Impacts of Private Prison Contracting on Inmate Time Served and Recidivism

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Online Appendix

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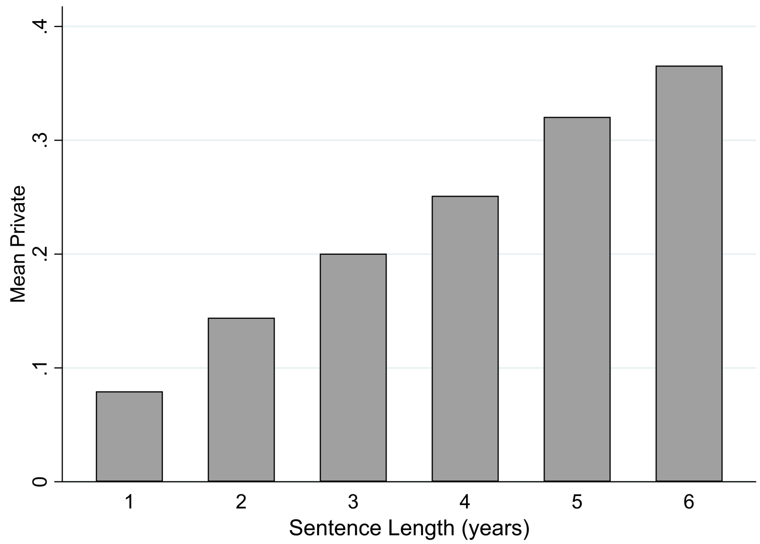
A Appendix Figures and Tables

Figure A.1: Inmate Exposure to Private Prison by Sentence Length

Panel A



Panel B

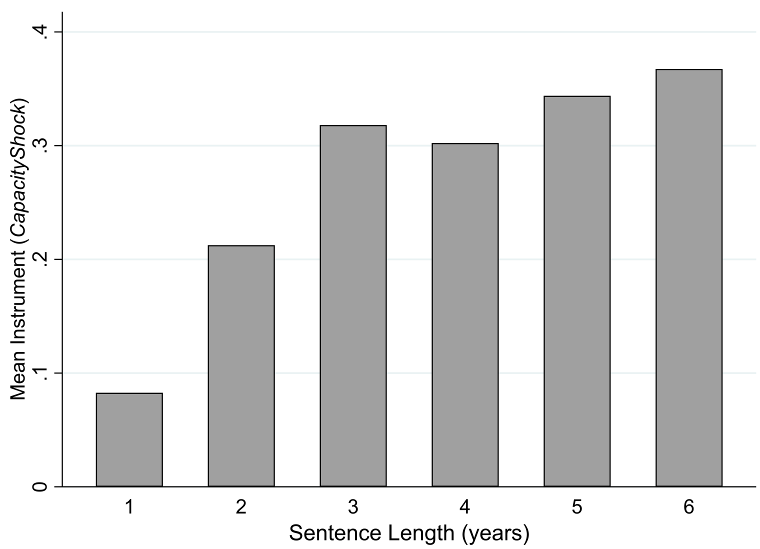
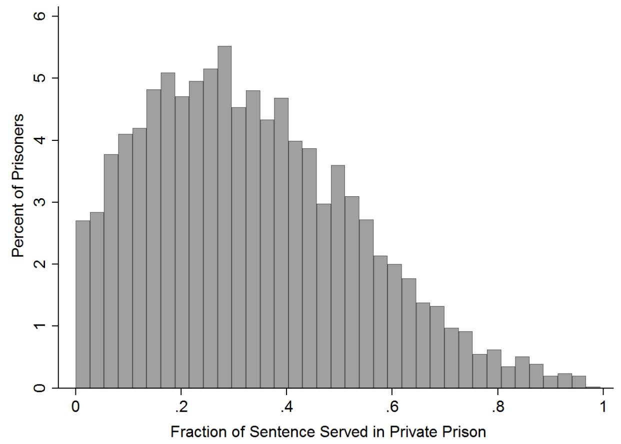


Figure shows the mean proportion of inmates who went to private prison by sentence length (rounded to the nearest year) in Panel A, and the mean level of the instrumental variable *CapacityShock* along the same dimension in Panel B. *CapacityShock* is defined as the net number of private prison beds that opened over the course of an inmate's assigned sentence (divided by 1,000 here for illustration). $N = 26,593$.

