# Online Appendix for:
# Can you Erase the Mark of a Criminal Record? Labor Market Impacts of Criminal Record Remediation

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# A Additional Figures and Tables

Table A.1: Survey 1 of Hiring Professionals on Criminal Background Check Procedures

| | Yes | No | Unsure/Mi |
|---|---|---|---|
| *Full Sample, N=806* | | | |
| Perform criminal background check? | 0.68 | 0.23 | 0.09 |
| Knowledgeable about background check procedure? | 0.59 | 0.39 | 0.02 |
| *Background Check & Knowledgeable Sample, N=382* | | | |
| **How Background Check Performed?** | | | |
| Known CRA (able to name) | 0.77 | | |
| Unknown external agency | 0.11 | | |
| Government Official Records | 0.08 | | |
| Perform "in-house" | 0.04 | | |
| **Distinguish between felony and misdemeanor?** | | | |
| More likely to hire if misdemeanor than felony | 0.72 | | |
| Did not distinguish | 0.24 | | |
| Other/No Response | 0.04 | | |

**Notes:** Survey of 806 individuals with hiring experience in the United States in the past 5 years asked about firms' criminal background check practices for **entry-level** positions.

Table A.2: Summary Statistics: First-Event Analysis Estimation Sample, Before and After First Charge/Disposition

(a) Misdemeanor Non-convictions , MD and Bexar, TX

| | Two Years Before | Year After | Five Years After |
|---|---|---|---|
| Files 1040 | 0.711 | 0.682 | 0.659 |
| | | (0.002) | (0.003) |
| Has Labor Earnings | 0.804 | 0.780 | 0.746 |
| | | (0.001) | (0.002) |
| Has W2 Earnings | 0.768 | 0.745 | 0.716 |
| | | (0.001) | (0.002) |
| W2 Earnings (1000 $) | 14.594 | 13.147 | 12.794 |
| | | (0.067) | (0.139) |
| Has SE Earnings | 0.068 | 0.065 | 0.058 |
| | | (0.001) | (0.002) |
| SE if Has Earnings | 0.084 | 0.084 | 0.082 |
| | | (0.001) | (0.002) |
| Has 1099 NEC | 0.076 | 0.077 | 0.067 |
| | | (0.001) | (0.002) |
| EITC Claimant | 0.247 | 0.240 | 0.233 |
| | | (0.001) | (0.002) |
| N | 160072 | | |

(b) Felony Non-convictions, MD, NJ, and Bexar, TX

| | Two Years Before | Year After | Five Years After |
|---|---|---|---|
| Files 1040 | 0.635 | 0.574 | 0.592 |
| | | (0.003) | (0.006) |
| Has Labor Earnings | 0.754 | 0.691 | 0.682 |
| | | (0.003) | (0.005) |
| Has W2 Earnings | 0.719 | 0.657 | 0.652 |
| | | (0.003) | (0.005) |
| W2 Earnings (1000 $) | 11.593 | 8.639 | 9.564 |
| | | (0.122) | (0.241) |
| Has SE Earnings | 0.067 | 0.063 | 0.057 |
| | | (0.002) | (0.003) |
| SE if Has Earnings | 0.089 | 0.095 | 0.089 |
| | | (0.003) | (0.004) |
| Has 1099 NEC | 0.061 | 0.054 | 0.051 |
| | | (0.002) | (0.003) |
| EITC Claimant | 0.266 | 0.248 | 0.254 |
| | | (0.003) | (0.005) |
| N | 37891 | | |

(c) Misdemeanor Convictions, MD, NJ, PA, and Bexar, TX

| | Two Years Before | Year After | Five Years After |
|---|---|---|---|
| Files 1040 | 0.654 | 0.593 | 0.598 |
| | | (0.002) | (0.004) |
| Has Labor Earnings | 0.792 | 0.749 | 0.725 |
| | | (0.002) | (0.004) |
| Has W2 Earnings | 0.770 | 0.728 | 0.703 |
| | | (0.002) | (0.004) |
| W2 Earnings (1000 $) | 11.084 | 9.125 | 9.419 |
| | | (0.082) | (0.172) |
| Has SE Earnings | 0.046 | 0.045 | 0.046 |
| | | (0.001) | (0.002) |
| SE if Has Earnings | 0.058 | 0.062 | 0.068 |
| | | (0.001) | (0.003) |
| Has 1099 NEC | 0.062 | 0.061 | 0.062 |
| | | (0.001) | (0.002) |
| EITC Claimant | 0.187 | 0.166 | 0.177 |
| | | (0.002) | (0.003) |
| N | 108397 | | |

(d) Felony Convictions, MD, PA, and Bexar, TX

| | Two Years Before | Year After | Five Years After |
|---|---|---|---|
| Files 1040 | 0.550 | 0.427 | 0.478 |
| | | (0.002) | (0.003) |
| Has Labor Earnings | 0.714 | 0.584 | 0.607 |
| | | (0.002) | (0.003) |
| Has W2 Earnings | 0.690 | 0.565 | 0.587 |
| | | (0.002) | (0.003) |
| W2 Earnings (1000 $) | 9.358 | 4.891 | 5.765 |
| | | (0.064) | (0.121) |
| Has SE Earnings | 0.045 | 0.034 | 0.036 |
| | | (0.001) | (0.002) |
| SE if Has Earnings | 0.063 | 0.062 | 0.067 |
| | | (0.001) | (0.002) |
| Has 1099 NEC | 0.046 | 0.034 | 0.036 |
| | | (0.001) | (0.001) |
| EITC Claimant | 0.194 | 0.145 | 0.161 |
| | | (0.002) | (0.003) |
| N | 123429 | | |

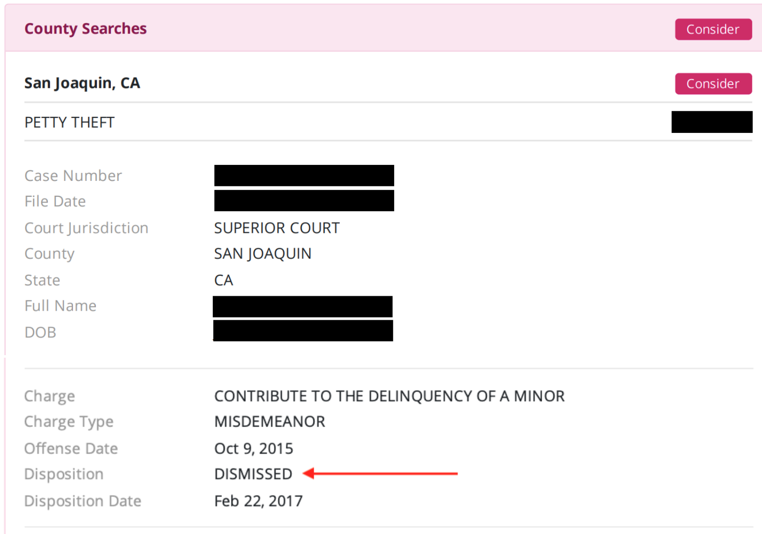
Notes: Table displays mean outcome levels two years prior to an initial criminal history event, where the type of event differs across panels. The sample is the same as in Figure 2, pooling across jurisdictions as specified in table headers. Table also presents mean outcomes one and five years after the specified event implied by our event study estimates of Equation 1, which estimate the change relative to period -2 controlling for aging and macroeconomic conditions. Specifically, we add our estimates of $\beta_1$ and $\beta_5$ from Equation 1 for each event type (displayed in Figure A.4) to the means two years prior to the event. Standard errors reflect estimation of event-study coefficients but not estimation of sample means in period -2. For this analysis, we restrict the full sample to have been 18 by the time the first charge appears in the data for both non-convictions and conviction. Data from 2000-2020. The sample is restricted to events occurring between 1996-2011 to correspond to the event-study sample used to estimate Equation 1. W2 earnings are winsorized at the 99th percentile.

Table A.3: Summary Statistics: Last-Event Analysis Estimation Sample, Two Years Before Last Charge/Disposition.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Last Event is Non-Conv & No Other Conv | | Last Event is Conv. | |
| | Misdemeanor | Felony | Misdemeanor | Felony |
| *2 Years Before Charge/Disposition:* | | | | |
| Any Wages | 0.781 | 0.725 | 0.693 | 0.602 |
| Any 1099 NEC | 0.079 | 0.065 | 0.074 | 0.051 |
| Filed Taxes | 0.716 | 0.639 | 0.627 | 0.475 |
| Any SE Income | 0.059 | 0.061 | 0.050 | 0.040 |
| Total Obs | 87,681 | 21,607 | 204,084 | 183,069 |

Notes: Table displays summary statics for sample in Figure 3, pooling individuals across the states presented within each panel of Figure 3.

Figure A.1: Example Background Check from a Major Provider



**County Searches** Consider

**San Joaquin, CA** Consider

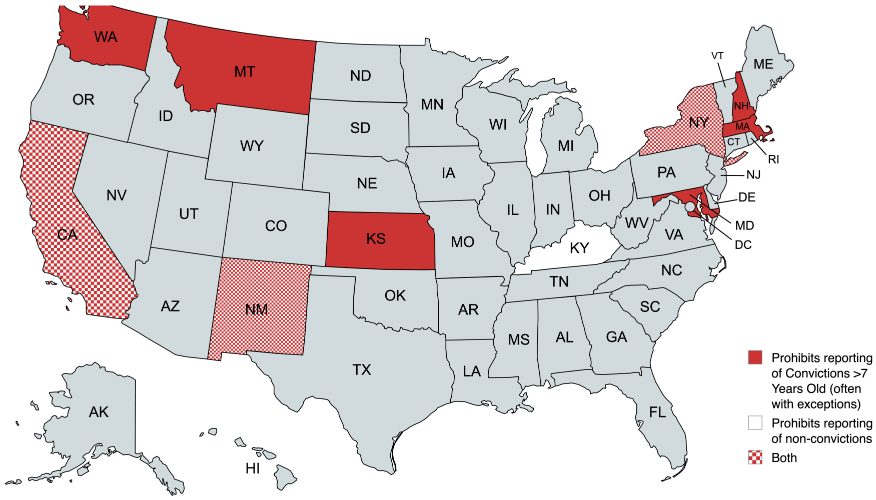
PETTY THEFT [redacted]

| | |
|---|---|
| Case Number | [redacted] |
| File Date | [redacted] |
| Court Jurisdiction | SUPERIOR COURT |
| County | SAN JOAQUIN |
| State | CA |
| Full Name | [redacted] |
| DOB | [redacted] |

