593	26,593	26,593
Rho	0.161***	0.165	0.036	0.814***	0.036	0.031
Lambda	0.028***	0.029	0.006	0.406***	0.015	0.013

IV1 refers to the capacity-based instrument and IV2 is the leave-one-out instrument. All regressions control for admission time trends include a linear time trend and interactions with both original sentence and its square, offense fixed effects (10 total) and county fixed effects. Correlation (Rho) indicates the correlation between the error terms in the selection equation and the outcome equation; a positive sign means that someone who has a positive shock to treatment probability also has a positive shock the outcome. Lambda is the loading factor on unobserved heterogeneity, and the positive sign of this coefficient implies positive correlation between the errors of the selection and outcome equations. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 13: Stability of Results by Prisoner Admission Year

	1996 (1)	1997 (2)	1998 (3)	1999 (4)	2000 (5)	2001 (6)	2002 (7)	2003 (8)	2004 (9)
Panel A – Dep. Var.: Fraction of Sentence Served									
Private	0.083***	0.084***	0.079***	0.086***	0.086***	0.069***	0.069***	0.065***	0.047***
	(0.013)	(0.009)	(0.012)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)
R-squared	0.327	0.238	0.212	0.246	0.284	0.321	0.332	0.339	0.374
Panel B – Dep. Var.: Days Served									
Private	126.9***	118.0***	100.9***	120.8***	118.0***	89.2***	94.0**	90.1***	68.9**
	(31.0)	(20.2)	(17.0)	(23.3)	(23.1)	(19.6)	(26.4)	(20.0)	(18.2)
R-squared	0.714	0.746	0.777	0.802	0.771	0.762	0.742	0.695	0.704
Panel C – Dep. Var.: Recidivism									
Private	0.021	0.006	0.019	-0.015	0.005	0.010	0.008	0.010	0.021
	(0.038)	(0.024)	(0.025)	(0.012)	(0.031)	(0.024)	(0.009)	(0.020)	(0.025)
R-squared	0.112	0.110	0.124	0.110	0.127	0.094	0.105	0.107	0.132
Observations	1,620	2,917	3,115	3,187	3,450	3,494	3,498	3,123	2,189

Each coefficient reports the result from a separate regression. Each regression controls for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Per-Diem Contracts Versus 90 percent Guarantee Contracts

	Dep. var.: Fraction Served		Dep. var.: Recidivism	
	(1)	(2)	(3)	(4)
Private	0.064***		0.012	
	(0.004)		(0.009)	
Private: Per-Diem		0.066***		0.014
		(0.008)		(0.015)
Private: 90 percent Guarantee		0.063***		0.011
		(0.006)		(0.013)
Sentence Length	-0.168***	-0.168***	-0.212***	-0.212***
	(0.042)	(0.042)	(0.061)	(0.061)
Sentence Length Sq.	0.019**	0.019**	0.033***	0.033***
	(0.008)	(0.008)	(0.010)	(0.010)
Prior incarcerations	0.011**	0.011**	0.053***	0.053***
	(0.005)	(0.005)	(0.007)	(0.007)
Age ÷ 100	0.222***	0.222***	-0.292***	-0.293***
	(0.020)	(0.021)	(0.032)	(0.033)
Black	0.013**	0.013**	0.020*	0.020*
	(0.005)	(0.005)	(0.010)	(0.010)
Single	0.029***	0.029***	0.036**	0.036**
	(0.005)	(0.005)	(0.016)	(0.016)
Education < HS	-0.012***	-0.012***	0.004	0.004
	(0.004)	(0.004)	(0.009)	(0.009)
Constant	1.246***	1.246***	0.323***	0.323***
	(0.045)	(0.045)	(0.097)	(0.097)
R-squared	0.321	0.321	0.082	0.082
Observations	12,304	12,304	12,304	12,304

Data is from January 1, 2001 to July 31, 2004. Recidivism window is 36 months. "Private" equals 1 if the prisoner ever went to private prison over the course of his sentence. "Private: Per-Diem" equals 1 if the prisoner went to one of the two private prisons that did not have 90 percent guarantee contracts and maintained the per-diem contracts; it equals zero otherwise. "Private: 90 percent Guarantee" equals 1 if the prisoner went to one of the two private prisons that entered 90 percent guarantee contracts; it equals zero otherwise. The contract changes for the two prisons occured in 2000. All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Marginal effects are reported for the probit model in columns (1) to (3). Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 15: Reduced Form Equations for Placebo Test: Fraction of Sentence Served

	Dep. Var.: Fraction of Sentence Served					
	Instrument: Ramp			Instrument: Leave-one-out		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Ramp}$	0.051**	0.017	0.018			
	(0.023)	(0.075)	(0.202)			
$\widehat{Leaveoneout}$				0.043**	0.018	0.019
				(0.022)	(0.071)	(0.168)
Sentence Length	-0.138***	-0.121***	-0.039	-0.137***	-0.121***	-0.038
	(0.012)	(0.035)	(0.089)	(0.012)	(0.035)	(0.087)
Sentence Length Sq.	0.018***	0.014***	0.011	0.018***	0.014***	0.011
	(0.002)	(0.005)	(0.012)	(0.002)	(0.005)	(0.012)
Prior incarcerations	0.011***	0.025***	-0.018	0.011***	0.025***	-0.018
	(0.002)	(0.008)	(0.038)	(0.002)	(0.008)	(0.038)
Age ÷ 100	0.150***	0.116**	-1.238	0.146***	0.120**	-1.222
	(0.017)	(0.052)	(0.873)	(0.016)	(0.051)	(0.878)
Black	0.014***	0.022***	0.036*	0.014***	0.022***	0.036*
	(0.003)	(0.007)	(0.020)	(0.003)	(0.007)	(0.021)
Single	0.024***	0.025***	0.039*	0.025***	0.025***	0.039*
	(0.002)	(0.007)	(0.022)	(0.002)	(0.007)	(0.021)
Education < HS	-0.001	-0.015**	0.009	-0.001	-0.015**	0.009
	(0.002)	(0.006)	(0.017)	(0.002)	(0.006)	(0.017)
Constant	0.977***	0.999***	1.109***	0.978***	0.999***	1.105***
	(0.020)	(0.061)	(0.220)	(0.020)	(0.060)	(0.217)
R-squared	0.246	0.325	0.317	0.246	0.325	0.317
Observations	26,593	3,299	854	26,593	3,299	854