Figure A.2: Distributions of Time Served in Private Prison

Panel A



Panel B

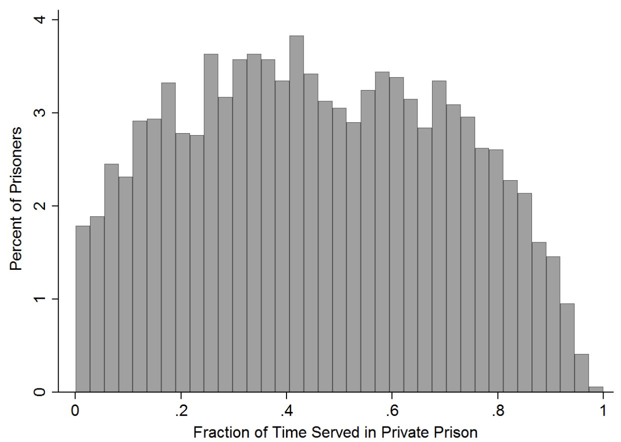
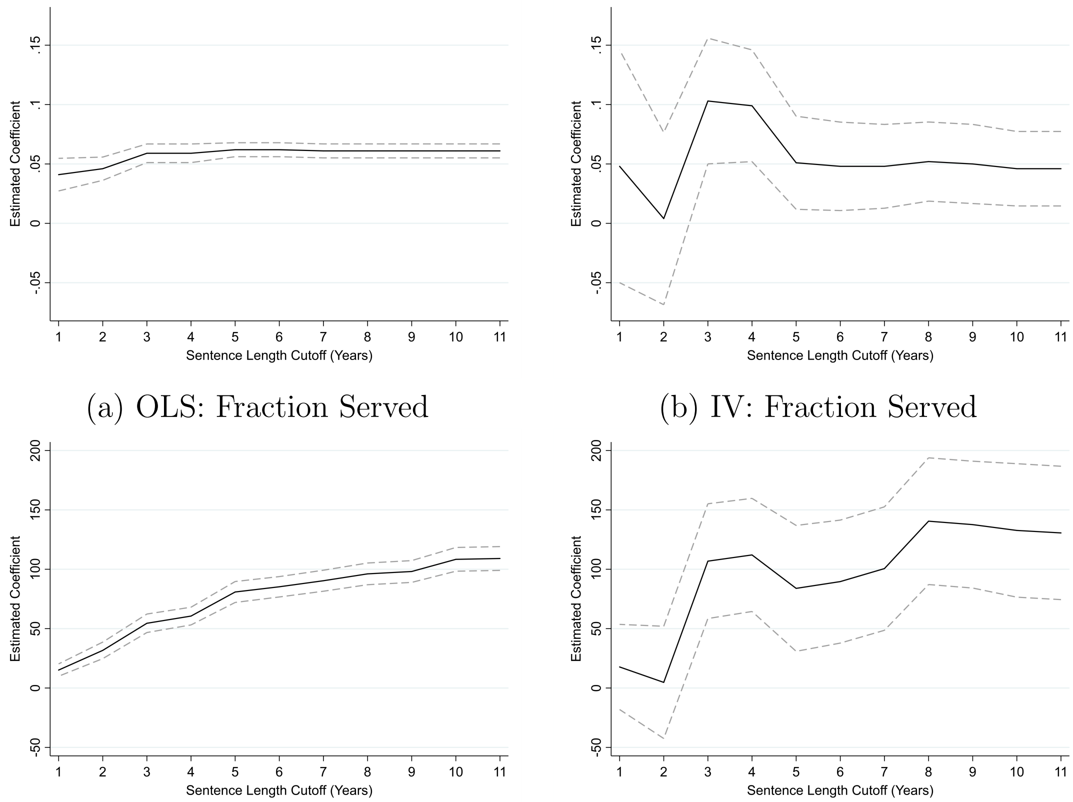


Figure shows histograms related to time served for private prison inmates. Panel A shows the histogram of the fraction of sentenced days served in private prison. Panel B shows the histogram of the fraction of time served in private prison.

Figure A.3: Impact of Private Prison on Time Served by Sampling Frame



(a) OLS: Fraction Served

(b) IV: Fraction Served

(c) OLS: Days Served

(d) IV: Days Served

Figure shows plots of the estimates from OLS and IV (using the *CapacityShock* instrument) regressions of private prison exposure on time served, measured as days served or fraction of sentence served, by varying sentence length cutoffs. The estimate for each cutoff reports a result from a different regression. The main estimates in the paper are from a sentence length cutoff of six years. The dashed lines represent 95 percent confidence intervals. For this analysis, I do not examine recidivism because I do not observe three years post-release for all inmates.

Table A.1: Impacts of Private Prison by Contract Type

Dependent variable:	Days Served		Fraction Served		Recidivism (36-month)	
	(1)	(2)	(3)	(4)	(5)	(6)
Private	77.156		0.057		0.017	
	(5.787)		(0.004)		(0.010)	
Private: 90 Percent Guarantee		91.516		0.061		0.019
		(8.827)		(0.006)		(0.015)
Private: Per-Diem		68.187		0.054		0.015
		(7.136)		(0.005)		(0.012)
Prior incarcerations	13.271	13.490	0.011	0.011	0.080	0.080
	(7.734)	(7.753)	(0.006)	(0.006)	(0.018)	(0.018)
Age $\div$ 100	271.470	266.159	0.234	0.233	-0.278	-0.279
	(24.594)	(24.590)	(0.018)	(0.018)	(0.042)	(0.043)
Black	19.658	19.654	0.013	0.013	0.021	0.021
	(4.536)	(4.531)	(0.004)	(0.004)	(0.009)	(0.009)
Single	28.983	29.005	0.029	0.029	0.036	0.036
	(4.410)	(4.404)	(0.004)	(0.004)	(0.009)	(0.009)
Education $<$ HS	-11.942	-11.619	-0.009	-0.009	0.007	0.008
	(3.651)	(3.653)	(0.003)	(0.003)	(0.008)	(0.008)
Dep. var. mean	688.53	688.53	0.68	0.68	0.25	0.25
R-squared	0.722	0.722	0.339	0.339	0.092	0.092
Observations	12,304	12,304	12,304	12,304	12,304	12,304
Offense Variables	Y	Y	Y	Y	Y	Y
Classification	Y	Y	Y	Y	Y	Y
Time Trends	Y	Y	Y	Y	Y	Y
County FEs	Y	Y	Y	Y	Y	Y

Table shows OLS estimates of the impact of private prison (*Private*) separated by contract type. See notes for Table 2 for a list of the detailed controls. *Private: 90 Percent Guarantee* indicates whether the inmate ever went to one of the two private prisons that entered 90 percent guarantee contracts. *Private: Per-Diem* indicates whether the inmate ever went to one of the two private prisons that maintained the per-diem contracts. The contract changes for the two prisons occurred in May 2001, hence the sample includes inmate-sentences from 5/1/2001 to 7/31/2004. Columns (1), (3), and (5) show the OLS estimate of *Private* on inmate outcomes for comparison to columns (2), (4), and (6), which break down *Private* into the contract types. Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.2: 2SLS Estimates of Private Prison Impact on Inmate Outcomes

