

# Increasing the Demand for Workers with a Criminal Record\*

Zoë Cullen<sup>†</sup>

Will Dobbie<sup>‡</sup>

Mitchell Hoffman<sup>§</sup>

September 2021

## Abstract

State and local policies increasingly restrict employers' access to criminal records, but without addressing the underlying reasons that employers may conduct criminal background checks. Employers may thus still want to ask about a job applicant's criminal record later in the hiring process or make inaccurate judgments based on an applicant's demographic characteristics. In this paper, we use a field experiment conducted in partnership with a nationwide staffing platform to test policies that more directly address the reasons that employers may conduct criminal background checks. The experiment asked hiring managers at nearly a thousand U.S. businesses to make actual hiring decisions under different randomized conditions. We find that 39% of businesses in our sample are willing to work with individuals with a criminal record at baseline, which rises to over 50% when businesses are offered crime and safety insurance, a single performance review, a background check covering just the past year, or objective information on the productivity of these individuals. Wage subsidies can achieve similar increases but at a substantially higher cost. Based on our findings, the staffing platform relaxed the criminal background check requirement and offered crime and safety insurance to interested businesses.

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\*We thank Amanda Agan, Paul Goldsmith-Pinkham, Sara Heller, Larry Katz, Judd Kessler, Eddie Lazear, Melvin Stephens, Crystal Yang, and numerous seminar participants for helpful comments and suggestions. Dylan Balla-Elliott, Dan Ma, and Alexia Olaizola provided excellent research assistance. We thank the Abdul Latif Jameel Poverty Action Lab (J-PAL), the Michael Lee-Chin Family Institute for Corporate Citizenship, and the Social Sciences and Humanities Research Council (SSHRC) for financial support. The views expressed here are those of the authors alone and do not necessarily reflect those of the institutions or funders involved with this work. The RCT and a pre-analysis plan were pre-registered with the AEA RCT registry under ID [AEARCTR-0005200](#). We are deeply grateful to Wonolo Inc. for their support of this work. *JEL Codes:* C93, J23, J24.

<sup>†</sup>Harvard Business School and NBER. Email: [zcullen@hbs.edu](mailto:zcullen@hbs.edu)

<sup>‡</sup>Harvard Kennedy School, J-PAL, and NBER. Email: [will\\_dobbie@hks.harvard.edu](mailto:will_dobbie@hks.harvard.edu)

<sup>§</sup>U. Toronto Rotman School of Management, NBER, and CEPR. Email: [mitchell.hoffman@rotman.utoronto.ca](mailto:mitchell.hoffman@rotman.utoronto.ca)

# 1. Introduction

Employers are significantly less likely to interview or hire workers with a criminal record (WCs) compared to otherwise similar workers without a record (e.g., Pager, 2003; Holzer et al., 2006; Holzer, 2007; Agan and Starr, 2017). In 2008, for example, the average unemployment rate among formerly incarcerated people—27%—was higher than the U.S. unemployment rate for the general population at any point in history, including the Great Depression (Couloute and Kopf, 2018). The limited employment opportunities for WCs exacerbate existing socioeconomic and racial inequalities and likely contribute to the high rates of recidivism among recently released individuals (e.g., Yang, 2017; Schnepel, 2018).

In an attempt to mitigate the scarring effects of a criminal record, 35 states and over 150 cities and counties have adopted “Ban the Box” (BTB) policies that delay questions about a job applicant’s arrest and conviction record. These policies are meant to increase hiring and employment among WCs by making it more difficult to screen applicants based on their criminal history, helping WCs get “a foot in the door” when seeking employment. However, BTB policies do not address the underlying reasons that employers may conduct criminal background checks, such as the potential for lower productivity or higher downside risk. Employers may therefore still want to ask about an applicant’s criminal record later in the hiring process or make inaccurate judgments about an applicant’s criminal record based on their race or other demographic characteristics (e.g., Bushway, 2004; Holzer et al., 2006; Stoll, 2009; Agan and Starr, 2018; Doleac and Hansen, 2020).<sup>1</sup>

In this paper, we use a field experiment involving actual hiring decisions at nearly a thousand U.S. businesses to test several alternative approaches to increasing the demand for WCs. The alternatives we consider are meant to address potential underlying reasons that businesses may conduct criminal background checks. We offer crime and safety insurance to address downside risk concerns, and screening on past performance reviews and on the time since the most recent criminal record to address downside risk and productivity concerns. We also provide objective information on the average productivity of WCs compared to non-WCs to address downside risk and productivity concerns through a different channel, including the possibility that manager beliefs about WC productivity may be inaccurate. We benchmark the effects of each of these alternatives against the effects of a wage subsidy, a natural but potentially costly approach to increasing the demand for WCs.

The partner for our study is a large nationwide staffing platform based in the United States (hereafter, “the Platform”), which third-party businesses use to connect with available workers.

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<sup>1</sup>Perhaps as a result, existing work shows mixed effects of BTB policies on the employment of WCs and other populations of interest. Jackson and Zhao (2017) find, for example, that a 2010 law in Massachusetts that included a BTB provision had a small negative impact on the employment and earnings of ex-offenders, while Rose (2021) finds negligible impacts of a 2013 Seattle law prohibiting employers from asking about an applicant’s arrest and conviction record until after an initial screening. By contrast, Craigie (2020) finds that BTB policies increase the probability of public-sector employment for WCs. In aggregate data that include both those with and without a criminal record, Doleac and Hansen (2020) find that state and local BTB laws decrease employment rates for young, low-skill Black and Hispanic men, while Shoag and Veuger (2016) find that these state and local BTB laws increase employment rates in high-crime counties.

Businesses submit job requests to the Platform that include a job description (typically short term), the pay for the job, and qualifying criteria. The Platform sends out the job offer to workers who meet the qualifying criteria and workers can then accept the job on a first-come, first-serve basis. Businesses rarely cancel jobs after they have been accepted due to clear procedures and fee structure. Cancellations occur in less than 1% of cases. Presenting workers with the option to accept a job is therefore equivalent to that business extending a job offer to those workers.

The Platform’s design allows us to ask hiring managers to make incentive-compatible choices over *actual hiring decisions*, as opposed to callback or interview decisions that have generally been considered in past work.<sup>2</sup> Hiring managers that use the Platform were already familiar with submitting criteria for workers who can accept their jobs. We truthfully informed these managers that, in the same way, their responses during the experiment constituted high-stakes decisions that could determine whether WCs would be allowed to accept their jobs in the future. For example, if a hiring manager indicated that they would be willing to work with WCs under a certain insurance policy during the experiment, then WCs would be eligible to accept jobs posted by that manager after such an insurance policy is made available. The high-stakes nature of these choices was not just theoretical—the choices that hiring managers made during the experiment actually affected whether WCs could accept their posted jobs, as we describe below.

In the experiment, the Platform asked hiring managers at nearly 1,000 businesses whether they would allow WCs to accept their jobs given the availability and level of wage subsidies, crime and safety insurance, past performance history, and a more targeted screening of criminal records. Starting with the baseline level of demand for WCs in our sample, we find that a sizable share of businesses, 39%, are willing to work with WCs without additional incentives or conditions. The level of demand, still without additional incentives or conditions, increases to 45% for jobs that do not involve customer interactions and 51% for jobs that do not involve high-value inventory, consistent with businesses perceiving risks related to customer safety or inventory theft. We also find that the share of businesses willing to work with WCs increases to 68% if businesses are having a hard time filling a job, consistent with businesses being more likely to consider non-traditional workers in tight labor markets.

Turning to our main results, we find that the share of businesses willing to work with WCs further increases by at least 10 percentage points when businesses are offered a modest level of crime and safety insurance, or when WCs must have received a single positive performance review to qualify, or when a background check rules out bad events in (just) the past year. Wage subsidies can achieve similar increases but only at relatively high subsidy levels that may be cost prohibitive.<sup>3</sup> Providing crime and safety insurance covering damages up to \$5,000 increases the level of demand for WCs by

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<sup>2</sup>Workers who use the Platform to connect with third-party businesses are independent contractors. Accordingly, many of the terms in this paper (e.g., “employment,” “hire,” “hiring managers,” “wages,” etc.) are used only for convenience and simplicity, and do not legally apply to the Platform or to the workers who use it.

<sup>3</sup>We find that the share of businesses willing to work with WCs increases by approximately 2.1% for every 10% increase in the offered wage subsidy, broadly consistent with elasticities discussed as reasonable for low-wage workers in Katz (1996). We show in Section 7 that these estimates imply that all of the non-subsidy policies we consider can increase the demand for WCs at one-half to one-tenth the cost of wage subsidies under reasonable assumptions.

12 percentage points, approximately equivalent to the effects of an 80% wage subsidy according to our experimental subsidy estimates. A specification that WCs have successfully completed one prior job posted on the Platform similarly increases the level of demand by 13 percentage points, again roughly equivalent to the effect of an 80% wage subsidy. Limiting the pool of WCs to those who have maintained a clean record for at least one year increases the level of demand by 22 percentage points, greater than the effect of a 100% wage subsidy.

The final option we consider is providing hiring managers with objective information on the performance of WCs. We exploit the fact that some WCs inadvertently accessed the Platform before their background screening results were known, allowing us to compare the customer performance ratings of WCs and non-WCs in their first jobs objectively. Using incentive compatible elicitation about performance beliefs in our experiment, we find that hiring managers underestimate the performance of WCs, in terms of the share of both high- and low- performance ratings. Providing objective information on the true share of high-performance ratings received by WCs leads to more accurate beliefs and increases WC hiring by 7 percentage points, equivalent to the effect of a 45% wage subsidy. Providing objective information on the share of low-performance ratings, typically resulting from no-shows, also leads to more accurate beliefs but only increases WC hiring by a statistically insignificant 1.5 percentage points. The muted effect of low-performance ratings compared to high-performance ratings suggests that businesses may be less concerned with no-shows when deciding whether to work with WCs, and more concerned that WCs might not satisfactorily meet their performance standards while on the job.<sup>4</sup>

Based on our findings, the Platform carried out a staged roll-out to relax the criminal background check procedures it coordinates for customers. First, using the responses we collected in our experiment, the Platform extended job offers to WCs from businesses that responded affirmatively to working with WCs under then-current Platform conditions. Second, the Platform created the option for thousands of businesses posting new jobs to allow WCs to accept their jobs with up to \$1 million covered by crime and safety insurance, one of the most promising randomized conditions tested in this study. Eventually, the Platform plans for the inclusion of WCs to be the default option for all businesses, with businesses needing to pay an additional cost to exclude WCs from the pool of qualified workers. Through August 2021, demand from our study participants and the staged roll-out led to over 12,000 jobs being available to WCs on the Platform. This rapid expansion in the number of jobs available to WCs opens new questions for future research, including the evolution of demand as businesses gain experience working with WCs and the opportunities created for WCs that accept jobs posted on the Platform.

Beyond demonstrating that a range of policies can increase the demand for WCs, our paper provides new evidence on why businesses may conduct criminal background checks and hence what types of policies are likely to increase the demand for WCs. Several of our results, including the

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<sup>4</sup>Our high-performance estimates are sizable compared to other information treatment experiments. Bursztyn et al. (2020) find that correcting beliefs about male support for female labor market participation in Saudi Arabia increases the likelihood that husbands sign up their wives for job platform by 9 percentage points, or 36%, while Allcott (2011) find that a letter on energy use comparisons reduces consumption by 2%.

large demand response to crime and safety insurance and the even larger response to insurance among businesses whose jobs involve customer interaction or high-value inventory, suggest that businesses are particularly sensitive to the downside risk of hiring WCs. Other results, including the large response to objective information on the productivity of WCs, are consistent with the view that some businesses view WCs as less productive on average than otherwise similar non-WCs (a view that is incorrect in our setting). The positive effects of the wage subsidies, performance screening, and screening of the most recent records are consistent with both explanations.<sup>5</sup>

Our paper also builds on important work by Holzer (2007), Holzer et al. (2007), and Hunt et al. (2018) measuring the demand for WCs using employer surveys. In a survey of 107 businesses, for example, Hunt et al. (2018) find that employers report being more willing to hire WCs if there are wage subsidies, certificates of validated work performance history, or guaranteed replacement workers. These employers also report that “any violent felony conviction” and the “skills to get the job done” are their two most serious concerns with hiring WCs in the absence of these policies in these studies. However, the hypothetical and low-stakes nature of these surveys makes it difficult to know whether employers are expressing their true preferences or just their aspirations. We add to this literature by measuring the demand for WCs using the actual hiring choices of nearly a thousand U.S. businesses under different counterfactual policies.

The remainder of the paper is organized as follows. Section 2 describes the experimental context and design. Section 3 presents our baseline estimates of the labor demand for WCs with and without wage subsidies. Section 4 presents results for our primary experimental interventions. Section 5 presents results from the experiment on providing businesses information on the average productivity of WCs relative to non-WCs. Section 6 discusses alternative explanations for our results, and Section 7 concludes. The Online Appendix provides additional results and details of the experimental design.

## 2. Context and Experimental Design

### 2.1. The Platform

The context for our study is a leading online labor platform that thousands of third-party businesses use to connect with workers seeking short-term jobs. Businesses use the Platform to connect with workers to fill a wide range of entry-level jobs in sectors that report being more willing to hire WCs, such as general labor and transportation, as well as entry-level jobs in customer-facing or administrative sectors that are traditionally more averse to hiring WCs (e.g., Holzer et al., 2004; Raphael, 2011; Yang, 2017; Schnepel, 2018). The Platform is hosted on the internet, but the work they support generally does not involve computers or the internet, nor does it require a college degree or significant prior experience. The variety of job types and focus on entry-level jobs provides an ideal setting for estimating the demand for WCs under different policy alternatives.

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<sup>5</sup>These results are related to the literature in personnel and organizational economics on hiring (see Oyer and Schaefer (2011) for a review of recent work in this area). While past work explores the option value of hiring high-variance workers for long-term positions (Lazear, 1998; Bollinger and Hotchkiss, 2003), we explore how to protect businesses from the perceived downside potential of hiring disadvantaged workers for short-term positions.

Three institutional features of the Platform are critical for our analysis. First, the Platform’s labor market allows us to ask businesses to make incentive-compatible choices over hiring decisions. Businesses submit job requests to the Platform that include a job description, the pay for the job, and qualifying criteria. For example, some requests specify that workers must have experience driving a truck or be comfortable with heavy lifting. Businesses do not decide whether to work with individual workers. The Platform extends the job offer to workers who meet the job qualifications. Workers then have the option to accept or reject these job offers on a first-come, first-serve basis, at their discretion. Upon acceptance, the job is reserved for the worker who accepted it (i.e., other workers no longer have the ability to accept the job). Posted jobs are typically accepted within a few hours of the initial posting, though jobs can sometimes go unaccepted for several days. If a business wishes to cancel a job request that has been accepted within 12 hours of the start time for the job, the business generally must pay a cancellation fee consisting of a set percentage of the anticipated payment for the job. Less than 1% of accepted job requests are canceled in practice. By asking businesses to make decisions about what workers they would allow in their pool, we are therefore asking businesses to make incentive-compatible choices on *actual hiring decisions*, as opposed to callback or interview decisions that have generally been considered in previous work. While a particular job may be short-term (1 day, 1 week or 1 month), 54% of workers who accept a job with a given business will later be re-hired by the same business, suggesting potential for long term employment relationships.

Second, the performance data collected by the Platform allows us to provide hiring managers with objective information about the performance of both WCs and non-WCs. At the end of each job, the business’s hiring manager is asked to rate each worker’s overall performance on a scale of 1 to 5.<sup>6</sup> In 2019, roughly 85% percent of the overall ratings are perfect 5-star ratings and 1.3% are 1- or 2-star ratings. No-shows comprise an additional 4% of the overall job ratings. Given the bimodal nature of the reviews, we refer to information about the share of jobs resulting in 5-star ratings as “high-performance” information and information about the share of jobs resulting in a 1- or 2-star rating or a no-show as “low-performance” information. The intuition for considering the two ends of the performance spectrum separately is that they are only weakly correlated—a worker can perform at a high level conditional on completing the job while also exhibiting high no-show rates. Some businesses might care more about mitigating poor performance and absenteeism than about the ability to perform well.

Finally, like many other labor platforms for independent contract workers (e.g., Uber, Lyft), up to 30% of Platform applicants are currently screened out by a criminal background check, and the company incurs a cost to run each background check. The researchers’ collaboration with the Platform grew out of a series of conversations between the researchers and the Platform’s Chief Executive Officer, Chief Technology Officer, board members, and other top executives and managers, each party recognizing that the costs and benefits of the criminal background check were largely

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<sup>6</sup>Hiring managers also rate workers on specific attributes such as timeliness, cooperation, and quality of work. In practice, however, hiring managers only complete the more comprehensive review after 8% of jobs compared to 86% for the overall ratings. We therefore focus on the overall ratings throughout the paper.



unknown despite its significant impact on operations.

## 2.2. Experimental Design

The experiment came about through an intense multi-year collaboration between the research team and the Platform’s top executives and managers following the initial conversations discussed above. The goal of the collaboration was to understand the potential barriers to including WCs in the pool of independent contract workers on the Platform so that the company could modify, reduce, or eliminate the criminal background check requirement and provide opportunities to a broader set of workers. The Platform’s top executives and managers piloted the randomized conditions, while the Platform’s general counsel closely scrutinized and edited the conditions to ensure that the hiring managers’ responses could legally determine whether WCs would be allowed to accept their business’ jobs in the future (hence, ensuring the high-stakes nature of the responses provided during the experiment). The Platform’s general counsel also ensured that the proposed policies were in compliance with the relevant local, state, and federal laws.

A central feature of the experiment is that hiring managers make *ex-ante* incentive-compatible choices over actual hiring decisions under different randomized conditions. As discussed above, the Platform’s labor market features a matching process where workers who meet the posted job requirements are matched on a first-come, first-served basis, with no additional screening after the initial matching process. In addition, hiring managers on the Platform were already familiar with submitting criteria for workers who can accept their jobs, making the high-stakes nature of their choices both apparent and natural. These institutional features, as well as the input of the Platform’s general counsel, allowed the Platform to truthfully inform hiring managers that their responses during the experiment constituted high-stakes decisions that could determine whether WCs would accept their jobs in the future.<sup>7,8</sup>

The *ex-ante* incentive-compatible nature of the hiring managers’ choices was reinforced by two *ex-post* actions taken by the Platform following the experiment. First, the Platform immediately implemented businesses’ choices by allowing WCs to accept jobs posted by the businesses that were

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<sup>7</sup>Incentive compatibility can be judged by whether the questions are perceived by respondents as having the potential to affect their outcome, with the exact probability that a choice is implemented generally mattering relatively little (Carson and Groves, 2007; Charness et al., 2016). The Platform carefully crafted the initial outreach to businesses to elicit truthful answers: “Please share your truthful and considered views—they matter to us,” and the Platform’s executives and board members were especially committed to making it possible for those who expressed interest in hiring WCs to do so. As a result, the questions were designed to be both directly implementable and to change the Platform’s practices moving forward.

<sup>8</sup>Methodologically, we build on Mas and Pallais (2017), Low (2017), and Kessler et al. (2019) to generate incentive-compatible responses in field experiments. Mas and Pallais (2017) examine the choice of applicants regarding schedule flexibility over jobs within a call center. Low (2017) and Kessler et al. (2019) examine hypothetical candidates (for dating and hiring, respectively) with randomized attributes, where respondents are truthfully informed that their decisions will affect who can accept their jobs. In the experiment, businesses make multiple decisions about hiring under different randomized conditions, where the Platform truthfully informs them that their decisions may affect whether WCs are included among the workers who can accept their jobs and under what conditions. Our approach is also similar to the “strategy method” in lab experiments (Brandts and Charness, 2011), where players make multiple conditional decisions (e.g., a different decision for each information set) and one decision is potentially randomly chosen to count for pay.

willing to work with WCs under current Platform conditions if there was a pool of WCs in the businesses’ location. Second, the Platform used businesses’ choices to set Platform-wide policy. The Platform offered crime and safety insurance up to \$1 million, regardless of client choices or participation in the experiment. The Platform is also planning to change the default option to allow WCs to accept the jobs businesses post, while retaining the crime and safety insurance, in the coming months. The connection of WCs to study participants and these platform-wide changes have already generated over 12,000 jobs (through August 2021) newly open to WCs, with additional jobs being opened to WCs each day.