All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Note that the instruments $\widehat{Ramp}$ and $\widehat{Leaveoneout}$ are the predicted probabilities from a probit regression of whether the prisoner went to private prison on the instrument and all covariates for the adult males in the sample. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 16: Reduced Form Equations for Placebo Test: Recidivism

	Dep. Var.: Recidivism					
	Instrument: Ramp			Instrument: Leave-one-out		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Ramp}$	-0.065	-0.051	-0.133			
	(0.056)	(0.158)	(0.492)			
$\widehat{Leaveoneout}$				-0.027	-0.071	-0.581
				(0.053)	(0.150)	(0.409)
Sentence Length	-0.106***	-0.111	-0.103	-0.108***	-0.110	-0.053
	(0.028)	(0.075)	(0.218)	(0.028)	(0.075)	(0.212)
Sentence Length Sq.	0.009**	0.013	0.008	0.009**	0.013	0.006
	(0.004)	(0.012)	(0.030)	(0.004)	(0.012)	(0.030)
Prior incarcerations	0.055***	0.033**	0.030	0.055***	0.033**	0.025
	(0.005)	(0.017)	(0.092)	(0.005)	(0.017)	(0.091)
Age ÷ 100	-0.347***	-0.192*	-4.678**	-0.330***	-0.200*	-5.051**
	(0.040)	(0.110)	(2.126)	(0.039)	(0.107)	(2.134)
Black	0.021***	-0.003	0.076	0.022***	-0.003	0.073
	(0.006)	(0.015)	(0.050)	(0.006)	(0.015)	(0.050)
Single	0.071***	0.058***	0.176***	0.070***	0.059***	0.188***
	(0.006)	(0.015)	(0.053)	(0.006)	(0.015)	(0.051)
Education < HS	-0.012**	0.003	-0.073*	-0.013**	0.003	-0.070*
	(0.005)	(0.014)	(0.042)	(0.005)	(0.014)	(0.042)
Constant	0.394***	0.121	1.078**	0.393***	0.122	1.048**
	(0.049)	(0.127)	(0.535)	(0.049)	(0.127)	(0.527)
R-squared	0.076	0.095	0.174	0.076	0.095	0.176
Observations	26,593	3,299	854	26,593	3,299	854

All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Note that the instruments $\widehat{Ramp}$ and $\widehat{Leaveoneout}$ are the predicted probabilities from a probit regression of whether the prisoner went to private prison on the instrument and all covariates for the adult males in the sample. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

A Additional Material

A.1 OLS Bias in a Potential Outcomes Framework

The source of selection bias is well illustrated within the potential outcomes framework developed in Angrist, Imbens and Rubin (1996). Let Y_i denote the observed re-offense status of prisoner i. The potential outcomes are Y_{0i}, which is the re-offense status of a prisoner that spent no time in private prison, and Y_{1i}, which is the re-offense status of a prisoner that spent at least some time in private prison. In this framework, the treatment variable is $Private_i$, which is defined as whether the prisoner i was ever assigned to private prison over the course of his sentence. The potential outcomes framework is based on the idea that only one outcome is ever observed: the counterfactual outcome had the prisoner only served time in public facilities is never available. Hence, we observe:

$$Y_i = Y_{0i} \cdot (1 - Private_i) + Y_{1i} \cdot Private_i \tag{24}$$

If we conduct our comparison of prisoners in public versus private settings on the basis of observed treatment status, we would be ignoring any potential non-random assignment of prisoners to private prison. We would be analyzing:

$$\begin{aligned} & E[Y_i|Private_i = 1] - E[Y_i|Private_i = 0] \\ &= E[Y_{1i}|Private_i = 1] - E[Y_{0i}|Private_i = 0] \\ &= \underbrace{E[Y_{1i} - Y_{0ij}|Private_i = 1]}_{\text{Average Treatment on the Treated}} + \underbrace{[E[Y_{0i}|Private_i = 1] - E[Y_{0i}|Private_i = 0]]}_{\text{Selection Bias}} \end{aligned} \tag{25}$$

In equation 25, the first term is the average causal effect of treatment on the treated (ATT), which is one of the standard parameters of interest in program evaluation Heckman and Robb (1985), and the second term characterizes the selection bias. (Normally we might also worry about treatment compliance, but in the context of prisons, we can safely assume that if a prisoner is assigned to private prison, he goes there with 100 percent probability.)

A.2 Details on Variable Creation

Calculation of Sentenced Days: The demographics file that describes the offense for each prisoner contains a great level of detail regarding the nature of the offense(s) committed, whether the judge decided that the sentences should be concurrently or consecutively served. For each admission date that a prisoner has, I calculate the number of court-ordered sentenced days using the variables and verify this calculation with a separate entry in the "inmate record" file. I can also observe whether the prisoner incurred a new sentence while serving the current sentence, and in these cases, I add the required number of additional days to be served (taking into account whether the days must be served concurrently or consecutively) to the original admission date. This allows me to calculate the relevant fraction of sentence served and ensures that the fraction is bounded between 0 and 1.

