Minor *et al. IZA Journal of Labor Policy* (2018) 7:8
https://doi.org/10.1186/s40173-018-0101-0

IZA Journal of Labor Policy

ORIGINAL ARTICLE Open Access

Criminal background and job performance

Dylan Minor, Nicola Persico and Deborah M. Weiss*

* Correspondence: deborah.weiss@northwestern.edu
Northwestern University, Evanston, IL, USA

Abstract

Job applicants with criminal records are much less likely than others to obtain legitimate employment. Recent efforts to address this problem include campaigns to persuade employers to hire applicants with a record voluntarily and legislation such as Ban the Box laws. The success of any remedial strategy depends on whether employer concerns are founded on an accurate view of how employees with a criminal background behave on the job if hired. Little empirical evidence now exists to answer this question. This paper attempts to fill this gap by examining firm-level hiring practices and worker-level performance outcomes. Our data indicate that individuals with criminal records have a much longer tenure and are less likely to quit their jobs voluntarily than other workers. Some results, however, differ by job: sales employees with a criminal record have a higher tendency than other workers to leave because of misconduct, while this effect is smaller and less significant for customer service workers. By examining psychometric data, we find evidence that bad outcomes for sales people with records may be driven by job rather than employee characteristics. We find some evidence that psychometric testing might provide a substitute for the use of criminal records, but that it would not in our own sample.

Keywords: Criminal records, Discrimination, Personnel economics, Job performance

JEL Classification: K14, J24, J78

1 Introduction

Job applicants with a criminal record are much less likely than others to receive an offer of employment. Recent audit studies suggest that lower human capital does not fully explain this difference, and that employers apply a hiring penalty to job applicants with a criminal background. Recent legislation and initiatives have attempted to improve the labor market prospects of individuals with a criminal record. One approach, known as Ban the Box, would restrict or prohibit employer inquiries about an applicant's criminal record until a conditional offer of employment has been made. Alternative approaches include attempts to encourage voluntary efforts by employers either through persuasion or tax incentives.

The success of any approach to improve the employment prospects of those with a criminal record depends on why firms impose a hiring penalty. Are employers primarily concerned with potential workplace misconduct or are they using a criminal record as a proxy for the personality characteristics associated with job instability or poor performance? Is either fear founded on an accurate view of how individuals with records behave on the job if they are hired?

This paper addresses these questions leveraging a dataset drawn from the client firms of a hiring consultancy whose data has been previously used in academic work

(Burks et al. 2015). The data consists of observations of individual applicants to, and employees holding, low-skill white-collar jobs, primarily at call centers. The data includes information available at the time of hiring, such as criminal record and job qualifications, and for those hired, it contains tenure-related outcomes such as length of service and, if the employee separated, the circumstances of separation.

In positions in which turnover is a major labor cost determinant, we find that workers with criminal records have a longer tenure and are less likely to quit their jobs voluntarily than other workers. This finding suggests that individuals with criminal records represent an untapped productivity pool. However, when we disaggregate by job, we find that the association between criminal record and termination for misconduct is heterogeneous and differs between customer service and sales, suggesting the need for caution in drawing general conclusions.

We examine the differences in outcomes between jobs using psychometric test results of the type commonly used in hiring. First, we find striking differences between the psychometric predictors of poor outcomes in sales jobs and customer service jobs. Second, we find psychometric differences between sales people and customer service workers with criminal records. These results suggest that bad outcomes for sales people with records may be driven by differences either in worker or in job characteristics.

We then use detailed psychometric data on workers to show that criminal background predicts longer tenure even after controlling for personality traits. In theory, psychometric testing might provide a mechanism to allow employers to ignore criminal records entirely by testing directly for the characteristics that cause difficulties in a subset of employees with criminal records. In our data, we find that the psychometric variables have a reasonable degree of association with both a criminal record and job outcomes. However, they do not reduce the value of a criminal record in predicting misconduct, and further research is required to determine whether they could do so.

In considering the policy implications of these findings, one qualification is critical. Especially since employers apply a hiring penalty to individuals with criminal records, those who are actually hired are presumably more qualified than those who are not, and the instances in which we find better performance of employees with a criminal record cannot be generalized to the entire applicant pool. However, we believe we can make some reasonable inferences about marginal hires with a criminal record, and our results suggest that some employers could be missing profitable opportunities to hire low turnover workers. Our contribution to the existing literature is as follows. To the best of our knowledge this is the first paper to study the correlation between criminal background and productivity in a civilian setting. Unusually, we have data on the criminal background and psychological characteristics of *all applicants* merged with tenure data. Consistent with the literature that focuses on the hiring process, we find that applicants with criminal records are penalized at the hiring stage conditional on observable characteristics. Furthermore, we find that criminal history seems to be associated with better performance overall in customer service positions and is ambiguous in sales positions. These associations persist even after conditioning on psychological characteristics and other observables that employers use in the hiring process. These findings suggest that, at least with regard to customer service positions, there are unexploited opportunities to expand marginally the hiring toward applicants with a criminal background in a way that makes sense both on efficiency and on moral grounds.

2 Related literature

Observational studies have repeatedly found that job applicants with criminal records are much less likely than others to obtain legitimate employment (Western et al. 2001). Six months or so after release, 50 to 80% of the formerly incarcerated are not employed in the legitimate labor market (Visher et al. 2011; Petersilia 2003).

Establishing whether a causal relation exists between a criminal record and poor employment prospects is difficult, but studies using a variety of methods suggest that traditional human capital measures alone do not explain the hiring penalty associated with a criminal record, and that employers consider a criminal record a liability in job applicants.[1] Survey evidence confirms these findings and indicates that 69% of organizations conduct criminal background checks on all of their job candidates (Holzer et al. 2004; Society for Human Resource Management 2012).

The poor employment prospects of individuals with criminal records are of considerable policy concern. Technological changes continue to make background checking easier, and evidence suggests that lower costs have driven the increased use of these checks (Bushway 2004; Finlay 2009). The incarceration rate in the USA has grown considerably over the past several decades and now far exceeds that of any other country in the world. Over 650,000 offenders are released from prison each year (Carson and Golinelli 2013). The post-release employment prospects of inmates are of great practical consequence. Over half of released prisoners are reconvicted within 3 years (Durose et al. 2014). A failure to obtain legitimate employment is one of the strongest correlates of criminal recidivism, and recent evidence suggests that this relation may be causal (Uggen and Shannon 2014; Yang 2017).

Recent legislation and initiatives have attempted to improve the labor market prospects of applicants with criminal records. Some approaches restrict the use that employers can make of a criminal record. Ban the Box statutes prohibit employer inquiries about an applicant's criminal record until a conditional offer of employment has been made and sometimes restrict the type of records that can be used or prohibit the employer from withdrawing the offer unless certain conditions are met.[2] The Equal Employment Opportunity Commission (EEOC) has challenged criminal background checks on the grounds that they have a disparate impact on African Americans and encourages employers to meet the requirements of disparate impact doctrine by procedures similar to those in Ban the Box laws.[3]

Alternative policy approaches attempt to encourage voluntary employer efforts. The Obama administration launched an initiative called "Take the Fair Chance Pledge." Businesses and educational institutions have been asked to commit to employing fairly those with a criminal record. Over 100 organizations in a variety of industries signed on, including such companies as American Airlines, Coca-Cola, Koch Industries, Google, Starbucks, and Walmart.[4] Related policies attempt to provide incentives or remove disincentives for hiring people with criminal records. The Work Opportunity Tax Credit allows employers to reduce their federal income tax liability by $2400 for hiring ex-felons within 1 year after their conviction or release from prison.[5]

An employer who hires an applicant with a criminal record faces a double risk: the employee's criminal record will preclude the employer from obtaining private insurance against misconduct, and if the employee commits a wrongdoing on the job that harms another individual, the criminal record is generally admissible as evidence of negligence. To address this, the Federal Bonding Program provides limited bonding for some employers during the first 6 months of an eligible employee's employment.[6] Some jurisdictions have limited the extent to which an employee's criminal record can be the basis of employer liability for negligent hiring.[7]

Yet another approach attempts to improve the employability of people with criminal records by identifying those at low risk for recidivism[8] or improving human capital through job training or services directed toward individual change (Visher et al. 2017).

These policies are based on widely varying assumptions about the nature and accuracy of the business rationale for the hiring penalty. Employers often claim to use criminal records primarily from concern about liability for negligent hiring.[9] Fewer state, when asked, that they are using criminal records as evidence regarding the personality characteristics they seek. However, studies have found that employers overstate their overall willingness to hire applicants with a criminal record (Pager and Quillian 2005), and in surveys, they may well de-emphasize reasons for non-hiring that they perceived as socially disfavored, such as using criminal records as a personality proxy.[10]

If little is known about exactly why employers use criminal records, still less is known about whether this use is based on accurate assumptions about how those with criminal records perform once hired or whether there are general characteristics that explain why employees with criminal records are at higher risk of bad job outcomes. Our paper aims to shed some light on these issues.

Only one other paper examines the job performance of people with criminal records. Lundquist et al. (2018) compare the performance of felons and non-felons using data drawn from the military. Like us, Lundquist et al. (2018) find that military personnel with a felony record are more attached to the job than other personnel and appear better on some performance dimensions, though different ones than we use. In contrast to our results, they find weaker performance and retention among those with a history of lesser offenses. On the other hand, Lundquist et al. (2018) provide an extensive qualitative analysis of selection procedures but not an estimate of the hiring penalty, while we provide an estimate of the hiring penalty with less institutional detail regarding the hiring process itself. We thus view the two papers as complementary, examining different labor markets, civilian, and military, and providing different perspectives on the selection process.

Somewhat more evidence bears on the personality characteristics of those with criminal records and the value of personality in predicting work outcomes. Psychologists define personality as "enduring patterns of perceiving, relating to, and thinking about the environment and oneself that are exhibited in a wide range of social and personal contexts" (American Psychiatric Association and others 2013, Glossary). In the last 20 years, the most frequently used framework for personality psychology has been trait theory, which typically begins with the responses of adult lay subjects to self-descriptive words (Goldberg 1990) or sentences (Costa and McCrae 1992a, 1992b). The personality evidence in our data consists of responses to 15 sentences of the type used in trait methodology.

The descriptive categories of trait analysis were developed by grouping the responses of a pool of subjects using factor analysis (Block 2010).[11] The most specific, lowest-level category is called a facet, of which there are generally thought to be about 25–30. Researchers agree that there is at least one higher-level category, factors, and the most common number of top levels is five, notably in the Five Factor Approach (FFA), sometimes called the Big Five (Lee and Ashton 2004). A commonly used version of the FFA describes the five factors as conscientiousness, agreeableness, neuroticism, extraversion, and openness to experience (Costa and McCrae 1992a, 1992b).

Although early work focused on higher-level factor analysis, more recent work has found that the less aggregated facet level is more predictive (Judge et al. 2013; Paunonen and Ashton 2001). Factors do remain useful because of data constraints as well as their use by much of the existing literature. For instance, each of the 15 questions in our data can be roughly associated with a factor, although, as will always be the case, most sentences load on more than one factor.

Although a number of previous studies have examined the predictive value of FFA in employment settings, most of these studies are small and study highly specific outcomes. Useful conclusions, therefore, require meta-analyses, of which the most comprehensive and recent are Judge et al. (2013) and Barrick et al. (2001). Both find that neuroticism usually has a negative effect on work outcomes and that, broadly speaking, all other factors have on average a positive effect, with conscientiousness the most important. However, there is a great deal of occupation and task specificity, with different factors predictive in different settings. The more recent of the two meta-analyses stresses that lower-level traits like facets are much more predictive than higher-level factors (Judge et al. 2013).

Relatively little work has been done on the relation between FFA and criminal behavior due both to the relative newness of the FFA and to the unpopularity among criminologists of personality-based theories compared with theories based on factors such as social class (Andrews and Bonta 2014; Jones et al. 2011).

Within this literature, most studies do find that the population of interest differs from the population as a whole in some personality traits. Most commonly, people with criminal records or related traits score high in extraversion and neuroticism and low in conscientiousness and agreeableness (Jones et al. 2011; O'Riordan and O'Connell 2014). Since low neuroticism and high scores on other factors tend to predict good job outcomes, these findings suggest that people with criminal records may not perform well on the job.

3 Data description and summary statistics

The dataset contains information on all the applicants to low-skilled white-collar jobs—typically, customer service or sales representatives in a call center. Unsuccessful applicants show up only once in the data. Successful applicants will typically occur repeatedly in the dataset, with reoccurrences indicating key HR events such as changes in position or termination. The data cover the period May 2008 to January 2014. The data are provided by a hiring consultancy whose business model was to provide a number of corporate clients with hiring recommendations. In the process, the consultancy administered pre-employment exams, including the psychological questions examined here.