We leverage this high-stakes setting to test several approaches to increasing the demand for WCs on the Platform. Each of the alternatives we consider is meant to address the underlying reasons that businesses may screen workers using a criminal background check. We began by asking hiring managers about their willingness to accept WCs under one of several randomly assigned wage subsidy levels (0%<sup>9</sup> or one of several positive levels) to establish the baseline level of demand and provide a benchmark for the other randomized treatments. We then asked hiring managers about their willingness to accept WCs under different randomized conditions, including different levels of crime and safety insurance and past performance reviews, as well as background checks covering only the most recent criminal records. We then asked a series of descriptive questions about the hiring practices at the business and the types of jobs posted on the Platform to allow for heterogeneity analyses, before concluding with an information experiment motivated by the large dispersion in prior beliefs about the performance of WCs on the Platform. The randomly assigned subsidy level remained in place throughout all of these subsequent questions.

The remainder of this section summarizes the most important details of the experiment, also detailed in Table 1 and Appendix Table A.1. We begin by describing how the Platform contacted hiring managers, before describing each of the main experimental conditions and subsample comparisons.

**Outreach.** From March 6, 2020 to April 11, 2020, the Platform emailed active hiring managers the following message: “We are considering expanding the pool of [workers] who can perform the jobs that you post, and we want your guidance.” Interested hiring managers were instructed to click on a link that took them to the hiring flow questions that constitute our randomized experiment. The initial outreach emails did not mention WCs, and hiring managers were not aware that they were part of a randomized study at any point during the outreach or experiment. The Platform sent the emails from a Platform-branded account using their own signature (“Sincerely, [Platform] Management”) and logo. The Platform also offered a \$35 or \$50 cash gift for complete answers to underscore the value of thoughtful and considered responses, as well as to motivate businesses to complete all questions. Such cash transfers are standard practice for the Platform when requesting input from hiring managers to make Platform design decisions.<sup>10</sup>

Following a series of short introduction questions, the Platform explained:

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<sup>9</sup>In the case of 0% subsidy, we made no mention of the subsidy at all.

<sup>10</sup>The Platform emailed all hiring managers who had been active in listing positions on the Platform in the last 16 months up to five times during the outreach period. The Platform did not email hiring managers who had joined within the last 3 months at the request of the company’s account managers.



We are considering expanding our pool of [Platform Workers] to include individuals that have a criminal record. We want to learn whether this expanded pool would suit your needs.

If you indicate that you're interested in connecting with [Platform Workers] with a criminal record, then (and only then) your choice could affect whether these [Platform Workers] are able to accept jobs you post. These individuals would be at most 5% of your pool of possible matches.

The Platform then asked participating hiring managers about their willingness to work with WCs under different randomized conditions, where randomization occurred at the business level to ensure that hiring managers at the same business were not given conflicting options.

In total, 1,095 hiring managers from 913 businesses completed the hiring flow questions. Eighty-six percent of hiring managers completed the hiring flow questions conditional on opening the email, with 91% of managers completing the questions conditional on reaching the first question related to WCs. Eighty percent of the hiring managers in our sample report having the authority to unilaterally allow WCs to perform the jobs they post or to significantly influence this decision. Our results are qualitatively unchanged if we calculate upper and lower bounds of all treatment effects that account for early attrition or restrict the sample to the subset of hiring managers with unilateral authority to allow WCs to be hired or either the unilateral authority or the power to influence this decision.<sup>11</sup>

**Baseline Demand.** We measure the baseline demand for WCs with no additional incentives or conditions by simply asking hiring managers whether their business would permit WCs to accept their jobs:

Would you permit [Platform Workers] with a criminal background to perform jobs you post?

We asked 1/5 of hiring managers this question, meant to measure demand for WCs under the Platform's current conditions and establish a baseline for a wage subsidy of 0%. Hiring managers were given the option of selecting "Yes," "Only if it's hard to fill my jobs," or "No." Answering "Yes" to this question immediately extended permission to the Platform to allow WCs to accept the client's job posting, without any policy changes or conditions being met.

**Wage Subsidies.** We measure demand for WCs under different wage subsidies by asking hiring managers whether their business would permit WCs to accept their jobs under one of several randomly assigned wage subsidy levels:

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<sup>11</sup>The Platform emailed 7,450 during the outreach, meaning that 14% of hiring managers opened the email and completed all of the hiring flow questions. The Platform generally expects less than 10% of the full pool of past hiring managers to respond when requesting input to make Platform design decisions.

If the [Platform] gave you a [Wage Subsidy] discount for [Platform Workers] with a criminal record, would you permit such [Workers] to perform jobs you post? This means you would only pay  $(100 - [\text{Wage Subsidy}])$  of the wage for those with a criminal record. All [Platform Workers] would still receive the full pay amount after the discount (the [Platform] would pay the difference).

The wage subsidy levels were 5%, 10%, 25%, 50%, and 100%, randomly assigned with probabilities 1/10, 1/10, 1/5, 1/5, and 1/5, respectively. The remaining 1/5 of hiring managers were randomly assigned to no subsidy condition described above. The wide range of randomized subsidy levels allows us to trace out a labor demand curve with minimal assumptions and explore whether there are non-linear effects of very small or very large wage subsidies. We cover a range of economically relevant subsidy levels, with the Federal Work Opportunity Tax Credit (WOTC) currently offering a 25% wage subsidy to businesses who employ WCs for at least 120 hours in their first year of employment and a 40% wage subsidy to businesses who employ WCs for at least 400 hours in their first year. For expository purposes, we pool the 5% and 10% subsidy levels, which results in a uniform number of observations across values displayed.

**Crime and Safety Insurance.** We measure the effect of crime and safety insurance by asking hiring managers if, at a given subsidy level, their business would permit WCs to accept their jobs under one of several randomly assigned insurance levels:

If the [Platform] could cover damages up to [Crime and Safety Insurance Cap] related to theft or safety incurred by [Platform Workers] with a criminal record, would you permit such [Workers] to perform jobs you post? The [Platform] would still give you a [Wage Subsidy] discount, but no other supplementary policies would apply.

The randomly assigned insurance levels were \$1,000, \$5,000, \$100,000, and \$5 million, randomly assigned with probabilities of 1/6, 1/6, 1/3, and 1/3, respectively. These randomized insurance levels cover a wide range of economically relevant values. The U.S. Federal Bonding Program, for example, offers an insurance bond of \$5,000 to provide insurance against liability for relatively less serious crimes like robbery or theft. The highest level of insurance in our experiment, \$5 million, would also provide liability against much more serious crimes like sexual assault and murder.<sup>12</sup> Crime and safety insurance directly addresses the concern that a WC might act violently towards coworkers or customers. For expository purposes, we pool the \$1,000 and \$5,000 insurance levels, which results in a uniform number of observations across values displayed.

**Screening Based on Performance History.** We measure the effect of having a satisfactory performance history on the Platform by asking hiring managers if, at a given subsidy level, their business would permit WCs to accept their jobs under one of several randomly assigned job histories:

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<sup>12</sup>We selected the \$5 million cap to cover plausible damages from sexual harassment cases. For example, an Uber driver was ordered to pay \$8.2 million for sexually assaulting a customer in December 2019 (<https://molawyersmedia.com/2019/12/17/uber-assault-case-results-in-8-2-million-judgment/>) and Airbnb currently offers insurance up to \$1 million to hosts.

If the [Platform] required [Platform Workers] with a criminal record to have satisfactorily completed [Performance History] job(s), receiving more than 85% 5-star reviews, would you permit such [Workers] to perform jobs you post? The [Platform] would still give you a [Wage Subsidy] discount, but no other supplementary policies would apply.

The randomly assigned job histories consisted of 1, 5, and 25 jobs, randomly assigned with 1/3 probability each. These randomized job histories again cover a wide range of economically relevant values. Pallais (2014) shows that workers having 1 prior job substantially increases the chance of getting hired on oDesk, motivating the inclusion of this job history in our experiment, while the highest value of 25 jobs corresponds to an above the 90th percentile of past performance history on the Platform. Performance screening could potentially address business concerns about both productivity and on-the-job crime.

**Screening Based on Criminal Record History.** We measure the effect of more targeted screening by asking hiring managers if, at a given subsidy level, their business would permit WCs to accept their jobs if the WC committed their last offense at least 1, 3, or 7 years ago, with these values randomly chosen with 1/3 probability each. We chose these randomized values because the probability of criminal re-offending is particularly high in the first two years post-incarceration, while background checks often extend to criminal convictions within the last 7 years.

We additionally measure the effect of selectively screening by conviction type by asking hiring managers if, at a given subsidy level, their business would permit WCs to accept their jobs if they were convicted for a distinct category of crimes, including a property/financial felony, a violent felony, a substance-related felony, a property/financial misdemeanor, a violent misdemeanor, and a substance-related misdemeanor. These categories include a wide variety of crimes, but do not encompass all possible conviction types and do not include arrests that do not result in a conviction but nevertheless are reported on a criminal background check. We therefore do not expect these conviction results to aggregate to our baseline results that include all arrest and conviction types.

**Objective Performance Information.** We measure the effect of providing hiring managers with objective information about the average performance of WCs on the Platform on hiring managers' beliefs and subsequent hiring choices using an information experiment embedded in the hiring flow questions. Here, we exploit the fact that some WCs inadvertently accessed the Platform before their background screening results were known, allowing us to compare the performance ratings of WCs and non-WCs in their first jobs on the Platform.

We first measure baseline performance beliefs using an incentive-compatible guessing game about the relative performance of WCs on the Platform that rewards accuracy. Rewards in the guessing game ranged between \$2 and \$10 for an answer within 5% of the truth, where in unreported results we find no difference in respondent accuracy across the reward amounts. For approximately one-half of the participants, the guessing game asked the following question about the share of high-performance ratings:

In 2019, 86% of jobs on the [Platform] resulted in a 5-star rating. What percentage of jobs completed by [Platform Workers] with a criminal record do you think would result in a 5-star rating on the [Platform] or a similar platform? If your guess is within 5% of the truth, we will send you an additional [\[Bonus\]](#) reward!

We asked the other one-half of participants about the share of low-performance ratings in the guessing game:

In 2019, 5% of jobs on the [Platform] resulted in either a no-show or low rating (1 or 2 stars). What percentage of jobs completed by [Platform Workers] with a criminal record do you think would result in a no-show or low rating on the [Platform] or a similar platform? If your guess is within 5% of the truth, we will send you an additional [\[Bonus\]](#) reward!

One-half of participants who initially made guesses about the share of high-performance ratings randomly received objective information about the true share of high-performance ratings:

The truth is that 87% of jobs completed by [Platform Workers] with a criminal record resulted in a 5-star rating on the same or a similar platform—actually better than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

Similarly, one-half of the participants who initially made guesses about the share of low-performance ratings received objective information about the true share of low-performance ratings:

The truth is that only 3% of jobs completed by [Platform Workers] with a criminal record resulted in either a no-show or a low rating (1 or 2 stars) on the same or a similar platform—actually fewer no-shows and low ratings than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

We then asked all participants, regardless of whether or not they were shown the new objective information, to report their posterior beliefs about the performance of WCs using the same incentive-compatible guessing game question.<sup>13</sup> Finally, we allowed all participants, again regardless of whether or not they were shown the new objective information, to revise their answer to the very first question about hiring WCs with or without a wage subsidy. By allowing participants to revise their willingness to work with WCs, we can learn how the objective information about WC performance on the Platform impacts hiring decisions.

**Heterogeneity by Labor Market Conditions.** We also explore heterogeneity across labor market conditions, testing whether particular business concerns are more salient under different

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<sup>13</sup>We state to participants: "We want to give you the opportunity to reassess your answer to the question below. This opportunity is given automatically to all survey participants, regardless of their responses."

market conditions. For all of the questions in the experiment, hiring managers were given the option of selecting “Only if it’s hard to fill my jobs,” providing a targeted measure of labor market tightness that is specific to each business’s context. In addition, we explore the effects of local labor market unemployment, a more traditional measure of labor market tightness, by asking whether a hiring manager would want to work with WCs if the local unemployment rate were to be at a certain level, randomized between 2%, 6%, or 10%. Finally, we estimate results separately for businesses located in counties with above- and below-median unemployment rates as of early March 2020 (e.g., Los Angeles County with 6.6% unemployment vs. San Francisco County with 3.1% unemployment) and for businesses located in counties in the top and bottom three quartiles of COVID-19 rates as of March 2020 (e.g., Cook County, IL (Chicago) vs. Los Angeles County), providing an additional set of estimates related to local labor market tightness.

**Heterogeneity by Job Characteristics.** Finally, we asked hiring managers about the typical jobs they post, including whether there are any customer interactions or access to high-value inventory, thereby allowing us to explore to what extent businesses are concerned about theft as compared to violence when considering downside risk. We also asked hiring managers whether their business has a hiring policy related to WCs.

### 2.3. Motivating Framework

The experiment is motivated by a stylized theoretical framework that explains why businesses may conduct criminal background checks and decide not to work with WCs. The framework formalizes the idea that businesses may use a criminal record as a (potentially inaccurate) signal of lower productivity or higher downside risk. The framework helps explain how we can use our results to understand why businesses may want to conduct criminal background checks and what types of policies are likely to increase the demand for WCs.

Consider a single business deciding whether to work with a single WC. The business’s expected profits from working with the WC is a function of expected productivity and the risk of a costly event occurring on the job:

$$\pi = y - w - b \cdot \max\{k - I, 0\}$$

where  $y$  is the expected productivity of the WC (e.g., the rate at which the worker packs boxes),  $w$  is the WC’s wage,  $b$  is the probability of a bad event occurring as a result of the WC’s behavior (e.g., theft),  $k \geq 0$  is the cost of a bad event (e.g., the value of the stolen inventory), and  $I \geq 0$  is the amount of crime and safety insurance provided, if any. The business has an unobserved shadow value,  $\theta$ , of not hiring the WC (e.g., there is some probability that the business can fill the slot with a non-WC). The business chooses to work with the WC,  $H = 1$ , when  $\pi > \theta$ . The first prediction is that wage subsidies increase demand for WCs regardless of expected productivity or downside risk. We are thus able to use the effect of the wage subsidy as a benchmark, comparing its effect to policies that primarily target either expected productivity or downside risk. Our framework yields the following subsequent predictions.

**Crime and Safety Insurance.** Crime and safety insurance (i.e., greater  $I$ ) increases the demand for WCs as long as downside risk is a relevant factor for businesses. The effect of insurance on hiring should be larger for businesses with a greater probability of, or larger costs from, a bad event. This would include businesses with jobs that involve high-valued inventory or frequent customer interactions. If the primary downside risks involve infrequent but very costly events (e.g., violent crimes), then we expect that an insurance policy with a low cap will not impact hiring demand but a very generous insurance policy will. If, on the other hand, the primary downside risks are minor infractions (e.g., petty crime), then we expect the effect of insurance policies with low and high insurance caps per event to similarly increase hiring demand.

**Screening Based on Performance History and Objective Performance Information.** Requiring that WCs successfully complete a prior job can be viewed as increasing the expectation about productivity,  $y$ , for that worker. While screening could also decrease the perceived probability of a bad event  $b$ , our conversations with the Platform suggest that expected productivity is the primary signal contained in prior ratings. Nevertheless, screening based on performance history should increase the demand for WCs if either productivity or downside risk is a relevant factor for businesses. If businesses have negatively biased beliefs about  $y$  and  $b$  for WCs, providing objective performance information regarding WC performance can also increase the demand for WCs.

**Screening Based on Criminal Record History.** Expected productivity  $y$  may be higher and both the probability of a bad event  $b$  and the cost of that bad event  $k$  may be lower for WCs with less recent criminal histories or convicted of less serious crimes. This combination of lower  $b$  and  $k$  leads to higher demand for WCs with less recent criminal histories or convicted of less serious crimes compared to WCs with more recent criminal histories or convicted of more serious crimes if either productivity or downside risk is a relevant factor for businesses.

**Heterogeneity by Labor Market Conditions.** When local labor market conditions are such that the business has strong alternative options to hiring WCs, the shadow value of labor in our framework,  $\theta$ , rises. The business chooses to work with the WC,  $H = 1$ , when the value reaped from hiring is greater than the alternative,  $\pi > \theta$ . Hence, we expect that demand for WCs is lower when the businesses face favorable labor market conditions and their jobs are easy to fill.

**Heterogeneity by Job Characteristics.** Businesses with jobs that involve high-valued inventory likely face a higher probability of a bad event occurring (i.e., higher  $b$ ) and a higher cost from such a bad event (i.e., higher  $k$ ). Thus, businesses with jobs involving high-valued inventory should have relatively lower demand for WCs if downside risk is a relevant factor. Similarly, businesses with jobs that require frequent customer interactions likely have more opportunities for costly infractions to occur (i.e., higher  $b$ ) and a higher cost from such an infraction event (i.e., higher  $k$ ), again leading to relatively lower demand for WCs if downside risk is a relevant factor.



## 2.4. Descriptive Statistics and Randomization Assessment

Table 2 presents descriptive statistics for the experimental sample comprised of the 1,095 hiring managers from 913 businesses that completed the experiment, and a broader set of businesses in the United States.<sup>14</sup> Panel A reports information on basic business characteristics from the Infogroup Historical Business Database (Infogroup, 2016), which contains basic profile data for more than a million U.S. businesses. Businesses in our experimental sample are broadly representative of U.S. businesses in terms of industrial composition, but skew older (19 years vs. 16 years) and larger (40 employees vs. 2.5 employees). Businesses in our experimental sample are also somewhat more likely to be in manufacturing (19% vs. 6%), transportation (10% vs. 3%), and public administration (10% vs. 2%), and less likely to be in service (31% vs. 37%), finance (3% vs. 7%), and construction (1% vs. 8%).

Panel B reports information on WC hiring policies, where information for the broader set of U.S. businesses comes from a nationwide survey of over 1,000 HR professionals commissioned by the Society for Human Resource Management (SHRM) (Society for Human Resource Management, 2018). Compared to other U.S. businesses, businesses in our experimental sample are somewhat less likely to have a business-wide WC hiring policy (45% vs. 66%) and to indicate that they want to work with the best candidate for the job regardless of criminal history (46% vs. 53%). Slightly more businesses in our sample indicated that they would want to work with WCs to help give individuals a second chance (50% vs. 38%) or for financial incentives (8% vs. 2%), and a similar number of businesses in both samples are concerned about local or state regulations that make hiring WCs difficult (26% vs. 22%). Section 6 explores how our results change if weight observations to match either the distribution of firms in the U.S. economy based on industry and firm size or based on answers to the SHRM questions about attitudes and policies in place with respect to WCs.

Table 3 shows that the randomization was balanced in our experimental sample. We regress seventeen business characteristics on indicator variables for all levels of the six randomized treatments. Table 3 reports p-values from an F-test of each of the 90 regressions. Only four of the p-values are statistically significant at the 5% level and only an additional four are significant at the 10% level, which is to be expected given the number of tests. These results indicate that randomization was performed correctly and that our sample is balanced across treatment arms.

## 3. The Labor Demand for Workers with a Criminal Record

In this section, we measure the baseline demand for WCs using the randomized wage subsidies. We first analyze the effects of the wage subsidies on the willingness to work with WCs for all jobs, before turning to its effects for different types of jobs and local labor market conditions. We present our

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<sup>14</sup>In unreported results, we find that businesses in the analysis sample are generally representative of all businesses on the Platform. Businesses in our experiment have used the platform for slightly longer than average (1.3 years vs. 1.2) and are slightly less likely to be in the transportation and public utilities sector (10% vs. 13%). However, we have similar numbers of businesses in all other industries, including service (both 31%), manufacturing (19% vs. 20%), and retail (15% vs. 14%).

results graphically, providing corresponding regression tables and standard errors in the Appendix.<sup>15</sup>

### 3.1. Baseline Results

Figure 1 plots the fraction of businesses that are willing to work with WCs by the effective wage, equal to 100% minus the randomized wage subsidy. We show our baseline results, where we code businesses as willing to work with WCs if they responded “Yes” and unwilling to work with WCs if they responded “No” or “Only if it’s hard to fill my jobs.” We pre-registered our main analyses using this form of the dependent variable since the answer of “Yes” is unambiguous and allows for choices to be legally binding. Figure 2, discussed in more detail below, shows results where we code businesses as willing to work with WCs if they responded “Yes” or “Only if it’s hard to fill my jobs” to the relevant question and unwilling to work with WCs if they responded “No.” Appendix Table A.2 presents the results from Figures 1 in regression form with standard errors clustered by business, the level of random assignment.

