# LOCAL LABOR MARKETS AND CRIMINAL RECIDIVISM

Crystal S. Yang*

This Version: December 2016

**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.
JEL Codes: J23, K14, K40

* Assistant Professor of Law, Harvard Law School. I am very grateful to Amanda Agan, Will Dobbie, Jennifer Doleac, Hank Farber, Alan Krueger, Alex Mas, Jeff Morenoff, Michael Mueller-Smith, J.J. Prescott, Betsey Stevenson, numerous seminar participants, the editor Julie Berry Cullen, and two anonymous referees for helpful comments and suggestions. Molly Bunke and Scott Dorsett provided excellent research assistance. All errors are my own. E-mail: cyang@law.harvard.edu.

## 1. Introduction

Every week, over 10,000 prisoners are released from federal and state prisons, with over 650,000 offenders returning to their communities each year (Carson and Golinelli 2013). Within three years of release, over two-thirds of released offenders are rearrested, over half are reconvicted, and over 40 percent are returned to custody (Beck and Shipley 1989, Langan and Levin 2002, Durose et al. 2014). As a result, ex-offenders constitute a growing share of overall crime rates (Rosenfeld et al. 2005). One potential explanation for high recidivism rates is limited labor market opportunities for ex-offenders. Indeed, one year after release, as many as 60 to 75 percent of former offenders are not employed in the legitimate labor market (Petersilia 2003, Visher et al. 2008).

An important question is therefore whether labor market opportunities affect the recidivism of recently released offenders. The answer to this question is of growing importance given the resources spent on rehabilitation and reentry efforts. Since Congress passed the Second Chance Act in 2007, the federal government alone has spent more than $475 million on reentry programs aimed at reducing recidivism. In recent years, federal and state governments have also considered reforms to reduce the ability of employers to consider criminal history in making hiring decisions. For instance, in April of 2012, the Equal Employment Opportunity Commission issued guidance stating that an employer cannot categorically ban the hiring of a convicted felon unless the disqualification is "job-related" or "consistent with business necessity." In addition, cities and states have begun a movement known as "ban the box" to limit the ability of employers to ask individuals about their criminal history.

However, the impact of economic conditions on recidivism is theoretically ambiguous. Ex-offenders may be responsive to opportunities to engage in legitimate work during good economic times, decreasing the returns to new criminal activity (Uggen 2000, Kling 2006). However, the vast majority of ex-offenders have low human capital, limited job experience, and suffer from mental and substance abuse issues (Petersilia 2003, Visher et al. 2008), potentially impeding their ability to obtain employment regardless of criminal history. To the extent that individual characteristics such as ability or individual preferences for criminal behavior are the primary determinants of recidivism, stronger labor markets may have little impact on reoffending. In addition, the stigma associated with incarceration (Pager 2003, Holzer et al. 2003, Dobbie et al. 2016) and legal bans in certain occupations that prohibit the hiring of ex-offenders suggest that employers may be unwilling to hire ex-offenders compared to other low-skilled workers even when the labor market is tight.

Empirically estimating the impact of employment opportunities on recidivism has been hampered by three main problems. First, there are limited panel datasets that link prison spells for the

same individual over time due to confidentiality concerns. Second, existing panel datasets contain very small samples or are restricted to a small number of states that give access to administrative correctional data, making estimates prone to external validity concerns. Third, state-level data often do not identify the local communities that offenders are likely to return to, making it impossible to identify the impact of local labor markets versus aggregate state economic conditions.

To overcome these obstacles, this paper uses new offender-level administrative data on prisoner admissions and releases collected by the Bureau of Justice Statistics (BJS) as part of the National Corrections Reporting Program (NCRP). The NCRP contains data from state Departments of Corrections and Parole and covers persons admitted to or released from state prison from 2000-2013. In recent years, the NCRP linked prison terms using defendant and offense identifiers, allowing for a large-scale and geographically representative analysis of criminal recidivism. Importantly, the data contain information on the county in which each offender was sentenced, representative of where the offender resides and returns to after release, which is used to assign local labor markets. With four million offenders released to over 2,000 counties during a period of economic expansion followed by the Great Recession, I am able to exploit substantial variation in the timing and severity of local economic conditions experienced by offenders upon release from prison.

Controlling for demographic and offense characteristics of each offender, as well as county and time fixed effects, I find that an increase in low-skilled wages in an offender's local labor market significantly reduces the risk of returning to prison. My estimates suggest that the typical wage growth during a business cycle decreases the risk of recidivism by 2.3 to 4.0 percent. These results are driven by labor market demand shocks in sectors that report a willingness to hire ex-offenders, such as construction and manufacturing. Black offenders and first-time offenders are also most responsive to changes to wages. The results are robust to additional controls that proxy for police and corrections behavior, and cannot be explained by the differential release of certain prisoners during good or bad economic times, or selection due to correlation between economic conditions at prison entry and prison exit.

These results indicate that the cohorts of offenders released during the Great Recession may have been exposed to a particularly heightened risk of recidivism.[1] In fact, some states like California released many inmates during the economic downturn in order to reduce overcrowding, but the tough job market may have impeded the ability of ex-offenders to find employment, potentially increasing future recidivism and endangering public safety. For example, the estimates in this paper suggest that compared to a counterfactual in which real wages remained constant, the

[1]For instance, data from Indiana suggest that the employment rate for released offenders decreased from 40.1 percent in 2006 to 25 percent in 2009. See http://eric.ed.gov/?id=EJ1011632. Certain prisons may have profited from the recession, with industry executives noting that because people released during the downturn were less likely to find jobs, demand for prison beds would increase. See http://www.newyorker.com/news/news-desk/why-the-u-s-is-right-to-move-away-from-private-prisons?intcid=mod-latest.

recidivism risk of offenders released during the Great Recession increased by 5.5 to 9.6 percent.

This paper is most closely related to a number of prior studies. First, Myers (1983) finds that among a sample of 432 male offenders released from Maryland state prisons, higher average weekly wages reduce the probability of rearrest. More recently, Sabol (2007) finds that a one percent increase in county unemployment rates decreases the probability of a released prisoner exiting the initial spell of unemployment by about five percent among a sample of released prisoners in Ohio. Raphael and Weiman (2007) find a small, but positive relationship between local unemployment rates and the probability of returning to custody among a sample of released prisoners in California. Wang, Mears, and Bales (2010) find a similar relationship between unemployment rates and re-conviction rates for black offenders released in Florida. In another sample of released prisoners from California, Schnepel (2016) finds that increases in construction and manufacturing employment opportunities at the time of release are associated with significantly lower recidivism.

This paper is also directly related to two other strands of research. The first strand explores the impact of economic conditions on aggregate crime rates (e.g., Gould et al. 2002, Raphael and Winter-Ember 2001, Machin and Meghir 2004, Corman and Mocan 2005). This paper differs from these studies in measuring individual ex-offender responses to local economic conditions, which is of independent interest given the recent focus on rehabilitation and reentry programs for ex-offenders.[2] Additionally, this paper focuses on wages of low-skilled men, a demographic group most similar to ex-offenders, rather than aggregate economic conditions.

The second strand of research is an experimental literature testing the impact of various reentry interventions on employment and recidivism. This experimental literature includes, among others, the Baltimore Living Insurance for Ex-Prisoners (LIFE) experiment (Mallar and Thornton 1978), which found that providing financial and job search assistance to ex-offenders had no detectable effect on recidivism. More recently, MDRC evaluated the Center for Employment Opportunities program, which provided transitional jobs to parolees in New York City, finding that while employment increased during the first year when transitional jobs were offered, there was no significant change in recidivism during that period of increased employment (Redcross et al. 2012). In combination, the prior experimental literature finds limited evidence that temporary programs which improve employment opportunities affect recidivism (Cook et al. 2014).

In contrast to these experiments, this paper cannot identify the precise employment effect on recidivism. Instead, this paper estimates the reduced form effect of improved labor market opportunities on recidivism, which combines any direct employment effect with indirect channels such as changes in criminal opportunities. Nevertheless, the estimates in this paper may more accurately

[2]In general, the estimates in this paper are comparable in magnitude to prior studies estimating the effect of economic conditions on aggregate crime rates. For example, Gould et al. (2002) find that a one percent increase in the county-level wages of unskilled men is associated with a 0.52 to 1.35 percent decrease in overall crime.

reflect the effects of providing employment for ex-offenders compared to the experimental literature. For example, providing an ex-offender with job search assistance or a temporary subsidized job often does not lead to an unsubsidized job in the regular labor force. In addition, subsidized jobs offered in prior experiments were often minimum-wage jobs, whereas improvements in labor market opportunities might lead not only to employment, but also higher paying jobs.[3]

The remainder of the paper is structured as follows. Section 2 provides a conceptual framework for the relationship between local labor market conditions and criminal recidivism. Section 3 describes the data and provides summary statistics. Section 4 describes the empirical strategy. Section 5 estimates the impact of local labor market conditions on the risk of returning to prison. Section 6 concludes.