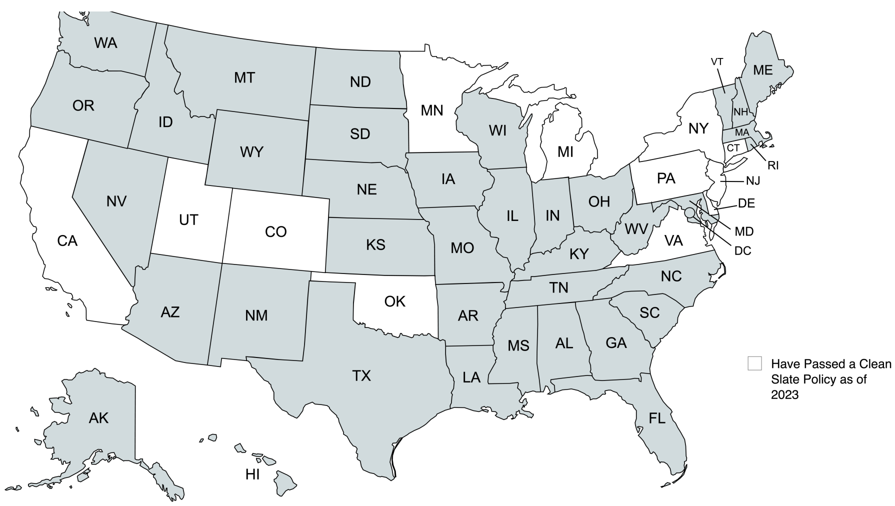
| | |
|---|---|
| Charge | CONTRIBUTE TO THE DELINQUENCY OF A MINOR |
| Charge Type | MISDEMEANOR |
| Offense Date | Oct 9, 2015 |
| Disposition | DISMISSED |
| Disposition Date | Feb 22, 2017 |

Figure A.2: Criminal Record Remediation Policies by State

(a) State Level CRA Reporting Limitations



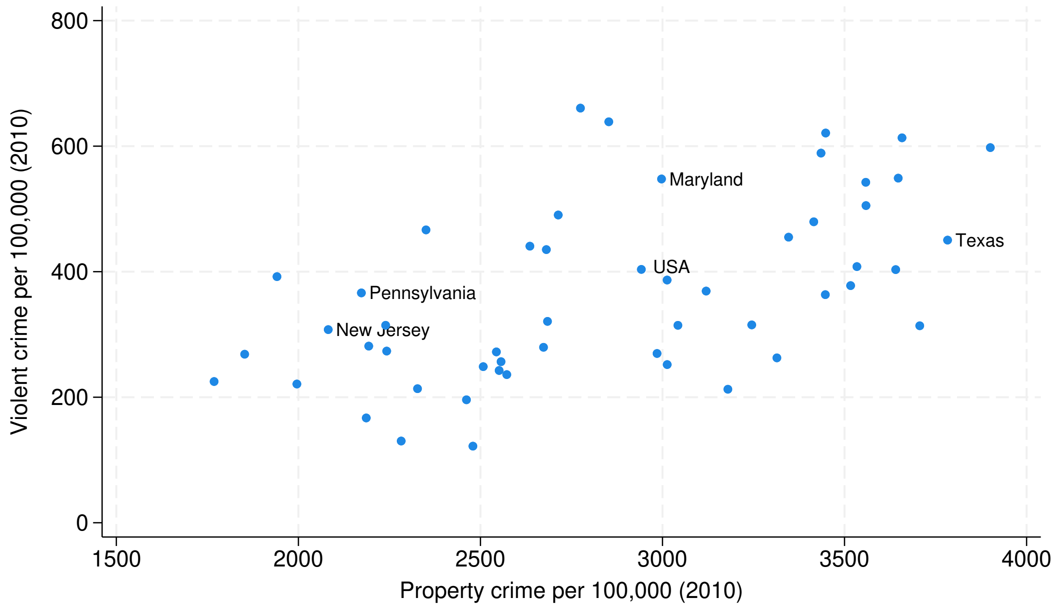

(b) "Clean Slate" Policies



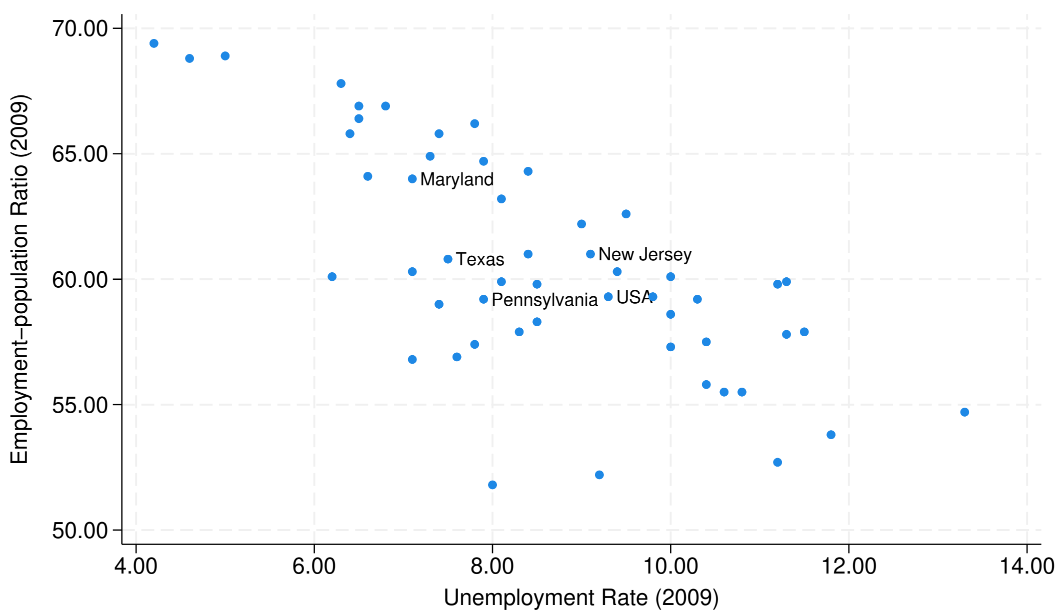

Notes: Panel A shows state CRA reporting limitations that are stronger than FCRA. Note that Texas and Colorado have restrictions in their laws that prohibit the reporting of convictions but these were preempted by the Federal Consumer Credit Reporting Reform Act of 1996. States that had stronger state laws *prior* to the 1996 law were able to keep them, but those that were passed after were preempted and in practice older convictions are reported in TX and CO. The Clean Slate policies listed are policies that have *passed* as of 2023 that meet the criteria of the Clean Slate Initiative; these criteria include that eligible record clearance is automated and there is automatic clearance upon eligibility. What is eligible to be cleared, however, varies state by state. Map created via mapchart.net

Figure A.3: Comparison of our Sample States with U.S. on Crime and Labor Market Outcomes

(a) Crime

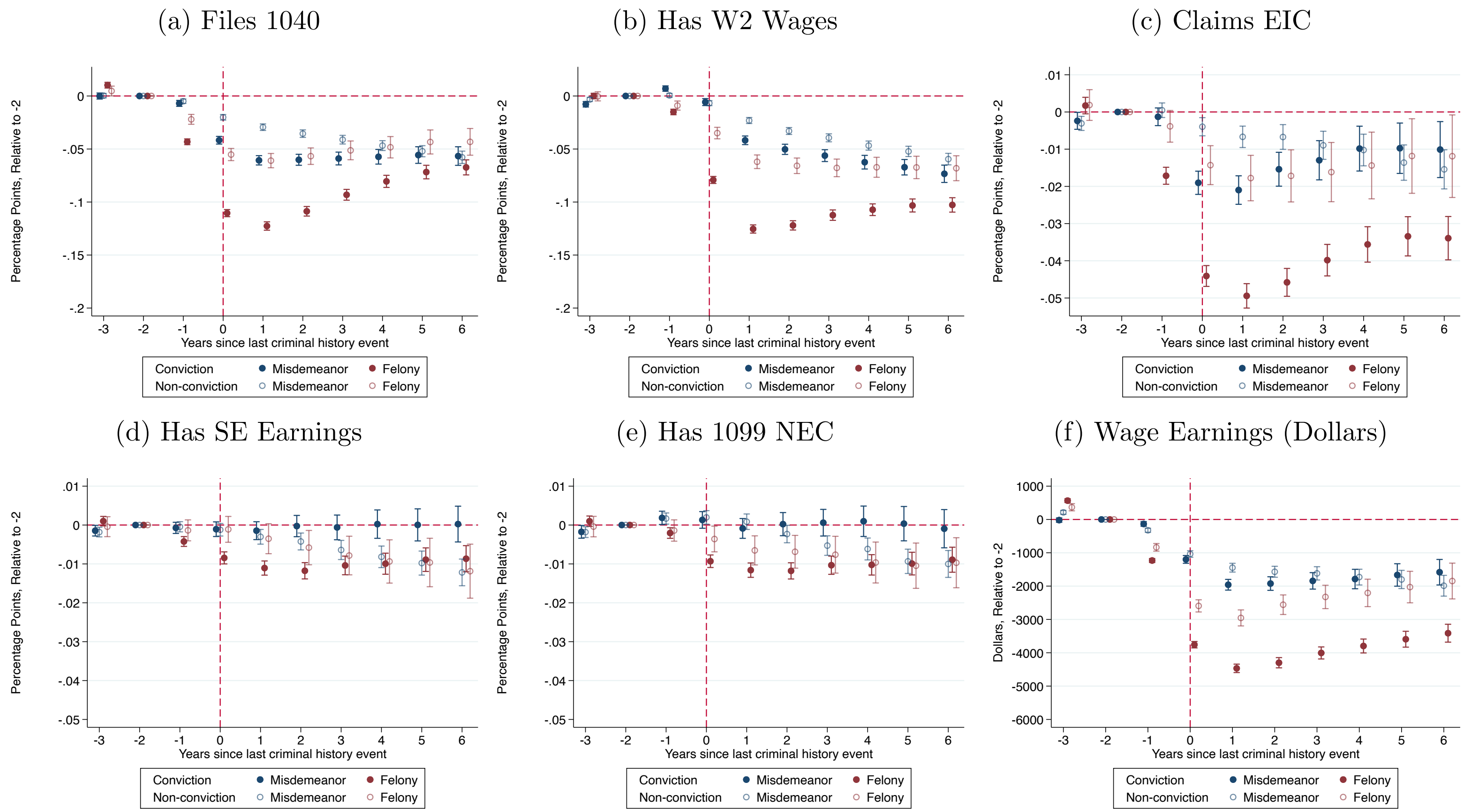



(b) Labor Market




Notes: These scatter plots compare the states in our data (Maryland, Pennsylvania, New Jersey, and Texas) to other states and the entire US on crime and labor market conditions. Panel A uses violent and property crime rates from 2010 (Federal Bureau of Investigation 2014). Panel B uses 2009 unemployment and employment-to-population ratios from the Bureau of Labor Statistics Current Population Survey (U.S. Bureau of Labor Statistics 2009).

