Effect of Economic Circumstances on Crime

Economic Circumstances and Crime

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September 19, 2025

Outline for Today

1. **Summarize Yang (2017)**

2. **Summarize Palmer, Phillips, Sullivan (2019)**

Tulane University

Yang (2017)

Abstract

Abstract: “This paper estimates the impact of local labor market conditions on criminal recidivism using administrative prison records on four million offenders released from 43 states between 2000 and 2013. Exploiting the timing of each offender’s release from prison, I find that being released to a county with higher low-skilled wages significantly decreases the risk of recidivism. The impact of higher wages on recidivism is larger for both black offenders and first-time offenders, and in sectors that report being more willing to hire ex-offenders. These results are robust to individual- and county-level controls, such as policing and corrections activity, and do not appear to be driven by changes in the composition of released offenders during good or bad economic times.”

Summary Statistics

- This is a summary statistics table showing you what her data looks like
- This one shows facts about how often people return to prison (recidivate)

Table 1
Distribution of time until return to prison.

	No. of obs	Probability of return to prison in			
		≤ 1 year	≤ 2 years	≤ 3 years	≤ 5 years
All prisoners	4,029,781	0.146	0.227	0.268	0.304
Demographics					
White	1,888,533	0.139	0.216	0.254	0.289
Black	1,491,470	0.148	0.240	0.288	0.331
Hispanic	701,319	0.139	0.202	0.230	0.252
Male	3,501,023	0.151	0.235	0.278	0.315
Female	527,741	0.113	0.172	0.202	0.230
Age under 25	825,430	0.204	0.311	0.362	0.404
Age 25–40	1,974,349	0.143	0.224	0.266	0.304
Age over 40	1,229,591	0.112	0.174	0.207	0.235
Less HS degree	1,326,984	0.136	0.227	0.275	0.322
HS degree	1,064,684	0.126	0.200	0.238	0.273
College degree	27,073	0.077	0.124	0.150	0.180
Prior felony incarceration	662,673	0.153	0.230	0.270	0.307
No prior felony	2,148,616	0.141	0.221	0.261	0.297
Type of offense					
Violent offense	979,874	0.139	0.219	0.260	0.296
Property offense	1,120,922	0.178	0.268	0.311	0.349
Drug offense	1,168,453	0.131	0.209	0.250	0.285
Reason for first prison spell admittance					
Court commitment	3,279,972	0.136	0.214	0.253	0.288
Parole revocation	199,508	0.211	0.328	0.383	0.427
Probation revocation	322,983	0.194	0.292	0.341	0.385
Reason for first prison spell release					
Discretionary parole	1,177,321	0.166	0.260	0.302	0.335
Mandatory parole	767,042	0.236	0.336	0.382	0.415
Shock probation	415,490	0.126	0.218	0.266	0.308
Expiration of sentence	1,069,258	0.049	0.101	0.138	0.180

Notes: This table presents descriptive statistics for the unconditional probabilities of returning to prison for the full sample of prisoners released between 2000–2013 in 43 states.

Summary Statistics

- This is another summary statistics table, showing what her sample looks like
- E.g., what is the demographic and educational make-up of her sample?
- What kind of offenses were committed?

Table 2
Summary statistics of prisoners released 2000–2013.

	Offender sample		Offender-quarter sample	
Variable	Mean	SD	Mean	SD
NCRP data				
White	0.498	0.500	0.502	0.500
Black	0.393	0.488	0.391	0.488
Hispanic	0.197	0.398	0.201	0.401
Male	0.869	0.337	0.864	0.342
Female	0.131	0.337	0.136	0.342
Age at release	34.383	10.636	34.802	10.658
Less HS degree	0.511	0.500	0.516	0.500
HS degree	0.410	0.492	0.406	0.491
Some college	0.063	0.243	0.063	0.244
College degree	0.010	0.102	0.011	0.103
Prior felony incarceration	0.236	0.424	0.230	0.420
Violent offense	0.245	0.430	0.243	0.429
Property offense	0.280	0.449	0.269	0.444
Drug offense	0.292	0.455	0.301	0.459
Number of counts	1.234	1.314	1.225	1.302
Total sentence (years)	4.718	6.123	4.709	6.222
Time served (years)	2.161	3.289	2.173	3.287
Court commitment	0.831	0.375	0.838	0.368
Parole revocation	0.051	0.219	0.048	0.214
Probation revocation	0.082	0.274	0.079	0.270
Discretionary parole	0.306	0.461	0.284	0.451
Mandatory parole	0.199	0.399	0.192	0.394
Shock probation	0.108	0.310	0.107	0.309
Expiration of sentence	0.278	0.448	0.312	0.463
Missing crime Characteristics	0.006	0.078	0.007	0.083
Missing race	0.059	0.236	0.057	0.232
Missing Hispanic	0.116	0.320	0.123	0.329
Missing education	0.356	0.479	0.344	0.475
Missing prior	0.302	0.459	0.305	0.460
Labor market variables (in logs)				
Low-skilled wages	7.369	0.149	7.369	0.151
Low-skilled construction wages	7.454	0.204	7.451	0.204
Low-skilled manufacturing wages	7.512	0.200	7.515	0.201
Low-skilled transportation wages	7.380	0.179	7.380	0.180
Low-skilled finance wages	7.676	0.230	7.679	0.232
Low-skilled professional services wages	7.617	0.231	7.622	0.232
Low-skilled management wages	7.630	0.302	7.638	0.305