## 2. Conceptual Framework

Following the framework of Becker (1968) and Ehrlich (1973), local economic conditions may affect recidivism through two main channels: (1) an employment and earnings channel and (2) a criminal opportunities channel.

*Employment and Earnings Channel* - There are at least four ways that local economic conditions could affect recidivism through an employment and earnings channel. First, increases in local employment and wages may directly reduce the likelihood of recidivating if better economic conditions increase the probability of employment and the potential return to work for ex-offenders, leading to a substitution effect that shifts ex-offenders away from the illegal sector toward the legitimate labor market. For example, Sabol (2007) finds a negative relationship between the unemployment rate at release and the probability of finding employment in the formal labor market. Second, increased employment and higher wages may also lead to an income effect that reduces the incentive to seek supplemental income from any source. If an ex-offender relies on family members or friends for economic support, better economic conditions may also improve the labor market outcomes of these other individuals, reducing the offender's incentive to recidivate regardless of his own employment status. Third, employment can also be a form of "incapacitation" by keeping ex-offenders occupied and less likely to engage in criminal activity during work hours. Fourth, ex-offenders may develop their human capital during employment, potentially changing their preferences for criminal behavior.

[3]Outside of the criminal justice setting, this paper is also related to a literature documenting the negative and persistent employment effects of graduating from college during an economic downturn. For example, Kahn (2010) finds that a one percentage point increase in the unemployment rate is associated with an initial wage loss of seven percent for college graduates in the United States. Similarly, Oreopoulos, von Wachter, and Heisz (2012) find that a five percentage point increase in the unemployment rate implies an initial earnings loss of nine percent among Canadian college graduates. The results from this paper suggest that economic downturns adversely affect not only college graduates but also ex-offenders who enter the labor market after a period of absence.

Of course, ex-offenders may be unresponsive to labor market opportunities if the traits associated with criminal behavior are immutable and impede the ability to get a job. In general, offenders have low ability, low levels of work experience, and a high prevalence of mental and substance abuse issues. In addition, erosion of human capital during incarceration and the stigma of incarceration may make hiring ex-offenders undesirable to employers, even compared to other low-skilled labor.

*Criminal Opportunities Channel* - Criminal opportunities may also change depending on local employment opportunities. Theoretically, an improved local labor market may increase the number of criminal opportunities if there are more goods to steal, leading to potentially more rather than less recidivism. In particular, if ex-offenders do not benefit from labor demand shocks, greater job opportunities for others may increase recidivism among offenders (Freedman and Owens 2016). Improved economic conditions might also affect recidivism if jurisdictions spend more on police and corrections during good economic times. For example, an increased police presence during good economic times may reduce criminal behavior through a deterrence channel. In Section 5.4, I attempt to account for some of these potential non-employment related channels. Nevertheless, the estimates in this paper capture the combined reduced form effect of many potential mechanisms.

## 3. Data

### 3.1. National Corrections Reporting Program

Data on prison spells are obtained from the NCRP. The data are constructed using administrative data voluntarily provided by states on prison admissions and releases from 2000-2013, with almost all offenders entering prison between 1990 and 2013. 38 states have provided some data since 2000 and 48 states provided data in 2013.

Prior to 2013, the NCRP data comprised separate and non-linkable files for prison admissions, prison custody, and prison releases. In recent years, the BJS retroactively linked prison spells from 2000 onwards using inmate ID numbers, dates of birth, admission, release, offense, and sentencing information in the NCRP data. Years and states in which data were incomplete or in which counts were substantially different from the National Prisoner Statistics (NPS) data were excluded.[4] Approximately 14 percent of all prison releases reported to the NCRP were excluded

[4]Several other studies using the older versions of the NCRP prison admissions and release data have used a subset of states to ensure reliability. For instance, Pfaff (2011) compared counts of individuals entering and exiting into state prisons from NCRP (1983-2002) to other official counts such as NPS data. According to Pfaff, eleven states consistently reported data: California, Colorado, Illinois, Kentucky, Michigan, Minnesota, Nebraska, New Jersey, South Dakota, Virginia, and Washington. Neal and Rick (2014) conduct several checks both internally within the NCRP data and with other data sources such as the NPS using data from 1983 to 2009. After several tests, the authors restrict their analysis to eight states: California, Colorado, Michigan, New Jersey, North Dakota, South Carolina, Washington, and Wisconsin. Comparing parole data from the NCRP against other sources, Mechoulan and Sahuguet

for these reasons. However, 44 states were able to have records linked for some period of time for which they submitted data between 2000 and 2013.[5] See Appendix Table 1 for a list of the states in the sample and the years for which they provided data used to construct reliable prison spells.

Demographic characteristics for each offender include age at release, race, Hispanic ethnicity, highest grade completed, gender, and whether the individual has previously been convicted and incarcerated for a felony. For each prison spell, I also observe the most serious offense of conviction, the number of conviction counts for each offense, and the total sentence imposed. Because I observe the exact prison admission date and prison release date for each period of incarceration, I calculate the actual time served for each period of incarceration. This actual time served can differ from the total sentence imposed because of early release through parole or good time credited. For each prison spell, the data also include information on the type of facility the prisoner entered into, the reason why the prisoner entered into the custody of the correctional facility,[6] and the reason why the prisoner was released.[7]

Most importantly, the data contain information on the county where each sentence was imposed, which is where the overwhelming majority of prisoners return after prison. Offenders who are turned over to state parole are generally required under state statute to remain in the original county of conviction or last county of residence, with over 90 percent of offenders residing in the county of conviction post-release (Raphael and Weiman 2007, Sabol 2007, Schnepel 2016). Following the prior literature, I use this county of conviction as a proxy for each offender's local labor market.

I make six sample restrictions. First, I keep only the first observed prison spell for each offender to specifically explore the impact of local labor market conditions on the first return to prison.[8] Second, I drop observations in which county of sentencing is missing, about 2.7 percent of the observations, leaving me with a sample from 43 states. Third, I drop counties that released less than 100 offenders during the full sample period, 0.7 percent of the sample. Fourth, I drop left-

(2015) retain ten states for their analysis: Michigan, North Dakota, Utah, Colorado, Wisconsin, Texas, Missouri, Arkansas, New York, and California. While this study uses the newly constructed NCRP dataset, my findings are robust to these subsamples of states.

[5]For a description on how prison terms were created, see http://www.icpsr.umich.edu/files/NACJD/ncrp/white-paper-computing-code.pdf.

[6]The overwhelming majority of offenders are committed by the court under a new offense, or recommitted due to a parole or probation revocation.

[7]Prisoners can be conditionally released by parole boards through discretionary release or by statute through mandatory release when their time served plus any good time earned equals the original sentence. Another form of conditional release comes through shock probation, where a judge can impose a brief period of incarceration designed to shock a first-time offender, followed by release under supervision. In other states, prisoners may be released unconditionally following the expiration of their sentence, in which case they have served the maximum court sentence and there is no community supervision upon release.

[8]Because I do not observe complete histories of every offender, it is likely that some of the observed "first" spells are in fact higher spells.

censored spells (offenders with missing prison release dates) because it is not possible to determine when an offender was released from prison, another 13.8 percent of the sample. Fifth, I drop individuals who were released from prison prior to 2000. Finally, I drop individuals who were "released" from prison because of death, 0.7 percent of the sample. After these restrictions, there are a total of 4,029,781 offenders released from prison between 2000-2013 and therefore 4,029,781 non-custody spells ("offender sample").

There are two main limitations to the data. First, the NCRP data only link prison spells within a state, so any reoffending in a different state is not captured and is indistinguishable from an individual who is not recommitted in the same state.[9] Second, the data only capture return to custody, not rearrest or prosecution. As a result, the estimates in this paper may underestimate the impact of local labor market conditions on broader definitions of recidivism.

Table 1 presents the unconditional probabilities of returning to prison for offenders after their first observed prison release, in the aggregate and by prisoner characteristics. Because I limit the sample to one prison release per offender, these recidivism rates do not include the contribution of offenders who recidivate two or more times during the sample period, who are likely higher risk. I define recidivism as return to prison within the same state whether due to a "new commitment" or technical parole violation, given evidence that law enforcement officials often classify a new offense as a technical violation because it is easier to ensure a period of incarceration (Kuziemko 2013, Austin and Lawson 1998). In Section 5.3, I specifically explore whether labor market conditions affect returning to prison for a new offense.