	(1) Days Served	(2) Fraction Served	(3) Recidivism (36-month)	(4) Private (1st Stg.)
Private	-672.411	-0.530	-0.166	
	(91.648)	(0.067)	(0.097)	
Prior incarcerations	9.470	0.007	0.061	-0.005
	(12.382)	(0.009)	(0.016)	(0.014)
Age ÷ 100	-124.018	-0.081	-0.388	-0.433
	(47.324)	(0.036)	(0.053)	(0.027)
Black	13.890	0.012	0.022	-0.003
	(5.446)	(0.004)	(0.006)	(0.005)
Single	51.939	0.042	0.072	0.026
	(5.580)	(0.004)	(0.007)	(0.005)
Education < HS	0.247	0.003	-0.010	0.010
	(4.644)	(0.004)	(0.005)	(0.005)
CapacityShock (÷ 1000)				0.037
				(0.004)
Dep. var. mean	722.7	0.71	0.25	0.19
R-squared	0.312	-0.878	0.061	0.155
F-statistic	-	-	-	109
Observations	26,593	26,593	26,593	26,593
Offense Variables	Y	Y	Y	Y
Classification	Y	Y	Y	Y
Time Trends	Y	Y	Y	Y
County FEs	Y	Y	Y	Y

Table shows 2SLS regression estimates of the impact of private prison ($Private$) on inmate outcomes. See notes for Table 2 for a list of the detailed controls. Columns (1) through (3) display the estimates on the key outcomes of interest. Column (4) shows the results from a linear first stage regression of whether the inmate ever went to private prison on $CapacityShock$; as shown, the F-statistic associated with this first stage is 109. Standard errors in parentheses are robust and clustered by admission month-year and sentence length. Appendix D provides an explanation for why the 2SLS results differ from those presented in the main analysis.

Table A.3: Impacts of Private Prison, using Alternative Clustering

Dependent variable:	(1) Days Served	(2) Fraction Served	(3) Recidivism (36-month)	(4) Private (Probit Eqn.)	(5) Private (1st Stg.)
Private	89.627	0.048	0.017		
	(27.552)	(0.021)	(0.039)		
Prior incarcerations	11.921	0.009	0.062	-0.002	-0.002
	(6.360)	(0.005)	(0.016)	(0.012)	(0.013)
Age $\div$ 100	199.981	0.164	-0.310	-0.456	0.059
	(21.316)	(0.017)	(0.035)	(0.033)	(0.034)
Black	16.601	0.014	0.023	-0.007	0.002
	(3.245)	(0.003)	(0.006)	(0.005)	(0.005)
Single	29.612	0.025	0.067	0.023	-0.005
	(3.119)	(0.003)	(0.007)	(0.005)	(0.005)
Education < HS	-4.852	-0.001	-0.011	0.008	-0.001
	(2.931)	(0.003)	(0.005)	(0.005)	(0.005)
CapacityShock $\div$ 1,000				0.034	
				(0.003)	
Instrument (Predicted Probit)					1.155
					(0.034)
Dep. var. mean	722.7	0.71	0.25	0.19	0.19
R-squared	0.737	0.279	0.084	-	0.177
Observations	26,593	26,593	26,593	26,589	26,593
Offense Variables	Y	Y	Y	Y	Y
Classification	Y	Y	Y	Y	Y
Time Trends	Y	Y	Y	Y	Y
County FEs	Y	Y	Y	Y	Y

Table shows IV estimates of the impact of private prison (*Private*) on inmate outcomes, using the *CapacityShock* instrument. See notes for Table 2 for a list of the detailed controls. Column (4) shows the results of the "0^{th}" stage probit equation, with the *CapacityShock* instrument defined in Section VII-C. Column (5) shows the first stage estimates using the resulting instrument, i.e., the predicted probit probabilities from column (4). The dependent variable in columns (4) and (5) is thus *Private*, i.e., whether the inmate ever went to private prison. Mean marginal effects are reported for the probit model in column (4). Standard errors in parentheses are robust and clustered by admission month-year.

Table A.4: Impacts of Private Prison, using Alternative Time Trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Days Served		Fraction Served		Recidivism (36-month)		Private	Private
	OLS	IV	OLS	IV	OLS	IV	(Probit Eqn.)	(1st Stg.)
Private	91.865	269.527	0.066	0.173	0.015	0.061		
	(4.343)	(24.101)	(0.003)	(0.018)	(0.007)	(0.042)		
Prior incarcerations (5 year)	13.701	14.952	0.010	0.011	0.061	0.062	-0.004	-0.001
	(6.641)	(6.988)	(0.005)	(0.005)	(0.016)	(0.016)	(0.013)	(0.013)
Age ÷ 100	207.272	284.901	0.178	0.224	-0.310	-0.290	-0.462	0.067
	(17.907)	(19.791)	(0.014)	(0.016)	(0.031)	(0.036)	(0.028)	(0.028)
Black	16.095	16.594	0.014	0.015	0.023	0.023	-0.007	0.002
	(3.351)	(3.419)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)
Single	31.363	26.724	0.027	0.024	0.067	0.066	0.022	-0.004
	(3.004)	(3.003)	(0.002)	(0.002)	(0.006)	(0.006)	(0.005)	(0.004)
Education < HS	-7.284	-9.058	-0.003	-0.004	-0.011	-0.011	0.008	-0.002
	(2.805)	(2.856)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
CapacityShock ÷ 1,000							0.022	
							(0.008)	
Instrument (Predicted Probit)								1.166
								(0.037)
Dep. var. mean	722.7	722.7	0.71	0.71	0.25	0.25	0.19	0.19
R-squared	0.741	0.718	0.291	0.254	0.086	0.084	-	0.183
Observations	26,593	26,593	26,593	26,593	26,593	26,593	26,593	26,593
Offense Variables	Y	Y	Y	Y	Y	Y	Y	Y
Classification	Y	Y	Y	Y	Y	Y	Y	Y
Time Trends†	Y	Y	Y	Y	Y	Y	Y	Y
County FEs	Y	Y	Y	Y	Y	Y	Y	Y

Table shows IV estimates of the impact of private prison (*Private*) on inmate outcomes, using the *CapacityShock* instrument. See notes for Table 2 for a list of the detailed controls, noting that time trends are different. Column (7) shows the results of the "0^{th}" stage probit equation, with the *CapacityShock* instrument defined in Section VII-C. Column (8) shows the first stage estimates using the resulting instrument, i.e., the predicted probit probabilities from column (7). The dependent variable in columns (7) and (8) is *Private*, i.e., whether the inmate ever went to private prison. Mean marginal effects are reported for the probit model in column (7); the t-statistic on *CapacityShock* is 2.83. Standard errors in parentheses are robust and clustered by admission month-year.
† Time trends include year fixed effects, and interactions of these fixed effects with sentence length dummies.

