For Online Publication

Mental Health Consequences of Correctional Sentencing

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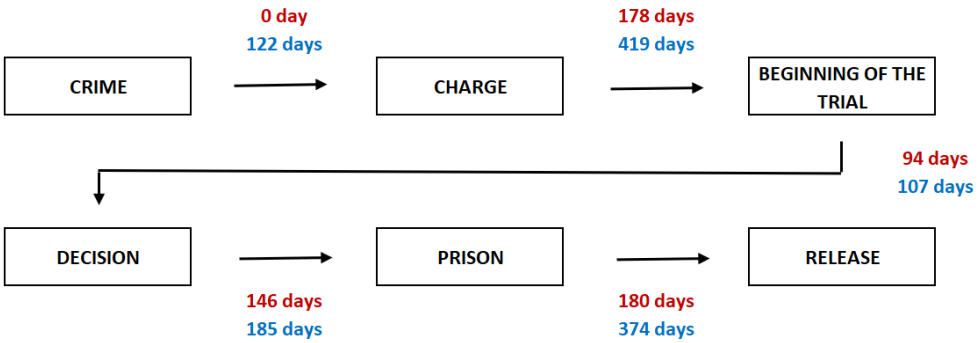
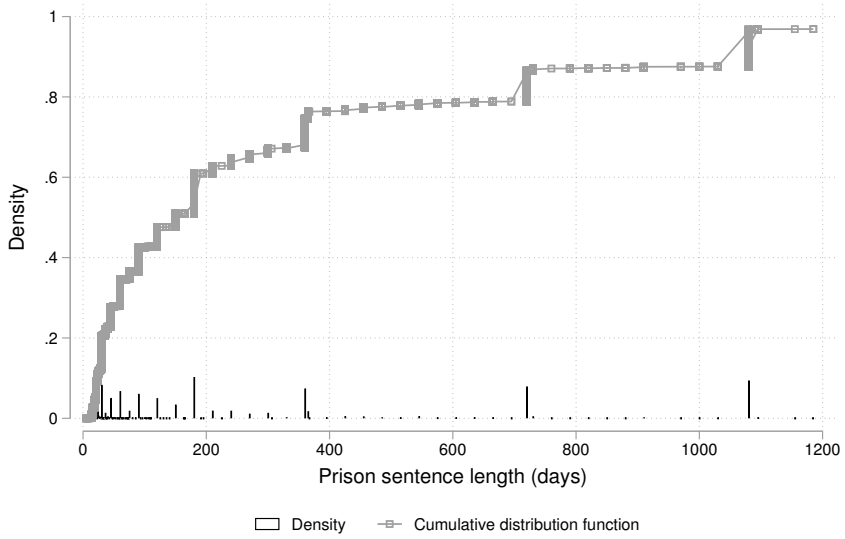
ONLINE APPENDIX A. ADDITIONAL FIGURES AND TABLES

Figure A1. : Timeline from Crime to Prison Release.



Notes: This figure plots the median (top figure in red) and average (bottom figure in blue) time between each step of the timeline for the sample of nonconfession criminal cases sentenced to prison and processed in 2011–2014.

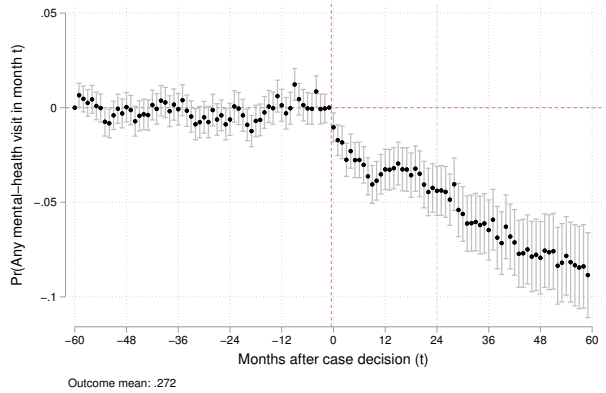
Figure A2. : Cumulative Distribution and Density of Prison Spell Length.



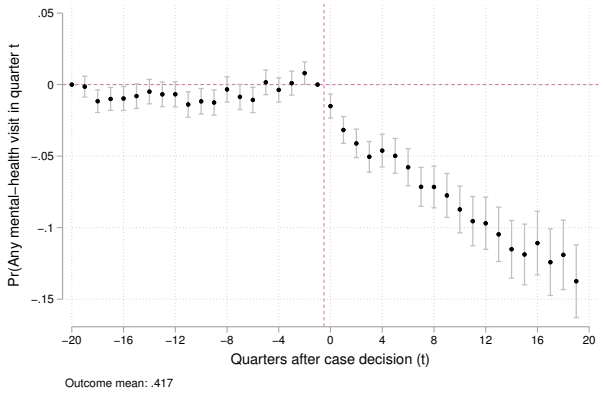
Notes: The sample of nonconfession criminal cases sentenced to prison and processed in 2005–2014. The graph plots the density and cumulative distribution function of prison sentence length.

