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HIRING FRICTIONS AND THE PROMISE OF ONLINE JOB PORTALS: EVIDENCE FROM INDIA

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Abstract

Traditional recruitment networks restrict the pool of workers available to firms and may limit hiring. Job portals can ease these frictions, but firms unaccustomed to recruiting online may be hesitant to hire unfamiliar candidates. We show that firms are significantly more likely to fill a vacancy—across all recruitment methods—when they receive interventions allowing them to attract skilled applicants and screen them on a portal. These interventions jointly induce firms to engage with unfamiliar applicants and increase portal-based hiring. Portal-based hires are retained beyond the standard assessment period, suggesting these firms successfully recruited suitable matches outside their networks.

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1 Introduction

Firms across the developing world report difficulties recruiting skilled workers (Abebe et al., 2021b). Nevertheless, many firms remain hesitant to hire outside traditional recruitment networks[1], although they limit the quantity and quality of potential employees. Though limited in scope, these networks implicitly screen worker quality and offer security to firms for whom worker unobservables like trustworthiness may be especially important (Chandrasekhar et al., 2020). Online job portals allow firms to expand their recruitment networks but remain heavily underutilized: just 2% of firms report using the internet for recruitment in urban India, the setting of our study.[2] As firms expand beyond the boundaries of their traditional networks—whether online or offline—they may both struggle to attract interest from skilled candidates unfamiliar with their business, and be themselves reluctant to hire unfamiliar candidates whose trustworthiness they cannot assess.[3]

In this paper, we use a field experiment to investigate whether providing firms with services that allow them to attract and screen skilled candidates on a job portal can improve their ability to fill a posted vacancy. To do so, we partnered with QuikrJobs, an online job portal in India that specializes in lower-wage occupations in the retail and service sectors. At the outset, just 12% of (control) firms posting vacancies on QuikrJobs report successfully hiring through the portal and, overall, 23% of vacancies remained unfilled in spite of recruitment through both traditional and online methods. Our key result is that when firms are provided with a combination of premium advertising services—increasing interest from skilled applicants—and the ability to verify the identity of these candidates, they increase hiring through the portal and are more likely to successfully fill their posted vacancy.

Our experiment spans 1,719 vacancies posted by firms in Bengaluru, a large urban labor market in India. We randomly assigned these vacancies to a control group or one of three treatment groups: $Scale$, $Verification$, or $Joint$. The first treatment, $Scale$, increased the supply of applicants to firms via promotional advertising. Giving firms access to a greater number of interested applicants may improve the likelihood of finding a suitable match. The second treatment, $Verification$, provided firms with access to verified background information on applicants. Once a job seeker applied to any vacancy in the experiment, they were offered the opportunity to verify their identity using government-issued documents. The verification outcomes were then privately revealed to firms randomly assigned to receive this information. We also varied whether firms were shown information on half or all of their applicants, generating both within and across employer variation in access to verification information. Finally, we implemented a third treatment, $Joint$, that gave firms access to the $Scale$ and the $Verification$ treatments simultaneously.

[1] We define these networks as family, friends, coworkers, and their resulting referrals. Recent estimates for network-based hires range from 20-35% in the US (Burks et al., 2015; Maurer, 2017) and 45-70% in India (Munshi and Rosenzweig, 2006; Dhillon et al., 2021).

[2] Authors' calculation using data from the National Sample Survey 2015-16.

[3] Recent work suggests trustworthiness—e.g., how likely employees are to be honest and not to steal or misbehave at work—play a role in hiring in both low-income (Caria and Falco, 2022) and high-income countries (Cullen et al., 2022).

We establish *three* sets of results that describe how these treatments influence employer interactions with the portal and hiring outcomes. *First, premium advertising attracts more skilled candidates, but leaves the average skill composition of applicants to these vacancies unchanged.* The *Scale* and *Joint* treatments double the average number of candidates who apply to a vacancy—51 to 55.4 compared to 25.2 in control. To examine how the skills of applicants change, we use profile attributes reported by applicants to construct a skills index.[4] We find no differences in the *average* value of the skills index across treatments, but the top-ranked applicant to a vacancy in the *Scale* or *Joint* treatments is more skilled (0.31-0.34 s.d.) and firms in these treatments attract twice as many applicants with scores above (and below) the median of the skills index (normalized relative to control).