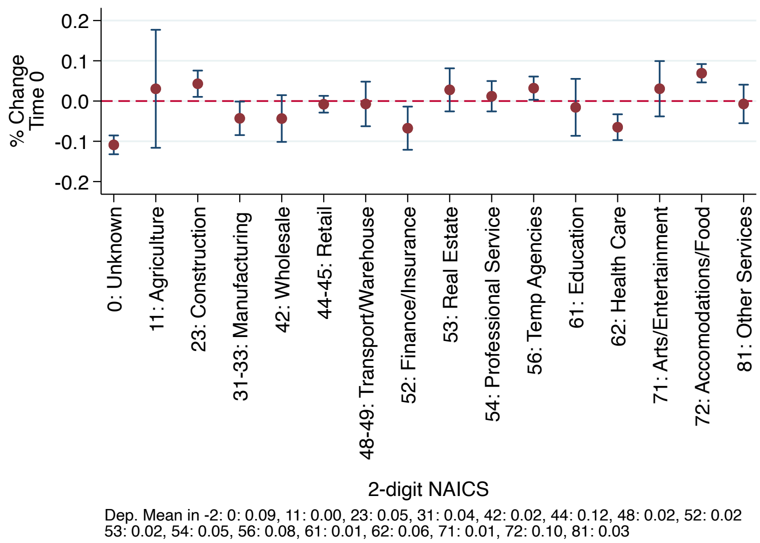
Figure A.4: Reductions in Tax Filing After First Event, Additional Outcomes



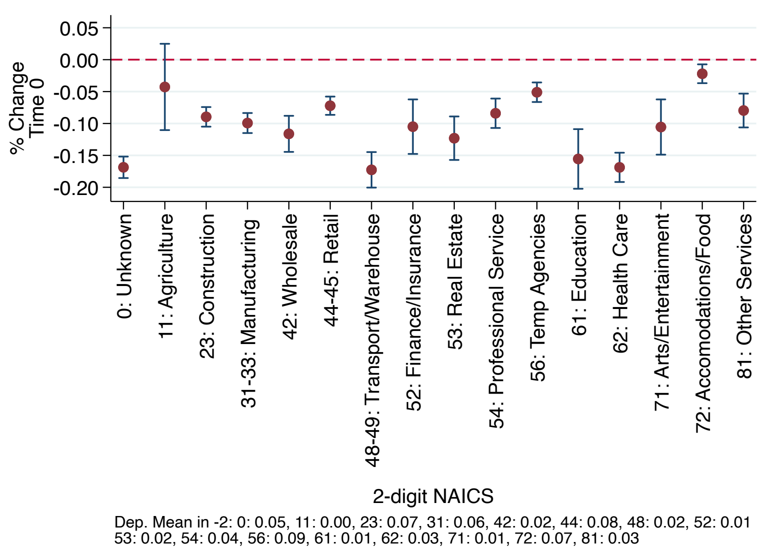

Notes: Each panel plots selected event study coefficients for the specified outcome after an initial criminal history event following Equation 1 in the text, where the type of event is as specified in the legend. Analysis pool data across with data on specified events as described in table headings in Appendix Table A.2. For this analysis, we restrict the full sample to have been 18 by the time the first charge appears in the data for both non-convictions and conviction. This event is the charge date for non-convictions and disposition date for convictions. Coefficients are relative to 2 years before the event. We run separate event studies for each event type and outcome. Data from 2000-2020. The sample is restricted to events occurring between 1996-2011 to ensure the regression is balanced in the event window.

Figure A.5: Event Study of Any Wages Around Last Criminal History Event, By 2-digit NAICS Industry

(a) Non-Convictions



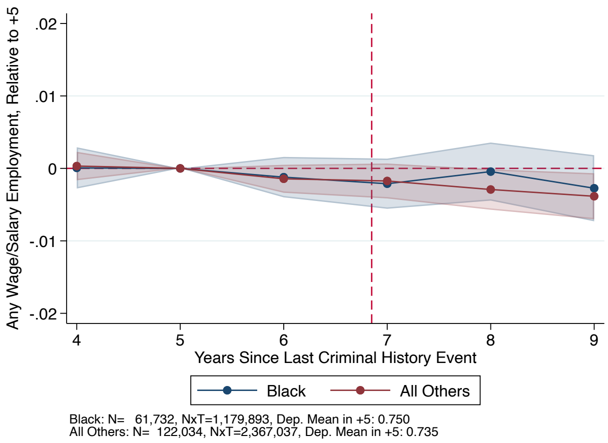

(b) Convictions



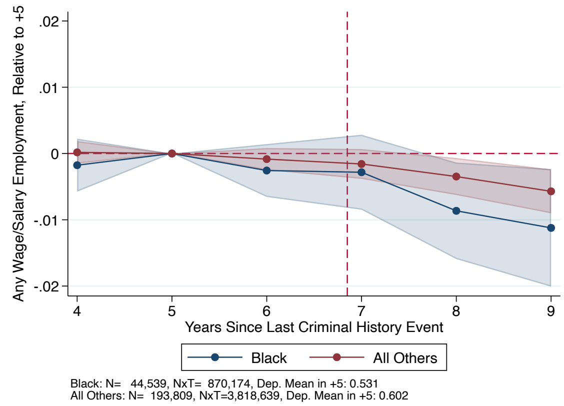

Notes: Figure reports event study estimates at time 0 of W-2 issued by a payer firm in the specified 2-digit NAICS code based on the firms' tax return in that year. We run separate event studies by industry around the criminal history event, and divide by the mean share in the in the industry in -2 to convert to percent.

Figure A.6: FCRA Event Study of Any Wages Around Removal (Year 7), By Race

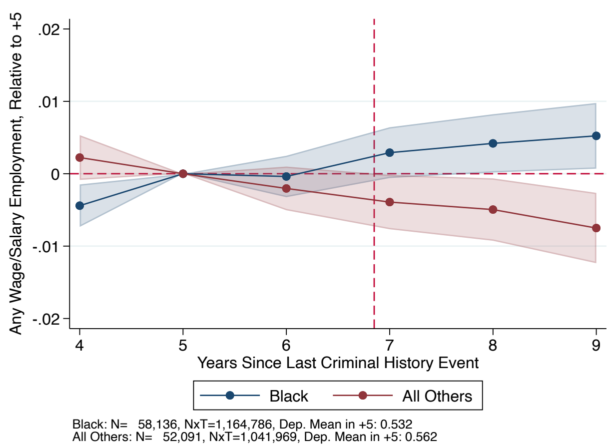
(a) Non-Convictions




(b) Convictions in PA, NJ and TX




(c) Convictions in MD

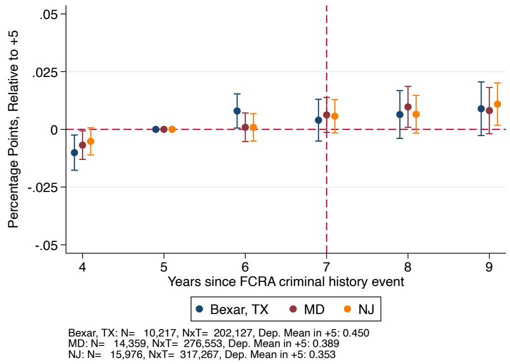



Notes: Each panel plots selected event study coefficients for the share with any wages around 7 years after the event, following specification 1 in the text. Timing from the event is based on the charge date for non-convictions and disposition date for convictions. Coefficients are relative to +5 periods after the event (2 years prior to the year 7 FCRA event, if applicable). We run separate event studies for each state in each panel. Data from 2000-2020. The sample is restricted to events occurring between 1996-2011 to ensure the regression is balanced in the event window. We run separate event studies for Black individuals and all those of all other racial identities.

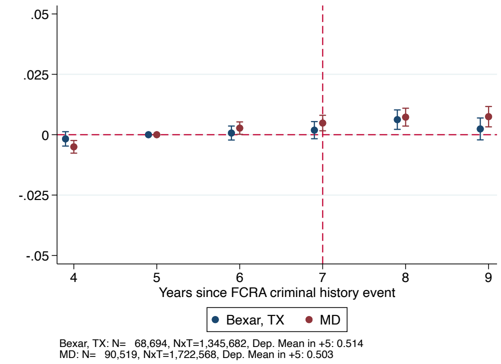
Figure A.7: FCRA Event Study of Any Wages >$15,000 Around Removal (Year 7)

Note: MD has State FCRA for Convictions

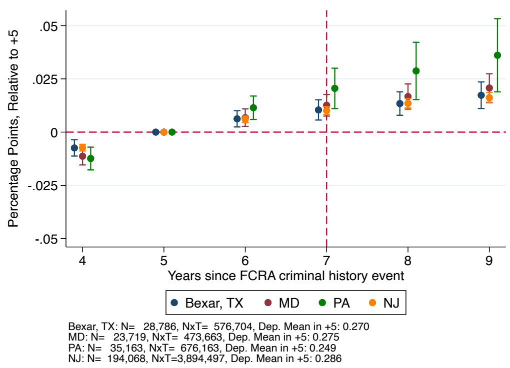
(a) Felony Non-Convictions, no other convictions



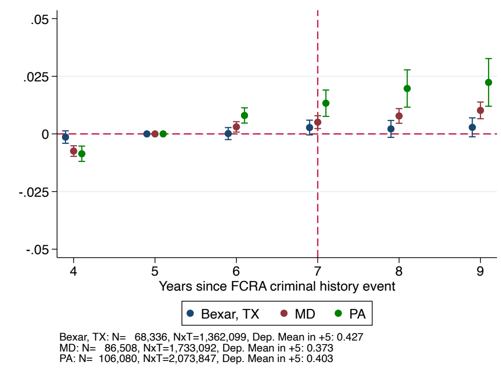

(b) Mis. Non-Convictions, no other convictions




(c) Felony Convictions




(d) Misdemeanor Convictions

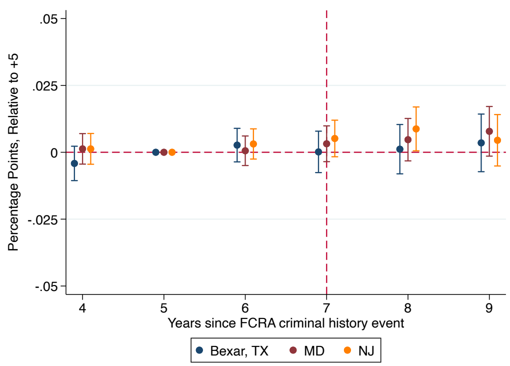



Notes: Each panel plots selected event study coefficients for the share with any wages > $15,000 around 7 years after the event, following specification 1 in the text. Timing from the event is based on the charge date for non-convictions and disposition date for convictions. Coefficients are relative to +5 periods after the event (2 years prior to the year 7 FCRA event, if applicable). We run separate event studies for each state in each panel. Data from 2000-2020. The sample is restricted to events occurring between 1996-2011 to ensure the regression is balanced in the event window.

