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GOOD JOBS AND RECIDIVISM*

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I estimate the impact of employment opportunities on recidivism among 1.7 million offenders released from a California prison between 1993 and 2008. The institutional structure of the California criminal justice system as well as location, skill, and industry-specific job accession data provide a unique framework for identifying a causal effect of job availability on criminal behaviour. I find that increases in construction and manufacturing opportunities at the time of release are associated with significant reductions in recidivism. Other types of opportunities, including those characterised by lower wages that are typically accessible to individuals with criminal records, do not influence recidivism.

Prisons in the United States are built with revolving doors – more than two-thirds of individuals released from prison in California recidivate (return to prison) within three years. The scale of incarceration in the United States is largely driven by the failure of former inmates to re-enter non-institutionalised society successfully. Released offenders undoubtedly face a number of social, housing and financial challenges upon leaving prison and an inability to obtain employment is often cited as one of the most important factors that contributes to recidivism.

A great deal of empirical evidence supports basic theoretical predictions of a negative relationship between employment opportunities and criminal activity.[1] We may also expect local labour markets to influence released prisoners based on results from an emerging literature that documents long-term detrimental effects for high school or college graduates who enter more depressed local labour markets (Kahn, 2010; Oreopoulos *et al.*, 2012; Maclean, 2013; Cutler *et al.*, 2015). Recently, Bell *et al.* (2014) estimated higher rates of lifetime crime and incarceration among those who leave high school during recessions in the US and the UK. Surprisingly however, prior research does not find strong ties between labour market conditions at the time of prison release and recidivism rates (Bolitzer, 2005; Raphael and Weiman, 2007). Recent evaluations of re-entry programmes in which minimum-wage jobs are randomly assigned to released offenders find mixed results as to whether these employment opportunities can reduce recidivism (Redcross *et al.*, 2011; Jacobs, 2012).

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[1] Mustard (2010) and Bushway (2011) provide recent reviews of a large empirical literature within economics and criminology. The standard economic model of criminal behaviour predicts a decrease in the amount of time devoted to criminal behaviour following an increase in job availability (Becker, 1968; Ehrlich, 1973; Grogger, 1998). Life course theories from the sociology and criminology literature emphasise employment as a turning point in the life of an ex-convict that reduces criminal behaviour (Laub and Sampson, 1993; Uggen, 2000).

This article suggests that specific types of employment opportunities affect the behaviour of released offenders. There are two important reasons it is necessary to distinguish between different types of jobs. First, a large portion of employment opportunities are not accessible to released offenders due to factors such as education requirements and employer reluctance to hire applicants with criminal records. Panel (*a*) of Figure 1 displays the distribution of private-sector workers who had been recently incarcerated across industries.[2] Since legitimate employment opportunities for former offenders are heavily concentrated in a small number of industries, it is not surprising that researchers using local unemployment rates to measure employment opportunities find small and/or insignificant effects on recidivism. Aggregate fluctuations do not accurately measure changes in labour market conditions relevant to individuals with a criminal record who are searching for work.

Second, within the limited set of employment opportunities accessible to this population, certain jobs are clearly superior to others. Panel (*b*) of Figure 1 displays average monthly earnings for recently hired low-skill (high school diploma or less) employees in California – workers can expect to earn 33% to 100% more in construction or manufacturing than in retail or food services. In theory, a construction or manufacturing job opportunity should deter more crime than one with lower expected wages.

In this article, I link outcomes for more than 1.7 million former offenders in California with measures of employment opportunities at the time and location of labour market entry. The rigid institutional features of the California criminal justice system provide a setting in which the timing and location of release from prison are exogenous to variation in local labour market conditions. Labour market data recording the number of low-skill individuals hired (job accessions) within each industry and county allow estimation of heterogeneous effects across different types of employment opportunities. Job accessions are my preferred measure of job opportunities since employment levels can mask job openings that are a result of other workers leaving the industry.[3] While changes in job accessions may also measure changes in labour supply, this is less of a concern in this setting since the industries relevant to released offenders tend to be those with little excess demand.[4]

Overall, I find that the existence of low-skill manufacturing and construction employment opportunities at the time of labour market entry is associated with significant reductions in the number of released offenders who return to prison. A one-standard-deviation increase in the number of workers starting a new job in construction is associated with a 2.2% decrease in the number of released inmates returning to prison within one year; a one-standard-deviation increase in

[2] Data from the National Longitudinal Survey of Youth 1979 (Bureau of Labor Statistics, 2011) is used to calculate the distribution of former offenders across industries. I focus on private sector industry concentration since the labour market flow data used in my analysis is only available for private sector employers in California during my time period of analysis.

[3] While industries with high turnover may offer fewer permanent jobs to released offenders, a high turnover rate can also lead to more opportunities at the time of release.

[4] Using the Job Openings and Labour Turnover Survey data, I calculate a ratio of hires to openings of 3.3 for construction and 1.4 for manufacturing for the period between 2000 and 2008. The average of this ratio across all industries is 1.3.

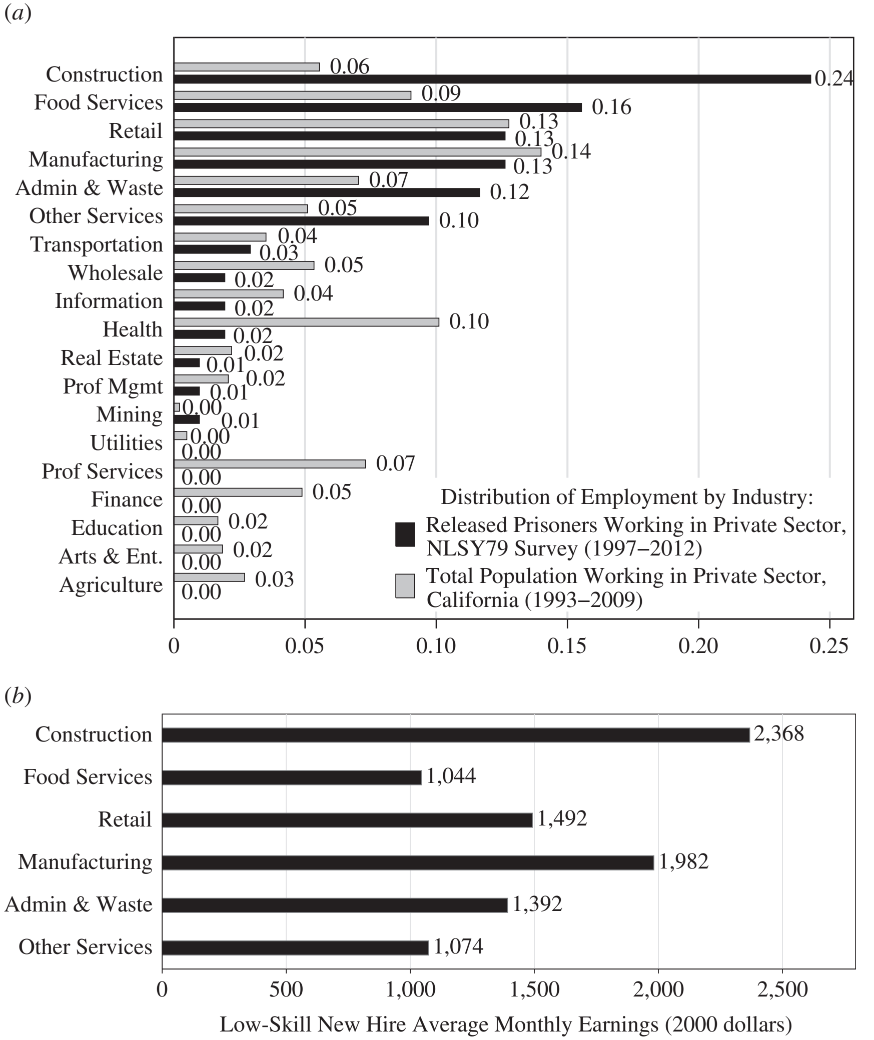

Fig. 1. *Employment Opportunities for Released Offenders. (a) Which Industries Employ Offenders Released from Incarceration? (b) How Much can Released Offenders Expect to Earn in Relevant Industries?*