Table A.5: First Stage Results by Inmate Characteristics

	Dependent variable: Private (i.e., did the inmate ever go to private prison?)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-Black	Black	Couple	Single	Edu. $\geq$ HS	Edu. $<$ HS	Age $<$ 30	Age $\geq$ 30
Instrument (Predicted Probit)	1.196	1.120	1.123	1.174	1.169	1.094	1.163	1.101
	(0.064)	(0.046)	(0.060)	(0.053)	(0.052)	(0.050)	(0.052)	(0.061)
Prior incarcerations	0.001	-0.003	-0.004	0.002	0.002	-0.004	-0.003	-0.003
	(0.025)	(0.015)	(0.023)	(0.017)	(0.019)	(0.019)	(0.024)	(0.016)
Age $\div$ 100	0.064	0.053	0.037	0.083	0.057	0.036	0.232	0.021
	(0.043)	(0.037)	(0.034)	(0.048)	(0.042)	(0.039)	(0.154)	(0.042)
Black	-	-	0.001	0.001	0.003	0.001	0.002	0.002
	-	-	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.007)
Single	-0.006	-0.004	-	-	-0.004	-0.003	-0.006	-0.002
	(0.009)	(0.006)	-	-	(0.007)	(0.006)	(0.007)	(0.006)
Education $<$ HS	-0.000	-0.001	0.001	-0.002	-	-	-0.000	0.000
	(0.008)	(0.006)	(0.006)	(0.007)	-	-	(0.007)	(0.006)
Dep. var. mean	0.18	0.20	0.15	0.23	0.18	0.20	0.24	0.14
R-squared	0.179	0.187	0.163	0.182	0.180	0.186	0.192	0.151
Observations	8,511	18,082	11,391	15,202	12,326	14,267	13,616	12,977
Offense Variables	Y	Y	Y	Y	Y	Y	Y	Y
Classification	Y	Y	Y	Y	Y	Y	Y	Y
Time Trends	Y	Y	Y	Y	Y	Y	Y	Y
County FEs	Y	Y	Y	Y	Y	Y	Y	Y

Table shows the first stage estimates using the probit-corrected *CapacityShock* instrument (detailed in Section IV-B). Each column presents results by a split of the inmate population: columns (1) and (2) show Non-Black and Black; columns (3) and (4) show couples and singles; columns (5) and (6) show education greater than or equal to and less than high school; columns (7) and (8) show age less than and greater than or equal to 30. Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.6: Correlation between the Instrument and Inmate Characteristics

	CapacityShock
CapacityShock	1.00
Years served	0.06
Fraction of Sentence Served	-0.11
Recidivism (36-month)	-0.01
Any Infraction?†	0.15
Black	0.02
Age ÷ 100	-0.01
Single	0.05
Education < HS	-0.07
Sentence Length (years)	0.12
Prior incarcerations (5 years)	-0.06
Number of Offenses	0.02
Primary Offense:	
Aggravated Assault	0.01
Burglary	0.02
Drug Possession	-0.00
Drug Selling	-0.00
Felony DUI	-0.10
Fraud	-0.00
Robbery	0.01
Theft	0.00
Other	0.05
Custody Designation:	
A	0.11
B	-0.08
C	0.02
D	-0.01
Unclassified	-0.05
Medical Class:	
A	-0.01
B	0.02
C	-0.01
D	-0.01
E	0.01
Level of Care:	
A	-0.02
B	-0.01
C	0.02
D	0.01
E	0.01

Table shows the Pearson's correlation of the *CapacityShock* instrument with key model variables. N = 26,593.

† Infractions data are available post-2000.

Table A.7: Impact of Private Prison on Recidivism (with Release Period Controls)

	Dep. Var.: Recidivism (36-month)		
	(1) OLS	(2) Probit	(3) IV
Private	0.013	0.014	0.011
	(0.007)	(0.010)	(0.042)
Prior incarcerations	0.062	0.052	0.062
	(0.016)	(0.029)	(0.016)
Age ÷ 100	-0.313	-0.337	-0.314
	(0.031)	(0.170)	(0.037)
Black	0.023	0.024	0.023
	(0.006)	(0.013)	(0.006)
Single	0.066	0.067	0.066
	(0.006)	(0.034)	(0.006)
Education < HS	-0.011	-0.009	-0.011
	(0.005)	(0.007)	(0.005)
Dep. var. mean	0.25	0.25	0.25
R-squared	0.085	-	0.085
Observations	26,593	26,593	26,593
Unemployment	Y	Y	Y
Crime Rates	Y	Y	Y
Offense Variables	Y	Y	Y
Classification	Y	Y	Y
Time Trends	Y	Y	Y
County FEs	Y	Y	Y

Table shows regression estimates of the impact of private prison (*Private*) on 36-month recidivism (binary), including release period controls. See notes for Table 2 for a list of the detailed controls and the first stage estimates related to column (3). Unemployment controls include the Mississippi's unemployment rate in the year of inmate release. Crime Rate controls include Mississippi's crime rates for the following crimes in the year of inmate release: violent crime, murder/manslaughter, rape, robbery, aggravated assault, property crime, burglary, larceny/theft, and motor vehicle theft. Mean marginal effects are reported for the probit model in column (2). Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.8: Impacts of Private Prison, using Intensity of Private Prison Exposure

Dependent variable:	(1) Days Served	(2) Fraction Served	(3) Recidivism (36-month)
Fraction Private	292.316	0.211	0.015
	(11.819)	(0.007)	(0.017)
Prior incarcerations	11.386	0.009	0.062
	(6.831)	(0.005)	(0.016)
Age ÷ 100	206.420	0.176	-0.315
	(17.901)	(0.014)	(0.031)
Black	16.257	0.014	0.023
	(3.342)	(0.003)	(0.006)
Single	29.022	0.025	0.067
	(2.982)	(0.002)	(0.006)
Education < HS	-4.847	-0.001	-0.011
	(2.731)	(0.002)	(0.005)
Dep. var. mean	722.7	0.71	0.25
R-squared	0.742	0.292	0.084
Observations	26,593	26,593	26,593
Offense Variables	Y	Y	Y
Classification	Y	Y	Y
Time Trends	Y	Y	Y
County FEs	Y	Y	Y