Figure A3. : Robustness: Alternative Frequencies for Measurement of Mental Health Visits.

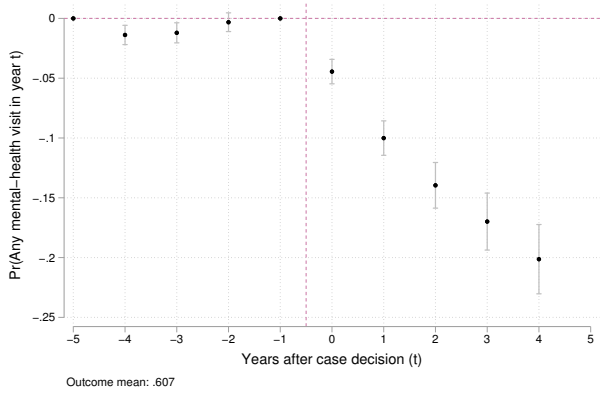
(a) Monthly Frequency



(b) Quarterly Frequency



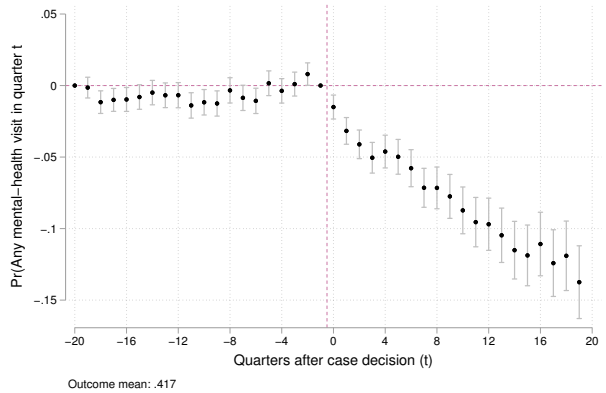
(c) Yearly Frequency



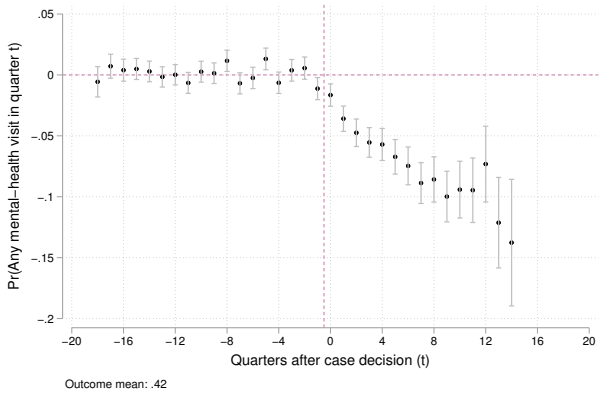
Notes: The Figures (a) and (b) are built on a sample of nonconfession criminal cases sentenced to prison and processed in 2011–2014. Figure (c) is built on a sample of nonconfession criminal cases sentenced to prison and processed in 2011–2014 to observe five years before and after decision. The estimation includes controls for case and month × year FEs for Figure (a), case and quarter × year FEs for Figure (b), and case and year FEs for Figure (c). Standard errors clustered at the case level. 95% confidence intervals. The graph plots the coefficients from the distance dummies.

Figure A4. : Robustness: Alternative Event-Study Estimators.

(a) Baseline (Quarterly Frequency)

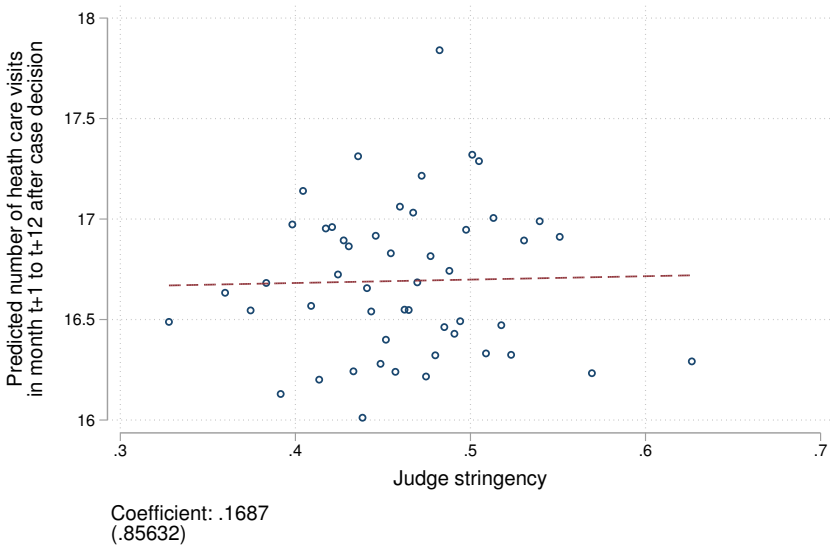


(b) Callaway and Sant'Anna Estimator



Notes: The sample of nonconfession criminal cases sentenced to prison and processed in 2011–2014. Panel (a) shows our baseline event study at a quarterly frequency (as in Figure A3, Panel (b)). Panel (b) uses the *csdid* package based on Callaway and Sant'Anna (2021). The estimation includes controls for case and quarter × year FEs. Standard errors clustered at the case level. 95% confidence intervals. The graphs plot the coefficients from the distance dummies.