Second, conditional on receiving premium advertising, identity verification services increase employer engagement with candidates. Employers are *required* to click on applicant profiles to initiate contact. Using these 'click' data, we find that firms in the *Scale* and *Joint* treatments increase the number of unique applicants with whom they engage by 67.5% and 147.4%, respectively, relative to control (2.5 applicants). This difference between *Scale* and *Joint* is statistically significant (p-value = 0.05), suggesting *Joint* employers valued the additional information provided by identity verification; these employers also report an increase of 25.6% in the likelihood of interviewing a candidate relative to control. Using within-vacancy experimental variation in the revelation of verification outcomes, we find that employers increase their engagement with applicants who have passed verification when this information is revealed.

Third, receiving both premium advertising and verification increases hiring through the portal, the overall success in filling a vacancy, and the incidence of out-of-network employees. *Joint* firms are 67.8% or 8.2 percentage points (p.p.) more likely to hire workers through the portal relative to control. In contrast, *Scale* and *Verification* yield insignificant point estimates for portal-based hiring that are close to zero—though we are likely under-powered to detect small effect sizes—and we can reject that they are equal to *Joint* (p-value $\leq$ 0.07). Overall, control firms hire workers for 76.7% of their vacancies, the majority of whom (84.2%) continue to be sourced through traditional networks. *Joint* firms do not compensate for increased portal hiring by reducing hiring through traditional networks and, consequently, fill significantly more (10.7%, 8.2 p.p.) vacancies than control. At the time of the six month follow-up survey, *Joint* firms are 72.6% (11.4 p.p.) more likely to currently employ a worker hired through the portal. This result suggests that portal-based hires are good matches retained well-beyond the standard two-month probationary period and that the interventions successfully induced employers to hire beyond their traditional networks.

Our results suggest that neither providing firms with access to expanded recruitment networks, nor access to identity verification services alone, *significantly* improves their ability to fill the posted vacancy. Employers in both the *Joint* treatment and the *Scale* treatment receive more (observably) skilled applicants, but may also value less observable traits such

[4] This index is a weighted average of (normalized) education level, language skills, job skills, certifications, experience, whether the applicant shared their CV and ID information, and the number of profile attributes.

as trustworthiness. We develop a conceptual framework to show how verification services act as a screening tool that reveals valuable information on applicant trustworthiness and why employers who especially value this information are more likely to benefit from the verification technology, while seeing limited benefits from expanded recruitment networks alone.[5]

To examine this proposition, we estimate treatment effects by firm size and the 'trust-sensitivity' of jobs—vacancies where the job description mentions cash, merchandise delivery, customer interactions, or trust. Small firms in our setting are more likely to report hiring concerns related to trustworthiness, consistent with an increased reliance on traditional recruitment networks. We find that small firms (less than 10 employees) are only induced to engage more with applicants, as measured by click data, in the *Joint* treatment; in contrast, both the *Joint* and *Scale* treatments lead to (statistically indistinguishable) increases in engagement for large firms. We find entirely analogous treatment effects for *Joint* and *Scale* when comparing firms hiring for trust-sensitive jobs—38% of sample vacancies—versus jobs that are not trust-sensitive.

In the framework, we also derive the conditions under which the treatments generate a complementarity that increases a firm's likelihood of hiring through the portal instead of through traditional networks—their outside option. We find support for the hypothesis that the *Joint* effect on portal hiring is greater than the sum of the effects for *Scale* and *Verification* (p-value = 0.09). However, even among the *Joint* firms, the majority of hires continue to be sourced through traditional networks, suggesting that in many cases the outside option continues to be preferred to hiring online, thereby reducing our power to detect a complementarity in the overall likelihood of filling a vacancy. While our estimates suggest the *Joint* treatment consistently improves hiring outcomes, we advise some caution in interpreting per-comparison p-values as adjustments for testing multiple hypotheses leaves some coefficients above standard thresholds for rejection.