Table shows OLS estimates of the impact of the fraction of the inmate's assigned sentence length that was served in private prison (*Fraction Private*) on inmate outcomes. See notes for Table 2 for a list of the detailed controls. Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.9: Impacts of Private Prison, including Inmates with Fraction Served < 25 percent

Dependent variable:	(1) Days Served	(2) Fraction Served	(3) Recidivism (36-month)
Private	242.383	0.163	0.019
	(8.694)	(0.004)	(0.007)
Prior incarcerations	17.902	0.013	0.067
	(9.578)	(0.007)	(0.016)
Age $\div$ 100	533.464	0.399	-0.342
	(30.950)	(0.020)	(0.028)
Black	44.049	0.034	0.015
	(4.438)	(0.003)	(0.005)
Single	33.501	0.029	0.071
	(3.967)	(0.003)	(0.005)
Education < HS	4.418	0.008	-0.008
	(3.694)	(0.003)	(0.005)
Dep. var. mean	622.39	0.60	0.24
R-squared	0.481	0.325	0.077
Observations	32,275	32,275	32,275
Offense Variables	Y	Y	Y
Classification	Y	Y	Y
Time Trends	Y	Y	Y
County FEs	Y	Y	Y

Table shows OLS estimates of the impact of private prison (*Private*) on inmate outcomes. Sample includes inmate-sentences with fraction served less than 25 percent. See notes for Table 2 for a list of the detailed controls. Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.10: Impacts of Private Prison, using an Alternative IV (Leave-one-out)

Dependent variable:	(1) Days Served	(2) Fraction Served	(3) Recidivism (36-month)	(4) Private (Probit Eqn.)	(5) Private (1st Stg.)
Private	90.838	0.044	0.038		
	(26.678)	(0.019)	(0.038)		
Prior incarcerations	11.925	0.009	0.062	-0.002	-0.001
	(6.732)	(0.005)	(0.016)	(0.013)	(0.013)
Age ÷ 100	200.497	0.163	-0.301	-0.456	0.050
	(19.149)	(0.015)	(0.036)	(0.028)	(0.029)
Black	16.605	0.014	0.023	-0.007	0.002
	(3.359)	(0.003)	(0.006)	(0.006)	(0.005)
Single	29.577	0.026	0.066	0.024	-0.004
	(3.113)	(0.002)	(0.006)	(0.005)	(0.005)
Education < HS	-4.860	-0.001	-0.011	0.006	-0.001
	(2.780)	(0.002)	(0.005)	(0.005)	(0.005)
Leave-one-out Instrument				0.714	
				(0.051)	
Instrument (Predicted Probit)					1.131
					(0.037)
Dep. var. mean	722.7	0.71	0.25	0.19	0.19
R-squared	0.737	0.279	0.083	-	0.178
F-statistic	-	-	-	-	935
Observations	26,593	26,593	26,593	26,593	26,593
Offense Variables	Y	Y	Y	Y	Y
Classification	Y	Y	Y	Y	Y
Time Trends	Y	Y	Y	Y	Y
County FEs	Y	Y	Y	Y	Y

Table shows IV estimates of the impact of private prison ($Private$) on inmate outcomes, using an alternate instrument. See notes for Table 2 for a list of the detailed controls. Column (4) shows the results of the "0^{th}" stage probit equation, with the leave-one-out instrument defined in Section VII-C. Column (5) shows the first stage estimates using the resulting instrument, i.e., the predicted probit probabilities from column (4). Mean marginal effects are reported for the probit model in column (4). Standard errors in parentheses are robust and clustered by admission month-year and sentence length.

Table A.11: Summary Statistics for Restricted Sample Matching Analysis

Sample:	All (1)	Public (2)	Private (3)	t-test (4)
Outcomes				
Years served	2.73	2.64	2.82	**
Fraction of Sentence Served	0.74	0.71	0.76	***
Recidivism (36-month)	0.26	0.26	0.25	-
Any Infraction?†	0.05	0.03	0.06	***
Demographics				
Black	0.78	0.79	0.76	-
Age $\div$ 100	0.29	0.29	0.28	-
Single	0.60	0.59	0.61	-
Education $<$ HS	0.58	0.58	0.58	-
Offenses (proportions)				
Aggravated Assault	0.07	0.07	0.07	-
Burglary	0.20	0.20	0.20	-
Drug Possession	0.13	0.13	0.13	-
Drug Selling	0.17	0.17	0.17	-
Felony DUI	0.01	0.01	0.01	-
Fraud	0.03	0.03	0.03	-
Robbery	0.09	0.09	0.09	-
Theft	0.09	0.09	0.09	-
Other	0.20	0.20	0.20	-
Offenses				
Sentence Length	3.92	3.92	3.93	-
Number of Offenses	1.18	1.18	1.18	-
Prior incarcerations (5 years)	0.14	0.12	0.15	-
Custody Designation (proportions)				
A	0.12	0.12	0.12	-
B	0.85	0.85	0.85	-
C	0.01	0.01	0.01	-
D	0.00	0.00	0.00	-
Unclassified††	0.01	0.01	0.01	-
Medical Class (proportions)				
A	0.90	0.90	0.90	-
B	0.03	0.03	0.03	-
C	0.06	0.06	0.06	-
D	0.00	0.00	0.00	-
E	0.01	0.01	0.01	-

(cont'd)

Summary Statistics for Restricted Sample Matching Analysis (continued)

Level of Care (proportions)				
A	0.01	0.01	0.01	-
B	0.79	0.79	0.79	-
C	0.12	0.12	0.12	-
D	0.07	0.07	0.07	-
E	0.01	0.01	0.01	-
Observations	2,018	1,009	1,009	

Table is analogous to Table 2 and shows how inmate outcomes and characteristics differ for the 1,009 matched inmate pairs. The sample is restricted to inmates with an admission date within 90 days of the private prison opening or expansion (the closing is not used in this analysis). Stars denote statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

† Infractions data are available post-2000.