Calculation of Recidivism: The recidivism variable is calculated as follows: using the identifier that matches all felony records for the same prisoner, I first sort all observations for each prisoner by admission date and facility date. I then calculate the difference in days between a new admission date and the previous felony's release date. If the new felony occurs within 36 months of the previous felony's release date, I record that prisoner as having recidivated.

Winsorizing Fraction of Sentence Served: About 0.03 percent of prisoners are held for up to 28 days past the end of the original sentence. My conversations with MDOC officials indicates that this can occur if there is a delay in processing the release of the prisoner due to lack of post-release services such as housing or continued treatment programs. For these cases, I winsorize the fraction served to 100 percent.

Cleaning Movement File: The movement file contains information about each facility that a prisoner spends time in during his stay in prison. The movement file also records visits to primary care, the hospital and funerals. To begin cleaning the file, I drop all within-facility moves (i.e., bed transfers within the same prison) since the goal of this paper is to compare prisoner outcomes across public and private prisons. Second, I omit all "transit" moves: basically, if a prisoner goes from facility A to "transit", and then "transit" to facility B, I modify the data file so that the prisoner goes directly from facility A to facility B. I do not lose any prisoner-days in this exercise since virtually every transit move occurs within one day. Fourth, similar in spirit to omitting the "transit" moves, I drop any facility at which the prisoner spent less than one day. This occurred in very few cases, but would entail a prisoner going from facility A to B, then B to C, all in one day: I modify these observations such that the prisoner goes directly from facility A to C in the same day.

A.3 Extending the Model to Allow Re-Optimized Release Policies

The main text considers the case where the state does not re-optimize prisoner release decisions after private contracting. This case appears to be the one of relevance given that the policy narratives around privatization are more about cost-cutting than holding prisoners longer, although much of private contracting has *followed* from sentencing or parole reform that effectively increase the number of prisoners in prison at a given point in time. In this section, I allow for the state to re-optimize its release decision with private contracting and show that the main model's results are still applicable.

Abstracting away from the extensive margin question of how many individuals to incarcerate at a given time, the intuition of my model is that the state re-optimizes the intensive margin, i.e., release decisions, for each prisoner due to the innovation in marginal costs offered by the private contractor. Private contractors in Mississippi (and most states) are required to be at least 10 percent cheaper on a per-prisoner, per-day basis than state prisons and offer a marginal cost saving technology measured on this per-prisoner, per-day basis. As a result, because state prison beds and private prison beds are substitutable, the state re-optimizes its overall release policy but does *not intend* to adopt different release policies for prisoners in state versus public prison.

Recall that the state chooses s_i such that:

$$\underset{s_i}{min} \quad \overbrace{Cs_i}^{Incarceration\ costs} \quad + \overbrace{\int_{s_i}^{\infty} r_i(t)\,dt}^{Recidivism\ costs} . \tag{26}$$

Consider that the state can contract with private operators to incarcerate each prisoner at daily cost $C' < C$. With a lower marginal cost of daily incarceration, equation 26 implies that the optimal s_i, or time served in prison, increases; the state will incorporate this into its overall cost minimization problem and re-optimize s_i. Let B_S and B_P be the number of state beds and privately operated beds available in the prison system, respectively; also let the per-diem cost saving offered by the private operator equal γ percent so that $C' = (1-\gamma)C$. Then the state's *overall* change in marginal cost is given by:

$$C''' = \frac{C \cdot B_S + C(1-\gamma) \cdot B_P}{B_S + B_P}. \tag{27}$$

By construction, as long as the private operator provides cost savings $\gamma > 0$, the inequality $C' < C''' < C$ will be satisfied.[34] Returning to equation 2, the state now seeks to release

[34]For a numerical example, imagine that there are 10,000 beds operated by the state, and 1,000 beds operated by the private company at a 10 percent daily discount off of the state's cost of \$50: i.e., $B_S = 10,000$; $B_P = 1,000$; $C = \$50$ and $\gamma = 10 percent$. Then, the private operator charges $(1-0.10)*50 = \$45$ per prisoner-day. The idea is that rather than treating the private operator as having a lower marginal cost technology, the state incorporates this saving into its overall optimization and now makes decisions based on $C''' = \frac{50 \cdot 10,000 + 50(1-0.10) \cdot 1,000}{10,000+1,000} = \$49.55 < \$50$.

prisoners where $r_i(s) = C'''$; the key implication is that there should be no difference in s_i owing to whether the prisoner was assigned to a state or private prison.

The source of the friction that remains is that the private contractor treats C', i.e., $(1-\gamma)C$ as its *marginal revenue*, not its marginal cost. The model then yields the same implications as in Section 3.

B Welfare Analysis

In this section, I present back-of-the-envelope calculations to assess the welfare implications of private prison contracting. Consider that each prisoner-day costs the state \$50 (Mississippi Department of Corrections 2012); then, taking the conservative estimate of 60 "extra days", the additional incarceration costs are \$3,000. Let the prisoner have a value of freedom worth \$670, since (Abrams and Rohlfs 2011) estimate \$1,000 for every 90 days. Additionally, let the cost of each felony be approximately \$80,000 as discussed in (Kuziemko 2013).