Notes. Panel (*a*) The industry distribution of recently released prisoners was calculated from National Longitudinal Survey of Youth 1979 (NLSY79) for the years 1997–2012 (Bureau of Labor Statistics, 2011). For each survey participant exiting jail or incarceration, the first industry of employment within 12 months from release was obtained (n = 103). These estimates are based on a small number of individuals in a national sample which is, on average, younger than the average prisoner released in California. However, the distribution of workers across industries is consistent with the estimated industry distribution of individuals in the Survey of Inmates in State and Correctional Facilities (SISCF) reporting pre-incarceration occupations. Panel (*b*) Average monthly earnings by industry for low-skill (high school graduate and less) individuals hired by private sector employers is calculated using statewide California data from the Quarterly Workforce Indicator (QWI) dataset for the years 1993–2009. The QWI contains skill- and industry-specific average monthly earnings for individuals hired during each quarter. These average earnings by quarter are converted to 2000 dollars using the CPI index and then averaged over all quarters between 1993 and 2009 for each industry relevant to released offenders.

manufacturing hires is associated with a 1.36% decrease in one-year return rates. By contrast, low-skill employment opportunities in low-wage industries (such as retail and food services), or opportunities requiring higher levels of education, do not have similar effects on offender behaviour. Effects are largest among drug offenders and individuals released between the ages of 35 and 45. Several robustness tests support a causal interpretation of my results: I find no significant effect from increases in manufacturing and construction hires just prior to release; my results are robust to the inclusion of local crime rates; and are robust to the inclusion of a lagged dependent variable. These results help to eliminate concerns of any bias from unobserved determinants of offender behaviour that could be correlated with manufacturing and construction-specific labour demand at the time of release.

This article is organised as follows: Section 1 describes the institutional setting of parole in California; Section 2 describes the offender and labour market data used in my analysis; I outline and justify my empirical methodology in Section 3; I discuss the estimates from several econometric specifications in Section 4; and I provide concluding remarks in Section 5.

1. Parole in California

Before a determinate sentencing law was passed in 1976, the decision to release an offender in California to parole supervision was made by a parole board.[5] 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 behaviour.

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 releases many offenders from supervision after 13 months. 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 *et al.*, 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 (Wiles and Costello, 2000; Bernasco *et al.*, 2012). Raphael and Weiman (2007) analyse prisoners released in California and document that more than 90% of prisoners released are returned to the county of sentencing. Furthermore, my primary regressors of interest

[5] The Uniform Determinate Sentencing Act, SB 42, passed in 1976 and which became effective during 1977, began the 'Determinate Sentencing Era' in California.

are aggregated to the commuting zone level.[6] Thus, any labour mobility outside counties but within commuting zones would not bias my estimates.

The key outcome in my analysis is recidivism, defined as a return to prison. The Bureau of Justice Statistics describes 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 do not include individual arrest information, I use the 'return to prison' version of the recidivism definition. While the majority of parolees return to prison are done so for some criminal violation, a large fraction have their parole revoked due to a technical violation, such as absconding supervision or other violations of the parole process.

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 three-year outcomes. More than 80% of offenders who eventually return to prison do so within the first year.

2. Data

2.1. *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 admissions (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.[7]

I focus my analysis on working-age (18–65) males released from a California state correctional facility to mandatory parole supervision during the years 1993 to 2008. Due to insufficient data on skill and industry-specific job accessions in small California counties, I drop offenders sentenced in 12 out of the 58 counties in California.[8] Table 1 provides descriptive statistics for my estimation sample of more than 1.7 million parolees. Over two-thirds of prisoners released return to prison and do not successfully complete their parole supervision; the majority (53%) return to prison within one year from their date of release. Among male offenders paroled in California, 40% are white, 30% are black, and 30% are Hispanic. The average sentence for my estimation sample is slightly greater than three years. When classified by the most serious type of criminal offence associated with an offender's incarceration spell,

[6] Commuting zones are geographic units used to define local labour markets and were first developed by Tolbert and Sizer (1996) using data from the 1990 Census.

[7] The combination of date of birth, date of release and county of sentencing is unique for all but 0.15% of the total number of observations. Estimates from models dropping potential absconders (individuals not observed in the parole release data set within three years of release) are similar to those presented.

[8] Counties for which Quarterly Workforce Indicator (QWI) data are not available for each industry and skill level cell for my time period of analysis include: Alpine, Sierra, Modoc, Trinity, Mono, Mariposa, Inyo, Plumas, Colusa, Del Norte, Glenn and Lassen.

Table 1

Released Offender Descriptive Statistics

	Mean	SD
Return rate (within three years)	0.68	(0.07)
Return rate (within one year)	0.53	(0.09)
Male	0.90	(0.02)
Age at prison release	35.23	(1.37)
Black	0.30	(0.16)
Hispanic	0.30	(0.14)
White (non black, non hispanic)	0.40	(0.17)
Sentence length (months)	37.93	(4.28)
Percent of sentence served	0.59	(0.07)
Prior felony conviction	0.25	(0.09)
First parole term	0.36	(0.07)
Drug	0.33	(0.06)
Property	0.32	(0.04)
Violent	0.23	(0.04)
Observations	1,915,180	

Note. Means are reported with standard deviations in parentheses. *Source*. National Corrections Reporting Programme (Bureau of Justice Statistics, 2009).

drug and property offenders each represent a third of the total sample and 23% were incarcerated for a violent crime.[9]

2.2. *Labour Market Data*

Quarterly Workforce Indicator data provide quarterly employment totals, counts of job accessions and separations, 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. First, QWI data include employment flows rather than just reporting employment (or unemployment) levels. Using QWI data, I am able to extract the number of workers who started a new job in a specified county and quarter who were not ‘recalls’, or workers previously employed by the same employer within the same year. Furthermore, I can distinguish between workers of different education levels and specific industries. Counts of low-skill workers who started a new job by industry provide a more specific measure of job opportunities at the time of release compared to fluctuations in unemployment rates or employment-to-population ratios.