Figure 1 also includes an estimate of the demand elasticity,  $\epsilon^D$ . To estimate  $\epsilon^D$ , we first estimate the following linear specification that includes one observation per respondent:

$$\text{Hire}_i = \gamma_0 + \gamma_1 \cdot \text{EffectiveWage}_i + u_i \quad (1)$$

where  $\text{Hire}_i$  is an indicator that represents whether business  $i$ ’s is willing to work with WCs and  $\text{EffectiveWage}_i$  is equal to 100% minus the assigned wage subsidy in the set  $\{0\%; 10\%; 25\%; 50\%; 100\%\}$ , as a pseudo-continuous variable, and  $u_i$  is an error term. We then calculate  $\epsilon^D = \hat{\gamma}_1 \cdot \frac{\bar{w}}{\bar{h}}$ , where  $\bar{w}$  and  $\bar{h}$  are the average effective wage and hiring rates, respectively. Appendix Table A.3 explores robustness to alternate methods of calculating the demand elasticity.

We find that 39% businesses are willing to work with WCs in our baseline case when there is no wage subsidy and the effective wage is 100%. The share of businesses willing to work with WCs is generally increasing in the subsidy level, with 54% of businesses willing to work with WCs when there is a full wage subsidy and no out-of-pocket costs for the business.<sup>16</sup> Estimates of (1) that use information from all of the randomized subsidy levels show that the share of businesses willing to work with WCs increases by approximately 2.1% for every 10% increase in the offered wage subsidy, broadly consistent with elasticities discussed as reasonable for low-wage workers in, for example, Katz (1996). The baseline number of businesses willing to work with WCs is also qualitatively similar to other reported estimates, such as the approximately 40% of employers that would “definitely” or “probably” hire WCs in most low-stakes surveys (e.g., Holzer, 2007).

Appendix Table A.4 presents descriptive statistics for the businesses that are and are not willing to hire WCs at different subsidy levels to better understand the results from Figure 1 and the

<sup>15</sup>Our empirical analysis closely follows our pre-analysis plan, available at [AEARCTR-0005200](#).

<sup>16</sup>The estimates shown in Figure 1 are non-monotonic over some ranges, with a slightly lower fraction of businesses willing to work with WCs at an effective wage of 75% compared to an effective wage of 90%. The hiring rates are statistically indistinguishable at these effective wage levels, however, with the simplest explanation for these results being that our non-parametric estimates include significant sampling error due to the relatively small number of businesses randomized to each effective wage level.

hesitation of many businesses to hire WCs even when there are no out-of-pocket costs. Businesses that are and are not willing to hire WCs are similar in terms of hiring manager experience and business size, but those that are willing to hire WCs are less likely to have a business-wide policy in place regarding WCs and utilize the Platform less frequently compared to business that are not willing to hire WCs. Businesses that are willing to hire WCs are also more likely to say that they want to hire the best candidate regardless of criminal history and that they want to give people a second chance. These businesses are also more confident that WCs will perform well and less concerned that WCs will put others at risk or steal or cause damage while on the job. These patterns generally hold regardless of the subsidy offer, suggesting that the wage subsidies do not substantially change the mix of businesses willing to hire WCs. The remainder of this section will explore how these baseline results change when businesses that use the Platform are having a hard time filling jobs and provide a more formal heterogeneity analysis motivated by our theoretical framework.

### 3.2. Heterogeneity in Demand by Labor Market Conditions

Figure 2 plots the fraction of businesses that are willing to work with WCs by the effective wage, where we now code businesses as willing to work with WCs if they responded “Yes” or “Only if it’s hard to fill my jobs” and unwilling to work with WCs if they responded “No.” These results thus present evidence on the willingness to work with WCs in a tight labor market using a targeted, context-specific measure rather than the rough proxies typically used in past work, e.g., local unemployment rates.

We also report the average regression-weighted difference between the baseline demand curve presented in Figure 1 and the new demand curve in Figure 2. To estimate the average difference between the two demand curves, denoted in Panel B of Figure 1 by  $\Delta$ , we estimate the following “stacked” regression specification that includes two observations per respondent:

$$\text{Hire}_{il} = \text{HardtoFill}_l + \sum_{k \in K} \lambda_k \cdot \text{Subsidy}_{ik} + e_{il} \quad (2)$$

where the first observation codes willingness to work with WCs using our original definition ( $\text{Hire}_{i0}$ ) and the second observation codes willingness to work with WCs using this alternate definition reflecting a tight labor market ( $\text{Hire}_{i1}$ ).  $\text{HardtoFill}_l$  is then simply an indicator that is zero for the original definition, and one for the alternative definition ( $\mathbb{1}\{l = 1\}$ ),  $\text{Subsidy}_{ik}$  is a set of indicator variables for the assigned wage subsidy in the set  $K = \{0\%; 10\%; 25\%; 50\%; 100\%\}$ , and  $e_{il}$  is an error term. We include all possible wage subsidy levels and omit the constant term. Appendix Table A.2 again presents the results in regression form with standard errors, along with our estimated elasticity for this alternative outcome measure.

We find that the share of businesses willing to work with WCs increases by 29 percentage points, to 68%, if the Platform is having a hard time filling a job in our baseline case when there is no wage subsidy and the effective wage is 100%. The increase in the fraction of businesses willing to

work with WCs when jobs are hard to fill is again roughly constant at different effective wage levels, with an average increase of 25 percentage points according to our estimates from (2). These results indicate that businesses are more likely to consider non-traditional workers when jobs are hard to fill, consistent with prior work showing that individuals released from prison when local economic conditions are good are less likely to re-offend (e.g., Yang, 2017).

By comparison, we find no economically significant differences in the willingness to work with WCs by actual local unemployment rates, the randomized unemployment rate, or the intensity of the COVID-19 pandemic during our sample frame, as shown in Appendix Figure A.1. In unreported results, we similarly find no effect if we focus on the local unemployment rate for workers with a high-school degree or less. We interpret these results as suggesting that measures such as local unemployment rates do not capture all of the relevant variation in labor market tightness for the businesses in our sample and that more targeted measures are required to accurately understand the importance of labor market conditions on the demand for WCs.

### 3.3. Heterogeneity by Job Characteristics

Figure 3 explores heterogeneity in the demand for WCs by whether the job involves high-value inventory and customer interactions, two highly salient characteristics that map to our motivating framework. Each panel plots the fraction of businesses that are willing to work with WCs by effective wage in each group and the average difference between the group-specific demand curves, estimated using a version of the regression specification (2) described above. Following our baseline results, we code businesses as willing to work with WCs if they responded “Yes” to the relevant question and unwilling to work with WCs if they responded “No” or “Only if it’s hard to fill my jobs.” Appendix Table A.2 again presents the results in regression form with standard errors.

In our baseline case when there is no wage subsidy and the effective wage is 100%, we find that the share of businesses willing to work with WCs increases by 6 percentage points, to 45%, when jobs do not involve customer interactions. The average increase in the fraction of businesses willing to work with WCs when jobs involve customer interactions across all subsidy levels is 13 percentage points. We similarly find that the share of businesses willing to work with WCs increases by 12 percentage points, to 51%, for jobs that do not involve high-value inventory in our baseline case when there is no wage subsidy, with an average increase of 18 percentage points across all subsidy levels.

The results in Figure 3 are consistent with businesses perceiving greater risks related to customer safety or inventory theft when hiring WCs, as suggested by our motivating framework. These results are also consistent with prior work suggesting that employers with jobs that require “trust” are generally less willing to hire WCs (e.g., Holzer, 2007).

## 4. Crime and Safety Insurance and Targeted Screening

This section tests several approaches to increasing the demand for WCs that directly address the reasons that businesses may conduct criminal background checks, such as lower average productivity and higher downside risk. We begin by measuring the effects of crime and safety insurance that is meant to address downside risk concerns. We then measure the effects of performance screening and screening based on criminal record history, policies that are meant to address both average productivity and downside risk concerns.

### 4.1. Crime and Safety Insurance

Figure 4 plots the fraction of businesses that are willing to work with WCs at each effective wage and randomly assigned level of crime and safety insurance. We also plot the baseline level of demand from Figure 1 and report the average difference between the baseline curve and each of the new demand curves that include \$5,000, \$100,000, or \$5m of crime and safety insurance, estimated using a version of the regression specification (2) described above. Appendix Table A.2 provides the results from Figure 4 in regression form with standard errors clustered by business, along with estimates of the demand elasticities at each level of insurance.

We find that providing crime and safety insurance significantly increases the level of demand for WCs, consistent with concerns about downside risk when hiring WCs. In our baseline case with no wage subsidy, insurance that covers damages up to \$5,000 increases demand for WCs by 12 percentage points, to 51%. The increase in the fraction of businesses willing to work with WCs with insurance that covers damages up to \$5,000 is roughly constant at different effective wage levels, with an average increase of 12 percentage points. This 12 percentage point increase is equivalent to the effects of an 80% wage subsidy, based on a linear extrapolation of our baseline estimates from Figure 1. We find somewhat larger effects of insurance coverage at higher amounts, with an insurance policy with a cap of \$100,000 increasing the share of businesses willing to work with WCs by 17 percentage points when averaged over all the subsidy levels. Providing \$5m in insurance similarly increases the share of businesses willing to work with WCs by 17 percentage points when averaged over all the subsidy levels.

The results from Figure 4 suggest that businesses are particularly concerned about the types of moderate risks covered by low levels of insurance (e.g., due to petty theft), as well as the more severe tail risk events that are only covered by the higher levels of insurance (e.g., due to violence). Our results for the \$5,000 cap are particularly striking, as the \$5,000 cap is equal to that of the rarely-used U.S. Federal Bonding program. This estimate thus raises the possibility that the Bonding program’s low usage reflects non-demand-based reasons (e.g., that businesses do not know about it or that its use is stigmatized). This interpretation of the results is also broadly consistent with Leasure and Andersen (2016), who find similar call-back rates for individuals with and without a one-year-old felony drug conviction after the adoption of Ohio’s “Certificate of Qualification of Employment” program that lifted occupational licensing restrictions, limited employer liability for

negligent hiring claims, and advertised the existence of the Federal Bonding program for WCs.

## 4.2. Screening Based on Performance History

Figure 5 plots the baseline mean willingness to work with WCs at each effective wage and randomly assigned performance history. We again report the baseline level of demand and the average difference between the baseline curve and each of the new demand curves that include 1, 5, or 25 successfully completed jobs on the Platform, estimated using a version of the regression specification (2) described above. Appendix Table A.5 provides the results in regression form with standard errors clustered by business, along with estimates of the demand elasticities at each level of performance history.

Screening by performance history substantially increases the demand for WCs.<sup>17</sup> In our baseline case with no subsidy, businesses are 11 percentage points more willing to work with WCs if they know that they successfully completed at least 1 prior job, increasing total WC demand to 50%. The increase in the fraction of businesses willing to work with WCs who have completed at least 1 prior job is roughly consistent across effective wage levels, with an average increase of 13 percentage points. This 13 percentage point increase is roughly equivalent to the effect of \$5,000 crime and safety insurance or an 80% wage subsidy. The demand for WCs increases by a modest amount if WCs are required to have completed more than 1 prior job satisfactorily. Requiring WCs to have completed 5 or 25 prior jobs increases demand by 20 and 12 percentage points, respectively, relative to the baseline of no performance screening when averaged across the effective wage levels.

The results from Figure 5 suggest that businesses see WCs as heterogeneous in their productivity or downside risk, with just a single positive or negative review providing valuable information on who to hire. These results are consistent with Pallais (2014), who similarly finds that randomly providing a single job’s worth of experience along with a positive review leads to economically large increases in future employment and wages for inexperienced workers on the online platform oDesk.

## 4.3. Screening Based on Criminal Record History

Figure 6 plots the baseline mean willingness to work with WCs at each effective wage and randomly assigned time since the most recent arrest or conviction. We again report the baseline level of demand and the average difference between the baseline curve and each of the new demand curves representing 1, 3, or 7 years since the most recent arrest or conviction. Appendix Table A.5 provides the results in regression form with standard errors clustered by business, along with estimates of the demand elasticities at each randomly assigned time since the most recent arrest or conviction.

We find that offering businesses the opportunity to screen just the most recent arrests or convictions can substantially increase the demand for WCs, again consistent with concerns about

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<sup>17</sup>This is consistent with concerns about both productivity and downside risk since such screening could reveal instances of both poor productivity and risky behavior on previous jobs; however, according to accounts from Platform designers and clients, past performance ratings are considered primarily interpreted as a measure of ability to satisfactorily complete the job rather than a measure of bad events that may have occurred on the job.



both worker productivity and downside risk. In our baseline case with no subsidy, screening WCs so that they are only permitted to accept jobs if it has been at least one year since their most recent arrest or conviction increases demand by 22 percentage points, increasing total WC demand to 61%. The increase in the fraction of businesses willing to work with WCs is roughly constant at different effective wage levels, with the mean effect across all effective wages compared to the baseline equaling 18 percentage points. These results are greater than the crime and safety estimates, the performance screening estimates, and the effects of a 100% wage subsidy. Effects are even larger if it has been at least 5 or 7 years since the most recent arrest or conviction, with screening out WCs whose arrest or conviction is less than 5 or 7 years old increasing demand by 26 and 28 percentage points, respectively, when averaged across the effective wage levels.

Figure 7 similarly plots mean willingness to work with WCs at each effective wage and specific conviction type. However, we now report the mean impact of each crime type on willingness to work with WCs relative to the baseline crime type of a violent felony, as we did not attempt to ask about every arrest and conviction type, and we do not expect the results in Figure 7 to aggregate to the baseline results. Appendix Table A.5 reports the regression version of these results, along with estimates of the demand elasticities.

Businesses are consistently most willing to work with WCs convicted of less serious or drug-related crimes and least willing to work with WCs convicted of more serious and violence-related crimes. Compared to WCs convicted of a violent felony, businesses are 45.6 percentage points more willing to work with WCs convicted of a substance-related misdemeanor and 23.6 percentage points more willing for WCs convicted of a substance-related felony when averaged across the effective wage levels. Businesses are similarly 24.5 percentage points more willing to work with WCs convicted of a property-related misdemeanor and 6.6 percentage points more willing for WCs convicted of a property-related felony when averaged across the effective wage levels and compared to WCs convicted of a violent felony. By comparison, businesses are only 4.5 percentage points more willing to work with WCs convicted of a violent misdemeanor compared to WCs convicted of a violent felony.

Taken together, the results in Figures 6 and 7 show that targeted screening based on criminal record history can significantly increase the demand for WCs. This finding could reflect the concern that WCs with recent or more serious convictions may have a higher risk of recidivism (e.g., given that the hazard of recidivism is downward-sloping) or that these individuals may be less productive or have higher no-show rates. These results are also broadly aligned with other research findings in this area. For example, Holzer et al. (2007) find that employers report being more willing to hire workers with drug and property convictions compared to other types of convictions, while audit studies show that there are relatively small effects of having a misdemeanor arrest (Uggen et al., 2014) but large effects of any type of both felony drug and property convictions on call-back rates (Agan and Starr, 2017).

#### 4.4. Heterogeneity by Job Characteristics

Appendix Figures A.2 and A.3 explore heterogeneity by whether the job involves high-value inventory and customer interactions, following our baseline heterogeneity results discussed above. Each panel plots the fraction of businesses that are willing to work with WCs by effective wage and randomized condition and shows the average difference between the demand curves estimated using a version of the regression specification (2) described above.

The most important finding in these results is that the impact of insurance on hiring is largest for jobs involving high-value inventory, consistent with the idea that businesses are sensitive to the downside risk of hiring WCs. For example, \$5m in insurance boosts hiring by 10 percentage points in jobs without high-value inventory, but by 20 percentage points in jobs with high-value inventory. We are thus able to reject the null hypothesis that the elasticity of hiring with respect to the insurance level is the same across jobs with and without high-value inventory ( $p < 0.001$ ). In our motivating framework, this prediction follows because insurance is more valuable to businesses with a greater chance or cost from a loss.

By comparison, the impact of screening on performance history or criminal history is similar across businesses with and without high-value inventory and where there are no clear theoretical predictions. We similarly find that the effect of insurance is larger for jobs involving customer interactions, with no clear differences in the effects of performance or criminal history screening.

### 5. Objective Performance Information

The final policy we consider is providing hiring managers with objective information about the average performance of WCs on the Platform in an effort to correct mistaken perceptions about the productivity and risk of WCs. We first describe the misperceptions of hiring managers, we then measure the effect of providing objective information on hiring managers' beliefs, and finally, we examine the effects on hiring decisions.

#### 5.1. Correcting Misperceptions in Beliefs

Panels A and B of Figure 8 plot the distribution of prior beliefs and posterior beliefs following the provision of the objective information, with both sets of beliefs elicited using the incentive-compatible guessing game described above. The solid lines show posterior beliefs for the respondents who were shown objective information about WC performance. The dashed lines show the prior beliefs of these same participants. The vertical dash-dotted lines show the true average performance of WCs on the Platform.

Prior beliefs about the performance of WCs vary substantially, but on average, hiring managers underestimate the likelihood of a WC earning a 5-star rating by 12% and overestimate the likelihood of a low-performance rating by 16%. These mistaken and pessimistic beliefs are consistent with businesses incorrectly using a criminal record as a signal of lower average productivity and higher

average downside risk, creating the potential for more explicit performance information to replace WC status signals.

Providing objective information about the average performance of WCs on the Platform led participants to update their beliefs toward the truth, as indicated graphically by the compression of posterior beliefs around the truth in Figure 8. On average, treated participants shifted their beliefs downwards about the likelihood of receiving a no-show or low rating by 5.4 percentage points (31%, 0.25 standard deviations) and upwards about the likelihood of receiving a 5-star rating by 6.7 percentage points (9%, 0.35 standard deviations).

## 5.2. Revisions in Hiring

Panels C and D of Figure 8 plot the fraction of businesses that are willing to work with WCs by the effective wage before and after the provision of objective performance information. We also report the average difference in willingness to work with WCs after the provision of objective performance information, representing the reduced form effect of the information treatment. We estimate these reduced form effects using a version of the regression specification (2) described above.<sup>18</sup>

Providing information about the share of high-performance ratings increases hiring by a statistically significant 10.5 percentage points, which is approximately equivalent to the effect of a 50% wage subsidy. The 10.5 percentage point effect is also only slightly less than that of providing \$5,000 of insurance or of requiring WCs to have successfully completed at least 1 prior job.

By comparison, providing information about the share of low-performance ratings only increases the share of businesses willing to work with WCs by a statistically insignificant 3.3 percentage points. The muted effect of low-performance ratings, which primarily reflect no-shows, suggests that businesses are less concerned with no-shows when deciding whether to work with WCs and more concerned that WCs might not meet their performance standards. This is consistent with the view that some businesses view WCs as less productive on average than otherwise similar non-WCs.

## 6. Threats to Validity

In this section, we describe how the details of the experimental design and setting may affect the interpretation of our results.

### 6.1. Social Desirability Bias

One important consideration is that hiring managers may express interest in hiring WCs out of a desire to appear socially conscious. The *ex-ante* incentive-compatible structure of our experiment

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<sup>18</sup>In Appendix B, we measure the effect of correcting misperceptions in beliefs by exploiting the interaction of cross-business variation in prior beliefs and our randomized information intervention. We find that for an information shock that raises the business’s beliefs about performance by 10%, willingness to hire WCs rises by 15%, implying a hiring elasticity of 1.5 with respect to beliefs about performance. In settings where the intervention to shift beliefs differs considerably from ours, this elasticity may be more helpful than our reduced form estimates in approximating the effect on hiring outcomes.

and the fact that hiring managers were not aware that they were part of a research study directly addresses this concern. Our study is based on businesses making real, high-stakes choices. From a participating hiring manager’s perspective, the Platform—to whom they had ceded discretion over circulating their posted jobs—was asking direct questions about whether their business would allow WCs to accept their jobs. The hiring managers were also not aware that they were part of a research study at any point during the outreach or experiment. There is therefore no reason for the hiring managers to express interest in hiring WCs other than if they are actually interested in allowing WCs to match to their jobs.