After dropping repeated observations referring to the same worker, we are left with 1,163,384 observations, each of which refers to a unique applicant. We further drop a comparatively small number of observations that pertain to establishments located outside of the USA. We are left with 1,144,575 observations and will refer to this dataset as the "applicant pool." Table 1, panel A, provides summary statistics about the

Table 1 Summary statistics for the applicant pool

	Mean	sd	Min	Max	Count
Panel A: Summary statistics for the applicant pool, all observations					
crim_rec	.0850228	.2789161	0	1	264,094
school	.4339291	.4956163	0	1	285,065
fewer_short_jobs	− 1.783947	.8724028	− 5	− 1	753,259
longest_job	4.351786	1.417482	1	6	760,943
position_id	520.7322	304.4393	193	1233	264,094
loc_new	86.18591	53.31425	1	148	242,681
job_app_	.2060669	.4044793	0	1	1,144,575
hired	.0515274	.221071	0	1	1,144,575
Observations	1,144,575				
Panel B: Summary statistics for the applicant pool, sample estimated					
crim_rec	.0996549	.2995413	0	1	73,885
school	.2711511	.4445569	0	1	73,885
fewer_short_jobs	− 1.85966	.861079	− 5	− 1	73,885
longest_job	4.431501	1.29493	1	6	73,884
position_id	398.3541	235.7445	193	1117	73,885
loc_new	91.80543	58.9545	1	147	73,885
job_app_	1	0	1	1	73,885
hired	.1934628	.3950153	0	1	73,885
Observations	73,885				

available variables for the applicant pool. Note that fields are often missing. We believe this occurred because different clients requested that the consultancy collect different data and provided different elements of their own data for merging. For most applicants, we have data on schooling and prior jobs. The school variable is an indicator that equals 1 if the applicant has schooling above high school.[12] Two variables indicate the applicant's stability on previous jobs. The fewer_short_jobs variable codes the answer to the question "In the last five years, how many full-time jobs have you held for less than six months, other than jobs you had while in school?" This variable takes value − 1 when the answer was "None," − 2 when the answer was "One job," all the way down to − 5 when the answer was "More than 6 jobs." The variable longest_job codes the answer to the question "What is the longest amount of time that you ever worked for a single company?" This variable takes value 1 when the answer was "Not applicable/Less than 3 months," all the way up to 6 when the answer was "More than 5 years." The variable hired records whether the applicant was in fact hired.

The variable pre_crim is a field that can be zero or one, depending on whether the applicant is recorded as having a criminal history. This field is recorded for only about 264,000 observations out of the entire sample. Because this is the key variable in this paper, we investigated possible reasons why it could be missing. We concluded, based on a cross-analysis with other missing fields, that the occurrences in which pre_crim is missing reflect a deliberate decision by an employer not to collect criminal records information, rather than a choice by an applicant to not respond.[13] We are somewhat reassured by this conclusion, but still we acknowledge that a selection bias might occur if, even within our narrow occupational range, some jobs entailed a higher risk or cost of crime. Such employers would be less likely than average to hire applicants with a criminal record. However, no evidence of such selection is evident in our data.[14] The applicant pool contains 110,023 observations that have data on criminal record, schooling, and job stability. The data do not contain the position_type, firm, or location for applicants who were not hired, but for many non-hired applicants we were able to reconstruct the values for position and location.[15] We were not able to reconstruct values for the firm applied to. However, the data indicate a good though not perfect association between firms and location. As discussed below, our sample of the hired was limited to sales and customer service workers, so for consistency, we also limited our applicant sample to these jobs. After dropping observations for other positions and where key fields were missing, we were left with 73,885 observations described in Table 1, panel B.

Table 2, panel A, provides summary statistics for the subset of applicants who were in fact hired. We refer to this subset as the "hired pool." A number of additional variables are available for hired workers. For example, hired employees have an anonymized identifier of their employer called firm_id; a location field that encodes the city and state in which the employee was hired[16]; a position_type field describing the type of job held by the worker (agent, customer service, sales, technical support, or other)[17]; a variable LOE recording the length of employment, in days[18]; and the cause of termination either voluntary (TERM_V) or involuntary (TERM_I) when known.[19] For 4.5% of our employees, the cause of termination was "misconduct." All applicants took a personality test that including three proprietary questions and 15 FFA questions. The 15 FFA questions were grouped by the consultancy's industrial psychologist into the standard FFA categories of conscientiousness, agreeableness, neuroticism, extraversion, and openness to experience.[20] Our variables neurtot, opentot, extratot, contot, and agreetot represent the sum total of answers chosen that support the respective personality factor of the FFA. These values can range from zero to three for each of these variables. Our variables neur1-neur3 and so on represent answers to individual questions that support the respective personality factor of the FFA. The three proprietary variables—badservice, confidence_regress, and rulebreaker—will be described in greater detail in Section 6.

The total number of hired applicants is 58,977. Criminal record was only available for a subset of the sample, leaving 18,142 observations of hired workers. In most of our estimates, the employee's position was an important control, and the limited availability of pre_crim reduced the number of observations for jobs other than sales and customer support below the usable level.[21] Retaining only customer service and sales left 17,256 observations, or over 95% of all those hired for whom we had criminal record information. Finally, we eliminated observations which did not have all of our explanatory variables (job stability, school, and the psychometric variables) or outcome variables (related to turnover), leaving a total sample of 10,699 hired workers described in Table 2, panel B.

4 Hiring penalty attached to criminal record and selection bias

We examine the hiring penalty attached to a criminal record and the resulting selection bias in the pool of employees with a criminal record. We restrict attention to the

Table 2 Summary statistics for the hired pool

	Mean	sd	Min	Max	Count
Panel A: Hired pool, all					
pre_crim	.1188468	.3236171	0	1	18,141
school	.2770204	.4475335	0	1	32,716
fewer_short_jobs	− 1.692396	.8102683	− 5	− 1	57,704
longest_job	4.429908	1.268667	1	6	57,703
position_id	360.3037	188.725	193	1117	18,141
location	91.05809	47.74724	1	148	58,856
position_type	3.097801	.6080918	1	5	58,977
firm_id	135.2293	55.54774	3	224	58,508
neurtot	1.489581	.7607951	0	3	58,977
opentot	1.049375	.7420475	0	3	58,977
extratot	1.301863	.7302858	0	3	58,977
contot	1.426064	.7932229	0	3	58,977
agreetot	1.685233	.7598676	0	3	58,977
LOE	164.3096	175.8667	1	1936	58,287
TERM_ANY	.8002611	.3998074	0	1	58,977
TERM_I	.3349611	.4719809	0	1	58,977
TERM_V	.4616715	.498533	0	1	58,977
misconduct	.0482466	.2142892	0	1	47,651
badservice	.1423275	.3493887	0	1	57,178
confidence	.0060283	.2351492	− .2419459	.9176778	58,977
rulebreaker1	.102916	.3038519	0	1	54,355
Observations	58,977				
Panel B: Hired pool, sample estimated					
pre_crim	.114964	.3189934	0	1	10,699
school	.242546	.4286428	0	1	10,699
fewer_short_jobs	− 1.791382	.8344094	− 5	− 1	10,699
longest_job	4.335545	1.316852	1	6	10,699
position_id	340.2147	153.4029	193	1117	10,699
location	100.6803	49.02598	1	147	10,699
position_type	3.504907	.4999993	3	4	10,699
firm_id	117.5748	51.10813	3	217	10,699
neurtot	1.573792	.8154937	0	3	10,699
opentot	1.108421	.7627664	0	3	10,699
extratot	1.471166	.7601654	0	3	10,699
contot	1.293766	.7155625	0	3	10,699
agreetot	1.831853	.727405	0	3	10,699
LOE	168.9602	190.5253	1	1936	10,699
TERM_ANY	.772876	.418993	0	1	10,699
TERM_I	.3318067	.470884	0	1	10,699
TERM_V	.4377979	.496139	0	1	10,699
misconduct	.0453313	.2080395	0	1	10,699
badservice	.1856248	.3888218	0	1	10,699
confidence	.0324628	.2456392	− .2419459	.9033776	10,699

Table 2 Summary statistics for the hired pool *(Continued)*

	Mean	sd	Min	Max	Count
rulebreaker1	.1040284	.3053117	0	1	10,699
Observations	10,699				

sample of applicants for sales or customer service jobs for whom we have information about criminal record and all controls.

Our model of hiring, whose results are shown in Table 3, is as follows:

$$y_{ijl} = \alpha_l + \beta\cdot\text{pre\_crim}_i + \mathbf{X}_i\cdot\gamma + \delta\cdot j + \zeta\cdot(\text{pre\_crim}_i * j) + \varepsilon_{ijl},$$

where y_{ijl} is a dummy which equals 1 if applicant i was hired in any job (sales or customer service) and in any location; α_l is a location fixed effect; pre_crim_i is a dummy that equals 1 if individual i has a criminal record; $\mathbf{X}_i$ is a vector of applicant-specific characteristics including education and job history; j is a dummy which equals 1 if the job to which the worker applied was a sales job; and $(\text{pre\_crim}_i * j)$ is an interaction term. Following a referee's suggestion, we cluster standard errors at the location level as a proxy for clustering at the firm level. We were not able to reconstruct firm for the applicant sample, but regard location, which we could reconstruct, as a reasonable substitute, since it captures some of the variation associated with firms,[22] and since the residual might also be correlated with the local labor market conditions. Without any controls, we find that having a criminal record per se does not have a hiring penalty: a criminal history is actually positively correlated with the probability of being hired

Table 3 Correlates of hiring rates (customer service and sales)

	(1)	(2)	(3)	(4)	(5)	(6)
	Hired	Hired	Hired	Hired	Hired	Hired
pre_crim	0.0410*	0.0440*	− 0.0398***	− 0.0280*	− 0.0394***	− 0.0263
	(1.73)	(1.84)	(− 3.02)	(− 1.77)	(− 2.98)	(− 1.59)
school		− 0.0142			0.0062	0.0061
		(− 1.14)			(1.28)	(1.28)
fewer_short_jobs		0.0225***			0.0183***	0.0182***
		(5.43)			(11.52)	(11.60)
longest_job		− 0.0081			0.0041	0.0042
		(− 1.55)			(1.62)	(1.64)
pos_applied==Sales				0.2752***	− 0.1357	− 0.1308
				(4.42)	(− 1.10)	(− 1.05)
crim*sales						− 0.0282
						(− 1.16)
Constant	0.1894***	0.2706***	0.1556***	0.1219***	0.1674***	0.1671***
	(4.91)	(4.53)	(4.27e+11)	(9.06)	(14.78)	(14.82)
location dummies	No	No	Yes	No	Yes	Yes
Observations	73,885	73,884	73,885	73,885	73,884	73,884
R-squared	0.001	0.004	0.248	0.094	0.250	0.251
Adjusted *R*-squared	0.001	0.004	0.248	0.094	0.250	0.250

Sample contains only applicants for whom information about criminal background is available. *t*-statistics in parentheses. Standard errors clustered by location

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

(Table 3, column 1). This average effect can be gleaned directly from a comparison with pre_crim means in Tables 1 and 2, which shows that there are more individuals with a criminal background among the hired than in the applicant pool. The human capital controls alone do not change the positive effect of the criminal record (Table 3, column 2).

However, after controlling for either location or the position to which the applicant applied, the effect of a criminal record becomes negative (Table 3, columns 3–4), as suggested by previous studies (Pager 2003; Holzer et al. 2004, 2006; Uggen et al. 2014; Agan and Starr 2018; Doleac and Hansen 2016). With full controls other than the position interaction term (column 5), a criminal record lowers the probability of being hired about 4% from the 20% absolute probability of being hired in our sample. Comparable results for the sign and magnitude of the effect of a criminal record are found when a logit model of the same variables is estimated (Table 15 in Appendix 1).

This coefficient reversal from columns 1 and 2 to 3 through 6 suggests that those with a criminal history in our sample are applying to jobs and in locations with better hiring rates than those of the average position. To explore whether these higher hiring rates are for the job generally or represent a greater willingness to hire applicants with criminal records, we add an interaction of sales with pre_crim. The results, which are reported in column 6, suggest possible heterogeneity of the hiring penalty across positions. The baseline customer service positions have a penalty of 2.6% while sales positions have a hiring penalty of an additional 2.8% for a total of 5.4%, although neither coefficient is significant. The logit version does not show a significant difference between the hiring penalty for the two jobs (Table 15 in Appendix 1, column 6).

5 Tenure and separation of employees with a criminal record

Job performance can include many potential measures, which may vary depending on the type of position. Tenure is an important measure of employment outcomes, as finding and training a new worker can be very expensive.[23] Of course, there are many other potentially important measures of job performance. However, due to data availability, we focus on job tenure, separation, and reason for separation. We restrict analysis to the 10,698 observations for which all of our explanatory variables and outcome measures are available.

To measure whether employees with a criminal record have longer tenure, we construct a variable called length of employment (LOE). This variable measures the number of days that elapse between the hire date and the termination date or the date of final data entry, whichever is smaller. The average length of employment in our sample is 169 days (Table 2, panel B). Note that this variable is subject to right-censoring.

