JOB MARKET PAPER

Labor Market Opportunities and Crime: Evidence from Parolees

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March 8, 2013

Abstract

Identifying a causal effect of labor market opportunities on criminal behavior is difficult given (a) an endogenous relationship between labor markets and crime and (b) the challenge of using aggregate measures to capture employment opportunities for individuals on the margin of criminal activity. The institutional structure of the California criminal justice system as well as location-, skill-, and industry-specific employment measures provide a unique framework to identify a causal effect. I find that a one-standard-deviation increase in the prevalence of *relevant* employment opportunities is associated with a 1 percentage point decrease in the probability that released offenders will return to prison within one year.

JEL Classification codes: J01, J08, J18, J21, J24, J48, J61, J68, K14, K42

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Funding for this research was generously provided by a research grant jointly administered by the American Statistical Association and the U.S. Bureau of Justice Statistics.

1 Introduction

In theory, employment opportunities and criminal behavior should be negatively related (Becker, 1968; Ehrlich, 1973; Grogger, 1998; Burdett et al., 2004). However, identifying the causal effect of employment opportunities on crime is difficult because readily-available variables such as unemployment rates and employment-to-population ratios may not capture the relevant opportunities for individuals on the margin of criminal activity. Criminal activity may also directly impact employment opportunities.[1]

Using data on individuals released from prison in California for the period 1993 through 2008, I examine the relationship between employment opportunities and the probability a released offender returns to prison. This unique data set allows me to address the dual challenges of reverse causality and the accurate measurement of labor market opportunities. Specifically, the rigid institutional features of the California criminal justice system provide a setting in which the timing and location of release from prison are plausibly exogenous to variation in local labor market conditions. Moreover, low levels of completed education among paroled offenders and limited employer demand for criminal applicants allow me to obtain a more specific measure of *relevant* employment opportunities. I find that skill- and industry-specific economic conditions at the time of labor market entry are important determinants of recidivism among recently-released prisoners who are required to return to their prior county of residence.[2]

Overall, I find that a one percentage point increase in the ratio of *relevant* employment to the population of working-age county residents (a measure of job density) is associated with a four percent decrease in the probability of returning to prison within one year for working-age men released from prison in California from 1993 through 2008. This finding is particularly interesting

[1] In a recent review of the literature, Mustard (2010) discusses reverse causality concerns and also emphasizes the need for studies that use variables that truly measure the labor market opportunities for individuals on the margin of legal and illegal activity. Mustard (2010) also provides a thorough explanation of potential mechanisms for bias arising from reverse causality and omitted variables, and discusses several papers addressing these biases.

[2] Applying a similar identification strategy, Oreopoulos, von Wachter and Heisz (2012) find that economic conditions at the time of labor market entry are important determinants of short- and long-term earnings for college graduates. The identification assumptions are more assured in my setting since prisoners released in California cannot choose their immediate post-incarceration location.

since I do not detect a statistically significant change in recidivism associated with changes in less relevant employment or with changes in wages. A one percentage point increase in the relevant job density measure is not uncommon; the average standard deviation in the annual job density measure of interest across all counties in California is 0.9 percentage points. Holding other factors constant, my estimates predict that 5.5 percent more parolees returned to prison from 2008 through the second quarter of 2010 as a result of the 1.3 percentage point decline in relevant employment opportunities in California during the most recent recession (Q1 2008 through Q2 2009).[3] These estimates also imply that an offender released to a county in the 90th percentile of relevant job opportunities would be 27 percent less likely to return to prison within one year than an identical offender released to a county in the 10th percentile of relevant job opportunities.[4]

Many empirical studies have explored the relationship between aggregate employment fluctuations and crime, and results vary across empirical specifications and populations. Despite clear theoretical predictions, most studies estimating the relationship between crime rates and unemployment rates typically find a precise but small effect for property crime and no effect for violent crime in standard OLS regression models (Freeman, 1995; Raphael and Winter-Ebmer, 2001; Donohue and Levitt, 2001; Gould et al., 2002; Machin and Meghir, 2004; Levitt, 2004; Öster and Agell, 2007; Lin, 2008). However, several papers report estimates from instrumental variable (IV) models two to three times larger than the OLS estimates, suggesting that OLS estimates are biased downwards (Raphael and Winter-Ebmer, 2001; Öster and Agell, 2007; Lin, 2008). Moreover, researchers focusing on released prisoners find substantively small effects of unemployment rates (or employment-to-population ratios) on recidivism rates (Bolitzer, 2005; Raphael and Weiman, 2007).[5] My estimates using skill- and industry-specific employment measures help explain these mixed results.

[3]The average change in county low-skill parole-industry employment (weighted by the working-age population) from January 2008 to June 2009 is calculated to be 1.3 percentage points using the Quarterly Workforce Indicator data (discussed in Section 4).

[4]I calculated the average job density measure of interest for the period 1993 through 2009 for each county. The 90th percentile job density measure is 12.1 percent and the 10th percentile is 5.6 percent, a difference of 6.5 percentage points. Since I find that a one percentage point increase in this measure is associated with a 4.2 percent decrease in recidivism, this difference would imply a (6.5×4.2) 27.3 percent difference in the probability of returning to prison within one year of release, holding all else constant.

[5]Bushway (2011) reviews research that has consistently found that "the average criminal is not very responsive to work incentives."

First, I provide a potential explanation for the large disparity between estimates from instrumental variable (IV) models and those from OLS specifications. Through choosing an instrumental variable involving an interaction between manufacturing employment and a macroeconomic shock, Raphael and Winter-Ebmer (2001), Öster and Agell (2007) and Lin (2008) each estimate a parameter measuring the effect of unemployment on the criminal behavior of individuals affected by a shock to the manufacturing sector.[6] My results suggest that parolees are sensitive to fluctuations in employment opportunities in the manufacturing sector and a few other industries. It is likely that a substantial fraction of those affected by changes in manufacturing opportunities may be individuals on the margin of criminal activity. Therefore, the local average treatment effects identified in the IV specifications may not be very informative about the overall effect of a change in employment on the rate of crime.

Second, despite predictions from life course theories on employment as a turning point in the life of an ex-convict, prior researchers find little evidence of a relationship between aggregate employment opportunities and recidivism (Bolitzer, 2005; Raphael and Weiman, 2007). My results illustrate that these prior findings can be attributed to the use of measures which do not accurately reflect job opportunities for a population of ex-offenders. My results also support recent experimental evaluations of transitional employment programs which find a decrease in recidivism among certain types of offenders (Western, 2008; Raphael, 2010).

In addition to providing methodological implications for the large labor market and crime literature, estimates specific to released prisoners are of interest in their own right. More than 700,000 felons were released from prison in the United States during 2010, and likely had difficulties finding full-time employment.[7] Released prisoners are also large contributors to the overall crime rate. Us-

[6] Lin (2008) reports results from models using six different instruments in Table 6 of his paper. The instruments used are (1) real exchange rate change*state employee percentage in the manufacturing sector; (2) real exchange rate*state GDP percentage in the manufacturing sector; (3) real exchange rate change*state union membership percentage; (4) oil price*state employee percentage in the manufacturing sector; (5) oil price*state GDP percentage in the manufacturing sector; and (6) oil price*state union membership percentage. Overall, models using instruments involving a state's employee percentage in the manufacturing sector yield the largest estimates. Results from (3) and (6), using union membership rates are also much larger than OLS estimates. This is not surprising since industries more likely to hire individuals with criminal records, such as manufacturing, also have higher rates of union membership.

[7] According to the "Prisoners in 2010" report prepared by the Bureau of Justice Statistics, 708,677 prisoners were

ing data from a national recidivism study, Rosenfeld et al. (2005) found that prisoners released in 1994 accounted for more than 10 percent of all arrests for property crime and more than 15 percent of arrests for violent crime from 1994 through 1997—an alarming rate considering this group represented less than 0.5 percent of the U.S. adult population. If offense rates were similar for prisoners released in years before and after 1994, these estimates would suggest that a substantial portion of crime can be attributed to recently-released prisoners. Furthermore, the population of individuals with a criminal record has increased rapidly over the past few decades, and recent research suggests that a criminal record can compound the effects of racial discrimination and deepen economic disadvantages for young African American men applying for jobs (Pager, 2003; Pager et al., 2009). It is now estimated that 25 percent of African Americans and 6 percent of non-African Americans have a felony conviction (Shannon et al., 2012). My results for African Americans suggest that diminished access to relevant job opportunities contributes to the large racial differences in crime and recidivism rates.[8]

This paper is organized as follows. In Section 2, I briefly review theoretical predictions on labor markets and crime that guide my empirical work. Section 3 describes the institutional setting of parole in California, and Section 4 describes the offender and labor market data used in my analysis. I outline my empirical methodology and describe my labor market measures of interest in Section 5. I discuss the estimates from several econometric specifications in Section 6 and provide concluding remarks in Section 7. Finally, I include several robustness checks and estimates from alternative specifications in the Appendix.

released from state and federal correctional facilities during 2010 (Guerino et al., 2012).

[8]Two recent papers in the criminology literature have investigated whether racial differences in recidivism rates can be attributed to racial differences in manufacturing job opportunity (Wang et al., 2010; Bellair and Kowalski, 2011). Using a Cox proportional hazards model, Bellair and Kowalski (2011) find that lower availability of manufacturing jobs in areas where black offenders are released can explain much of the racial differences in recidivism for a sample of 1,568 offenders released in Ohio during the first six months of 1999.

2 Theoretical Perspectives on Labor Markets and Crime

The standard economic model of criminal behavior predicts that if released offenders make choices between labor, leisure, and crime, then an increase in job availability should decrease the amount of time devoted to criminal behavior since the opportunity cost of time spent in both criminal activity and in prison if caught rises (Becker, 1968; Ehrlich, 1973; Grogger, 1998). These theories predict an inverse relationship between labor market conditions and crime.[9] Mustard (2010) and Bushway (2011) provide recent reviews of a large empirical literature within economics and criminology that test these predictions.

Other theories of criminal behavior include predictions specific to individuals with criminal records. Engelhardt (2010) modifies an on-the-job search model of crime first proposed by Burdett, Lagos and Wright (2004) to evaluate how employment frictions affect crime among two types: criminals and non-criminals. An increase in job opportunities for individuals just released from prison would reduce employment frictions and reduce recidivism in the context of Engelhardt's job search model. Moreover, life course theories from the sociology and criminology literature emphasize employment as a turning point in the life of an ex-convict that reduces criminal behavior by encouraging non-criminogenic social ties (Laub and Sampson, 1993; Uggen, 2000). Recent research in the life course literature also suggests that work effects are not uniform across age groups and predict a larger change in criminal behavior among older offenders presented with employment opportunities (Uggen, 2000). I am able to assess these predictions by estimating separate specifications for released prisoners based on their age at the time of release.

My approach is also related to literature on the Spatial Mismatch Hypothesis (SMH), which asserts that employment opportunities for low-income individuals are frequently located away from their residences, leading to low rates of employment (Kain, 1968; Ihlanfeldt and Sjoquist, 1990). The SMH has previously been used as a framework to explain spatial variation in crime by estimating

[9] A few researchers discuss ways in which improvements in economic conditions can *increase* criminal behavior. Crime could increase if improving labor market conditions provide more opportunities to steal (when people are at work) and increase the value of the objects typically stolen (i.e. your neighbor buys a brand new car) (Freedman and Owens, 2012; Cantor and Land, 1985). Procyclical increases in alcohol consumption could also cause increases in crime (Cook and Zarkin, 1985).

the relationship between "accessible" jobs and criminal activity (Ihlanfeldt, 2006, 2007). Although accessibility measures have traditionally been defined using only the location of employment relative to the location of residence, Gould, Weinberg and Mustard (2002) combine the location of jobs with skill requirements to estimate the relationship between low-skill employment rates and county crime rates in the United States. I use an approach similar to that of Ihlanfeldt (2006, 2007) by defining accessible jobs along three dimensions: the location of the job relative to the county of required parole supervision, the skill requirements of the job, and the propensity of employers in the industry to consider criminal applicants.

While I focus on employment ratios in this paper, theoretical models of work and crime also predict an inverse relationship between expected legal earnings and criminal activity. Many empirical studies focus on earnings rather than employment rates.[10] In empirical models including skill-specific wages and unemployment rates, Gould, Weinberg and Mustard (2002) and Machin and Meghir (2004) find that low-skill wages explain more of the variation in crime rates than unemployment rates. Recently, Mocan and Unel (2011) estimate large elasticities between low-skill earnings and criminal activity using both aggregate panel data and longitudinal individual-level data. Although changes in wages likely contribute to changes in recidivism rates, reentry programs as well as prior research almost exclusively focus on employment opportunities for released offenders (Western, 2008). I focus the following analysis on the effect of fluctuations in employment opportunities on recidivism among paroled offenders in California but also include skill- and industry-specific measures of earnings in all of my empirical models and report their estimated coefficients.[11]

[10]The review by Mustard (2010) provides a comprehensive discussion of research that estimates the impact of earnings measures on crime.