For the full sample of over four million prisoners released between 2000-2013 in 43 states, 15 percent return to prison within one year of release and 30 percent return to prison within five years of release.[10] Black offenders have higher rates of recidivism than white and Hispanic offenders. Males and younger offenders are also more likely to return to prison than females and older offenders, respectively. The higher the educational attainment of an offender, the lower the rate of recidivism. Offenders who have a prior felony incarceration have roughly similar recidivism rates compared to those without, although 30 percent of individuals are missing this information in the data.[11] By type of primary offense, prisoners convicted of property offenses are more likely to recidivate than those convicted of violent or drug offenses. By type of prison admittance, prisoners

[9]The BJS estimates that within five years of release, approximately ten percent of released offenders are arrested in a state other than the one that released them. See http://www.bjs.gov/content/pub/pdf/rprts05p0510.pdf. Incarceration in another state is therefore some fraction of this ten percent of released offenders. However, if offenders move out of states with poor economic conditions, this mobility may lead to a downward bias in the main estimates.

[10]These recidivism rates are comparable to other statistics on recidivism using the new NCRP Data. See Rhodes et al. (2014).

[11]States completely missing information on prior felony incarceration in all years include Alabama, Alaska, Indiana, Iowa, Kansas, Maine, Maryland, Massachusetts, Minnesota, Mississippi, Montana, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Pennsylvania, and Rhode Island.

who enter into custody due to a parole or probation violation have higher rates of recidivism than those with a new court commitment. Finally, prisoners released through mandatory parole are more likely to recidivate than those released through the discretion of a parole board, or those released through shock probation. Prisoners who serve the full maximum court sentence have the lowest rates of recidivism, likely because they are not under supervision following release and therefore cannot be recommitted for technical parole violations.

Figure 1 presents unconditional empirical hazard rates by month since release, calculated as the number of failures (offenders returning to prison) in a month divided by the size of the risk set at the beginning of the same month. This figure shows that the hazard rate peaks within the first year since release and then declines exponentially, indicating that offenders are at the highest risk of recidivism in the first few years post-release.

Given that the hazard rate is approximately flat beyond three years post-release, I censor all spells at 36 months (or 12 quarters) after release in order to focus on the risk of returning to prison in the three years post-release. Results are robust to alternative censoring lengths. I transform the data to allow for multiple observations per offender, such that each observation represents a quarter in each offender's non-custody spell. For instance, an offender released in June 2000 and who returned to custody in June 2001 would have four observations for each quarter between release and readmission. I allow for multiple observations per offender to allow local economic conditions to vary during the course of each offender's non-custody spell. After this transformation of the data, the offender sample of 4,029,781 released offenders results in 35,508,672 observations ("offender-quarter sample").

### 3.2. Local Labor Market Variables

Ideally, one would like to observe local labor market demand for ex-offenders. Prior studies (Raphael and Weiman 2007, Sabol 2007) have utilized local unemployment rates as the sole proxy for ex-offender labor demand. In contrast, I proxy for labor demand using average wages following Machin and Meghir (2004) and Grogger (1998). Wages may be a better proxy for the labor market prospects of ex-offenders given that wages reflect longer-term changes to labor market conditions than unemployment, which is often short-lived and highly cyclical (Gould et al. 2002). In robustness checks, I explore the sensitivity of my results to other measures of labor demand, including employment per capita and average wages of new hires in each quarter.

I obtain employment and earnings measures from the Quarterly Workforce Indicators collected from the Longitudinal Employer-Household Dynamics dataset, which allows for disaggregation by sector and worker demographics.[12] From the Quarterly Workforce Indicators data, I obtain

[12]Public data from the Quarterly Workforce Indicators are available for all states other than Massachusetts, and for

county-level quarterly data on average monthly earnings in the aggregate, by sector, and by sex-education bin.[13] In the main results, I focus in particular on average wages of non-college educated men given that over 90 percent of ex-offenders in the sample have a high school degree or less. This metric captures earnings opportunities in each offender's local labor market, proxying for underlying demand for ex-offender labor.

Because I observe the county in which each prisoner is convicted and sentenced at the beginning of the first observable spell, labor market variables are assigned to each prisoner in each quarter out of custody based on this county. In contrast to the demographic and offense characteristics in the NCRP data, these local labor market variables vary over the course of each offender's non-custody spell.

Recall that offenders turned over to state parole are generally required by statute to remain in the county of conviction or last county of residence, with over 90 percent of offenders residing in the county of conviction post-release. Nevertheless, the assignment of labor market conditions based on the county of sentencing may introduce measurement error and bias. For example, classical measurement error of the county that an offender returns to will attenuate my estimates towards zero. My estimates will also be biased if offenders leave their county of conviction (either by permission or by absconding from supervision) for counties with better economic conditions, whether to commit new crimes or to seek employment. In the full sample of approximately four million released offenders, I observe that among those who recidivate during the sample period, the county of conviction for the new offense differs from the county of the first observed offense 10.1 percent of the time, consistent with national statistics that indicate a nine percent rate of absconding from parole (Bonczar 1999). In robustness checks, I explore the potential bias due to selective migration by controlling for economic conditions in a broader labor market.

Table 2 presents summary statistics for both the offender sample (4,029,781 observations) and offender-quarter sample (35,508,672 observations). The top panel presents summary statistics on demographic and crime characteristics in each sample. For example, in the offender sample between 2000-2013, 49.8 percent of released offenders are white and 39.3 percent are black. 19.7 percent of released offenders are Hispanic and over 86 percent are male. The average age at release is 34.4 years and over half of offenders have less than a high school degree. Only 1.0 percent of released offenders have a college degree. 23.6 percent of offenders in the sample were previously incarcerated for a felony. The three most common crimes are violent, property, and drug offenses, representing 24.5 percent, 28.0 percent, and 39.2 percent of the sample, respectively.

Summary statistics on log average monthly real wages for low-skilled men are presented in the bottom panel of Table 2. There is substantial variation in labor market conditions for low-

most years between 2000-2013.

[13]Nominal wages are converted to real wages using the CPI.

skilled men across counties and time. For example, log average monthly wages range from 5.9 to 10.1. County labor market conditions also vary within state. In Texas, the state with the largest number of released prisoners in the sample, log average monthly wages range from 6.7 to 8.9. In California, the state with the second largest number of released prisoners, log average monthly wages range from 6.9 to 10.1. During the sample period, average wages of low-skilled men are relatively lower in industries open to hiring ex-offenders like construction, manufacturing, and transportation, compared to industries like finance, professional services, and management.

## 4. Empirical Methodology

To estimate the effect of local labor market conditions on criminal recidivism, I estimate a proportional hazard model that allows for a flexible baseline hazard in the duration of non-custody spells and allows for time-varying covariates.[14] In this model, the hazard rate represents the probability of leaving a state in the $t^{th}$ period given continuous participation in that state for the last $t-1$ periods. From this hazard rate, one can construct a duration density distribution and a survivor function, which can be conditioned on various covariates and on initial entry into a state. The parameters of the continuous time duration model are estimated using maximum-likelihood.

I right-censor non-custody spells if an individual has still not been recommitted by the end of the sample period for each state. For instance, Arizona provided data from 2000-2012, so all spells are censored as of December 2012. Given that the hazard rate declines rapidly after approximately three years post-release (Figure 1), I censor all spells at 36 months after release in order to focus on the risk of returning to prison in the three years after release.

In particular, I estimate a model with the following specification:

$$h_{iqtc} = \alpha_q \text{exp}(\beta_1 X_i + \beta_2 L_{tc} + \gamma_t + \delta_c) \tag{1}$$

where $h_{iqtc}$ is the hazard rate for returning to prison in quarter $q$ after release, with each spell beginning in the quarter-year that the offender is first released from prison. The baseline hazard, $\alpha_q$, is estimated flexibly using indicator variables for each quarter $q$ post-release.

$X_i$ includes time-invariant characteristics of each offender at the time of first release: race, ethnicity, gender, age, age squared, highest graded completed, prior felony incarceration indicator, main offense type, number of convicted counts, total sentence imposed, type of prison admission (new commitment, parole violation, etc.), type of facility, reason for release, time served, and time served squared. I also include indicators for missing data on each of these time-invariant characteristics.

[14] This specification has been used widely in the literature on unemployment duration (see e.g., Meyer 1990, Card et al. 2007) and welfare exits and reentry (see Blank and Ruggles 1996, Hoynes 2000).

The independent variable of interest, $L_{tc}$, is the log average monthly real wages of low-skilled men in quarter-year $t$ and county $c$. The coefficient of interest is $\beta_2$, which captures the effect of local labor market conditions on the hazard rate. Given the functional form on log wages, $\beta_2$ can be interpreted as the elasticity of the hazard rate with respect to wages, such that a one percent increase in wages leads to a $\beta_2$ percent change in the hazard.

One potential threat to identification is that offenders with higher rates of recidivism may be located in areas with poor economic conditions. To account for these time-invariant unobservable characteristics, I control for county fixed effects, $\delta_c$. I also control for calendar year fixed effects, $\gamma_t$, to account for factors such as changes in criminal justice or welfare policies that may be correlated with both local economic conditions and recidivism. Standard errors are clustered at the county level to account for serial correlation within counties.