Table 4 takes a first pass at the data by regressing LOE on pre_crim. We run the following model:

$$LOE_{ijfl} = \alpha_f + \alpha_l + \beta \cdot \text{pre\_crim}_i + \mathbf{X}_i \cdot \gamma + \delta \cdot j + \zeta \cdot (\text{pre\_crim}_i * j) + \varepsilon_{ijfl},$$

where LOE_{ijfl} is the employment duration of employee i who was hired to perform job j (sales or customer service) by firm f at location l; α_f is a fixed effect for firm; α_l is a fixed effect for location; pre_crim_i is a dummy that equals 1 if individual i has a criminal record; j is a dummy which equals 1 if the job to which the worker applied was a sales job; and $\mathbf{X}_i$ is a vector of employee-specific characteristics which, in addition to

Table 4 Correlates of length of employment, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
pre_crim	18.9664**	16.7731**	16.5098**	17.7470**	18.6532	15.5804	15.1885	16.0485	20.6284**	19.6851**	19.4344**	22.4486**
	(2.41)	(2.40)	(2.35)	(2.61)	(1.69)	(1.62)	(1.59)	(1.68)	(2.23)	(2.12)	(2.03)	(2.46)
sales	− 113.4119***	− 118.8626***	− 124.0721***	− 69.9048***								
	(− 7.46)	(− 7.56)	(− 8.27)	(− 3.24)								
school		− 1.2225	− 2.4141	− 1.7923		1.9270	0.9519	0.5464		− 3.3279	− 4.6141*	− 3.1864
		(−0.48)	(−0.91)	(−0.71)		(0.50)	(0.23)	(0.14)		(− 1.36)	(− 1.69)	(− 1.12)
fewer_short_jobs		8.3934***	8.0471***	7.3944***		8.6225*	8.3008*	8.0564*		7.9525***	7.4542***	6.2850***
		(3.45)	(3.29)	(3.11)		(1.96)	(1.87)	(1.80)		(3.84)	(3.54)	(3.09)
longest_job		7.8540***	7.4660***	8.2519***		8.9060***	8.4112***	9.4796***		6.3588***	5.8821***	6.9036***
		(4.72)	(4.44)	(4.96)		(3.33)	(3.10)	(3.72)		(5.45)	(5.43)	(5.56)
badservice			4.7773				8.3546				− 2.3144	
			(1.19)				(1.19)				(− 0.68)	
confidence			− 25.6951***				− 25.8342***				− 27.5452*	
			(− 3.58)				(− 4.78)				(− 1.75)	
rulebreaker1			4.6127				− 3.8881				15.0785**	
			(1.07)				(− 0.94)				(2.66)	
open1				10.7522***				10.9779**				10.5110**
				(3.24)				(2.37)				(2.18)
open2				− 29.8031*				72.8791***				− 39.7706**
				(− 1.78)				(6.21)				(− 2.51)
open3				1.5238				− 0.8795				3.5340
				(0.37)				(− 0.15)				(0.52)
con1				4.2707				1.0363				7.7012**

Table 4 Correlates of length of employment, OLS *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
				(1.54)				(0.26)				(2.47)
con2				6.5186**				4.9525				8.4729
				(2.00)				(0.84)				(1.64)
con3				− 19.4901***				− 9.5269				− 21.9944***
				(− 4.17)				(− 0.48)				(− 4.48)
extra1				− 7.9939**				− 15.3407***				1.3196
				(− 2.20)				(− 3.34)				(0.26)
extra2				− 10.7999*				− 14.3397***				− 3.9990
				(− 1.79)				(− 5.00)				(− 0.26)
extra3				11.5721***				12.8660***				10.5244**
				(4.09)				(4.44)				(2.24)
agree1				5.5521				12.7077				− 2.5295
				(1.02)				(1.69)				(− 0.60)
agree2				0.7225				− 4.5640				5.6775
				(0.24)				(− 1.19)				(1.09)
agree3				− 44.5771**				50.9987***				− 44.5049**
				(− 2.56)				(11.38)				(− 2.55)
neur1				− 0.4072				− 1.6039				1.1931
				(− 0.10)				(− 0.25)				(0.25)
neur2				2.0334				3.8971				0.0249
				(0.69)				(0.84)				(0.01)
neur3				9.5797**				6.7000				17.1011***
				(2.12)				(0.89)				(4.07)

Table 4 Correlates of length of employment, OLS *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
Constant	247.0000	240.7641***	233.9013***	290.4578***	− 41.5923***	− 66.9899**	− 78.0466***	− 125.3095***	247.0000	245.4222***	227.7935***	279.5057***
	(.)	(23.63)	(24.17)	(17.88)	(− 4.30)	(− 2.90)	(− 3.23)	(− 3.51)	(.)	(26.80)	(21.28)	(17.30)
firm_id dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,699	10,699	10,699	10,699	5402	5402	5402	5402	5297	5297	5297	5297

Notes: Sample contains only hired workers for which information about criminal background is available. t-statistics in parentheses. Standard errors clustered by firm
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

education and job history, now includes psychometric measurements. Following a referee's suggestion we cluster standard errors at the firm level.

For the sample of both sales and customer service employees and with controls only for location, position, and firm, the estimates indicate that employees with a criminal background stay employed on average 19 days longer than those who do not have a criminal background (Table 4, column 1).

LOE combines the effect of voluntary and involuntary terminations. Involuntary termination is by definition associated with weaker performance, while studies indicate that voluntary termination is most common among highest and lowest performers.[24] The expected sign of the human capital variables is thus ambiguous, since departing employees include both the best and the worst. Schooling does not predict LOE, but the coefficients on both job history variables are positive and statistically significant in all specifications (Table 4, columns 2–4). Job history and school together reduce the LOE associated with pre_crim by about 2 days (Table 4, columns 1–2). Controlling for proprietary psychometric variables and FFA reduce the additional LOE of employees with criminal records to about 16.5 and 17.7 days, respectively (Table 4, columns 3–4). The effect of the psychometric variables will be considered at more length in the next section.

To quantify the economic significance of longer LOE, we obtained estimates from the consultancy on the average cost of replacing a worker found in our dataset. This figure amounted to $4000 per termination. At average values of other variables, a worker without a criminal record lasts 167 days while a worker with a record lasts 183 days.[25] Since the average wage for call center employees is about $30,000 per year, this amounts to a savings of about 2.5% of wages per year for these employees.[26] However, if applicants with records were hired in greater numbers, their quality, and therefore the associated employer savings, might well drop.

The LOE of employees varies strikingly with the job held (Table 4, columns 1–4). Because the effect is so large, we examine the possibility that different models underlie each job (Table 4, columns 5–12). With only location and firm as controls, sales people with criminal records last about 19 days longer than others, while customer service agents with a record last about 21 days longer. The coefficient in the sales estimate is not significant; the p values are between .11 and .14. Schooling has no effect in any estimate. In most specifications, the job stability and school variables together reduce the effect of a criminal record slightly. The psychometric variables will be discussed in the next section.

We next conduct a more refined analysis to account both for different types of separation and for the censoring that results from the unknown ultimate length of employment of those workers who were employed when the data collection ended. About 77% of all workers had separated by the end of data collection, and about 55% of all separations were voluntary. We run the following Cox proportional hazards model to predict employment tenure:

$$h_{ijfl} = h_0(t) \cdot \exp\left(\alpha_f + \alpha_l + \beta \cdot \text{pre\_crim}_i + \mathbf{X}_i \cdot \gamma + \delta \cdot j\right),$$

where h_{ijfl} is the hazard that employee i, who was hired to perform job j (sales or customer service) by firm f at location l, separates t days after being hired; $h_0(t)$ is the baseline hazard rate; α_f is a fixed effect for firm; α_l is a fixed effect for location; pre_crim_i is a dummy that equals 1 if individual i has a criminal record; $\mathbf{X}_i$ is a vector of employee-specific characteristics; and *j* is a dummy which equals 1 if the job to which the worker applied was a sales job.

We begin by applying this model to voluntary separations. Table 5 provides the estimated coefficients of a Cox proportional hazard model in which only voluntary separations are counted as "failures." For the whole pool, a criminal background has a consistently negative and statistically significant impact on voluntary separations, suggesting that having a criminal background makes an employee less likely to leave voluntarily (Table 5, columns 1–4). This result could be due to several factors. Workers with a criminal record presumably have fewer external labor market opportunities. They may also feel a sense of loyalty or gratitude to an employer who has given them a second chance. Again, the coefficient on job type is highly significant (Table 5, columns 1–4), and we therefore also examine each job separately (Table 5, columns 5–12). A criminal record decreases the voluntary separation rates of customer service employees more than that of sales employees, though both effects are significant and negative (Table 5, columns 5–12). Like LOE, voluntary departures are driven by a mix of high and low performers, and thus, the expected signs on the human capital coefficients are ambiguous. Schooling seldom predicts voluntary separation for either the entire sample or for the sales sample, but for the customer service sample is positive and significant at the 5 or 10% level (Table 5, columns 2–4, 6–8, and 10–12). One of the job history variables, longest_job, is significant and negative for the whole sample and sales, but is insignificant for customer service; the other, fewer_short_jobs is significant (and positive) for customer service only and insignificant otherwise (Table 5, columns 2–4, 6–8, and 10–12). Two psychometric variables are predictive for sales and one is predictive for customer service––we discuss these in more detail later.

Table 6 provides the estimated coefficients of the Cox proportional hazard model in which only involuntary terminations are counted as failures. Since involuntary termination is associated with lower quality workers, coefficients should now have the sign associated with lower quality. For the whole sample, a criminal background predict involuntary terminations at the 10% significance level in two of four specifications. (Table 6, columns 1–4). Other variables are much more significant. As expected, involuntary terminations are more likely among workers who would be regarded as lower quality by traditional measures: better schooling (Table 6, columns 2–4) and higher job stability (Table 6, columns 2–4) reduce involuntary termination in all four specifications at the 1% significance level. Again, the coefficient on a sales position is highly significant (Table 6, columns 1–4), so we examine the two jobs separately. A criminal record does not predict involuntary termination for customer service jobs (Table 6, columns 9–12) but is highly predictive for sales jobs in all specifications (Table 6, columns 5–8). School and one job stability variable are, as expected, negative and significant in all specifications in both positions. The other job stability variable is negative for all specifications, but significant only for customer service. Again, the psychometric predictors are somewhat different for the two jobs, a finding we discuss further in the next section.

So far, the evidence on tenure has shown that having a criminal background makes an employee less likely to leave voluntarily and likely to have a longer tenure. Employees with a criminal record are no more likely to be terminated involuntarily in customer service positions, but more likely in a sales position. Since involuntary turnover

Table 5 Correlates of voluntary separation, Cox Proportional Hazard Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
pre_crim	− 0.1894***	− 0.1726***	− 0.1730***	− 0.1780***	− 0.1750**	− 0.1574**	− 0.1571**	− 0.1582**	− 0.2136**	− 0.1988**	− 0.2000**	− 0.2115**
	(− 3.35)	(− 3.21)	(− 3.28)	(− 3.47)	(− 2.46)	(− 2.32)	(− 2.38)	(− 2.34)	(− 2.32)	(− 2.15)	(− 2.12)	(− 2.55)
sales	0.3762***	0.3773***	0.3763***	0.3811***								
	(5.94)	(5.76)	(5.65)	(5.32)								
school		0.0393	0.0405	0.0492*		− 0.0026	− 0.0026	0.0029		0.0902*	0.0938**	0.1009**
		(1.42)	(1.44)	(1.73)		(− 0.11)	(− 0.11)	(0.11)		(1.91)	(2.05)	(2.02)
fewer_short_jobs		0.0178	0.0164	0.0210		− 0.0141	− 0.0159	− 0.0104		0.0807**	0.0806**	0.0856**
		(0.84)	(0.75)	(0.93)		(− 0.58)	(− 0.61)	(− 0.38)		(2.04)	(2.02)	(2.27)
longest_job		− 0.0374***	− 0.0381***	− 0.0388***		− 0.0460***	− 0.0463***	− 0.0472***		− 0.0180	− 0.0184	− 0.0216
		(− 3.16)	(− 3.14)	(− 3.23)		(− 3.54)	(− 3.39)	(− 3.41)		(− 0.87)	(− 0.89)	(− 1.06)
badservice			− 0.0594				− 0.0602				− 0.0413	
			(− 1.24)				(− 0.96)				(−0.69)	
confidence			− 0.0007				− 0.0036				0.0189	
			(− 0.01)				(− 0.11)				(0.10)	
rulebreaker1			− 0.0136				0.0198				− 0.1079**	
			(− 0.45)				(0.68)				(− 2.39)	
open1				− 0.0980***				− 0.1253***				− 0.0477
				(− 3.07)				(− 4.24)				(− 0.65)
open2				− 0.1535**				0.0108				− 0.1273
				(− 2.03)				(0.03)				(− 1.15)
open3				− 0.0133				0.0214				− 0.0765
				(− 0.48)				(0.98)				(− 1.47)
con1				− 0.0282				− 0.0164				− 0.0503

Table 5 Correlates of voluntary separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
				(− 0.94)				(− 0.39)				(− 1.52)
con2				− 0.0427				− 0.0463				− 0.0394
				(− 0.99)				(− 0.70)				(− 1.17)
con3				0.0111				0.1378				0.0223
				(0.12)				(0.70)				(0.22)
extra1				0.0642**				0.0925***				0.0093
				(2.14)				(2.60)				(0.14)
extra2				0.0481**				0.0398				0.0787
				(1.96)				(1.49)				(1.19)
extra3				− 0.0430				− 0.0503				− 0.0395
				(− 1.29)				(− 1.37)				(− 0.58)
agree1				− 0.0428				− 0.0652				0.0052
				(− 0.94)				(− 1.07)				(0.11)
agree2				− 0.0092				0.0258				− 0.0793
				(−0.29)				(1.28)				(− 1.31)
agree3				− 0.0695				0.0852				− 0.0283
				(− 1.30)				(0.24)				(− 0.43)
neur1				− 0.0207				− 0.0262				− 0.0122
				(− 0.74)				(− 0.89)				(− 0.21)
neur2				− 0.0121				− 0.0312				0.0209
				(− 0.47)				(− 1.26)				(0.46)
neur3				− 0.0466				− 0.0620				− 0.0237
				(− 0.91)				(− 1.00)				(− 0.54)

Table 5 Correlates of voluntary separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
firm_id dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,699	10,699	10,699	10,699	5402	5402	5402	5402	5297	5297	5297	5297
Pseudo R-squared	0.013	0.013	0.013	0.013	0.005	0.005	0.005	0.006	0.008	0.009	0.009	0.009