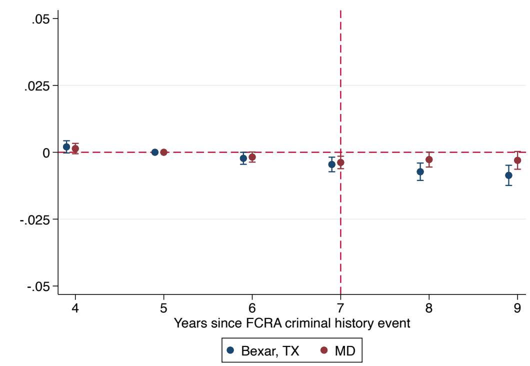
Figure A.8: Robustness to Alternative DD-Estimators: FCRA Event Study of Any Wages Around Removal (Year 7)

Note: MD has State FCRA for Convictions

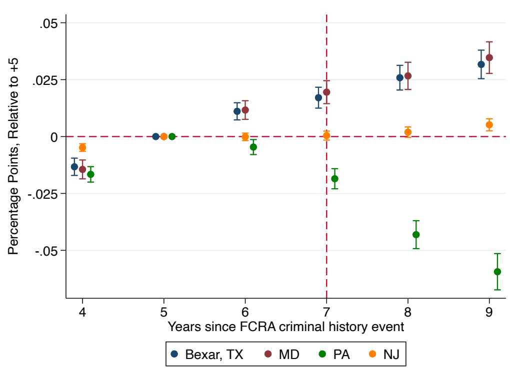
(a) Felony Non-Convictions, no other convictions



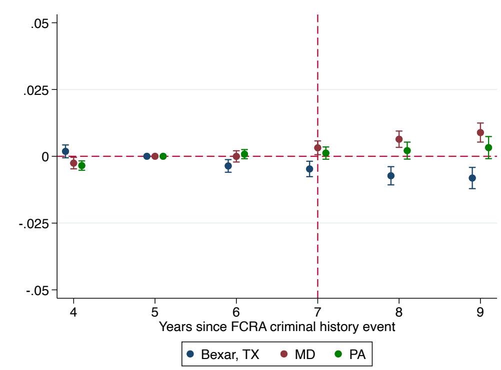

(b) Mis. Non-Convictions, no other convictions




(c) Felony Convictions



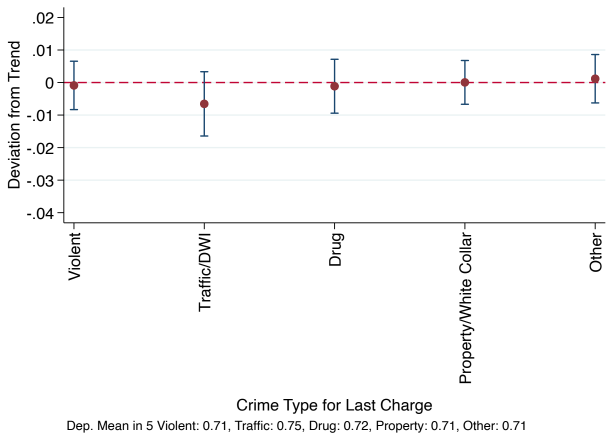

(d) Mis. Convictions



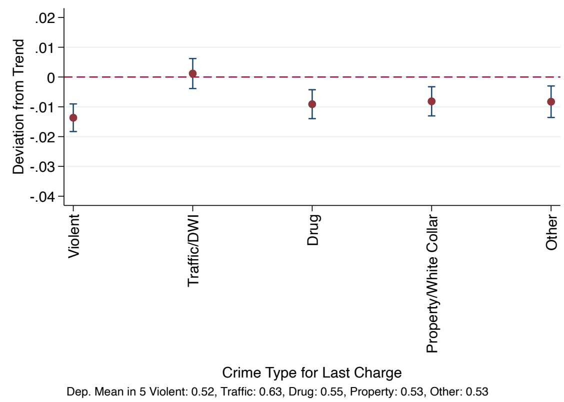

Notes: Each panel plots selected event study coefficients for the share with any wages > \$0 around 7 years after the event, from event-study estimation following Sun and Abraham (2020). Year 7 events occurring in 2021 are used as the last treated group. Timing from the event is based on the charge date for non-convictions and disposition date for convictions. Coefficients are relative to +5 periods after the event (2 years prior to the year 7 FCRA event, if applicable). We run separate event studies for each state in each panel. Data from 2000-2020. The sample is restricted to events occurring between 1996-2014.

Figure A.9: FCRA Event Study of Any Wages Around Removal (Year 7), Deviation from Trend, By Crime-Type of Last Conviction

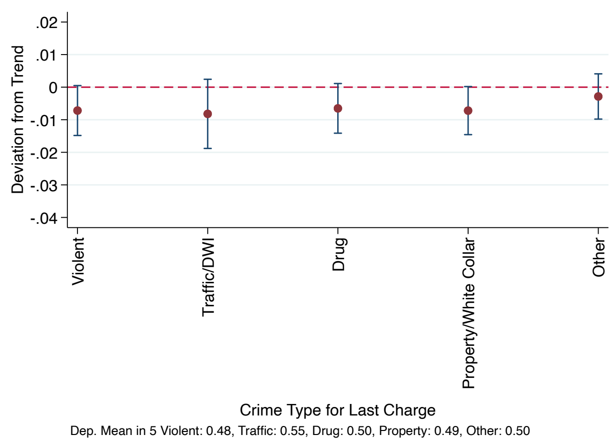
(a) Non-Convictions




(b) Convictions in PA, NJ and TX




(c) Convictions in MD

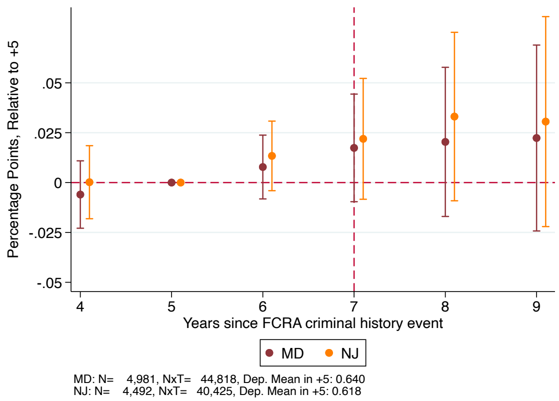



Notes: Figure reports results from a test of whether the event study coefficients 7 years after the last charge are different from a linear trend. Specifically, figure reports $2 \times \beta_{+4} + \beta_{+7}$.

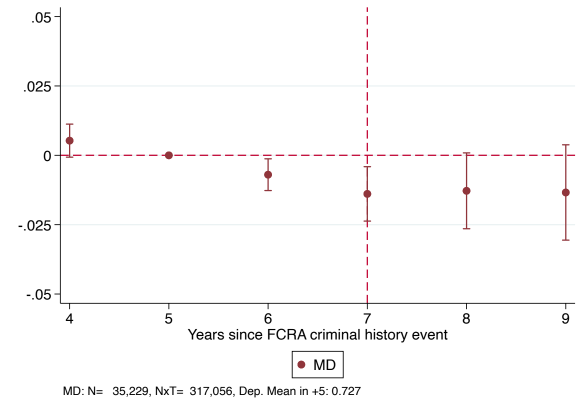
Figure A.10: FCRA Event Study of Any Wages Around Removal (Year 7) occurring between 2015-2018

Note: MD has State FCRA for Convictions

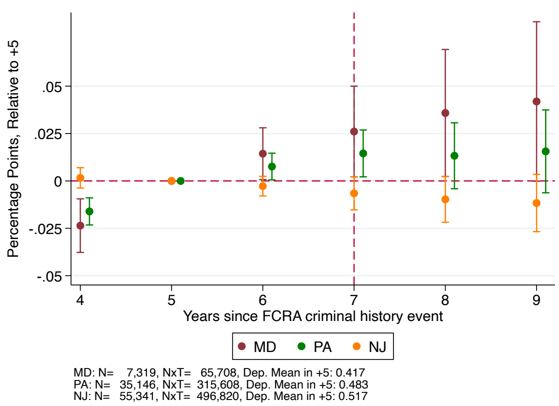
(a) Felony Non-Convictions, no other convictions



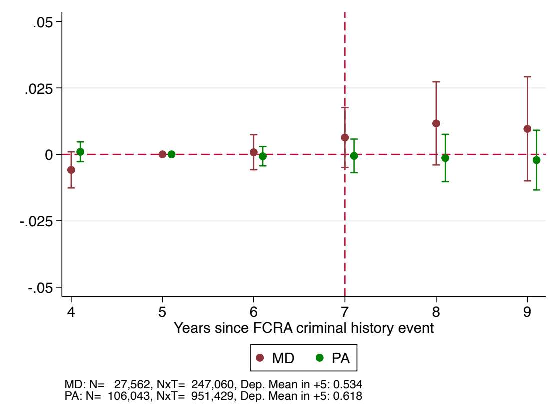

(b) Mis. Non-Convictions, no other convictions




(c) Felony Convictions




(d) Misdemeanor Convictions




Notes: For this figure, the sample is restricted to removal (Year 7) events occurring 2015–2018, with corresponding last criminal history events occurring 2008–2011.

Table A.4: Impact of PA Clean Slate Reductions on Employment Outcomes - Excluding Philadelphia

(a) DD Estimates

| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | 0.004 | -0.003 | 0.002 | -0.000 | 0.001 | -0.001 | -0.003 |
| | (0.003) | (0.004) | (0.004) | (0.002) | (0.002) | (0.004) | (0.002) |
| 2017 × Cleared | -0.003 | -0.002 | 0.010* | -0.002 | -0.006* | -0.006 | -0.006* |
| | (0.004) | (0.004) | (0.004) | (0.001) | (0.003) | (0.004) | (0.002) |
| 2016 × Cleared | 0.001 | -0.002 | 0.005 | 0.001 | -0.004 | -0.004 | -0.003 |
| | (0.004) | (0.005) | (0.005) | (0.001) | (0.003) | (0.005) | (0.003) |
| Dep. Mean (2018) | 0.824 | 0.638 | 0.498 | 0.009 | 0.055 | 0.739 | 0.050 |
| N | 38,268 | 38,268 | 38,268 | 38,268 | 38,268 | 38,268 | 38,268 |
| NxT | 229,872 | 229,872 | 229,872 | 229,872 | 229,872 | 229,872 | 229,872 |
| Age Controls | X | X | X | X | X | X | X |
| Indiv. FE | X | X | X | X | X | X | X |
| Year FE | X | X | X | X | X | X | X |

(b) By months since charge

| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | 0.003 | -0.003 | -0.009 | 0.004 | -0.001 | 0.002 | -0.000 |
| | (0.008) | (0.010) | (0.010) | (0.004) | (0.005) | (0.010) | (0.005) |
| Post (2019-2021) × Cleared × Months since charge | -0.000 | 0.000 | 0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Post (2019-2021) × Months since charge | 0.000** | -0.000 | -0.000** | 0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2017 × Cleared | -0.003 | -0.002 | 0.010* | -0.002 | -0.005* | -0.006 | -0.006* |
| | (0.004) | (0.004) | (0.004) | (0.001) | (0.003) | (0.004) | (0.002) |
| 2016 × Cleared | -0.000 | -0.002 | 0.005 | 0.001 | -0.004 | -0.003 | -0.003 |
| | (0.004) | (0.005) | (0.005) | (0.001) | (0.003) | (0.005) | (0.003) |

Notes: Table reports difference-in-differences results comparing outcomes for individuals who had all their non-convictions cleared by PA's Clean Slate law by 2020, compared with those who did not. Data from 2016-2021. Sample is restricted to ages 18-25 to ensure they had no other prior convictions by the start of our charge data, which begins in 2008. Standard errors clustered on individual are reported in parentheses. [a] p<0.1, * p<0.05, ** p<0.01, *** p<0.001