The question for the state—even without considering the prisoner's value of freedom—is whether the additional cost of incarceration is offset by reductions in recidivism. Given that the additional incarceration costs are about \$3,000[35], the state would require recidivism to be decreased by $\frac{3{,}000}{80{,}000} = 3.8$ percent for private prison contracting to be cost neutral. Adding the prisoner's value of freedom to the equation requires that recidivism must decrease by $\frac{3{,}670}{80{,}000} = 4.6$ percent for the same effect. Since the IV estimate in Table 5 suggests a point estimate of -2 percent with a 95 percent confidence interval of [-0.10,0.06], private prison contracting will only yield a positive social welfare if recidivism is reduced by at least 3.8 percent (or 4.6 percent, if considering the prisoner's value of freedom).

In sum, private prison contracting may provide a welfare benefit to the state depending on its effect on recidivism. These calculations, however, ignore a central component of social welfare: justice. To the extent that society cares about the *equal* delivery of punishment, private contracting is undesirable solely because it results in significant distortions to prisoner time served.

[35]Some of these additional costs are offset by the lower cost incarceration provided by private prisons for the majority of the days served.

C Additional Tables and Figures

Figure B.1: Daily Prison Population by Private Prison, 1996-2012

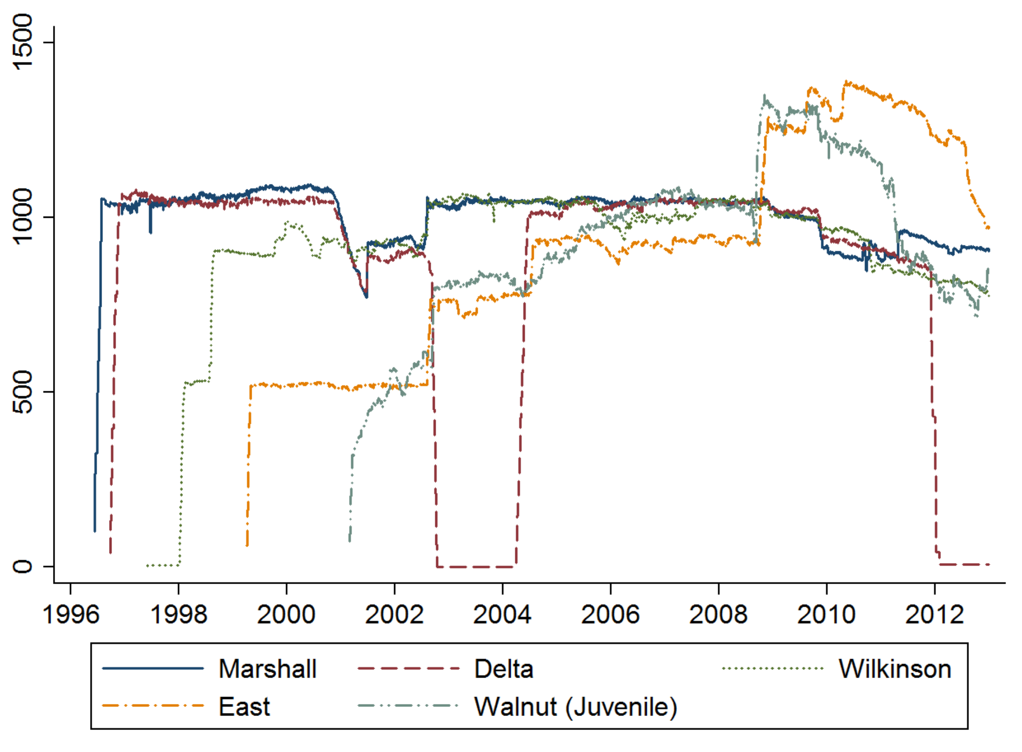


Figure shows the daily prisoner population for each private prison for prisoners admitted between May 1, 1996 and May 1, 2012. The spikes in the daily population of the private prison population correspond to shocks in the private prison capacity either through private prison entry, closure or bed expansion. Even though the juvenile prison is not studied in this paper, I have included its capacity line to illustrate its interaction with the capacity lines of Marshall and Walnut.