Figure A5. : Correlation between Predicted Health-Care Visits and Judge Stringency.



Notes: Sample of all nonconfession criminal cases decided in 2006–2014. The number of health-care visits has been predicted using the same set of sociodemographic and past and current crime variables as those in Table A12.

Table A1—: Top 15 Most Common Addiction Diagnoses.

	Number	Frequency	Cumulative Frequency
1. Drug abuse	46212	45.37	45.37
2. Mental and behavioural disorders due to use of opioids : dependence syndrome	13428	13.18	58.55
3. Medication abuse	5992	5.88	64.43
4. Chronic alcohol abuse	5846	5.74	70.17
5. Mental and behavioral disorders due to multiple drug use and use of other psychoactive substances : dependence syndrome	4786	4.7	74.87
6. Mental and behavioral disorders due to use of alcohol : dependence syndrome	3157	3.1	77.97
7. Mental and behavioural disorders due to use of cannabinoids : dependence syndrome	3019	2.96	80.93
8. Mental and behavioral disorders due to multiple drug use and use of other psychoactive substances : harmful use	2790	2.74	83.67
9. Mental and behavioral disorders due to use of alcohol : harmful use	2007	1.97	85.64
10. Mental and behavioral disorders due to use of other stimulants, including caffeine : dependence syndrome	1716	1.68	87.32
11. Acute alcohol abuse	1071	1.05	88.37
12. Mental and behavioral disorders due to use of cannabinoids : harmful use	874	0.86	89.23
13. Mental and behavioral disorders due to use of other stimulants, including caffeine : harmful use	628	0.62	89.85
14. Mental and behavioral disorders due to multiple drug use and use of other psychoactive substances : unspecified mental and behavioral disorder	589	0.58	90.43
15. Mental and behavioral disorders due to use of alcohol : dependence syndrome	567	0.56	90.98
Number of Observations		101,867	

Notes: This table reports the most common diagnoses defined as addiction related for 2010 in the sample of nonconfession criminal cases processed in 2005–2014 with at least one addiction diagnosis in 2010.

Table A2—: Top 15 Most Common Depression or Mood Disorder-Related Diagnoses.

	Number	Frequency	Cumulative Frequency
1. Depressive disorder	15429	14.57	14.57
2. Anxiety disorder/anxiety state	10667	10.08	24.65
3. Hyperkinetic disorder	8496	8.02	32.67
4. Acute stress reaction	5577	5.27	37.94
5. Sleep disturbance	5568	5.26	43.2
6. Feeling anxious/nervous/tense	4056	3.83	47.03
7. Psychological disorders, other	4038	3.81	50.85
8. Psychological symptom/complt other	3849	3.64	54.48
9. Disturbance of activity and attention	3472	3.28	57.76
10. Affective psychosis	2823	2.67	60.43
11. Schizophrenia	2237	2.11	62.54
12. Feeling depressed	2121	2	64.54
13. Personality disorder	2022	1.91	66.45
14. Mental disorder, not otherwise specified	1921	1.81	68.27
15. Phobia/compulsive disorder	1869	1.77	70.03
Number of Observations		105,872	

Notes: This table reports the most common diagnoses defined as depression or mood disorder-related for 2010 in the sample of nonconfession criminal cases processed in 2005–2014 with at least one depression or mood disorder diagnosis in 2010.

Table A3—: Top 15 Most Common Physical Health Diagnoses.

	Number	Frequency	Cumulative Frequency
1. General disease NOS	24908	9.96	9.96
2. Back symptom/complaint	6944	2.78	12.73
3. Limited function/disability NOS	6606	2.64	15.37
4. Low back symptom/complaint	5202	2.08	17.45
5. Back syndrome without radiating pain	5012	2.00	19.45
6. Back syndrome with radiating pain	4737	1.89	21.35
7. Neck symptom/complain	3953	1.58	22.93
8. Shoulder symptom/complaint	3307	1.32	24.25
9. General symptom/complaint other	3153	1.26	25.51
10. Upper respiratory infection acute	3142	1.26	26.77
11. Shoulder syndrome	3035	1.21	27.98
12. Knee symptom/complaint	2937	1.17	29.15
13. Abdominal pain/cramps general	2603	1.04	30.19
14. Asthma	2349	0.94	31.13
15. Muscle pain	2323	0.93	32.06
Number of Observations		292,659	

Notes: This table reports the most common diagnoses defined as physical health-related for 2010 in the sample of nonconfession criminal cases processed in 2005–2014 with at least one physical health diagnosis in 2010.

Table A4—: Comparisons of the General Population and the Sample of Defendants.