[11]Since employment and earnings could be jointly determined, I estimate models excluding earnings measures and obtain estimates very similar to those reported in this paper. My econometric strategy is designed to identify the effects of short-term shocks to the labor market measures of interest. Wages change slowly over time, making it difficult to obtain precise estimates of the relationship between wages and recidivism given my empirical models.

3 Parole in California

Prior to the passing of a determinate sentencing law in 1976, the decision to release an offender to parole supervision before the completion of his or her sentence was made by a parole board.[12] The 1976 law eliminated this discretionary step for the majority of prisoners and required released offenders to complete a mandatory post-prison parole term, regardless of whether the offender was released before the completion of his prison sentence. During the time period of my analysis, the length of time a convicted offender spends in prison is solely determined by his sentence and the amount of time subtracted for good behavior.[13]

Parole supervision is typically required for three years from the date of prison release for individuals incarcerated in California, although the Board of Parole Hearings (BPH) releases many offenders from supervision after 13 months.[14] The basic requirements of parole to which all California parolees must adhere include: immediately reporting to the assigned parole agent in the offender's last legal county of residence, reporting any address or employment change to the parole agent, and obeying all parole agent instructions (Grattet, Petersilia and Lin, 2008). Some parolees are subject to other special requirements such as drug and alcohol testing, registration as a sex offender, or not associating with gang members.

A released offender must return to his last county of legal residence in California unless he applies for and receives permission to relocate. Throughout my analysis I use the county of sentencing as a proxy for each individual's location post-release. The county of sentencing is likely the offender's county of pre-incarceration residence, given evidence from the criminology literature on criminal mobility.[15] Raphael and Weiman (2007) analyze prisoners released in California and document that

[12] The Uniform Determinate Sentencing Act, SB 42, passed in 1976 and became effective during 1977, beginning the "Determinate Sentencing Era" in California.

[13] Good behavior time can be up to 50 percent for nonviolent offenders and 15 percent for a violent offense, but this has changed over time. From a regression model with the percentage of sentence served as a dependent variable (Appendix Table 11), it does not appear that good behavior time is manipulated based on local economic conditions.

[14] The Board of Parole Hearings consists of 17 commissioners appointed by the Governor and confirmed by the California State Sentate. Commissioners sometimes conduct revocation hearings themselves, but most BPH reviews are made by Deputy Commissioners.

[15] Papers investigating the distance between a crime committed and a place of residence has consistently found that a crime is most often within a few miles of the offender's residence (Bernasco et al., 2012; Wiles and Costello, 2000). A difference in the county of residence and county of sentencing would most likely introduce measurement

more than 90 percent of prisoners released are returned to the county of sentencing.

The key outcome in my analysis is recidivism, defined as a return to prison. The Bureau of Justice Statistics measures recidivism as "criminal acts that result in the rearrest, reconviction, or return to prison with or without a new sentence during a three-year period following the prisoner's release." Since my data does not include individual arrest data, I use the "return to prison" version of the recidivism definition.[16] To avoid any selection bias caused by the early release of certain offenders from parole supervision, I focus my analysis on outcomes during the first year of parole but also report estimates from models with two- and three-year outcomes. The majority of offenders who eventually return to prison do so within the first year.

If a parolee violates any of the supervision requirements he or she can be sent back to prison, but most returns in California are the result of a criminal violation (rather than a technical parole violation). An in-depth study of the California parole system during 2003 and 2004 by Grattet, Petersilia and Lin (2008) found that 84 percent of the parolees who returned to prison committed at least one criminal violation.[17]

4 Data

4.1 Offender Data

I use prison release and parole outcome data from the National Corrections Reporting Program (NCRP) for prisoners released from 1993 through 2008 (Bureau of Justice Statistics, 2009). The NCRP provides information on *every* prisoner entering and exiting the custody of the California Department of Corrections and consists of three separate individual-level data sets: prison admis-

error and attenuate my estimates.

[16]Note that this recidivism definition is contingent on a parolee returning to prison in California. Since released offenders are required to complete their parole supervision within their county of residence, it is unlikely that any offenders supervised through the California parole system would be returned to a prison outside of the state correctional system.

[17]This calculation is based on my own tabulation of the restricted data from the study available through the Interuniversity Consortium for Political and Social Research (ICPSR) (Study #27161). The data is described in detail by Grattet, Petersilia and Lin (2008). For offenders released for the first time onto parole for a conviction, 89 percent of parolees reincarcerated return because of some criminal violation.

sions (Part 1), prison releases (Part 2), and parole releases (Part 3). I observe whether an individual released from prison in California returns to prison within a specified time period by matching the prison release record with a parole release record using a combination of three variables common to each data set: exact date of birth, exact date of prison release, and county of sentencing.[18]

I focus my analysis on a selected subsample of the population of individuals released from a California State Correctional Facility during the years 1993 through 2008. For reasons discussed below, analysis on this subsample is preferable to an analysis that includes all prison releases. Still, results for the total population are provided in the Appendix and are similar to the results for my preferred subsample.

Figure 1 illustrates the construction of my final estimation sample. First, I limit my analysis to working-age (18 to 65) males released to mandatory parole supervision—who represent close to 90 percent of all prison releases from 1993 through 2008 (steps 1 through 3, Figure 1). I further limit my sample by focusing my analysis on individuals serving the first parole supervision term associated with a sentence imposed by a criminal court (step 4, Figure 1). Due to very high return rates in California, the majority of individuals on parole at any given time have already returned to prison at least once. I eliminate this large group of parolees from my estimation sample since additional prison time served as the result of a parole failure is relatively short (less than 12 months) and determined by the Board of Parole Hearings. The amount of time served on a parole revocation could be influenced by local labor market conditions, threatening my identification strategy discussed in the next section. Similarly, in order to avoid bias caused by short-term persistence of labor market conditions, I estimate models only for those sentenced to at least 2 years in prison (step 5, Figure 1). Finally, I eliminate any individuals who participated in a community release program (such as a

[18]The combination of date of birth, date of release, and county of sentencing is unique for all but 0.15 percent of the total number of observations. These observations are deleted from my analysis. Also, approximately 5 percent of individuals released from prison to parole are never observed in the parole release data set. This could be due to measurement error or these offenders have not yet been released from parole supervision. Individuals still on parole after three years of supervision are likely parole absconders, meaning they have violated their parole supervision agreement but cannot be located. The NCRP does not allow me to observe whether or not a parolee absconds supervision. My models treat all individuals who do not return to prison within one year as still on parole supervision. Estimates from models dropping potential absconders (individuals not observed in the parole release data set within three years of release) yield similar results.

halfway house) since these individuals could search and find work prior to the start of their parole term.

Table 1 provides descriptive statistics for the entire population of offenders released from a California state prison between 1993 and 2008 and for my estimation sample. An alarming number of prisoners released return to prison and do not successfully complete their parole supervision with nearly two-thirds returning to prison while on parole (65.6%). More than half (51.7%) of those released return within one year from their date of release. The majority of prisoners in California are male, and are fairly evenly distributed among race and ethnicity classifications (black, white, Hispanic). Almost every prisoner is released to mandatory parole supervision (a discretionary parole release is only available for individuals with a life sentence), and the average sentence is around three years (38.65 months). The majority of individuals are incarcerated for a property or drug crime with only 10 percent of those released having been convicted of a violent crime for their most serious offense.[19]

Table 1 also allows comparisons along selected observable characteristics between the population of offenders released from prison and my estimation sample. There are important differences between my final estimation sample and all individuals released from prison in California. The individuals in my sample are less likely to return to prison: 36 percent of the individuals in my estimation sample return to prison within one year, while 51 percent of all prisoners released are back in prison within a year. This difference can be mostly attributed to eliminating individuals who are on their second or higher parole term for a conviction. Also, due to the two-year-minimum sentence restriction, violent criminals comprise a greater portion of my estimation sample. The racial composition of the estimation subsample differs with fewer black and white offenders, but more Hispanic parolees. However, despite these differences, the general reincarceration patterns persist with higher return rates among the young, black, and those incarcerated for property crimes.[20] The final estimation sample of 424,536 releases represents a large and important fraction of individuals released from

[19]I classify the type of offender by the conviction offense carrying the longest sentence if there are multiple convictions.

[20]Return rates (within one year) for my estimation sample by demographic characteristic or conviction offense are provided at the top of each regression for each group.

prison in California.

4.2 Labor Market Data

The Quarterly Workforce Indicator (QWI) data set provides quarterly employment totals and average earnings by county, industry, and skill level (United States Census Bureau LEHD Program, 2011). This data set offers several advantages over traditionally used county unemployment rates or total employment levels.[21] First, the county unemployment rates, available through the Local Area Unemployment Statistics (LAUS) program at the Bureau of Labor Statistics (BLS), are thought to be measured with error since the rates are imputed using self-reported data from the Current Population Survey (CPS) and various other data sources (Bartik, 1996).[22] In contrast, the QWI tabulates employment levels and earnings that firms report to the California Unemployment Insurance (UI) program, which represents more than 99 percent of wage and salary civilian employment in the state.[23] Since the UI employment records do not contain information on demographic characteristics of each employee, the Longitudinal Employer-Household Dynamics (LEHD) program links records from state unemployment insurance programs to Census Bureau data to provide a longitudinal employment and earnings database with demographic characteristics. The QWI data set is an aggregated version of this individual-level data, providing more precise measures of labor market conditions for different types of workers than the traditionally used labor market data.[24]

For each of the 192 potential release months between January 1993 and December 2008, I create forward-looking 12-month averages of county employment levels and earnings. I then calculate job density measures equal to the average number of jobs in a county relative to the population of working-age residents. I provide a detailed description of the various job density measures used in my analysis in the following empirical methodology section. Since my analysis focuses on the

[21] The Census Bureau publishes the QWI data at lehd.did.census.gov/led/ . The complete set of QWI data is available for downloading through the Cornell Virtual Reasearch Data Center at www.vrdc.cornell.edu/qwipu/ .

[22] LAUS county unemployment rates are imputed using the "handbook method." More information is available at www.bls.gov/lau/laumthd.htm .

[23] Employment counts by month, county, and industry are also available from the Quarterly Census and Wage (QCEW) data provided by the BLS. This data is formerly known as "202 data" and comes from state UI systems. However, unlike the QWI data, the QCEW data does not include counts by the education level of the employee.

[24] For a full description of QWI data and imputation methods used for missing data see Abowd et al. (2009).

availability of jobs rather than wages, I only provide formulas below for the job density measures in the discussion. Wage measures are calculated using the same methodology.

5 Empirical Methodology

5.1 Total Job Density

To estimate the effect of job density and expected earnings on parole outcomes, I first estimate the following logistic regression model:

$$ln\left(\frac{p_{ict}}{1-p_{ict}}\right) = \alpha + \beta JD_{ct} + \delta W_{ct} + X'_{ict}\Pi + \phi_t + \theta_c + \tau_c t + u_{ict} \tag{1}$$

where $p_{ict} = Pr(\text{return within 1 yr}_{ict} = 1)$ is the probability of reincarceration within one year of release for parolee i, sentenced in county c, leaving prison in month t. JD_{ct}, a measure of job density, is the average ratio of total county employment to the population of working-age residents for the first 12 months after release from prison.[25] W_{ct} is the natural log of monthly wages (adjusted for inflation) for all employed individuals in county c during the quarter of release. The coefficient, δ, measures the elasticity of the odds of reincarceration to a percent change in average monthly wages while β measures the effect of one percentage point change in the county job density on the probability of reincarceration for a paroled offender.

Fixed effects for year-by-month of release, ϕ_t, and county of sentencing, θ_c, are included in all specifications. I focus my discussion on specifications including county-specific linear trends, τ_c, but estimates are also reported from models that exclude county-specific trends as well as specifications including both county-specific linear and quadratic trends. X'_{ict} is a vector of control variables that include individual demographic characteristics, criminal history and length of incarceration, and other county-level determinants of parolee behavior discussed in more detail in Section 6.1. To account for correlation within counties over time, I cluster standard errors at the county-level in all

[25]This is simply an employment-to-population ratio where the denominator is the working-age (18-65) population rather than the total population.

empirical specifications.

5.2 Skill-Specific Job Density

The total county-level job density, JD_{ct}, may not accurately reflect employment opportunities relevant to a released offender since many types of jobs are inaccessible to the average parolee. Work that requires a high school diploma or a more advanced degree is not likely relevant to the typical parolee since more than 50 percent of incarcerated individuals have not finished high school. Estimates of the educational attainment of prisoners in California are provided by the 2004 wave of the Survey of Inmates in State and Federal Correctional Facilities (SISFCF). More than 80 percent of incarcerated individuals have not been educated past high school levels and 51 percent are high school dropouts.