Figure B.2: Mississippi Prison Locations

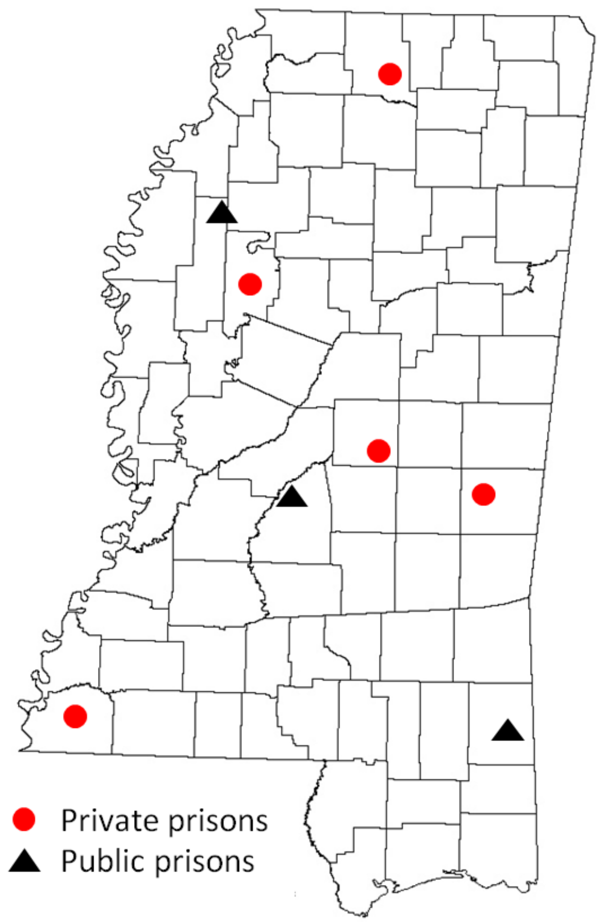
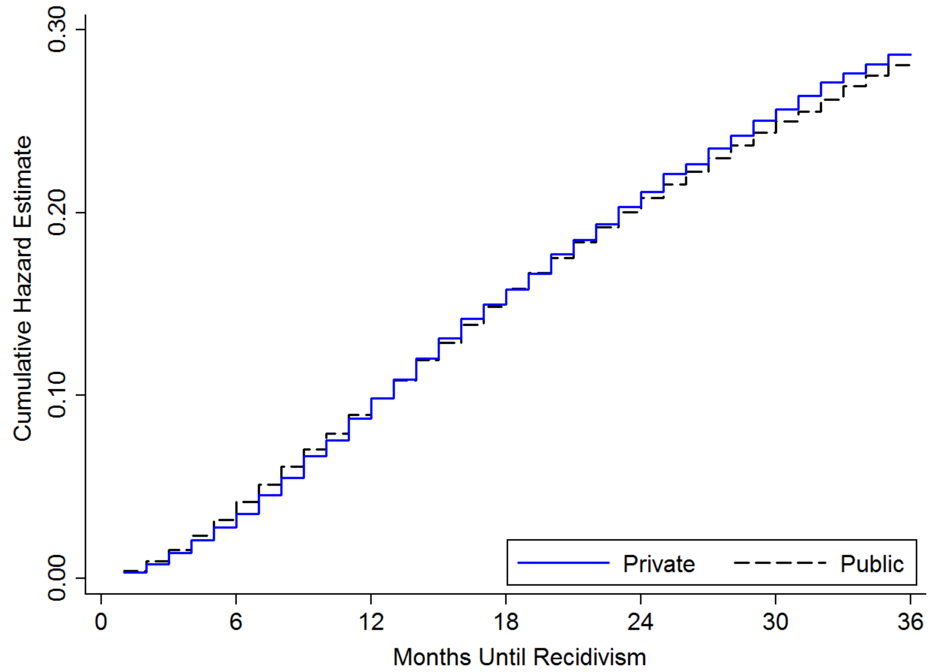


Figure shows the location of the state and private prisons in Mississippi. The prison locations were obtained from the Mississippi Department of Corrections 2002 Annual Report.

Figure B.3: Recidivism Hazard Function by Private Prison Exposure

Panel A



Panel B

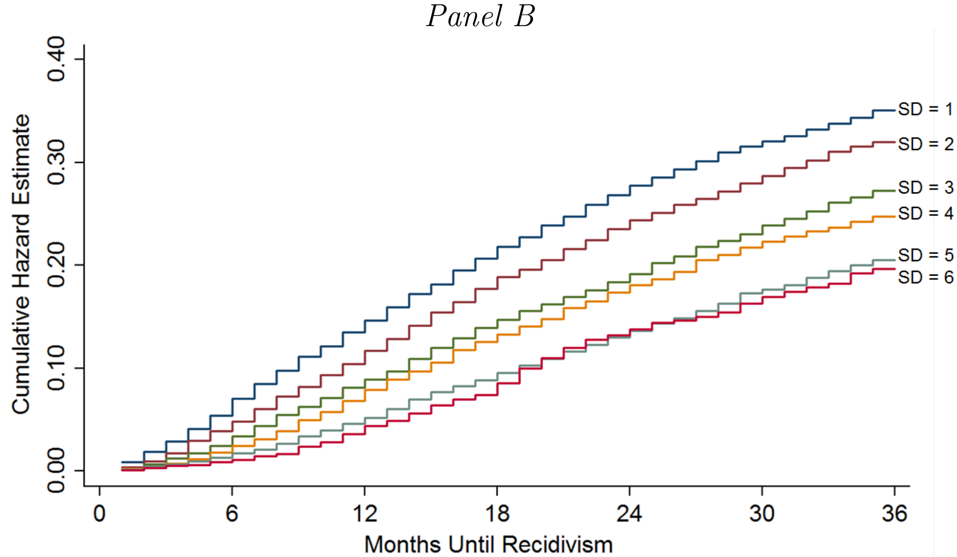


Figure shows the Nelson-Aalen cumulative hazard estimates of 36-month recidivism by private prison assignment. Panel A shows the full sample and Panel B shows the hazard rates by sentence length.