	(1)	(2) Raw Numbers	(3)	(4) Standardized Differences	(5)
	Matched General Population Controls	Incarcerated Defendants	Non-incarcerated Defendants	(2)–(3)	(2)–(1)
Pr(Any health care visit)	0.758	0.869	0.875	-0.010	0.284***
				0.008	0.009
Pr(Any physical-health visit)	0.709	0.790	0.803	0.003	0.205***
				0.009	0.009
Pr(Any mental-health visit)	0.139	0.478	0.455	-0.111***	0.993***
				0.015	0.012
No. of Health-Care Visits	7.155	14.440	14.716	-0.032	0.654***
				0.018	0.013
No. of Physical-Health Visits	5.201	6.599	7.003	0.015	0.180***
				0.013	0.011
No. of Mental-Health Visits	1.045	5.674	5.540	-0.082**	0.924***
				0.025	0.017
Number of Observations	24,797	17,597	19,651	37,096	42,302

This table reports summary statistics in 2010 for the matched general population and the sample of nonconfession criminal cases processed in 2005-2014. Controls from the general population are matched 1-to-1 (without replacement) to incarcerated defendants. The sample of controls are individuals from the general population who were never involved in any criminal activity as measured by police arrests. The matching is based on the following variables: time-invariant variables (female, foreignborn, month of birth) and time-varying variables matched on years 1, 2, 3, 4, and 5 before case decision (years of education, marital status, number of children, employment status, number of hours worked, if parents had a charge or prison spell).

Table A5—: Summary Statistics on the Sample of Defendants.

	Mean	SD	p10	p50	p90
Age at the time of case decision	32.524	11.663	19	30	49
Female	0.119	0.324			
Foreign-born	0.148	0.355			
Married in year t-1	0.102	0.302			
Number of children in year t-1	0.840	1.279			3
High school by year t-1	0.184	0.388			
Some college education in year t-1	0.054	0.226			
Type of crime: Violent crime	0.284	0.451			
Type of crime: Property crime	0.117	0.322			
Type of crime: Economic crime	0.097	0.295			
Type of crime: Drug-related crime	0.150	0.357			
Type of crime: Drunk driving	0.077	0.267			
Type of crime: Traffic violation (speeding, no license)	0.054	0.225			
Missing data on demographics	0.031	0.174			
Court decision: incarceration	0.555	0.497			
Days between crime and case decision	710.898	1047.584	133	357	1643
Days between case decision and prison entry	244.915	280.269	0	165	596
Days of prison sentence if incarcerated	374.184	462.749	28	180	1080
Employed in year t-1	0.326	0.469			
Ever employed in years t-2 to t-5	0.460	0.498			
Ever Charged in year t-1	0.474	0.499			
Ever Charged in years t-2 to t-5	0.653	0.476			
Ever incarcerated in year t-1	0.134	0.340			
Ever incarcerated in years t-2 to t-5	0.294	0.455			
Ever health-care visit in months t-1 to t-12	0.905	0.293	1	1	1
No. of health-care visits in months t-1 to t-12	16.807	22.692	1	9	42
Ever physical health visit in months t-1 to t-12	0.825	0.380	0	1	1
No. of physical health visits in months t-1 to t-12	6.888	12.535	0	3	16
Ever mental health visit in months t-1 to t-12	0.554	0.497	0	1	1
No. of mental health visits in months t-1 to t-12	7.263	14.380	0	1	22
Observations		21,928			

The sample of nonconfession criminal cases processed in 2011–2014 with nonmissing demographics, type of crime, past work, crime, and health history variables.

Table A6—: Summary Statistics for the Sample of Incarcerated Defendants.

	mean	sd	p10	p50	p90
Age at the time of case decision	33.013	11.129	2	31	48.899
Female	0.080	0.272			
Foreign-born	0.149	0.356			1
Married	0.094	0.291			
Number of children in year t-1	0.840	1.270			3
High school by year t-1	0.178	0.383			1
Some college education in year t-1	0.047	0.211			
Type of crime: Violent crime	0.319	0.466			1
Type of crime: Property crime	0.117	0.321			1
Type of crime: Economic crime	0.077	0.267			
Type of crime: Drug-related crime	0.136	0.343			1
Type of crime: Drunk driving	0.083	0.275			
Type of crime: Traffic violation (speeding, no license)	0.047	0.212			
Missing data on demographics	0.036	0.186			
Days of prison sentence if given prison	374.184	462.749	28	180	1080
Days between crime and case decision	723.692	1132.849	123	328	1814
Days between case decision and prison entry	185.408	203.273	0	146	410
Employed in year t-1	0.313	0.464			
Ever employed in years t-2 to t-5	0.462	0.499			
Ever Charged in year t-1	0.525	0.499			
Ever Charged in years t-2 to t-5	0.705	0.456			
Ever incarcerated in year t-1	0.184	0.387			
Ever incarcerated in years t-2 to t-5	0.378	0.485			
Ever health-care visit in months t-1 to t-12	0.908	0.289	1	1	1
No. of health-care visits in months t-1 to t-12	17.004	22.944	1	9	43
Ever physical health visit in months t-1 to t-12	0.825	0.380	0	1	1
No. of physical health visits in months t-1 to t-12	6.833	12.798	0	3	16
Ever mental health visit in months t-1 to t-12	0.571	0.495	0	1	1
No. of mental health visits in months t-1 to t-12	7.440	14.326	0	1	22
Observations		12,007			

The sample of nonconfession criminal cases processed in 2011–2014 with nonmissing demographics, type of crime, past work, crime and health history variables that were sentenced to prison.