Second, QWI data are derived from administrative earnings records, which measure labour market conditions with less error than estimated county unemployment rates (Bartik, 1996). The QWI data are aggregated from employment data reported by firms to the California Unemployment Insurance (UI) programme, which represents more than 99% of formal wage and salary civilian employment in the state.[10] Since the UI

[9] I classify the type of offender by the offence carrying the longest sentence length. The violent category includes murder, assault, sex crimes, robbery and weapons offences. Property crimes include burglary and theft offences.

[10] Informal employment opportunities are not captured by the QWI, which may be an important source of income for released prisoners.

Table 2

Labour Market Descriptive Statistics

	Mean	SD
All new hires	118.53	(40.22)
Low-skill new hires	42.72	(28.75)
High-skill new hires	35.91	(9.74)
Construction low-skill new hires	3.57	(1.24)
Manufacturing low-skill new hires	2.29	(1.36)
Food services low-skill new hires	3.52	(1.18)
Retail low-skill new hires	3.40	(0.94)
Admin/waste low-skill new hires	3.98	(1.87)
Other services low-skill new hires	2.08	(1.02)
All other low-skill new hires	23.15	(28.25)
Unemployment rate	9.06	(5.04)
Low-skill share of employment	0.36	(0.07)
Female share of employment	0.46	(0.03)
Observations	1,020	

Notes. Means are reported with standard deviations in parentheses. All job accession measures (new hires) are calculated as counts per 1,000 working age persons in the commuting zone containing the county of sentencing. Commuting zone boundaries used are introduced in Tolbert and Sizer (1996), with crosswalk files provided by David Dorn on his website http://www.cemfi.es/dorn/data.htm (last accessed: 10 September 2014). *Source*. Quarterly Workforce Indicator Data (United States Census Bureau LEHD Program, 2011).

employment records do not contain information on demographic characteristics of each employee, the Longitudinal Employer-Household Dynamics (LEHD) programme links records from state unemployment insurance programmes 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.[11]

For each of the 64 potential release quarters between January 1993 and December 2008, I obtain quarter-of-release county job accessions.[12] I aggregate county-level job accession data to commuting zones by adding accessions across all counties within each commuting zone and then matching these commuting zone labour market measures with each county-quarter release cohort.[13] Table 2 provides summary statistics for the labour market data.

3. Empirical Methodology

To measure the impact of labour demand on recidivism, the following equation is estimated using panel data of individuals released from a California state prison to parole supervision during the period 1993 to 2008:

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

[12] Unfortunately public sector data are not reliable prior to the second quarter of 2000 in the California QWI data. For this reason, my analysis focuses on private sector accessions. A comparison of estimates using only private sector totals post Q2 2000 with estimates using public and private yield very similar results.

[13] All specifications allow for arbitrary correlation of unobservables within commuting zones since my key variable of interest is constant across counties within a particular commuting zone. Commuting zones are geographic units used to define local labour markets and were first developed by Tolbert and Sizer (1996), using county-level commuting data from the 1990 Census. Commuting zones have been used extensively in the economics literature to define local labour markets. I am grateful for crosswalk files provided by David Dorn at http://www.cemfi.es/dorn/data.htm (last accessed: 10 September 2014).

$$\ln(\text{Recid}_{czt}) = \alpha + \beta^k \text{New Hires}_{zt}^{s,k} + \mathbf{X}'_{czt}\Pi + \mathbf{Z}'_{czt}\Gamma + \tau_t + \phi_c + \lambda_{ct} + \epsilon_{czt}. \tag{1}$$

Each observation is a cohort of released prisoners entering parole supervision with c indexing the county of release (as proxied by the county of sentencing), z indexing the commuting zone, and t indexing the quarter of release. Since the primary independent variable of interest varies across counties and across time periods, I collapse the individual-level data at the level of release cohort and initial county of residence. There are a couple advantages of this approach: first, estimates provide a more conservative approach to inference with each additional observation a county-cohort cell rather than an individual. Second, aggregate cohort estimations are less computationally intensive due to the large number of individual-level observations.[14] The dependent variable represents the natural log of the number of former inmates within each release cohort returning to prison within one year. The dependent variable is logged to facilitate comparison of estimates across multiple specifications. The total size of each release cohort is included as an independent variable rather than used to scale the dependent variable so as not to impose any restriction on the effect of release cohort size.

Fixed effects for year-by-quarter of release (τ_t) and county of sentencing (ϕ_c) are included in all specifications along with a county-specific linear time trend (λ_{ct}). I also add county-specific quadratic trends to allow for non-linear trends as well as county-quarter fixed effects to control for county-specific seasonal patterns. Other control variables include characteristics of each release cohort ($\mathbf{X}'_{ct}$) as well as county-level characteristics ($\mathbf{Z}'_{ct}$). Release cohort controls include: percentage black, percentage Hispanic, average age, percentage with a prior felony conviction, average sentence length, average percentage of sentence served, as well as the percent of offenders in each crime category (drug, property, violent). County-level control variables include: low-skill and female share of total employment, percentage in poverty, median household income (CPI adjusted), the natural log of the police force size and the arrest clearance rate for total offences. To control for the supply of labour, I include the unemployment rate during the quarter prior to release as well as the size of the release cohort. To account for correlation within counties and commuting zones over time, I cluster standard errors at the commuting zone level in all empirical specifications. There are 15 commuting zones in California. Results are robust to the wild-cluster-bootstrap procedure suggested by Cameron *et al.* (2008) and Cameron and Miller (2013).[15] Since observations are at the cohort level, all specifications are weighted by the average size of county release cohorts.

The variables of interest, New Hires$_{zt}^{s,k}$, measure the number of workers (per 1,000 working-age population) of skill-level s starting a new job within industry k and commuting zone z, during quarter t. Since total hires can be decomposed into recalls (workers starting a job at an employer who had employed them during the previous year) and other new hires, I use counts of new hires not including recalls to best

[14] Results from analysis at the individual level using both logit and linear probability models are consistent with the cohort model results and are available upon request.

[15] All specifications were re-estimated using the *cgmwildboot* program created by Judson Caskey and accessed at https://sites.google.com/site/judsoncaskey/data (last accessed: 10 September 2014).

measure labour demand relevant to people just entering the workforce after a period of incarceration.[16] The coefficient, $\beta^{s,k}$ measures the effect of a change in the number of workers hired equivalent to one person per 1,000 working-age population within a commuting zone for skill-level s and industry k.

Models are first estimated where the variable of interest represents the total number of new hires across all education levels and industries. Since work that requires more than a high school diploma is not relevant to the typical parolee – 85% of males with an incarceration history in the United States do not have any education beyond a high school degree (Raphael, 2014) – I decompose total new hires into low-skill (high school graduate and below) and high-skill (any college and above). Still, a significant fraction of low-skill job openings may also be irrelevant to individuals recently released from prison, since certain employers are prohibited by law from hiring convicted felons and many others choose not to consider applicants with criminal records.[17] Using information available through the National Longitudinal Survey of Youth 1997 (Bureau of Labor Statistics, 2011), I identify six primary industries in which former inmates find work: construction, food services, retail, manufacturing, administrative services and waste management and other services.[18] To measure the effects of different types of job opportunities relevant to released offenders, I include counts of new hires specific to each of the six primary (relevant) industries along with low-skill accessions among the other 13 less relevant industries and high-skill accessions.