Sample contains only hired workers for whom information about criminal background is available. t-statistics in parentheses. Standard errors clustered by firm
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Table 6 Correlates of involuntary separation, Cox Proportional Hazard Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
pre_crim	0.0578	0.0699*	0.0738*	0.0626	0.1162**	0.1220***	0.1267***	0.1193***	− 0.0402	− 0.0277	− 0.0234	− 0.0520
	(1.33)	(1.71)	(1.75)	(1.45)	(2.28)	(3.04)	(2.88)	(3.08)	(− 0.43)	(− 0.30)	(− 0.25)	(− 0.57)
sales	0.8457***	0.8433***	0.8332***	0.8564***								
	(8.07)	(8.35)	(8.02)	(8.02)								
school		− 0.0980***	− 0.0888***	− 0.0869***		− 0.0780***	− 0.0686**	− 0.0824***		− 0.1075***	−0.0985**	− 0.0878**
		(− 3.63)	(− 3.21)	(− 3.57)		(− 2.64)	(− 2.12)	(− 2.71)		(− 2.58)	(−2.37)	(− 2.50)
fewer_short_jobs		− 0.1028***	− 0.0955***	− 0.1006***		− 0.0849**	− 0.0749**	− 0.0827**		− 0.1152***	− 0.1101***	− 0.1133***
		(− 5.16)	(− 4.83)	(− 5.09)		(− 2.28)	(− 2.07)	(− 2.12)		(− 6.46)	(− 6.55)	(− 7.48)
longest_job		− 0.0623***	− 0.0551***	− 0.0632***		− 0.0364	− 0.0267	− 0.0386		− 0.0870***	− 0.0811***	− 0.0881***
		(− 3.52)	(− 3.19)	(− 3.61)		(− 1.19)	(− 0.87)	(− 1.38)		(−4.36)	(−4.49)	(−4.23)
badservice			0.0962***				0.1043***				0.0804	
			(4.00)				(3.71)				(1.60)	
confidence			0.3350***				0.4113***				0.2671**	
			(5.40)				(8.53)				(2.35)	
rulebreaker1			− 0.0597				0.0405				−0.1445***	
			(− 1.28)				(0.62)				(−2.81)	
open1				− 0.1308***				− 0.0434				− 0.1948***
				(− 2.80)				(− 1.17)				(− 2.88)
open2				− 0.0459				− 1.1571***				0.1609
				(− 0.30)				(− 5.99)				(1.11)
open3				0.0038				0.0123				− 0.0069
				(0.11)				(0.21)				(− 0.13)
con1				0.0070				0.0195				− 0.0191

Table 6 Correlates of involuntary separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
				(0.20)				(0.30)				(− 0.61)
con2				− 0.0405				0.0078				− 0.0793
				(− 0.82)				(0.09)				(− 1.54)
con3				− 0.0592				− 0.4028***				0.0038
				(− 1.33)				(− 4.50)				(0.09)
extra1				0.0592				0.0991				0.0069
				(1.28)				(1.55)				(0.15)
extra2				− 0.0259				0.0445				− 0.1113
				(− 0.61)				(0.94)				(− 1.53)
extra3				− 0.0650				− 0.0148				− 0.1103
				(− 1.26)				(− 0.24)				(− 1.55)
agree1				0.0373				0.0577**				0.0357
				(1.14)				(2.56)				(0.59)
agree2				0.0265				0.0561				0.0032
				(1.08)				(1.30)				(0.09)
agree3				0.0013				−0.9510***				0.0386
				(0.01)				(−3.72)				(0.24)
neur1				0.0062				0.0203				−0.0147
				(0.27)				(0.49)				(−0.45)
neur2				0.0031				0.0134				−0.0045
				(0.12)				(0.34)				(−0.13)
neur3				−0.1141***				−0.0388				−0.2422***
				(−2.62)				(−0.87)				(−5.70)

Table 6 Correlates of involuntary separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
firm_id dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,699	10,699	10,699	10,699	5402	5402	5402	5402	5297	5297	5297	5297
Pseudo R-squared	0.010	0.011	0.011	0.011	0.010	0.011	0.012	0.012	0.010	0.012	0.012	0.013

Sample contains only hired workers for whom information about criminal background is available. t-statistics in parentheses. Standard errors clustered by firm
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

is associated with weaker performance and turnover is costly, this evidence taken together suggests that customer service employees with a criminal background are, at least at the current margin, a promising pool for employers. Sales employees present a slightly more mixed picture, since they do appear to have higher rates of involuntary terminations.

To further explore the cost of involuntary terminations, we examine a subset of these terminations, those that involve misconduct. Note that the concept of "misconduct," as used in the human resource setting, corresponds to the definition found in unemployment insurance (UI) law. Employers keep records of misconduct discharges for the purpose of UI reporting: if an employer discharges an employee for misconduct, the employee receives reduced UI or none at all, and thus, the discharge has a lesser effect on the employer's UI premiums. Although the term "misconduct" seems to imply severe misbehavior, it may also include much lesser failings such as excessive absenteeism or even the use of profanity.[27]

Misconduct discharges are a relatively rare event, occurring in 4.5% of our sample of the hired (Table 2, panel B). Termination for misconduct is generally more common in sales, occurring in 5.9% of sales positions compared with 3.1% of customer service positions. For the sample of both positions, a criminal record is associated with a higher risk of misconduct (Table 7, columns 1–4). Because of the apparently different underlying models, we again examine each job separately. A criminal record is significantly associated with an increased risk of misconduct in sales jobs (Table 7, columns 5–12). Sales workers with a criminal record are about 34% more likely to be terminated for misconduct than those without.[28] In customer service jobs, the coefficient on a criminal record is about 40% smaller than is sales and borderline significant, suggesting a possible connection but weaker than that in sales.

Our results suggest that all employees with a criminal record have longer tenure and lower voluntary turnover than other employees. Customer service employees with a criminal record are also not significantly more likely to be terminated involuntarily or for misconduct, though a higher misconduct rate cannot be ruled out. Sales employees with a record display a more complicated pattern. The value of their longer tenure is at least partly offset by their significant and slightly higher rates of involuntary discharge and their significant and clearly higher rates of misconduct discharge. The discrepancy between sales and customer service jobs is particularly striking since the hiring penalty seems to be greater for sales jobs (Table 3, column 6): despite the higher degree of selection, more misconduct is observed. We consider our finding a cautionary tale of the risks of drawing broad conclusions based on one type of position or industry.

The observational nature of our data means that we cannot draw conclusions about the pool of the non-hired, and applicants who were not hired may have been those at greater risk of poor outcomes. Instead, since our estimates describe average values for those hired, they are not conclusive of how marginal applicants with a criminal record might perform. Although we have no direct evidence of which employees were marginal, we do have some indirect evidence. For each firm, we can calculate the percent of the workforce with a criminal record (crimper) and examine the association of this with the likelihood of misconduct by individual workers (Table 8). For the whole sample and the sales and customer service jobs estimated separately, we find that the likelihood of misconduct is actually lower in firms with a larger number of workers

Table 7 Correlates of misconduct separation, Cox Proportional Hazard Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
pre_crim	0.2405***	0.2546***	0.2597***	0.2710***	0.2755***	0.2903***	0.2886***	0.3094***	0.1712*	0.1714	0.2265*	0.1601
	(3.39)	(3.76)	(3.40)	(4.02)	(2.80)	(3.22)	(2.95)	(3.42)	(1.65)	(1.46)	(1.95)	(1.38)
sales	0.0741	0.0559	0.0368	0.0709								
	(0.58)	(0.42)	(0.26)	(0.62)								
school		− 0.1465	− 0.1119	− 0.1421		− 0.1325	− 0.0919	− 0.1352		− 0.1761	− 0.1542	− 0.1410
		(−1.19)	(− 0.92)	(−1.13)		(− 0.77)	(− 0.53)	(− 0.75)		(− 1.09)	(− 0.99)	(− 1.02)
fewer_short_jobs		− 0.1671***	− 0.1479***	− 0.1666***		− 0.1350**	−0.1147**	− 0.1364**		− 0.2299***	− 0.2125**	− 0.2396***
		(− 3.58)	(− 3.09)	(− 3.54)		(− 2.48)	(−2.02)	(− 2.31)		(− 2.79)	(− 2.42)	(− 2.85)
longest_job		− 0.0826***	− 0.0739***	− 0.0884***		− 0.0644*	− 0.0550	− 0.0688*		− 0.1219**	−0.1138**	− 0.1330***
		(− 3.02)	(− 2.79)	(− 3.21)		(− 1.75)	(− 1.56)	(− 1.81)		(− 2.34)	(− 2.21)	(− 2.61)
badservice			0.1997				0.1368				0.3750	
			(1.64)				(1.23)				(1.41)	
confidence			0.5401***				0.6111***				0.4174*	
			(4.57)				(4.33)				(1.90)	
rulebreaker1			− 0.3712*				− 0.2786				− 0.5956**	
			(− 1.81)				(− 1.14)				(− 2.27)	
open1				− 0.0612				0.0364				− 0.2687**
				(− 0.84)				(0.60)				(− 2.37)
open2				− 0.0345				14.7302				− 0.0995
				(− 0.08)				(.)				(− 0.20)
open3				− 0.0289				− 0.0327				− 0.0748
				(− 0.25)				(− 0.20)				(− 0.65)
con1				0.1072				0.1392*				0.0318

Table 7 Correlates of misconduct separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
				(1.33)				(1.73)				(0.15)
con2				0.0812				0.2190*				− 0.1947
				(0.62)				(1.75)				(− 1.37)
con3				− 0.1556				− 0.6501				− 0.0860
				(− 1.04)				(− 1.22)				(− 0.52)
extra1				− 0.0628				− 0.0701				− 0.1024
				(− 0.77)				(− 0.74)				(− 0.65)
extra2				− 0.0167				− 0.0299				− 0.0014
				(− 0.13)				(− 0.17)				(− 0.01)
extra3				− 0.0952*				− 0.0299				− 0.2488**
				(− 1.70)				(− 0.89)				(− 2.20)
agree1				− 0.0940				− 0.0063				− 0.2636*
				(− 1.17)				(− 0.06)				(− 1.67)
agree2				0.0935				− 0.0162				0.3266*
				(1.06)				(− 0.13)				(1.85)
agree3				0.2678				14.9843***				0.3783
				(0.58)				(85.25)				(0.77)
neur1				0.0629				0.0650				0.0396
				(0.40)				(0.28)				(0.34)
neur2				− 0.0277				− 0.0472				0.0333
				(− 0.31)				(− 0.46)				(0.20)
neur3				− 0.1141				− 0.0660				− 0.2821*
				(− 0.89)				(− 0.44)				(− 1.82)

Table 7 Correlates of misconduct separation, Cox Proportional Hazard Model *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
firm_id dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,699	10,699	10,699	10,699	5402	5402	5402	5402	5297	5297	5297	5297
Pseudo R-squared	0.033	0.035	0.038	0.037	0.016	0.017	0.020	0.019	0.044	0.049	0.053	0.056

Sample contains only hired workers for whom information about criminal background is available. *t*-statistics in parentheses. Standard errors clustered by firm
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Table 8 Percent of employees with a criminal record as a correlate of misconduct, Cox Proportional Hazard Model

	(1)	(2)	(3)
	All	Sales	Cust. Serv.
pre_crim	0.2762***	0.3254***	0.1768
	− 3.44	− 3.1	− 1.53
school	− 0.142	− 0.135	− 0.1745
	(− 1.14)	(− 0.77)	(− 1.08)
fewer_short_jobs	− 0.1649***	− 0.1321**	− 0.2311***
	(− 3.40)	(− 2.37)	(− 2.79)
longest_job	− 0.0799***	− 0.0607	− 0.1233**
	(−2.82)	(−1.60)	(−2.36)
sales	−1.5842*		
	(−1.86)		
crimper	−9.9982***	−16.0613***	−6.4242**
	(−2.92)	(−7.11)	(−2.14)
firm_id dummies	Yes	Yes	Yes
location dummies	Yes	Yes	Yes
Observations	10,699	5402	5297
Pseudo R-squared	0.036	0.021	0.049

Sample contains only hired workers for whom information about criminal background is available. t-statistics in parentheses. Standard errors clustered by firm
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

with a criminal record. There are at least two possible explanations for this surprising result. First, firms with a comparative advantage in managing misconduct are more likely to hire workers with a higher propensity to misconduct. Second, firms with high levels of misconduct-prone workers may learn to manage misconduct better. The second explanation is a plausible explanation of the present findings because the workplaces in our sample are relatively homogeneous. In either case, these results do not suggest a story in which rising levels of workers with records rapidly drive up the overall misconduct level.

Our findings provide an interesting comparison to those of the only other study of the job performance of employees with criminal records, which was conducted on armed forces data (Lundquist et al. 2018). Military personnel with the most serious criminal records appeared to be no more likely than personnel without a criminal record to leave for performance-related reasons, including misconduct, and to be superior to others on several performance dimensions. Interestingly, military personnel with less serious criminal records performed worse than other personnel across various measures of attrition and promotion, including misconduct. As the authors of that study note, this initially puzzling difference may be explained by military screening procedures, which add extra scrutiny for applicants with criminal records, and more stringent checks for more serious offenses. Perhaps, the civilian firms in our study should consider using different screening methods for customer service and sales jobs.

We next compare the level of misconduct among firms that request criminal records with the level among those that do not. In Table 9, our sample includes both firms that do and do not ask for criminal information, and we include a variable indicating whether the employer had this information at the time of hiring. We find that whether the employer had information about an employee's criminal record does not predict the likelihood of employee misconduct.