Notes: This table presents summary statistics on the full sample of released prisoners from 2000–2013 from 43 states. The offender sample contains one observation per prisoner and labor market summary statistics are presented for the quarter of release. The offender-quarter sample contains one observation for each quarter out of prison.

Methodology

- Yang's general approach is a version of a difference-in-differences
- The idea to compare people released from prison in the same county in good economic conditions versus bad economic conditions
- Yang measures economic conditions through wages in low skilled jobs
- These are the jobs that are most likely to hire those with criminal records
- By looking at people within the same county, during times with higher vs. lower wages, it removes any bias for the fixed differences between counties
    - Recidivism rates and other factors may be different between counties
- Comparisons between, rather than within counties would be more of an "apples to oranges" comparison
- Like other DiD examples, where there are fixed differences that exist between groups

Methodology

- An assumption is required for Yang's approach to provide an unbiased estimate of the causal effect of local economic conditions on crime
- The assumption is that when comparing those within the same county in good and bad economic times, there are no differences other than the different economic circumstances
- The ideal would be like a randomized control trial (RCT) $\rightarrow$ higher/lower wages are randomly assigned over time

Methodology

- Obviously, that's not possible
- But hopefully there are no important differences between good and bad economic times other than the economy
- Otherwise the treatment and control groups would be different. The key example of possible differences are that the types of people released during good economic times, within the same county, could differ from those released during bad economic times, within the same county
- While some of this can be controlled for in the regression analysis (i.e. control variables), any differences that are not controlled for could cause bias

Results

- This is the main results table
- Results show that if the low-skill wage is higher, then recidivism decreases (hence the negative coefficient)
- Results are very similar even when control variables are added
- Other results:
  - Blacks, non-Hispanics, younger people, those with less education, men, and those with less time served are more likely to recidivate

Table 4
Main results.

	(1)	(2)	(3)
Log low-skill wage	−0.436***	−0.435***	−0.462***
	(0.057)	(0.060)	(0.060)
Black		0.133***	0.159***
		(0.008)	(0.009)
Not Hispanic		0.240***	0.223***
		(0.023)	(0.021)
Female		−0.304***	−0.309***
		(0.014)	(0.009)
HS degree		−0.066***	−0.077***
		(0.016)	(0.017)
Some college		−0.131***	−0.151***
		(0.016)	(0.016)
College degree		−0.294***	−0.301***
		(0.027)	(0.027)
Age at release		−0.049***	−0.044***
		(0.004)	(0.000)
No prior felony		−0.516***	−0.469***
		(0.038)	(0.047)
Time served (years)			−0.012***
			(0.004)
Observations	34,872,568	34,872,568	34,872,568
Defendant controls	No	Yes	Yes
Crime controls	No	No	Yes

Notes: This table presents proportional hazard estimates for the sample of prisoners released between 2000–2013 in 43 states. Each column represents a separate regression. Column 2 adds controls for defendant demographics: race, ethnicity, gender, age, age squared, highest graded completed, prior felony incarceration indicator. Column 3 adds controls for crime and prison characteristics: main offense type, number of convicted counts, total sentence imposed, type of prison admission, type of facility, reason for release, time served, time served squared. All specifications include year and county fixed effects. Standard errors are clustered at the county level.
*** significant at 1 percent level.

Results

Table 5
Results by industry.