3.1. *Identification of Labour Market Parameters*

I interpret variation in job accessions as arising from changes in aggregate labour demand that are uncorrelated with unobserved determinants of recidivism among the release cohorts. My empirical methodology controls for unobserved influences that are constant across offenders in a particular time period, such as changes to any state parole policies, by including year-by-quarter fixed effects. The suite of fixed effect parameters account for the vast majority of unobserved prison conditions, training, or benefits available to parolees which may influence recidivism rates since institutional changes are typically made at the state level. Moreover, a county release cohort will include offenders who served time in a wide variety of institutions, since incarceration location will be based on availability of beds and security levels of different facilities. It is also highly unlikely that industry-specific job accessions will be correlated with location-specific changes in unobserved institutional characteristics. The labour market effects in each of the models specified are identified from deviations in job

[16] Results using total new hires (recalls + other hires) are very similar to those reported using non-recall new hires.

[17] 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% of employers always check the criminal backgrounds of job applicants and more than 70% 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 opening (Raphael, 2010, 2014).

[18] The fraction of employed former inmates working in each industry is displayed in panel (*a*) of Figure 1. In this nationally representative survey, I am able to record the industry code of the first job (within one year) following a spell of jail or incarceration. Among all individuals who report employment in the year following release, I calculate the probability of employment within each industry sector.

accessions from an arbitrary common trend across counties, and deviations from within-county linear, quadratic, and seasonal trends.

Ensuring my results measure the effect of job opportunities on offender behaviour relies on an accurate measure of employment opportunities for individuals released from prison which does not capture other location-specific factors impacting offender behaviour (such as gentrification of neighbourhoods or housing availability). To test whether some unobserved factor is driving my results, I include job accession measures during the quarter of release as well as job accession measures in the quarter prior to release. Controlling for the number of new hires when an offender is released from prison, the number of new hires prior to release will not measure employment opportunities but will be correlated with other unobserved factors that may be driving my results. I detect no effect among labour demand measures prior to labour market entry as reported in Table 2. Furthermore, since manufacturing and construction employment opportunities are primarily relevant to men, I test whether these fluctuations influence female behaviour since any unobserved determinants of offender behaviour should impact both male and female parolees. I only find effects among male offenders, supporting my interpretation that the results measure the effect of changes in job opportunities.

Estimates of labour demand effects could also be biased if unobserved criminogenic characteristics of the community to which the prisoner is released are correlated with both recidivism and industry-specific labour 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 the county crime rates 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 labour market measures if there is bias arising from omitted variables. Results from the primary specifications are presented in Table 3. Results from specifications including crime rates are presented in Table 4 and are very similar to the main results presented in Table 3. I also estimate models including lagged values of the dependent variable (ln(Returns)) to control for any other omitted time varying characteristics. Again, Table 4 reports estimates consistent with baseline effects in Table 3.[19]

While very unlikely in my period of analysis, it is possible that more prisoners are released during periods of a state or county budget crises which could plausibly be correlated with industry-specific labour demand fluctuations. Although the timing of prison release is determined by the original sentence minus automatic credits for good behaviour, and year-by-quarter fixed effects pick up any state-wide trends in return rates, I test whether job accession variables are related to the number of prisoners released. Replacing our dependent variable with the total number of prisoners released in each county-quarter cohort, Table 4 shows no influence of construction or manufacturing job accessions on the size of each release cohort. I am also able to assess

[19] Because the introduction of a lagged dependent variable in a fixed effects model can introduce bias if the number of time periods is small, the purpose of including a lagged-dependent variable is solely to provide additional evidence that the estimated effect of labour market fluctuations on recidivism is not biased by omitted variables.

Table 3
New Hires and Recidivism

	(1)	(2)	(3)
New hires	−0.0000	0.0001	−0.0000
	(0.0001)	(0.0001)	(0.0001)
Total hires by skill level			
Low-skill new hires	−0.0000	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0004)
High-skill new hires	0.0001	0.0004	0.0004
	(0.0004)	(0.0003)	(0.0006)
Total new hires by skill level and industry			
Construction low-skill new hires	−0.0153**	−0.0133***	−0.0176***
	(0.0053)	(0.0042)	(0.0033)
Manufacturing low-skill new hires	−0.0036	−0.0059*	−0.0105**
	(0.0031)	(0.0029)	(0.0043)
Food services low-skill new hires	0.0058	0.0023	0.0045
	(0.0050)	(0.0056)	(0.0092)
Retail low-skill new hires	0.0036	0.0019	0.0002
	(0.0050)	(0.0047)	(0.0056)
Admin/waste low-skill new hires	0.0012	0.0002	−0.0005
	(0.0019)	(0.0018)	(0.0014)
Other services low-skill new hires	0.0032	0.0023	−0.0000
	(0.0018)	(0.0021)	(0.0024)
All other low-skill new hires	0.0003	−0.0000	0.0006
	(0.0003)	(0.0003)	(0.0006)
High-skill new hires	0.0002	0.0013*	0.0015*
	(0.0005)	(0.0006)	(0.0008)
Observations (cohorts)	2,944	2,944	2,944
Number of individuals	1,714,664	1,714,664	1,714,664
Average return rate	0.573	0.573	0.573
County and year-quarter FE	Y	Y	Y
County linear trend	Y	Y	Y
County quadratic trend	N	Y	Y
County-quarter FE	N	N	Y

Notes. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors robust to arbitrary within-commuting zone correlation in parentheses. There are 15 commuting zones in California. Statistical significance of results is robust to the 'Wild cluster-bootstrap percentile-t procedure, imposing the null hypothesis' suggested by Cameron *et al.* (2008). All specifications are weighted by the average size of release cohorts by county. All job accession measures (new hires) are calculated as counts per 1,000 working age persons in the commuting zone containing the county of sentencing. This Table reports results from linear regressions as specified in Section 3. The estimation sample includes all male offenders released to mandatory parole supervision in California between January 1993 and December 2008. Control variables include: unemployment rate (quarter prior to release), low-skill employment share, female employment share, percentage in poverty, median household income, log of police, arrest clearance rate, natural log of release cohort size, percentage black, percentage Hispanic, average age at release, percentage with prior felony conviction, average sentence length, average percentage of sentence served.

the degree to which there could be a mechanical relationship between the number of offenders released and job accessions in relevant industries through this specification. If accessions increase due to an increase in labour supply from cohorts of released offenders entering the labour market, I expect a significant correlation between the relevant industries and the total size of the release cohort. I do not find a significant