Our primary contribution is to the literature investigating hiring frictions in low-income countries. Prior work has addressed these frictions using a range of worker-level[6] and firm-level interventions.[7] Our paper examines a relatively understudied firm-level intervention: direct recruitment assistance. In contrast to Hensel et al. (2021), who find no hiring impacts of recruitment assistance to Ethiopian firms, we show how easing hiring frictions for small firms can improve both the scope and success of recruitment. Our findings are consistent with hiring frictions in lower-income countries contributing to the misallocation of labor (Chandrasekhar et al., 2020).

Second, we contribute to a literature examining the role of the internet in labor market matching in lower-income countries. Existing evidence focuses on job seekers with mixed

[5]In the experiment, 20% of job seekers submit information for verification, and, of these, 89% pass and 11% fail verification, suggesting the verification technology provides meaningful variation for employers.

[6]For example, improving signaling through reference letters or skill certificates (e.g., Abel et al., 2020; Bassi and Nansamba, 2022; Carranza et al., 2022), providing search support (e.g., Abebe et al., 2021a), or facilitating matches directly (e.g., Beam, 2016; Bandiera et al., 2022).

[7]For example, placement of apprentices in firms (Hardy and McCasland, 2022) and wage subsidies (de Mel et al., 2019; Groh et al., 2016).

results. Kelley et al. (2022) find that providing access to an online job portal in India does not improve employment outcomes, whereas Wheeler et al. (2022) show that training workers to use an online networking site in South Africa increases employment. We contribute to this literature by showing that a screening technology—identity verification—can increase employer engagement with unfamiliar applicants and induce hiring outside traditional networks. Our findings are consistent with macro evidence from high-income countries, which suggest that internet expansion and accompanying advances in screening technologies have greatly improved labor market matching (Kuhn and Mansour, 2014; Bhuller et al., 2021; Pries and Rogerson, 2022).

2 Context

2.1 Online Recruitment and QuikrJobs

In India, the rapid expansion of low-cost mobile and internet technologies over the last ten years has led to substantial growth in the online search and recruitment industry. At least 22 job portals catered to the Indian market by 2017 , but in spite of this growth, just 11% of firms in urban India report using the internet—let alone job portals—in 2016 (Nomura et al., 2017).

In this study, we partnered with QuikrJobs—an online job portal that specializes in entry-level, low-wage positions in the retail and services sectors—to understand the hiring frictions firms may face in using job portals. On QuikrJobs, an employer can post vacancies at no cost, though they may also purchase paid recruitment services. The most popular service is premium advertising, which prioritizes a vacancy's placement in search results and in promotional emails and text messages to registered job seekers for a fixed time period.[8] Meanwhile, a job seeker can browse and apply to an unrestricted number of vacancies at no cost. Each application requires the job seeker to provide their name and phone number or email address, with an option to volunteer details such as age, sex, education, and skills. Matching occurs in a decentralized manner as job seekers choose which vacancies to which they apply and employers decide whether they wish to contact applicants.

2.2 Hiring Frictions and Study Setting

Our study takes place in Bengaluru, a city of over 12 million people in the state of Karnataka. We sample firms posting vacancies on the QuikrJobs portal and our sample firms are more likely to be active in service-oriented sectors and to employ hired labor relative to the population of firms in urban Karnataka (see Appendix A.2). The posted jobs are for full-time positions, offering an average minimum monthly salary of Rs. 12,847 (USD 182.5) and requiring less than one year of experience (see Appendix C.1).

Over two-thirds of these firms report recruitment-related constraints as a key barrier to their growth (see Table A3 in Appendix A.3). While the primary concern cited by these

[8] At the time our project began, less than 10% of employers active on the portal had ever purchased the service.

firms is a difficulty finding applicants with suitable technical skills, 53% of firms report 'trust-related' concerns about employee behavior (e.g., theft or crime). With over one million job seekers in Bengaluru alone, the QuikrJobs portal provides access to larger recruitment networks, but general concerns about screening workers are likely exacerbated by the portal and perhaps explain why just 35% of employers attempt to initiate contact with any applicant.