Table 9 Availability of criminal records as a correlate of misconduct separation, Cox Proportional Hazard Model (customer service and sales)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
missing_crim	0.169	0.185	0.206	0.166	−0.232	− 0.245	− 0.209	− 0.336	0.00174	0.0121	0.0305	0.0686
	(1.24)	(1.26)	(1.36)	(1.06)	(−0.28)	(− 0.29)	(− 0.24)	(− 0.39)	(0.02)	(0.12)	(0.29)	(0.51)
sales	20.93***	22.07***	22.94***	21.72***								
	(143.59)	(134.07)	(131.46)	(112.88)								
school		−0.112	−0.0819	− 0.0904		− 0.131	− 0.0903	− 0.132		− 0.0939	−0.0743	− 0.0560
		(−1.73)	(−1.25)	(−1.36)		(− 0.78)	(−0.54)	(− 0.75)		(−1.35)	(− 0.98)	(− 0.86)
fewer_short_jobs		− 0.172***	− 0.159***	− 0.169***		− 0.143**	− 0.123*	− 0.144*		− 0.163***	− 0.157***	− 0.153***
		(−5.86)	(−5.12)	(− 6.04)		(−2.68)	(−2.24)	(−2.46)		(−4.13)	(−3.96)	(−4.19)
longest_job		−0.0888***	−0.0784**	− 0.0904***		− 0.0548	− 0.0461	− 0.0584		− 0.118***	−0.109***	− 0.121***
		(− 3.37)	(− 2.90)	(− 3.35)		(− 1.50)	(− 1.30)	(− 1.59)		(− 3.61)	(− 3.36)	(− 3.56)
badservice			0.151				0.141				0.158	
			(1.66)				(1.30)				(0.96)	
confidence			0.465***				0.595***				0.283	
			(3.82)				(4.22)				(1.38)	
rulebreaker1			−0.337**				−0.287				−0.304	
			(−2.71)				(−1.18)				(−1.62)	
open1				−0.188**				0.0240				−0.303***
				(−2.73)				(0.43)				(−5.09)
open2				−0.0791				14.65				0.0882
				(−0.52)				(.)				(0.60)
open3				0.0531				−0.0340				0.00142
				(0.59)				(−0.20)				(0.02)
con1				0.0435				0.138				0.00801

Table 9 Availability of criminal records as a correlate of misconduct separation, Cox Proportional Hazard Model (customer service and sales) *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
				(0.70)				(1.80)				(0.12)
con2				0.0338				0.205				−0.0752
				(0.51)				(1.64)				(−1.21)
con3				−0.0693				− 0.676				−0.0538
				(−1.26)				(− 1.27)				(−0.87)
extra1				0.0107				−0.0632				0.0186
				(0.25)				(−0.67)				(0.33)
extra2				0.0450				−0.0205				0.0578
				(0.41)				(−0.12)				(0.40)
extra3				−0.110				−0.00755				−0.143
				(−1.32)				(−0.17)				(−0.98)
agree1				−0.0578				−0.0105				−0.0839
				(−1.22)				(−0.10)				(−1.83)
agree2				−0.0719				−0.0193				−0.0910
				(−1.19)				(−0.16)				(−1.62)
agree3				0.177				14.90***				0.393**
				(1.29)				(86.12)				(2.68)
neur1				0.120				0.0563				0.0878
				(1.12)				(0.25)				(0.80)
neur2				0.00666				−0.0560				−0.0117
				(0.08)				(−0.51)				(−0.10)
neur3				− 0.157				−0.0643				−0.241**
				(−1.52)				(−0.42)				(−2.62)

Table 9 Availability of criminal records as a correlate of misconduct separation, Cox Proportional Hazard Model (customer service and sales) *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	All	Sales	Sales	Sales	Sales	Cust. Serv.	Cust. Serv.	Cust. Serv.	Cust. Serv.
firm_id dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,300	21,300	21,300	21,300	5417	5417	5417	5417	14,538	14,538	14,538	14,538

Sample includes all hired workers, regardless of whether criminal background information is available. t-statistics in parentheses. Robust standard errors
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

This result may seem surprising, since a criminal record is predictive of misconduct, at least for those entering sales positions. Table 10 examines the hiring of firms who do not use information about criminal records. Columns 1 and 2 examine correlates of a criminal record within the applicant pool. Those with criminal records have more short jobs, though a longer longest job than those without records. They also have less schooling than those without records, although this association is weaker controlling for location. Columns 3 and 4 show the correlates of being hired without criminal record information: these employees tend to have more school, a shorter tenure in their longest job, and fewer short jobs, all of which are associated with not having a criminal record. Although any firms in our sample that declined to use criminal records information probably did so voluntarily, this finding is consistent with the result of studies that find that Ban the Box legislation increases statistical discrimination based on characteristics associated with a criminal record (Agan and Starr 2018; Doleac and Hansen 2016). However, we are not able to examine the effect of non-use of criminal record information on characteristics such as race, since these factors were not provided to us.

6 Personality, criminal background, and job performance

The key findings of the previous section are that employees with a criminal record are less likely to quit any job, while exhibiting varying levels of misconduct that are clearly higher in some jobs and possibly not higher in others. These results raise a number of further questions that we now address using the psychometric questions in our data, which are similar to those now commonly used in hiring. The 18 questions in our data are sufficient to be suggestive of how useful psychometric testing could be in this context but are not intended as an exhaustive consideration of the issues.[29]

We first examine the extent to which the two jobs, sales and customer service, may differ in ways other than the outcomes for workers with a criminal record. To do this,

Table 10 Correlates of criminal records in applicant pool compared with correlates of missing records in hired pool (customer service and sales)

	(1)	(2)	(3)	(4)
	Applicant pool		Hired pool	
	Has criminal record	Has criminal record	Missing criminal records	Missing criminal records
school	−0.0099***	− 0.0045*	0.0170**	− 0.0028
	(−4.04)	(−1.83)	(2.50)	(−1.36)
fewer_short_jobs	−0.0114***	− 0.0112***	0.0271***	0.0052***
	(−8.83)	(−8.76)	(7.64)	(4.75)
longest_job	0.0151***	0.0162***	−0.0041*	− 0.0013*
	(18.33)	(19.58)	(−1.75)	(−1.79)
sales	0.1185***	0.0323	−0.6308***	−0.0002
	(39.86)	(1.41)	(−95.64)	(−0.04)
Constant	−0.0177***	−0.0946***	0.6964***	0.3453***
	(−4.01)	(−21.04)	(54.99)	(62.60)
location dummies	No	Yes	No	Yes
Observations	73,884	73,884	20,005	19,955
R-squared	0.033	0.052	0.321	0.937
Adjusted *R*-squared	0.033	0.051	0.321	0.937

t-statistics in parentheses. Robust standard errors
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

we examine whether in each of our jobs the psychometric variables have the same association with our two measures of poor performance, misconduct and involuntary termination.[30] The psychometric variables perform well in comparison with other explanatory variables,[31] but show entirely different patterns in each job, summarized in Table 11. [32]These differences raise the possibility that differences in job characteristics rather than differences in the applicant pool might drive the different outcomes observed for employees with a criminal record. Perhaps something in the sales environment affects everyone, but those with criminal records more so.

We next examine whether employees with criminal records in sales have any specific psychometric characteristics that might explain why their outcomes differ from both sales people of all types and customer service people with criminal records. Regressing each psychometric variable on position, criminal record, and the interaction of the two, we find that sales people and customer service workers clearly have different psychological profiles (Table 16 in Appendix 1).[33] The different outcomes we observe for sales and customer service representatives with criminal records might therefore be explained by either differences in worker characteristics or differences in job characteristics. However, the observational nature of our data prevents us from drawing any conclusions about causality, since selection both by workers and by firms affects the assignment of workers with various personality traits to each job.

Table 11 Psychometric predictors in different jobs

	(1)	(2)	(3)	(4)
	Involuntary separation		Misconduct	
	Cust. serv.	Sales	Cust. serv.	Sales
badservice	0.0804	0.1043***	0.3750	0.1368
confidence	0.2671**	0.4113***	0.4174*	0.6111***
rulebreaker1	−0.1445***	0.0405	−0.5956**	− 0.2786
open1	−0.1948***	− 0.0434	− 0.2687**	0.0364
open2	0.1609	−1.1571***	− 0.0995	14.7302
open3	−0.0069	0.0123	−0.0748	−0.0327
con1	−0.0191	0.0195	0.0318	0.1392*
con2	−0.0793	0.0078	−0.1947	0.2190*
con3	0.0038	−0.4028***	−0.0860	− 0.6501
extra1	0.0069	0.0991	−0.1024	−0.0701
extra2	−0.1113	0.0445	−0.0014	−0.0299
extra3	−0.1103	−0.0148	− 0.2488**	−0.0299
agree1	0.0357	0.0577**	−0.2636*	−0.0063
agree2	0.0032	0.0561	0.3266*	−0.0162
agree3	0.0386	−0.9510***	0.3783	14.9843***
neur1	−0.0147	0.0203	0.0396	0.0650
neur2	−0.0045	0.0134	0.0333	−0.0472
neur3	−0.2422***	−0.0388	− 0.2821*	−0.0660
Controls		school, job stability, crim. rec., firm, location		
Source	Table 6	Table 6	Table 7	Table 7
	cols 11–12	cols 7–8	cols 11–12	cols 7–8

Sample contains only hired workers for whom information about criminal background is available. Standardized beta coefficients. *t*-statistics in parentheses. Robust standard errors
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

We finally examine whether these psychometric variables can be used to reduce the value of a criminal record in predicting job outcomes and find that they cannot.[34] Indeed, they do not even have the same association with misconduct and involuntary termination. In the misconduct estimate for sales, the inclusion of the proprietary variables lowers the coefficient on pre_crim slightly while the inclusion of the FFA variables increases the coefficient on pre_crim also very slightly (Table 7, columns 7–8). In the involuntary termination estimate for sales, the reverse is true: the inclusion of the proprietary variables raises the coefficient on pre_crim slightly while the inclusion of the FFA lowers slightly the coefficient on pre_crim (Table 6, columns 7–8). Overall, controlling for the psychometric variables does not sizably affect the relationship between criminal background and productivity. Moreover, although the psychometric questions appear well correlated with criminal background,[35] the psychometric factors associated with either set of poor job outcomes were not consistently related to those associated with a criminal record.[36] This was surprising, since prior work often found that traits associated with criminal behavior were those that tended to produce worse work outcomes.[37] The pessimistic implication of these findings is that psychometrics is not yet useful for eliminating the predictive value of a criminal record. The optimistic implication is that even simple psychometric tests have some predictive value, and the development of better tests may eventually eliminate the incentive for employers to use criminal records in all jobs.

In sum, our analysis of psychometric variables suggests two interesting lines of future inquiry. First, our evidence suggests that either differences in worker characteristics or differences in job characteristics might explain the different misconduct levels observed for employees with criminal records in sales and customer service positions. Second, the psychometric variables have a reasonable degree of association with both a criminal record and job outcomes. However, in our data, they do not reduce the value of a criminal record, and further research is required to determine whether they could do so.

7 Conclusions

Using a unique source of data, we find that employees with a criminal record have a much longer tenure and are less likely to quit their jobs voluntarily than other workers. We further find that in certain jobs, employees with a criminal record are no more likely than those without a record to leave their job involuntarily or for reasons of misconduct. These workers with a criminal background appear to be no worse than, and possibly even better than, workers without such a background. In our data, this low-risk job is customer service. In other jobs, however, employees with a criminal record do appear more likely to leave for reasons of misconduct. In our data, the high-risk job is sales, and we conjecture that whatever factors create the overall high misconduct rate observed in sales jobs may have an even greater effect on employees with criminal records.

The precise cost of this excess risk is highly speculative: the term "misconduct" encompasses behavior ranging from excessive absenteeism to a variety of criminal conduct. Surveys suggest that employers are primarily concerned about large negligent hiring judgments for violent acts (Walker and Miller 2009; Platt 1993), but no systematic evidence supports this concern.[38] The primary employer losses from misconduct are probably more pedestrian. Only one published study has any bearing on this and, though small and highly specific, suggests that the work-related misconduct of workers with criminal records is on average less serious than that of other workers.[39] With this in mind, we use dishonesty, a serious but non-catastrophic type of employee misconduct, as a basis for a rough estimate of the cost-benefit calculation facing an employer. The National Retail Federation estimates the loss from each dishonest employee case is about $1546 (National Retail Federation 2015). Only sales workers with a criminal record pose an excess misconduct risk: about 5.9% of sales workers with a criminal record are discharged for misconduct compared with 3.1% of other sales workers, a difference of 2.8%.[40] An employer who hired a worker with a criminal record rather than a worker without a record increased its expected theft-related costs by about 2.8% of $1546, or $43. The same employer saved about $746 in turnover costs on that worker.

Our results are subject to an important qualification: our estimates were made on *employees*, in other words, on those applicants who had been filtered through a hiring process that discriminated based on their criminal record. If discrimination against these applicants decreased, either by employer choice or through legislation, the employee group would change, and the new group of employees with records might not exhibit tenures as long as those we observe. All we can say is that, *at the current margin*, employers may be missing opportunities to hire quality employees by applying a hiring penalty of the current magnitude to a criminal record.

Our findings are not simple, and neither are their policy implications. Finding gainful employment for individuals with criminal records is an important public priority: without such employment, recidivism is almost inevitable, at great cost to both the individual and the community. At the same time, employers are concerned that employing individuals with records may carry risks, and our study does not entirely dispel those fears. On the whole, our results provide support for efforts to expand hiring of applicants with a criminal record *at the margin*, but one qualification is critical. The instances in which we find better performance of employees with a criminal record cannot be generalized to the entire pool.

Ban the Box laws have come to dominate the policy discussion of how to improve the employment prospects of people with criminal records. These laws apply uniform rules to all employees and employers. Yet a clear takeaway from our study is that not all workforces are the same. Employers should be encouraged to re-examine their assumptions about applicants with criminal records by studying their own workforce. A wide variety of measures could promote this self-examination. For example, the current Work Opportunity Tax Credit is only available to employers who hire ex-felons within 1 year after their conviction or release from prison even though employers appear to discriminate against applicants with criminal records long after release or conviction, and some employers apply a hiring penalty to those with a misdemeanor or even arrest record. Policy to reintegrate individuals with criminal records should consider the variety of job applicants, of jobs, and of employer motivation.

Endnotes

[1]That a hiring penalty is attached to a criminal record has been found in audit studies (Pager 2003; Uggen et al. 2014; Agan and Starr 2018); employer survey data (Holzer et al. 2006); by examining changes in employer behavior resulting from Ban the Box (Doleac and Hansen 2016); and by examining the employer response to the availability of information about criminal records (Bushway 2004; Finlay 2009).