	(1)	(2)	(3)	(4)	(5)	(6)
Construction log low-skill wage	−0.164***					
	(0.040)					
Manufacturing log low-skill wage		−0.231***				
		(0.060)				
Transportation log low-skill wage			0.007			
			(0.040)			
Finance log low-skill wage				0.089***		
				(0.035)		
Prof. services log low-skill wage					−0.064	
					(0.048)	
Management log low-skill wage						0.018
						(0.026)
Other log low-skill wage	−0.308***	−0.291***	−0.470***	−0.584***	−0.422***	−0.585***
	(0.080)	(0.067)	(0.069)	(0.069)	(0.079)	(0.086)
Observations	34,823,482	34,713,772	34,574,189	31,979,852	32,710,100	28,660,000
Defendant controls	Yes	Yes	Yes	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents proportional hazard estimates for the sample of prisoners released between 2000–2013 in 43 states. Each column represents a separate specification controlling for industry specific county-level log wages and log wages in all other industries. I consider three low-skilled sectors most willing to hire ex-offenders: construction; manufacturing; and transportation, and three high-skilled sectors least willing to hire ex-offenders: finance and insurance; professional, scientific, and technical services; and management of companies and enterprises. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.
*** significant at 1 percent level.

Results: Heterogeneity

Table 6
Results by offender demographics.

	All	Male	Female	White	Black	<25	25 to 40	>40
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log low-skill wage	−0.462***	−0.463***	−0.480***	−0.364***	−0.539***	−0.415***	−0.430***	−0.502***
	(0.060)	(0.061)	(0.097)	(0.052)	(0.096)	(0.074)	(0.062)	(0.069)
3 year recidivism	0.268	0.278	0.202	0.254	0.288	0.362	0.266	0.207
Observations	34,872,568	30,139,485	4,721,248	16,465,378	12,982,650	6,612,160	17,130,434	11,127,386
Defendant controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents proportional hazard estimates for subsamples of prisoners released between 2000–2013 in 43 states. Each column represents a separate specification. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.
*** significant at 1 percent level.

Table 7
Results by criminal history and crime type.

	Prior felony	No prior	Violent	Property	Drug
	(1)	(2)	(3)	(4)	(5)
Log low-skill wage	−0.227**	−0.690**	−0.471***	−0.461***	−0.445***
	(0.096)	(0.079)	(0.086)	(0.067)	(0.069)
3 year recidivism	0.270	0.261	0.260	0.311	0.250
Observations	5,533,463	18,762,280	8,454,298	9,353,063	10,496,821
Defendant controls	Yes	Yes	Yes	Yes	Yes
Crime controls	Yes	Yes	Yes	Yes	Yes

Notes: This table presents proportional hazard estimates for subsamples of prisoners released between 2000–2013 in 43 states. Each column represents a separate specification. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.
*** significant at 1 percent level.
** significant at 5 percent level.

Palmer, Phillips, Sullivan (2019)

Tulane University

Abstract

Abstract: “Does emergency financial assistance reduce criminal behavior among those experiencing negative shocks? To address this question, we exploit quasi-random variation in the allocation of temporary financial assistance to eligible individuals and families that have experienced an economic shock. Chicago's Homelessness Prevention Call Center (HPCC) connects such families and individuals with assistance, but the availability of funding varies unpredictably. Consequently, we can determine the impact of temporary assistance on crime by comparing outcomes for those who call when funds are available to those who call when no funds are available…

What do they do?

- Linking this call center information to arrest records from the Chicago Police Department, we find some evidence that total arrests fall between 1 and 2 years after the call
- For violent crime, police arrest those for whom funds were available 51% less often than those who were eligible but for whom no funds were available.
- Single individuals drive this decrease.
- The decline in crime appears to be related, in part, to greater housing stability—being referred to assistance significantly decreases arrests for homelessness-related, outdoor crimes such as trespassing

What do they do?

- However, we also find that financial assistance leads to an increase in property crime arrests
- This increase is evident for family heads, but not single individuals;
- The increase is mostly due to shoplifting; and the timing of this increase suggests that financial assistance enables some families to take on financial obligations that they are subsequently unable to meet
- Overall, the change in the mix of crime induced by financial assistance generates considerable social benefits due to the greater social cost of violence”

Call Volumes

- The researchers use “eligible calls”, which are the people who are eligible, based on the HPCC’s criteria, for the assistance
- For these people it’s almost a coin toss if they get the funding

Table 1
Call volume, HPCC, January 20, 2010-September 14, 2012.