## 6.2. Screening Expectations

A second consideration is that hiring managers could have mistakenly assumed that WCs on the Platform would be pre-screened in some way. This concern is alleviated by the fact that we asked the direct question about whether businesses would allow WCs to perform their jobs twice, once at the start of the experiment and again at the end of the experiment. In between these two questions, hiring managers were asked to consider WCs who were convicted of specific crimes, ranging from substance-related misdemeanors to violent felonies. As a result, it was likely very clear that the pool of WCs included individuals convicted of more serious crimes. Yet, 85% of hiring managers that did not receive performance information gave the same answer to the direct questions about whether businesses would allow WCs to perform their jobs. The consistency of the answers at the start and end of the experiment suggests that mistaken beliefs about screening cannot explain our results, as well as any concerns about measurement error from participants who may not have been paying full attention.

## 6.3. Multiple Hypothesis Testing

A third consideration is that we are detecting false positives due to multiple hypothesis-testing, i.e., that many of our results are statistically significant due to chance alone. To control for the family-wise error rate, defined as the probability of making one or more false discoveries when performing multiple hypothesis tests, we employ a step-down algorithm similar to those described by Westfall and Young (1993). For a given family of  $k$ -hypothesis tests, the algorithm uses a step-down procedure that employ permutation calculations to estimate dependence relationships and provide corrected p-values. Westfall-Young adjusted p-values calculated using 10,000 bootstrap samples are reported in brackets in Appendix Table A.5 for the mean effect of each level of each policy (e.g., \$5k insurance or 1 completed job) across all subsidy levels as compared to the baseline or to an omitted group. The adjusted p-values are calculated based on families of hypotheses grouped by each panel. For the adjusted p-values in Panel A, the family of 10 hypotheses include 5 for the mean effect of crime and safety insurance and 5 for the mean effect of performance history. For the adjusted p-values in Panel B, the family of 16 hypotheses include 5 for the mean effect of years since arrest or conviction and 11 for the mean effect of restrictions based on crime type. The adjusted p-values for the mean effect of requiring at least 1 year since arrest or conviction relative to the baseline and

for the mean effect of requiring the completion of at least 1 previous job relative to the baseline are 0.055. However, our main findings are qualitatively the same and the adjusted p-values for all the other mean effects relative to the baseline are statistically significant at the 5% level.

## 6.4. External Validity

A final and more general consideration is the external validity of our estimates. The setting for our study is a leading online labor platform that thousands of traditional businesses use to source workers for temporary staffing across a wide range of entry-level roles. We expected this setting to offer a large and concentrated pool of appropriate jobs for WCs re-entering the workplace. When extrapolating to other settings, it is important to keep in mind that the demand for WCs may be very different for permanent positions or more senior roles. While we believe the jobs offered through the Platform often convert to longer term work based on the high share of repeat hires (e.g., over 54% of workers paired with a business once through the Platform will return to a job at the same business), the Platform does not track long-term outcomes. We also cannot speak to the evolution of demand after businesses gain experience working with WCs or over the business cycle. Finally, our finding that the level of customer interactions and presence of high-value inventory affect demand for WCs suggests that role-specific traits are meaningfully correlated with demand and must be taken into consideration when extrapolating to other settings.

To partially explore these issues, Appendix Figure A.4 shows results where we (1) restrict our sample to firms with information on firm size, industry type, and WC hiring policies; (2) weight observations to more closely match the distribution of firms in the U.S. economy based on industry and firm size; and (3) weight observations to more closely match the distribution of answers to nationwide responses to SHRM questions about attitudes and policies in place with respect to WCs. We weight observations using the iterative proportional fitting (IPF) algorithm following Deming and Stephan (1940) to adjust for consistency with the marginal distributions of industry shares and firm sizes and then WC hiring policies. The weights were calculated through stepwise adjustment and was repeated for 50 iterations using the implementation of the IPF algorithm developed by Bergmann (2011). Our results are qualitatively unchanged across these conditions, with slightly lower demand for WCs in both our restricted sample and our reweighted samples. For example, we find that 35% to 40% of businesses are willing to work with WCs in our baseline case with no wage subsidy when we reweight our sample, compared to 39% in the full unweighted sample and 35% in the restricted unweighted sample. In unreported results, we similarly find that the demand elasticities range from 0.22 to 0.25 when we reweight our sample, compared to 0.21 in the full unweighted sample and 0.19 in the restricted unweighted sample.

## 7. Conclusion

This paper uses information from a discrete choice field experiment on a nationwide staffing platform to test several approaches to increasing the demand for WCs, each of which is intended to directly

address a potential underlying reason that employers choose to conduct criminal background checks. We find that 39% of businesses on the Platform are willing to work with WCs at baseline, with higher levels of demand for jobs that do not involve customer interactions or high-value inventory and when the Platform is having a hard time filling a job. The level of demand also increases to 50% or higher when businesses are offered a modest level of crime and safety insurance, a single performance review, screening of the most recent criminal records, or objective information about the productivity of WCs. All of our results suggest that policymakers may affect WC demand by directly addressing the underlying reasons that employers choose to conduct background checks, rather than simply prohibiting or delaying questions about job applicants' arrest and conviction record during the hiring process.

An important open question is whether these alternative approaches are more cost-effective than wage subsidies, which can achieve similar gains at high enough subsidy levels. While a comprehensive cost comparison is beyond the scope of this paper, we can calculate the direct costs of increasing the demand for WCs for each of our main treatments under reasonable assumptions. These calculations reveal that all of these policies can significantly increase demand for WCs at a fraction of the cost of wage subsidies. Performance screening, for example, can achieve notable gains in the share of businesses willing to work with WCs at near-zero cost because a large number of businesses are willing to work with and provide WCs with their first performance review, opening the door to businesses that highly value that first positive review. Providing objective information on the average productivity of WCs can similarly increase the share of businesses hiring WCs at essentially zero additional cost to the Platform. Revising background check matrices to only exclude candidates with the most recent criminal records requires no new costs for the Platform. Finally, we calculate that crime and safety insurance can increase the demand for WCs at one-half to one-tenth the cost of wage subsidies under realistic assumptions of the probability of damages due to WC misbehavior.<sup>19</sup> These calculations suggest that all of the options we consider are substantially more cost-effective than wage subsidies, at least in this context.

Based on the findings from our study, the Platform is changing its user interface nationwide. Businesses that join after the close of our experiment will also have the option to allow WCs accept their jobs, with crime and safety insurance coverage provided by the Platform. To date, demand from our study participants combined with the permanent policy changes made following the result of our experiment led to over 12,000 jobs being made available to WCs through August 2021. This rapid expansion in the number of jobs available to WCs opens new questions for future research, including the evolution of demand as businesses gain experience working with WCs and the long-term employment opportunities created for WCs that accept jobs on the Platform.

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<sup>19</sup>For example, increasing the number of businesses willing to work with WCs by approximately 10% would require a 50% wage subsidy. Using a typical Platform wage of \$15 per hour, the subsidy approach would thus cost \$60 per worker per day. Providing a \$5,000 crime and safety insurance policy could also increase WC demand by approximately 10%. Assuming that WCs have either a 1 in 1,000 or 1 in 200 daily chance of incurring \$5,000 in damages, this insurance policy would thus have an expected cost of \$5 to \$25 per worker per day.



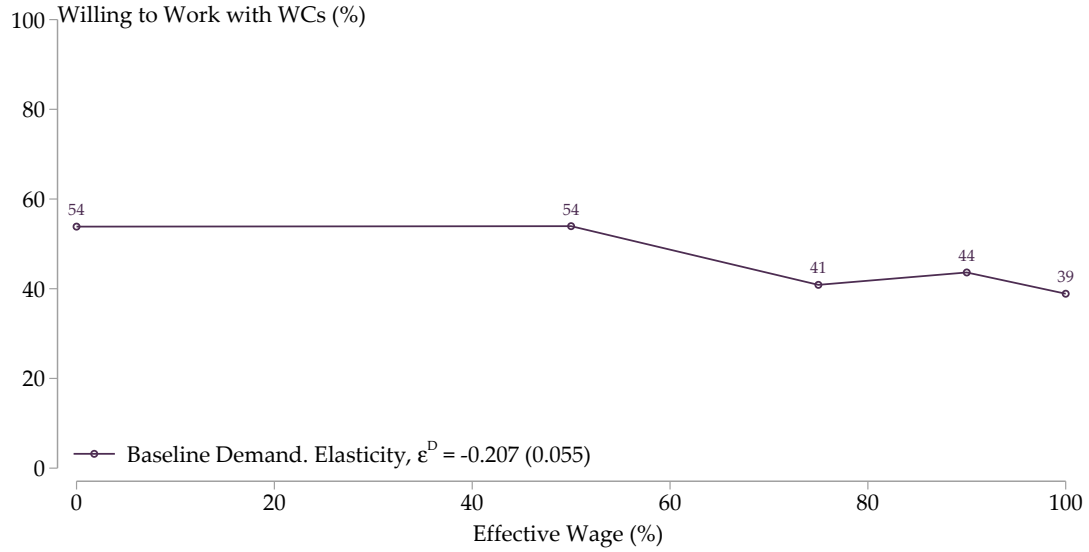
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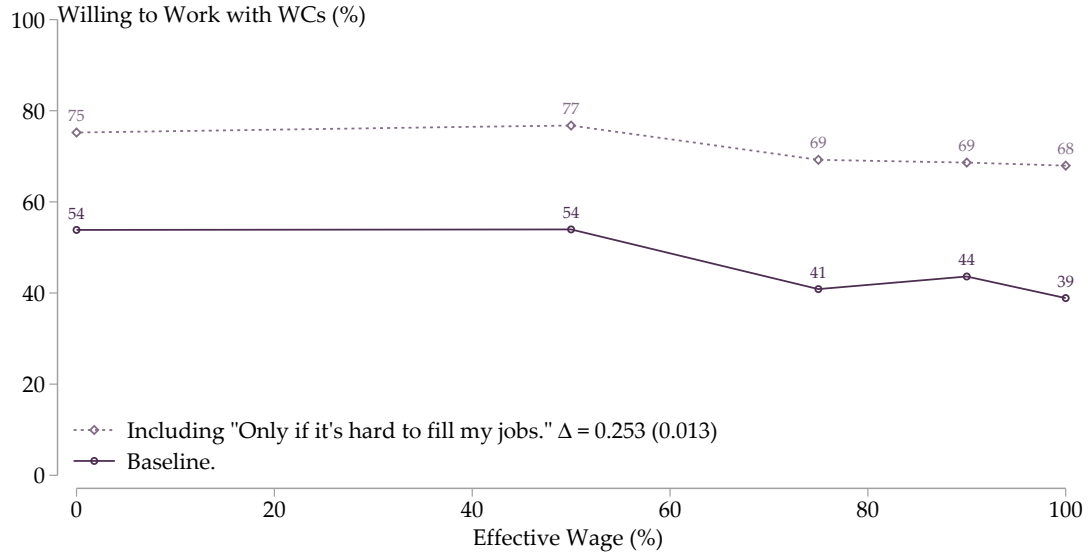
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Figure 1: Labor Demand for Workers with a Criminal Record



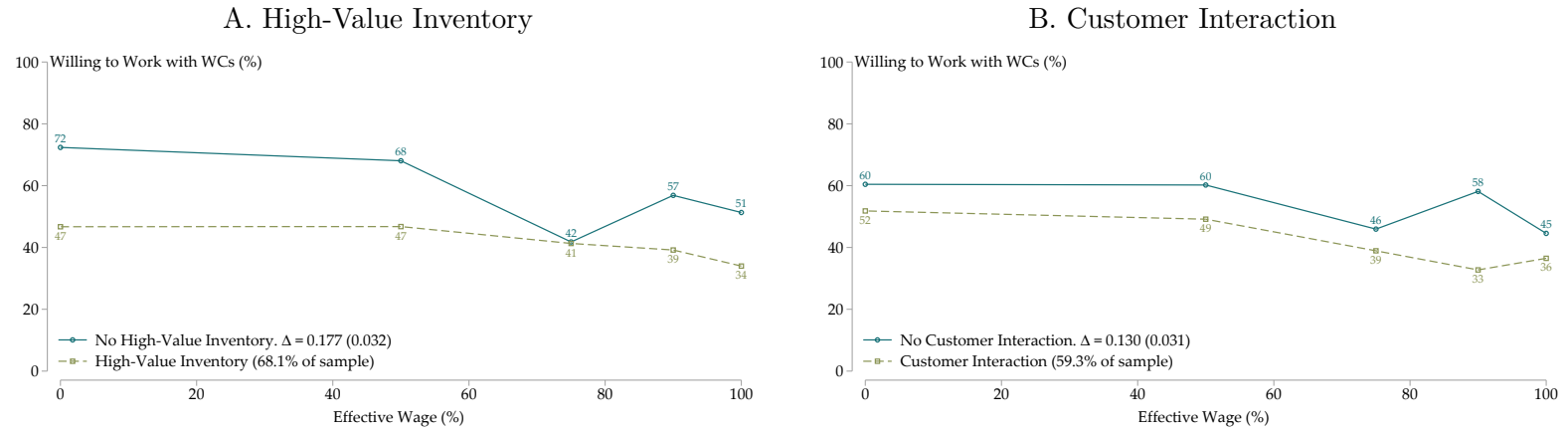
*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The effective wage is calculated as the share of the wage remaining after the subsidy is applied, or  $100 - \text{subsidy rate}$ . Respondents are asked if they are willing to work with a WC with this wage subsidy and can answer “Yes,” “Only if it’s hard to fill my jobs,” or “No.” We report results including only those who answer “Yes” as willing to work with WCs. This is our baseline definition of willingness to work with WCs that we use throughout. We also report the baseline labor demand elasticity estimated using the regression described in text. The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Column 1 of Appendix Table A.2.

Figure 2: Heterogeneity in Labor Market Conditions



*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The effective wage is calculated as the share of the wage remaining after the subsidy is applied, or  $100 - \text{subsidy rate}$ . Respondents are asked if they are willing to work with a WC with this wage subsidy and can answer “Yes,” “Only if it’s hard to fill my jobs,” or “No.” The solid line reports results including only those who answer “Yes” as willing to work with WCs. The dotted line reports results including respondents who answer “Yes” or “Only if it’s hard to fill my jobs” as willing to work with WCs.  $\Delta$  is the mean difference between the baseline series and the series that includes respondents selecting “Only if it’s hard to fill my jobs.” The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Columns 1 and 2 of Appendix Table A.2.

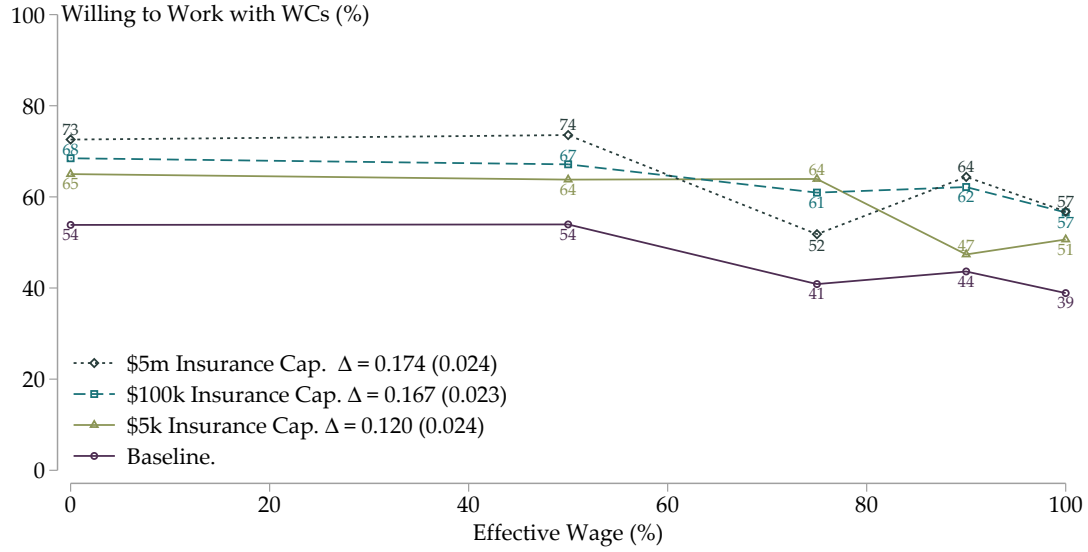
Figure 3: Heterogeneity by Job Characteristics



*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. Panel A reports results separately for businesses who report that their jobs do or do not involve high-value inventory. Panel B reports results separately for businesses who report that their jobs do or do not involve customer interaction. In each panel, we report an estimate of the mean difference  $\Delta$  between the two demand curves. The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Columns 5-6 (Panel A) and 3-4 (Panel B) of Appendix Table A.2.

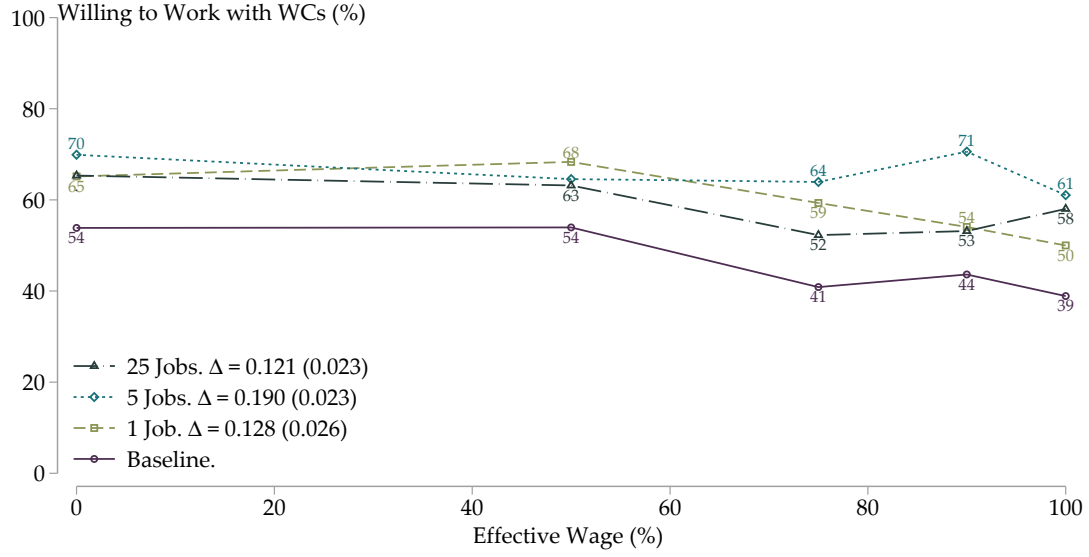


Figure 4: Crime and Safety Insurance



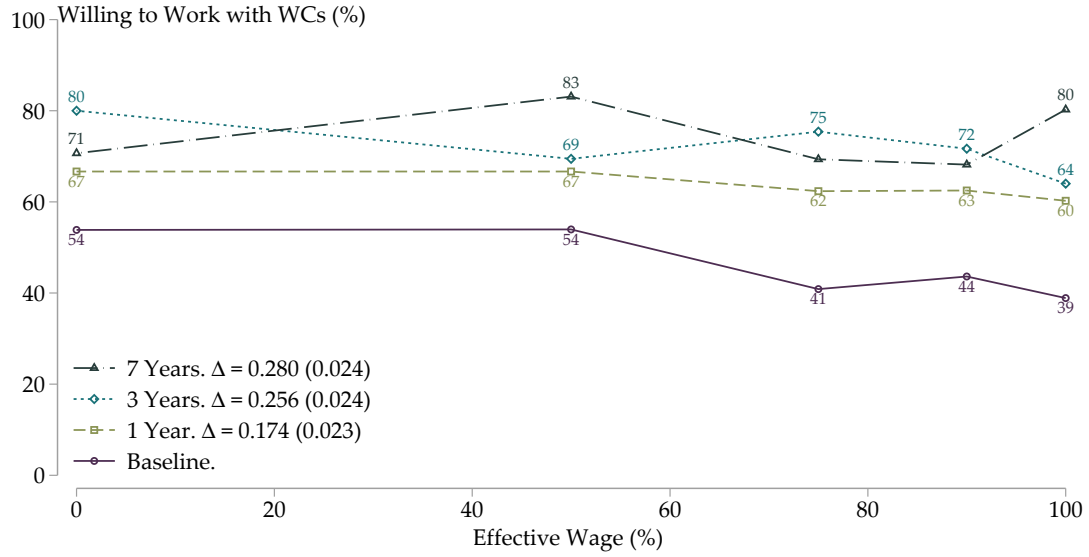
*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The solid baseline curve displays baseline hiring rates shown in Figure 1. The three upper curves display the effect of the Platform providing a crime and safety insurance policy that covers damages up to \$5,000, \$100,000, or \$5 million. The  $\Delta$  values estimate the mean effect of each level of insurance across subsidy levels compared to the baseline. The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Columns 1-4 of Panel A of Appendix Table A.5.