In addition to estimating the impact of average low-skilled wages on recidivism, I consider the impact of low-skilled wages in different sectors. To separately identify the impact of industry-specific low-skilled wages, I estimate the following specification for industry $j$:

$$h_{iqtc} = \alpha_q \text{exp}(\pi_1 X_i + \pi_2 L_{tcj} + \pi_3 L_{tc,-j} + \gamma_t + \delta_c) \tag{2}$$

controlling for low-skilled wages in industry $j$, $L_{tcj}$, and average low-skilled wages in all other industries, $L_{tc,-j}$. In this specification, the coefficient of interest is $\pi_2$, which captures the effect of local labor market conditions in a particular industry on the risk of returning to prison, controlling for wages in all other industries.

My identification strategy exploits the timing of each offender's release from prison. Intuitively, I compare recidivism outcomes of observably similar offenders who have served the same amount of time for the same crime but who return to counties when labor market conditions are more or less favorable. If the timing and county of release are uncorrelated with unobservable characteristics of prisoners, my estimates capture the causal effect of local labor market conditions on recidivism.

To partially test the identifying assumption that local labor market conditions at the time of release are orthogonal to unobservable characteristics of ex-offenders, I regress a few selected demographic and crime characteristics of released offenders on labor market conditions in the quarter of release, controlling for year of release fixed effects, and county fixed effects. Standard errors are clustered at the county level. Table 3 presents these balance tests using the offender sample. In general, I find no significant effect of low-skilled wages on most demographic and crime characteristics of offenders, such as crime type and prior incarceration history. Offenders released during good times are slightly less likely to be male and more likely to be black, although the magnitudes of the estimates are small relative to the means. To assess overall balance, I combine all offender-level observable characteristics into a single risk index. I estimate the probability

of recidivism as a function of demographic, crime, and prison characteristics, as well as county of conviction. I find no significant relationship between log wages in the quarter of release and predicted risk, consistent with the timing of release being uncorrelated with unobservables that predict recidivism. However, I find a significant positive relationship between log wages at the time of prison entry and prison exit, suggesting a strong correlation between economic conditions across years. In Section 5.4, I explore the potential selection bias that can arise due to correlation of economic conditions.

## 5. Results

### 5.1. Main Hazard Estimates

Table 4 presents main results for the hazard rate of returning to prison, censored at three years. In all results, I report coefficients rather than hazard ratios such that a positive coefficient indicates that a variable increases the recidivism risk and vice versa. I present results with and without offender-level controls as described in Section 4 to assess the sensitivity of the estimates to observable heterogeneity following Card and Levine (2000).

In column 1 of Table 4, I control only for county log wages of low-skilled workers, in addition to county and year fixed effects. Recall that given the functional form on log wages, $\beta_2$, the coefficient of interest, can be interpreted as the elasticity of the hazard rate with respect to wages. With the addition of county fixed effects, $\beta_2$ is identified from fluctuations in labor market conditions over time within each county. Column 2 adds the full set of demographic controls, and column 3 adds the full set of crime and prison controls.

I find that increases in low-skilled wages are negatively associated with the risk of returning to prison. According to column 1, a one percent increase in average low-skilled wages reduces the hazard by 0.44 percent (column 1). With the addition of offender demographic controls, a one percent increase in low-skilled wages reduces the hazard by 0.43 percent (column 2), and with crime and prison controls, a one percent increase in low-skilled wages reduces the hazard by 0.46 percent (column 3). The similarity of the estimates with and without offender demographic and crime controls suggests that the results are not very sensitive to controlling for observed heterogeneity and, therefore, may not be biased by unobservable heterogeneity either.[15]

[15] As another partial check on unobservable heterogeneity, I compare the characteristics of offenders who have not yet returned to prison at different points in time. For example, at one quarter since release, 86.9 percent are male, 50.0 percent are white, 23.5 percent have been previously incarcerated for a felony, and the average age is 34.4. At four quarters since release, 86.9 percent of at risk offenders are male, 50.0 percent are white, 23.4 percent have previously been incarcerated for a felony, and the average age is 34.5. At eight quarters since release, 86.7 percent of at risk offenders are male, 50.1 percent are white, 23.2 percent have previously been incarcerated for a felony, and the average age is 34.6. Given the similarity in observable characteristics at various points in time, it is unlikely that unobservable heterogeneity leads to substantial bias in the estimates.

Estimates presented for some key offender and offense characteristics in Table 4 indicate that black offenders are significantly more likely to recidivate than similar white offenders (the omitted group) after controlling for observables. Non-Hispanic defendants are more likely to recidivate than similar Hispanic defendants. In contrast, female defendants are significantly less likely to recidivate than male defendants. Recidivism also decreases with educational attainment. Compared to the omitted group of offenders with less than an eighth grade degree, offenders with a high school degree, some college, or a college degree are increasingly less likely to recidivate. Finally, older offenders, those with no prior felony incarceration, and those who have served more time for the current offense are less likely to recidivate than their counterparts.

Overall, these results suggest that ex-offenders are responsive to labor market conditions as measured by low-skilled earnings. Between 2001-2007, within-county real wages increased by roughly four to five percent, variation that is typical during a standard business cycle (Hoynes 2000). Placing the estimates in the context of this variation, a five percent increase in real wages reduces the recidivism risk by approximately 2.3 percent. This percent decrease corresponds to a 0.09 percentage point reduction in the mean quarterly hazard (3.8 percentage points) in the first year after release.

In Table 5, I consider the impact of low-skilled wages in specific industries on recidivism, controlling for wages of low-skilled men in all other industries. In columns 1 through 3, I present results from specification (2) for three sectors known for a willingness to hire ex-offenders and which employ a disproportionate share of low-skilled men: construction, manufacturing, and transportation (Holzer et al. 2004, Raphael 2010).[16] Controlling for low-skilled wages in all other industries, I find that a one percent increase in low-skilled wages in the construction sector reduces the recidivism risk by 0.16 percent. Similarly, a one percent increase in manufacturing wages further reduces the recidivism risk by 0.23 percent. These results indicate that wage increases in some of the sectors most likely to hire ex-offenders substantially reduce the risk of recidivism.

As a counterfactual, columns 4 through 6 present results for three sectors that employ the lowest shares of low-skilled labor, and which are likely unwilling to hire ex-offenders: finance, professional services, and management.[17] In contrast to the previous results, I find little evidence that wage increases in these industries correspond with reductions in recidivism after controlling for wages in other industries. In fact, I find a significant and positive relationship between low-skilled wages in the finance industry and the risk of returning to prison after accounting for conditions in the rest of the economy. Overall, these results are consistent with increased earnings reducing the likelihood of recidivism through an employment or earnings channel, particularly in industries

[16] See also http://articles.latimes.com/2010/nov/30/business/la-fi-felon-jobs-20101130.

[17] According to Raphael (2010), establishments willing to hire ex-offenders (particularly construction) are also more likely to hire less educated individuals (high school degree or less) compared to sectors less willing to hire ex-felons.

more willing to hire ex-offenders.

### 5.2. Treatment Heterogeneity

In Table 6, I estimate subsample results to assess whether certain types of offenders are more sensitive to local labor market fluctuations. The specifications control for the full set of demographic and crime characteristics, as well as county and year fixed effects. In column 1 of Table 6, I replicate the main findings from column 3 of Table 4 for the full sample of released offenders.

In columns 2 and 3, I separately estimate the main specification for male offenders and female offenders, respectively. I find that the impact of low-skilled wages on recidivism is not significantly different by gender, despite the generally lower recidivism risk of female offenders. In columns 4 and 5, I separately estimate the main specification for white offenders and black offenders. I find that increases in low-skilled wages reduce recidivism risk significantly more for black offenders than for white offenders (p-value = 0.04). A one percent increase in low-skilled wages reduces the hazard rate by 0.36 percent for white offenders, compared to 0.54 percent for black offenders, suggesting that black offenders are substantially more responsive to increases in wages than similar white offenders.

In columns 6 through 8, I estimate the main specification separately for offenders in different age groups. I find evidence that older ex-offenders are more responsive to increases in earnings prospects than younger ex-offenders. A one percent increase in low-skilled wages reduces the recidivism risk by 0.42 percent for offenders aged 25 or under, 0.43 percent for offenders aged 25 to 40, and by 0.50 percent for offenders released at age 40 or older. Although the differences by age are not statistically significant, larger effects of wages on older ex-offenders are consistent with both employer preference for older offenders, and/or older offenders being more responsive to earnings opportunities (Uggen 2000).