Table A7—: Health Variable Distribution in the Sample of Defendants.

	Mean	SD	Percentile			Mean Difference: Non-incarcerated – Incarcerated Defendants
			10	50	90	
Pr(Any health care visit in month t)	0.405	0.491				-0.012
						0.003
Number of health care visits in month t	1.134	2.194	0	0	3	-0.068
						0.011
Pr(Any physical health visit)	0.245	0.430				0.007
						0.002
No. of physical health visits	0.472	1.224	0	0	2	0.013
						0.006
Pr(Any mental health visit)	0.189	0.391				-0.023
						0.002
No. of mental health visits	0.456	1.376	0	0	2	-0.056
						0.007
Pr(Any of substance abuse visit)	0.087	0.281				-0.021
						0.001
No. of substance abuse visits	0.230	1.091	0	0	0	-0.053
						0.006
Pr(Any drug-related visit)	0.067	0.250				-0.018
						0.001
No. of drug-related visits	0.180	0.978	0	0	0	-0.046
						0.005
Pr(Any alcohol-related visit)	0.011	0.104				-0.001
						0.001
No. of alcohol-related visits	0.022	0.283	0	0	0	0.001
						0.001
Pr(Any opioid-related visit)	0.013	0.114				-0.004
						0.001
No. of opioid-related visits	0.027	0.316	0	0	0	-0.005
						0.002
Pr(Any depression-related visit)	0.030	0.171				0.003
						0.001
No. of depression-related visits	0.054	0.402	0	0	0	0.006
						0.002
Pr(Any light mood disorder-related visit)	0.043	0.202				-0.006
						0.001
No. of light mood disorder-related visits	0.072	0.422	0	0	0	-0.004
						0.002

This table reports summary statistics for the sample of non confession criminal cases processed in 2006–2014 measured in 36–30 months before the case decision.

Table A8—: Robustness: Impacts on Mental Health Visits Using Alternative Estimators.

A. Probability of Mental Health Visit		
	BJS	**CS**
	(1)	**(2)**
Quarters 1-20	-0.057***	-0.062***
	(0.005)	(0.006)
Dependent Mean	0.371	0.371
B. Number of Mental Health Visits		
	BJS	**CS**
	(1)	**(2)**
Quarters 1-20	-0.182***	-0.146***
	(0.049)	(0.051)
Dependent Mean	1.785	1.785
Number of Observations	12,314	12,314
Case × Individual FEs	✓	✓
Period FEs	✓	✓

The sample of nonconfession criminal cases processed in 2011--2014. Standard errors clustered at the case level. 95% confidence intervals. The table reports the estimates of the effect of being incarcerated on the probability (Panel A) and number (Panel B) of mental health visits, measured at a quarterly frequency. Column (1) reports the Borusyak-Jaravel-Spiess (BJS) estimates using the *did_imputation* package based on Borusyak, Jaravel and Spiess (2021), while column (2) reports the Callaway-Sant'Anna (CS) estimates using the *csdid* package based on Callaway and Sant'Anna (2021). The dependent mean is the mean of the outcome in the sample included in the regression. *p<0.1, **p<0.05, ***p<0.01.

Table A9—: Heterogeneity Effects by Employment History, Type of Crime and Sentence Length.

	Employment History		Type of Crime		Sentence Length	
	Employed	Non-Employed	Violent	Non-Violent	< Median	> Median
	(1)	(2)	(3)	(4)	(5)	(6)
A. Probability of Mental Health Visit						
Months 13–60	-0.056***	-0.038***	-0.057***	-0.042***	-0.033***	-0.058***
	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)
Dependent mean	0.204	0.274	0.179	0.270	0.223	0.263
B. Number of Mental Health Visits						
Months 13–60	-0.067**	-0.079**	-0.127***	-0.048	-0.024	-0.114***
	(0.032)	(0.031)	(0.030)	(0.030)	(0.035)	(0.031)
Dependent mean	0.478	0.695	0.411	0.677	0.541	0.657
Number of Observations	5,884	6,430	3,966	8,348	6,859	5,455

Notes: The sample of nonconfession criminal cases processed in 2011–2014. The estimation has been run separately for each subgroup, and always includes controls for case and period (month × year) FEs. Standard errors clustered at the case level. Subgroups according to employment history have been defined as in Bhuller et al. (2020). Defendants are classified as previously employed if they were working in at least one of the past five years; the other individuals are defined as previously non-employed. 48% of our sample is defined as previously employed. Sentence length is split at the median, which is 6 months. 28% of our sample has committed a violent crime. The dependent mean is the mean of the outcome in the sample included in the regression. *p<0.1, **p<0.05, ***p<0.01.

Table A10—: Robustness: IV Estimates of the Effects of Incarceration on Mental Health Visits.