Table A.12: Impacts of Private Prison, using Restricted Sample Matching

Dependent variable:	(1) Days served	(2) Fraction Served	(3) Recidivism (36-month)
Private	71.191	0.052	0.026
	(11.454)	(0.009)	(0.022)
Dep var. mean	779.62	0.73	0.26
Pool of Matches	4,393	4,393	4,393

Table shows matching estimates of the impact of private prison (*Private*) on inmate outcomes. The sample is restricted to inmates who are eligible for transfer to private prison during the expansion periods, as explained in Section VII-C. Estimates are obtained via nearest neighbor matching with exact matches on sentence length (rounded to the nearest year), primary offense type, number of offenses, and classification variables. The other variables included in the matching estimation are the second and third offense types, if any, number of prior felonies and their offense type(s) in the past five years, age, race (whether black), marital status (whether single), and education (whether less than high school). Standard errors in parentheses are independent and identically distributed as in **?**.

B 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. Here, I show that the main results are still applicable if states re-optimize their release decisions under private prison contracting.

Abstracting away from the extensive margin question of how many individuals to incarcerate at a given time, the intuition of the 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 thus offer a marginal cost saving technology. Because state and private prison beds are substitutable, the state can use these cost savings to re-optimize its overall release policy.

Recall that the state chooses s_i according to equation (1). Consider that the state can contract with private operators to incarcerate each prisoner at a per-diem payment of $P < C^{gov}$. With a lower marginal cost of daily incarceration, equation (1) implies that the optimal s_i, or time served in prison, increases; the state will incorporate this cost saving into its overall cost minimization problem and re-optimize s_i. Let B^{gov} and B^{priv} 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 a proportional γ such that $P = \gamma C^{gov}$. Then the state's adjusted marginal cost is given by: $C_{\text{adjusted}} = \frac{C^{gov} \cdot B^{gov} + P \cdot B^{priv}}{B^{gov} + B^{priv}}$.

As long as the private operator provides cost savings $\gamma < 1$, the inequality $P < C_{\text{adjusted}} < C^{gov}$ will be satisfied and the state can reduce its daily incarceration cost with private contracting.[1] Returning to equation (1), the state will now seek to release inmates when $r_i(s_i^*) = C_{\text{adjusted}}$; the key implication is that there should be no difference in s_i^* owing to whether the prisoner was in public or private prison. The source of the friction that remains is that the private contractor treats P, i.e., γC^{gov} as its marginal revenue, not its marginal cost. The model then yields the same implications as in Section II.[2]

C Parole Guidelines in Mississippi

As described in Section B, parole is the process by which inmates may be released prior to the completion of their assigned sentence. Below are the official parole guidelines from

[1]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., $B^{gov} =$ 10,000; $B^{priv} = 1{,}000$; $C^{gov} = \$50$ and $\gamma = 0.9$. Then, the private operator charges $0.90 \times 50 = \$45$ 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 $C_{\text{adjusted}} = \frac{50 \times 10{,}000 + 50 \times (0.90) \times 1{,}000}{10{,}000 + 1{,}000} = \$49.55 < \$50$.

[2]Note that these implications are true even if private prisons are more expensive, i.e., if $\gamma > 1$. In this case, however, states would not seek private contracting unless facing a challenge such as capacity constraints in the public prisons.

the Mississippi Department of Corrections:

"Depending on various factors including an inmate's criminal history, crime, crime commit date, and sentence, some inmates may be eligible for parole consideration after serving a portion of their sentence. Although an inmate may be eligible for parole, it is not guaranteed that an inmate will be granted parole. Whether or not an inmate is released early to parole is within the complete discretion of the Mississippi State Parole Board. A list of all inmates eligible for parole is generated each month and sent to the Parole Board. When considering whether to grant or deny parole the Board considers a multitude of factors including, but not limited to, the following:

- Severity of offense;
- Number of offenses committed;
- Psychological and/or psychiatric history;
- Disciplinary action while incarcerated;
- Community Support or Opposition;
- Amount of Time Served;
- Prior misdemeanor or felony conviction(s);
- Policy and/or juvenile record;
- History of drug or alcohol abuse;
- History of violence;
- Crimes committed while incarcerated;
- Escape history;
- Participation in rehabilitative programs;
- Arrangements for employment and/or residence;
- Whether the offender served in the US Armed Forces and received an honorable discharge.

Victims and family members of victims are allowed to make impact statements to the Parole Board." (Source: https://www.mdoc.ms.gov/Community-Corrections/Pages/Parole.aspx, accessed May 1, 2019.)

Inmates convicted of murder, manslaughter, sex crimes, and kidnapping became ineligible for parole in Mississippi as of June 30, 1995. There are also some statutory minimum years served beyond 25 percent of the sentence for inmates with longer sentences. In practice, however, these inmates may still be released early under "earned supervised release," a special type of parole. These affected inmates are excluded from the sample due to restrictions on sentence length.

D Simulation Study for the 2SLS with Probit Correction Method

I adopt the two-stage least squares (2SLS) with probit correction method outlined in **?** and discussed in **?** to produce the instrumental variable (IV) estimates in the main text. This correction involves estimating a probit regression with the endogenous variable (i.e., whether the inmate went to private prison) on the left hand side as a "0^{th}" stage regression with all controls. The predicted values of the endogenous variable from this regression are then used as instruments in a traditional 2SLS framework with linear first and second stages. Here, I show through Monte Carlo simulation that this probit correction method produces estimates that are more efficient.