Table 4

Specifications to Test Causal Interpretation

	(1) Hires prior to release	(2) Include crime rates	(3) Include Lag dep. var.	(4) Dep. var. = ln(Released)
Quarter of release				
Construction low-skill new hires	−0.0146***	−0.0161***	−0.0158***	−0.0019
	(0.0029)	(0.0025)	(0.0026)	(0.0076)
Manufacturing low-skill new hires	−0.0115***	−0.0104**	−0.0094**	0.0043
	(0.0037)	(0.0037)	(0.0036)	(0.0042)
Food services low-skill new hires	0.0052	0.0026	0.0035	−0.0036
	(0.0097)	(0.0092)	(0.0086)	(0.0110)
Retail low-skill new hires	−0.0011	−0.0021	0.0002	0.0100*
	(0.0055)	(0.0055)	(0.0051)	(0.0055)
Admin/waste low-skill new hires	−0.0011	−0.0013	−0.0014	0.0003
	(0.0020)	(0.0015)	(0.0013)	(0.0019)
Other services low-skill new hires	0.0005	0.0001	−0.0001	0.0020
	(0.0026)	(0.0026)	(0.0025)	(0.0046)
All other low-skill new hires	0.0006	0.0005	0.0005	0.0004
	(0.0006)	(0.0005)	(0.0005)	(0.0007)
High-skill new hires	0.0014	0.0016*	0.0017*	−0.0021**
	(0.0009)	(0.0008)	(0.0008)	(0.0010)
Quarter prior to release				
Construction low-skill new hires	−0.0033			
	(0.0054)			
Manufacturing low-skill new hires	0.0022			
	(0.0037)			
Property crime rate		0.0009		
		(0.0009)		
Violent crime rate		0.0002		
		(0.0013)		
Drug arrest rate		0.0052		
		(0.0040)		
Ln(Recid)			0.0839**	
			(0.0328)	
Observations (cohorts)	2,898	2,898	2,898	2,898
Number of individuals	1,695,705	1,695,705	1,695,705	1,695,705
Average return rate	0.575	0.575	0.575	0.575
County and year-quarter FE	Y	Y	Y	Y
County linear trend	Y	Y	Y	Y
County quadratic trend	Y	Y	Y	Y
County-quarter FE	Y	Y	Y	Y

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors robust to arbitrary within-commuting zone correlation in parentheses. This table reports results from linear regressions as specified in Section 3. The sample and controls included are listed in Table 3. While only results on the lag construction and manufacturing accessions are reported, the specification for column (1) includes lags for each category of accessions. Crime rates included in column (2) are obtained from FBI Uniform crime reports.

correlation. This is not surprising since the average number of prisoners released in a given county and quarter is <1% of the average number of quarterly job accessions.

As demonstrated, I do not find any evidence of bias from any of these primary threats to identification and interpretation of my results as the effect of job opportunities on recidivism. The variation in job accessions appears to be independent of potential confounding factors.

4. Results

First, I estimate the relationship between total job accessions at the time of release on the number of parolees returning to prison within one year (Table 3). Results presented in column (1) include county fixed effects, year-by-quarter fixed effects, and a county-specific linear trend. Column (2) adds a county-specific quadratic trend and column (3) adds county-quarter specific effects. The estimated coefficients are very small in magnitude and not statistically distinguished from zero. Changes in aggregate labour demand appear to have very little effect on the probability of returning to prison. Counts of new hires disaggregated by education level also do not influence recidivism as reported in the second panel of Table 3.

Once low-skill counts of new hires are disaggregated by industry, I find large and statistically significant decreases in recidivism associated with increases in the number of low-skill construction and manufacturing workers hired during the quarter of prison release which are fairly consistent across specifications (1) to (3). The preferred model in column (3), which includes county-specific linear and quadratic trends as well as county-quarter fixed effects, reports a 1.8% decrease in recidivism associated with one extra construction hire per 1,000 working-age individuals in a commuting zone during the quarter of prison release. A one-standard-deviation change in the number of low-skill new hires in construction is equal to 1.24 (as reported in Table 2). A similar increase in low-skill manufacturing hires is associated with a 1.0% decrease in recidivism. I do not detect a statistically significant influence of any other relevant industry (food services, retail, admin/waste, or other services) and detect a small and marginally significant increase in recidivism associated with an increase in the number of high-skill job accessions. These effects could be explained by increased returns to crime associated with increases in community income unrelated to an offender's own employment prospects.[20]

All results are robust to inclusion of lagged job accession measures. Although only coefficients on the lagged construction and manufacturing accessions are reported in Table 4, lagged values for each of the relevant industries, other low-skill new hires, and high-skill new hires were included in the regression. The estimated effects of industry-specific labour demand are also robust to the inclusion of county crime rates (property, violent and drug) just prior to release. Table 4 also reports estimated coefficients from a specification including a lagged-dependent variable (the natural log of the number of prisoners returned in the prior cohort), further supporting my interpretation of the estimated effects.

Throughout my analysis, construction and manufacturing opportunities yield significant effects. Further highlighting the relevance of these two industries, recent research suggests that trends in construction and manufacturing employment can explain most of the growth in unemployment among men without any post-secondary education in the United States (Charles *et al.*, 2013). My results build upon empirical evidence arguing that differential access to manufacturing opportunities contributes to

[20] A few researchers discuss ways in which improvements in economic conditions can increase criminal behaviour. Crime could increase if improving labour market conditions provide more opportunities to steal (when people are at work) and increase the value of the objects typically stolen (i.e. your neighbour buys a brand new car) (Cantor and Land, 1985; Freedman and Owens, 2016).

racial differences in recidivism rates (Wang *et al.*, 2010; Bellair and Kowalski, 2011) and also suggest that construction opportunities may exert even a larger influence compared to jobs in manufacturing.

The pattern of results suggests that the quality of the job is a crucial factor that does not just reflect differences across industries in employer willingness to hire applicants with criminal records. As previously discussed, Figure 1 indicates that employment in food services, retail and a few other industries is also common among released offenders. Supporting this assertion, Holzer *et al.* (2003) find similar rates of willingness to accept applicants with criminal backgrounds in retail establishments as compared to manufacturing and construction in a survey of employers in Los Angeles during 2001.

While results are specific to individuals released from prison in California, they contribute to research that estimates the relationship between local labour markets and local crime rates in a few ways. First, while the focus of the analysis is on job opportunities, my research contributes to prior work that demonstrates the influence of wages on crime (Grogger, 1998; Doyle *et al.*, 1999; Gould *et al.*, 2002; Machin and Meghir, 2004; Mocan and Unel, 2011). Doyle *et al.* (1999), Gould *et al.* (2002), and Machin and Meghir (2004) each find that low-skill wages greater than that of local unemployment rates. My results suggest that expected wage changes caused by industry employment trends could also be important determinants of crime. Second, my results suggest that the large disparity between OLS and IV estimates in recent work (Raphael and Winter-Ebmer, 2001; Gould *et al.*, 2002; Öster and Agell, 2007; Lin, 2008) could potentially be due to the use of an instrument specific to the manufacturing industry. I find that the manufacturing opportunities have a strong influence on recidivism relative to other types of opportunities and thus aggregate estimates exploiting shocks to this sector may overstate the effect of average labour market fluctuations.

4.1. *Heterogeneity by Type of Criminal*

Table 5 further examines the relationship between low-skill industry-specific new hires and recidivism for different types of parolees based on prior criminal histories. The average one-year recidivism rate for each group is reported at the bottom of each column for each sub-sample. I find particularly large and statistically significant effects of employment opportunities in construction and manufacturing for individuals incarcerated for drug crimes. The hiring of one construction worker per 1,000 working-age individuals in a commuting zone at the time of release is associated with a 2.4% decrease in one-year recidivism. A similar increase in the number of manufacturing workers hired decreases recidivism by 1.5%. Table 5 reports statistically significant effects for construction opportunities among property offenders and effects for manufacturing opportunities among violent offenders. These findings may be due to employer preferences; Holzer *et al.* (2006) and Raphael (2010) report evidence from employer surveys suggesting that among the very few employers who are willing to consider applicants with a criminal record, most favour drug offenders over property or violent criminals. 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.