To understand how engagement could be improved, we asked employers what additional applicant information they would value on the portal. A majority of employers requested identity-verified profiles and educational certificates, ahead of skill assessments, previous employer references, and other options (see Figure A3b in Appendix A.3). When asked why they care about identity verification of unfamiliar individuals, 81% of employers report that it builds trust in applicants—i.e., it provides reassurance that applicants are honest, less likely to steal or misbehave with customers, and are presenting truthful information on their profiles.

3 Design

Motivated by the constraints reported by employers in our setting, we randomly assigned 1,719 vacancies (1,576 unique firms) posted on the QuikrJobs portal to receive treatments intended to increase the volume of applicants to vacancies, *Scale* (n=367), provide employers with third-party verified information, *Verification* (n=467), a combination of these services, *Joint* (n=470), and no treatment, *Control* (n=415).[9] Vacancies in the *Verification* and *Joint* treatments were further randomized to receive verification information on either 50% or 100% of their applications. A vacancy was eligible if it was posted (*i*) in one of nine job categories; (*ii*) by a company with fewer than 50 employees; and (*iii*) by a user not already enrolled in the experiment.[10] Assignment was stratified by job category; firm size, and whether a user had previously used the portal or not.

The selection of vacancies for the experiment and the randomization to a treatment condition were programmed into the portal. As such, the randomization occurred near-instantaneously once an eligible vacancy was posted by an employer, after which they received an e-mail informing them of their assigned treatments, which are described below.

Scale: Vacancies assigned to this treatment receive access to premium advertising services that increase their visibility through time-limited, 'top-of-page' placement. The portal offers this service to expand the applicant pools available to vacancies. A vacancy granted access to this service was ordered at the top of applicant search results, displayed with a 'Gold' badge (Figure A4.1), and promoted via emails and text messages to job seekers registered on the portal. These promotional features remained active for 10 days following the posting date, after which the vacancy transitioned to 'Regular' status.

[9] see Appendix A.1 for details of the study design.

[10] The categories for eligible vacancies include: accountant, cashier, delivery/collections, driver, human resources/administrative staff, receptionist/front office, marketing, office assistant/helper, sales. These categories were selected because they represent over 50 percent of the employer traffic on the portal in Bengaluru in the year preceding the experiment. Users were asked to report the company size during vacancy posting.

Verification: Vacancies assigned to this treatment receive identity verification results for their applicants on the portal. Applicants to *all* vacancies in the experimental sample received an identity verification request, which asked them to submit details from government-issued identification (ID).[11] This request occurred *after* the initial application and all applicants were informed that the outcome may be shared with the employer. The results from the identity verification were only revealed to employers in the *Verification* and *Joint* via badges on application profiles. Verification badges captured whether the applicant passed verification ('ID Verified') or not ('ID Not Verified'), or did not submit ID details ('ID Not Submitted'), or whether verification was in process during the 72-hour submission window ('ID Verification in Process'): see Appendix A4.2. Over the course of the experiment, 20% of job seekers submitted their ID details for verification, and 89% of those who submitted passed verification.

4 Data & Empirical Strategy

4.1 Data Sources

We use administrative data recorded by the portal and two firm surveys to study impacts. A timeline of activities is available in Appendix A.5.

Administrative data: For all 1,719 vacancies in our study, we observe vacancy information including job category, salary offer range, experience requirements, and the individual applications each vacancy receives. We also observe employer engagement with individual applications as measured by 'click' actions taken by an employer to initiate contact with an individual applicant. For job seekers who applied to a sample vacancy, we observe their self-reported profile details, such as sex, age, education, etc.