Note that the 2SLS with probit correction method has been used in a number of prior studies that dealt with non-continuous endogenous variables (**?**; **?**; **?**; **?**; **?**). **?** notes that this method produces more efficient estimates when the probability of treatment is better approximated with a nonlinear versus a linear probability model. Thus, I begin by showing that in the empirical setting of the paper, the probit and linear probability models do indeed produce different predictions of the endogenous variable, which is whether the inmate ever went to private prison. Figure B.1 shows these predicted probabilities; not too surprisingly, the linear probability model generates many negative predictions, while the probit model has a noticeable density at zero. Recall from Table 1 that 5,144 inmates go to private prison, so the probability of treatment is 0.19.

The simulation study mirrors the empirical setup in the paper. To begin, consider the following terms, which will be used to construct variables analogous to the paper setting:

$$\begin{aligned}
\epsilon_i &= N(0,1), \\
\xi_i &= N(0,1) + \alpha\epsilon_i, \\
x_i &\sim N(\mu_x, \sigma_x), \\
z_i &\sim N(\mu_z, \sigma_z).
\end{aligned} \tag{1}$$

The key variables in the simulation exercise are defined using these variables. The analog of the binary endogenous treatment variable $Private_i$ from the main analysis is represented by d_i in the simulation:

$$d_i = \begin{cases} 1, & \beta_0 + \beta_1 z_i + \beta_2 x_i + \epsilon_i > 0, \\ 0, & \beta_0 + \beta_1 z_i + \beta_2 x_i + \epsilon_i \leq 0. \end{cases} \tag{2}$$

The variable d_i is the key treatment variable, and equals one if the covariates predict a positive probability of treatment, i.e., private prison assignment.

Figure B.1: Predicted Treatment by Probit versus Linear Probability Models

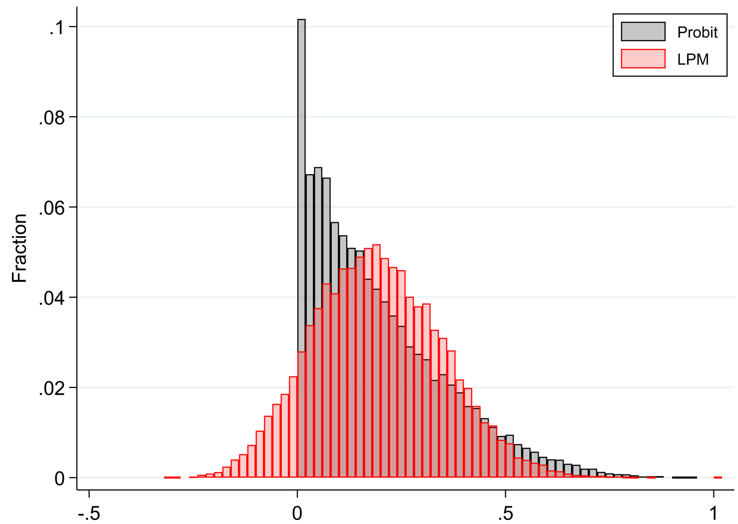


Figure shows the probit versus linear probability model (LPM) predictions of *Private* using the *CapacityShock* instrument and the full set of covariates, as in column (5) of Table 2 and column (4) of Table A2.

I then define y_i, which represents the dependent variables studied. In particular, y_i is a function of the binary and potentially endogenous treatment d_i and covariates x_i. (Note that the endogeneity is determined via the relationship between ξ_i and ϵ_i through α.)

$$y_i = \gamma_0 + \gamma_1 d_i + \gamma_2 x_i + \xi_i. \tag{3}$$

I use the values of $\mu_x = \mu_z = 0,\ \sigma_x = \sigma_z = 1,\ \beta_2 = 10,\ \gamma_0 = 0,\ \gamma_1 = 0.05$, and $\gamma_2 = 1$ for the simulation. Simply for context, the values of γ_1 are selected to be close to the main effect related to the impact of private prison on the fraction of sentence served in the paper, about 0.05 in column (4) of Table 2. I vary the values of α and β_0 to compare the estimation bias in the two approaches. The value of α represents the severity of the endogeneity and takes the value of 0, 0.5, and 1. The value of β_0 represents the fraction of treated individuals, which maps to the fraction of inmates sent to private prison in the paper. For this simulation, I use three β_0 values that lead to the fractions of treated individuals being 0.05, 0.2, and 0.5, respectively. The values of β_1 are set such that the F-statistic of the linear first stage instrument is about 100, mirroring that in the studied setting (column (4) of Table A2).

The goal of the estimation model in this simulation exercise is to recover γ_1, whose true value is 0.05. I present the results of this exercise in Table B.1. Each cell in the table represents 10,000 simulation runs, and each run simulates a dataset with 10,000 rows according to the structure described in equations (1) to (3). There are a total of nine cells in the table, each representing a combination of the three endogeneity levels, $\alpha = 0, 0.5, 1$, and three levels for the fraction of individuals that are treated, $\bar{d} = 0.05, 0.2, 0.5$.

Table B.1: Simulation Results by Method (for varying treatment and endogeneity levels)

	OLS			2SLS			2SLS with Probit Correction		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\bar{d} = 0.05$	$\bar{d} = 0.2$	$\bar{d} = 0.5$	$\bar{d} = 0.05$	$\bar{d} = 0.2$	$\bar{d} = 0.5$	$\bar{d} = 0.05$	$\bar{d} = 0.2$	$\bar{d} = 0.5$
$\alpha = 0$	0.050 (0.052)	0.050 (0.035)	0.050 (0.033)	0.056 (0.518)	0.054 (0.341)	0.054 (0.325)	0.050 (0.056)	0.050 (0.038)	0.050 (0.038)
$\alpha = 0.5$	0.185 (0.058)	0.216 (0.039)	0.262 (0.037)	0.057 (0.577)	0.053 (0.381)	0.053 (0.363)	0.051 (0.062)	0.051 (0.043)	0.050 (0.042)
$\alpha = 1$	0.319 (0.073)	0.383 (0.049)	0.474 (0.046)	0.057 (0.731)	0.053 (0.483)	0.052 (0.460)	0.052 (0.079)	0.051 (0.055)	0.050 (0.053)

Table shows the mean and standard deviation of regression estimates of the impact of d on y, as shown in equation (3). Each cell in the table represents 10,000 simulation runs, and each run simulates a dataset with 10,000 rows according to the structure described in equations (1) to (3). Parentheses contain the standard deviation of the 10,000 estimates in each cell. Columns (1) to (3) show the results of OLS estimates, columns (4) to (6) show the results of traditional (linear) 2SLS estimates, and columns (7) to (9) show the results of 2SLS with probit correction estimates. The different scenarios represent varying levels of treatment ($\bar{d}$) and endogeneity (α).