Figure 5: Screening Based on Performance History



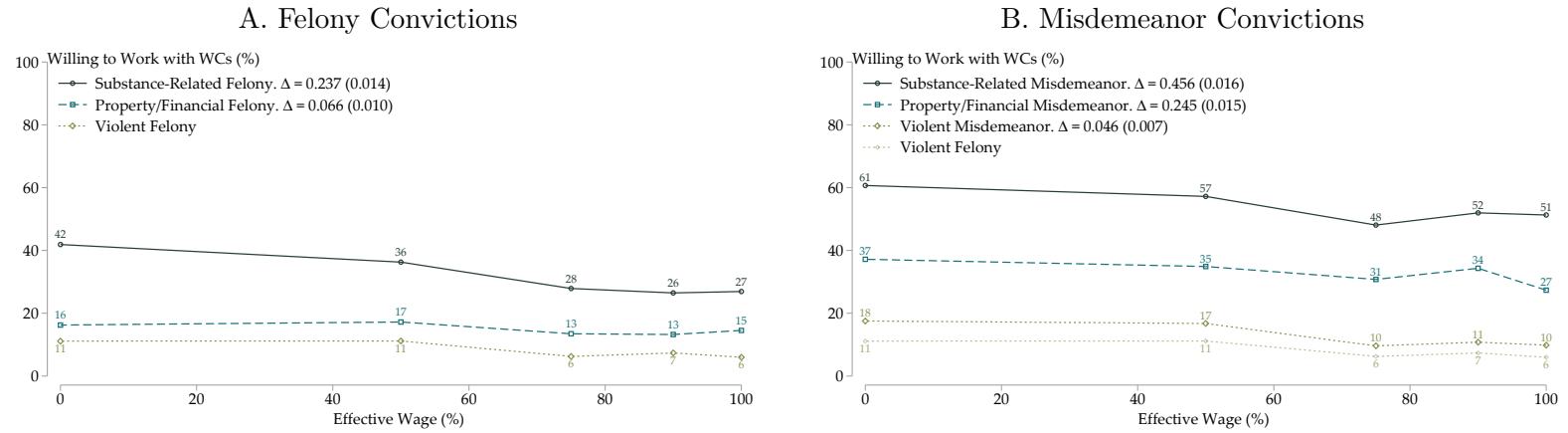
*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The solid baseline curve displays baseline hiring rates shown in Figure 1. The three upper curves display the effect of the individual having satisfactorily completed either 1, 5, or 25 previous jobs on the platform. The  $\Delta$  values estimate the mean effect of screening by each number of completed jobs compared to the baseline. The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Columns 1 and 5-7 of Panel A of Appendix Table A.5.

Figure 6: Screening Based on Years Since Most Recent Arrest or Conviction



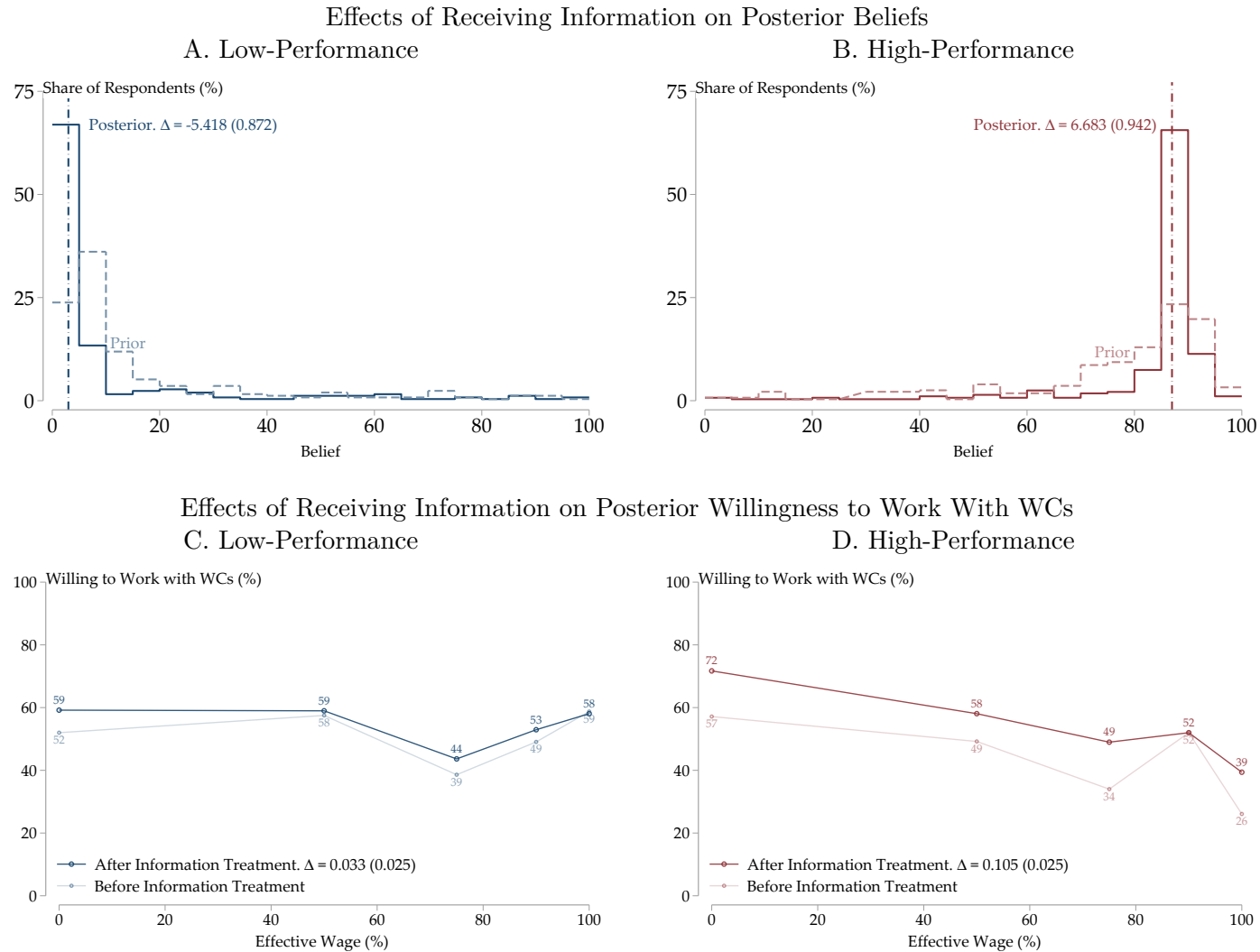
*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The solid baseline curve displays baseline hiring rates shown in Figure 1. The three upper curves display the effect of it having been 1, 3, or 7 years since the individual was most recently arrested or convicted. The  $\Delta$  values estimate the mean effects of screening on the numbers of years since arrest or conviction compared to the baseline. The estimates are based on the experimental sample described in Table 2. The sample includes 1,095 managers from 913 businesses. Point estimates are reported in Columns 1-4 of Panel B of Appendix Table A.5.

Figure 7: Screening Based on Conviction Type



*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage, given the specific conviction type and severity. Panel A plots willingness to work with WCs who have a substance-related felony, a property/financial related felony, or a violent felony. Panel B plots willingness to work with WCs who have a substance-related misdemeanor, a property/financial related misdemeanor, or a violent misdemeanor. The bottom dotted line in Panel B re-plots the estimates for violent felonies. The  $\Delta$  values estimate the mean difference between demand for each crime type relative to the violent felony crime type. The sample includes 1,095 managers from 913 businesses. The estimates are based on the experimental sample described in Table 2. Point estimates are reported for Panel A in Columns 5-7 and for Panel B in Columns 8-10 of Appendix Table A.5.

Figure 8: Objective Performance Information



*Notes.* Panels A and B report the posterior belief distributions about WC performance for respondents who were shown objective information about WC performance and for the control group. In these panels,  $\Delta$  values estimate the mean difference between the posterior and the prior beliefs for the subset that were shown information. Panels C and D report the baseline demand for WCs and the demand after receiving the information treatment only for the respondents who were shown objective information about WC productivity. In these panels,  $\Delta$  values estimate the mean difference between demand before and after receiving the information treatment. These estimates are based on the subset of 550 managers from 467 businesses who were shown the objective information. Appendix Figure A.5 presents the prior belief distributions.

Table 1: Description of Main Treatments

Treatment Name	Survey Question	Values
Wage Subsidy	If the [Platform] gave you a [Wage Subsidy] discount for [Platform Workers] with a criminal record, would you permit such [Workers] to perform jobs you post? This means you would only pay (100 - [Wage Subsidy]) of the wage for those with a criminal record.	0%; 5%; 10%; 25%; 50%; 100%
Crime and Safety Insurance	If the [Platform] could cover damages up to [Crime and Safety Insurance Cap] related to theft or safety incurred by workers with a criminal record, would you permit such [Workers] to perform jobs you post?	\$1k; \$5k; \$100k; \$5m
Performance History	If the [Platform] required [Platform Workers] with a criminal record to have satisfactorily completed [Performance History] job(s), receiving >85% positive reviews (5 stars), would you permit such [Workers] to perform jobs you post?	1 job; 5 jobs; 25 jobs
Clean Record Length	If the [Platform] required users with a criminal record to have maintained a clean record for at least [Clean Record Length] would you permit such users to perform jobs you post?	1 year; 3 years; 7 years
Conviction Type	Please indicate whether you would permit [Platform Workers] with these types of convictions to perform jobs you post. The [Platform] would still give you a [Wage Subsidy] discount, but no other supplementary policies would apply.	Felony; Misdemeanor; Violent; Substance-Related; Property/Financial
Objective Performance Information	The truth is that [Share]% of jobs completed by people with a criminal record resulted in a [Rating] on the same or a similar platform—actually better than everyone else.	Share: 13%; 87% Rating: no-show or a low rating; 5-star rating

*Notes.* This table summarizes the main experimental treatments. Black text in square brackets is redacted information identifying the Platform. Blue text in square brackets is a placeholder for the randomized values of each treatment.

Table 2: Descriptive Statistics

	Experimental Sample	Infogroup Database
<b>A. Firm Characteristics</b>		
Median Firm Age	19.0	16.0
Median Number of Employees	40	2.5
Service	0.31	0.37
Manufacturing	0.19	0.06
Retail	0.15	0.21
Public Administration	0.10	0.02
Transportation & Public Utilities	0.10	0.03
Wholesale Trade	0.09	0.08
Finance, Insurance, & Real Estate	0.03	0.07
Construction	0.01	0.08
Nonclassifiable	0.01	0.08
Firms with Nonmissing Age and Number Employees	666	3,260,733
with Nonmissing Industry Classification	518	1,245,145
<b>B. Hiring Policies and Views</b>		
	Experimental Sample	SHRM Survey
Firm-Wide WC Hiring Policy	0.45	0.66
Consider WCs Because Best Candidate	0.46	0.53
Consider WCs Because Second Chances Are Important	0.50	0.38
Consider WCs Because of Financial Incentives	0.08	0.02
Concerned About Customer Reactions	0.49	0.30
Concerned About Local, State, or Federal Regulations	0.26	0.22
Concerned About Performance	0.15	0.04
Firms with Nonmissing Hiring Policy Information	900	1,228

*Notes.* This table reports descriptive statistics for the experimental sample comprised of the 1,095 hiring managers from 913 businesses that completed the experiment. Panel A reports statistics for the 913 firms in our sample matched to the Infogroup Historical Business Database (column 1) and all firms in the Infogroup Historical Business Database (column 2), which contains basic profile data for more than a million U.S. businesses. The industry characteristics are further limited to the 518 firms in our sample with that data available in the Infogroup Database. Panel B reports information on WC hiring policies, where information for the broader set of U.S. businesses comes from a nationwide survey of over 1,000 HR professionals commissioned by the Society for Human Resource Management.



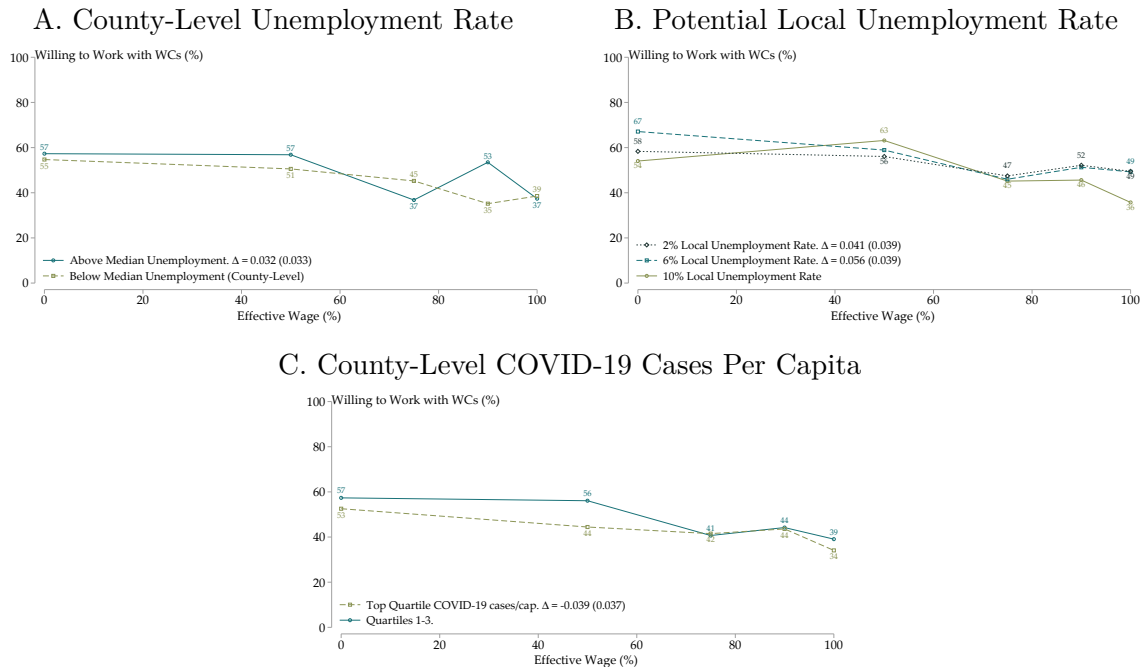
Table 3: Randomization Assessment  
p-values from Regressions of Covariates on Treatment Indicators

	Wage Subsidy	Crime Insurance	Performance History	Clean Record	Unemp. Rate	Shown Info.
A. Firm Characteristics and Policies						
Firm Age	0.291	0.646	0.407	0.268	0.271	0.347
Employees	0.257	0.858	0.099	0.009	0.613	0.424
Service	0.240	0.956	0.576	0.287	0.286	0.711
Manufacturing	0.045	0.277	0.949	0.877	0.269	0.386
Retail	0.393	0.138	0.036	0.684	0.873	0.231
Transportation & Public Utilities	0.691	0.908	0.625	0.434	0.765	0.988
Nonclassifiable & Misc. Industries	0.494	0.454	0.697	0.552	0.937	0.261
Firm-Wide WC Hiring Policy	0.779	0.673	0.728	0.513	0.491	0.229
Platform Tenure (Years)	0.099	0.075	0.602	0.518	0.224	0.947
Job Vacancy Rate	0.707	0.811	0.301	0.463	0.828	0.931
B. Firm Characteristics and Policies						
Job Involves Customer Interactions	0.675	0.595	0.429	0.356	0.628	0.710
Job Involves High-Value Inventory	0.277	0.450	0.242	0.531	0.467	0.437
Modal Job is Fulfillment / Warehousing	0.600	0.779	0.622	0.325	0.246	0.296
Modal Job is General Labor	0.004	0.102	0.738	0.654	0.303	0.148
Modal Job is Event Staff	0.463	0.881	0.617	0.357	0.710	0.781
Modal Job is Delivery	0.816	0.060	0.423	0.911	0.338	0.915
Modal Job is Washing & Cleaning	0.577	0.918	0.784	0.121	0.359	0.919
Firms	913	913	913	913	913	913
Managers	1,095	1,095	1,095	1,095	1,095	1,095

*Notes.* This table reports balance tests for the estimation sample described in Table 2. Each cell reports the p-value of an F-statistic from a separate regression of the baseline covariates listed in the rows on indicator variables for each value of the treatments listed in the columns. Standard errors are clustered at the firm level. Nonclassifiable & Misc. Industries is an aggregation of Nonclassifiable, Construction, Finance, Public Administration, and Wholesale Trade industries. See the Table 2 notes for additional details on the outcomes and sample.

## Appendix A. Additional Results

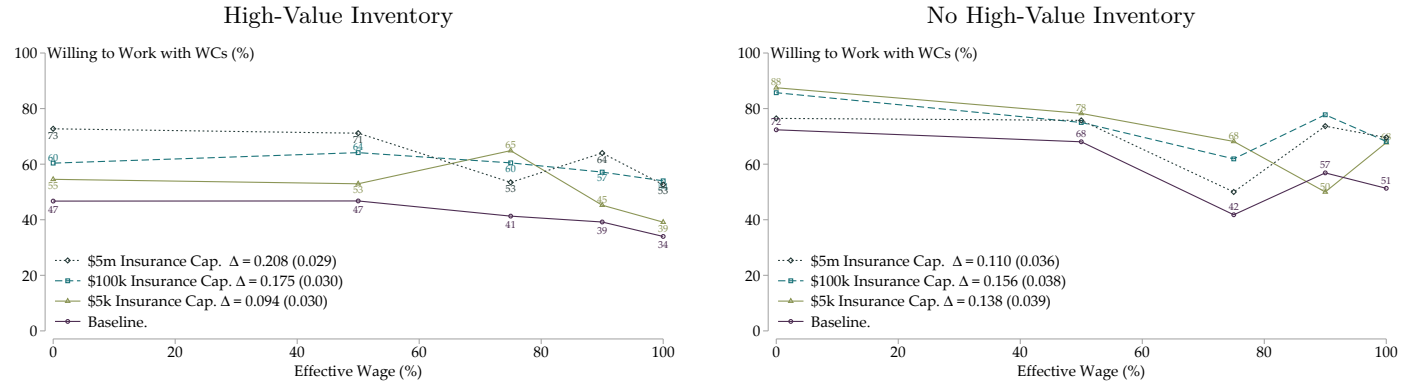
Appendix Figure A.1: Labor Market Conditions and COVID-19 Prevalence



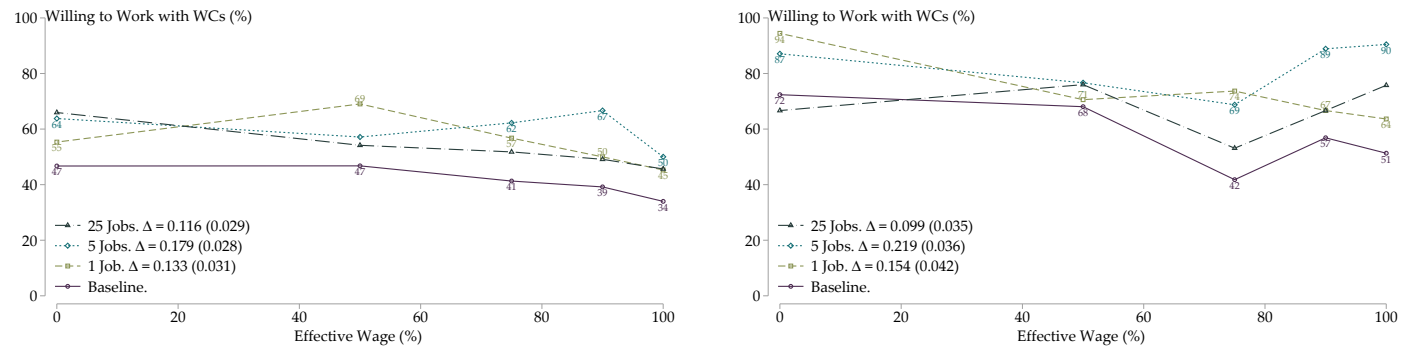
*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. Panel A splits respondents into above-median and below-median groups based on March 2020 unemployment rates in the business's county. The  $\Delta$  in Panel A represents the average difference between the two curves. Panel B reports willingness to work with under a randomly assigned potential local unemployment rate of 2, 6, or 10%. The  $\Delta$  in Panel B represents the average impact of the 2 or 6% unemployment rate compared to the 10% unemployment rate. Panel C reports results split based on county level COVID-19 prevalence in March, 2020 when the experiment was distributed. The solid line represents businesses whose county was in the top quartile of COVID-19 rates, and the dotted line represents businesses whose county was in the bottom three quartiles of COVID rates. The estimates in Panels A and B are based on the experimental sample described in Table 2. This sample includes 1,095 managers from 913 businesses. The estimates in Panel C exclude 62 observations from New York City counties due to data constraints.