Differences in the effect of local labor market conditions also appear by prior criminal history and crime type. In columns 1 and 2 of Table 7, I find evidence that offenders with no prior felony incarceration are much more responsive to changes in low-skilled wages than those with a prior felony incarceration (p-value = 0.0001). Among those without a prior felony incarceration, a one percent increase in wages reduces the recidivism risk by 0.69 percent compared to 0.23 percent for those with a prior felony incarceration. In columns 3 through 5, I present additional subsample results by crime type. I group the detailed offense types into three main crime categories. Violent crimes range from murders and rapes to armed robberies and aggravated assaults. Property offenses include burglary, arson, theft, and other economic crimes. Finally, drug offenses include drug trafficking and possession. I find evidence that offenders convicted of violent, property, and drug crimes are roughly equally responsive to changes in low-skilled wages.

Finally, I combine all observable characteristics into a single risk index to test for heterogeneous results. I estimate a hazard model controlling for the full set of offender demographic, crime, and prison characteristics, as well as county of conviction. I use a split-sample estimator to predict recidivism risk in a five percent random sample to avoid the bias that arises from endogenous stratification (Abadie et al. 2014). I then use these estimates to construct a predicted ex ante risk of recidivating in the other 95 percent of my offender-quarter sample. I divide offenders into above and below median risk of recidivating during the sample period, with those in the below median group having a 12.7 percent probability of recidivating in the three years post-release compared to 38.3 percent for the above median group. In Appendix Table 2, I present the main hazard model results separately for these two groups of offenders. I find that low-skilled wage increases have a similar effect on the recidivism risk of lower-risk offenders and higher-risk offenders.

### 5.3. Committing New Offenses

The previous results indicate that release from prison during favorable local labor market conditions significantly reduces the hazard of returning to prison within three years. Recall that I define recidivism as any return to prison, whether due to parole violations or the commission of a new offense, in large part because new offenses may be classified as technical violations by law enforcement officials (Kuziemko 2013). However, this measure of recidivism may not be the most relevant from a public safety perspective. For example, in some jurisdictions, searching for lawful employment can be a condition of parole, suggesting that increased recidivism during poor economic times may not generate any new criminal activity.

To assess whether improved labor market conditions reduce the risk of committing new crimes, I analyze the hazard of returning to prison for a new offense, as classified by each state's corrections system. Within three years post-release, 10.9 percent of ex-offenders return to prison for a new offense, explaining roughly forty percent of the overall three-year recidivism rates. In this specification, I right-censor non-custody spells for ex-offenders who do not recidivate for any reason and for those who do not return to prison for a new crime within 36 months after release.

Column 1 of Table 8 presents these results. I find that a one percent increase in low-skilled wages reduces the hazard rate for returning to prison for a new crime by 0.52 percent, suggesting that improved local labor markets also affect the commission of new offenses. Columns 2 through 4 explore the impact of labor market conditions on returning to prison for a new violent, property, and drug offense, respectively. While higher wages reduce the recidivism risk of all types of new offenses, the magnitude of the wage effect is somewhat larger for new violent offenses, driven largely by new assaults and robberies. In combination, these results suggest that poor economic conditions increase recidivism through both an increased risk of violating parole conditions and an

increased risk of committing new crimes.

### 5.4. Alternative Specifications

In Table 9, I test the robustness of the main results. In column 1, I add county-specific linear trends to the preferred specification (column 3 of Table 4), such that my estimates are identified off deviations from county trends. I find that a one percent increase in low-skilled wages is associated with a 0.39 percent reduction in the hazard rate. In column 2, I add additional county-year controls for per capita personal income and personal current transfer receipts from the Bureau of Economic Analysis (BEA). Personal current transfer receipts are benefits received by persons for which no current services are performed and accounted for almost 15 percent of total personal income at the national level in 2005. These controls proxy for changes in potential criminal opportunities or the opportunity cost of crime through both labor and non-labor channels. Results are similar with the addition of these county-level controls, suggesting that my reduced form results may be largely explained by increased employment and earnings opportunities for ex-offenders during good economic times.

In column 3, I control for county-year arrests collected from the Uniform Crime Reports (UCR) to address the concern that changes in police enforcement may be correlated with local economic conditions. I also control for the total number of prison admittances per county-quarter based on the NCRP data to address the concern that courts are more likely to incarcerate ex-offenders, conditional on arrest, during poor economic times. I find that even accounting for local changes in arrests and prison admittances, increases in wages are associated with lower recidivism risk.

Another concern is that parole officers may be differentially willing to report violations (both technical and new crimes) during good or bad economic times. Budget cuts during economic downturns generally lead to increased workloads for parole officers, causing them to have less time to supervise their parolees, which suggests that parole officers may be less likely to detect or report violations during poor economic conditions, leading to a potential downwards bias in my estimates. To partially test this concern, I replicate the main specification looking only at ex-offenders who served the full expiration of their sentence minus any credits received, and who are released without any term of community supervision. Because these ex-offenders are not under any correctional or community supervision, they are likely not affected by any potential changes in parole officer behavior. In column 4, I find similar results among this subsample of ex-offenders with a one percent increase in low-skilled wages reducing recidivism risk by 0.49 percent.

In column 5, I control for state-by-year fixed effects, relying solely on variation across counties within the same state. I find that within the same state-year, a one percent increase in low-skilled wages reduces the recidivism risk by 0.44 percent. Results in column 6 are similar controlling

for MSA-by-year fixed effects. Within the same MSA-year, a one percent increase in low-skilled wages reduces the recidivism risk by 0.47 percent. Finally, in column 7, I replicate the main specification on the sample of 17 states that provided data for the full sample period from 2000-2013 to explore whether selective reporting biases the findings. I find very similar results in this subsample, with a one percent increase in low-skilled wages associated with a 0.37 percent decline in the recidivism risk.

In columns 1 and 2 of Table 10, I explore whether I find similar results splitting the sample before and after the Great Recession. Given the housing and related construction boom pre-2007 and subsequent bust post-2007, the availability of low-skilled jobs differed greatly across these two time periods. The effects of higher low-skilled wages on recidivism persist across both time periods, although I find somewhat larger wage effects during the housing boom.

Next, I analyze several sources of potential bias. One concern is if the timing of release from prison is correlated with local economic conditions, as mentioned previously in Section 4. For instance, state parole boards may let out certain lower-risk prisoners earlier during worse economic times. If these early release prisoners also have a lower propensity to recidivate, I may underestimate the effects of local economic conditions on recidivism.[18] To test the magnitude of this bias, I replicate my main results on a subsample of states in which there is no discretion in prison release date. As of the beginning of my sample period, 16 states had abolished discretionary parole for almost all offenders: Arizona, California, Delaware, Florida, Illinois, Indiana, Kansas, Maine, Minnesota, Mississippi, North Carolina, Ohio, Oregon, Virginia, Washington, and Wisconsin.[19] NCRP prison spell data are available for all these states except for Virginia. In column 3 of Table 10, I replicate the preferred specification in these 15 states with no discretionary parole. I find similar and larger results in this sample of states, with a one percent increase in wages reducing the recidivism risk by 0.81 percent, suggesting that correlation between the timing of release and economic conditions may in fact underestimate the true impact of labor market conditions on recidivism. The estimate in this subsample suggests that the typical business cycle growth in real wages reduces the risk of recidivism by 4.0 percent.

A second potential source of bias comes from the unobservable propensity to commit crime during different economic conditions. An offender who commits an offense during good economic times is likely unobservably different from one who commits an offense during bad economic times. If local conditions affect the initial entry into prison of individuals with particular unobserved characteristics, and economic conditions at entry and exit are correlated, my estimates may be biased by selection. To partially test for this source of bias, I explore whether correlation

[18]The only state with an official early release policy in the last decade is California, whose Realignment program did not begin until the end of my sample. Absent an official policy, parole boards are not authorized to explicitly consider economic conditions in making parole decisions.

[19]See http://www.bjs.gov/content/reentry/releases.cfm.

in local labor market conditions at the time of the offense and the time of release can explain my results. In column 4 of Table 10, I replicate the main specification but add additional controls for log county average wages both in the quarter-year of admission to prison and lagged one year to account for the delay from offense commission to prison admission.[20] I find that current wages are still highly predictive of recidivism risk even after controlling for historical conditions, suggesting that correlation between past and current labor market conditions cannot fully account for my findings.[21] In column 5, I also find similar results restricting the sample to individuals who served at least three years in prison given that correlation in economic conditions fades after roughly three years (Oreopoulos et al. 2012).

In column 6, I assess to what extent selective migration across county borders may bias my estimates. In this specification, I control for both county wages and average wages of all other counties in the same commuting zone. I find nearly identical estimates to my preferred specification, suggesting that selective migration is not a large source of bias in this setting.