Table 5

Heterogeneous Effects by Type of Criminal

	(1) Drug	(2) Property	(3) Violent	(4) First	(5) Repeat
Construction low-skill new hires	−0.0237***	−0.0177**	−0.0037	−0.0191**	−0.0166***
	(0.0053)	(0.0065)	(0.0065)	(0.0072)	(0.0031)
Manufacturing low-skill new hires	−0.0151**	−0.0091	−0.0163**	−0.0218**	−0.0079*
	(0.0064)	(0.0079)	(0.0067)	(0.0087)	(0.0041)
Food services low-skill new hires	0.0126	−0.0001	0.0120	0.0050	0.0059
	(0.0150)	(0.0102)	(0.0122)	(0.0153)	(0.0107)
Retail low-skill new hires	0.0048	−0.0009	−0.0036	−0.0040	0.0011
	(0.0061)	(0.0045)	(0.0091)	(0.0099)	(0.0047)
Admin/waste low-skill new hires	−0.0036	0.0046*	−0.0066*	−0.0065	0.0007
	(0.0037)	(0.0023)	(0.0034)	(0.0037)	(0.0014)
Other services low-skill new hires	0.0093	−0.0033	−0.0083***	0.0001	0.0003
	(0.0068)	(0.0044)	(0.0025)	(0.0047)	(0.0029)
All other low-skill new hires	0.0022***	0.0010	−0.0005	0.0014	0.0003
	(0.0006)	(0.0006)	(0.0012)	(0.0013)	(0.0004)
High-skill new hires	0.0004	0.0002	0.0025**	0.0044**	0.0007
	(0.0012)	(0.0013)	(0.0010)	(0.0016)	(0.0007)
Observations (cohorts)	2,911	2,936	2,923	2,929	2,942
Number of individuals	555,620	542,247	416,826	572,107	1,142,502
Average return rate	0.537	0.647	0.544	0.413	0.652

	(6) Repeat drug	(7) Repeat property	(8) Repeat violent	(9) Time served < 15 months	(10) Time served ≥ 15 months
Construction low-skill new hires	−0.0254***	−0.0155***	−0.0110	−0.0126**	−0.0253***
	(0.0062)	(0.0050)	(0.0073)	(0.0052)	(0.0062)
Manufacturing low-skill new hires	−0.0080	−0.0070	−0.0138***	−0.0109***	−0.0119
	(0.0076)	(0.0078)	(0.0044)	(0.0026)	(0.0072)
Food services low-skill new hires	0.0100	−0.0005	0.0134	0.0048	0.0037
	(0.0167)	(0.0122)	(0.0166)	(0.0102)	(0.0097)
Retail low-skill new hires	0.0017	0.0006	0.0002	0.0042	−0.0031
	(0.0066)	(0.0042)	(0.0085)	(0.0054)	(0.0077)
Admin/waste low-skill new hires	−0.0018	0.0079**	−0.0083**	0.0015	−0.0028
	(0.0019)	(0.0030)	(0.0037)	(0.0016)	(0.0018)
Other services low-skill new hires	0.0063	−0.0006	−0.0057	−0.0001	−0.0008
	(0.0068)	(0.0035)	(0.0037)	(0.0032)	(0.0032)
All other low-skill new hires	0.0017***	0.0007	−0.0008	0.0015**	−0.0003
	(0.0005)	(0.0007)	(0.0015)	(0.0005)	(0.0007)
High-skill new hires	−0.0007	−0.0003	0.0024**	0.0002	0.0028**
	(0.0014)	(0.0013)	(0.0010)	(0.0006)	(0.0010)
Observations (cohorts)	2,882	2,924	2,895	2,939	2,941
Number of individuals	364,918	388,076	263,668	854,848	859,787
Average return rate	0.640	0.696	0.633	0.625	0.525
County and year-quarter FE	Y	Y	Y	Y	Y
County linear trend	Y	Y	Y	Y	Y
County quadratic trend	Y	Y	Y	Y	Y
County-quarter FE	Y	Y	Y	Y	Y

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors robust to arbitrary within-commuting zone correlation in parentheses. Column (4) provides results for cohorts of offenders released for the first time to parole without any prior felony convictions. Columns (5), (6), (7) and (8) provide results for cohorts of individuals who either have a prior felony conviction or prior parole failure. Column (9) provides results for released offenders serving <15 months (the median time served for the full sample) and column (10) presents results for those serving more than 15 months.

However, I do find evidence that manufacturing opportunities can influence recidivism among violent offenders.

Columns (4) and (5) of Table 5 split offenders by whether they are released to parole for the first time and are not recorded as having any prior felony convictions (first-time offenders) and those who are repeat offenders. I estimate a similar response to construction fluctuations among both groups but a much larger decrease in recidivism for first-time offenders in response to an increase in the number of manufacturing opportunities at the time of release. Again, this could be driven by employer demand since employers likely prefer first-time offenders.

To explore heterogeneity in effects across these offender types further, I report estimates for the different types of repeat offenders (drug, property, and violent) in columns (6), (7) and (8) of Table 5. These offenders have much higher rates of reoffending and thus their response to employment opportunities is important from a policy perspective. Overall, the pattern of results suggest that repeat offenders do respond to job opportunities with statistically significant effects found for low-skill construction accessions among the drug and property offenders; and for manufacturing opportunities among the violent criminals.[21] I also estimate separate effects for offenders above and below the median amount of time served, which is 15 months, in columns (9) and 10 of Table 5. Those serving more time appear to be more responsive to construction jobs than those serving <15 months.

4.2. *Heterogeneity by Demographic Characteristics*

To investigate whether changes in skill and industry-specific job opportunities have differential effects by race and ethnicity, I separately estimate models for black (non-Hispanic), Hispanic, and white (non-Hispanic) offenders (Table 6). The effects of increases in construction opportunities on recidivism are similar across these three groups. I find a stronger response to manufacturing opportunities among Hispanic offenders. These results suggest that diminished access to relevant job opportunities in disadvantaged communities could potentially contribute to the large racial and ethnic differences in crime and recidivism. Two recent papers in the criminology literature have investigated whether racial differences in recidivism 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. In my setting, fluctuations in demand for low-skill manufacturing workers influence return rates among black offenders, but this effect is not statistically significant. My results suggest that access to construction jobs may be a more important determinant of racial and ethnic differences in recidivism.

I do not find that female inmates are very responsive to skill and industry-specific fluctuations in job accession rates at the time of release. While I do not expect a large

[21] Estimates for first-time offenders split by type of criminal offence are less precise but yield similar patterns. These estimates are available upon request.