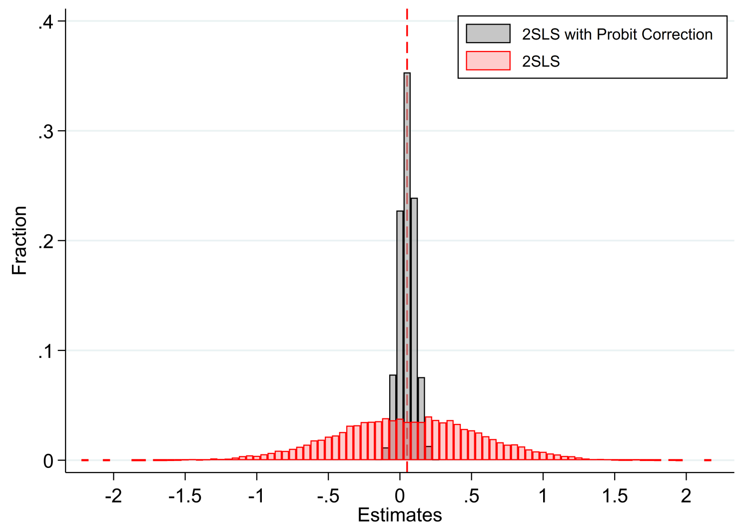
I highlight a few observations based on the simulation results in Table B.1. For $\alpha = 0$, there is no endogeneity in the model, so the OLS estimates in columns (1) to (3) are not biased. Also, as expected, both the 2SLS and 2SLS with probit correction methods yield unbiased estimates. The standard errors of the 2SLS estimates are, however, an order of magnitude larger. For example, when $\bar{d} = 0.05$, the standard error of the traditional 2SLS estimates is 9.3 times larger than that of the 2SLS with probit correction method.

Figure B.2 demonstrates the extent of efficiency gain by the probit correction procedure. Panel A of the figure is plotted for the case without any endogeneity, i.e., $\alpha = 0$. I observe that the estimated coefficients with the probit correction method are much more tightly centered on the true estimate, explaining why this method appears to be more reliable than the relatively noisy estimates produced by the traditional 2SLS method.

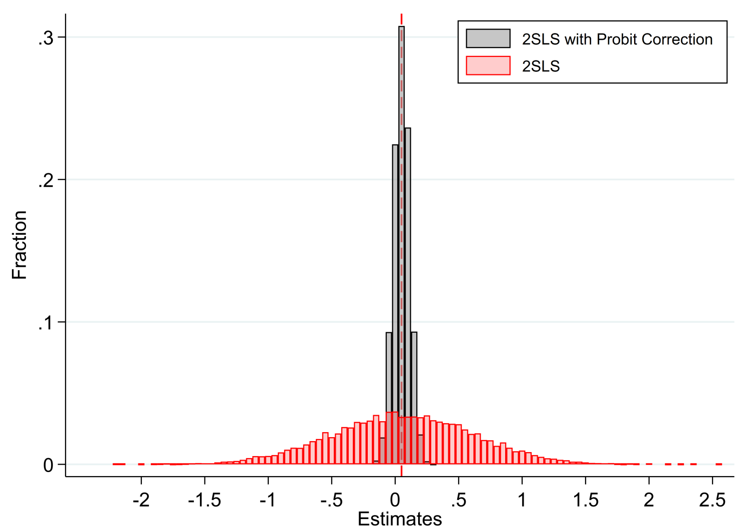
For non-zero levels of endogeneity (i.e., $\alpha = 0.5$ or 1), OLS is biased and both IV methods are useful at correctly for the bias produced by the endogeneity. Again, the estimates produced by the 2SLS with probit correction method are more precise. Therefore, while both IV methods are able to correct for the endogeneity, the 2SLS with probit correction is about an order of magnitude more efficient. For example, when $\bar{d} = 0.05$ and $\alpha = 0.5$, the standard error of 2SLS estimate is 9.3 times larger than the 2SLS estimate with probit correction. Another observation is that while the standard errors of estimates increase as the level of endogeneity increases, the efficiency advantage of 2SLS with probit correction is not sensitive to the level of endogeneity. For example, when $\bar{d} = 0.2$, the ratios of the standard errors for the two methods are 9.0 and 8.9 for $\alpha = 0.5$ and $\alpha = 1$, respectively.

I also observe that the efficiency advantage of the 2SLS with probit correction increases as the fraction of treated individuals decreases. For example, for $\alpha = 0$, the ratios of the standard errors are 9.3 and 8.6 for $\bar{d} = 0.05$ and $\bar{d} = 0.5$, respectively. Panel B of Figure B.2 demonstrates the extent of efficiency gain by the probit correction procedure when $\alpha = 0.5$. The purpose of this figure is simply to demonstrate that the efficiency gain is not limited to the case with no endogeneity. Finally, I have repeated this analysis with uniformly distributed errors (instead of normally distributed errors) in equation (1), and the efficiency gains from the 2SLS with probit correction method remain.

Figure B.2: Distributions of Simulation Estimates by Method (for varying endogeneity levels)



Panel A (without endogeneity, $\alpha = 0$)



Panel B (with endogeneity, $\alpha = 0.5$)

Figure shows histograms of the estimates obtained from the 10,000 simulations in estimating equation (3) when $\bar{d} = 0.05$. Panel A represents the case without endogeneity ($\alpha = 0$), and Panel B represents the case with endogeneity ($\alpha = 0.5$). The different bars show the estimates from the 2SLS and 2SLS with probit correction methods. The true coefficient on d is 0.05 and indicated by the vertical dashed line in each plot.