Firm surveys: Firms were surveyed in-person twice—once after vacancy posting ('baseline') and again roughly 6 months later ('follow-up'). Unfortunately, due to the COVID-19 pandemic our survey operations were interrupted indefinitely and completion rates for the follow-up survey are 50% (N=794 firms).[12] We discuss attrition in greater detail in Section 6.1. At baseline, a firm owner or an employee tasked with recruitment provided us with details on the operations of their business and employees. Our main source of hiring outcomes is the follow-up survey. To maximize response rates for hiring outcomes, we administered a 'long' and 'short' version of this follow-up survey. In both versions, we collected information on new hires since vacancy posting, employee composition, and firm size. In the long version (589 firms), we additionally collected details about the recruitment process and worker-level details for up to 10 new hires and conducted a willingness-to-pay exercise for verification services with a randomly selected 25% of this sample (see Appendix A.6).

[11] Applicants could choose to provide the name and unique code associated with one of two types of widely-available, government-issued, IDs: their Aadhar number, a 12-digit identifier for all residents, or their Permanent Account Number (PAN), a 10-character alphanumeric identifier used for taxation purposes.

[12] Phone-based surveying proved to be an inadequate substitute for in-person surveying in our setting.

4.2 Empirical Strategy

Our main specification compares outcomes across treatment groups using OLS:

$$Y_{is} = \beta_0 + \beta_1 Verification_{is} + \beta_2 Scale_{is} + \beta_3 Joint_{is} + \delta_s + \varepsilon_{is} \quad (1)$$

where i denotes a vacancy and s denotes randomization strata. The unit of analysis can be either a vacancy or a firm, depending on the outcome and the associated data source.[13] Y_{is} is the outcome of interest and δ_s are strata fixed effects. $Verification$ is an indicator for *only* receiving access to verification information of applicants. $Scale$ is an indicator for *only* receiving access to larger applicant pools via premium advertising services. $Joint$ is an indicator for vacancies that receive both treatments.

4.3 Randomization Balance

Appendix C.1 summarizes balance checks using pre-treatment vacancy covariates entered by employers during the vacancy posting process. We compare each treatment group ($Verification$, $Scale$, and $Joint$) to control vacancies and to each other. In bilateral comparisons, only 4 out 42 comparisons are significantly different across groups at the 10% level, as one would expect to occur by chance.[14]

5 Results

In the results we report below, we pool together the 50% and 100% verification cells to improve power. Our qualitative conclusions are largely unchanged when we estimate a fully saturated model (see Appendix C.8), as suggested by Muralidharan et al. (2019).

5.1 Effects on the Quantity and Composition of Applicants

We first document how the quantity and composition of applicant pools changes in response to treatments in Table 1. Using the portal's administrative data, we find that vacancies in the $Scale$ and $Joint$ treatment arms receive more than double the average number of applications: from 25.2 applications in control to 51 in $Scale$ and 55.4 in $Joint$ (column 1). There is no corresponding difference in applications in the $Verification$ treatment.

To understand whether changes in quantity lead to changes in applicant composition, we construct a 'skills index,' which incorporates applicants' self-reported qualifications and

[13]While a user could only be sampled once, a *firm* could have been sampled more than once if multiple users from the same firm posted vacancies; this was not very common however as 94 percent of firms have only a single vacancy in the sample. Nevertheless, in the firm-level analysis, we use the treatment assignment of the first vacancy posted by the firm.

[14]We also show balance on firm-level variables in Appendix C.2.

the completeness of their profile.[15] Higher values of the skills index represent more skilled applicants *as* observed by employers when reviewing their applicants.

Despite the large increase in the number of applications in the *Scale* and *Joint* treatments, we do not find a change in the *mean* of the skills index across treatment arms (column 2).[16] The absence of differences in applicant attributes across treatments suggests that premium advertising increases the salience of a vacancy, rather than altering applicant beliefs about employer or job quality. In addition, premium advertising alters the *range* of applicant skills observed by firms in the *Scale* and *Joint* treatments. These firms observe both better and worse applicants (see Appendix B.2), but the highest skilled applicants these firms receive have significantly higher scores on the skill index than control (Table 1, column 3).