Table 6

Heterogeneous Effects by Demographic Characteristics

	(1) Black	(2) Hispanic	(3) White	(4) Male	(5) Female
Construction low-skill new hires	−0.0201***	−0.0152*	−0.0138***	−0.0176***	−0.0038
	(0.0035)	(0.0077)	(0.0036)	(0.0033)	(0.0135)
Manufacturing low-skill new hires	−0.0115	−0.0246*	−0.0005	−0.0105**	0.0136
	(0.0078)	(0.0139)	(0.0033)	(0.0043)	(0.0081)
Food services low-skill new hires	0.0036	0.0096	0.0057	0.0045	0.0041
	(0.0100)	(0.0203)	(0.0105)	(0.0092)	(0.0295)
Retail low-skill new hires	−0.0096	0.0094	0.0026	0.0002	0.0048
	(0.0057)	(0.0114)	(0.0070)	(0.0056)	(0.0192)
Admin/waste low-skill new hires	−0.0058***	−0.0047	0.0009	−0.0005	−0.0095
	(0.0012)	(0.0057)	(0.0021)	(0.0014)	(0.0076)
Other services low-skill new hires	0.0018	−0.0048	−0.0021	−0.0000	0.0248***
	(0.0054)	(0.0088)	(0.0022)	(0.0024)	(0.0081)
All other low-skill new hires	0.0010*	−0.0001	0.0006	0.0006	0.0018
	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0021)
High-skill new hires	0.0022**	0.0030	0.0001	0.0015*	−0.0022
	(0.0009)	(0.0017)	(0.0006)	(0.0008)	(0.0027)
Observations (cohorts)	2,638	2,686	2,941	2,944	2,717
Number of individuals	511,845	532,680	669,577	1,714,664	182,083
Average return rate	0.662	0.490	0.588	0.573	0.489

	(6) 18–25	(7) 25–35	(8) 35–45	(9) 45–55	(10) 55–65
Construction low-skill new hires	−0.0121	−0.0183***	−0.0194**	−0.0272*	0.0308
	(0.0093)	(0.0059)	(0.0068)	(0.0135)	(0.0225)
Manufacturing low-skill new hires	−0.0060	−0.0115	−0.0183***	0.0045	−0.0089
	(0.0091)	(0.0084)	(0.0047)	(0.0080)	(0.0193)
Food services low-skill new hires	0.0096	0.0091	0.0014	0.0187	−0.0528
	(0.0136)	(0.0123)	(0.0142)	(0.0168)	(0.0545)
Retail low-skill new hires	−0.0041	0.0038	−0.0061	−0.0003	0.0072
	(0.0123)	(0.0076)	(0.0066)	(0.0125)	(0.0395)
Admin/waste low-skill new hires	−0.0009	−0.0001	0.0004	−0.0036	0.0014
	(0.0062)	(0.0026)	(0.0029)	(0.0052)	(0.0135)
Other services low-skill new hires	−0.0102	−0.0022	0.0046	0.0023	−0.0162
	(0.0083)	(0.0032)	(0.0045)	(0.0060)	(0.0127)
All other low-skill new hires	0.0030**	0.0003	0.0019***	0.0003	−0.0020
	(0.0012)	(0.0009)	(0.0005)	(0.0012)	(0.0034)
High-skill new hires	−0.0003	0.0011	0.0018	0.0006	−0.0017
	(0.0025)	(0.0013)	(0.0011)	(0.0019)	(0.0046)
Observations (cohorts)	2,837	2,937	2,928	2,829	2,167
Number of individuals	184,372	607,284	514,209	217,077	37,567
Average return rate	0.631	0.580	0.578	0.542	0.530
County and year-quarter FE	Y	Y	Y	Y	Y
County linear trend	Y	Y	Y	Y	Y
County quadratic trend	Y	Y	Y	Y	Y
County-quarter FE	Y	Y	Y	Y	Y

Notes. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors robust to arbitrary within-commuting zone correlation in parentheses. This Table reports results from linear regressions as specified in Section 3 separately run for cohorts defined by the race/ethnicity, gender, and age of released offenders. The sample and controls included are listed in Table 3.

response to changes in predominantly male industries such as construction and manufacturing I expect other types of employment opportunities to be relevant to released female offenders. Surprisingly, column (5) of Table 6 reports a positive estimated effect between new hires in 'other services' and female recidivism, which I cannot explain. Prior evaluations of the relationship between labour market opportunities and recidivism do not separately estimate effects by gender and further research is needed to investigate this relationship. In general, women are less likely to be employed and more likely to depend on public assistance prior to incarceration (Reisig *et al.*, 2006), suggesting that employment may be a less important determinant of successful re-entry among released female offenders than for their male counterparts.

Table 6 presents estimated coefficients for models restricting the estimation sample to certain age groups. The results indicate that the parole behaviour of older offenders (up to the age of 55) is more responsive to relevant labour market fluctuations than the behaviour of younger offenders. Individuals released between the ages of 35 and 45 respond most to construction and manufacturing opportunities. This result is consistent with the notion of this type of work being difficult for older individuals who are more likely to have physical limitations. This pattern of results is also consistent with theories suggesting that the causes of crime are age-graded and vary over the life cycle (Sampson and Laub, 2005). These life course theories predict that effects of employment opportunities on recidivism will not be uniform across age groups. My results line up with these theories and are also consistent with prior empirical research that documents a larger response in criminal behaviour among older offenders presented with employment opportunities (Uggen, 2000).[22] Given that the average recidivism rate among 18–25 year olds is nearly 10% higher than that of individuals between 35 and 45, older offenders are closer to the margin between offending and successful re-entry and I expect those closer to the margin to be more responsive to changes in incentives.

4.3. *Alternative Outcomes and Robustness Checks*

Finally, Table 7 reports estimates for three-year-return rates. As previously discussed, these estimates could be biased by parolees released from parole supervision early (after 13 months) since these parolees are not observed for the same time period as those serving the standard three-year-parole term. While effects for construction opportunities are not statistically significant, the magnitude is consistent with the main results. A one-unit increase in manufacturing opportunities at the time of release is associated with a 1.3% decline in three-year recidivism. A larger long-term effect for manufacturing employment could be driven by differences in the permanence of manufacturing jobs compared with construction jobs. Redefining my labour market demand variables of interest using the average number of quarterly hires within the first two quarters post-release (column (2)), or within the first year post-release (column (3)) also yield consistent results. Although manufacturing hire coefficients

[22] A few recent evaluations of summer youth employment programmes find significant effects on offending among juveniles (Gelber *et al.*, 2014; Heller, 2014). These results are intriguing given a lack of prior research finding a response among younger offenders to employment opportunities.