In Appendix Table 3, I explore the sensitivity of my results to alternative measures of ex-offender labor demand: log low-skilled employment per capita,[22] and log wages of men with strictly less than a high school degree, log wages of all men, and log wages of new hires in each quarter. I also consider a Bartik-style wage to address the concern that county-level demand for low-skilled workers, as measured by log wages, may be endogenous to recidivism rates. For example, high-income individuals or employers may leave areas with higher crime rates, or employers may have to pay more to workers in high crime areas. To identify exogenous variation in low-skilled labor demand, I construct wages that weight average state wages (excluding own county) for low-skilled men (less than college degree) in each industry with county-specific shares of low-skilled men in those industries following Bartik (1991), Blanchard and Katz (1992), and Aizer (2010), among others. Intuitively, variation in this alternative wage measure captures the fact that state-level increases in wages for workers in a particular industry will lead to larger predicted increases in wages in counties with a higher share of low-skilled men (a proxy for ex-offenders) in those industries. Results are qualitatively similar using these alternative measures of labor demand.

Finally, in Appendix Table 4, I present results under different regression models using the offender sample. I estimate ordinary least squares specifications for the probability of returning to custody within three years of release and one year of release. Because ordinary least squares models do not allow for time-varying covariates, I control for local average wages in the first

[20]Unfortunately, the NCRP data do not contain information on when the offense was committed or when the prisoner was arrested. However, the BJS estimates that the median time from arrest to sentencing for felony convictions in state court was 265 days in 2006. See http://www.bjs.gov/content/pub/pdf/fssc06st.pdf.

[21]In addition, I find that labor economic conditions in the quarter of prison admittance are positively correlated with recidivism risk, suggesting that offenders who commit crimes during good economic times are higher-risk.

[22]A regression of log low-skilled employment on log low-skilled monthly wages, controlling for county and year fixed effects, yields a coefficient of 0.394.

quarter post-release.[23] I find a negative and statistically significant relationship between average wages in the quarter of release and the probability of recidivism within either three years or one year of release. I also estimate a censored regression model for the log time until return to prison (censored at 36 months post-release) controlling for log wages in the quarter of release. Under this model, I find that higher average wages in the quarter of release are associated with a longer time until return to prison, consistent with a lower risk of recidivism. These results indicate that my findings are robust across different specifications.[24]

## 6. Conclusion

This paper estimates the impact of local labor market conditions on criminal recidivism using administrative data on over four million released offenders. Estimating the transition back into prison, I find that ex-offenders are responsive to local earnings opportunities experienced upon release from prison. The typical wage growth during a business cycle decreases the risk of recidivism by 2.3 to 4.0 percent. These results are robust to accounting for unobserved county differences and underlying county trends, and are largely driven by wage increases in sectors that report a willingness to hire ex-offenders. In addition, I find that the results are unlikely to be explained by selective release of certain types of prisoners during good or bad economic times, or changes in policing and corrections activity.

These findings are largely consistent with a literature establishing a negative relationship between improvements in economic conditions and aggregate crime rates, but suggest that ex-offenders in particular are responsive to improvements in local labor market opportunities. In contrast, these findings differ slightly from an experimental literature that finds mixed evidence of an effect of job assistance or transitional jobs on recidivism. While this paper is not able to precisely identify the magnitude of a direct employment effect on recidivism, there is evidence that labor market improvements lead to increased employment among ex-offenders and low-skilled men (Sabol 2007, Holzer and Offner 2002). The difference in results may be driven by this paper's ability to measure the effects of regular labor market opportunities for ex-offenders rather than job search assistance

[23] In unreported results, I test the dynamic impact of labor market conditions on three-year recidivism by controlling for labor market conditions experienced in the quarter of release, and conditions in the one, two, and three years post-release. I find that conditions in the quarter of release have the largest impact on recidivism.

[24] The estimates from the OLS results are very similar in magnitude compared to the main hazard results. For example, the three-year OLS results suggest that a one percent increase in wages is associated with a 0.05 percentage point decrease in the probability of returning to prison. Transforming the main hazard estimates (column 3 of Table 4) into a three-year cumulative survival probability suggests that a one percent increase in wages in every quarter of release is associated with a 0.06 percentage point decrease in the probability of returning to prison. In contrast, estimates from the censored regression model are smaller than the hazard model estimates. A one percent increase in wages increases the log time until return to prison by 0.18 percent under the censored regression model versus 0.46 percent under the hazard model.

or a temporary subsidized job, which rarely leads to a regular unsubsidized job, highlighting the importance of employer demand.

Overall, the findings suggest that the release of a large number of ex-offenders during the Great Recession likely had substantial consequences for recidivism, particularly because of contractions in industries traditionally open to hiring ex-offenders, such as manufacturing and construction.[25] Between the fourth quarter of 2007 and the first quarter of 2009, real average monthly earnings for low-skilled men fell by 12 percent, with real wages in the construction and manufacturing sectors falling by 19 percent and 12 percent, respectively. Even by the first quarter of 2013, real wages for low-skilled men remained depressed, still six percent less than in the fourth quarter of 2007. The estimates in this paper suggest that compared to a counterfactual in which real wages remained constant, the recidivism risk of offenders released during the Great Recession increased by 5.5 to 9.6 percent. With approximately one million offenders released during the Recession, the heightened recidivism rate during depressed economic times may account for at least an additional 55,000 offenders returning to prison within the coming years. Among those offenders who recidivate, the average time served upon return to prison is over one year. With an average cost of $30,000 to house an inmate in state prison, these offenders may entail over $1.6 billion in costs, in addition to decreases to public safety.

One limitation of this paper is that it only measures the impact of local labor markets on criminal recidivism. Improved employment and earnings prospects likely also impact non-criminal outcomes. In addition, this paper is unable to identify the precise mechanisms through which labor market opportunities affect recidivism. Analyzing the impact of the direct employment channel as well as the effect of other components of successful offender reintegration, such as access to housing and public assistance, is an important area for future research.

[25] "We have a record high number of people coming out of prison each year into the highest rate of unemployment since the Great Depression," said Marc Mauer of the nonprofit Sentencing Project. "As difficult as the recession has been on people, it's twice as difficult for people with a felony to make it in this economy." See http://articles.latimes.com/2010/nov/30/business/la-fi-felon-jobs-20101130.

## References


[1] Abadie, Alberto, Matthew M. Chingos, and Martin R. West. 2014. "Endogenous Stratification in Randomized Experiments." NBER Working Paper No. 19742.

[2] Aizer, Anna. 2010. "The Gender Wage Gap and Domestic Violence." American Economic Review, 100(4): 1847-59.

[3] Austin, James, and Robert Lawson. 1998. "Assessment of California Parole Violations and Recommended Intermediate Programs and Policies." San Francisco: National Council on Crime and Delinquency.

[4] Bartik, Timothy J. 1991. Who Benefits from State and Local Economic Development Policies? Kalamazoo, Michigan: W. E. Upjohn Institute for Employment Research.

[5] Beck, Allen J., and Bernard E. Shipley. 1990. Recidivism of Prisoners Released in 1983. Bureau of Justice Statistics.

[6] Blanchard, Olivier J., and Lawrence F. Katz. 1992. "Regional Evolutions." Brookings Papers on Economic Activity, 1992(1): 1-61.

[7] Blank, Rebecca M., and Patricia Ruggles. 1996. "When Do Women Use Aid to Families with Dependent Children and Food Stamps? The Dynamics of Eligibility Versus Participation." Journal of Human Resources, 31(1): 57-89.

[8] Bonczar, Thomas, and Lauren Glaze. 1999. Probation and Parole in the United States 1998. Bureau of Justice Statistics.

[9] Card, David, Raj Chetty, and Andrea Weber. 2007. "The Spike at Benefit Exhaustion: Leaving the Unemployment System or Starting a New Job?" American Economic Review, 97(2): 113-118.

[10] Card, David, and Phillip B. Levine. 2000. "Extended Benefits and the Duration of UI Spells: Evidence from the New Jersey Extended Benefit Program." Journal of Public Economics, 78: 107-138.

[11] Carson, E. Ann, and Daniela Golinelli. 2013. Prisoners in 2012: Trends in Admissions and Releases, 1991-2012. Bureau of Justice Statistics.

[12] Cook, Philip J., Songman Kang, Anthony A. Braga, Jens Ludwig, and Mallory E. O'Brien. 2014. "An Experimental Evaluation of a Comprehensive Employment-Oriented Prisoner Re-entry Program." Journal of Quantitative Criminology, 31(3): 355-382.

[13] Corman, Hope, and Naci Mocan. 2005. "Carrots, Sticks, and Broken Windows." Journal of Law and Economics, 48(1): 235-266.

[14] Durose, Matthew R., Alexia D. Cooper, and Howard N. Snyder. 2014. Recidivism of Prisoners Released 30 States in 2005: Patterns from 2005 to 2010. Bureau of Justice Statistics.

[15] Freedman, Matthew, and Emily Owens. Forthcoming. "Your Friends and Neighbors: Localized Economic Development and Criminal Activity." Review of Economics and Statistics.

[16] Freeman, Richard. 2003. Can We Close the Revolving Door?: Recidivism vs. Employment of Ex-Offenders in the U.S. Urban Institute Reentry Roundtable.