Definition of Judge Stringency IV: No. of Cases Handled By Judge:	Baseline IV	Number of Cases Handled by Judge		Definition of Judge Stringency IV	
	Random cases $\geq$ 50 cases	Random cases $\geq$ 75 cases	Random cases $\geq$ 100 cases	Non-confession cases $\geq$ 50 cases	Reverse sample $\geq$ 50 cases
	(1)	(2)	(3)	(4)	(5)
A. First-Stage Estimates					
Incarcerated	0.337***	0.359***	0.386***	0.286***	0.440***
	(0.085)	(0.088)	(0.090)	(0.072)	(0.068)
Dependent Mean	0.547	0.548	0.548	0.547	0.547
B. IV Estimates: Probability of Mental Health Visit					
Months 1-60	-0.183	-0.157	-0.108	-0.106	-0.093
	(0.116)	(0.110)	(0.103)	(0.104)	(0.067)
Dependent Mean	0.261	0.261	0.262	0.261	0.261
C. IV Estimates: Number of Mental Health Visits					
Months 1-60	-0.935**	-0.811*	-0.535	-0.510	-0.546**
	(0.464)	(0.440)	(0.415)	(0.419)	(0.272)
Dependent Mean	0.681	0.680	0.682	0.681	0.681
No. of Observations	22,456	21,859	20,762	22,456	22,456
Controls:					
Demographics	✓	✓	✓	✓	✓
Type of crime	✓	✓	✓	✓	✓
Past work & criminal history	✓	✓	✓	✓	✓
Court $\times$ Year FE	✓	✓	✓	✓	✓

Sample of non-confession criminal cases processed 2011-2014. All estimations include court $\times$case entry year FEs and demographics (age, sex, foreign-born status, number of children, marital status, level of education), type of crime, past work and crime history (indicator for being employed in year t-1 to t-5 before the year of crime, indicator for being ever charged in year t-1 to t-5 before the year of crime, indicator for being ever incarcerated in year t-1 to t-5 before the year of case decision) controls. Standard errors are two-way clustered at the judge and defendant level in the IV estimation. 95% confidence intervals. The first column reproduces the baseline IV estimation presented in Table 2. Columns (2) and (3) vary the definition of the sample and exclude, respectively, judges who handled less than 75 and 100 randomly assigned confession or non-confession cases between the years 2005 and 2014. Column (4) excludes confession cases for the computation of the judge stringency score. *p<0.1, **p<0.05, ***p<0.01.

Table A11—: First-Stage Estimates: The Effect of Judge Stringency on Incarceration Probability.

Estimation sample:	(1) **Time of decision**	(2) **Month 12 after decision**	(3) **Month 24 after decision**	(4) **Month 36 after decision**	(5) **Month 48 after decision**	(6) **Month 60 after decision**
Dependent variable:	**Pr(Incarcerated)**					
A. Court × Year of Court Case Registration Interacted Fixed Effects						
Leave-Out Case Judge Stringency (by regular/irregular), DA extract 1	0.3812***	0.3786***	0.3760***	0.3711***	0.3689***	0.3662***
	(0.0546)	(0.0550)	(0.0552)	(0.0554)	(0.0552)	(0.0558)
F-stat(Instrument)	48.65	47.35	46.39	44.82	44.58	43.04
B. Add Controls for Demographics and Type of Crime						
Leave-Out Case Judge Stringency (by regular/irregular), DA extract 1	0.3683***	0.3649***	0.3623***	0.3591***	0.3577***	0.3566***
	(0.0536)	(0.0540)	(0.0542)	(0.0545)	(0.0542)	(0.0547)
F-stat(Instrument)	47.17	45.74	44.64	43.39	43.63	42.53
C. Add Controls for Demographics, Type of Crime, Past work and Criminal History						
Leave-Out Case Judge Stringency (by regular/irregular), DA extract 1	0.3606***	0.3583***	0.3589***	0.3569***	0.3569***	0.3548***
	(0.0493)	(0.0497)	(0.0499)	(0.0502)	(0.0502)	(0.0508)
F-stat(Instrument)	53.45	51.88	51.64	50.65	50.46	48.82
Dependent mean	0.5301	0.5292	0.5278	0.5261	0.5251	0.5239
Number of Observations	59,556	59,059	58,118	57,193	56,341	55,459

The sample of non-confession criminal cases processed 2006-2014. The estimation includes controls for case × case decision year FEs. Reported F-statistic refers to a joint test of the null hypothesis for all variables. The omitted category for education is "Less than high school, year t-1" and the omitted category for type of crime is "Other crimes". Standard errors are two-way clustered at judge and defendant level. *p<0.1, **p<0.05, ***p<0.01.

Table A12—: Tests of Randomization.