## Table A.5: Impact of PA Clean Slate Reductions on Employment Outcomes - Black Defendants

### (a) DD Estimates

| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | 0.005 | 0.007 | 0.007 | 0.001 | -0.001 | 0.014$^{a}$ | -0.005 |
| | (0.006) | (0.008) | (0.008) | (0.004) | (0.004) | (0.008) | (0.004) |
| 2017 × Cleared | -0.009 | 0.002 | 0.018* | -0.001 | -0.009* | -0.018* | -0.005 |
| | (0.006) | (0.008) | (0.008) | (0.003) | (0.005) | (0.008) | (0.004) |
| 2016 × Cleared | 0.003 | 0.003 | 0.009 | 0.005 | -0.004 | -0.011 | -0.002 |
| | (0.008) | (0.010) | (0.009) | (0.003) | (0.005) | (0.009) | (0.005) |
| Dep. Mean (2018) | 0.813 | 0.569 | 0.409 | 0.019 | 0.049 | 0.645 | 0.053 |
| N | 13,889 | 13,889 | 13,889 | 13,889 | 13,889 | 13,889 | 13,889 |
| NxT | 83,538 | 83,538 | 83,538 | 83,538 | 83,538 | 83,538 | 83,538 |
| Age Controls | X | X | X | X | X | X | X |
| Indiv. FE | X | X | X | X | X | X | X |
| Year FE | X | X | X | X | X | X | X |

### (b) By months since charge

| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | 0.027$^{a}$ | 0.022 | 0.004 | 0.008 | -0.003 | 0.032$^{a}$ | -0.016$^{a}$ |
| | (0.015) | (0.019) | (0.019) | (0.008) | (0.009) | (0.019) | (0.009) |
| Post (2019-2021) × Cleared × Months since charge | -0.001* | -0.000 | 0.000 | -0.000 | 0.000 | -0.001$^{a}$ | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Post (2019-2021) × Months since charge | 0.001** | 0.000 | -0.000$^{a}$ | 0.000* | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2017 × Cleared | -0.013$^{a}$ | 0.002 | 0.018* | -0.003 | -0.010$^{a}$ | -0.022* | -0.010* |
| | (0.007) | (0.009) | (0.009) | (0.003) | (0.005) | (0.009) | (0.005) |
| 2016 × Cleared | 0.009 | 0.002 | 0.004 | 0.004 | -0.007 | -0.011 | -0.005 |
| | (0.008) | (0.010) | (0.010) | (0.003) | (0.005) | (0.010) | (0.005) |

Notes: Table reports difference-in-differences results comparing outcomes for individuals who had all their non-convictions cleared by PA's Clean Slate law by 2020, compared with those who did not. Data from 2016-2020. Sample is restricted to ages 18-25 to ensure they had no other prior convictions by the start of our charge data, which begins in 2008. Standard errors clustered on individual are reported in parentheses. $^{a}$ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A.6: Impact of PA Clean Slate Reductions on Employment Outcomes - Defendants Other Races

(a) DD Estimates

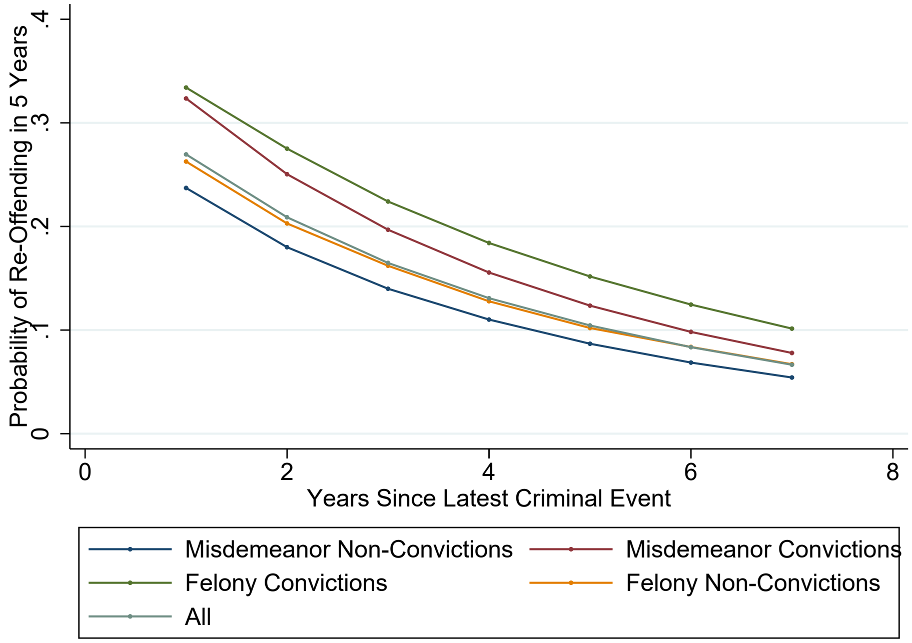
| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | 0.005 | -0.003 | 0.000 | -0.001 | 0.000 | 0.004 | -0.003 |
| | (0.004) | (0.005) | (0.005) | (0.002) | (0.003) | (0.005) | (0.003) |
| 2017 × Cleared | 0.000 | -0.001 | 0.009[a] | -0.001 | -0.005[a] | -0.001 | -0.005[a] |
| | (0.004) | (0.005) | (0.005) | (0.001) | (0.003) | (0.005) | (0.003) |
| 2016 × Cleared | -0.005 | -0.001 | 0.007 | 0.000 | -0.004 | -0.002 | -0.002 |
| | (0.005) | (0.006) | (0.006) | (0.001) | (0.003) | (0.005) | (0.003) |
| Dep. Mean (2018) | 0.807 | 0.639 | 0.511 | 0.008 | 0.059 | 0.742 | 0.051 |
| N | 31,996 | 31,996 | 31,996 | 31,996 | 31,996 | 31,996 | 31,996 |
| NxT | 192,096 | 192,096 | 192,096 | 192,096 | 192,096 | 192,096 | 192,096 |
| Age Controls | X | X | X | X | X | X | X |
| Indiv. FE | X | X | X | X | X | X | X |
| Year FE | X | X | X | X | X | X | X |

(b) By months since charge

| | (1) Any Wages>$0 | (2) ...>$7,500 | (3) ...>$15,000 | (4) Any Gig | (5) Any Other 1099 | (6) Files 1040 | (7) Files SE |
|---|---|---|---|---|---|---|---|
| Post (2019-2021) × Cleared | -0.007 | -0.015 | -0.016 | 0.003 | 0.000 | -0.009 | 0.006 |
| | (0.010) | (0.012) | (0.012) | (0.004) | (0.006) | (0.011) | (0.006) |
| Post (2019-2021) × Cleared × Months since charge | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Post (2019-2021) × Months since charge | 0.000[a] | -0.000 | -0.000* | 0.000 | -0.000 | -0.000 | 0.000[a] |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2017 × Cleared | 0.000 | -0.004 | 0.008 | -0.001 | -0.004 | 0.000 | -0.005[a] |
| | (0.004) | (0.005) | (0.005) | (0.001) | (0.003) | (0.005) | (0.003) |
| 2016 × Cleared | -0.004 | -0.003 | 0.006 | 0.001 | -0.003 | -0.001 | -0.002 |
| | (0.005) | (0.006) | (0.006) | (0.001) | (0.003) | (0.005) | (0.003) |

Notes: Table reports difference-in-differences results comparing outcomes for individuals who had all their non-convictions cleared by PA's Clean Slate law by 2020, compared with those who did not. Data from 2016-2020. Sample is restricted to ages 18-25 to ensure they had no other prior convictions by the start of our charge data, which begins in 2008. Standard errors clustered on individual are reported in parentheses. [a] $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Figure A.11: Probability of Re-Offending in 5 Years, By Initial Event




Notes: Data are from Bexar County, TX.

# B Survey Details

## B.1 Survey 1

The first survey was conducted in May 2021 through Prolific and designed using Qualtrics. Prolific was selected because it allows for the pre-screening of respondents based off of their responses to prepared questions. We selected people who responded "Yes" to the question: "Do you have any experience in making hiring decisions (i.e. have you been responsible for hiring job candidates)?" And later also added the criteria that the respondents should be located in the USA, after a pilot of the study accidentally included respondents in the UK. We additionally asked (though could not screen participants out based on responses, per Prolific guidelines): "In the past 5 years, have you had experience working in the United States in human resources and/or dealing with hiring processes for a firm with more than 1 employee?"

The survey starts with questions about recent hiring experience and a series of opening questions about the type of office the respondent worked in: the location, size, and industry of the firm. Then the survey asks the same set of questions twice about the most recent position in which the respondent had experience in making hiring decisions: first, for the position "closest to 'entry-level', meaning a job which required the least amount of experience and/or education in that firm," then, later for the position, "closest to 'mid-level', meaning a job which required several years of experience." The respondent's were compensated 2$ for their responses.

### B.1.1 Sample Size, Compensation, and Technical Details

A small pilot was launched in May 2021 which helped us refine questions (results are not used in analysis). On May 26, 2021 we launched with 500 respondents. And on June 2, 2021 we requested an additional 500 respondents. In the full sample of 1000 responses, there are 808 valid responses (had recent hiring experience in the U.S. with a firm with more than 1 employee), of which 77% say their firm conducted a criminal background check. In total, there are 550 respondents who were aware of the background check process.

## B.2 Survey 2

A second survey was designed and launched in late September to early October of 2021. The scope of this survey was broadly the same as the first, but the second survey was not a direct follow-up. The purpose of the second survey was to once again survey people with hiring experience in the United States and see how they would assess the risk of someone with a criminal record re-offending over time by asking them whether they would hire someone with a criminal record after X number of years.

There are two levels of randomization in the survey. The first is the nature of the crime that is posed in the hypothetical scenario asked to the hiring agent. There are four types of crimes: Felony Theft, Felony Drug Possession, Misdemeanor Theft, and Misdemeanor Drug Possession. There are also two possible dispositions: charged and convicted or charged and not convicted. In total, this creates eight options for the randomization, which are selected randomly by Qualtrics. When a respondent is sorted into one of these eight categories, they only respond to questions responding to that crime/disposition pair.

There is another level of randomization which is that each respondent receives one year since charge that they are asked about before all of the other years. For example, someone might be first asked if they would hire someone with a felony drug possession conviction 6 years ago. Someone else might be asked about conviction 4 years ago. The year value is randomized between 1 and 10.

The respondents also respond to the same question about whether they would hire someone with a charge from X years ago for all 10 years: only the first question is randomized. We ask the question in this format because we want to avoid biasing responses as respondents go through all the years. It also provides us a means through which we can make an assessment of the quality of the response: if the response in the first question does not match the response for the year in the second question, this might be a sign that the response is a low quality response.

The randomization was to ensure that the characteristics of respondents who answered about different types of crimes or times since crime were all similar. These were not randomized treatments.

The third question relevant to our main results is a question about whether the firm at which the respondent last had hiring experience has any policies about hiring individuals with given crime type and conviction after one through ten years. Unlike the other question, we only ask for the respondent to answer the question for all ten years, and do not present one randomized year.

Respondents were once again compensated 2$ for their participation. It should be noted that the same survey was retained in Prolific so that the same individual could not be surveyed twice through the various versions of the second survey. The same person could be surveyed between the first and the second survey however.

### B.2.1 Sample Size, Compensation, and Technical Details

For the final version of the survey that included randomization of the type of crime is the reported on in the paper. For this 1961 people were surveyed.[1] 440 responses were discarded because two typos were found in the survey, responses before these typos were fixed were thrown out. Technically, the responses only applied to one eighth of the results, but for the sake of keeping the sample sizes and timings balanced, we discard all responses before 12:04 PM, which was when the typos were corrected.