Using the skill-specific employment numbers in the QWI data, I obtain an employment measure that better reflects work opportunities for recently-released prisoners. I define low-skill (LS) employment opportunities as jobs requiring a high-school diploma or less.[26] I calculate the average low-skill job density for the first year outside prison for an offender released in county c and month t as follows:

$$JD_{ct}^{LS} = \frac{1}{12}\sum_{\tau=t}^{t+11}\frac{\text{Low-Skill Employed}_{c\tau}}{\text{Wk Age Population}_{c\tau}}.$$

I also calculate a measure for high-skill job density and skill-specific average earnings, and estimate the following logistic regression model:

$$\begin{aligned} ln\left(\frac{p_{ict}}{1-p_{ict}}\right) =& \alpha + \beta^{LS}JD_{ct}^{LS} + \beta^{HS}JD_{ct}^{HS} + \delta^{LS}W_{ct}^{LS} + \delta^{HS}W_{ct}^{HS} \\ &+ X_{ict}'\Pi + \phi_t + \theta_c + \tau_c t + u_{ict} \end{aligned} \tag{2}$$

where all of the other variables are as described after Eq. 1.

[26] I provide estimates from a regression model in which I redefine low-skill as jobs held by individuals without a high school diploma in the robustness checks presented in the Appendix.

5.3 Skill- and Industry-Specific Job Density

The labor market opportunities for paroled offenders are limited by low levels of education, so the low-skill job density measure provides a more accurate reflection of employment opportunities for this population than the aggregate measure. Still, a significant fraction of low-skill job openings may also be irrelevant to individuals recently released from prison. Certain employers are prohibited by law from hiring convicted felons, and many others choose not to consider applicants with criminal records.[27]

In addition to providing information about the educational attainment of the California prison population, the SISFCF lists an inmate's most recent occupation held for at least two weeks as reported by the offender. I use this information, along with an indicator as to whether the inmate was previously employed while on parole, to identify industries more likely to employ parolees. Since the SISFC data set only provides occupational information for parolees who eventually return to prison, I use this survey only to identify relevant industries, not to obtain precise estimates of parolee employment.

To identify industries relevant to California parolees searching for work, I combine the occupations reported in the SISFCF with information on the industrial concentration of these occupations in the 2000 U.S. Census. First, I estimate the probability of employment in a particular occupation conditional on being employed while on parole.[28] Table 2 lists the top 10 parole occupations (by three-digit census occupation codes) for the California inmates surveyed in 2004 and indicates that nearly 40 percent were unemployed during the month preceding their arrest.[29] Parolees are typically

[27]Bushway and Sweeten (2007) estimate that employment of convicted felons is prohibited for approximately 800 occupations across the country. A 2003 survey of California employers found that 60 percent of employers always check the criminal backgrounds of job applicants and over 70 percent of employers would "probably not accept" or "definitely not accept" an individual with a criminal record for the most recent non-professional, non-managerial job openning (Raphael 2010).

[28]I first count the number of surveyed inmates who reported that they were on parole prior to their current incarceration and who were employed within the month prior to their arrest. I then calculate the fraction of this group within each occupation code. This provides a conditional probability for each three-digit census occupation code: the probability a surveyed inmate was employed in occupation k conditional on being on parole and employed prior to his current incarceration spell.

[29]This is lower than unemployment rates reported in data matching Unemployment Insurance (UI) administrative records to released prisoners in other states (Pettit and Lyons, 2007; Sabol, 2007; Tyler and Kling, 2007). The true unemployment rate at the time of arrest would be slightly higher since the time frame of the SISFCF survey question

employed in low-skill occupations such as freight and construction work, cooking, mechanics, and maintenance.[30] Not surprisingly, such occupations are overwhelmingly held by individuals with low levels of education.[31]

Next, I estimate the concentration of parolee employment by industry using the occupation information contained in the SISFCF survey. Since employment levels by occupation codes are not included in the QWI data, I combine the occupational concentration of California inmates surveyed in the SISFCF with the distribution of each occupation across industries in California from the 2000 Census to estimate the industrial concentration of parolee employment in California.[32] Estimates of the industrial composition of parolee employment are presented in Table 3. It appears that parolees most often find work in the construction, manufacturing, retail, and food service sectors. Due to the concentration of parolee job opportunities in specific industries, I separate these industries from other industries in my empirical analysis. I define parole industries as those estimated to employ more than five percent of the employed parolees in the SISFCF. In total, I categorize seven industries as parole friendly: construction, manufacturing, retail trade, other services, administrative and waste services, accommodations and food services, and transportation and warehousing. I estimate that nearly 80 percent of inmates who reported having a job while on parole prior to their current incarceration spell were employed in one of these seven industries.

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is within the month before arrest. This discrepancy could be explained by employment among released offenders who are not covered by the state unemployment insurance systems—only 80 percent of inmates who report having been employed report full-time employment. Furthermore, over 20 percent of inmates report income from illegal activities, and may report the source of their income as a "job" or a "business." It is possible that my estimates over report pre-incarceration employment rates, but the occupation distribution of parolee jobs would be skewed only if inmates misreported their type of pre-incarceration occupation types.

[30]These occupations are consistent with the types of vocational training programs in the California correctional system. A table of inmate vocational programs in 2007 is available in the LAO report, "From Cellblocks to Classrooms: Reforming Inmate Education To Improve Public Safety." Available at www.lao.ca.gov/2008/crim/inmate_education/inmate_education_021208.pdf .

[31]Based on my own calculations from the 2000 U.S. Census, more than 30 percent of individuals within these occupations do not have a high school diploma or GED certificate, almost three times greater than the portion of high school dropouts across all occupations in the U.S.

[32]To estimate the probability an inmate was employed in a particular two-digit industry code, I first count the number of individuals employed in a particular occupation for each county in California according to the 2000 Census. Then, I calculate the fraction of those employed in a given occupation in each 2-digit industry code. This fraction represents a conditional probability: the probability that an individual is employed in industry j conditional on being employed in occupation k. I then multiply this conditional probability by the probability that a surveyed inmate who was previously employed and on parole was employed in occupation k. Finally, to obtain the probability that a previously employed parolee was in industry j, I add this product over all occupations for each industry.

Using the skill- and industry-specific employment levels available in the QWI data, I calculate skill-specific job density measures for both parole industries and non-parole industries. The job density measure for low-skill parole industries for an offender sentenced in county c and released in month t is calculated as follows:

$$JD_{ct}^{P,LS} = \frac{1}{12}\sum_{\tau=t}^{t+11}\sum_{j=1}^{J}\frac{\text{Low-Skill Employed}_{cj\tau}}{\text{Wk Age Population}_{c\tau}}$$

where, j $\in${construction, manufacturing, retail trade, other services, administrative and waste services, accommodations and food services, transportation and warehousing}.

I am able to isolate the effects of changes in low-skill (LS) job opportunities in the parole industries (P) from changes in job opportunities for which a paroled offender is not qualified or is unlikely to be considered by including the low-skill parole industry job density and earnings measures along with low-skill (LS), non-parole (NP) industry measures and high-skill (HS) measures and estimate the following model:

$$\begin{aligned} ln\left(\frac{p_{ict}}{1-p_{ict}}\right) =& \alpha + \beta^{LS,P}JD_{ct}^{LS,P} + \beta^{LS,NP}JD_{ct}^{LS,NP} + \beta^{HS}JD_{ct}^{HS} \\ &+ \delta^{LS,P}W_{ct}^{LS,P} + \delta^{LS,NP}W_{ct}^{LS,NP} + \delta^{HS}W_{ct}^{HS} \\ &+ X_{ict}'\Pi + \phi_t + \theta_c + \tau_c t + u_{ict}. \end{aligned} \tag{3}$$

Equation 3 is identical to Equation 2 with the exception of a decomposition of the low-skill job density and earnings measures into two types: parole friendly and non-parole friendly. The first and second empirical models are nested in the third as indicated by the following equality:

$$JD_{ct}^{LS,P} + JD_{ct}^{LS,NP} + JD_{ct}^{HS} = JD_{ct}^{LS} + JD_{ct}^{HS} = JD_{ct}.$$

Figure 2 displays the contribution of each component of the job density measure to the total state-wide job density measure for the period 1993 through 2009. Throughout this period of analysis, approximately 10 percent of the California working age population is made up of low-skill parole industry employees. Figure 2 helps illustrate why aggregate employment measures are poor measures of employment opportunities for individuals with criminal records who are searching for work—a large fraction of the variation in the aggregate measures is due to changes in employment that are not relevant to the population analyzed. Figure 3 decomposes the contribution of each of the seven parole industries to the low-skill employment density in California. Manufacturing jobs represent the largest category of parole industry employment at the beginning of the analysis period (1993), but the sector experienced a large decline over the 16-year period. It appears that much of the decline in the low-skill job density for the parole industries can be attributed to the decline in manufacturing employment in California. However, the contribution of manufacturing employment to the decline in parole industry employment varies across counties. Recent studies by criminologists have recognized the importance of the manufacturing industry to the ex-offender population and isolate the effect of manufacturing employment on recidivism (Wang et al., 2010; Bellair and Kowalski, 2011).

5.4 Identification of Job Density Parameters

I interpret the variation in job densities used to identify the effects of employment opportunities on recidivism as arising from changes in aggregate labor demand that are uncorrelated with the criminal propensity or other characteristics of different prison release cohorts. My analysis controls for unobserved differences between prisoners released at different times at the state level as well as changes to any state parole policies by including year-by-month fixed effects. The labor market effects in each of the models specified are identified from deviations in employment density (or earnings) from an arbitrary common trend across counties, and deviations from within-county trends.

My identification strategy requires variation in industry specific low-skill job density across counties and within counties over time. To give a sense of this variation, Figure 4 plots low-skill parole industry and low-skill non-parole industry employment for four California counties:

Los Angeles, San Bernadino, Santa Clara, and Fresno.[33] Clearly, there is variation both across and within counties in the job density measures of interest. Although trends in low-skill jobs for parole and non-parole industries are similar, it appears that there is sufficient variation to separately identify the effects of different types of low-skill job growth on recidivism. Figure 5 shades California counties by the percent change in parole industry low-skill employment over the period of analysis, and Figure 6 provides a map of counties by the percent change in parolee recidivism. The largest decreases in low-skill parole industry employment appear to be somewhat concentrated in the central and northern regions of the state. The northern regions also appear to have experienced the greatest increase in recidivism rates over the time period.

While I address several potential biases and present robustness checks in an appendix, two primary threats to my identification strategy deserve attention here. First, estimates of the job density parameters could be biased if unobserved criminogenic characteristics of the community to which the prisoner is released are correlated with both recidivism and labor market conditions. To assess whether unobserved criminogenic factors, such as changes in the market for crack cocaine or changes in policing strategies, are influencing my results, I estimate an additional specification including a quadratic polynomial of the county crime rate just prior to release. It is reasonable to assume that any unobserved criminogenic factors would be correlated with the amount of crime in the community so including the crime rate as a control should influence the estimated effect of the labor market measures if there is an omitted variable bias arising.

Another important threat to my identification strategy arises from the relationship between conditions at the time the prisoner committed his original crime and conditions at the time of his release. Persistence in economic conditions could bias the estimated effects of labor market conditions at the time of release. In order to test whether my results are influenced by such a relationship, I estimate a specification including the labor market job density (and earnings) measures at the time of prison admission.

I do not find any evidence of a bias from either of these threats and present results from these

[33] These four counties were chosen to illustrate within-state differences in industrial composition and employment trends.

two models in the following section. I also address other threats to my identification strategy in the Appendix, including: whether the timing of release from prison is affected by changes in local employment densities; whether my results could be biased by offenders not returning to the county of sentencing; and whether my results are sensitive to my classification of accessible jobs by type and location. Additionally, I report results from an analysis of the entire population of offenders, using two- and three-year recidivism outcomes as the dependent variable of interest and a linear probability model as well as a probit specification in the Appendix. Overall, the variation in the job density measures appears to be independent of potential confounding factors, and my main results discussed in the next section are robust against alternative specifications.

6 Results

NOTE: I am adding tables and changing the discussion of the magnitude of the results to reflect marginal effects at the mean, rather than the below interpretation of the exponentiated logit coefficients

First, I estimate the relationship between aggregate job density (Eq. 1) and whether a parolee returns to prison within a year (Table 4). Results are presented without county-specific trends (Col. 1), with county-specific linear trends (Col. 2), and with county-specific linear and quadratic trends (Col. 3). Although a marginally significant decrease in recidivism is detected in the specification without county trends, the estimated coefficient becomes indistinguishable from zero once county trends are included. Changes in aggregate job density appear to have very little effect on the probability of returning to prison.