Sample composition	N	% funds available	# prior calls	Proportion with a prior call
All calls	200,661	5.4	0.7	0.31
Eligible calls	14,819	47.9	1.1	0.47
First call within last week	12,880	48.1	0.9	0.41
First call within last six months	8655	50.0	0.3	0.15
First call since June 2009	7222	49.8	0.0	0.00

Notes: The sample restrictions for each row include the restrictions imposed in all rows above it. For example, the sample in the third row that is restricted to first calls in the last week is also restricted to eligible calls.

Funding is Random

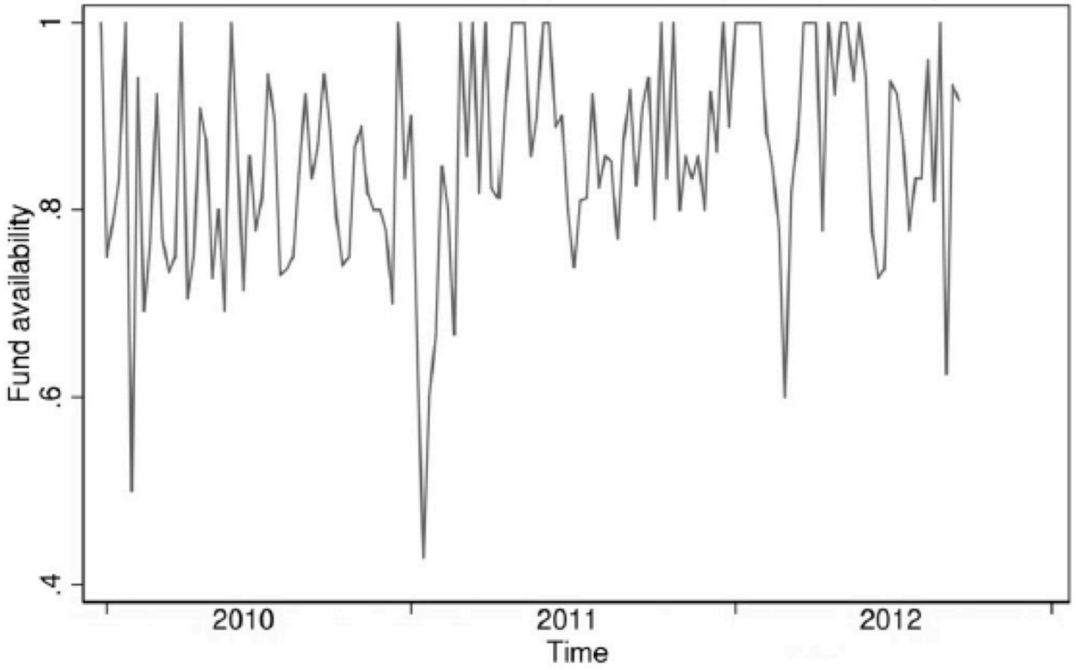

Fig. 2. Fund availability rate, by week, eligible callers to the HPCC. *Notes*: This figure is similar to Evans et al. (2016), but for a slightly different sample. Sample includes all eligible callers from 2010 to 2012 who are seeking rent assistance with need amounts between \$300 and \$900, who are non-veterans, who neither receive housing subsidies nor request more than one month of rent, who report both Social Security Numbers and family-scaled incomes below twice the poverty line, and who are not homeowners ($N = 2035$). The fund availability rate is the frequency of fund availability to those eligible callers who call within that week.

Sample of Callers

Table 3
Mean characteristics of eligible, first-time callers for all types of assistance.