This final version of the survey was launched on October 6th, 2021. Following the first and pilot version, this final version of the survey was designed that randomized the crime type and severity of the charge presented in hypothetical scenario. The following adjustments were also made:

- Size bins were changed in the question about firm size
- The industry options were modified in the question about the industry of the firm
- The wording of responses were changed in question 45.

Roughly 440 respondents were surveyed with a survey instrument that had a typo. In the remaining sample of 1521 respondents, 1003 end up being valid responses that are not excluded as a result of any of our criteria (had recent hiring experience in the U.S. and passed our attention check). This resulted in roughly 250 respondents in each randomization bin for crime severity, though there is naturally some variation in the exact number for each category.

## B.3 Representativeness

Table B.1 considers how representative the set of firms that our survey respondents answered about with national statistics. National statistics are employment-weighted data from the US Census Bureau 2021 Statistics of U.S. Businesses Data Tables (U.S. Census Bureau 2021). We had to aggregate firm sizes into 3 categories in order to be able to compare results across our 2 surveys and the national statistics. Region comes from the state headquarters of the firm the respondents were answering about. Survey 1 did not include "Mining, Quarrying...", "Utilities", or "Public Administration" as options in the drop-down menu about industries.

Our surveys tended to have slightly larger employers than the average employee in the United States works at. Our geographic distributions tend to be fairly similar to the average US employee. With regards to industry, our surveys tended to overrepresent the Information and Educational Services industries and underrepresent the Wholesale Trade, Admin and Support, and Health Care industries.

[1] Initially 20 people were part of the pilot of the survey. That number was then raised to 50 people. The first finalized version of the survey was then launched with 500 respondents without any randomization of the type of crime.

Table B.1: Survey 1 of Hiring Professionals on Criminal Background Check Procedures

| | National | Survey 1 | Survey 2 |
|---|---|---|---|
| **Firm Size:** | | | |
| 1–10 employees | 0.101 | 0.150 | 0.174 |
| 11–100 employees | 0.224 | 0.394 | 0.374 |
| 100+ employees | 0.675 | 0.457 | 0.452 |
| **Industry (2 Digit NAICS):** | | | |
| 11-Agriculture, Forestry, Fishing and Hunting | 0.001 | 0.004 | 0.008 |
| 21-Mining, Quarrying, and Oil and Gas Extraction | 0.004 | | 0.001 |
| 22-Utilities | 0.005 | | 0.007 |
| 23-Construction | 0.055 | 0.037 | 0.046 |
| 31-Manufacturing | 0.091 | 0.061 | 0.062 |
| 42-Wholesale Trade | 0.046 | 0.009 | 0.008 |
| 44-Retail Trade | 0.121 | 0.094 | 0.105 |
| 48-Transportation and Warehousing | 0.044 | 0.021 | 0.016 |
| 51-Information | 0.027 | 0.145 | 0.077 |
| 52-Finance and Insurance | 0.053 | 0.080 | 0.086 |
| 53-Real Estate and Rental and Leasing | 0.017 | 0.010 | 0.015 |
| 54-Professional, Scientific, and Technical Services | 0.074 | 0.066 | 0.088 |
| 55-Management of Companies and Enterprises | 0.027 | | 0.006 |
| 56-Admin and Support | 0.097 | 0.009 | 0.032 |
| 61-Educational Services | 0.027 | 0.135 | 0.123 |
| 62-Health Care and Social Assistance | 0.161 | 0.109 | 0.101 |
| 71-Arts, Entertainment, and Recreation | 0.014 | 0.046 | 0.064 |
| 72-Accommodation and Food Services | 0.095 | 0.062 | 0.069 |
| 81-Other Services (except Public Administration) | 0.040 | 0.002 | 0.065 |
| 92-Public Administration | | | 0.024 |
| 99-Industries not classified | 0.000 | 0.111 | |
| **Region:** | | | |
| Midwest | 0.221 | 0.200 | 0.208 |
| Northeast | 0.180 | 0.218 | 0.173 |
| South | 0.370 | 0.355 | 0.351 |
| West | 0.229 | 0.218 | 0.263 |
| Missing | | 0.009 | 0.004 |

**Notes:** National data is employment weighted data from the 2021 Census Statistics of U.S. Businesses Data Tables. These Census data cover all private employment in the United States and does not include Public Administration (NAICS 92). Region is Census region of the headquarters of the firm the survey respondent was answering about. Survey 1 did not include "Mining, Quarrying...", "Utilities", or "Public Administration" as options in the drop down menu question about industry of the firm. Survey 1 is our Survey 1 as described in Section B.1 above and used in Appendix Table A.1; Survey 2 is our Survey 2 as described in Appendix Section B.2 above and used in Table 1.

# C FCRA Data Details

## C.1 Bexar County, Texas

The Bexar County, Texas data was downloaded from the Bexar County Criminal Courts in May 2017. Similar data is also used in Freedman, Owens and Bohn (2018) and Agan, Freedman and Owens (2021). Before matching we do string cleaning of names, addresses, and flag and drop definite businesses.

### C.1.1 Matching Defendants Across Cases

Unique to Bexar County, there is a pre-existing defendant ID in the dataset called "SID". Our matching process assumes that the SID never inaccurately links defendants, but that it could miss links between people. For instance, there are people in the Bexar county dataset how have the same first name, last name, and DOB, but different SIDs.

Since we know SID is unique to a person, we first fill in missing name and DOB information by SID. There are some SIDs that are missing for people who have non-missing name and DOB information. Thus, our naive ID is based off of SID and the grouping on name and DOB for observations that have identifiable ID information but are missing SID.

While we feel it is too risky to match on name and address only[2], we are comfortable filling in missing DOB information if there is a first name, last name, and address match. We match on these factors and generate an ID ONLY to update DOB if missing according to this ID. We do not match individuals or update ID in this step.

Next we match on first name, last name, and DOB.

Next we match if the address and DOB are the same and the combined first last name is less than or equal to a string distance of 3[3]. In other words, we do a row-wise comparison of name string distance for names that have the same address and DOB. We compare up to 3 rows which we feel is very thorough without compromising the efficiency of the code.

After doing this matching we reshape wide to long to wide on the new ID to update

Next we match people that have the same first name, last name, address and a DOB that is "close". DOB errors often appear as a typo in either the day, month, or year. Thus we consider a DOB "close" if at least the two elements of the day, month, and year are the same. This means that we would match two IDs with the same name and address and DOBs of 4/12/1980 and 9/12/1980. We do a row-wise comparison of DOBs to check to see if the are "close" according to the above definition, and match close DOBs that have the same address and name. We compare up to 3 rows.

Unlike other states we do not need to match on name and DOB again. We confirmed that the above matching did not provide any new demographic information such that we would get any updated IDs on a repeated name and DOB match.

[2]This could be risky if an address is for a group home or shelter that our address cleaning did not pick up. It is conceivable that multiple people with the same name live in one of these group locations.

[3]More specifically, we look at the levenshtein string distance between the last, first name of the current row to the last, first name of the next [up to 20] rows. The string distance usually ranges from 1 to 35. A string distance less than or equal to 3 is very close.

### C.1.2 Charge Categorization

There are 1,551,880 charges which link to defIDs that have identifiable information. We create an indicator variable "isConvicted" which is a 1 if the disposition category is "guilty" or the disposition description is "DEF ADJ TERM UNSAT[4]", 0 if the disposition category is "not guilty at trial", "Dismissed", and missing otherwise. Only 4% of charges have a missing isConvicted status.

## C.2 Maryland

The Maryland criminal records were drawn from several tables hosted on the Maryland Volunteer Lawyers Service (MVLS) database. The Maryland data cover all charges filed between 1990 and 2018. The two main courts are the Circuit Court and the District Court. The District Court is the lower criminal court and handles cases such as traffic violations, tenant disputes, or domestic violence. The Circuit Court is the higher criminal court and handles more serious cases. There are 3 separate data sets of higher criminal court hearings originating from Baltimore City, Prince George County, and Montgomery County[5]. Any upper court cases that originate outside of these places are in the circuit regular dataset. For the most part, similar information is contained in the various datasets with some exceptions such as Prince George missing date of birth information.

We clean and standardize name and address entries and standardize abbreviations (e.g. "Street"→"St") in order to decrease the number of unique address entries in the dataset and make the matching on address more accurate.

We are fairly confident that tracking number is unique to a person and it used to link cases that move between courts (e.g. a district case that is elevated to the circuit court will have different case numbers in the district and circuit court, but would have the same tracking number.) For the most part, names and DOBs are consistent with tracking number, but not always. This could be caused by alternate names and DOBs or because a tracking number was used for a co-defendant. Given this, we think it is too aggressive to match people on tracking number, but we do fill in missing name and DOB by tracking number. Recall, Prince George is missing DOB, but we can get DOB if the tracking number links to the district court where DOB is not missing.

### C.2.1 Matching Defendants Across Cases

Our matching algorithm uses tracking number, district case number, DOB, name, and address to link people. We first create a naive ID which is a grouping of first name, last name, and DOB. If name is missing, naive ID is a grouping of DOB and address, and if DOB is missing, naive ID is a grouping of name and address. If naive ID is still missing for an entry, we drop it, since it only has one piece of identifying information (i.e. only name or only DOB or only address), and we cannot reliably match on this.

[4]Unsatisfactory deferred adjudication turns into a conviction.

[5]These 3 places use a different court number filing system, a single event could have multiple cases (each with multiple charges). In all other places in MD, a single event corresponds to a single case.

Recall that while we filled in missing information by tracking number, we did not match by tracking number. Instead, we link IDs if there is a match on tracking number and last name or a match on tracking number and DOB.

Another variable which can be used for matching is the district case number. This variable is found in upper level court court datasets and links to the case number in the district court dataset. Similar to the above, we link IDs if there is a match on district case number and last name or a match on district case number and DOB.

While we feel it is too risky to match on name and address only[6], we are comfortable filling in missing DOB information if there is a first name, last name, and address match. We match on these factors and generate an ID ONLY to update DOB if missing according to this ID. We do not match individuals or update ID in this step. For example, if there is a Maria Evanston born on 8/20/1988 who lives at 100 Cherry Hill and another Maria Evanston with a missing DOB, but the same address, we fill in the missing DOB with 8/20/1988. However, if there are two observations with the same name and address but with different DOBs, nothing is updated.

Next we match on first name, last name, and DOB. Recall that we generated the naive ID when data was unique on casenumber and long on demographics, so the naive ID was just based on firstName1 lastName1 and DOB1. Here we compare every combination of name and DOB within a given ID to all other name and DOB combinations within IDS to link ID.

Next we match if the address and DOB are the same and the combined first last name is less than or equal to a string distance of 3[7]. In other words, we do a row-wise comparison of name string distance for names that have the same address and DOB. We compare up to 20 rows which we feel is very thorough without compromising the efficiency of the code.

Next we match people that have the same first name, last name, address and a DOB that is "close". DOB errors often appear as a typo in either the day, month, or year. Thus we consider a DOB "close" if at least the two elements of the day, month, and year are the same. This means that we would match two IDs with the same name and address and DOBs of 4/12/1980 and 9/12/1980. We do a row-wise comparison of DOBs to check to see if the are "close" according to the above definition, and match close DOBs that have the same address and name. We only compare up to 10 rows, which is more than enough (DOB typos are much rarer than name typos.)