[17] Gould, Eric D., Bruce A. Weinberg, and David B. Mustard. 2002. "Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997." Review of Economics and Statistics, 84(1): 45-61.

[18] Grogger, Jeff. 1998. "Market Wages and Youth Crime." Journal of Labor Economics, 16(4): 756-791.

[19] Harding, David, Jessica Wyse, Cheyney Dobson, and Jeffrey Morenoff. 2014. "Making Ends Meet After Prison." Journal of Policy Analysis and Management, 33(2): 440-470.

[20] Holzer, Harry J., Steven Raphael, and Michael A. Stoll. 2003. Employment Barriers Facing Ex-Offenders. Urban Institute Reentry Roundtable.

[21] Holzer, Harry J., Steven Raphael, and Michael A. Stoll. 2004. "How Willing are Employers to Hire Ex-Offenders?" Focus, 23(2): 40-43.

[22] Hoynes, Hilary Williamson. 2000. "Local Labor Markets and Welfare Spells: Do Demand Conditions Matter?" Review of Economics and Statistics, 82(3): 351-368.

[23] Kahn, Lisa. 2010. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy." Labour Economics, 17(2): 303-316.

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

[25] Langan, Patrick A., and David J. Levin. 2002. Recidivism of Prisoners Released in 1994. Bureau of Justice Statistics.

[26] Lynch, James P., and William J. Sabol. 2001. Prisoner Reentry in Perspective. Urban Institute Crime Policy Report.

[27] Machin, Stephen, and Costas Meghir. 2004. "Crime and Economic Incentives." Journal of Human Resources, 39(4): 958-979.

[28] Mallar, Charles D., and Craig V. D. Thornton. 1978. "Transitional Aid for Released Prisoners: Evidence from the Life Experiment." Journal of Human Resources, 13(2): 208-236.

[29] Mechoulan, Stephane, and Nicolas Sahuguet. 2015. "Assessing Racial Disparities in Parole Release." Journal of Legal Studies, 44(1): 39-74.

[30] Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." Econometrica, 58(4): 757-782.

[31] Myers, Samuel L. 1983. "Estimating the Economic Model of Crime: Employment Versus Punishment Effects." Quarterly Journal of Economics, 98(1): 157-166.

[32] Neal, Derek, and Armin Rick. 2014. "The Prison Boom and the Lack of Black Progress after Smith and Welch." NBER Working Paper No. 20283.

[33] Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." American Economic Journal: Applied Economics, 4(1): 1-29.

[34] Pager, Devah. 2003. "The Mark of a Criminal Record." American Journal of Sociology, 108(5): 937-975.

[35] Petersilia, Joan. 2003. When Prisoners Come Home: Parole and Prisoner Reentry. New York: Oxford University Press.

[36] Pfaff, John F. 2011. "The Myths and Realities of Correctional Severity: Evidence from the National Corrections Reporting Program on Sentencing Practices." American Law and Economics Review, 13(2): 491-531.

[37] Raphael, Steven, and Weiman, David F. 2007. "The Impact of Local Labor Market Conditions on the Likelihood that Parolees Are Returned to Custody." In S. Bushway, M. A. Stoll, and D. Weiman (Eds.), Barriers to Reentry? The Labor Market for Released Prisoners in Post-Industrial America. New York: Russell Sage Foundation.

[38] Raphael, Steven, and Rudolf Winter-Ebmer. 2001. "Identifying the Effect of Unemployment on Crime." Journal of Law and Economics, 44(1): 259-283.

[39] Raphael, Steven. 2010. "Improving Employment Prospects for Former Prison Inmates: Challenges and Policy." NBER Working Paper No. 15874.

[40] Redcross, Cindy, Megan Millenky, et al. 2012. "More Than a Job: Final Results from the Evaluation of the Center for Employment Opportunities (CEO) Transitional Jobs Program." New York, NY. U.S. Department of Health and Human Services.

[41] Rhodes, William, Gerald Gaes, Jeremy Luallen, Ryan Kling, Tom Rich, and Michael Shively. 2014. "Following Incarceration, Most Released Offenders Never Return to Prison." Crime and Delinquency, 1-23.

[42] Rosenfeld, R., J. Wallman, and R. Fornango. 2005. "The Contribution of Ex-Prisoners to Crime Rates." In Prisoner Reentry and Crime in America, ed. Travis, Jeremy, and Visher, Christy Ann. New York: Cambridge University Press.

[43] Sabol, William J.. 2007. "Local Labor Market Conditions and Post-Prison Employment: Evidence from Ohio." In S. Bushway, M. A. Stoll, and D. Weiman (Eds.), Barriers to Reentry? The Labor Market for Released Prisoners in Post-Industrial America. New York: Russell Sage Foundation.

[44] Schnepel, Kevin. "Good Jobs and Recidivism." Economic Journal, forthcoming.

[45] Uggen, Christopher. 2000. "Work as a Turning Point in the Life Course of Criminals: A Duration Model of Age, Employment, and Recidivism." American Sociological Review, 67: 529-546.

[46] Walmsley, Roy. 2013. World Prison Population List (Tenth Edition). International Centre for Prison Studies.

[47] Wang, Xia, Daniel P. Mears, and William D. Bales. 2010. "Race-Specific Employment Contexts and Recidivism." Criminology, 48(4): 1171-1211.

[48] Western, Bruce. 2006. Punishment and Inequality in America. New York: Russell Sage Foundation.

[49] Visher, Christy, Sara Debus, and Jennifer Yahner. 2008. Employment After Prison: A Longitudinal Study of Releasees in Three States. Urban Institute Research Brief.

Table 1. Distribution of Time Until Return to Prison

| | | Probability of Return to Prison in | | | |
|---|---|---|---|---|---|
| | No. of Obs | $\leq$ 1 Year | $\leq$ 2 Years | $\leq$ 3 Years | $\leq$ 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.

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.

Table 3. Balance of Released Offender Characteristics

| | Male | Black | Prior Incarceration | Violent Offense | Property Offense | Predicted Risk | Wage At Entry |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Log Low-Skill Wage | $-0.014^{**}$ | $0.037^{*}$ | $-0.006$ | $0.001$ | $0.009$ | $-0.004$ | $0.221^{***}$ |
| | $(0.007)$ | $(0.022)$ | $(0.026)$ | $(0.010)$ | $(0.010)$ | $(0.006)$ | $(0.010)$ |
| Observations | 3,930,386 | 3,699,618 | 2,749,224 | 3,917,461 | 3,917,461 | 3,931,394 | 3,891,208 |

Notes: This table presents results from OLS regressions of released offender characteristics on labor market conditions. Each column represents a separate regression. Specifications include year of release fixed effects and county fixed effects. Standard errors are clustered at the county level.

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.

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.

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 Yr 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.

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 Yr 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.

Table 8. Committing New Offenses

| | Any New | New Violent | New Property | New Drug |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log Low-Skill Wage | $-0.517^{***}$ | $-0.598^{***}$ | $-0.402^{***}$ | $-0.540^{***}$ |
| | $(0.086)$ | $(0.126)$ | $(0.087)$ | $(0.100)$ |
| 3 Yr Recidivism | 0.109 | 0.024 | 0.035 | 0.030 |
| Observations | 39,485,395 | 41,538,130 | 41,236,156 | 41,376,059 |
| Defendant Controls | Yes | Yes | Yes | Yes |
| Crime Controls | Yes | Yes | Yes | Yes |

Notes: This table presents proportional hazard estimates for the full sample 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.

Table 9. Alternative Specifications

| | County Trends | County Controls | County Arrests | No Supervision | State*Year FE | MSA*Year FE | Balanced Panel |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| Log Low-Skill Wage | $-0.390^{***}$ | $-0.428^{***}$ | $-0.417^{***}$ | $-0.508^{***}$ | $-0.437^{***}$ | $-0.466^{***}$ | $-0.542^{***}$ |
| | $(0.046)$ | $(0.045)$ | $(0.053)$ | $(0.098)$ | $(0.043)$ | $(0.038)$ | $(0.077)$ |
| Observations | 34,872,568 | 34,872,568 | 32,032,664 | 10,552,881 | 34,872,568 | 34,872,568 | 19,373,650 |
| Defendant Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crime Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table presents proportional hazard estimates for the full sample of prisoners released between 2000-2013 in 43 states. Each column represents a separate specification. Column 1 adds county-specific linear trends to the specification from column 4 in Table 4. Column 2 adds county-year controls for per capita personal income, and personal current transfer receipts. Column 3 adds county-year arrests and county-quarter prison admissions. Column 4 estimates the main specification for offenders who served the full expiration of their sentence and are not released into community supervision. Column 5 adds state-by-year fixed effects. Column 6 adds MSA-by-year fixed effects. Column 7 estimates the main specification on offenders released in 18 states that provided data every year from 2000-2013. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.