Appendix Figure A.2: Heterogeneity in Treatment Effects, High-Value Inventory

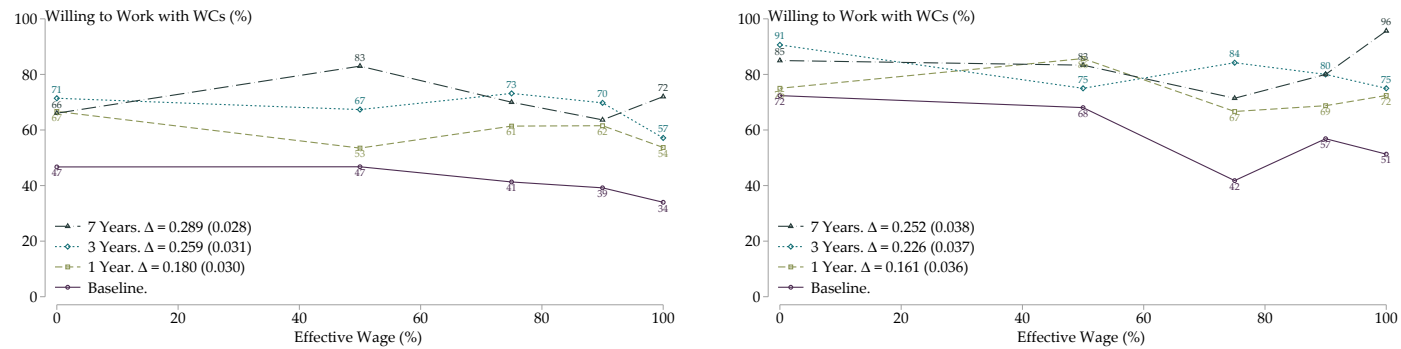
A. Crime and Safety Insurance



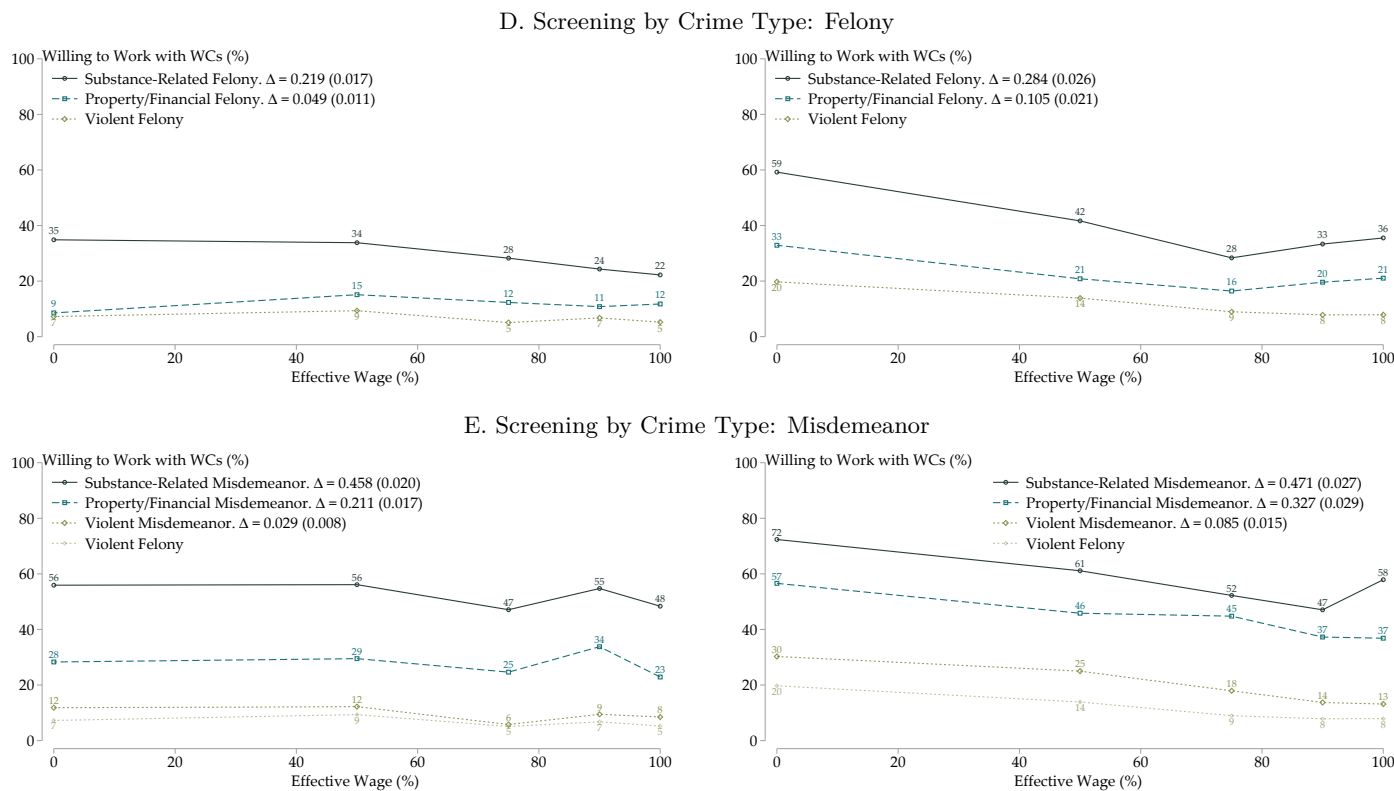
B. Performance History



C. Screening by Years since Most Recent Arrest or Conviction



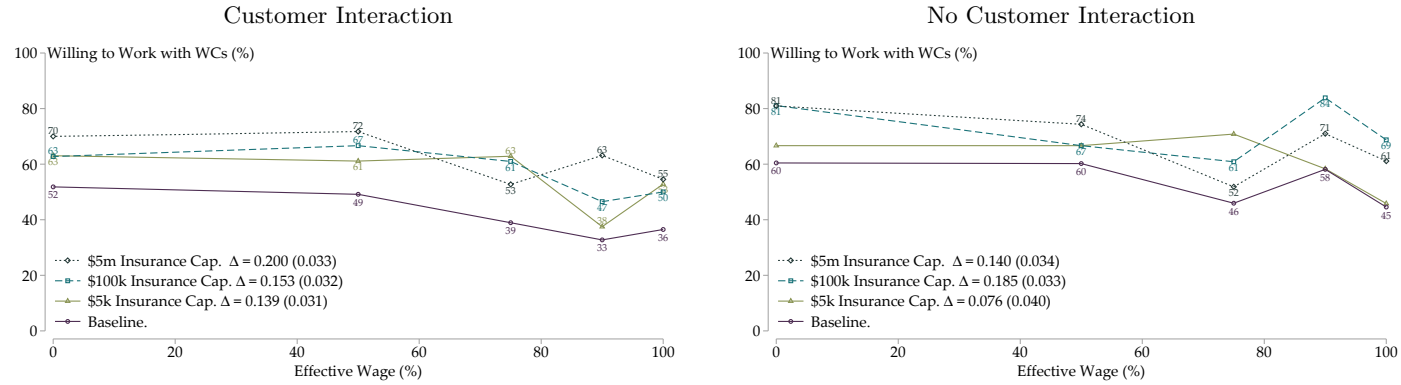
Appendix Figure A.2: Heterogeneity in Treatment Effects, High-Value Inventory



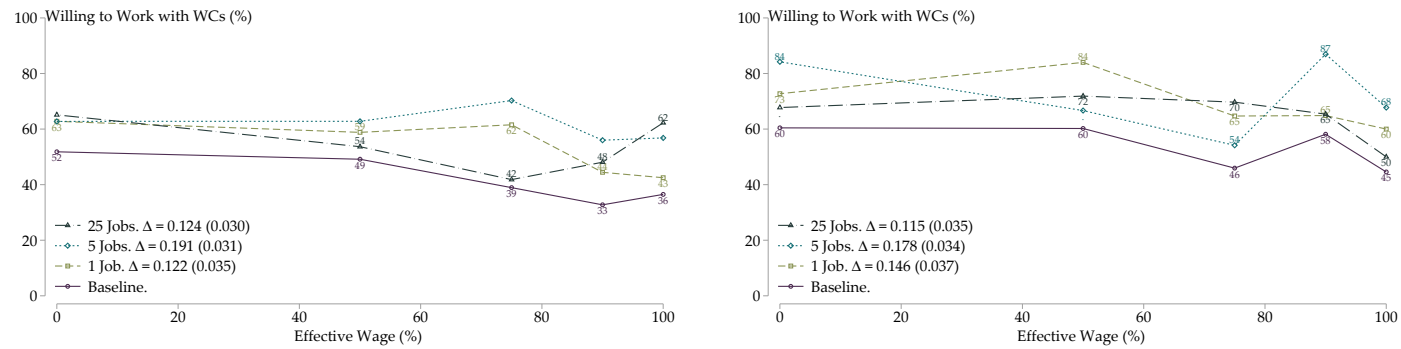
*Notes.* This figure plots the differential effects of several policies on mean willingness to WCs against the randomized effective wage, split by whether businesses report that their jobs involve customer interaction. The left-hand graph in each panel presents mean willingness to work with WCs for the 68.1% of our sample that reports that their jobs involve high-value inventory. The right-hand graph in each panel presents mean willingness to work with WCs for the 31.9% of our sample whose jobs do not involve high-value inventory. In Panels A, B, and C,  $\Delta$  represents the mean effect of each level of each policy (e.g., \$5k insurance or 1 completed job) across all subsidy levels as compared to the baseline. In Panels D and E,  $\Delta$  represents the mean difference between demand for each crime type relative to the violent felony crime type.

Appendix Figure A.3: Heterogeneity in Treatment Effects, Customer Interaction

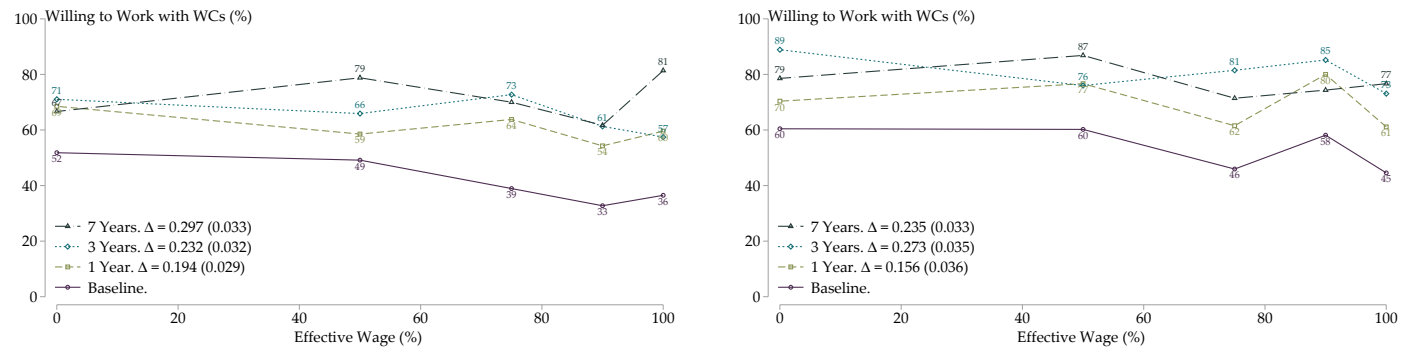
A. Crime and Safety Insurance



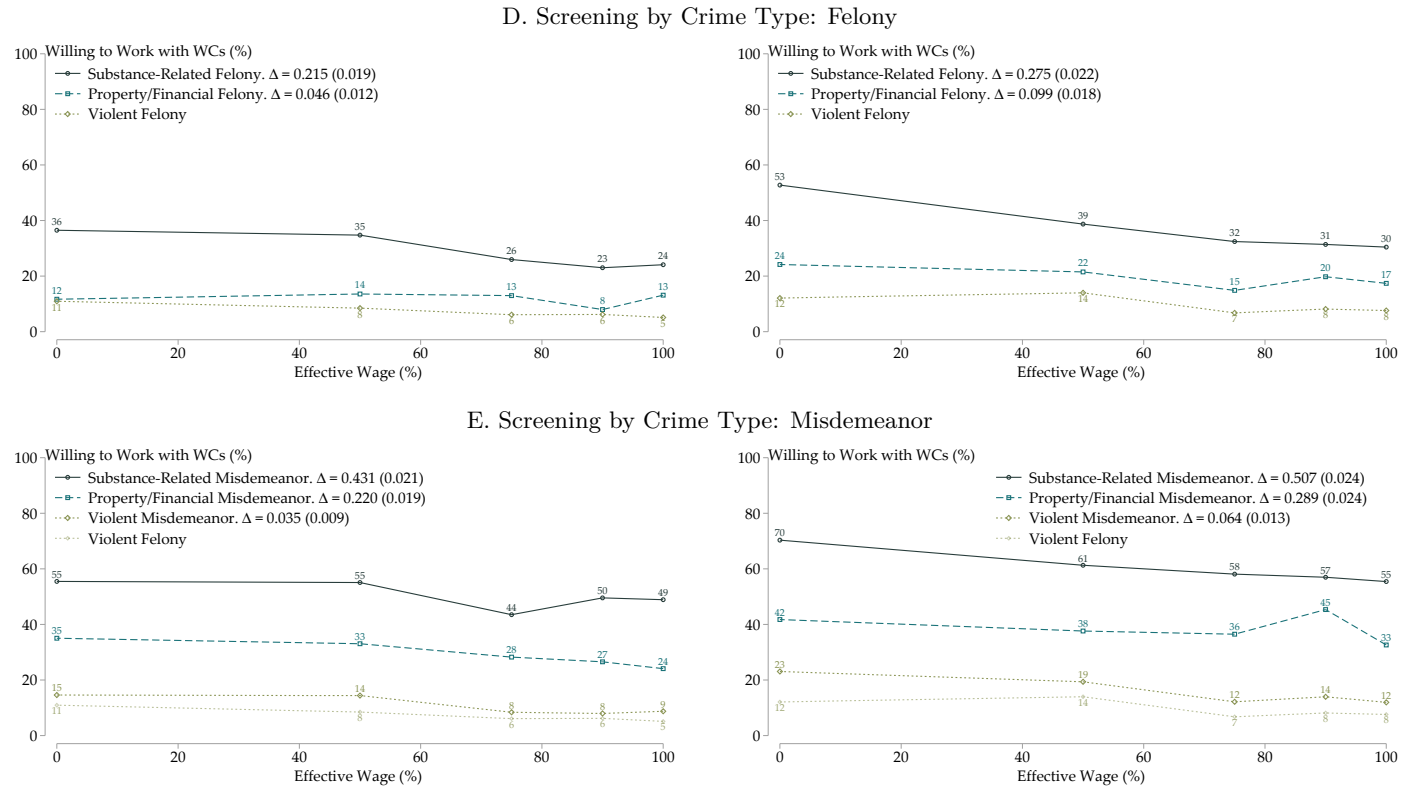
B. Performance History



C. Screening by Years since Most Recent Arrest or Conviction

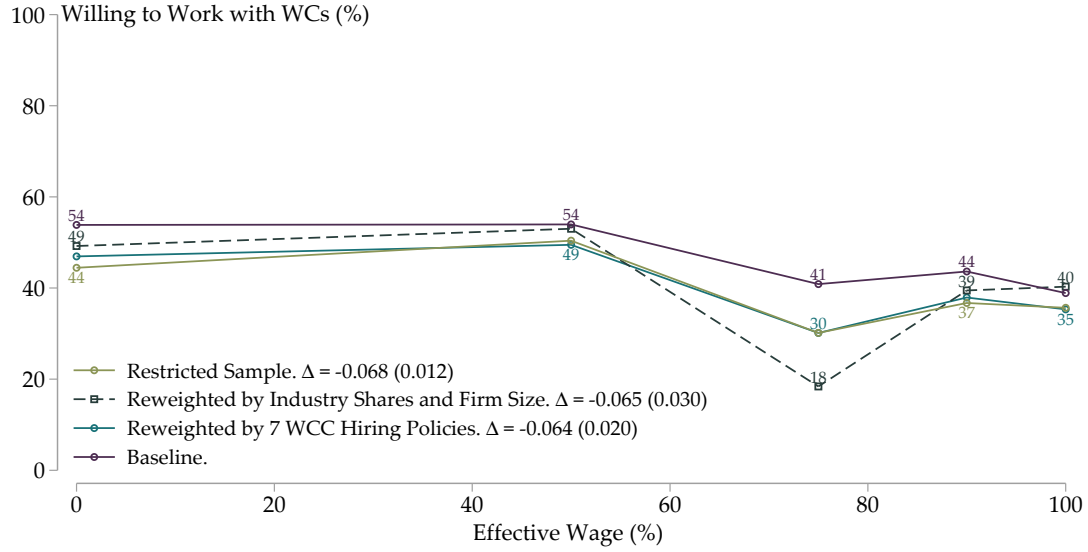


Appendix Figure A.3: Heterogeneity in Treatment Effects, Customer Interaction



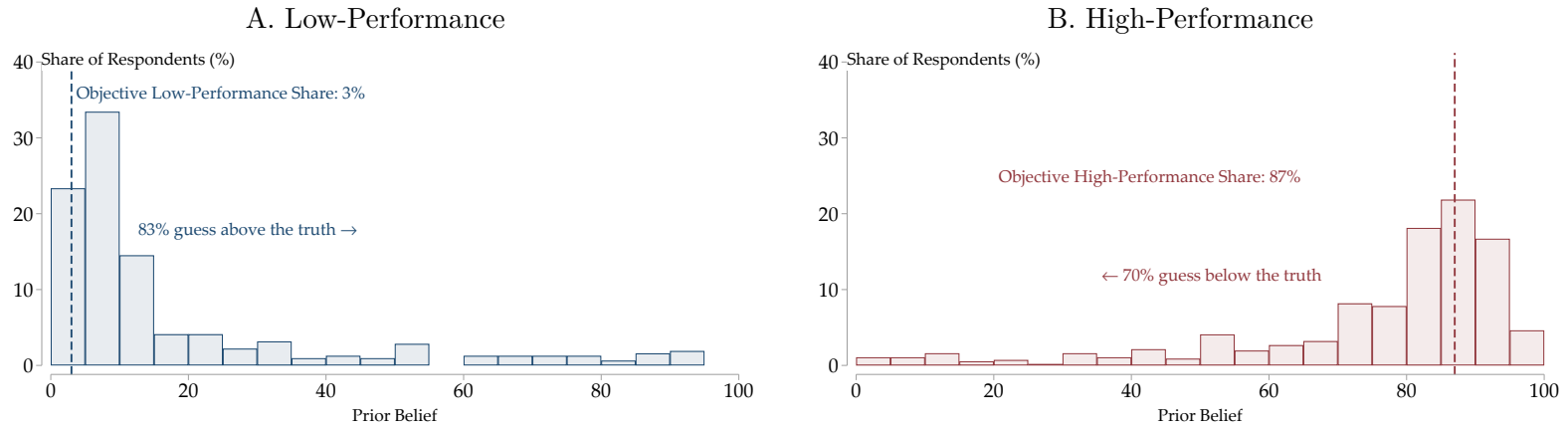
*Notes.* This figure plots the differential effects of several policies on mean willingness to work with WCs against the randomized effective wage, split by whether businesses report that their jobs involve high-value inventory. The left-hand graph in each panel presents mean willingness to work with for the 59.3% of our sample that reports that their jobs involve customer interaction. The right-hand graph in each panel presents mean willingness to work with for the 40.7% of our sample whose jobs do not involve customer interaction. In Panels A, B, and C,  $\Delta$  represents the mean effect of each level of each policy (e.g., \$5k insurance or 1 completed job) across all subsidy levels as compared to the baseline. In Panels D and E,  $\Delta$  represents the mean difference between demand for each crime type relative to the violent felony crime type.