	Pr(Incarcerated)		Judge stringency	
Age at the time of case decision	0.0035***	(0.0003)	0.0000	(0.0000)
Female	-0.0589***	(0.0054)	-0.0014***	(0.0005)
Foreign-born	0.0054	(0.0044)	0.0003	(0.0004)
Married	-0.0203**	(0.0089)	-0.0012	(0.0009)
Number of children in year t-1	-0.0016	(0.0023)	0.0004	(0.0002)
High school by year t	-0.0013	(0.0062)	0.0013**	(0.0007)
Some college education in year t	-0.0440***	(0.0093)	-0.0007	(0.0012)
Type of crime: Violent crime	0.0945***	(0.0066)	-0.0005	(0.0008)
Type of crime: Property crime	-0.0432***	(0.0088)	-0.0003	(0.0009)
Type of crime: Economic crime	-0.0684***	(0.0091)	0.0007	(0.0010)
Type of crime: Drug-related crime	-0.0649***	(0.0079)	-0.0012	(0.0010)
Type of crime: Drunk driving	0.0713***	(0.0096)	-0.0011	(0.0009)
Type of crime: Traffic violation (speeding, no license)	-0.0574***	(0.0107)	-0.0012	(0.0011)
Missing Xs	-0.2960***	(0.0995)	0.0053	(0.0114)
Employed, year t-1	0.0180***	(0.0062)	-0.0006	(0.0007)
Ever employed in years t-2 to t-5	0.0163***	(0.0062)	-0.0011*	(0.0006)
Ever Charged in year t-1	0.0529***	(0.0053)	-0.0004	(0.0006)
Ever Charged in years t-2 to t-5	0.0589***	(0.0061)	0.0001	(0.0007)
Ever incarcerated in year t-1	0.1472***	(0.0078)	-0.0001	(0.0009)
Ever incarcerated in years t-2 to t-5	0.1658***	(0.0069)	0.0009	(0.0007)
Number of health-care visits, month t-1	-0.0058**	(0.0028)	0.0000	(0.0003)
Number of mental-health visits, month t-1	0.0043	(0.0031)	-0.0002	(0.0003)
Number of physical-health visits, month t-1	0.0026	(0.0033)	0.0002	(0.0003)
Missing health information	0.0809**	(0.0324)	0.0012	(0.0036)
F-statistic for joint test	152.126		1.288	
p-value	(0.000)		(0.163)	
Dependent variable mean	0.5301		0.4617	
Dependent variable sd	0.4991		0.0725	
Number of cases	59,556		59,556	

The sample of non-confession criminal cases processed 2006-2014. All estimations include controls for court × case decision year FEs. Reported F-statistic refers to a joint test of the null hypothesis for all variables. The omitted category for education is "Less than high school, year t-1" and the omitted category for type of crime is "Other crimes". Standard errors are two-way clustered at judge and defendant level. *p<0.1, **p<0.05, ***p<0.01.

ONLINE APPENDIX B. RANDOM JUDGE DESIGN

We describe below an IV strategy that takes advantage of the random assignment of cases to judges to estimate the causal effects of prison relative to alternative sentences, building upon Bhuller et al. (2020). We are interested in estimating the following relationship:

$$Y_{i,t} = \beta_t I_{i,0} + X_i^{'}\theta_t + \upsilon_{i,t} \tag{B1}$$

where β_t is the coefficient of interest, $I_{i,0}$ is an indicator variable equal to one if individual i has been sentenced to prison at time zero (normalized to be the time of the court decision), and $Y_{i,t}$ is the outcome variable measured in time t after individual i's court decision. As the randomization of cases to judges occurs within the pool of available judges within a court-by-year cell, we always include fully interacted court-by-year FEs among the vector of controls $X_i^{'}$.

The OLS estimation of Equation (B1) could raise concerns of a selection bias, as incarcerated defendants are unlikely to be comparable to the unincarcerated (see Online Appendix Table A7). The random judge design addresses this concern by exploiting the fact that cases are conditionally randomly assigned to judges and that some judges are systematically more stringent that others. Taken together, this leads to as-good-as random variation in the probability a defendant will be incarcerated depending on the judge the case is assigned. We utilize this exogenous variation in $I_{i,0}$ to draw inferences about the causal effects of incarceration on defendant health. Our main analysis is based on the two-stage least squares (2SLS) estimation of β_t with Equation (B1) as the second-stage equation and a first-stage equation specified as:

$$I_{i,0} = \gamma Z_{j(i)} + X_i^{'}\delta + \eta_{i,0} \tag{B2}$$

where $Z_{j(i)}$ is the leave-out mean incarceration stringency of judge j assigned to handle the case of individual i.[48] Under the assumptions of instrument exogeneity and monotonicity, the 2SLS estimand can be interpreted as the positive weighted average of the causal effect of incarceration among defendants that are more likely to receive an incarceration decision if assigned to a stricter judge, and vice versa. This means that, unlike the event study, the IV approach yields an estimate of the effect of incarceration on the population of compliers. To improve precision, we include, in addition to the court-by-year FEs, a rich set of background characteristics capturing defendants demography, type of crime, past work, and criminal history in the vector of control variables $X_i^{'}$.