Once the job density is disaggregated by skill level (Eq. 2), I estimate a significant decrease in recidivism associated with a one-percentage-point increase in low-skill jobs within the county of release for the first two specifications (4.9 percent decrease and 3.5 percent decrease, respectively). All estimates reported are from logit regression specifications and can be converted to odds ratios by exponentiating the reported coefficient (i.e. $\exp(-0.035) \approx 0.966$). The odds ratio can be interpreted in the following manner: an individual released when the low-skill job density is one percentage point higher is 3.44 percent less likely to recidivate within a year of release. For ease of discussion, I interpret the logit coefficient as a percent decrease associated with a one-unit change in the regressor variable.

I disaggregate low-skill job density further into a parole industry and non-parole (other) industry component (Eq. 3) and present the estimated coefficients for the labor market measures in the third panel of Table 4. As predicted from the standard economic model of crime, recidivism rates are most responsive to changes in low-skill jobs in industries that have a greater tendency to employ parolees. Estimates are similar across models that do not include trends, county-specific linear trends, or both linear and quadratic county-specific trends. Although the estimate is no longer statistically distinguishable from zero once a county-specific quadratic trend is included (p-value is 0.101), the size of the effect is consistent with estimates from the other models. Across each specification, I estimate approximately a 4-percent decrease in the probability of recidivism associated with a one-percentage-point increase in the low-skill parole industry job density. Furthermore, Appendix Table 8 reports estimated coefficients from a model without controls and the estimates do not appear to be sensitive to inclusion of the demographic and neighborhood controls, supporting my identification assumption that the low-skill parole industry employment fluctuations are independent of individual or county determinants of recidivism.

Although I estimate a significant decrease in recidivism associated with an increase in other (non-parole) low-skill job density in the specification without county-specific trends, I do not detect effects distinguishable from zero once county trends are included in Columns 2 and 3 of Table 4. Overall, it does not appear that parolee recidivism in California is significantly affected by changes to low-skill jobs outside of the seven industries classified as parole industries. These results provide further evidence that employers willing to hire applicants with criminal records are concentrated in just a few industries. As discussed previously, most parolees would not qualify for jobs requiring an advanced degree, and I do not estimate a statistically significant relationship between changes in high-skill jobs and recidivism. The small and imprecise estimates on the high-skill job density and low-skill non-parole industry job density measures reinforce my causal interpretation of the estimated coefficients on the low-skill parole industry job density measure.

I also do not find a statistically significant relationship between wages and recidivism. Figure 7 shows wages changing gradually over the analysis period, which makes it difficult to identify the effect of a change in wages on recidivism given my empirical specification that includes time-fixed effects and time trends. Moreover, averages for skill- and industry-specific wages may not accurately measure expected wages for released offenders if individuals with criminal records are paid less than the average worker in a skill and industry category. The imprecise coefficients are also small in magnitude: a 0.1-unit increase in the log measure represents approximately a 10 percent increase in average earnings.

Tables 5 and 6 further examine the relationship between low-skill parole industry job density and recidivism for different types of parolees. They also provide evidence of heterogeneity in the effects of job availability on parolee recidivism. All specifications in Tables 5 and 6 include county fixed effects, year-by-month fixed effects, and county-specific linear trends. Results with county-specific quadratic trends are not reported since, for some of the subsamples with smaller sample sizes, logit models including county-specific quadratic trends do not converge. The average prison return rate for each group is reported at the top of each table.

I find large and significant effects for individuals incarcerated for drug crimes and do not detect a significant effect of low-skill job density on the behavior of those incarcerated for a violent offense. A one-percentage-point increase in the county low-skill parole industry job density is associated with a 9.8-percent decrease in the probability of returning to prison within one year for individuals incarcerated for drug crimes. I also estimate an increase in recidivism among property offenders associated with increasing low-skill parole industry job density.

Next, I examine whether heterogeneous effects exist across offenders based on the extent of their prior criminal history. Individuals with prior felony incarcerations appear to be more responsive to changes in low-skill parole industry job densities. However, as shown in Table 9, there is a larger response in to changes in local low-skill parole industry job densities among older offenders.

These offenders are more likely to have a prior felony conviction, so the difference in effects by past criminal history may be driven by age composition of the population analyzed. The availability of low-skill parole industry jobs does not appear to influence the probability of recidivism for offenders under the age of 25.

To investigate whether changes in low-skill parole industry job opportunities have differential effects by race and ethnicity, I separately estimate models for white (non-Hispanic), black (non-Hispanic), and Hispanic offenders. The effects of increases in low-skill parole industry jobs appear slightly more salient for black and Hispanic offenders (Table 6, Columns 1 through 3), suggesting that these jobs may provide a better measure of job opportunities for released black and Hispanic offenders. I detect a marginally significant decrease in the recidivism of white offenders associated with a increase in low-skill jobs in non-parole industries, suggesting that white applicants may have opportunities outside of the parole industries.

6.1 Non-Labor Market Determinants of Recidivism

In order to isolate the effect of changes in job density and earnings on the behavior of California parolees, I include several other individual and county variables associated with parolee deviance in all of my empirical specifications. Regression coefficients for the control variables are not reported in the main empirical tables but are reported in Appendix Table 8 for models with and without county time trends. Race and age are strong predictors of return, with black and young parolees much more likely to return to prison within a year. In addition, the type of criminal and whether he has a prior felony incarceration are strongly associated with return. Property criminals are also more likely to return to prison.

County prosperity (or economic disadvantage) could affect the resources available to parolees, attitudes toward parolee deviance, and other important influences of parolee behavior. The county fixed effects control for county characteristics that do not change over time. To control for time-varying community influences, annual measures of median household income and the percent of the population below the poverty line are included for each county, though they do not appear to be significantly associated with return rates. The number of police per capita in the county of sentencing is negatively correlated with recidivism. Unfortunately, counts of parole agents by county were not available from the California Department of Corrections. As another measure of deterrence, I include the arrest clearance rate, but it also does not appear to be a statistically significant determinant of parolee deviance.

6.2 Robustness Checks

Table 7 presents results that address the two primary endogeneity concerns introduced in Section 5.4. First, my estimates could be biased if unobserved criminogenic factors are correlated with recidivism and labor market conditions. The first column reports results from the preferred specification model (Eq. 3), including a quadratic polynomial of the average county crime rate for the six-months prior to release. Although an increase in the amount of crime in the county is positively associated with higher recidivism rates, the effect is not statistically significant. More importantly, the coefficient on the relevant job density measure does not change once I include the county crime rate—the estimate without the crime rate is -0.0422 which is very close to the -0.0417 estimated effect in the specification including the crime rate polynomial.

Second, to check whether conditions at the time of admission could bias my estimates, I limit my sample to individuals incarcerated in 1994 or later since 1993 is the first year the QWI labor market data is available. Column 2 of Table 7 reports estimates from a model including the employment measures for the year prior to prison admission. These measures should represent conditions at the time the incarceration crimes were committed. I detect a slightly larger effect from changes to low-skill parole industry job density on recidivism once admission conditions are included, alleviating any concern that my estimates are inflated by the relationship between labor market conditions pre- and post-incarceration.[34] Results from several other robustness checks are presented and discussed

[34]On average, conditions at admission are positively correlated with conditions at release. This would only exaggerate my estimates only if offenders entering prison during bad labor market conditions are more likely to recidivate than those entering during good conditions. The regression estimates in Table 7 indicate the opposite: individuals entering prison during time periods of higher levels of relevant job opportunities are more likely to return to prison within a year after release.

in the Appendix.

7 Remarks

Overall, my empirical results support predictions from the standard theoretical models that relate crime to economic incentives. They indicate that individuals recently released from prison adjust their criminal activity in response to changes in relevant labor market opportunities. This study finds a much larger response to labor market fluctuations than previous analyses of released prisoners by Raphael and Weiman (2007) and Bolitzer (2005). My findings also support predictions of heterogeneous effects across different types of offenders. First, I observe a larger effect for individuals incarcerated for drug or property crimes than for violent offenders. This finding may be due to employer demand; Holzer, Raphael and Stoll (2006) and Raphael (2010) report evidence from employer surveys suggesting that very few employers are willing to consider applicants with a violent conviction. The heterogeneous effects could also be due to supply factors; to the extent that offenders continue to commit the same types of crimes, my results support the notion that violent offenders are less motivated by economic incentives. I also find the effect of employment opportunities to vary by the age of the offender, supporting research by Uggen (2000) that documents a large difference in the response to employment opportunities by age. Furthermore, black and Hispanic offenders are more sensitive to changes in low-skill employment in parole industries, suggesting that diminished access to relevant job opportunities contribute to the large racial differences in crime and recidivism rates.[35]

Given the fact that released offenders are important contributors to the overall crime rate, my results suggest that prior instrumental variable estimates finding a four- to six-percent increase in crime associated with a one-percentage-point increase in the local unemployment rate likely overstate the expected effect of a typical change in labor market conditions. On average, a one-

[35]Two recent papers in the criminology literature have investigated whether racial differences in recidivism rates can be attributed to racial differences in manufacturing job opportunity (Wang et al., 2010; Bellair and Kowalski, 2011). Using a Cox proportional hazards model, Bellair and Kowalski (2011) find that lower availability of manufacturing jobs in areas where black offenders are released can explain much of the racial differences in recidivism for a sample of 1,568 offenders released in Ohio during the first six months of 1999.

percentage-point increase in the county unemployment rate in California is associated with a 0.17 percentage point decrease in the low-skill parole industry job density measure.[36] The true effect of a *typical* one-percentage-point increase in the unemployment rate may be closer to the one to two percent increase in crime detected in the OLS estimates. My results suggest that policies affecting certain industries or policies broadening the number of industries that are willing to hire individuals with criminal records may be more effective in reducing crime than policies stimulating aggregate employment growth at the local level.

While the effect of relevant job opportunities on criminal activity among released offenders is likely driven by the effect of finding a job on criminal behavior, my reduced form estimates also include other important structural effects such as: the effect of a change in relevant job opportunities on the probability a released offender finds a job; the social effect of criminal activity among others in the reentry community affected by the same employment fluctuations; and the effect of labor market fluctuations on the behavior of the unemployed.[37] Future research that combines location-, skill-, industry-specific employment data with detailed information on employment outcomes and criminal behavior among released offenders can tease out the structural effect of finding a job on recidivism. This is an essential parameter to evaluate reentry programs designed to provide jobs to offenders leaving prison.

[36] To calculate this relationship, I regressed the end-of-year county low-skill parole industry job density on the beginning of year low-skill parole industry job density as well as the beginning- and end-of-year county unemployment rates (available from the BLS through the LAUS program) and county fixed effects. The coefficient on the end-of-year unemployment rate can be interpreted as the average correlation between a one-percentage-point increase in the unemployment rate during the year and the low-skill parole industry job density measure.

[37] Raphael and Weiman (2007) divide their estimated effect of a one-percentage-point increase in county unemployment rates on parolee recidivism in California by an estimate from Sabol (2007) of the effect of a similar unemployment rate fluctuation on the probability an offender released in Ohio in 1999 or 2000 is employed post-release. This approach assumes that the relationship between unemployment rates and parolee employment is similar in California and Ohio and that the reduced form effect is *only* the product of two structural effects: the effect of employment conditions on the probability a released offender finds a job and the effect of finding a job on recidivism. While Raphael and Weiman (2007)are cautious in their interpretation of their back-of-the-envelope estimate, the reduced form effect should also include a social multiplier effect if the employment (and criminal behavior) of a released offender's peer group is also affected by similar labor market fluctuations—Drago and Galbiati (2012) estimated a large social multiplier effect of crime among offenders released from prison in Italy. Additionally, this approach assumes that an improvement in labor market conditions does not effect crime rates among unemployed parolees.

References

Abowd, John M., Bryce E. Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L. McKinney, Marc Roemer, and Simon Woodcock, *The LEHD infrastructure files and the creation of the Quarterly Workforce Indicators*, University of Chicago Press, 2009.

Bartik, Timothy J., "The Distributional Effects of Local Labor Demand and Industrial Mis: Estimates Using Individual Panel Data," *Journal of Urban Economics*, 1996, *40* (2), 150–178.

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

Bellair, Paul E. and Brian R. Kowalski, "Low-Skill Employment Opportunity and African American-White Difference in Recidivism," *Journal of Research in Crime and Delinquency*, 2011, *48* (2), 176–208.

Bernasco, Wim, Richard Block, and Stijn Ruiter, "Go Where the Money is: Modeling Street Robbers' Location Choices," *Journal of Economic Geography*, 2012, *12* (2), 1–25.

Bolitzer, Benjamin, "Essays on Crime, Incarceration and Labor Markets." PhD dissertation, University of California, Los Angeles 2005. ID number: 0496157035.

Burdett, Kenneth, Ricardo Lagos, and Randall Wright, "An On-The-Job Search Model Of Crime, Inequality, And Unemployment," *International Economic Review*, 2004, *45* (3), 681–706.

Bureau of Justice Statistics, "National Corrections Reporting Program Series 1993-2009," http://www.icpsr.umich.edu/icpsrweb/NACJD/series/38/studies/30799?archive=NACJD&sortBy=7 2009.