[2]For example, Hawaii requires that a conviction record bear a rational relationship to the duties and responsibilities of the position and only allows the use of records less than 10 years old (Hawaii Revised Statutes (HRS) § 378-2.5 (Supp. 2007)). Minnesota

also allows a record to be used only if it "directly relates" to the position (Minn. Stat. § 364). New York and Wisconsin also prohibit employment discrimination against those with a criminal record unless an employer can show that a person with a propensity for the kind of crime the prospective employee had previously committed would be unable to successfully perform the relevant job (Wis. Stat. § 111.325–111.335 (2003); N.Y. Correct. Law §§750-55 (2003) (amended in 2007)). New York, however, permits inquiry about a criminal record at any stage of an application.

[3]Equal Employment Opportunity Commission. "Enforcement Guidance 915.002: Consideration of Arrest and Conviction Records in Employment Decisions Under Title VII of the Civil Rights Act of 1964," https://www.eeoc.gov/laws/guidance/arrest_conviction.cfm.

[4]The White House. "Take the Fair Chance Pledge." https://obamawhitehouse.archives.gov/issues/criminal-justice/fair-chance-pledge (accessed September 28, 2016).

[5]26 U.S. C. § 51.

[6]Federal Bonding Program, *Answers to Questions About Fidelity Bonding,* http://www.bonds4jobs.com/highlights.html (Accessed 22 Aug 2018).

[7]The most comprehensive protection is provided by Texas. *Tex. Civ. Prac. & Rem.*, §142.002 which provides that "[a] cause of action may not be brought against an employer, general contractor, premises owner, or other third party solely for negligently hiring or failing to adequately supervise an employee, based on evidence that the employee has been convicted of an offense."

[8]Some states, such as Florida, disallow the use at any time of expunged records and permit job candidates to lie if asked (Fla. Stat. ch. § 943.0585 4(a)). Most states have procedures that attempt to identify individuals with records who have been rehabilitated and either expunge their records or grant a Certificate of Good Conduct, which leaves their conviction standing but testifies to their rehabilitation since that time (Jacobs 2015, 143–49).

[9]Surveys suggest that employers consider criminal records to reduce legal liability for negligent hiring (52%); to ensure a safe work environment for employees (49%); to reduce theft and other criminal activity (38%); to comply with laws requiring checks (28%); and to assess the overall trustworthiness of a candidate (17%) (Society for Human Resource Management 2012).

[10]The continued importance of character proxy use may be indicated by a recent Supreme Court case, *NASA v. Nelson*, 131 S. Ct. 746, 760 (2011), that accepted a defendant's argument that questions about illegal drug use are a useful way of determining which employees will "'efficiently and effectively' discharge their duties" (upholding the constitutionality of government use of criminal background checks absent any specific statutory prohibition).

[11]These categories have been validated by replicability across samples rather than by prediction of real world outcomes (Hogan 2005, 332)

[12]In our sample, 27% of those with criminal records had more than high school compared with 40% of those without a record. Another study found that only about 10% of individuals with criminal records had more than a high school education (Yang 2017), so our sample appears to be more educated than the population with a criminal record as a whole, though it may be typical of those who apply for white-collar jobs.

[13]We found that applicants are missing pre_crim if and only if they are missing position_id. This suggests that the occurrences in which pre_crim is missing reflect a deliberate decision by an employer not to collect criminal records information for a set of jobs indicated by a position_id rather than a selective response on the part of

applicants. Furthermore, we examined applicants who were hired to check whether the establishment (firm_id) predicts the missing pre_crim and found that indeed there is a strong correlation. Establishments are sharply divided into two groups; those for which the pre_crim field is missing for almost all employees and those for which the pre_crim field is complete for almost all workers. This indicates that information on criminal background was fully recorded for some establishments and fully missing for the vast majority of the rest of the establishments in our sample.

[14]Although comprehensive data on employee crime is not available, the financial services sector appears, not surprisingly, to be especially vulnerable, and FDIC insured firms have a strong incentive to conduct background checks (12 U.S.C. 1829). In our sample, however, noninsurance financial services are actually more than average likely to be missing criminal records (Table 12 in Appendix 1).

[15]For about 264,000 applicants we know the value of a field called position_id. By examining applicants who were hired, we can see that position_id combines information about the type of job to which the applicant applied and the location variable. For example, almost all employees for whom position_id is coded 193 are customer service representatives in location 10. For many non-hired applicants, we were therefore able to reconstruct location code (loc_new) and position applied for. The variable job_app_equals 1 when we were able to impute a position (Table 1).

[16]In order to preserve the anonymity of its clients, the consultancy masked the codes so that we were able to identify groups of employees who were hired at the same location, but not to identify the location itself. We do have reason to think that none of the firms, whether or not they collected criminal records information, were in a state that had Ban the Box legislation at the time of data collection. We can make a few educated guesses about the geographic distribution of our firms. The hiring consultancy told us that its client sites were overwhelmingly located in the South and continental West, and we have some corroboration for this. In addition to the location code, the data contain state and city fields that are empty for observations that have criminal record information, but had values for some of the observations that do not. Within this group of observations, 50.4% are in the West, 36% are in the South, 9% are in the Midwest, and 4% are in the East. This group of observations might have differed from the ones we analyze here, since by definition observations that had criminal records information were in states that, at the time of application, did not ban the box, while those for which criminal records information was missing might or might not have been in such states. However, any such difference is likely to be small. During the period of data collection, only four states covering about 5% of the US population banned the box for private employers (Hawaii, Rhode Island, Massachusetts, and Minnesota). Moreover, not one identifiable observation was in any of these four states. The group with identifiable states was slightly skewed away from states that have since banned the box for private employers. Five other states (Connecticut, Illinois, New Jersey, Oregon, and Vermont) passed laws after data collection, and about 14% of the US population now lives in a state that bans the box for private employers. Only one state that could be identified in the data, Oregon, now has a private employer Ban the Box law. It accounts for 1.2% of the US population though about 7.3% of all observations for which the state could be identified.

[17]This field sometimes changes through a worker's tenure, presumably because the employer has shifted the worker to a different job. We retain the most recently recorded position_type and use it as a control for occupation held in our analysis of the employee pool.

[18]This variable is censored for those workers who had not yet separated when the data collection ended.

[19]A variable TERM_ANY was constructed to take value 0 for any observation for which the cause of termination was not recorded and 1 otherwise; thus, from Table 2, panel B, we see that 77% of our sample had separated from their job by the time data collection ended.

[20]"Openness to experience" reflects the individual's degree of intellectual curiosity, creativity, and a preference for novelty and variety. "Conscientiousness" is the tendency to be organized and dependable, show self-discipline, act dutifully, aim for achievement, and prefer planned rather than spontaneous behavior. "Extraversion" includes energy, positive emotions, surgency, assertiveness, sociability, and talkativeness. "Agreeableness" is the tendency to be compassionate and cooperative rather than suspicious and antagonistic toward others. "Neuroticism" is the tendency to experience unpleasant emotions easily, such as anger, anxiety, depression, and vulnerability.

[21]The number of observations of "Agent" and "Technical Support" was below the level needed to draw useful inferences; we therefore dropped these positions. Although the number of observations of "Other" with pre_crim was reasonably large, it shrank when other variables like school were added. Since "Other" also represents a heterogeneous group, results would be hard to interpret, and we dropped it as well.

[22]Of 110 unique locations, 42 had values for only one firm and 73 had three firms or less. Five locations were associated with 10 or more firms, with a high of 20 firms.

[23]In general, lower turnover is associated with higher firm value, although the relationship is not linear (Hancock et al. 2013).

[24]A literature review finds a wide range of results regarding the relationship between voluntary turnover and performance, with slightly more studies finding a weak negative association (Allen and Griffeth 1999).

[25]The difference in turnover rates is (365/183–365/167), or 19%; multiplying by $4000 per turnover implies a cost difference of $764.

[26]In 2015, the average wage for all customer services representatives was about $34,000. The workers in our sample typically did not have specialized skills, and their wages were likely closer to the sub-category "Business support services", for which the average wage was about $28,000. https://www.bls.gov/oes/2015/may/oes434051.htm (accessed February 1, 2017).

[27]The Vermont definition of misconduct includes profanity, 21 V.S.A. § 1344; a number of states include absenteeism without fault as misconduct (Ark. Code Ann. § 11-10-514). Minn. Stat. Ann. § 268.09(1)(2). *Campbell v. Minneapolis Star & Tribune Co.*, 345 N.W.2d 803 (Minn. Ct. App. 1984); *Clark v. Iowa Dep't of Job Serv.*, 317 N.W.2d 517 (Iowa Ct. App. 1982); and one case held sleeping on the job was misconduct. *L. Washington & Associates, Inc. v. Unemployment Compensation Bd. of Review*, 662 A.2d 1148 (Pa. Commw. Ct. 1995).

[28]Since most firms would not use these particular psychometric variables in hiring, column 6 of Table 7 is most relevant to a typical firm's risk assessment. The antilog of the regression coefficient on pre_crim yields a hazard ratio of about 1.34.

[29]Our data contain two kinds of psychometric questions, 15 FFA questions and three proprietary questions. Fifteen questions are considered valid for assessment at the factor level (Donnellan et al. 2006), but that number is not enough to distinguish among the 30 or more categories at the facet level, and is below the preferred level for comprehensive assessment.

[30]As noted earlier, LOE and voluntary turnover can result from a number of factors both good and bad. Thus, the signs on explanatory variables do not have clear interpretations.

[31]For example, when the psychometric variables are included in the misconduct estimate for sales, the coefficients on the significant psychometric variables are about as large or larger (confidence regress = .61; con2 = .22; agree3 = 15) than that on pre_crim (.28–.31) (Table 7, columns 7–8).

[32]In the misconduct estimates for sales employees, three FFA questions, con1, con2 and agree3, have significant positive coefficients, with agree3 extremely large and highly significant. In comparison, in the misconduct estimates for customer service, five FFA variables have predictive value and not one of these is significant in the sales regression (Table 11, columns 3–4). In our estimates of involuntary termination, four of the fifteen FFA variables are significant for sales and two for customer service, but no FFA variable is significant in both estimates. (Table 11, columns 1–2). In addition to the FFA, we examine three measures based on proprietary psychometric tests of the hiring consultancy. Again, the predictive power of these variables is not always the same for customer service and sales. One, confidence_regress, is a measure of overconfidence that is notable for combining self-reports and objective information. Applicants were asked how confident they felt in their technical skills without knowing that they would later take a computer test. Confidence_regress is based on the difference between the applicant's reported self-confidence and his or her actual performance on the later test. Confidence_regress performs well: it is highly significant in both the misconduct and the involuntary termination estimates for sales; it is significant for customer service in predicting both involuntary termination and misconduct, but with smaller coefficients and lower confidence levels (Table 11). A second proprietary variable, rulebreaker, is a forced choice variation of the first two FFA conscientiousness questions. Rulebreaker is significant in predicting involuntary termination and misconduct for customer service but not for sales (Table 11). A third measure is badservice, which is meant to predict poor customer service skills. Badservice had some predictive power for involuntary separation in sales but not in customer service, and none for misconduct (Table 11).

[33]The position term is significant, usually highly, in 17 of 18 regressions: a criminal record is significant in 6 of 18 estimates and the interaction term is significant in 5 of 18. The five psychometric measures for which the interaction term is significant do not correspond to the measures that are associated with poor performance outcomes (Tables 6 and 7, columns 7–8, and Table 16 in Appendix 1). The sales*criminal record interaction is negatively associated with confidence regress, but confidence_regress is positive and significantly associated with both involuntary termination and misconduct. The sales*criminal record interaction is positively associated with con3, but con3 is unrelated to misconduct and has a significant negative association with involuntary termination. The interaction term is significant and negatively associated with variables extra2 and extra3, but extra2 and extra3 are unrelated to either work outcome. The interaction term is significant and negatively associated with agree3, and while agree3 is significant and negatively associated with involuntary termination it is positively associated with misconduct. However, without random assignment of workers to jobs, no causal conclusions can be drawn from this.

[34]We restrict our analysis to the hired pool because personality variables are available only for this group. We report the results for the sample restricted to sales and customer service jobs. Results for the whole hired pool are consistent and are provided in Tables 13 and 14 of Appendix 1.

[35]Of the 15 FFA questions, 7 are predictive in both specifications (Table 19 in Appendix 1, columns 4 and 6) and our results generally correspond with the prior literature. See Appendix 2. One of the three proprietary questions, badservice, is positively correlated with a criminal record (Table 19 in Appendix 1, columns 3 and 5).

[36]Table 17 in Appendix 1 compares psychometric variables as predictors of a criminal record and of poor employment outcomes for sales workers. Since a criminal record, involuntary termination, and misconduct are all undesirable outcomes, we might expect to see psychometric variables tending to have the same signs in all three. However, Table 17 in Appendix 1 indicates that only one question with a significant association with misconduct in sales positions, agree3, has a significant association of the same sign in the criminal record estimate. Three other questions significantly associated with misconduct (confidence_regress, con1, and con2) are not significantly associated with a criminal record. Similarly, Table 17 in Appendix 1 shows only a minimal relationship between the predictors of involuntary termination in sales positions and a criminal record. Two questions, con3 and badservice, are significant and of the same sign in predicting involuntary termination and a criminal record. Six questions are associated with a criminal record but not involuntary termination, while one question is associated with involuntary terminations but not a criminal record. Two questions, open2 and agree3, have associations of opposite signs with involuntary terminations and a criminal record.

[37]High neuroticism and low conscientiousness and agreeableness usually lead to worse work outcomes (Judge et al. 2013; Barrick et al. 2001) and more criminal behavior (Jones et al. 2011; O'Riordan and O'Connell 2014). Only extraversion usually increases criminal behavior while improving work outcomes.