Finally we want to do a name and DOB match again since we have updated both of these pieces of information since we last matched solely on name and DOB.

### C.2.2 Charge Categorization

In total, there are 10,123,687 charge which link to IDs that have identifiable information. A few observations (0.004%) are duplicates in terms of case number and charge number, but are not full duplicates. In most instances, one of the duplicate charges contains more information (e.g. one is missing disposition date and the other is not) so we keep the version

[6] This could be risky if an address is for a group home or shelter that our address cleaning did not pick up. It is conceivable that multiple people with the same name live in one of these group locations.

[7] More specifically, we look at the levenshtein string distance between the last, first name of the current row to the last, first name of the next [up to 20] rows. The string distance usually ranges from 1 to 35. A string distance less than or equal to 3 is very close.

with more information. In the regular circuit court, there is a variable called sentence version. For duplicate charges with different sentence versions, we keep the most recent charge by sentence version.

Of note, 20% of the charges are District court charges that were elevated to an upper court. The elevated charges have a case disposition of "Forwarded to Circuit Court" or "Jury trial prayed" (which also means forwarded to the Circuit court). We do not drop these charges, but instead create indicators for "elevated charge" and "matched elevated charge". Matched elevated charges are a subset of elevated charges: in addition to having the case disposition of "Forwarded to Circuit Court" or "Jury trial prayed", they are also a duplicates charge in terms of defID, tracking number, charge number, and charge description. Of the 2,096,072 elevated charges, 15.8% are a matched elevated charge. This percentage may be low because charge descriptions and/or charge number can change when moving from the district court to the upper court. For example if two charges merge when the case is elevated, then the charge number for all other charges may change.

Another thing to note is that while 96% of elevated charges have a missing CHARGE disposition, 4%, have a non-missing charge disposition such as "Dismissed" or "Nolle Prosequi." Thus, not all elevated charges will have a missing Conviction status.

Next we categorize disposition based off of the charge disposition. These are the following categories:

0 "Not Guilty" 1 "Guilty" 2 "Guilty Plea" 3 "Dismissed" 4 "Withdrawn" 5 "CLOSED - JEOPARDY OR OTHER CONVICTION" 6 "STET[8]" 7 "Probation before judgment" 8 "Sent to Juvenile Court" 9 "Charge merged" 10 "Sent to uppercourt" 11 "Other/Missing"

We create an indicator variable "isConvicted" which is a 1 if the disposition category is "Guilty" or "Guilty Plea", 0 if the disposition category is "Not Guilty", "Withdrawn", or "Dismissed", and missing otherwise.

The court data does not have a variable for offense grade or felony/misdemeanor categorization. We are able to categorize 94% of charges using a "cjis-code"[9] (crime code) or the actual crime description.

In the final charge dataset, we keep the following variables: defID, filingdate, dispositiondate_charge, dispositiondate_case, sentencedate, verdictdate, isConvicted, isFelony, viol_prob, traffic_viol, elevated_charge, matched_elevated_charge.

## C.3 New Jersey

The New Jersey criminal records were obtained by a public access information request application submitted to New Jersey courts. These files contain records from January 1st, 1980 to May 30, 2018 and have no restrictions on their usage, though they did require a fee. There are two main files: CCFOCN25, referred to as "Master Defendant List", and CCC1022, "Pleas Guilty, Not Guilty, & Dismissed by Judge".

New Jersey does not use a "felony" versus "misdmeanor" distinction, but rather distinguishes between "indictable offenses" and "disorderly person" offenses. Indictable offenses

[8]STET means that case is going to be inactive for a period of time (maybe 6 months or a year), usually in order for the defendant to complete some agreed upon conditions like community service hours, counseling courses, anger management classes, payment of restitution, etc.

[9]Montgomery County is missing the cjis-code variable.

fairly closely align with what would be felonies in other states, and disorderly persons offenses with misdemeanors. On the criminal side, the Superior Court hears cases for "indictable" offenses, and thus we only have data on these types of offenses for New Jersey and throughout the paper we refer to these offenses as felonies to more closely align with terminology from other states.

CCFOCN25 contains data on 1.5 million defendants, including their names, case numbers, defendant numbers, county and date of birth. The data set also includes an information on indictment date and dispositions.

CCC1022 includes data on 3.1 million dispositions. The dispositions correspond to individual charges brought against a defendant, who can have multiple charges brought against them on a case.

We begin by merging the master defendant list with the disposition list on case, indictment number, defendant number and county code. Of 3.2 million person-case-disposition pairs, 163,352 remain unmatched. We assume that this is because of clerical errors that identify multiple defendant numbers in one case or different case numbers with the same indictment level. To remedy these errors, we sort on county, name, indictment and merge status. Under the assumption that the errors are only in the entry of case numbers, this sorting should identify from the master and using data the observations that were not matched to the corresponding entries. We then fill in the missing information, date of birth and indictment date, into the disposition data. This leaves around 71,362 observations still unmatched: 67,006 unmatched from the master data and 4,356 unmatched in the using data.

We attempt to further remedy the number of unmatched cases by identifying unmatched cases in the master and using data respectively that match on indictment number, county, and defendant number. These are the cases where indictment number, county, and defendant number all match, but the defendant name does not, likely because the name was entered in two different forms. We assume that the name in the defendant data set is the "correct" name, since the disposition data set contains multiple names, while the defendant data set contains only one. We then drop the remaining clerical errors, since we have done all that we can do to fix them. This then leaves 67,243 cases unmatched. In total, we have 3,104,529 matched observations at the person-case-disposition level.

We drop all observations for which the indictment date is before January 1st, 1980, since this must have been erroneously included in the data. We also drop date of births that are equal to indictment dates, since these must be errors. We then fix the presentations of names since they are inconsistent across observations: we attempt to drop all observations in which the defendant is a business and remove irregular dashes, commas, and suffixes. As a result, we have information on the individual dispositions—the charges, sentencing and disposition dates, and dispositions result (guilt, not guilty, dismissed), and counts by individual of the total number of cases corresponding to each disposition result—with additional information on the defendants date of birth and indictment date. There is also a range of other information included in the data: including attorney and judge names and whether or not the defendant posted bail.

We also resolve 780 cases where there seem to be errors in the entry of dates: where the indictment date and the sentencing date are the same, and the month and date are equal to the disposition date but not the year. We resolve similar issues for the sentencing date.

### C.3.1 Matching Defendants Across Cases

Note that in NJ, we do not have address information; the most specific geographic information we have is county code. This means that we cannot fill in missing DOB by address and name like we do in other states

We match if the county code and DOB are the same and the combined first last name is less than or equal to a string distance of 2[10]. In other words, we do a row-wise comparison of name string distance for names that have the same address and DOB. We compare up to 20 rows which we feel is very thorough without compromising the efficiency of the code.

Next we match people that have the same first name, last name, county code and a DOB that is "close". DOB errors often appear as a typo in either the day, month, or year. Thus, we consider a DOB "close" if at least the two elements of the day, month, and year are the same AND the DOBs are within a year of each other. This last restriction is not present in MD or Bexar because in those places we had address, but here we only have county code, so we include the extra year restriction to balance out the less specific demographic information. We compare up to 5 rows.

Finally we want to do a name and DOB match since we have updated both of these pieces of information since we last matched solely on name and DOB (the original naiveID was the first match on just name and DOB.

### C.3.2 Charge Categorization

The NJ charge files already have indicators for isGuilty, isNotGuilty, and isDismissed, so we base the isConvicted on these variables where isConvicted=1 for guilty charges, 0 for dismissed or not guilty charges and missing otherwise. isConvicted is missing for 7.31% of charges.

## C.4 Pennsylvania

We obtained Pennsylvania court data from the Administrative Office of Pennsylvania Courts (AOPC) via a Public Access request. The data cover all cases in the Magisterial District Court system (which handles misdemeanors) and Courts of Common Pleas system (which handles felonies) filed between May 2008 and April 2018.

### C.4.1 Matching Defendants Across Cases

We begin by appending the MDJS cases onto the original PA dataset. We then clean names. Next, we link the upper and lower level court cases. Most upper level court cases (hereafter CP) originate at the lower level (MJ or MC). We don't want to double count the cases that have been elevated so we link lower and upper court docket number using the offense tracking number (OTN). About a quarter of CP court cases do not link to the lower level which could be due to court records at the lower level court be expunged.

We drop lower court cases that link to the upper court and are missing disposition or have a charge disposition such as "elevated to the the upper court". For these cases, we

[10] In other states where we had address, we were less strict about the string distance requirement than we are here when we only have county code

merge the lower level birth date (used later as alternate DOB), earliest name, earliest filing date, and all the reshaped docket numbers onto the upper court case. There are 18K OTNs that have different birth dates at the CP and MJ court levels. We check if people differ within OTN by looking at birth dates and last names. If there is an OTN match but there is no last name OR birth date match, we do not link on tracking number. We drop the CP charges that have a disposition indicating they were handled at the lower level such as "Disposed (Lower Court)" and have a merged MJ docketnumber.

We get alternate names and DOBs if either of those differ within the linked OTN and then match people on shortened first and last name (up to 5 alt names) and DOB or alternate DOB. Note that PA does not include any specific address information so we cannot further match on that. After matching and assigning a unique ID, we reshape long and then wide for all demographic information to get modal name, dob and zip code as well as all alternate names, dobs, and zip codes. There is a succinct demographics dataset that just includes unique ID, modal name, dob, and zip code by ID. The wider demographics contains additional (non-modal) name, dob, and zip code information by unique ID.

### C.4.2 Charge Categorization

We then proceed with the charge analysis. We categorize crimes into felonies, misdemeanors, or summary offenses based on the offense grades present in the data. Offense grades that begin with M are misdemeanors, F are felonies, and H are heinous crimes, which are also categorizes as felonies. Offense grades of "S" or "IC" are statue or summary violations which we categorize separately from felonies and misdemeanors. There are 500K missing charge codes, for which we can fill in about 50% using the data from offense descriptions already categorized codes. If an offense description has at least 99% of observations as either of felony or misdemeanor, we use this to fill in the felony/misdemeanor status for the same offense descriptions with missing categorizations.

Next we drop duplicates in terms of the following variables: docketnumber, originatingoffensesequencenumber, offensedescription, offensedisposition, statutetitle, statutetype, statutesection, statutesubsection.

We then categorize dispositions into the following:"Not Guilty" 1 "Guilty" 2 "Guilty Plea" 3 "Dismissed" 4 "Withdrawn" 5 "Proceed to Court" 6 "AMP/ARD" 7 "No Contest" 8 "Nolle Prossed" 9 "Held for Court" 10 "Charge Changed" 11 "Moved to non-traffic". There is a default 12 "other" category which includes drug/veterans treatment courts, failures to appear, transfers, and other odd disposition descriptions.

The main variable of interest is whether the disposition was a conviction or not. We generate the indicator variable, *isConvicted* based off of the offense disposition [11]. *isConvicted* = 1 if the offense disposition is in categories 1, 2, or 7. *isConvicted* = 0 if the offense disposition is in categories 0, 3, 4, 5, 6, 8, 9, 10, or 11. *isConvicted* = . (missing) if the offense disposition is in the other category. The variable, *UnlcearConviction* is an indicator for if offense disposition is in categories 5, 6, 9, 10, or 11 since we are not confident that these dispositions are actually 0. (They may be missing.)