Appendix Figure A.4: Labor Demand for Workers with a Criminal Record, Reweighted Results



*Notes.* This figure plots mean willingness to work with WCs against the randomized effective wage. The solid baseline curve on top displays baseline hiring rates shown in Figure 1 and is based on the entire sample that includes 1,095 managers from 913 businesses described in Table 2. The lower three curves display the hiring rates for the 668 managers from 506 firms in the sample for which variables for firm size, industry type, and WC hiring policies are nonmissing. The solid green curve displays the baseline hiring rates across different effect wages for the subset with 668 managers. The dashed curve displays the hiring rates across different effect wages after reweighting the sample based on the Infogroup Database industry shares we report in Table 2. The solid blue curve displays the hiring rates across different effective wages after reweighting the sample to match the marginal distributions of the 7 WC hiring policies from the nationwide survey commissioned by the Survey for Human Resource Management that we report in Table 2. We weight observations using the iterative proportional fitting (IPF) algorithm conceived by Deming and Stephan (1940). The weights were calculated through stepwise adjustment and was repeated for 50 iterations using the implementation of the IPF algorithm developed by Bergmann (2011). The  $\Delta$  values estimate the difference between the baseline mean effect and the mean effect calculated using the subset with 668 managers, using the subset reweighted by industry and firm size, and using the subset reweighted by 7 WC hiring policies.

Appendix Figure A.5: Prior Beliefs about WC Productivity



*Notes.* This figure reports the prior distribution of business beliefs about WC productivity for all respondents. Panel A reports the distribution of prior beliefs about the share of WCs who receive low performance ratings (no-shows and either 1- or 2-star ratings). The dotted vertical line indicates the true, objective share of WCs who receive low performance ratings. Panel B reports the distribution of prior beliefs about the share of WCs who receive high-performance ratings (5-star ratings). The dotted vertical line indicates the true, objective share of WCs who receive high-performance ratings. The estimates are based on the experimental sample described in Table 2. This sample includes 1,095 managers from 913 businesses.



Appendix Table A.1: Description of Additional Characteristics

Job Characteristic	Survey Question
Customer Interactions	Do your jobs involve [Platform] users having contact with customers?
High-Value Inventory	At your jobs, is there cash or high-value inventory that [Platform] users could steal?
Hiring Policies	Does your company or organization currently have a hiring policy regarding individuals with a criminal record?
Potential Unemployment Rate	If the unemployment rate were [Unemployment Rate], meaning the local labor market was [ $\mathbf{a} \in \{\text{"doing very well", "doing about average", "not doing so well"}\}$ ] and [ $\mathbf{b} \in \{\text{"a less than typical", "an average", "a more than typical"}\}$ ] share of people were looking for jobs, would you permit [Platform Workers] with a criminal record to perform jobs you post?
Prior High-Performance Beliefs	In 2019, 85% of jobs on the Platform resulted in a 5-star rating. What percentage of jobs completed by people with a criminal record do you think would result in a 5-star rating on the Platform or a similar platform? If your guess is within 5% of the truth, we will send you an additional [bonus] reward!
Prior Low-Performance Beliefs	In 2019, 5 of jobs on the Platform resulted in a no-show or low rating (1 or 2 stars). What percentage of jobs completed by people with a criminal record do you think would result in a no-show or low rating (1 or 2 stars) on the Platform or a similar platform? If your guess is within 5% of the truth, we will send you an additional [bonus] reward!

*Notes.* This table summarizes the main job and firm characteristics used in our analysis, as well as the measure of prior information on WC performance. Black text in square brackets is redacted information identifying the Platform. Blue text in square brackets is a placeholder for the randomized values of each treatment.

Appendix Table A.2: Labor Demand for Workers with a Criminal Record

	Baseline	Including Only If It's Hard to Fill My Jobs"	Customer Interactions	No Customer Interactions	High-Value Inventory	No High-Value Inventory
No Subsidy	0.389 (0.032)	0.679 (0.032)	0.365 (0.042)	0.446 (0.051)	0.340 (0.038)	0.513 (0.055)
10% Subsidy <sup>†</sup>	0.436 (0.037)	0.686 (0.033)	0.327 (0.047)	0.581 (0.054)	0.392 (0.043)	0.569 (0.070)
25% Subsidy	0.409 (0.037)	0.692 (0.035)	0.389 (0.047)	0.459 (0.058)	0.413 (0.048)	0.418 (0.057)
50% Subsidy	0.540 (0.036)	0.767 (0.030)	0.492 (0.047)	0.602 (0.052)	0.468 (0.044)	0.681 (0.053)
100% Subsidy	0.538 (0.032)	0.752 (0.028)	0.518 (0.044)	0.604 (0.050)	0.467 (0.039)	0.724 (0.054)
Elasticity	-0.207 (0.055)	-0.072 (0.032)	-0.247 (0.073)	-0.173 (0.085)	-0.155 (0.067)	-0.323 (0.094)
Mean Effect vs. Baseline	—	0.253 (0.013)	-0.043 (0.021)	0.078 (0.024)	-0.048 (0.019)	0.122 (0.026)
Mean Effect vs. Omitted Group	—	—	—	0.130 (0.031)	—	0.177 (0.032)
Firms	913	913	533	392	614	319
Managers	1,095	1,095	636	436	730	342

*Notes.* This table reports estimates of the effects of wage subsidies on firms' willingness to work with workers with a criminal record. It also reports how these estimates vary across firms with jobs that involve customer interaction or access to high-value inventory. The regressions are estimated on the experimental sample described in Table 2. Column 1 reports the fraction of managers choosing to work with WCs at each subsidy level. We report results including only those who answer 'Yes' as willing to work with WCs. Column 2 also reports this fraction, but now we report results including respondents who answer 'Yes' or 'Only if it's hard to fill my jobs' as willing to work with WCs. Columns 3-4 report this fraction for firms with jobs that do or do not involve interaction with customers. Columns 5-6 report this fraction for firms with jobs that do or do not involve access to high-value inventory. Mean effects are estimated using regressions that include non-interacted controls for the subsidy level. All specifications report standard errors clustered at the firm level. See the Table 2 notes for additional details on the outcomes and sample.

<sup>†</sup> We use different values for low levels of subsidy (5% and 10%). For exposition, we pool the 5 and 10 percent subsidy levels, which results in a uniform number of observations across values displayed under the label 10%.

Appendix Table A.3: Labor Demand Elasticities

	Linear	Quadratic	Non-Parametric
10% Subsidy <sup>†</sup>	-0.354 (0.094)	-0.748 (0.341)	-1.091
25% Subsidy	-0.300 (0.080)	-0.548 (0.220)	0.360
50% Subsidy	-0.203 (0.054)	-0.272 (0.079)	-0.690
100% Subsidy	-0.071 (0.019)	-0.030 (0.039)	0.001
Average Elasticity	-0.207 (0.055)	-0.273 (0.078)	-0.161
Firms	913	913	913
Managers	1,095	1,095	1,095

*Notes.* This table reports alternate estimates of labor demand elasticity. Column 1 reports linear estimates, calculated as  $(dH/dW)(w/H)$ , where  $dH/dW$  represents the slope from a linear regression of willingness to work with WCs on effective wage and is constant across rows.  $w$  and  $H$  represent the midpoint between two effective wage levels of the effective wage and mean willingness to work with WCs, respectively. For example, in the 10% subsidy row,  $w$  is the midpoint between a 100% and 90% effective wage. Column 2 reports quadratic estimates, again calculated as  $(dH/dW)(w/H)$ , where  $dH/dW$  represents the marginal effect from a regression of willingness to work with WCs on effective wage and effective wage squared. The marginal effect is calculated at the midpoint between two effective wage levels and as such varies across columns.  $w$  and  $H$  are defined as in column 1. Column 3 reports non-parametric estimates, calculated as the percent change in willingness to work with WCs over the percent change in effective wage between two effective wage levels. The average elasticity in Column 1 reports the elasticity measure shown in Appendix Table A.2, calculated as  $(dH/dw)(\bar{w}/\bar{H})$ , where  $dH/dw$  represents the slope from the linear regression of willingness to work with WCs on effective wage, and  $\bar{w}$  and  $\bar{H}$  represent mean effective wage and willingness to work with WCs across all subsidy levels. The average elasticity in Column 2,  $(dH/dW)(w/H)$ , is instead calculated as the marginal effect at the mean from the quadratic regression. In Column 3, it is the percent change from 0% effective wage to 100% effective wage. See the Table 2 notes for additional details on the sample. <sup>†</sup> We use different values for low levels of subsidy (5% and 10%) in two survey arms. For exposition, we pool the 5 and 10 percent subsidy levels which results in a uniform number of observations across values displayed under the label 10%.

Appendix Table A.4: Descriptive Statistics by Willingness to Hire WCs

	No Subsidy		10% Subsidy		25% Subsidy		50% Subsidy		100% Subsidy		p(F-stat)	N
	Work w/ WCs?		Work w/ WCs?		Work w/ WCs?		Work w/ WCs?		Work w/ WCs?			
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No		
A. Firm Characteristics												
Years Experience of Hiring Manager	7.43 (0.55)	7.28 (0.48)	6.02 (0.56)	7.76 (0.58)	7.20 (0.59)	8.23 (0.51)	7.42 (0.55)	7.37 (0.57)	6.28 (0.45)	8.09 (0.60)	0.027	1,095
Employees	1,717 (1,521)	2,042 (1,411)	3,459 (2,963)	2,152 (1,055)	349 (105)	2,171 (1,533)	7,333 (4,172)	9,218 (3,770)	689 (341)	2,411 (1,095)	0.549	824
N. Jobs Posted on Platform	245 (83)	633 (136)	126 (46)	1,663 (1,013)	397 (113)	325 (90)	703 (346)	1,176 (415)	228 (99)	475 (143)	<0.001	1,095
Service	0.28 (0.07)	0.41 (0.06)	0.28 (0.07)	0.31 (0.06)	0.37 (0.10)	0.41 (0.10)	0.20 (0.06)	0.27 (0.08)	0.37 (0.07)	0.36 (0.06)	0.576	687
Manufacturing	0.19 (0.05)	0.06 (0.02)	0.24 (0.08)	0.25 (0.08)	0.13 (0.06)	0.12 (0.04)	0.26 (0.06)	0.21 (0.07)	0.13 (0.04)	0.21 (0.05)	0.259	687
Retail	0.20 (0.06)	0.20 (0.05)	0.13 (0.05)	0.12 (0.04)	0.13 (0.06)	0.16 (0.05)	0.15 (0.06)	0.25 (0.07)	0.13 (0.05)	0.10 (0.04)	0.798	687
Transportation & Public Utilities	0.07 (0.04)	0.11 (0.03)	0.07 (0.04)	0.14 (0.06)	0.21 (0.08)	0.04 (0.02)	0.17 (0.07)	0.17 (0.08)	0.07 (0.03)	0.07 (0.03)	0.206	687
Wholesale	0.09 (0.04)	0.09 (0.03)	0.11 (0.05)	0.06 (0.03)	0.03 (0.03)	0.10 (0.04)	0.09 (0.04)	0.03 (0.02)	0.13 (0.05)	0.18 (0.05)	0.295	687
Finance, Insurance, & Real Estate	0.02 (0.02)	0.01 (0.01)	0.04 (0.03)	0.02 (0.02)	0.03 (0.03)	0.03 (0.02)	0.02 (0.02)	0.03 (0.02)	0.03 (0.02)	0.04 (0.02)	0.973	687
Construction	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.03 (0.02)	0.02 (0.02)	0.00 (0.00)	0.00 (0.00)	0.02 (0.02)	0.210	687
Firm-Wide WC Hiring Policy	0.42 (0.05)	0.55 (0.05)	0.37 (0.05)	0.50 (0.05)	0.41 (0.05)	0.54 (0.05)	0.41 (0.05)	0.51 (0.05)	0.36 (0.04)	0.56 (0.05)	<0.001	1,075
B. Policies Concerning Whether WCs can Work												
Consider WCs Because Best Candidate	0.64 (0.05)	0.37 (0.04)	0.61 (0.05)	0.21 (0.04)	0.63 (0.06)	0.22 (0.04)	0.70 (0.05)	0.19 (0.04)	0.62 (0.04)	0.27 (0.05)	<0.001	1,075
Consider WCs Because Second Chances Are Important	0.71 (0.05)	0.38 (0.05)	0.67 (0.05)	0.24 (0.04)	0.62 (0.05)	0.25 (0.04)	0.72 (0.04)	0.31 (0.05)	0.68 (0.04)	0.30 (0.04)	<0.001	1,075
Consider WCs Because of Financial Incentives	0.11 (0.03)	0.04 (0.02)	0.07 (0.03)	0.05 (0.02)	0.08 (0.03)	0.04 (0.02)	0.10 (0.03)	0.05 (0.02)	0.08 (0.02)	0.06 (0.02)	0.222	1,075
Concerned About Customer Reactions	0.54 (0.05)	0.57 (0.05)	0.40 (0.05)	0.50 (0.05)	0.45 (0.05)	0.48 (0.05)	0.47 (0.05)	0.45 (0.05)	0.45 (0.04)	0.53 (0.05)	0.542	1,075
Concerned About Performance	0.17 (0.04)	0.09 (0.02)	0.14 (0.04)	0.17 (0.03)	0.16 (0.04)	0.18 (0.04)	0.15 (0.03)	0.17 (0.04)	0.13 (0.03)	0.11 (0.03)	0.444	1,075
Concerned About Local, State, or Federal Regulations	0.33 (0.05)	0.22 (0.04)	0.20 (0.04)	0.29 (0.04)	0.34 (0.05)	0.23 (0.04)	0.27 (0.04)	0.27 (0.05)	0.27 (0.04)	0.25 (0.05)	0.119	1,075
C. WC Perceptions, Binary Scale												
Confidence a WCs will Perform Well	0.97 (0.02)	0.90 (0.03)	0.99 (0.01)	0.86 (0.03)	0.99 (0.01)	0.90 (0.03)	0.99 (0.01)	0.90 (0.03)	1.00 (0.00)	0.90 (0.03)	<0.001	1,095
Concern a WCs will Put Others at Risk	0.49 (0.05)	0.80 (0.03)	0.52 (0.05)	0.74 (0.04)	0.50 (0.05)	0.75 (0.04)	0.41 (0.05)	0.76 (0.05)	0.40 (0.04)	0.81 (0.04)	<0.001	1,095
Concern a WCs will Steal or Cause Damage	0.53 (0.05)	0.83 (0.03)	0.51 (0.06)	0.82 (0.04)	0.51 (0.05)	0.76 (0.05)	0.50 (0.05)	0.82 (0.04)	0.45 (0.04)	0.84 (0.03)	<0.001	1,095

*Notes.* Each row presents means of some attribute for each subsidy level, split by whether the respondent is willing to work with a WC at that subsidy level. Standard errors are clustered at the firm level. Column 11 shows the p-value associated with the F-statistic from the test that the means are equal for the hiring and not hiring groups at every subsidy level. Column 12 shows the number of respondents for whom the attribute of interest is available.

Appendix Table A.5: Crime and Safety Insurance, Performance History, and Criminal Record History

A. Additional Policy Treatment	Crime and Safety Insurance				Performance History		
	Baseline	\$5k <sup>†</sup>	\$100k	\$5m	1 Job	5 Jobs	25 Jobs
No Subsidy	0.389 (0.032)	0.118 (0.049)	0.177 (0.052)	0.179 (0.056)	0.111 (0.052)	0.222 (0.051)	0.191 (0.052)
10% Subsidy <sup>†</sup>	0.436 (0.037)	0.037 (0.060)	0.185 (0.057)	0.208 (0.053)	0.104 (0.054)	0.270 (0.062)	0.095 (0.052)
25% Subsidy	0.409 (0.037)	0.231 (0.057)	0.201 (0.054)	0.109 (0.051)	0.185 (0.066)	0.231 (0.060)	0.114 (0.047)
50% Subsidy	0.540 (0.036)	0.098 (0.056)	0.132 (0.057)	0.196 (0.047)	0.144 (0.062)	0.106 (0.048)	0.092 (0.050)
100% Subsidy	0.538 (0.032)	0.112 (0.045)	0.146 (0.046)	0.187 (0.051)	0.113 (0.054)	0.160 (0.045)	0.115 (0.052)
Elasticity	-0.207 (0.055)	-0.173 (0.076)	-0.120 (0.076)	-0.203 (0.083)	-0.180 (0.089)	-0.068 (0.077)	-0.133 (0.083)
Mean Effect vs. Baseline	–	0.120 (0.024) [0.055]	0.167 (0.023) [0.008]	0.174 (0.024) [0.008]	0.128 (0.026) [0.055]	0.190 (0.023) [0.001]	0.121 (0.023) [0.043]
Mean Effect vs. Omitted Group	–	– –	0.047 (0.036) [0.499]	0.055 (0.037) [0.499]	– –	0.062 (0.038) [0.499]	-0.007 (0.038) [0.798]
Firms	913	293	323	311	284	312	328
Managers	1,095	333	376	386	335	361	399

Appendix Table A.5: Crime and Safety Insurance, Performance History, and Criminal Record History

B. Selective Screening	Years Since Arrest or Conviction				Felony Type			Misdemeanor Type		
	Baseline	1 Year	3 Years	7 Years	Violent	Property	Drug	Violent	Property	Drug
No Subsidy	0.389 (0.032)	0.214 (0.049)	0.251 (0.054)	0.414 (0.048)	-0.329 (0.032)	-0.244 (0.030)	-0.120 (0.034)	-0.291 (0.031)	-0.115 (0.033)	0.124 (0.032)
10% Subsidy <sup>†</sup>	0.436 (0.037)	0.189 (0.060)	0.280 (0.059)	0.246 (0.057)	-0.363 (0.035)	-0.304 (0.035)	-0.172 (0.035)	-0.328 (0.035)	-0.093 (0.039)	0.083 (0.038)
25% Subsidy	0.409 (0.037)	0.215 (0.049)	0.345 (0.061)	0.285 (0.062)	-0.346 (0.035)	-0.274 (0.037)	-0.130 (0.035)	-0.313 (0.037)	-0.101 (0.037)	0.072 (0.035)
50% Subsidy	0.540 (0.036)	0.127 (0.054)	0.155 (0.050)	0.291 (0.047)	-0.428 (0.035)	-0.367 (0.037)	-0.177 (0.031)	-0.372 (0.037)	-0.191 (0.038)	0.033 (0.034)
100% Subsidy	0.538 (0.032)	0.128 (0.048)	0.262 (0.045)	0.168 (0.049)	-0.427 (0.032)	-0.376 (0.035)	-0.120 (0.036)	-0.363 (0.033)	-0.167 (0.038)	0.068 (0.032)
Elasticity	-0.207 (0.055)	-0.056 (0.060)	-0.107 (0.059)	0.014 (0.056)	-0.118 (0.052)	-0.062 (0.067)	-0.358 (0.088)	-0.185 (0.065)	-0.169 (0.087)	-0.232 (0.090)
Mean Effect vs. Baseline	–	0.174 (0.023) [0.003]	0.256 (0.024) [0.000]	0.280 (0.024) [0.000]	-0.379 (0.015) [0.000]	-0.313 (0.016) [0.000]	-0.142 (0.015) [0.000]	-0.333 (0.015) [0.000]	-0.134 (0.017) [0.002]	0.077 (0.015) [0.020]
Mean Effect vs. Omitted Group	–	–	0.083 (0.035) [0.180]	0.107 (0.034) [0.119]	–	0.066 (0.010) [0.003]	0.237 (0.014) [0.000]	0.046 (0.007) [0.003]	0.245 (0.015) [0.000]	0.456 (0.016) [0.000]
Firms	913	314	300	319	913	913	913	913	913	913
Managers	1,095	380	343	372	1,095	1,095	1,095	1,095	1,095	1,095

*Notes.* This table reports OLS estimates of the effects of different policies on firms' willingness to work with workers with a criminal record. In Panel A, Column 1 reports the baseline fraction of managers choosing to work with WCs at each subsidy level. Columns 2-4 report the additional effect of providing insurance covering damages related to theft or safety up to the indicated level. Columns 5-7 report the additional effect of the requiring that WCs satisfactorily complete the indicated number of jobs. In Panel B, Column 1 again reports the baseline willingness to work with WCs. Columns 2-4 report the additional effect of imposing a minimum time since arrest or conviction before allowing WCs to join the pool of workers. Columns 5-10 report the additional effect of restricting WCs to those with a given crime type. The additional effects are estimated using regressions that include interactions between the subsidy level and the indicated treatment. Mean effects are estimated using regressions that include non-interacted controls for the subsidy level. All specifications report standard errors clustered at the firm level. Westfall-Young adjusted p-values are reported in brackets, grouped by panel. See the Table 2 notes for additional details on the outcomes and sample.