Bushway, Shawn D., "Labor markets and crime," in James Q. Wilson and Joan Petersilia, eds., *Crime and Public Policy*, Oxford University Press, 2011, pp. 183–209.

Cantor, David and Kenneth C. Land, "Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis," *American Sociological Review*, 1985, pp. 317–332.

Cook, Phillip J. and Gary A. Zarkin, "Crime and the Business Cycle," *Journal of Empirical Legal Studies*, 1985, *14*, 115.

Donohue, John and Steven Levitt, "Legalized Abortion and Crime," *Quarterly Journal of Economics*, 2001, *116* (2), 379–420.

Drago, Francesco and Roberto Galbiati, "Indirect Effects of a Policy Altering Criminal Behavior: Evidence from the Italian Prison Experiment," *American Economic Journal: Applied Economics*, 2012, *4* (2), 199–218.

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

Engelhardt, Brian, "The Effect of Employment Frictions on Crime," *Journal of Labor Economics*, 2010, *28* (3), 677–718.

Freedman, Matthew and Emily Owens, "Your Friends and Neighbors: Localized Economic Development, Inequality, and Criminal Activity," 2012.

Freeman, Richard, "The Labor Market," in James Q. Wilson and Joan Petersilia, eds., *Crime*, San Francisco, California: ICS Press, 1995, pp. 171–192.

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

Grattet, Ryken, Joan Petersilia, and Jeffrey Lin, "Parole Violations and Revocations in California," Technical Report 224521, National Institute of Justice 2008.

Grogger, Jeff, "Market Wages and Youth Crime," *Journal of Labor Economics*, 1998, *16* (4), 756–791.

Guerino, Paul, Paige M. Harrison, and WIlliam J. Sabol, "Prisoners in 2010," in "Prisoners Series" Bureau of Justice Statistics 2012.

Holzer, Harry J, Steven Raphael, and Michael A Stoll, "Perceived Criminality, Criminal Background Checks, and the Racial Hiring Practices of Employers," *Journal of Law and Economics*, 2006, *49* (2), 451–480.

Ihlanfeldt, Keith R, "Neighborhood Crime and Young Males' Job Opportunity," *Journal of Law and Economics*, 2006, *49* (1), 249–283.

_ , "Neighborhood Drug Crime and Young Males' Job Accessibility," *The Review of Economics and Statistics*, 2007, *89* (1), 151–164.

_ **and David L Sjoquist**, "Job accessibility and Racial Differences in Youth Employment Rates," *The American Economic Review*, 1990, *80* (1), 267–276.

Kain, John F, "Housing Segregation, Negro Employment, and Metropolitan Decentralization," *The Quarterly Journal of Economics*, 1968, *82* (2), 175–197.

Laub, John H. and Robert J. Sampson, "Turning Points in the Life Course: Why Change Matters to the Study of Crime," *Criminology*, 1993, *31*, 301.

Levitt, Steven D., "Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not," *The Journal of Economic Perspectives*, 2004, *18* (1), 163–190.

Lin, Ming-Jen, "Does Unemployment Increase Crime?," *Journal of Human Resources*, 2008, *43* (2), 413–436.

Machin, Stephen and Costas Meghir, "Crime and Economic Incentives," *Journal of Human Resources*, 2004, *39* (4), 958–979.

Mocan, Naci H. and Bulent Unel, "Skill-biased Technological Change, Earnings of Unskilled Workers, and Crime," *NBER Working Papers*, 2011, (No. 17605).

Mustard, David B, "How Do Labor Markets Affect Crime?: New Evidence on an Old Puzzle," *IZA Discusson Papers*, 2010, (No. 4856).

Oreopoulos, Phillip, Till von Wachter, and Andrew Heisz, "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

ΩÖster and Agell

Öster, Anna and Jonas Agell, "Crime and Unemployment in Turbulent Times," *Journal of the European Economic Association*, 2007, *5* (4), 752–775.

Pager, Devah, "The Mark of a Criminal Record," *American Journal of Sociology*, 2003, *108* (5), 937–975.

_ **, Bruce Western, and Naomi Sugie**, "Sequencing Disadvantage: Barriers to Employment Facing Young Black and White Men with Criminal Records," *The ANNALS of the American Academy of Political and Social Science*, 2009, *623* (1), 195–213.

Pettit, Becky and Christopher J. Lyons, "Status and the Stigma of Incarceration: The Labor-Market Effects of Incarceration, by Race, Class, and Criminal Involvement," in Shawn D. Bushway, Michael A. Stoll, and David F. Weiman, eds., *Barriers to Reentry? The labor market for released prisoners in post-industrial America*, The Russell Sage Foundation, 2007, pp. 203–226.

Raphael, Steven, "Improving Employment Prospects for Former Prison Inmates: Challenges and Policy," *NBER Working Papers*, 2010, (No. 15874).

_ **and David F. Weiman**, "The Impact of Local Labor Market Conditions on the Likelihood that Parolees are Returned to Custody," in Shawn D. Bushway, Michael A. Stoll, and David F.

Weiman, eds., *Barriers to Reentry? The Labor Market for Released Prisoners in Post-Industrial America*, The Russell Sage Foundation, 2007, pp. 304–332.

— **and Rudolf Winter-Ebmer**, "Identifying the Effect of Unemployment on Crime," *Journal of Law and Economics*, 2001, *44* (1), 259–283.

Rosenfeld, Richard, Joel Wallman, and Robert Fornango, "The Contribution of Ex-Prisoners to Crime Rates," in Jeremy Travis and Christy Visher, eds., *Prisoner Reentry and Crime in America*, Cambridge University Press, 2005, pp. 80–104.

Sabol, William J, "Local Labor-Market Conditions and Post-Prison Employment Experiences of Offenders Released from Ohio State Prisons," in Shawn D. Bushway, Michael A. Stoll, and David F. Weiman, eds., *Barriers to Reentry? The labor market for released prisoners in post-industrial America*, The Russell Sage Foundation, 2007, pp. 257–303.

Shannon, Sarah, Cristopher Uggen, Melissa Thompson, Jason Schnittker, and Michael Massoglia, "Growth in the U.S. Ex-Felon and Ex-Prisoner Population 1948 to 2010," *Demography (forthcoming)*, 2012.

Tyler, John H. and Jeffrey R. Kling, "Prison-Based Education and Reentry into the Mainstream Labor Market," in Shawn D. Bushway, Michael A. Stoll, and David F. Weiman, eds., *Barriers to Reentry? The labor market for released prisoners in post-industrial America*, The Russell Sage Foundation, 2007, pp. 227–256.

Uggen, Christopher, "Work as a Turning Point in the Life Course of Criminals: A Duration Model of Age, Employment, and Recidivism," *American Sociological Review*, 2000, pp. 529–546.

United States Census Bureau LEHD Program, "Quarterly Workforce Indicators, 1993-2010," http://www.vrdc.cornell.edu/qwipu/ 2011.

Wang, Xia, Daniel P. Mears, and William D. Bales, "Race-Specific Employment Contexts and Recidivism," *Criminology*, 2010, *48* (4), 41.

Western, Bruce, "From Prison to Work: A Proposal for a National Prisoner Reentry Program," *The Hamilton Project*, 2008, (Discussion Paper 2008-16).

Wiles, Paul and Andrew Costello, "The 'road to nowhere': the evidence for traveling criminals," *UK Home Office Research Study 207*, 2000.