5.2 Effects on Employer Engagement

Our primary measure of employer engagement relies on administrative data tracking 'clicks' on the portal. As an employer *cannot* contact an applicant without clicking to unlock their contact details (see Figure A4.2, Panel B), these click data provide a useful proxy for employer engagement with applicants.

At the outset, just 34.9% of control group employers unlock the contact details for *any* application. Employers in the *Scale* treatment are 19.2% (6.7 p.p.) more likely to unlock contact information for at least one applicant to their vacancy, while employers in the *Joint* treatment are 36.1% (12.6 p.p.) more likely to do so (Table, 1, column 4). These impacts are even more pronounced on the intensive margin (column 5): employers in the *Scale* treatment click on substantially more applications (4.2 vs 2.5 in control), while *Joint* employers more than double the number of applications they click on relative to control click on (6.2 vs 2.5). While the *Scale* treatment induces increased applicant engagement, both point estimates are significantly higher in *Joint* than in *Scale* (p-value < 0.1), suggesting that *Joint* employers increase the *intensity* of their engagement with applicants.

These patterns of engagement are also consistent with self-reported data on interviews conducted by these firms. Firms in the *Joint* treatment are 25.6% (12.9 p.p.) more likely to have conducted an interview with an applicant from the portal (Table 1, column 6). Importantly, the outcomes on employer engagement are largely robust to adjustments for multiple hypothesis testing (see Panel A in Appendix C.9). We also find no evidence of compensating changes in applications or interviews for individuals recruited through alternative methods for the vacancy, suggesting that employers increased *overall* recruitment effort (see Appendix B.4).

Absent differences in the quantity and composition of applicants in the *Scale* and *Joint*

[15] Specifically, whether an applicant has a higher educational degree, English-language skills; job category-specific skills, certifications, or expertise; shares a resume, shares ID details for verification; and a count of the number of total attributes in their profile. The index reports the average across attributes, each of which is normalized with respect to the control group and weighted by the inverse of the variance-covariance matrix Anderson (2008).

[16] Appendix B.1 reports treatment effects for each component of the skills index at the vacancy level, comparing *Scale* to *Control*.

groups, greater recruitment effort by *Joint* employers is consistent with employers valuing the additional information provided by identity verification. To examine this more carefully, we use *within-vacancy* variation—produced by the 50% verification treatment arm—in whether the applicant's verification status is revealed to employers or not. We run an applicant-level regression with vacancy-fixed effects interacting an applicant's verification outcome with their randomly assigned revelation condition, and find that an employer is 16.3% (2.3 p.p.) more likely to click on an applicant who passed verification when this information is revealed, relative to a similarly verified applicant whose status is not revealed (see Appendix B.3). These results suggest that a verified identity may provide valuable information to employers about an applicant's suitability beyond observable dimensions of ability.

5.3 Effects on Hiring and Retention

We now compare hires at the firm level across the treatment groups in Table 2 by estimating Equation 1, using data from our follow-up surveys. Since posting the sample vacancy, 12.1% of *Control* firms report hiring from the portal. In comparison, 20.3% of *Joint* firms hire from the portal (column 1): an increase of 67.8% (8.2 p.p.). Estimates for the *Verification* and *Scale* treatments are much smaller, equal to or less 1.2 p.p., and not distinguishable from control firms; we are likely underpowered, however, to detect small positive effects. We can reject equality between the *Joint* and the *Verification* treatment (p-value = 0.048) as well as the *Scale* treatment (p-value = 0.072). In contrast, we do not find any statistically significant differences across treatments in hiring through traditional networks (see Appendix B.6).

Consistent with these two prior findings, we find that *overall* hiring increases for the *Joint* group. Relative to the control group, the point estimate reflects a 10.7% increase in hiring. This increase in hiring also has a dramatic effect on the *composition* of employees that were employed by *Joint* firms at the time of the follow-up survey: they are 76% (11.4 p.p.) more likely than control firms to report that a current employee was sourced from the portal, an estimate that is also statistically distinguishable from the unitary treatment arms (column 3). The latter result suggests the combination of treatments meaningfully induced employers to hire beyond their traditional networks. In addition, as 83% of employers in our sample state they assess worker quality within two months and the follow-up survey typically took place after six months, the change in employee composition also reveals that portal hires were good matches retained well beyond the standard assessment period.