Figure B.4: Infractions by Type

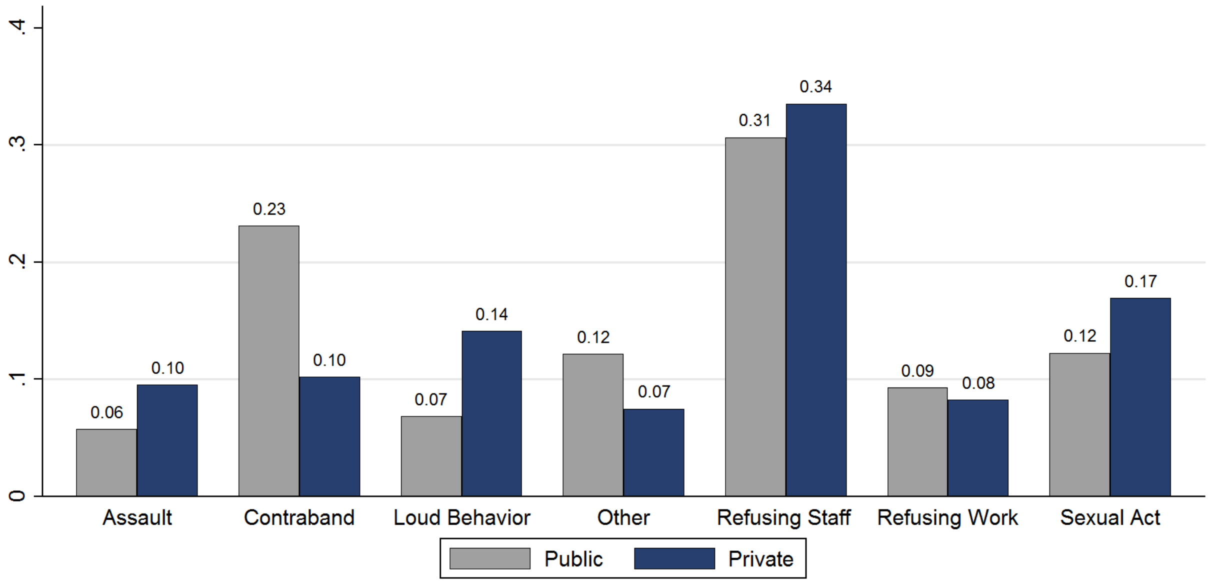
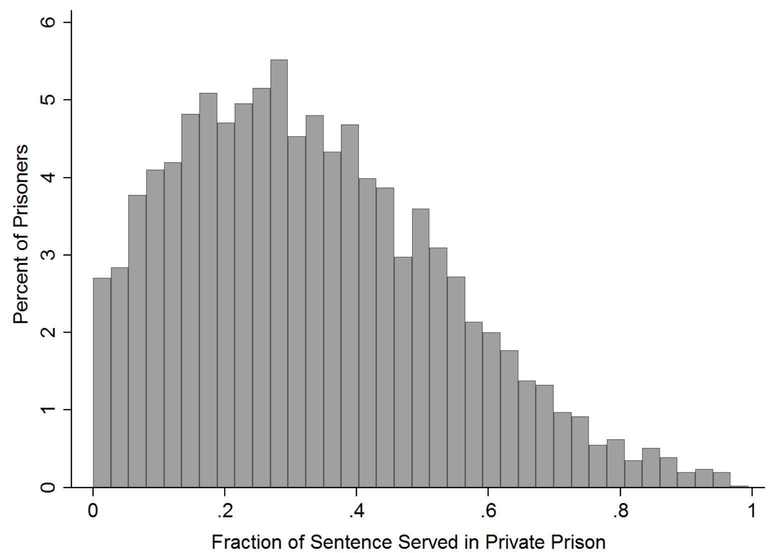


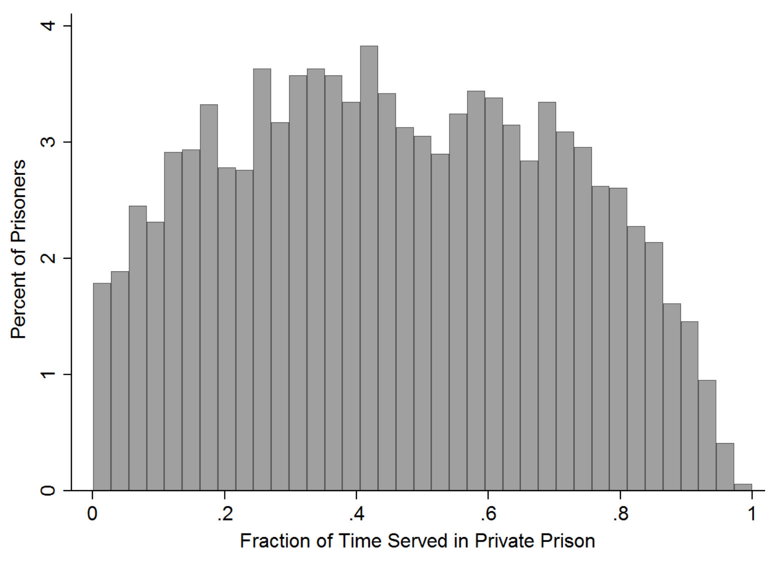
Figure shows the breakdown of infraction (prison conduct violation) types by whether the infraction was given by a private or public prison. Data includes all 6,807 infractions given to the primary sample of prisoners between January 1, 2000 and July 31, 2004.

Figure B.5: Fraction of Sentence Served in Private Prison

Panel A



Panel B



Panel A shows the probability density function of the fraction of court-ordered sentence says served in private prison. Panel B plots the fraction of time served in private prison. For the empirical analysis, I always use the variable shown in Panel A because the dividing by time served (instead of sentence days) creates an endogeneity problem if private prisons affect time served in prison. Sample for both histograms is limited to the 19 percent of prisoners that go to private prison.

Table B.1: Summary Statistics by Private Prison

	Private	Marshall	Delta	Wilkinson	East
	(1)	(2)	(3)	(4)	(5)
Outcomes					
Fraction of Sentence Served	0.73	0.72	0.74	0.76	0.82
Exactly 100 percent Served	0.17	0.15	0.17	0.19	0.28
Recidivism (36-month)	0.26	0.24	0.25	0.26	0.22
Years served	2.65	2.60	2.79	2.95	3.19
Sentence Length	3.68	3.69	3.80	3.93	3.94
Movement Variables					
Years in private prison	1.19	1.30	1.17	1.19	1.49
Years in jail	0.34	0.34	0.36	0.33	0.39
Years in court	0.14	0.11	0.13	0.17	0.15
Years until prison transfer	0.69	0.63	0.66	0.74	0.96
Demographics					
Black	0.71	0.69	0.76	0.64	0.69
Age ÷ 100	0.28	0.29	0.29	0.28	0.32
Single	0.67	0.62	0.67	0.69	0.63
Education < HS	0.56	0.55	0.54	0.53	0.61
Offenses (percent)					
Aggravated Assault	0.07	0.07	0.07	0.06	0.07
Burglary	0.21	0.15	0.18	0.21	0.22
Drug Possession	0.14	0.15	0.15	0.12	0.10
Drug Selling	0.15	0.17	0.18	0.13	0.10
Felony DUI	0.03	0.04	0.03	0.04	0.04
Fraud	0.04	0.05	0.03	0.06	0.03
Other	0.18	0.19	0.17	0.18	0.21
Robbery	0.09	0.08	0.08	0.10	0.10
Theft	0.10	0.10	0.10	0.10	0.12
Release Type (percent)					
House arrest	0.01	0.01	0.01	0.00	0.00
Term expiration	0.46	0.41	0.50	0.47	0.55
Probation	0.33	0.35	0.29	0.32	0.33
Parole	0.02	0.01	0.01	0.01	0.00
Earned supervised release	0.18	0.20	0.17	0.18	0.11
Observations	5,533	1,716	1,731	1,215	586