Table 10. Alternative Specifications

| | Released < 2007 | Released ≥ 2007 | No Parole | Economic Lags | Time Served ≥ 3 Yrs | Spatial Lags |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log Low-Skill Wage | $-0.536^{***}$ | $-0.433^{***}$ | $-0.809^{***}$ | $-0.429^{***}$ | $-0.375^{***}$ | $-0.457^{***}$ |
| | (0.068) | (0.086) | (0.106) | (0.060) | (0.081) | (0.061) |
| Observations | 16,770,682 | 18,101,886 | 14,419,088 | 34,389,865 | 6,946,388 | 34,753,567 |
| 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 full sample of prisoners released between 2000-2013 in 43 states. Each column represents a separate specification. Column 1 estimates the main specification on offenders released between 2000-2006. Column 2 estimates the main specification on offenders released between 2007-2013. Column 3 estimates the main specification on offenders released in 15 states with no discretionary parole. Column 4 estimates the main specification adding controls for labor market conditions in the quarter-year of prison admission and lagged one year before admission. Column 5 estimates the main specification of offenders who served at least three years in prison. Column 6 adds a spatial lag for the log low-skilled wage in the relevant commuting zone, excluding the county of conviction. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.

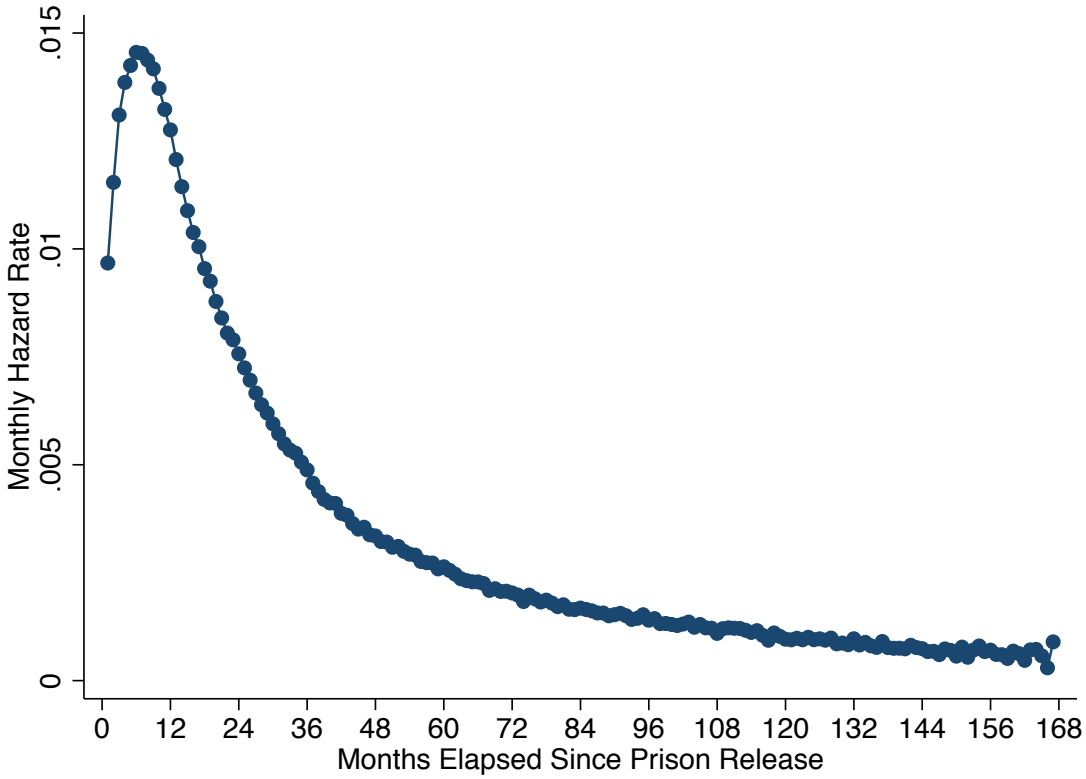


Figure 1. Hazard for Probability of Returning to Prison

*Notes*: Data are from the NCRP for prisoners released from 2000-2013. This figure calculates the unconditional probability of returning to prison in each month post-release conditional on having not yet returned to prison.

Appendix Table 1. States in NCRP Data on Prison Spells

| State | Years Data Provided |
|---|---|
| Alabama | 2007-2013 |
| Alaska | 2005-2012 |
| Arizona | 2000-2012 |
| California | 2000-2013 |
| Colorado | 2000-2013 |
| Delaware | 2009-2013 |
| Florida | 2000-2013 |
| Georgia | 2000-2013 |
| Idaho | 2008-2012 |
| Illinois | 2000-2003 |
| Indiana | 2002-2013 |
| Iowa | 2002-2013 |
| Kansas | 2011-2013 |
| Kentucky | 2000-2013 |
| Maine | 2012-2013 |
| Maryland | 2000-2012 |
| Massachusetts | 2010-2013 |
| Michigan | 2000-2013 |
| Minnesota | 2000-2013 |
| Mississippi | 2004-2013 |
| Missouri | 2000-2013 |
| Montana | 2010-2013 |
| Nebraska | 2007-2013 |
| Nevada | 2009-2013 |
| New Hampshire | 2011-2013 |
| New Jersey | 2003-2013 |
| New Mexico | 2010-2013 |
| New York | 2000-2013 |
| North Carolina | 2000-2013 |
| North Dakota | 2002-2013 |
| Ohio | 2009-2013 |
| Oklahoma | 2000-2013 |
| Oregon | 2001-2013 |
| Pennsylvania | 2001-2013 |
| Rhode Island | 2004-2013 |
| South Carolina | 2000-2013 |
| South Dakota | 2000-2012 |
| Tennessee | 2000-2013 |
| Texas | 2005-2013 |
| Utah | 2000-2013 |
| Washington | 2000-2013 |
| West Virginia | 2000-2013 |
| Wisconsin | 2000-2013 |
| Wyoming | 2006-2013 |

Notes: This table lists the states and years available in the NCRP data.

Appendix Table 2. Results by Risk Index

| | Below Median | Above Median |
|---|---|---|
| | (1) | (2) |
| Log Low-Skill Wage | $-0.413^{***}$ | $-0.433^{***}$ |
| | $(0.116)$ | $(0.060)$ |
| 3 Yr Recidivism | 0.13 | 0.38 |
| Observations | 16,602,563 | 16,514,692 |
| Defendant Controls | Yes | Yes |
| Crime Controls | Yes | Yes |

Notes: This table presents proportional hazard estimates for the full sample of prisoners released between 2000-2013 in 43 states. Each column represents a separate specification. Predicted risk is estimated in a five percent split sample, as described in the text. All specifications include year and county fixed effects. Standard errors are clustered at the county level.

Appendix Table 3. Alternative Labor Market Measures

| | Log | Log Wage | | | |
|---|---|---|---|---|---|
| | Emp/Pop | Men $<$ HS | All Men | New Hires | Bartik |
| | (1) | (2) | (3) | (4) | (5) |
| | $-0.198^{**}$ | $-0.392^{***}$ | $-0.264^{***}$ | $-0.163^{***}$ | $-0.721^{***}$ |
| | $(0.089)$ | $(0.060)$ | $(0.057)$ | $(0.029)$ | $(0.068)$ |
| Observations | 34,872,568 | 34,877,608 | 34,877,608 | 34,823,809 | 32,323,386 |
| Defendant Controls | Yes | Yes | Yes | Yes | Yes |
| Crime Controls | Yes | Yes | Yes | Yes | Yes |

Notes: This table presents proportional hazard estimates for the full sample of prisoners released between 2000-2013 in 43 states. Each column represents a separate specification. Column 1 controls for the log employment to population ratio. Column 2 controls for log average wages of men with less than a high school degree. Column 3 controls for log average wages of all men. Column 4 controls for log average wages of new hires at the beginning of the quarter. Column 5 controls for log wages that weight average state wages (excluding own county) for low-skilled men in each industry with county-specific shares of low-skilled men in those industries. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.

Appendix Table 4. Alternative Models

| | OLS 3 Yrs | OLS 1 Yr | Censored Log Time |
|---|---|---|---|
| | (1) | (2) | (3) |
| Log Low-Skill Wage | $-0.050^{***}$ | $-0.024^{**}$ | $0.180^{**}$ |
| | $(0.013)$ | $(0.010)$ | $(0.079)$ |
| Observations | 2,954,439 | 3,617,565 | 3,931,394 |
| Defendant Controls | Yes | Yes | Yes |
| Crime Controls | Yes | Yes | Yes |

Notes: This table presents alternative models for the full sample of prisoners released between 2000-2013 in 43 states. Each column represents a separate specification. Column 1 presents results from an OLS specification for the probability of return to custody within three years of release. Column 2 presents results from an OLS specification for the probability of return to custody within one year of release. Column 3 presents results from a censored normal regression for log time out of prison. Specifications include demographic, crime, and prison characteristics. All specifications include year and county fixed effects. Standard errors are clustered at the county level.