8 Tables and Figures

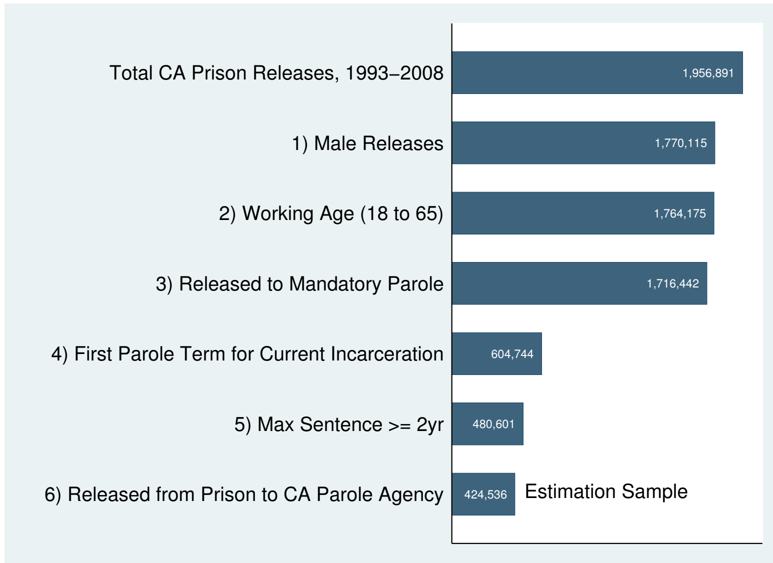

Figure 1: Construction of Estimation Sample, 1993-2008

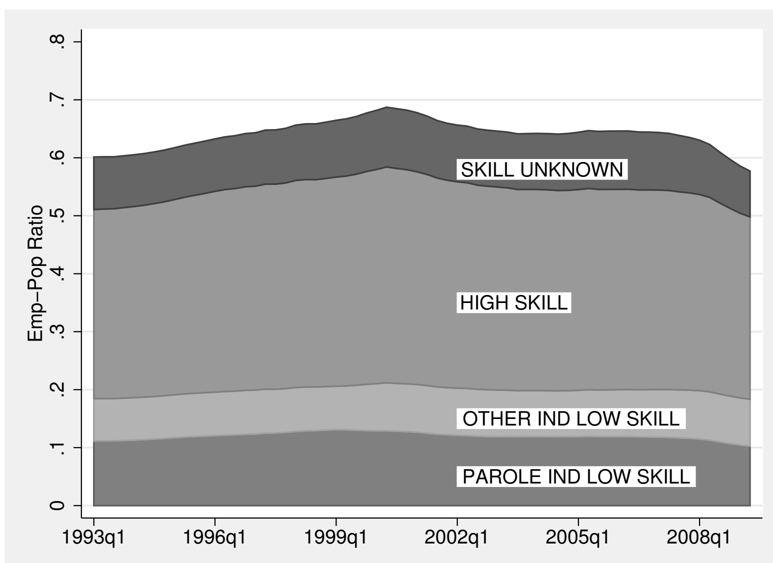

Figure 2: CA Job Density By Industry and Skill Type, 1993-2009

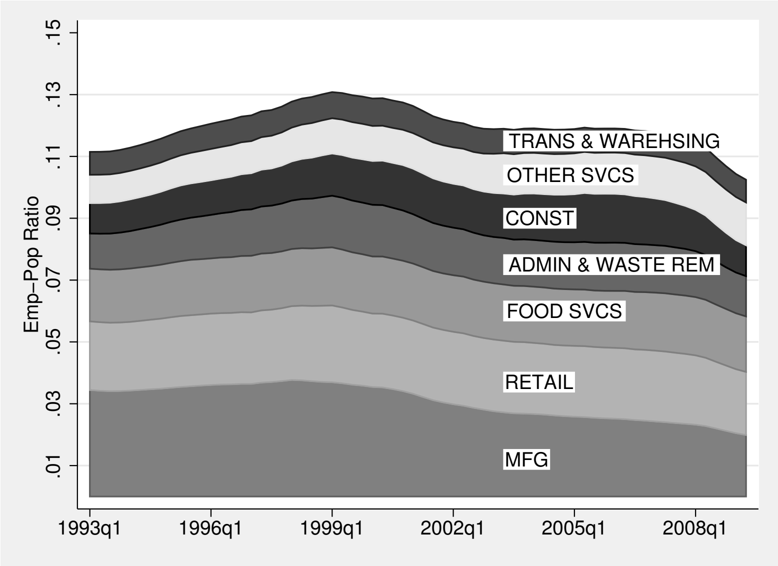

Figure 3: CA Parole Industry Low-skill Job Density, 1993-2009

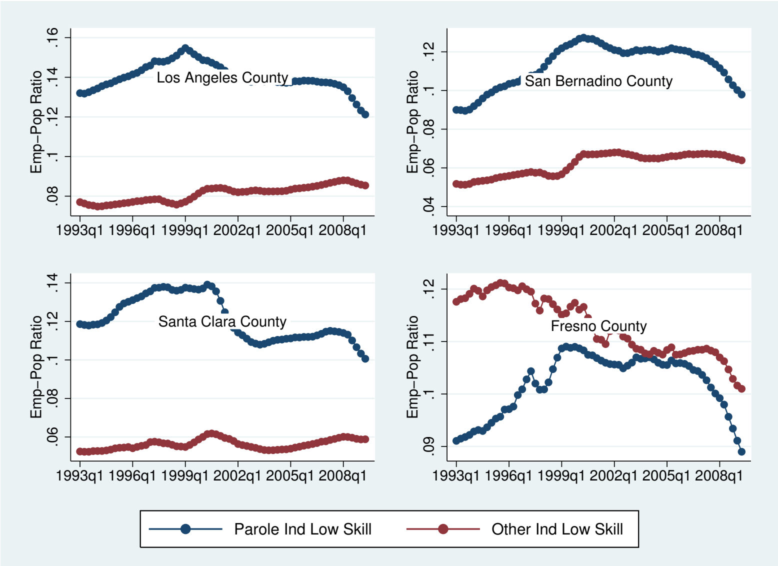

Figure 4: County Low-Skill Job Density, 1993-2009

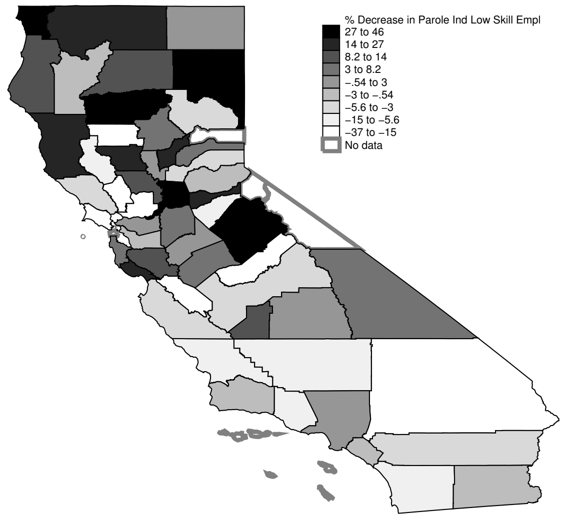

Figure 5: Percent Decrease in Parole Industry low-skill Employment, 1993-2008

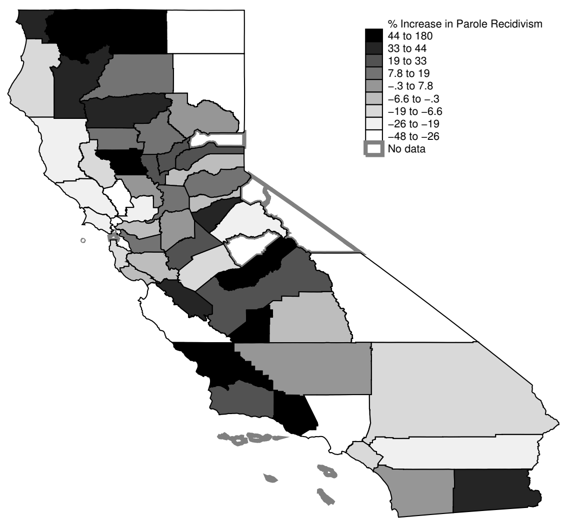

Figure 6: Percent Increase in 1 Year Prison Return Rates, 1993-2008

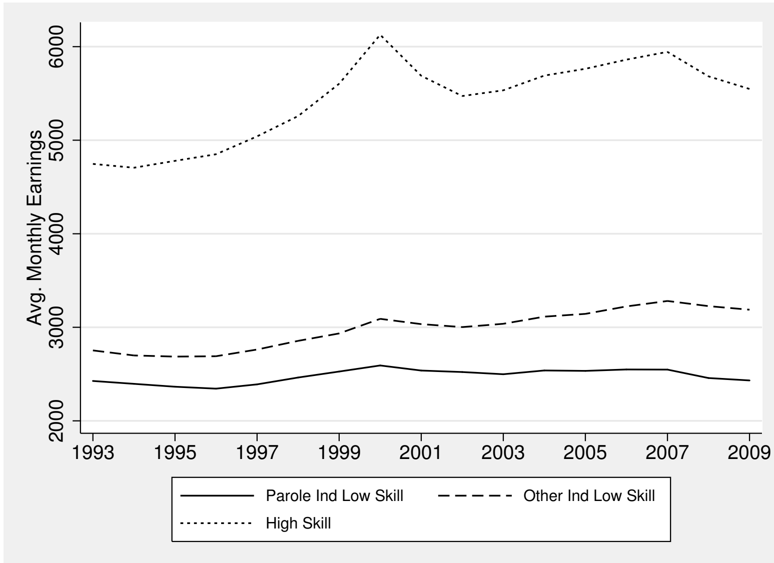

Figure 7: CA Avg. Monthly Real Earnings By Industry and Skill Type, 1993-2009

Table 1: Descriptive Statistics of Individuals Released from a California State Correctional Facility from 1993 through 2008

	(1) All Releases	(2) Estimation Sample
Reincarceration Rates		
Return before Parole Completion	0.656	0.544
Return w/in 1yr of Release	0.517	0.364
Basic Demographic Characteristics		
Male	0.905	1.000
Age (at prison release)	35.32	34.03
Black	0.301	0.238
White (non hispanic)	0.401	0.364
Hispanic	0.299	0.398
Crime & Incarceration Characteristics		
Mandatory Parole Release	0.973	1.000
Length of Sentence in months (non life)	38.65	47.17
Prior Felony Conviction	0.245	0.056
On Parole When Admitted to Prison	0.221	0.00
Type of Crime		
Property (Robbery, Burglary, Theft and Fraud)	0.397	0.337
Violent (Murder, Assault, Sex Crime, Weapons)	0.106	0.276
Drug and Alcohol (Drug Offense, DUI)	0.359	0.340
Observations	1,956,891	424,536

Source: National Corrections Reporting Program (NCRP), 1993-2008. Column (1) displays summary statistics for all individuals released from a CA state prison during the years 1993-2008. Column (3) displays statistics for my estimation final sample: males, 18-65, released from a correctional facility to mandatory parole for the first time following an incarceration spell carrying an original sentence of atleast 2 years. Individuals sentenced in Alpine County (FIPS 6003), Mono County (FIPS 6051) and Sierra County (FIPS 6091) were also deleted due to very few observations. A description of how the final sample in column (3) was obtained can be found in Section 4.1 and Figure 1. Classification of the type of criminal (property, violent, drug) is made using the conviction offense for which the longest sentence was imposed for offenders with multiple convictions.

Table 2: Top 10 parole occupations among male inmates in California, SISFCF 2004

Occupation Title	Parole Occupation Distribution
Laborers and Freight, Stock, and Material Movers (962)	7.9
Construction Laborers (626)	7.4
Automotive Service Technicians and Mechanics (720)	4.9
Grounds Maintenance Workers (425)	4.7
Carpenters (623)	3.5
Driver-Sales Workers and Truck Drivers (913)	3.1
Miscellaneous Agricultural Workers (605)	2.7
Cooks (402)	2.7
Welding, Soldering, and Brazing Workers (814)	2.5
Unemployed	37.9

Source: Survey of Inmates in State and Federal Correctional Facilities 2004. The percentages reported represent the number of inmates reporting their last job in each occupation divided by the number of inmates in California who were on parole prior to their current incarceration and had been employed or had a business in the month prior to the arrest leading to their current incarceration using the SISFCF weights provided (percentages are very close without use of the weights).

Table 3: Estimated industry concentration of parole occupations of male inmates in California, SISFCF 2004

Industry (2007 NAICS code)	Estimated Percent in Industry
Construction (23)	27.8
Manufacturing (31-33)	13.2
Retail Trade (44-45)	12.1
Other Services (81)	7.9
Administrative and Waste Services (56)	6.9
Accommodations and Food Services (72)	5.1
Transportation and Warehousing (48-49)	5.0
Wholesale Trade (42)	4.1
Agriculture, Forestry, Fishing and Hunting (11)	3.4
Public Administration (92)	2.2
Arts, Entertainment, and Recreation (71)	2.1
Information (51)	1.9
Health Care and Social Assistance (62)	1.6
Educational Services (61)	1.6
Real Estate and Rental and Leasing (53)	1.4
Mining, Quarrying, Oil and Gas Extraction (21)	1.4
Professional, Scientific, and Technical Services (54)	1.3
Utilities (22)	0.1
Finance and Insurance (52)	0.0
Management of Companies and Enterprises (55)	0.0

Source: Survey of Inmates in State and Federal Correctional Facilities 2004 and 2000 Census. Industry concentration of employed parolees in California is obtained by combining the occupational distribution from the SISFCF 2004 with the occupational mix of each industry in California obtained from the 2000 U.S. Census.

Table 4: Effect of Average County Employment on Incarceration within 1 year of Release, Logit Regression Models

	(1)	(2)	(3)
Regression Eq. (1)			
Total Job Density	-0.0091*	-0.0044	0.0023
	(0.0045)	(0.0036)	(0.0053)
ln(Avg Earnings)	0.5132*	0.0911	0.0986
	(0.2046)	(0.1467)	(0.1559)
Regression Eq. (2)			
Low Skill Job Density	-0.0493**	-0.0346**	-0.0266
	(0.0154)	(0.0111)	(0.0263)
High Skill Job Density	0.00951	0.0131	0.0192
	(0.0149)	(0.0112)	(0.0229)
ln(Avg Low Skill Earnings)	0.5841**	0.1216	0.1614
	(0.1969)	(0.1864)	(0.2006)
ln(Avg High Skill Earnings)	-0.0210	-0.0548	-0.0214
	(0.1470)	(0.1234)	(0.1262)
Regression Eq. (3)			
Parole Industry Low Skill Job Density	-0.0414*	-0.0422**	-0.0443
	(0.0181)	(0.0116)	(0.0270)
Other Industry Low Skill Job Density	-0.0641**	-0.0108	0.0143
	(0.0194)	(0.0202)	(0.0321)
High Skill Job Density	0.0098	0.0128	0.0225
	(0.0140)	(0.0112)	(0.0230)
ln(Avg Parole Ind Low Skill Earnings)	0.1914	0.1337	0.1385
	(0.1596)	(0.1589)	(0.1635)
ln(Avg Other Ind Low Skill Earnings)	0.2386	0.0831	0.1008
	(0.1203)	(0.1163)	(0.1114)
ln(Avg High Skill Earnings)	0.0352	-0.0801	-0.0540
	(0.0352)	(0.1280)	(0.1322)
County Effects	Y	Y	Y
Yr-Mo of Release Effects	Y	Y	Y
County Linear Trend	N	Y	Y
County Quadratic Trend	N	N	Y
Observations	424,536	424,536	424,536

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include the following controls in addition to the employment measures listed in the table: race, ethnicity, age category (18-20, 20-25, 25-35, 35-45, 45-55, 55-65), sentence length indicator variables (1 year, 2 years,..., 9 years, 10 plus years), percent of sentence served, incarceration offense category (murder, robbery, assault, sex crime, burglary, theft, drug crime, DUI, weapons offense), prior felony conviction indicator, county poverty rate and median household income, county police officers per capita, number of parolees released in same month, and county arrest clearance rate. Coefficients for control variables are reported in Appendix Table A2.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Effect of Average County Employment on Incarceration within 1 year of Release by Criminal Characteristics, Logit Regression Models

	All	Type of Offender			Criminal History	
		Property	Drug	Violent	No Prior	Prior Felony
Average 1 year Return Rate	0.364	0.434	0.337	0.311	0.362	0.411
Parole Industry Low Skill JD	-0.0422**	-0.0368*	-0.0981**	0.0279	-0.0387**	-0.1027**
	(0.0116)	(0.0170)	(0.0316)	(0.0221)	(0.0118)	(0.0354)
Other Industry Low Skill JD	-0.0108	0.0278	-0.0520	0.0241	0.0109	0.0321
	(0.0202)	(0.0376)	(0.0387)	(0.0494)	(0.0212)	(0.0551)
High Skill JD	0.0128	0.0154	0.0315	-0.0154	0.0112	0.0299
	(0.0112)	(0.0178)	(0.0196)	(0.0153)	(0.0123)	(0.0314)
ln(Parole Ind Low Skill Earn)	0.1337	0.0572	0.1250	0.3799+	0.1122	0.6658
	(0.1589)	(0.2774)	(0.2252)	(0.2289)	(0.1680)	(0.5597)
ln(Other Ind Low Skill Earn)	0.0831	0.1454	-0.1443	0.1256	0.0858	-0.1314
	(0.1163)	(0.1402)	(0.2036)	(0.2000)	(0.1103)	(0.3211)
ln(High Skill Earn)	-0.0801	-0.3157	-0.1564	0.0359	-0.0717	-0.1482
	(0.1280)	(0.1967)	(0.2599)	(0.2192)	(0.1301)	(0.3787)
County Effects	Y	Y	Y	Y	Y	Y
Yr-Mo of Release Effects	Y	Y	Y	Y	Y	Y
County Linear Trend	Y	Y	Y	Y	Y	Y
County Quadratic Trend	N	N	N	N	N	N
Observations	424,536	141,069	134,244	102,358	400,758	23,777

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include the following controls in addition to the employment measures listed in the table: race, ethnicity, age category (18-20, 20-25, 25-35, 35-45, 45-55, 55-65), sentence length indicator variables (1 year, 2 years,..., 9 years, 10 plus years), percent of sentence served, incarceration offense category (murder, robbery, assault, sex crime, burglary, theft, drug crime, DUI, weapons offense), prior felony conviction indicator, county poverty rate and median household income, county police officers per capita, number of parolees released in same month and county arrest clearance rate. Coefficients for control variables are reported in Appendix Table A2.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Effect of Average County Employment on Incarceration within 1 year of Release by Demographic Characteristics, Logit Regression Models