[38]No aggregate statistics are collected on this issue, and supposed evidence that a criminal record has a major effect on negligent hiring costs is basically folklore (Hickox and Roehling 2013). One often-cited article claims employers have lost 72% of negligent hiring cases with an average settlement of more than $1.6 million. It provides no evidence as to the use of a criminal background in such verdicts, no data on the frequency of such cases, and for the evidence it does provide it cites a broken web link to what appears to have been either a background check provider or a trade magazine (Connerley et al. 2001). Large judgments have indeed been rendered for the acts of employees with criminal backgrounds, Ward v. Trusted Health, No. 94-4297 (Suffolk Super. Ct. Mass) (1999)($26.5 million damages); *Tallahassee Furniture Co. v. Harrison*, 583 So. 2d 744 (Fla. Dist. Ct. App. 1991); but also for the acts of employees without a criminal record, *Diaz v. Carcamo*, 253 P.3d 535 (Ca. 2011) ($23 million award); *Glomb v. Glomb*, 530 A.2d 1362, 1364 (Pa. Super. Ct. 1987) ($1.5 million).

[39]Roberts et al. (2007) examined a birth cohort of about 900 New Zealand residents who had been tracked from birth to age 26. Adolescent criminal convictions were unrelated to committing counterproductive activities at work in general, and were actually negatively related to more serious counterproductive work behaviors such as fighting or stealing.

[40]Note that these rates are unadjusted raw numbers. The hazard ratios from our Cox estimate cannot be used here because Cox estimation does not produce a baseline hazard rate. However, the hazard ratio implied by these raw numbers is higher than the Cox hazard ratio, and the estimate in text is likely to be of the right order of magnitude but on the higher side.

Appendix 1

Table 12 Industry correlates of missing criminal record

	(1)
	missing_pre_crim
industry==Electronics	0.3090***
	(29.21)
industry==Financial	0.1815***
	(24.60)
industry==Healthcare	−0.0683***
	(−10.30)
industry==Insurance	−0.2626***
	(−35.72)
industry==Miscellaneous	−0.0866***
	(−17.08)
industry==Retail	−0.1902***
	(−23.61)
industry==Telecommunications	0.3852***
	(77.00)
position_type==Agent	0.3952***
	(36.58)
position_type==Customer_service	−0.0519***
	(−6.08)
position_type==Sales	−0.5887***
	(−66.50)
position_type==Technical_support	−0.0651***
	(−4.90)
Constant	0.6341***
	(69.08)
Observations	57,397
R-squared	0.590
Adjusted R-squared	0.590

t-statistics in parentheses. Robust standard errors
**p* < 0.10, ***p* < 0.05, ****p* < .01

Table 13 Factor-level correlates of criminal background in hired population (all positions)

	(1)	(2)	(3)	(4)
	pre_crim	pre_crim	pre_crim	pre_crim
school	− 0.0006			−0.0068
	(−0.09)			(−0.94)
fewer_short_jobs		−0.0207***		−0.0195***
		(−5.45)		(−5.14)
longest_job		0.0184***		0.0208***
		(8.84)		(9.60)
neurtot			0.0116***	0.0124***
			(3.14)	(3.36)
opentot			−0.0198***	−0.0178***
			(−4.82)	(−4.34)
extratot			0.0210***	0.0223***
			(5.05)	(5.39)
contot			−0.0281***	−0.0307***
			(−7.26)	(−7.93)
agreetot			0.0015	0.0013
			(0.37)	(0.32)
Constant	0.1141***	−0.0030	0.1207***	− 0.0042
	(32.71)	(−0.27)	(9.93)	(−0.26)
Observations	11,008	11,008	11,008	11,008
R-squared	0.000	0.008	0.010	0.019
Adjusted R-squared	−0.000	0.008	0.009	0.019

Sample contains only hired workers for whom information about criminal background is available. Standardized beta coefficients. *t*-statistics in parentheses. Robust standard errors
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Table 14 Question-level correlates of criminal background in hired population (all positions)

	(1)	(2)	(3)	(4)	(5)	(6)
	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim
school	−0.0006				−0.0109	−0.0018
	(−0.09)				(−1.49)	(−0.25)
fewer_short_jobs		−0.0207***			−0.0201***	−0.0189***
		(−5.45)			(−5.25)	(−4.99)
longest_job		0.0184***			0.0194***	0.0230***
		(8.84)			(8.94)	(10.50)
badservice			0.0178**		0.0183**	
			(2.15)		(2.21)	
confidence_regress			−0.0109		−0.0040	
			(− 0.88)		(− 0.32)	
rulebreaker1			−0.0098		− 0.0068	
			(−1.03)		(−0.72)	
open1				−0.0221***		−0.0228***
				(−3.50)		(−3.62)
open2				0.0744***		0.0830***

Table 14 Question-level correlates of criminal background in hired population (all positions) *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)
	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim
				(6.10)		(6.79)
open3				−0.0231***		− 0.0195***
				(−3.78)		(−3.19)
con1				0.0098		0.0064
				(1.43)		(0.93)
con2				−0.0099		−0.0079
				(−1.54)		(−1.24)
con3				−0.0840***		−0.0907***
				(− 13.36)		(− 14.24)
extra1				0.0152**		0.0136*
				(2.14)		(1.94)
extra2				0.0100		0.0130*
				(1.33)		(1.74)
extra3				0.0196***		0.0220***
				(3.04)		(3.43)
agree1				−0.0095		−0.0106
				(−1.43)		(−1.61)
agree2				0.0016		0.0044
				(0.24)		(0.66)
agree3				0.0878***		0.0888***
				(9.31)		(9.38)
neur1				−0.0036		−0.0039
				(− 0.60)		(− 0.64)
neur2				0.0132**		0.0148**
				(2.05)		(2.31)
neur3				0.0071		0.0072
				(1.00)		(1.02)
Constant	0.1141***	−0.0030	0.1120***	0.0396***	−0.0059	− 0.0970***
	(32.71)	(−0.27)	(32.22)	(2.93)	(−0.53)	(−5.52)
Observations	11,008	11,008	11,008	11,008	11,008	11,008
R-squared	0.000	0.008	0.001	0.021	0.009	0.032
Adjusted *R*-squared	−0.000	0.008	0.000	0.020	0.009	0.030

Sample contains only hired workers for whom information about criminal background is available. Standardized beta coefficients. *t*-statistics in parentheses. Robust standard errors
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

Table 15 Correlates of hiring rates, logit specification (customer service and sales)

	(1)	(2)	(3)	(4)	(5)	(6)
	Hired	Hired	Hired	Hired	Hired	Hired
pre_crim	0.2477*	0.2682**	−0.3064***	− 0.1723*	−0.3013***	− 0.3240
	(1.95)	(2.09)	(−3.30)	(− 1.74)	(−3.27)	(−1.35)
school		−0.0937			0.0537	0.0537
		(−1.27)			(1.17)	(1.17)
fewer_short_jobs		0.1474***			0.1606***	0.1606***
		(4.96)			(9.56)	(9.54)
longest_job		−0.0507*			0.0347*	0.0346*
		(−1.76)			(1.75)	(1.75)
pos_applied==Sales				1.5735***	−4.4892***	−4.4949***
				(5.61)	(−3.58)	(−3.56)
crim*sales						0.0334
						(0.13)
Constant	−1.4540***	−0.9385***	−1.6917***	−1.9813***	− 1.5885***	−1.5882***
	(−5.79)	(−3.06)	(−4.41e+12)	(−15.65)	(−16.06)	(− 16.04)
location dummies	No	No	Yes	No	Yes	Yes
Observations	73,885	73,884	67,700	73,885	67,699	67,699
Pseudo *R*-squared	0.001	0.004	0.082	0.087	0.087	0.087

Sample contains only applicants for whom information about criminal background is available. *t*-statistics in parentheses. Robust standard errors
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Table 16 Criminal record and position as correlates of psychometric variables (customer service and sales)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	badservice	confidence_regress	rulebreaker1	open1	open2	open3	con1	con2	con3	extra1	extra2	extra3	agree1	agree2	agree3	neur1	neur2	neur3
pre_crim	− 0.0016	0.0032	−0.0081	− 0.0617**	− 0.0026	− 0.0586**	0.0043	− 0.0378	− 0.1115***	0.0124	0.0628***	0.0852***	− 0.0252	− 0.0020	0.0646***	0.0259	0.0361	0.0028
	(−0.09)	(0.26)	(−0.51)	(−2.25)	(−0.16)	(−2.21)	(0.18)	(−1.45)	(−4.36)	(0.55)	(2.69)	(3.09)	(−1.03)	(−0.08)	(3.23)	(0.95)	(1.42)	(0.13)
position_ type==Sales	0.1050***	0.0747***	0.0117*	−0.0957***	0.0486***	0.0380***	−0.0333***	0.0237**	−0.3934***	−0.0734***	0.1449***	0.0785***	−0.0125	0.0308***	0.0697***	0.0086	0.0790***	0.2418***
	(13.19)	(14.82)	(1.85)	(−9.42)	(7.23)	(3.73)	(−3.54)	(2.38)	(−53.47)	(−8.15)	(16.51)	(7.66)	(−1.35)	(3.36)	(8.86)	(0.84)	(8.43)	(26.43)
crim*sales	0.0017	−0.0292*	−0.0028	0.0242	−0.0163	0.0086	0.0047	0.0212	0.0954***	0.0112	−0.0730**	−0.0549*	0.0126	−0.0018	− 0.0461*	−0.0466	− 0.0091	−0.0078
	(0.07)	(−1.89)	(−0.14)	(0.73)	(−0.80)	(0.27)	(0.16)	(0.67)	(3.70)	(0.40)	(−2.53)	(−1.66)	(0.43)	(−0.06)	(−1.96)	(−1.42)	(−0.30)	(− 0.28)
Constant	0.1327***	−0.0032	0.0993***	0.6144***	0.0967***	0.4148***	0.7193***	0.3683***	0.4164***	0.7767***	0.1737***	0.4362***	0.2902***	0.7114***	0.7844***	0.5638***	0.6619***	0.1796***
	(27.50)	(−1.00)	(23.34)	(88.74)	(23.00)	(59.19)	(112.55)	(53.68)	(59.39)	(131.14)	(32.24)	(61.84)	(44.95)	(110.39)	(134.12)	(79.93)	(98.37)	(32.89)
Observations	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698	10,698
R-squared	0.018	0.021	0.000	0.011	0.005	0.002	0.001	0.001	0.228	0.007	0.027	0.007	0.000	0.001	0.009	0.000	0.008	0.069
Adjusted R-squared	0.018	0.021	0.000	0.010	0.005	0.002	0.001	0.001	0.228	0.006	0.026	0.007	0.000	0.001	0.009	−0.000	0.008	0.069

Sample contains only hired workers for whom information about criminal background is available. *t*-statistics in parentheses. Robust standard errors
*$p < 0.10$, **$p < 0.05$, ***$p < .01$

Table 17 Correlates of poor job outcomes, correlates of criminal record, and characteristics of sales workers with criminal records

	(1) Criminal record (outcome)	(2) Involuntary separation, sales (outcome)	(3) Misconduct, sales (outcome)
badservice	0.0181**	0.1043***	0.1368
confidence_regress	−0.0007	0.4113***	0.6111***
rulebreaker1	−0.0056	0.0405	−0.2786
open1	−0.0224***	−0.0434	0.0364
open2	0.0877***	−1.1571***	14.7302
open3	−0.0205***	0.0123	−0.0327
con1	0.0036	0.0195	0.1392*
con2	−0.0087	0.0078	0.2190*
con3	−0.0935***	−0.4028***	− 0.6501
extra1	0.0123*	0.0991	−0.0701
extra2	0.0140*	0.0445	−0.0299
extra3	0.0209***	−0.0148	−0.0299
agree1	−0.0099	0.0577**	−0.0063
agree2	0.0030	0.0561	−0.0162
agree3	0.0940***	−0.9510***	14.9843***
neur1	−0.0031	0.0203	0.0650
neur2	0.0156**	0.0134	−0.0472
neur3	0.0062	−0.0388	−0.0660
Controls	school, job stability	school, job stability, crim. Rec., firm, location	
Source	Table 19 in Appendix 1, cols 5–6	Table 6, cols 7–8	Table 7, cols 7–8

*$p < 0.10$, **$p < 0.05$, ***$p < .01$

Table 18 Factor-level correlates of criminal background in hired population (customer service and sales)

	(1)	(2)	(3)	(4)
	pre_crim	pre_crim	pre_crim	pre_crim
school	−0.0017			−0.0080
	(−0.24)			(−1.08)
fewer_short_jobs		−0.0205***		−0.0192***
		(−5.32)		(−5.00)
longest_job		0.0183***		0.0208***
		(8.64)		(9.42)
neurtot			0.0121***	0.0129***
			(3.23)	(3.45)
opentot			−0.0205***	− 0.0184***
			(−4.92)	(− 4.42)
extratot			0.0207***	0.0220***
			(4.88)	(5.19)
contot			−0.0297***	− 0.0324***
			(−7.56)	(−8.20)
agreetot			0.0015	0.0014
			(0.37)	(0.33)
Constant	0.1154***	−0.0013	0.1239***	− 0.0006
	(32.51)	(−0.12)	(9.94)	(−0.04)
Observations	10,698	10,698	10,698	10,698
R-squared	0.000	0.008	0.010	0.020
Adjusted *R*-squared	−0.000	0.008	0.010	0.019

t-statistics in parentheses. Robust standard errors
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Table 19 Question-level correlates of criminal background in hired population (customer service and sales)