Dependent variable	Control group mean	Adjusted difference
Ever arrested before call	0.32	0.0074
Arrested 1 year before call or less	0.053	0.010[a]
Arrested 1 year before call or less – Violent	0.010	0.0020
Arrested 1 year before call or less – Property	0.0069	0.0025
Arrested 1 year before call or less – Drugs	0.0099	0.0011
Arrested 1 year before call or less – Other	0.021	0.0031
Female	0.83	−0.035[c]
White, non-Hispanic	0.063	0.011[a]
Black, non-Hispanic	0.89	−0.013[a]
Other, non-Hispanic	0.041	0.00045
Hispanic	0.072	0.00099
Age	40.8	−0.73[c]
Number of adults in caller's household	1.43	−0.021
Number of minors in caller's household	1.51	−0.072[b]
Percentage in ZIP code with HS degree (standardized)	0.00098	−0.019
Labor force participation rate in ZIP code (standardized)	−0.013	0.011
Unemployment rate in ZIP code (standardized)	0.0080	−0.018
Median age in ZIP code (standardized)	−0.0053	0.0047
Monthly housing cost in ZIP code (thousands, standardized)	0.014	−0.030
Median household income in ZIP code (thousands, standardized)	0.011	−0.015
Fraction black in ZIP code (standardized)	0.0054	−0.015
Fraction white in ZIP code (standardized)	0.00084	0.0060
Fraction other races in ZIP code (standardized)	−0.017	0.032
Applying due to benefit loss	0.12	−0.0055
Applying due to inability to pay bills	0.049	−0.010[b]
Applying due to exiting shared housing	0.058	0.0038
Applying to flee abuse	0.012	0.0014
Applying due to job loss	0.25	−0.0025
Monthly income (thousands)	1.08	−0.038[b]
Receiving SNAP benefits	0.69	−0.0083
Receiving child support	0.057	−0.0024
Receiving earned income	0.50	−0.0085
Receiving SSI	0.18	−0.0045
Receiving income from TANF	0.085	0.0054
Receiving unemployment payments	0.14	0.012
Receiving other income sources	0.082	−0.0076
Living situation: rent housing	0.84	−0.012
Living situation: shared housing	0.13	0.012
Shelter inhabitancy in past 18 months	0.047	0.014[b]
N	4328	8655

Notes: Results are for our main sample. The second column shows the coefficient on fund availability from a regression of the listed baseline characteristics on a fund availability dummy and controls for fund-specific restrictions.

[a] Significant at 10%; based on heteroskedasticity-robust standard errors.
[b] Significant at 5%; based on heteroskedasticity-robust standard errors.
[c] Significant at 1%; based on heteroskedasticity-robust standard errors.

Main Results

- Effect are strongest (more statistically significant) for violent arrests
- E.g., one year after getting the funding, violent arrests are 0.0087 lower
- Compared to average rate (control group mean of 0.017), this is a decrease of about 50%!!!

Table 4
OLS estimates of the effect of fund availability on arrests.

	(1) 1 year	(2) 2 years	(3) 3 years
Effect on all arrests	−0.0099[a]	−0.0080	−0.0031
	(0.0058)	(0.0071)	(0.0078)
Control group mean	0.055	0.087	0.108
Effect on violent arrests	−0.0087[c]	−0.0086[b]	−0.0086[a]
	(0.0033)	(0.0041)	(0.0046)
Control group mean	0.017	0.028	0.037
Effect on property arrests	0.0021	0.0052	0.010[c]
	(0.0024)	(0.0032)	(0.0037)
Control group mean	0.007	0.015	0.019
Effect on drug arrests	−0.00039	−0.0018	−0.0023
	(0.0026)	(0.0033)	(0.0039)
Control group mean	0.012	0.020	0.026
Effect on other arrests	0.0010	−0.0027	−0.0013
	(0.0042)	(0.0054)	(0.0061)
Control group mean	0.024	0.042	0.055
Controls for characteristics related to fund availability	Yes	Yes	Yes
Controls for other observable characteristics	Yes	Yes	Yes
N	8655	8655	8655

Notes: Results are for our main sample of eligible first-time calls within the last six months for rent, security deposit, utility, and other assistance, January 20, 2010–September 14, 2012. See text for additional restrictions. Each cell shows the coefficient on funds availability from a separate regression. The outcome is a dummy for being arrested for the listed type of crime within the listed time frame. Calendar and fund availability controls include linear controls for rank of the call within the day and ZIP code crimes rates for all crime, violent crime, and non-larceny crime as well as dummies for need amount category interacted with year and quarter, day of week, month, time of month, veteran status, housing subsidy receipt, needing >1 month rent, having income >2 times the poverty line, having an SSN, need request type, owning one's dwelling, senior status, and receiving disability payments. Other observable characteristics are the variables in Table 3, excluding lagged arrest records and shelter entry. We code missing values as zero and also include a set of dummy variables indicating when a variable is missing. Heteroskedasticity-robust standard errors are in parentheses.

[a] Significant at 10%.
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Main Results

- There is an increase in property arrests three years later, due to getting the funding
- The authors argue that this may be that when the families get the funding, they get requests for that money, and they overcommit on who they promise to give money to
- This could lead to an incentive to commit shoplifting once those “debts” catch up

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More Results

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Effects on Single Individuals vs Families