Importantly, the validity of our IV design requires the instrument to be relevant, i.e., that judge stringency has a significant impact on the incarceration probability of defendants. Our first-stage estimates show that being assigned to a judge with a 10-percentage point higher stringency increases the probability of being incarcerated increases by about 3.6 percentage points, with an F-statistic of around 50 (see Online Appendix Table A11). These estimates are robust to controlling for defendant demographics, type of crime and measures of past work and criminal history.

For our instrument to be valid, the stringency of a judge must also be uncorrelated with preexisting defendant and case characteristics that could affect a defendant's future outcomes (even conditional on fully interacted court-by-year FEs). Our tests of this implication show that while demographics, type of crime, past work, and criminal history variables are highly predictive of the incarceration decision, these factors are not associated with the stringency of the assigned judge (see Online Appendix Table A12). This provides evidence that the allocation of cases to judges is consistent with random assignment, conditional on court-by-year FEs. We also do not find any evidence of a systematic correlation between judge stringency and

[48] We calculate judge stringency as the leave-out mean judge incarceration rate for all randomly-assigned cases each judge has handled over the 2005–2014 period, including both past and future confession and nonconfession cases.

the predicted number of health-care visits using the same set of covariates as indicated above (see Online Appendix Figure A5).

The conditional random assignment of cases to judges is sufficient for a causal interpretation of the reduced form impact of being assigned to a stricter judge on defendant outcomes. However, interpreting the IV estimates as measuring the causal effect of incarceration further requires an exclusion restriction: the incarceration rate of the judge should affect the defendant's outcomes only through the incarceration sentencing channel and not directly in any other way. Under heterogeneous effects, monotonicity must also be assumed for the IV estimates to be interpreted as LATEs (Angrist and Imbens, 1994), which requires that defendants who are incarcerated by a lenient judge would also need to be incarcerated by a stricter judge, and vice versa for nonincarceration.[49]

EVIDENCE AND SENSITIVITY ANALYSIS.While our IV estimates are relatively imprecise, we perform some analyses to assess sensitivity (see Online Appendix Table A10, Columns (2)-(5)). We estimated IV models for cases assigned to judges who had handled at least 50 (baseline), 75 or 100 cases (to ensure sufficient number of cases to measure precisely judge stringency). We further assessed the sensitivity of estimates to calculating judge stringency using nonconfession cases only, while in our baseline, we used all randomly assigned cases (i.e., including confession cases). Furthermore, we estimated a reverse sample IV, where we randomly split our sample in half and used one half to calculate the average incarceration rate of each judge, and then used these measures of judge stringency as an IV for incarceration in the other half of the sample. While our estimates based on these approaches do not qualitatively change, their magnitude and precision vary across specifications. The point estimates always have the same sign as in our baseline IV model.

[49]Recent literature raises concerns about the monotonicity assumption in the random judge IV designs (see, e.g., Frandsen, Lefgren and Leslie (2023)). As our study uses the same random judge IV design as in Bhuller et al. (2020), we refer to Section IV.B in that paper for further discussion of the IV assumptions. We provide evidence from a reverse sample IV in Online Appendix Table A10, Column (5), that provides a test of an implication of monotonicity.

ONLINE APPENDIX C. DETAILS ON THE PREDICTION MODEL

Mental health score is computed by predicting the probability of at least one mental health-related visit in the 3–1 years before the crime. The prediction model is trained on the general population (excluding our sample) in the population register in 2009–2010. We then restrict the model to individuals aged 10 years or older in 2009 and alive by 2010. We retrieve their sociodemographic and health information from 2004 to 2010 and define a dummy variable equal to one if they had at least one mental health visit within the past 3 years. We then use a logit model – given the dependent variable is binary – that includes the following variables: female indicator, the year, deciles of age, indicator for foreign-born, the marital status the year before, the marital status 2 years before, number of children 1 and 2 years before (one indicator per value), employment status 1 year before, deciles of transfers received 1 year before, a set of indicators if a child has died within the last 5 years and was aged between 0–10 years, 11–20 years, etc., fixed effects for the municipality of residence 1 year before, and deciles of wage 1 and 2 years before. The total number of observations is 7,813,589 (3,950,508 individuals) and the pseudo-R^2 is 7.4%.

We use an alternative model where we predict the probability of at least one mental health visit 3 years before the crime (to be as far as possible from the event) using our full sample of nonconfession crimes processed between 2006 and 2014. This alternative model may better predict mental health as it is based on a sample of offenders but at the expense of using the same sample to train and test the model. We again use a logit model, where we include the following variables: a female indicator, dummies for each age value, dummies for each age-at-crime value, indicator for foreign-born, indicator for married the year before the crime, dummies for number of children the year before the crime, dummies for each year of education value 1 year before the crime, number of hours worked and monthly wage 36 months before the case decision, indicator equal to one if ever suspected or charged in the last 3 years before the case decision, number of suspected crimes and charges in the last 3 years before the case decision, indicator equal to one if ever suspected in years t-2 to t-5 before the year of the crime. In that case, the number of observations is equal to 35,363 and the pseudo-R^2 is 12.3%. Table correlates both measures with each other, with the actual probability of having at least one mental health visit in 3 years before the case decision. The correlation lies between 0.3 and 0.53.