	(1)	(2)	(3)	(4)	(5)	(6)
	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim
school	− 0.0017				− 0.0121	− 0.0029
	(− 0.24)				(−1.62)	(− 0.39)
fewer_short_jobs		−0.0205***			−0.0198***	−0.0187***
		(−5.32)			(−5.10)	(−4.86)
longest_job		0.0183***			0.0195***	0.0231***
		(8.64)			(8.80)	(10.31)
badservice			0.0178**		0.0181**	
			(2.11)		(2.14)	
confidence_regress			−0.0076		−0.0007	
			(−0.60)		(−0.06)	
rulebreaker1			− 0.0083		−0.0056	
			(−0.84)		(−0.57)	
open1				−0.0217***		−0.0224***
				(−3.38)		(−3.50)
open2				0.0798***		0.0877***
				(6.54)		(7.17)
open3				−0.0243***		−0.0205***
				(−3.91)		(−3.29)
con1				0.0070		0.0036
				(0.99)		(0.51)
con2				−0.0107		−0.0087
				(−1.64)		(−1.34)
con3				−0.0867***		−0.0935***
				(−13.56)		(−14.40)
extra1				0.0138*		0.0123*
				(1.91)		(1.71)
extra2				0.0112		0.0140*
				(1.46)		(1.84)
extra3				0.0187***		0.0209***
				(2.85)		(3.21)
agree1				−0.0088		−0.0099
				(−1.30)		(−1.48)
agree2				0.0001		0.0030
				(0.01)		(0.43)
agree3				0.0937***		0.0940***
				(10.06)		(10.06)
neur1				−0.0029		−0.0031
				(−0.46)		(− 0.50)
neur2				0.0139**		0.0156**
				(2.13)		(2.40)
neur3				0.0060		0.0062
				(0.83)		(0.86)

Table 19 Question-level correlates of criminal background in hired population (customer service and sales) *(Continued)*

	(1)	(2)	(3)	(4)	(5)	(6)
	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim	pre_crim
Constant	0.1154***	−0.0013	0.1128***	0.0389***	−0.0047	− 0.0970***
	(32.51)	(−0.12)	(31.90)	(2.84)	(−0.42)	(−5.41)
Observations	10,698	10,698	10,698	10,698	10,698	10,698
R-squared	0.000	0.008	0.000	0.022	0.009	0.032
Adjusted R-squared	−0.000	0.008	0.000	0.020	0.009	0.031

Sample contains only hired workers for whom information about criminal background is available. Standardized beta coefficients. *t*-statistics in parentheses. Robust standard errors
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < .01$

Appendix 2

Correspondence of FFA results to prior literature

The discussion in the main text uses the individual 15 questions as controls because these more closely approximate the trait level analysis that is currently preferred to the broader factor level approach. However, much of the earlier literature relies on factor analysis, and so we present factor variables here for purposes of comparing our results to prior research (Table 18 in Appendix 1, columns 3–7). In Table 18 in Appendix 1, the standardized coefficients in column 3 indicate that an increase of 1 standard deviation in neuroticism or extroversion increases the probability of having a criminal background by about 1.2% and 2.1% over its 12.4% baseline in the hired pool. An increase of 1 standard deviation in openness to experience and conscientiousness decrease the probability of having a criminal background by about 2% and 3%, respectively. Agreeableness has a small and insignificant coefficient.

As discussed in Section 2, the prior literature on the personality correlates of a criminal record is sparse, and much of the relevant work examines some different but related outcome such as aggression. However, two strong findings have emerged: a highly consistent positive correlation of related outcomes to neuroticism and a highly consistent negative correlation to conscientiousness. Our results are consistent with these, and also with the moderately consistent positive association found with extraversion (Jones et al. 2011; O'Riordan and O'Connell 2014). Openness has a negative association in our data, which may seem at first inconsistent with the usual finding in meta-analysis that it is insignificant (Jones et al. 2011; O'Riordan and O'Connell 2014). However, this can readily be explained by the fact that we do not have enough questions to examine all underlying facets.

Prior work finds differences among the approximately six lower order traits within each high-level five-factor (Jones et al. 2011, Table 3). In that literature, outcomes related to criminality are negatively associated with one facet of openness (feelings), sometimes positively associated with two others (actions and ideas), and not significantly associated with three (fantasy, esthetics, and, oddly, values). Consistent with this complex pattern, Table 19 in Appendix 1 shows that two of our openness questions are negatively associated and one positively associated with a criminal record. With only 15 questions, we observe a net negative effect. However, with a greater variety of questions comprehensively covering all facets of openness, various opposing effects might have canceled each other out. Variation in findings may also be partly explained by differences in the outcome studied. Low openness may be correlated to recidivism (Clower and Bothwell 2001) while high openness may be correlated to aggression (Barlett and Anderson 2012).

Agreeableness is negative, as expected from prior work finding that all facets of agreeableness are negatively correlated with outcomes related to criminality (Jones et al. 2011; O'Riordan and O'Connell 2014). It is, however, surprisingly small and insignificant. The explanation may lie in the fact that no individual question can be unambiguously assigned to any given facet or factor. Rather, test-makers assign questions to the factors or facets for which they have the highest loading, which may vary among tests. Of our agreeableness questions, one has the expected negative sign, one is insignificant. Only our question agree3 has a positive sign, and other tests group it with the facet assertiveness, which is part of extraversion, so that its positive sign is consistent with the usual sign of extraversion.

Acknowledgements
Weiss and Minor gratefully acknowledge the generous financial support of the Joyce Foundation. This paper has benefitted from the input of participants at the Society of Labor Economists Annual Meeting 2017, the 2017 APPAM Fall Research Conference, and the faculty colloquium of the Northwestern Pritzker School of Law. We would like to thank the anonymous referee and the editor for the useful remarks.
Responsible editor: Denis Fougère

Funding
Weiss and Minor gratefully acknowledge the generous financial support of the Joyce Foundation.

Availability of data and materials
The analysis in this paper was conducted on existing data not collected for research purposes and was fully de-identified—it therefore did not constitute human subjects research and did not require the approval of an institutional review board. A consultancy had collected the data for its own business purposes. Prior to delivering the data, the consultancy replaced the names of clients, applicants and employees with numeric codes. In addition, other information was omitted in order to foreclose any possibility of identifying firms or individuals. For example, the data did not contain any demographic data such as age, sex, or race.

Competing interests
The IZA Journal of Labor Policy is committed to the IZA Guiding Principles of Research Integrity. The authors declare that they have observed these principles.

Publisher's Note

Received: 7 January 2018 Accepted: 25 July 2018
Published online: 12 September 2018

References

Agan AY, Starr SB (2018) Ban the box, criminal records, and statistical discrimination: a field experiment. Q J Econ 133(1):191–235. https://doi.org/10.1093/qje/qjx028

Allen DG, Griffeth RW (1999) Job performance and turnover: a review and integrative multi-route model. Hum Resour Manag Rev 9(4):525–548. https://doi.org/10.1016/S1053-4822(99)00032-7

American Psychiatric Association, and others (2013) Diagnostic and statistical manual of mental disorders (DSM-5®). American Psychiatric Publishing, Arlington

Andrews DA, Bonta J (2014) The psychology of criminal conduct. Routledge, New York

Barlett CP, Anderson CA (2012) Direct and indirect relations between the big 5 personality traits and aggressive and violent behavior. Personal Individ Differ 52(8):870–875. https://doi.org/10.1016/j.paid.2012.01.029

Barrick MR, Mount MK, Judge TA (2001) Personality and performance at the beginning of the new millennium: what do we know and where do we go next? Int J Sel Assess 9(1 & 2):9–30

Block J (2010) The five-factor framing of personality and beyond: some ruminations. Psychol Inq 21(1):2–25. https://doi.org/10.1080/10478401003596626

Burks SV, Cowgill B, Hoffman M, Housman M (2015) The value of hiring through employee referrals. Q J Econ 130(2): 805–839. https://doi.org/10.1093/qje/qjv010

Bushway S (2004) Labor market effects of permitting employer access to criminal history records. J Contemp Crim Justice Spec Issue Econ Crime 20:276–291

Carson EA, Golinelli D (2013) Prisoners in 2012. Bur Justice Stat 2(3) https://www.bjs.gov/content/pub/pdf/p12ac.pdf. Accessed 22 Aug 2018

Clower CE, Bothwell RK (2001) An exploratory study of the relationship between the big five and inmate recidivism. J Res Pers 35(2):231–237

Connerley ML, Arvey RD, Bernardy CJ (2001) Criminal background checks for prospective and current employees: current practices among municipal agencies. Public Pers Manag 30(2):173–183

Costa PT, McCrae RR (1992a) Normal personality assessment in clinical practice: the NEO Personality Inventory. Psychol Assess 4(1):5

Costa PT, McCrae RR (1992b) Revised NEO Personality Inventory (NEO PI-R) and NEO Five-Factor Inventory (NEO FFI): professional manual. Psychological Assessment Resources

Doleac, Jennifer L., and Benjamin Hansen. 2016. Does 'ban the box' help or hurt low-skilled workers? Statistical discrimination and employment outcomes when criminal histories are hidden. National Bureau of economic research working paper 22469. http://www.nber.org/papers/w22469

Donnellan MB, Oswald FL, Baird BM, Lucas RE (2006) The mini-IPIP scales: tiny-yet-effective measures of the big five factors of personality. Psychol Assess 18(2):192

Durose MR, Cooper AD, Snyder HN (2014) Recidivism of prisoners released in 30 states in 2005: patterns from 2005 to 2010. Bureau of Justice Statistics, Washington, DC, p 28 http://www.bjs.gov/content/pub/pdf/rprts05p0510.pdf

Finlay K (2009) Effect of employer access to criminal history data on the labor market outcomes of ex-offenders and non-offenders. In: Autor DH (ed) Studies of labor market intermediation. University of Chicago Press, Chicago, pp 89–126

Goldberg LR (1990) An alternative 'description of personality': the big-five factor structure. J Pers Soc Psychol 59(6): 1216–1229. https://doi.org/10.1037/0022-3514.59.6.1216

Hancock JI, Allen DG, Bosco FA, McDaniel KR, Pierce CA (2013) Meta-analytic review of employee turnover as a predictor of firm performance. J Manag 39(3):573–603. https://doi.org/10.1177/0149206311424943

Hickox SA, Roehling MV (2013) Negative credentials: fair and effective consideration of criminal records. Am Bus Law J 50(2):201–227

Hogan R (2005) In defense of personality measurement: new wine for old whiners. Hum Perform 18(4):331–341

Holzer, H. J., S. Raphael, and M. A. Stoll. 2004. "The effect of an applicant's criminal history on employer hiring decisions and screening practices: evidence from Los Angeles" University of Michigan, National Poverty Center Working Paper 04–15

Holzer HJ, Raphael S, Stoll MA (2006) Perceived criminality, criminal background checks, and the racial hiring practices of employers. J Law Econ 49:451–480

Jacobs JB (2015) The eternal criminal record. Harvard University Press, Cambridge

Jones SE, Miller JD, Lynam DR (2011) Personality, antisocial behavior, and aggression: a meta-analytic review. J Crim Just 39(4):329–337. https://doi.org/10.1016/j.jcrimjus.2011.03.004

Judge TA, Rodell JB, Klinger RL, Simon LS, Crawford ER (2013) Hierarchical representations of the five-factor model of personality in predicting job performance: integrating three organizing frameworks with two theoretical perspectives. J Appl Psychol 98(6):875

Lee K, Ashton MC (2004) Psychometric properties of the HEXACO Personality Inventory. Multivar Behav Res 39(2):329–358

Lundquist JH, Pager D, Strader E (2018) Does a criminal past predict worker performance? Evidence from one of America's largest employers. Soc Forces 96(3):1039–1068. https://doi.org/10.1093/sf/sox092

National Retail Federation. 2015. "The 2015 National Retail Security Survey"

O'Riordan C, O'Connell M (2014) Predicting adult involvement in crime: personality measures are significant, socio-economic measures are not. Personal Individ Differ 68(October):98–101. https://doi.org/10.1016/j.paid. 2014.04.010

Pager D (2003) The mark of a criminal record. Am J Sociol 108(5):937–975. https://doi.org/10.1086/374403

Pager D, Quillian L (2005) Walking the talk? What employers say versus what they do. Am Sociol Rev 70(3):355–380

Paunonen SV, Ashton MC (2001) Big five factors and facets and the prediction of behavior. J Pers Soc Psychol 81(3):524–539

Petersilia J (2003) When prisoners come home: parole and prisoner reentry. Oxford University Press, New York

Platt BD (1993) Negligent retention and hiring in Florida: safety of customers versus security of employers. Fla St U L Rev 20:697

Roberts BW, Harms PD, Caspi A, Moffitt TE (2007) Predicting the counterproductive employee in a child-to-adult prospective study. J Appl Psychol 92:5

Society for Human Resource Management (2012) Background checking—the use of criminal background checks in hiring decisions. https://www.shrm.org/hr-today/trends-and-forecasting/research-and-surveys/Pages/criminalbackgroundcheck.aspx. Accessed 22 Aug 2018

Uggen C, Shannon SKS (2014) Productive addicts and harm reduction: how work reduces crime-but not drug use. Soc Probl 61(1):105–130

Uggen C, Vuolo M, Lageson S, Ruhland E, Whitham HK (2014) The edge of stigma: an experimental audit of the effects of low-level criminal records on employment. Criminology 52(4):627–654

Visher CA, Lattimore PK, Barrick K, Tueller S (2017) Evaluating the long-term effects of prisoner reentry services on recidivism: what types of services matter? Justice Q 34(1):136–165

Visher CA, Debus-Sherrill A, Yahner J (2011) Employment after prison: a longitudinal study of former prisoners. Justice Q 28(5):698–718

Walker JR, Miller JE (2009) Supervision in the hospitality industry: leading human resources. Wiley, Hoboken

Western B, Kling JR, Weiman DF (2001) The labor market consequences of incarceration. Crime Delinq 47(3):410–427. https://doi.org/10.1177/0011128701047003007

Yang CS (2017) Local labor markets and criminal recidivism. J Public Econ 147:16–29. https://doi.org/10.1016/j.jpubeco.2016.12.003