	RaceEthnicity			Age at Release			
	White (Non-Hispanic)	Black (Non-Hispanic)	Hispanic	18 through 25	26 through 35	36 through 45	46 through 65
Avg 1 year Return Rate	0.395	0.446	0.288	0.462	0.350	0.347	0.293
Parole Ind Low Skill JD	-0.0248	-0.0405*	-0.0509*	-0.0082	-0.0315	-0.079**	-0.0907*
	(0.0159)	(0.0189)	(0.0216)	(0.0274)	(0.0227)	(0.0196)	(0.0398)
Other Ind Low Skill JD	-0.0344+	0.0553	0.0344	-0.0350	0.0085	-0.0388	0.0184
	(0.0194)	(0.0539)	(0.0373)	(0.0486)	(0.0403)	(0.0334)	(0.0557)
High Skill JD	0.0059	-0.0039	0.0295+	0.0204	-0.0044	0.0362*	0.0194
	(0.0113)	(0.0217)	(0.0174)	(0.0199)	(0.0150)	(0.0150)	(0.0223)
ln(Parole Ind LS Earn)	0.2300	0.1982	-0.0747	-0.0850	0.1188	0.0755	0.7841+
	(0.2507)	(0.2215)	(0.3006)	(0.2630)	(0.2456)	(0.2418)	(0.4200)
ln(Other Ind LS Earn)	0.2052	-0.0018	-0.0132	-0.3457+	0.3570+	0.0769	0.0576
	(0.1873)	(0.1600)	(0.1865)	(0.2037)	(0.1989)	(0.1728)	(0.3409)
ln(High Skill Earn)	-0.0388	0.0521	-0.1414	0.3029	-0.1820	0.0074	-0.6351+
	(0.1875)	(0.2162)	(0.2570)	(0.3061)	(0.2464)	(0.2120)	(0.3824)
County Effects	Y	Y	Y	Y	Y	Y	Y
Yr-Mo of Release Effects	Y	Y	Y	Y	Y	Y	Y
County Linear Trend	Y	Y	Y	Y	Y	Y	Y
County Quadratic Trend	N	N	N	N	N	N	N
Observations	154,485	101,058	168,990	91,591	157,915	114,312	58,193

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include the following controls in addition to the employment measures listed in the table: race, ethnicity, age category (18-20, 20-25, 25-35, 35-45, 45-55, 55-65), sentence length indicator variables (1 year, 2 years,..., 9 years, 10 plus years), percent of sentence served, incarceration offense category (murder, robbery, assault, sex crime, burglary, theft, drug crime, DUI, weapons offense), prior felony conviction indicator, county poverty rate and median household income, county police officers per capita, number of parolees released in same month, and county arrest clearance rate. Coefficients for control variables are reported in Appendix Table A2.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7: Checks on Exogeneity of Labor Market Conditions, County Crime Rates and Labor Market Conditions at Admission

	Include County Crime Rates	Include Conditions at Admission
Parole Industry Low Skill JD	-0.0417**	-0.0538**
	(0.0125)	(0.0178)
Other Industry Low Skill JD	-0.0113	-0.0302
	(0.0207)	(0.0298)
High Skill JD	-0.0131	0.0237
	(0.0116)	(0.0132)
ln(Parole Ind Low Skill Earn)	0.1296	-0.0056
	(0.1632)	(0.1531)
ln(Other Ind Low Skill Earn)	0.0753	-0.0171
	(0.1154)	(0.1593)
ln(High Skill Earn)	-0.0640	0.0079
	(0.1301)	(0.1056)
Pre-Release County Crime Rate	0.0403	
	(0.0328)	
(Pre-Release County Crime Rate)^2	-0.0013	
	(0.0017)	
Pre-Admission Parole Industry Low Skill JD		0.0476*
		(0.0204)
Pre-Admission Other Industry Low Skill JD		0.0314
		(0.0255)
Pre-Admission High Skill JD		-0.0344
		(0.0186)
County Effects	Y	Y
Yr-Mo of Release Effects	Y	Y
County Linear Trend	Y	Y
County Quadratic Trend	N	N
Observations	424,536	371,035

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include the controls listed in Table 5. Column (1) contains estimated coefficients for a model including a quadratic in the county crime rate prior to release. Column (2) contains controls for average labor market conditions at time of prison admission. The model in Column (2) is limited to individuals whose month of prison admission is January 1993 or later because QWI labor market data for CA is available beginning in 1993.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A Appendix

The appendix is organized in the following manner. I first provide estimated coefficients for all control variables in four separate specifications of Eq. (3) in Table 8. I also extend the model to longer term outcomes and to the entire population of individuals released from prison in California in Table 10. As a further check on the identification assumptions discussed in Section 5.4, I test whether the timing or location of prison release appear to be related to local labor market conditions. I discuss the specifications below and present results in Table 11. Then, to test the validity of the results in Tables 5 through 8, I report results from several robustness checks in Table 12 and briefly discuss each specification.

A.1 Data Sources for Control Variables and Estimated Effects

Table 8 presents estimated coefficients for all regressor variables. The demographic characteristics, prior criminal history variables, and length of sentence indicators are all available through the NCRP data. The county disadvantage measures (percent of population below poverty line, and median county household income) were downloaded for each county in California from 1993 through 2009 from the Small Area Income and Poverty Estimates provide by the U.S. Census Bureau (http://www.census.gov/did/www/saipe/data/statecounty/data/index.html). The police officers per capita data for each county and year were obtained through the Police Employee segment of the FBI's Uniform Crime Reporting Program Data (http://www.icpsr.umich.edu/icpsrweb/NACJD/series/00057). The police per capita coefficient appears large, but is measured as the number of police officers per person and has a mean of 0.003. The arrest clearance rate was calculated using the Offenses Known and Clearances by Arrest segments of the Uniform Crime Reporting Program. Finally, the size of each release cohort was calculated using the NCRP data.

A.2 Additional Results

I re-estimate the empirical model replacing the dependent variable of interest (recidivism within one year from release) with a variable measuring recidivism within two years in the Column 1 of Table 10, and recidivism within three years in Column 2. Approximately 15 percent of parolees in California are released from parole supervision after 13 months so I focus my main analysis on a one year outcome to avoid any selection bias caused by the early release of certain offenders. The crime rates among those released early at 13 months are likely much lower than those who continue on parole supervision, but I do not observe whether any of these offenders released early re-offend after one year, which could bias estimated coefficients in models with the longer term dependent variables. I estimate declines in recidivism within two and three years associated with an increase in low-skill parole industry job density slightly smaller, but similar in magnitude to my main results using the one year measure of recidivism.

The final column of Table 10 presents estimated effects of changes in job densities on the parole outcomes for all offenders released to parole supervision in California between 1993 and 2008. This population of 1.7 million include male and female offenders, those sentenced less than two years, and those serving multiple parole terms (second or greater) associated with a particular prison spell. For reasons discussed in the paper, in order to identify a causal effect, I focus my analysis on a subsample of this population. However, the effect of a change in low-skill parole industry job densities on recidivism rates for the entire population is remarkably similar to estimates for the selected subsample. I estimate a 4.8 percent decrease in the probability of returning to prison within one year when released into an economy with a one percentage point higher low-skill parole industry job density.

A.3 Exogeneity of Local Labor Market Conditions

The exogeneity assumption would also not be valid if changes to local labor market conditions are correlated with the timing or location of release of either high or low risk offenders. For example, if the state correctional facility was able to expedite or delay the release of an offender based on the labor market conditions (or if incarcerated individuals adjusted their behavior inside prison based on expectations of job opportunities on the outside), my parameter estimates may be biased. As discussed previously, the determinate sentencing and mandatory parole requirements of the correctional system in California mitigate this type of endogeneity concern. The timing of release is mechanically determined by the imposed sentence and the amount of good behavior credits. Both sentencing and good time credits are subject to guidelines and it is unlikely that either is adjusted in anticipation of good or bad labor market conditions in the released offender's county of sentencing. Moreover, if those in charge of correctional supervision were somehow able to affect the timing of release and did so considering county economic conditions, it seems more likely that they would delay the release of high-risk offenders in bad economic conditions. This delay would bias my estimates, but they would be biased towards finding no effect.

To test whether the timing of release from prison is affected by changes in local employment densities or earnings, I regress the percent of sentence served by an individual on the post-release labor market regressors and the same independent variables included in the primary regression model (Eq. (3)) with the addition of fixed effects for the year of admission since minimum time served policies have changed over time. California law stipulates that offenders must serve a certain (fixed) percentage of their sentence in prison which dictates the maximum amount of good time credits that an offender can earn while in prison. These requirements have changed over time and vary depending on the offense committed. Thus, I test whether there is any response in the amount of time served based on labor market variables within these crime-sentence categories controlling for the year of admission. Results are reported in Appendix Table 11. Although I estimate a statistically significant negative effect of low-skill non-parole industry job density on the percent of time served in prison, these estimates are very small in magnitude. A one percentage point increase in the low-skill non-parole industry job density is associated with a 0.6 percentage point decline in the percent of of a sentence served. From the average sentence of 38 months of my sample, this equates to being released only one week early.

As a further check of the exogeneity of labor market conditions at the time of release, I estimate the average propensity to reoffend for each county-month release cohort based on all individual observable characteristics (demographic, criminal history) and test whether this predicted propensity is correlated with local labor market conditions at the time of release. If either individuals or correctional authorities adjusted the mix of offenders released based on local economic conditions, or if the mix of offenders released differed due to pre-prison labor market conditions, I would expect the predicted risk composition of each cohort released to be correlated with the local economic conditions at the time of release. I do not detect any relationship between release cohort risk composition and local labor market conditions (Table 11, Column 2).

Finally, the post-release location of the parolee is determined by the last legal residence, which I proxy with the county of sentencing. A fraction of paroled offenders do not return to the pre-prison county of residence and receive permission to locate elsewhere. This decision could indeed be affected by local labor market conditions. However, by using the county of sentencing as a proxy for the post-prison location, I use a measure that is exogenous to the labor market conditions at the time of release. Also, a motivated offender who receives permission to avoid the county of sentencing because of a bad labor market is probably less likely to recidivate, which would bias my estimates towards zero since I match that parolee's behavior to his county of sentencing. The NCRP data does not indicate the county of release, but it does provide information on whether the parolee is released to a parole agency outside of the state of California. In order to test whether parolees seek permission to adjust their post-release location based on job opportunities, I limit my sample to individuals sentenced in counties in California that border another state and regress the probability of out-of-state parole release on local labor market conditions. Results from this regression are presented in Column 3 of Table 11. Although the magnitude of the estimated effects are large, they are imprecise. This is not surprising as only 407 individuals (less than 1 percent of the total number paroled) sentenced in border counties are released to out-of-state parole agencies. There is no evidence that low-skill labor market opportunities for offenders sentenced in border counties influence whether the parolee is released to out-of-state parole supervision.

A.4 Robustness Checks

A.4.1 Model specification

To test whether results are sensitive to the choice of the logit model specification, I report results from a probit specification in the first column of Table 12 and results from a linear probability model in the second column. Interpretation of the estimated probit coefficients is not as straightforward as interpretations of the linear or logit coefficients. However, the marginal effect implied by the probit estimate is very close to that implied by the logit model. The linear coefficient of -0.01 implies that a one percentage point increase in the low-skill parole industry job density is associated with a one percentage point decrease in the probability of returning to prison within one year. From the average return rate of 36 percent, this implies a 2.7 percent decrease in recidivism with a one percentage point increase in low-skill parole industry job density. This result is smaller than the reported logit coefficient, but this model imposes a constant marginal effect across all observations.

A.4.2 Short term measures of job density

In Columns 3 and 4 of Table 12, I investigate whether my results are sensitive to using a 12 month average of job density following prison release. I replace the 12 month average job density measures with a three month average in Column 3 and a six month average in Column 4, and obtain estimated effects slightly smaller than the 12 month average but similar in direction and magnitude.

A.4.3 Redefine low-skill

As previously documented, more than half of offenders released from prison do not have a high school diploma. Because of this, I redefine low-skill to include employees without high school degrees and report estimated coefficients in Column 5 of Table 12. A one percentage point increase in the high school dropout employment density is associated with more than a 10 percent decrease in the probability of recidivism. It appears that increases in jobs available to individuals without high school degrees in parole industries have particularly large effects on successful re-entry among paroled offenders in California.