[11] There is also a case disposition, which we only use when offense disposition is missing

# D Fair Credit Reporting Act Differences by State

At the federal level, FCRA requires that all arrests, indictments, and other records older than 7 years that were dismissed or acquitted cannot be reported in a background check, but only if the person's expected salary is less than \$75,000. Convictions older than 7 years can still be reported. These states passed additional legislation that prohibits the reporting of certain criminal record information:

Alaska: prohibits the release of any non-conviction or correctional facility records, regardless of the age of the charge

Arkansas: prohibits reporting of non-felony arrest records, and prohibits the reporting of felony arrest records if the arrest is more than 3 years old

California: 7-year limitation on arrest, indictment, and conviction records, regardless of salary. Any arrest, indictment, or misdemeanor complaint information is prohibited (regardless of time) if the charge is still pending or did not result in a conviction

Colorado: 7-year limit on arrest, indictment, and conviction records for salaries of <\$75,000[12]

DC: cannot report convictions for which the sentence was completed more than 10 years ago

Kansas: For salaries <\$20,000 arrests, indictments, and convictions are prohibited. For salaries \$20,001-74,999, the standard FCRA rules apply.

Kentucky: records may only contain information related to a conviction

Maryland: see Kansas

Massachusetts: 7-year limitation on arrests, indictments, and convictions, regardless of salary

Montana: 7-year limitation on arrests, indictments, and convictions, regardless of salary

Nevada: removes salary requirement from FRCA

New Hampshire: For salaries <\$20,000, there is a 7-year limitation on arrests, indictments, and convictions. For salaries \$20,001-74,999, the standard FCRA rules apply

New Mexico: 7-year rule for arrests, indictments, and convictions. Arrests, indictments that did not lead to a conviction cannot be reported, regardless of time since occurrence

New York: cannot report any criminal information unless the charges are still pending or the charges led to a conviction. For salaries <\$25,000 the 7-year rule for convictions also applies

Texas: 7-year rule for arrests, indictments, and convictions if the expected salary <\$25,000. [13]

Washington: For salaries <\$20,000, prohibits reporting of arrests, indictments, convictions more than 7 years old.

[12] Superseded by 1996 Consumer Credit Reporting Reform Act of 1996. Convictions are reported in practice.

[13] Superceded by 1996 Consumer Credit Reporting Reform Act of 1996. Convictions are reported in practice.

# E Internet Search of Random Subset of our Sample

On reason for our null results could be that employers are searching the internet for job applicants and finding out information about crimes even when they are not reported on CRA-led background checks. To further investigate this possibility, in February 2025 we hired 3 ungraduate RAs at Cornell University. These RAs were each given a random sample of approximately 300 defendants from our sample, stratified on whether the most recent crime was less or more than 7 years from 2025 (where possible) and whether the defendant had any convictions. The list included name, date of birth, and jurisdiction (Maryland, NJ, Bexar County, or Pennsylvania).

The lists were then put into randomized order and given to each of the 3 RAs. They were told "Imagine you are an employer. You have a list of candidates you are considering hiring but you want to know if any of them have a criminal record but you do not want to do formal background checks. Please search for these applicants on the internet and see if any hits that would cause concern come up one the first 2 pages of search results." They were **not told** that all these applicants had a criminal history.

They were asked to search using google chrome in incognito mode and to try several search terms including "[firstName] [lastName]" [state] and "[firstName] [lastName]" [state] crime. They were told "Do not pay for any databases. If information is freely available and easy to click on, that would count. But do not sign up for any websites or pay for anything. I am only looking for things that are easy to find without extra steps like signing up for an external website."

For any hit they listed the URL and a "confidence score" about how confident they were that this was actually the defendant in question. A 5 means they could verify via name, DOB, and location. 1 means very likely not this person.

For the purposes of our analysis, we consider a crime hit any hit that was about crime that had a confidence score or 4 or 5. Each RA completed about 100 searches. And in the end 225 total defendants were searched for.

Search hits related to crimes in which the RA was fairly confident) it was the defendant (confidence score $\geq 4$) were found for 19.5% of defendants. If we relax this to confidence scores $>1$, this increases to 31.1% of defendants.

Overall, in order to fully explain our null results we would likely expect these search rate hits to be much higher.

# F Match Algorithm

This appendix outlines our approach to matching the names and birth dates to the IRS database. We also report match performance. We rely on a variety of different sources in an iterative process as follows.

## F.1 Step 1

We first search for a possible match in the Social Security database shared with IRS. This database provides date of birth and the first four letters of the last name (a field known as the "Name Control"), for every individual issued a Social Security Number or Individual Taxpayer Identification Number. The database includes a history of up to nine Name Controls ever-associated with an individual (for example, when a woman changes her last name after marriage, this would generate a new entry). We require an exact match on birthdate and first four letters of the last name in the database. For locations where gender is known (most cases in Bexar County, TX and Pennsylvania), we further restrict to gender matches.

## F.2 Step 2

Our procedure so far often results in multiple "hits." To whittle down possible duplicate matches and assess match quality, we match to the database of individual tax returns and the database of information returns (W2s, 1099s, etc), each of which contain full names and ZIP code each time a form is filed. We track match hits to each data source with indicator variables.

Based on these match indicators, we create a priority ranking of matches. The highest quality matches (rank 1) have an exact match on first and last name, birthdate, gender (when available as a match variable) and address (zipcode or state, when available as a match variable). If there is no address information available, or when the address information does not match, we prioritize matches of individuals residing in a state where the legal proceedings occurred. We consider matches on first, last name, and birthdate, but no geographic match, to be the second highest quality matches. The remaining matches will be lower quality: we may have a Name Control, birthdate and geography match, but not an exact match on first and last name; or an exact name and DOB match, but not a geographic match. If there are duplicates, we prioritize the highest quality match. When duplicates remain, we currently throw out all matches.

## F.3 Match performance: FCRA sample

In this Section we document match performance by location for each location we use in the FCRA analysis based on the criteria described above.

### F.3.1 Bexar County, TX

Starting N =562,434

| **Highest Match Rank** | **No. Unique Matches** | **% of Matches** | **Cum.** |
|---|---|---|---|
| 1 - DOB, Full name, address zipcode | 282,834 | 58.28 | 58.28 |
| 2 - DOB, Full name, address state | 127,315 | 26.23 | 84.51 |
| 3 - DOB, Full name, TX | 13,652 | 2.81 | 87.33 |
| 4 - DOB, Full name | 21,106 | 4.97 | 92.29 |
| 5 - DOB, Name control, geography | 27,015 | 5.57 | 97.86 |
| 6 - DOB, Name control-only | 10,384 | 2.14 | 100.00 |
| **Total** | 485,306 | | |

Overall match performance: 485,306/562,434=86.3%

### F.3.2 Maryland

Starting N=1,324,226

| Highest Match Rank | No. Unique Matches | % of Matches | Cum. |
|---|---|---|---|
| 1 - DOB, Full name, address zipcode | 569,822 | 58.62 | 58.62 |
| 2 - DOB, Full name, address state | 130,954 | 13.47 | 72.09 |
| 3 - DOB, Full name, MD | 28,547 | 2.94 | 75.03 |
| 4 - DOB, Full name | 76,041 | 7.82 | 82.85 |
| 5 - DOB, Name control, geography | 114,976 | 11.83 | 94.68 |
| 6 - DOB, Name control-only | 51,701 | 5.32 | 100.00 |
| **Total** | 972,041 | | |

Overall match performance: 972,041/1,324,226=73.4%.

### F.3.3 New Jersey

Starting N=778,582

| Highest Match Rank | No. Unique Matches | % of Matches | Cum. |
|---|---|---|---|
| 1 - DOB, Full name, NJ | 458,481 | 72.89 | 72.89 |
| 2 - DOB, Full name | 100,128 | 15.92 | 88.81 |
| 3 - DOB, Name control, NJ | 55,149 | 8.77 | 97.57 |
| 4 - DOB, Name control-only | 15,260 | 2.43 | 100.00 |
| **Total** | 629,018 | | |

Overall match performance: 629,018/778,582=80.8%.

### F.3.4 Pennsylvania

Starting N =1,187,199

| Highest Match Rank | No. Unique Matches | % of Matches | Cum. |
|---|---|---|---|
| 1 - DOB, Full name, address zipcode | 760,782 | 70.2 | 70.2 |
| 2 - DOB, Full name, PA | 197,409 | 18.22 | 88.42 |
| 3 - DOB, Full name | 65,492 | 6.04 | 94.46 |
| 4 - DOB, Name control, geography | 45,473 | 4.2 | 98.66 |
| 5 - DOB, Name control-only | 14,550 | 1.34 | 100.00 |
| **Total** | 1,083,706 | | |

Overall match performance: 1,083,706/1,187,199=91.3%

The following table shows our overall match performance by conviction status for our main estimation sample.

Table F.1: Summary Match Statistics on FCRA Estimation Sample

| | | Last event is Conviction | | Last Event is Non-Conv & No Other Conv | |
|---|---|---|---|---|---|
| | | Felony | Misdemeanor | Felony | Misdemeanor |
| **Bexar** | All | 78,622 | 186,167 | 25,894 | 204,612 |
| | **Match %:** | **86.2** | **84.5** | **85.0** | **86.5** |
| **PA** | All | 165,022 | 492,339 | 79,304 | 349,719 |
| | **Match %:** | **89.7** | **91.6** | **84.7** | **86.4** |
| **MD** | All | 59,449 | 232,248 | 90,635 | 530,403 |
| | **Match %:** | **82.9** | **72.3** | **69.0** | **65.8** |
| **NJ** | All | 517,983 | 0 | 89,026 | 0 |
| | **Match %:** | **78.1** | **-** | **68.6** | - |

Notes: Table reports total number of individuals in state court records and those matched to IRS data.

Table F.2: Match Rates (%), Overall versus FCRA Estimation Sample

| | Overall | FCRA Estimation Sample |
|---|---|---|
| **Bexar** | 86.3 | 85.6 |
| **PA** | 91.3 | 89.1 |
| **MD** | 73.4 | 68.9 |
| **NJ** | 80.8 | 76.7 |

# References

**Agan, Amanda, Matthew Freedman, and Emily Owens.** 2021. "Is your lawyer a lemon? Incentives and selection in the public provision of criminal defense." *Review of Economics and Statistics*, 103(2): 294–309.

**Federal Bureau of Investigation.** 2014. *Uniform Crime Reports for the United States, 2014.* U.S. Department of Justice.

**Freedman, Matthew, Emily Owens, and Sarah Bohn.** 2018. "Immigration, employment opportunities, and criminal behavior." *American Economic Journal: Economic Policy*, 10(2): 117–51.

**U.S. Bureau of Labor Statistics.** 2009. "Current Population Survey, Geographic Profile of Employment and Unemployment, 2009 Annual Averages."

**U.S. Census Bureau.** 2021. "2021 SUSB Annual Data Tables by Establishment Industry." Accessed: 2025-03-05.