This table repeats Table 1 for each private prison. Column (1) shows the summary statistics for all prisoners that went to private prison, and columns (2) to (5) provide a breakdown of these prisoners by the prison in which they served time. A handful of prisoners serve time in multiple private prisons, which is why the observation count for column (1) is not the sum of columns (2) to (5).

Table B.2: OLS Estimates of Private Prison Exposure and Days Served

	Dep. Var.: Days Served					
	Full Sample			Event Window Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	91.1***	94.7***	93.2***	92.6***	92.7***	84.6***
	(7.1)	(7.2)	(7.0)	(15.0)	(15.1)	(14.7)
Sentence Length	221.6***	223.3***	220.8***	229.9***	230.4***	225.4***
	(37.0)	(38.4)	(38.4)	(63.7)	(63.4)	(63.0)
Sentence Length Sq.	9.8	9.7	10.0	7.8	7.7	8.3
	(6.5)	(6.7)	(6.7)	(10.9)	(10.8)	(10.7)
Prior incarcerations	13.5***	9.1**	8.4*	2.3	-1.9	-2.7
	(4.6)	(4.5)	(4.5)	(6.1)	(6.0)	(5.9)
Age ÷ 100		220.3***	177.7***		148.2***	99.7***
		(28.8)	(25.8)		(30.4)	(30.6)
Black		16.1***	16.5***		19.0***	19.0***
		(4.5)	(4.5)		(5.8)	(5.7)
Single		29.6***	27.9***		25.8***	23.1***
		(5.1)	(5.0)		(5.9)	(5.8)
Education < HS		-3.6	-4.8		5.6	3.3
		(4.0)	(4.1)		(6.0)	(6.0)
Constant	126.2***	32.0	28.6	80.6	3.6	-9.1
	(43.5)	(48.7)	(48.7)	(77.3)	(80.8)	(79.3)
R-squared	0.730	0.733	0.734	0.696	0.697	0.699
Observations	26,593	26,593	26,593	13,282	13,282	13,282

All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table B.3: IV Estimates on Days Served in Prison

	Dep. Var.: Days Served		
	(1)	(2)	(3)
	OLS	IV 1	IV 2
Private	93.2***	61.0**	54.3**
	(7.0)	(25.0)	(24.2)
Sentence Length	220.8***	222.8***	223.2***
	(38.4)	(14.6)	(14.6)
Sentence Length Sq.	10.0	10.0***	10.0***
	(6.7)	(2.3)	(2.3)
Prior incarcerations	8.4*	8.2***	8.2***
	(4.5)	(2.8)	(2.8)
Age ÷ 100	177.7***	162.9***	159.9***
	(25.8)	(19.9)	(19.7)
Black	16.5***	16.4***	16.3***
	(4.5)	(3.2)	(3.2)
Single	27.9***	28.8***	29.0***
	(5.0)	(3.0)	(3.0)
Education < HS	-4.8	-4.5	-4.5
	(4.1)	(2.7)	(2.7)
Constant	28.6	29.6	29.9
	(48.7)	(25.5)	(25.6)
R-squared	0.734	0.733	0.733
Observations	26,593	26,593	26,593

All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01. Same probit and first stage equations as in Table 3.

Table B.4: Hazard Models – Recidivism

	Dep. Var.: Recidivism					
	Full Sample			Event Window Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	0.099***	0.020	-0.027	0.100***	0.033	-0.013
	(0.028)	(0.029)	(0.029)	(0.032)	(0.034)	(0.033)
Sentence Length	-0.243**	-0.301**	-0.394***	-0.026	-0.112	-0.227**
	(0.120)	(0.122)	(0.123)	(0.103)	(0.103)	(0.103)
Sentence Length Sq.	0.018	0.026	0.035*	-0.019	-0.007	0.005
	(0.019)	(0.019)	(0.019)	(0.017)	(0.016)	(0.017)
Prior incarcerations	0.288***	0.248***	0.222***	0.344***	0.323***	0.297***
	(0.017)	(0.021)	(0.022)	(0.025)	(0.025)	(0.025)
Age ÷ 100		-1.615***	-1.927***		-1.898***	-2.226***
		(0.117)	(0.127)		(0.186)	(0.194)
Black		0.103***	0.087***		0.161***	0.156***
		(0.023)	(0.023)		(0.028)	(0.028)
Single		0.451***	0.378***		0.301***	0.257***
		(0.047)	(0.042)		(0.046)	(0.049)
Education < HS		-0.052**	-0.060**		-0.070**	-0.086***
		(0.025)	(0.024)		(0.029)	(0.029)
Observations	26,593	26,593	26,593	13,282	13,282	13,282
Classification	N	N	Y	N	N	Y

All columns control for offense dummies, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and county fixed effects. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table B.5: IV without Probit Correction – Fraction of Sentence Served and Days Served