<sup>†</sup> We use different values for low levels of subsidy (5% and 10%) and crime and safety insurance (\$1k and \$5k) in two survey arms. For exposition, we pool the 5 and 10 percent subsidy levels and the \$1k and \$5k insurance levels, which results in a uniform number of observations across values displayed under the labels *10%* and *\$5k*, respectively.

## Appendix B. Correcting Misperceptions in Beliefs

This appendix measures the effect of correcting misperceptions in beliefs by exploiting the interaction of cross-business variation in prior beliefs and our randomized information intervention.

We follow Cullen and Perez-Truglia (2018) and estimate the impact of correcting misperceptions in beliefs using the following first- and second-stage specifications:

$$\begin{aligned} p_{\text{posterior},i} &= \pi_0 + \pi_1(p_{\text{signal},i} - p_{\text{prior},i}) + \pi_2(p_{\text{signal},i} - p_{\text{prior},i}) * \text{Info}_i + \eta H_{\text{prior},i} + \xi_i \quad (\text{B3}) \\ H_{\text{posterior},i} &= \beta_0 + \beta_1 \hat{p}_{\text{posterior},i} + \beta_2(p_{\text{signal},i} - p_{\text{prior},i}) + \gamma H_{\text{prior},i} + v_i \end{aligned}$$

where the information shock,  $(p_{\text{signal},i} - p_{\text{prior},i})$ , interacted with the treatment indicator,  $\text{Info}_i$ , is an instrument for hiring managers' posterior beliefs.  $H_{\text{prior},i}, H_{\text{posterior},i} \in \{0, 1\}$  are the hiring manager's prior and posterior willingness to work with WCs, respectively. We express prior and posterior beliefs in log terms throughout this subsection. Following Armantier et al. (2016), Cullen and Perez-Truglia (2018), and Fuster et al. (2018), this log model assumes that the relationship between outcomes and beliefs are linear in log beliefs and symmetric, consistent with the patterns seen in our data. We estimate Equation (B3) separately for respondents assigned to the high- and low-rating treatment arms.

Appendix Figure B.1 reports binned scatter-plot estimates of the impact of high- and low-performance information on business beliefs and hiring decisions to illustrate the variation underlying specification (B3). Panels A and B plot the difference between the reported performance beliefs at the end of the experiment and prior beliefs against the perception gap for the low- and high-performance treatments, respectively. For graphical exposition, we plot the belief update rather than the posterior belief as observations along the 45-degree line imply the manager updated completely from her prior to a posterior that exactly matches the information shown. These results show that treated hiring managers, by and large, eliminated nearly all of the error in their initial guesses about WC performance. Control hiring managers also partially eliminated the error in their initial guesses, likely because they were informed that some individuals would receive objective information. We do not expect this partial updating to bias our IV estimates given our direct measures of posterior beliefs for all participants.

Panels C and D of Appendix Figure B.1 plot the willingness to work with WCs at the end of the experiment against the fitted posterior belief predictions from the first stage regression, again for the low- and high-performance treatments, respectively. The results graphically corroborate the assumed linear relationship between (exogenously) shocked beliefs about WC performance and hiring demand. Panel D (high performance) reveals a linear positive relationship between instrumented posterior beliefs and hiring demand. Panel C (low performance) shows a much more muted and diffuse relationship.

Appendix Table B.1 reports formal regression estimates of the impact of high- and low-performance information on firm beliefs and willingness to work with WCs. Panel A provides results for the high-rating treatment arm while Panel B provides results for the low-rating treatment arm.

Column 1 presents first-stage estimates of the effect of information on (log) posterior beliefs, Column 2 presents OLS estimates of the relationship between (log) posterior beliefs and hiring decisions, Column 3 presents the main instrumental variable (IV) estimates of the effect of the information treatment on hiring decisions, and Column 4 presents reduced form estimates.

The first stage results in Column 1 show that, on average, treated hiring managers close the gap between their prior beliefs and the truth by 34% and 46% more than the control group, for the high- and low-performance treatment groups, respectively. The main IV results in Column 3, Panel A, show that the elasticity of hiring with respect to performance beliefs about WCs is 0.81, meaning that a 10% increase in managers' beliefs about WCs' performance leads to an 8.1 percentage point increase in willingness to work with WCs or a 15% increase in hiring. This means that causing managers to update their beliefs by 10% has a similar effect as providing a 100% wage subsidy, and only a slightly larger effect than providing businesses with \$5,000 of insurance or requiring WCs to successfully have completed at least 1 prior job.<sup>1</sup> In contrast, Panel B of Appendix Table B.1 shows that changing perceptions in the low-performance group has no impact on hiring decisions. The reduced form results in Column 4 are consistent with our IV results. Column 4 of Panel A shows that, on average, treated hiring managers are more likely to hire WCs than the control group, proportional to their pre-existing gap in beliefs about WC high-performance. Panel B shows this relationship is muted and statistically insignificant in the treatment group shown the low-performance information.

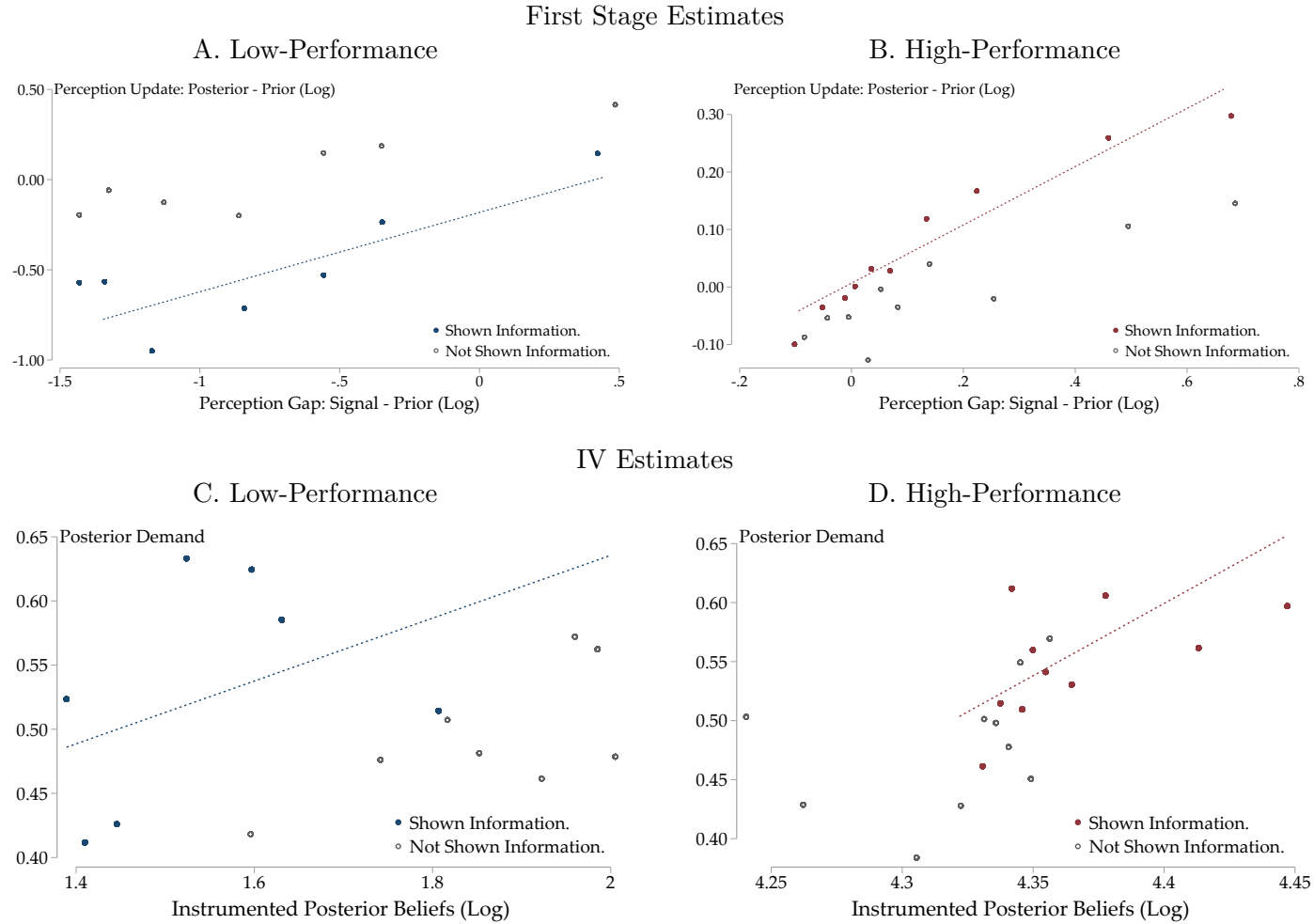
Our interpretation of these results is that the share of low ratings or no-shows is less salient and less relevant for WC hiring decisions. Consistent with this interpretation, hiring managers also have more dispersed priors about low ratings and no-shows at baseline.

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<sup>1</sup>The IV coefficient is 2.5 times larger than the OLS coefficient of 0.33 in Column 2, as is common in many information provision experiments (Gerber et al., 2020). This pattern is consistent with substantial attenuation bias due to measurement error in beliefs. Such measurement error likely reflects that predicting performance is unfamiliar to many businesses or just inattention on the part of hiring managers.



Appendix Figure B.1: First Stage and IV Estimates of Objective Performance Information



*Notes.* This figure reports binned scatter-plot estimates of the impact of high- and low-performance information on business beliefs and hiring decisions. Panels A-B plot the difference between the reported performance beliefs at the end of the experiment and prior beliefs against the perception gap. For graphical exposition, we plot the belief update rather than the posterior belief as observations along the 45-degree line imply the manager updated completely from her prior to a posterior that exactly matches the information shown. Panels C-D plot the willingness to work with WCs at the end of the experiment against the fitted posterior belief predictions from the first stage regression. Panels A and C present results for being shown information on the fraction of no-shows and either 1- or 2-star ratings. Panels B and D present results for being shown information on the fraction of 5-star ratings. See Section 5 of the text for additional details.

Appendix Table B.1: High- and Low-Performance Information

	First Stage	OLS	IV	Reduced Form
<b>A. Impact of High-Performance Information</b>				
Shown Info $\times$ (Signal - Prior Belief)	0.334 (0.0805)			0.273 (0.131)
ln(Posterior Belief)		0.338 (0.108)	0.818 (0.414)	
Mean: Dependent Variable	4.36	0.51	0.51	0.51
Kleibergen-Paap: Weak Identification F-Stat			17.25	
Firms	490	490	490	490
Managers	558	558	558	558
<b>B. Impact of Low-Performance Information</b>				
Shown Info $\times$ (Signal - Prior Belief)	0.447 (0.0474)			0.0302 (0.0327)
ln(Posterior Belief)		-0.0348 (0.0294)	0.0676 (0.0740)	
Mean: Dependent Variable	1.68	0.51	0.51	0.51
Kleibergen-Paap: Weak Identification F-Stat			88.85	
Firms	430	430	430	430
Managers	502	502	502	502

*Notes.* This table reports estimates of the impact of high- and low-performance information on firm beliefs and willingness to work with WCs. Panel A reports results for managers who were shown information on the fraction of 5-star ratings. Panel B reports results for managers who were shown information on the fraction of no-shows and either 1- or 2-star ratings. Column 1 reports first stage estimates of the effect of information on posterior beliefs. Column 2 reports OLS estimates of the cross-sectional relationship between posterior beliefs and willingness to work with WCs. Column 3 reports IV estimates of the causal impact of a change in posterior beliefs on willingness to work with WCs. Column 4 reports reduced form estimates of the effect of information on willingness to work with WCs. See Section 5 of the text for additional details.

## Appendix C. Complete List of Questions

This appendix lists all of the questions that the Platform gave to hiring managers.

Q1. How do you work with Platform A? (select all that apply)

Q1a. If "Other" is selected: You selected "Other". Please provide more information about your role in the company

Q2. What is your position in the company?

Q3. How many years of experience do you have in labor sourcing and/or hiring?

Q4. We are considering expanding our pool of users to include individuals that have a criminal record. We want to learn whether this expanded pool would suit your needs. If you indicate that you're interested in connecting with Platform A users with a criminal record, then (and only then) your choice could affect whether these users are able to accept jobs you post. These individuals would be at most 5 % of your pool of possible matches.

Q5. Would you currently have the authority to permit a user with a criminal record to accept a job you posted on Platform A?

Q5a. If "Yes" is not selected: Please continue answering the survey as if you had full authority to make the decision.

Q6. [Binary Choice] If Platform A gave you a wage subsidy discount for users with a criminal record, would you permit such users to perform jobs you post? This means you would only pay (100 - wage subsidy) of the wage for those with a criminal record. All Platform A users would still receive the full pay amount after the discount (Platform A would pay the difference).

Q6a. [Display this question if binary choice answer is not "Yes"] If Platform A could cover damages up to crime and safety insurance related to theft or safety incurred by workers with a criminal record, would you permit such Platform A users to perform jobs you post? Platform A would still give you a wage subsidy discount, but no other supplementary policies would apply. If you have any questions about what damages would or would not be included, please share those with us.

Q6b. [Display this question if binary choice answer is not "Yes"] If Platform A required users of Platform A with a criminal record to have satisfactorily completed performance history job(s), receiving more than 85% 5-star reviews, would you permit such users to perform jobs you post? Plat-

form A would still give you a wage subsidy discount, but no other supplementary policies would apply.

Q6d. [Display this question if binary choice answer is not "Yes"] If Platform A required users with a criminal record to have maintained a clean record for at least clean record length would you permit such users to perform jobs you post? Platform A would still give you a wage subsidy discount, but no other supplementary policies would apply.

Q7. If the unemployment rate were unemployment rate meaning the local labor market was labor market tightness and qualitative unemployment level share of people were looking for jobs, would you permit users with a criminal record to perform jobs you post? Platform A would still give you a wage subsidy discount, but no other supplementary policies would apply.

Q8. We will now ask you about individuals with particular criminal record. Please indicate whether you would permit Platform A users with these types of convictions to perform jobs you post. Platform A would still give you a wage subsidy discount, but no other supplementary policies would apply.

Q8a. Property/financial felony (example: breaking and entering, car theft, fraud, embezzlement over \$2,000)

Q8b. Violent felony (example: aggravated assault, domestic violence)

Q8c. Substance-related felony (example: drug trafficking/distribution, multiple DUIs)

Q8d. Property/financial misdemeanor: (example: petty theft, vandalism); financial misdemeanor (example: embezzlement under \$500)

Q8e. Violent misdemeanor (example: attempting to commit violent injury)

Q8f. Substance-related misdemeanor (example: drug possession, public intoxication)

Q9. Does your company or organization currently have a hiring policy regarding individuals with a criminal record?

Q10. Which of the following factor into your organization's decision to hire individuals with criminal records? (select all that apply or alternatively "we did not decide to hire individuals with a criminal background")

Q11. Think about other companies or organizations in your area. How much do you believe that the following are concerns to companies or organizations regarding hiring individuals with criminal

records?

Q12. Do your jobs involve Platform A users having contact with customers?

Q13. At your jobs, is there cash or high-value inventory that Platform A users could steal?

Q14. [Respondents were randomized to either a low rating or a high rating arm] In 2019, 86% of jobs on Platform A resulted in a 5-star rating. What percentage of jobs completed by people with a criminal record do you think would result in a 5-star rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q15. [Respondents were randomized to either a low rating or a high rating arm] In 2019, 5% of jobs on Platform A resulted in a either a no-show or low rating (1 or 2 stars). What percentage of jobs completed by people with a criminal record do you think would result in a no-show or low rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q16. Next, a group of individuals participating in this survey will be chosen to receive some information about the performance of people with a criminal background on the same or similar platforms. Please continue to the next screen to find out if you will be selected to receive this information.

Q17a. [Display if selected to receive information] The truth is that 87% of jobs completed by people with a criminal record resulted in a 5-star rating on the same or a similar platform - actually better than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

Q17b. [Display if selected to receive information] The truth is that only 3% of jobs completed by people with a criminal record resulted in a either a no-show or a low rating (1 or 2 stars) on the same or a similar platform - actually fewer no-shows and low ratings than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

Q18. [Display if not selected to receive information] You have not been selected to receive the following information. When you are ready, proceed to the next screen.

Q19. We want to give you the opportunity to reassess your answer to the question below. This opportunity is given automatically to all survey participants, regardless of their responses.

Q20a. In 2019, 86% of jobs on Platform A resulted in a 5-star rating. What percentage of jobs

completed by people with a criminal record do you think would result in a 5-star rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q20b. In 2019, 5% of jobs on Platform A resulted in either a no-show or low rating (1 or 2 stars). What percentage of jobs completed by people with a criminal record do you think would result in a no-show or low rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q21. Next, a group of individuals participating in this survey will be chosen to receive some information about the performance of people with a criminal background on the same or similar platforms. Please continue to the next screen to find out if you will be selected to receive this information.

Q21a. [ 25% of respondents] The truth is that only 3% of jobs completed by people with a criminal record resulted in a either a no-show or a low rating (1 or 2 stars) on the same or a similar platform—actually fewer no-shows and low ratings than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

Q21b. [ 25% of respondents] The truth is that 87% of jobs completed by people with a criminal record resulted in a 5-star rating on the same or a similar platform—actually better than everyone else. Please take some time to read and understand this information carefully. When you are ready, proceed to the next screen.

Q22a. In 2019, 86% of jobs on Platform A resulted in a 5-star rating. What percentage of jobs completed by people with a criminal record do you think would result in a 5-star rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q22b. In 2019, 5% of jobs on Platform A resulted in a either a no-show or low rating (1 or 2 stars). What percentage of jobs completed by people with a criminal record do you think would result in a no-show or low rating on Platform A or a similar platform? If your guess is within 5% of the truth, we will send you an additional \$2 reward!

Q23. We also give all participants the chance to reassess their answer to the earlier question regarding expanding the pool of Platform A users.

Q24. If Platform A gave you a wage subsidy discount for Platform A users with a criminal record, would you permit such Platform A users to perform jobs you post? This means you would only pay 100 - wage subsidy of the wage for those with a criminal record. All Platform A

users would still receive the full pay amount after the discount (Platform A would pay the difference).

Q25. Do you agree with the following statement? "In the types of jobs I post on Platform A, a user of Platform A with a criminal record is likely to perform well."

Q26. Do you agree with the following statement? "In the types of jobs I post on Platform A, a user of Platform A with a criminal record is likely to put other workers, clients or their supervisor at risk."

Q27. Do you agree with the following statement? "In the types of jobs I post on Platform A, a user of Platform A with a criminal record is likely to steal or cause damage to physical assets and property."

Q28. [Display this question if the respondent has indicated they do not have authority to permit users of Platform A with a criminal background to perform a job.] If you would like to refer us to someone with the appropriate authority to permit a user of Platform A with a criminal background to perform a job, please provide their name, email address, and any additional comments you would like to offer about how this decision will be made in your organization. We will only use this information to inquire about expanding the pool of users of Platform A to include individuals with a criminal record.

Q29. Did you have any technical or language-related issues with this survey?

Q30a. [Display this question if the respondent indicates that they had issues with the survey] What issues did you have with this survey?

Q30. Please share any other thoughts on this program to expand the group of users of Platform A who can perform jobs your business posts (optional)

Q31. Please select how you would like to receive your gift for completing this survey.