Overall, these effects suggest that access to larger applicant pools via advertising *and* verification services on the portal induce firms to fill vacancies that may have otherwise remained unfilled. We advise some caution in interpreting these estimates. While the per-comparison p-values for all hiring outcomes corresponding to *Joint* firms in Table 2 are significant, the result on employee composition is the only one that remains above standard threshold for rejection (p-value = 0.048) after adjusting these p-values for testing multiple hypotheses (see Panel B in Appendix C.9).

5.4 Heterogeneity by Employer and Job Type

Small firms ($<$ 10 employees) are significantly more likely to report being concerned by trust-related recruitment issues (e.g., concerns about employee behavior), rely on traditional recruitment networks, and possess less capacity to screen applicants (see Appendix A.3). In Table 3, we find that small firms in the *Joint* treatment double their level of engagement with applicants on the portal relative to the control group. In contrast, neither the *Verification* nor the *Scale* treatment increase engagement for small firms. For large firms, both the *Scale* and *Joint* treatments lead to similar increases in employer engagement.

Second, firms hiring workers who must deliver or collect cash or merchandise or interact directly with clients may be especially concerned about the reliability and reputation of the workers they hire. We classify vacancies involving these tasks as being 'trust-sensitive' (38% of the sample), using data from job descriptions provided by employers. For trust-sensitive vacancies, we again find that only the *Joint* treatment significantly increases employer engagement (column 3); we can reject equality between the *Scale* and *Joint* arms (p-value = 0.050). Meanwhile, for vacancies that are not coded as 'trust-sensitive', both *Scale* and *Joint* treatments increase employer engagement and we cannot reject equality between the two treatments.

6 Discussion of Results

6.1 Robustness: Attrition and Spillover Effects

Prior to discussing our results, we probe the robustness of our results to survey attrition and spillover effects. The COVID-19 pandemic influenced our fieldwork and, consequently, attrition from our follow-up survey. However, we do not find significant differences in completion rates between the treatments arms and control (see Appendix C.3) or evidence to support differential attrition by vacancy characteristics (see Appendix C.4). Further, our core results are robust to accounting for attrition using inverse probability weighting, accounting for sampling variation over time, and the inclusion of baseline controls suggested by post-double selection LASSO (Belloni et al. (2013): see Appendix C.6).

Second, the assignment of vacancies to premium advertising may influence vacancies—within and outside the experimental sample—by lowering their search rankings. As our experimental vacancies account for less than 1% of vacancies during this period, it is perhaps unsurprising that we do not evidence of spillover effects either within or outside our experimental sample (see Appendix C.7).

6.2 Hiring through an Online Portal

Our results suggest that providing firms with access to more skilled candidates alone does not improve the success of their recruitment efforts. Rather, identity verification services appear important in allowing firms to successfully leverage these expanded recruitment networks. To understand the role verification in hiring, we outline a simple framework explaining a firm's hiring decision. We assume firm i evaluates the match-specific productivity (y_{ij}) of candidate j using two independently distributed attributes: their ability (a_j) and their trustworthiness (θ_j). Firms observe $a_j \sim F(a)$ which has finite mean and variance, where $f(a_1) < f(a_2)$ where $a_1 > a_2$. Workers are either honest (θ_H) or dishonest (θ_D), where $\theta_H > \theta_D$, and firms initially know the expected value of trustworthiness: $\tilde{\theta}$. Employers evaluate y_{ij} for each applicant and choose to hire them if this exceeds their outside option, c_i, defined by hiring through traditional networks. As such, a firm i will hire candidate j if $E[y_{ij}|a_j] = \alpha_i a_j + \tilde{\theta} > c_i$, where α_i is a parameter that captures the firm-specific importance of ability relative to trustworthiness.