	1st Stg.	RF	IV1	IV1	1st Stg.	RF	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Private	Frac. Served	Frac. Served	Days Served	Private	Frac. Served	Frac. Served	Days Served
Private			0.812***	1019.443***			0.542***	692.268***
			(0.108)	(136.485)			(0.070)	(89.423)
Instrument	0.027***	0.022***			0.620***	0.336***		
	(0.003)	(0.001)			(0.056)	(0.026)		
Sentence Length	0.049**	-0.123***	-0.083***	290.824***	0.068***	-0.137***	-0.100***	270.225***
	(0.025)	(0.012)	(0.025)	(32.112)	(0.025)	(0.012)	(0.019)	(24.792)
Sentence Length Sq.	0.002	0.016***	0.017***	8.815*	-0.002	0.018***	0.017***	9.167**
	(0.004)	(0.002)	(0.004)	(4.805)	(0.004)	(0.002)	(0.003)	(3.749)
Prior incarcerations	-0.004	0.009***	0.006	1.168	-0.004	0.010***	0.008**	3.306
	(0.005)	(0.002)	(0.005)	(5.955)	(0.005)	(0.002)	(0.004)	(4.632)
Age ÷ 100	-0.467***	0.133***	-0.246***	-333.337***	-0.468***	0.131***	-0.122***	-183.056***
	(0.027)	(0.013)	(0.056)	(71.534)	(0.027)	(0.013)	(0.038)	(49.090)
Black	-0.005	0.014***	0.010*	11.279	-0.004	0.013***	0.011***	12.820**
	(0.005)	(0.003)	(0.005)	(6.876)	(0.005)	(0.003)	(0.004)	(5.359)
Single	0.024***	0.028***	0.047***	57.426***	0.025***	0.027***	0.040***	48.751***
	(0.005)	(0.002)	(0.006)	(7.292)	(0.005)	(0.002)	(0.004)	(5.480)
Education < HS	0.012**	-0.003	0.006	4.731	0.010**	-0.002	0.004	1.933
	(0.005)	(0.002)	(0.005)	(5.943)	(0.005)	(0.002)	(0.004)	(4.611)
Constant	0.024	0.987***	1.007***	66.013	-0.074*	1.037***	0.997***	55.000
	(0.043)	(0.020)	(0.043)	(54.502)	(0.044)	(0.021)	(0.033)	(42.485)
R-squared	0.130	0.253	-	-	0.131	0.251	-	-
Observations	26,593	26,593	26,593	26,593	26,593	26,593	26,593	26,593

Columns (2) and (4) show the reduced form equations for the instruments "ramp" and "leave-one-out", respectively when fraction served is the dependent variable. All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B.6: IV without Probit Correction – Recidivism

	Dep. Var.: Recidivism (36-month)			
	RF-IV1	IV1	RF-IV2	IV2
	(1)	(2)	(3)	(4)
Private		-0.046		0.051
		(0.123)		(0.103)
Instrument	-0.001		0.032	
	(0.003)		(0.064)	
Sentence Length	-0.109***	-0.107***	-0.109***	-0.113***
	(0.028)	(0.029)	(0.028)	(0.029)
Sentence Length Sq.	0.008*	0.009**	0.009**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Prior incarcerations	0.055***	0.055***	0.055***	0.056***
	(0.005)	(0.005)	(0.005)	(0.005)
Age ÷ 100	-0.318***	-0.339***	-0.318***	-0.294***
	(0.031)	(0.064)	(0.031)	(0.057)
Black	0.022***	0.021***	0.022***	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
Single	0.069***	0.070***	0.069***	0.067***
	(0.006)	(0.007)	(0.006)	(0.006)
Education < HS	-0.013**	-0.013**	-0.013**	-0.013**
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.392***	0.393***	0.386***	0.390***
	(0.049)	(0.049)	(0.050)	(0.049)
R-squared	0.076	0.074	0.076	0.075
Observations	26,593	26,593	26,593	26,593

Columns (1) and (3) show the reduced form estimates. IV1 refers to the capacity-based instrument and IV2 is the leave-one-out instrument. All columns control for offense dummies, county fixed effects, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and classification dummies. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Same first stage equations as in Table B.5.

Table B.7: Probit Model: Private Prison Exposure and Recidivism

	Dep. Var.: Recidivism					
	Full Sample			Event Window Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Private	0.034***	0.017**	0.010	0.017	0.015	0.006
	(0.008)	(0.008)	(0.008)	(0.015)	(0.014)	(0.015)
Sentence Length	-0.074**	-0.089***	-0.103***	-0.036	-0.055*	-0.076***
	(0.031)	(0.031)	(0.032)	(0.030)	(0.029)	(0.029)
Sentence Length Sq.	0.004	0.005	0.007	-0.002	0.000	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Prior incarcerations	0.065***	0.059***	0.054***	0.080***	0.077***	0.073***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Age ÷ 100		-0.313***	-0.353***		-0.377***	-0.413***
		(0.033)	(0.032)		(0.046)	(0.049)
Black		0.026***	0.024***		0.039***	0.037***
		(0.007)	(0.007)		(0.009)	(0.009)
Single		0.083***	0.070***		0.052***	0.044***
		(0.010)	(0.009)		(0.010)	(0.011)
Education < HS		-0.012*	-0.012**		-0.013	-0.015*
		(0.007)	(0.006)		(0.009)	(0.009)
Constant						
Observations	26,593	26,593	26,593	13,282	13,282	13,282
Classification	N	N	Y	N	N	Y

Marginal effects are reported. All columns control for offense dummies, admission time trends (linear, quadratic, each interacted with sentenced days), month of prison admission and county fixed effects. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.