Table 7

Other Outcomes and Robustness Checks

	(1) Dep. var.: return within 3 year	(2) New hires within 6 months	(3) New hires within 12 months	(4) Exclude Los Angeles	(5*a*) New hires within county	(5*b*) Other new hires within C-zone
Construction low-skill new hires	−0.0078	−0.0183***	−0.0158***	−0.0124***	−0.0179***	−0.0090**
	(0.0045)	(0.0034)	(0.0028)	(0.0037)	(0.0034)	(0.0041)
Manufacturing low-skill new hires	−0.0133**	−0.0087	−0.0066	−0.0064***	−0.0104**	−0.0079**
	(0.0047)	(0.0083)	(0.0103)	(0.0018)	(0.0040)	(0.0030)
Food services low-skill new hires	0.0116	0.0025	0.0107	0.0056	0.0042	0.0110
	(0.0088)	(0.0096)	(0.0121)	(0.0099)	(0.0094)	(0.0106)
Retail low-skill new hires	−0.0007	0.0003	0.0069	0.0031	0.0000	−0.0006
	(0.0037)	(0.0071)	(0.0073)	(0.0065)	(0.0056)	(0.0082)
Admin/waste low-skill new hires	0.0040	0.0006	0.0027	−0.0021	−0.0004	−0.0015
	(0.0033)	(0.0024)	(0.0029)	(0.0026)	(0.0014)	(0.0019)
Other services low-skill new hires	0.0019	−0.0004	0.0006	−0.0008	0.0001	0.0051
	(0.0020)	(0.0025)	(0.0027)	(0.0021)	(0.0024)	(0.0029)
All other low-skill new hires	0.0011*	0.0009	0.0030**	0.0004	0.0006	0.0006
	(0.0006)	(0.0009)	(0.0014)	(0.0007)	(0.0006)	(0.0008)
High-skill new hires	0.0009	0.0006	−0.0011	0.0010	0.0015*	0.0013
	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Observations (cohorts)	2,944	2,887	2,835	2,624	2,944	
Number of individuals	1,714,664	1,713,117	1,711,166	866,355	1,714,664	
Average return rate	0.700	0.574	0.574	0.578	0.573	
County and year-quarter FE	Y	Y	Y	Y	Y	
County linear trend	Y	Y	Y	Y	Y	
County quadratic trend	Y	Y	Y	Y	Y	
County-quarter FE	Y	Y	Y	Y	Y	

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors robust to arbitrary within-commuting zone correlation in parentheses. This Table reports results from linear regressions as specified in Section 3. The sample and controls included are listed in Table 3. Column (1) replaces the dependent variable of returns within one year with one measuring the number of returns within 3 years. Columns (2) and (3) report results from specifications redefining the accession measures with averages over the first two quarters and full year post-release. Column (4) reports estimates of the baseline model excluding the Los Angeles commuting zone which accounts for over half of the individual observations. Column (5) reports results from a model which decomposing new hires into those within the county of release (column (5*a*)) and those outside the county of release but within the same commuting zone (reported next to the w/in county coefficients in column (5*b*)). Estimated effects in Columns (5*a*) and (5*b*) are from the same empirical specification while other columns are separate specifications.

are no longer statistically significant, they are consistent in magnitude. Quarter-of-release measures are preferred since jobs available at the time of release plausibly have a larger influence on offender behaviour as found in a recent experimental evaluation in which recidivism effects of randomly assigned jobs were driven by those assigned work within the first three months after leaving prison (Redcross *et al.*, 2011). To confirm the results are not driven primarily by the Los Angeles area commuting zone, which captures more than 50% of California's parole population, I present results excluding this commuting zone in column (4) of Table 7. Estimates are smaller in magnitude but still consistent with those found for the entire sample and significant at the 99% confidence level.

Finally, while commuting zones are a standard measure of relevant labour markets since they are defined using data documenting residential and employment patterns in the US, the commute patterns of released offenders are likely more limited and dependent on public transit. Columns (5*a*) and (5*b*) of Table 7 test whether accessions closer in proximity to the likely residential location of the released offender exhibit a greater influence on employment opportunities relative to accessions within the commuting zone but not within the predicted county of residence. As expected, my results can largely be attributed to job opportunities located closer to the released offender. I do estimate a statistically significant impact of opportunities in the remainder of the commuting zone for the construction and manufacturing categories but effects are smaller than those of opportunities within the county.

5. Conclusion

The empirical results presented largely support predictions from the standard theoretical models that relate crime to economic incentives and provide an explanation why prior research examining the impact of local labour market conditions on recidivism finds small and/or statistically insignificant effects (Bolitzer, 2005; Raphael and Weiman, 2007). They indicate that individuals recently released from prison adjust their behaviour in response to changes in certain types of labour market opportunities. Specifically, offenders released from prison in California are less likely to return to prison if a greater number of construction and/or manufacturing opportunities are available at the time of release. Compared to other low-skill jobs accessible to individuals with criminal records, such as those in retail and food services, construction and manufacturing jobs pay significantly higher wages and are much more likely to be associated with other benefits which separate good jobs from others.

This study also helps explain mixed results in experimental evaluations of transitional job re-entry programmes (Redcross *et al.*, 2011; Jacobs, 2012; Raphael, 2014). While a programme offered by the Center for Employment Opportunities (CEO) in New York City found reductions in future criminal activity for offenders randomly assigned transitional jobs (Redcross *et al.*, 2011), the Transitional Jobs Reentry Demonstration (TJRD) implemented in Chicago, Detroit, Milwaukee and St. Paul did not find differences in future criminal activity across each of the locations (Jacobs, 2012). The CEO programme randomly assigned released offenders to work crews with other released offenders in which participants primarily did maintenance and repair work for city and state agencies. Offenders in the TJRD programme were randomly assigned to temporary minimum-wage jobs in a variety of settings.

Surprisingly, neither programme was associated with increases in employment or earnings following the first year, suggesting that these programmes did not facilitate a transition into more permanent or higher-wage work. Interestingly, Jacobs (2012) documents TJRD programme effects on recidivism, which differed considerably across the four locations. The largest benefits were observed in Chicago, where the TJRD programme participants all worked in a garbage recycling plant and experienced more than a 30% decrease in recidivism relative to the control group. Estimated benefits were much smaller in Detroit and St. Paul where offenders worked in Goodwill retail stores or in a light manufacturing plant. Given my estimates, it would be very interesting to see whether the effects of the programme in Detroit and St. Paul locations vary across the different types of work (retail *versus* manufacturing). Future randomised trials could test whether the quality of jobs matters by randomly assigning offenders to opportunities which vary by type and/or compensation.

My estimates suggest that any rise in recidivism as a result of the 30% decline in low-skill manufacturing employment between 1993 and 2006 in California was offset by the 60% growth in construction employment. Specifically, my estimates show, holding all other factors constant, that the proportion of released offenders returning to prison within one year would have been more than 12% higher had there been no growth in construction jobs during the past two decades and 10% lower had there been no decline in low-skill manufacturing jobs.

Overall, my study provides robust evidence that the quality of employment opportunities for released offenders may be more important than the quantity of employment opportunities. These results suggest that policies and/or programmes that create more good job opportunities for released offenders can reduce incarceration rates. Such policies might include: economic stimulus initiatives aimed at certain industries with high concentrations of good jobs, such as recent federal efforts to grow local manufacturing sectors; policies that increase the compensation for work within industries which do not offer good jobs for low-skill workers, such as minimum-wage increases or the implementation of 'living wages'; or policies and programmes that augment the skill levels of this population to increase the number of high-quality opportunities accessible, such as education or skill-specific training programmes in prison facilities. Further research is needed to evaluate the effect of these types of policies and programmes and to assess their cost-effectiveness.

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Additional Supporting Information may be found in the online version of this article:

Data S1.

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