A.4.4 Redefine parole industry

Construction and manufacturing jobs represent a large fraction of parole friendly occupations as reported in Table 5. I redefine parole industries just with construction and manufacturing employment in Column 6 of Table 12 and estimate a large change in recidivism associated with a percentage point increase in the local low-skill job density of these two industries. Due to a focus on manufacturing employment in prior criminology studies, I also estimate the change in only manufacturing employment on recidivism in Column 7 and find a 12 percent decrease in recidivism associated with a one percentage point increase in manufacturing employment. On average, approximately three percent of a county's working age population are employed in low-skill manufacturing jobs, so a one percentage point increase represents greater than 30 percent growth in these types of jobs. My results indicate that changes to construction and manufacturing industries are important determinants of recidivism rates. However, I prefer models including low-skill jobs from the other parole industries since these jobs may also be important, especially in counties with low levels of manufacturing or construction employment.

A.4.5 Exclude Los Angeles County

Over thirty percent of released offenders in my sample were sentenced in Los Angeles County. I report estimated coefficients excluding these observations in Column 8 and obtain estimates very close to those obtained for the full sample in Table 4. Changes in job density in LA County are not driving my overall results.

A.4.6 Redefine job accessibility area

As a final robustness check in Table 12, I report estimates from a model expanding my definition of accessible jobs by allowing jobs outside of the county of residence to influence recidivism probabilities. I use county worker flow data available from the 2000 U.S. Census to identify counties in which a substantial fraction of county residents commute to another county for work. I allow changes in job densities in neighboring counties to affect job availability for a released offender for areas in which at least five percent of the resident county population commutes to another county for work. I then weight the jobs in the neighboring county by the fraction of the working age population that commutes to that county for work. For example, approximately 20 percent of the working age population in El Dorado County commutes to neighboring Sacramento County for work. In my calculation of job densities relevant to individuals released to El Dorado County, I weight jobs within El Dorado by a factor of one and jobs within Sacramento County by a factor of 0.2 to allow employment changes in Sacramento County to affect job availability. Job mobility for released offenders is likely lower than that of the working age population due to parole supervision requirements and a lack of financial resources to incur the costs of long commutes. Expanding the accessible area yields estimated coefficients slightly smaller in magnitude and marginally significant, but the size and direction of the effects are similar to my main results.

Table 8: Effect of Average County Employment on Incarceration within 1 year of Release, Logit Regression Models

	(1)	(2)	(3)	(4)
Parole Industry Low Skill JD	-0.0399*	-0.0414*	-0.0422**	-0.0443
	(0.0170)	(0.0181)	(0.0116)	(0.0270)
Other Industry Low Skill JD	-0.0609**	-0.0641**	-0.0108	0.0143
	(0.0224)	(0.0194)	(0.0202)	(0.0321)
High Skill JD	0.00577	0.00980	0.0128	0.0225
	(0.0156)	(0.0140)	(0.0112)	(0.0230)
ln(Parole Ind Low Skill Earn)	0.280	0.191	0.134	0.139
	(0.215)	(0.160)	(0.159)	(0.163)
ln(Other Ind Low Skill Earn)	0.311*	0.239*	0.0831	0.101
	(0.147)	(0.120)	(0.116)	(0.111)
ln(High Skill Earn)	0.175	0.0352	-0.0801	-0.0540
	(0.172)	(0.145)	(0.128)	(0.132)
Demographic Characteristics				
(White, Age 56-65 omitted)				
Black		0.353**	0.354**	0.354**
		(0.0381)	(0.0380)	(0.0381)
Hispanic		-0.403**	-0.402**	-0.402**
		(0.0238)	(0.0231)	(0.0231)
Age 18-20		1.368**	1.369**	1.369**
		(0.0550)	(0.0546)	(0.0546)
Age 21-25		1.069**	1.070**	1.070**
		(0.0345)	(0.0346)	(0.0347)
Age 26-35		0.629**	0.630**	0.630**
		(0.0357)	(0.0359)	(0.0359)
Age 36-45		0.542**	0.543**	0.543**
		(0.0293)	(0.0293)	(0.0292)
Age 46-55		0.350**	0.350**	0.350**
		(0.0290)	(0.0290)	(0.0290)
Prior Criminal History				
Prior Felony Incarceration		0.317**	0.317**	0.317**
		(0.0326)	(0.0329)	(0.0328)
Murder		-0.651**	-0.653**	-0.653**
		(0.0433)	(0.0434)	(0.0434)
Robbery		-0.124**	-0.125**	-0.126**
		(0.0202)	(0.0201)	(0.0202)
Assault		-0.0731**	-0.0731**	-0.0742**
		(0.0242)	(0.0242)	(0.0242)
Sex Crime		-0.246**	-0.244**	-0.245**
		(0.0395)	(0.0389)	(0.0389)
Burglary		0.177**	0.178**	0.177**
		(0.0240)	(0.0239)	(0.0239)
Theft		0.273**	0.275**	0.274**
		(0.0289)	(0.0288)	(0.0288)
Drug		-0.290**	-0.290**	-0.290**
		(0.0378)	(0.0379)	(0.0380)
DUI		-0.621**	-0.622**	-0.621**
		(0.0319)	(0.0330)	(0.0331)
Weapons		0.0357+	0.0366+	0.0366+
		(0.0206)	(0.0205)	(0.0204)

(CONTINUED) Table 9: Effect of Average County Employment on Incarceration within 1 year of Release, Logit Regression Models

	(1)	(2)	(3)	(4)
Length of Sentence and Time Served				
(2yr omitted)				
Sentence 3yr		0.228^{**}	0.228^{**}	0.227^{**}
		(0.0503)	(0.0508)	(0.0507)
Sentence 4yr		0.206^{**}	0.206^{**}	0.206^{**}
		(0.0325)	(0.0325)	(0.0325)
Sentence 5yr		0.159^{**}	0.160^{**}	0.159^{**}
		(0.0349)	(0.0350)	(0.0350)
Sentence 6yr		0.0750^{*}	0.0748^{*}	0.0744^{*}
		(0.0329)	(0.0328)	(0.0327)
Sentence 7yr		0.0938^{**}	0.0950^{**}	0.0943^{**}
		(0.0210)	(0.0212)	(0.0212)
Sentence 8yr		0.0238	0.0248	0.0240
		(0.0303)	(0.0305)	(0.0304)
Sentence 9yr		-0.00122	-0.000684	-0.00136
		(0.0246)	(0.0244)	(0.0244)
Sentence 10yr plus		0.00736	0.00773	0.00739
		(0.0323)	(0.0325)	(0.0325)
Time Served as % of Sentence		-0.0151	-0.0156	-0.0158
		(0.0188)	(0.0192)	(0.0192)
County Disadvantage				
Percent Below Poverty		0.00993	-0.00975	-0.0195
		(0.00699)	(0.0119)	(0.0133)
Median HH Income (1000s)		0.00747	0.00674	-0.00286
		(0.00578)	(0.00652)	(0.00824)
Deterrence Measures and County Crime				
Police Officers Per Capita		-20.22^{+}	-13.42^{+}	-16.51^{*}
		(11.87)	(7.425)	(6.979)
Arrest Clearance Rate		-0.0205	0.104	0.0476
		(0.143)	(0.189)	(0.131)
Size of Release Cohort		0.00011^{**}	0.00003	-0.000008
		(0.00004)	(0.00004)	(0.00005)
County Effects	Y	Y	Y	Y
Year-Mo of Release Effects	Y	Y	Y	Y
Control Variables	N	Y	Y	Y
County Linear Trend	N	N	Y	Y
County Quadratic Trend	N	N	N	Y
Observations	424,536	424,536	424,536	424,536

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. County poverty and median household income estimates were obtained from the U.S. Census Small Area Income and Poverty Estimates available at http://www.census.gov/did/www/saipe/data/statecounty/data/index.html. County police officer counts were obtained from the FBI LEOKA database. County arrest clearance rates were obtained from the FBI's Uniform Crime Reports (UCR). All other variables were available in the NCRP.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 10: Effect of Average County Employment on Incarceration within 1 year of Release, Extensions

	(1)	(2)	(3)
	Return within 2 yrs	Return within 3 yrs	Return 1 yr, All Parole Releases
Parole Industry Low Skill JD	-0.0351*	-0.0308+	-0.0483**
	(0.0154)	(0.0180)	(0.0100)
Other Industry Low Skill JD	0.00569	0.0205	-0.0208
	(0.0243)	(0.0296)	(0.0184)
High Skill JD	0.0118	0.0120	0.0165+
	(0.0128)	(0.0145)	(0.00922)
ln(Parole Ind Low Skill Earn)	0.192	0.137	-0.0880
	(0.159)	(0.158)	(0.117)
ln(Other Ind Low Skill Earn)	0.0984	0.0274	-0.0468
	(0.115)	(0.121)	(0.119)
ln(High Skill Earn)	-0.203	-0.194	-0.00778
	(0.146)	(0.164)	(0.080)
County Effects	Y	Y	Y
Yr-Mo of Release Effects	Y	Y	Y
County Linear Trend	Y	Y	Y
County Quadratic Trend	N	N	N
Observations	393,163	361,047	1,715,581

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include same controls as listed in Appendix Table A2. Columns (1) and (2) extend the empirical model to measure the labor market effects on 2 and 3 year return rates. Column (3) estimates the preferred empirical model for all prisoners released to mandatory parole in California between 1993 and 2008.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 11: Checks on Exogeneity of Labor Market Conditions, Time and Location of Release

	Timing of Release		Location of Release
	Percent Time Served	Risk Composition of Release Cohort	Out of State Parole
Parole Industry Low Skill JD	-0.0005	-0.0007	0.332
	(0.0033)	(0.0011)	(0.3662)
Other Industry Low Skill JD	-0.0064*	0.00006	-0.4282
	(0.0027)	(0.0012)	(0.2891)
High Skill JD	0.0018	-0.0007	-0.0541
	(0.0034)	(0.00057)	(0.4033)
Observations	424,536	10,020	62,671

Standard errors clustered by county in parentheses. Results in column (1) are from a linear regression of the percent of sentence served and the same dependent variables included in the primary regression model (Eq. (3)) with the addition of fixed effects for the year of admission since minimum time served policies have changed over time. Column (2) provides another check to the exogeneity of the timing of release by examining whether the risk-composition of each county-month release cohort is correlated with local labor market conditions. The average predicted propensity to recidivate within one year is calculated for each county month cohort by obtaining the predicted return probability for each individual based on all observable individual characteristics (demographic and criminal history) and then averaging the predicted return over each cohort. The coefficients reported measure the relationship between the average predicted probability of return for each cohort and local labor market conditions, including fixed effects for county and month of release. Column (3) reports estimated coefficients from a logit model estimating the effect of labor market conditions on the an out-of-state parole assignment for individuals sentenced in counties bordering another state in California. Control variables include all those included in the main empirical specification.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 12: Effect of Average County Employment on Incarceration within 1 year of Release by Demographic Characteristics, Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probit	LPM	3 month Job Densities	6 month Job Densities	Low Skill= HS Dropout	Parole Ind=MFG, CONST	Parole Ind = MFG	No Los Angeles Cnty	Work Com-muting Area
Parole Industry Low Skill JD	-0.026**	-0.01**	-0.035**	-0.038**	-0.101**	-0.085**	-0.12**	-0.044**	-0.029+
	(0.007)	(0.003)	(0.013)	(0.012)	(0.029)	(0.026)	(0.042)	(0.013)	(0.015)
Other Industry Low Skill JD	-0.007	-0.003	0.009	0.012	-0.006	-0.015	-0.014	-0.009	-0.014
	(0.013)	(0.005)	(0.009)	(0.01)	(0.040)	(0.016)	(0.012)	(0.020)	(0.02)
High Skill JD	0.008	0.003	0.005	0.007	0.012	0.015	0.016	0.013	0.009
	(0.007)	(0.003)	(0.012)	(0.011)	(0.01)	(0.011)	(0.012)	(0.012)	(0.008)
County Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr-Mo of Release Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Quadratic Trend	N	N	N	N	N	N	N	N	N
Observations	424,536	424,536	424,536	424,536	424,536	424,536	421,194	287,333	424,536

Logit coefficients and associated standard errors are reported. Standard errors clustered by county in parentheses. Each employment variable listed above is calculated as a county-level average over a year after prison release. All results are based on logistic regressions and include same controls as listed in Appendix Table A2. Column (1) reports logit coefficients and column (2) reports estimated coefficients from a linear probability model. The next two columns (3) and (4) report estimates with different measures of the key regressors. Instead of measuring job densities over the first year of release, column (3) uses a 3-month average from release while column (4) uses a 6-month average. Column (5) reports estimates where the low skill is classified as below high school grad. Columns (6) and (7) vary the classification of parole industries. Construction and manufacturing are counted as parole industries for estimates reported in column (6) and only manufacturing is classified as a parole industry in column (7). Since parolees in Los Angeles county represent over 30 percent of my observations, column (8) estimates the main empirical model excluding the LA county observations. Column (9) reports results weighting job opportunities in surrounding counties with the percent of the county working age residents that commute to that county for work. This information is available from the county flow estimates available from the 2000 U.S. Census.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$