6.3 How Treatments Influence Portal Hiring

Consider a firm z assigned to *Control* and whose vacancy attracts a set of applicants P. Assume that the best applicant in P is not preferable to the outside option: $y^{MAX}_{zj,Control} < c_z$.

Verification: When firm z is randomly assigned to the *Verification* treatment, we assume that this service provides employers with information on applicant trustworthiness. In support of this assumption, a majority of employers (56%) we surveyed requested identity-verified profiles of which over 80% stated that that it builds trust in applicants (see Appendix A.3). To simplify exposition, we assume that the *Verification* treatment allows employers to observe θ perfectly.[17] As such, there may exist a subset of candidates $p_1 \subset P$ who are revealed as honest types (θ_H) and are now preferable to the outside option: $\forall j \in p_1 : \alpha_z a_j + \theta_H > c_z > \alpha_z a_j + \tilde{\theta}$.

Scale: Similarly, when firm z is instead assigned to *Scale*, they have a larger pool of applicants P' where $P \subset P'$. Under the assumption that premium advertising services induce more draws from the same ability distribution—an assumption consistent with empirical results in Section 5.1—firm z observes a more high-skilled candidate on average, $a^{MAX}_{j,Scale} > a^{MAX}_{j,Control}$.[18] As such, there may exist a subset of candidates $p_2 \in P'$ who are of sufficiently high ability that they too are preferable to the outside option:$\alpha_z a^{MAX}_{j,Scale} + \tilde{\theta} > c_z$. Note, by construction, $p_1 \cap p_2 = \emptyset$.

Joint: Finally, if firm z is instead assigned to the *Joint* treatment, they would have the same (larger) pool of applicants, P', as in *Scale* and the ability to observe applicant trustworthiness: θ_j. As with *Verification* firms, *Joint* firms strictly prefer candidates in p_1 to the outside option. Relative to *Scale*, however, some applicants in p_2 benefit under the *Joint* treatment because they are revealed as honest ($\theta_H > \tilde{\theta}$), while others are punished ($\theta_D < \tilde{\theta}$). Assume that the new set of applicants hired under *Joint* is $p_3 \in P'$. Conditional on receiving *Scale*, the net effect of verification on hiring is positive $p_3 \geq p_2$ if we additionally assume that high abilities are less frequent than lower abilities, i.e. $f(a)$ is non-increasing and we rule out outside options such that either everyone or nobody is preferable to the outside option

[17] The framework predictions would be unchanged if verification services instead provide an informative signal of applicant's trustworthiness.

[18] For a proof, see Appendix C.10.

under *Joint* (For a proof, see Appendix C.11). Intuitively, because higher ability candidates are relatively scarce, there are more marginally low ability applicants who gain from their trustworthiness being revealed than there are marginally high ability applicants who lose out.

6.4 Mapping the Framework to Results

Joint firms hire more through the portal relative to control and this effect is statistically greater than those corresponding to the *Verification* and *Scale* treatments. To examine whether the treatments generate a complementarity in portal hiring, as opposed to being substitutes, we test the null hypothesis that the *Joint* effect is equal to the sum of the *Verification* and *Scale* against the alternative (one-sided) hypothesis that *Joint* is greater than or equal to the sum of the individual treatment arms. We reject the null (p-value=0.09), and this this test provides suggestive evidence that identity verification services generate a complementarity that increases the return to accessing expanded recruitment networks online. On their own, the *Verification* and *Scale* treatments do not appear to induce additional hiring through the portal relative to control. While the point estimates are virtually zero, owing to the precision of these estimates we cannot rule out small positive effects.

Our framework focuses on hiring through a portal, but we note that while 77% of control firms successfully fill their vacancy, just 12% of these firms recruit through the portal. This suggests that in many cases, the outside option may be preferable to hiring online, reducing our power to detect effects on hiring through a portal and, especially, overall hiring. The framework also abstracts away from liquidity constraints and other stochastic shocks faced by firms that can make hiring an especially noisy outcome (Rosenzweig and Udry, 2020). However, we can also examine engagement with the portal as a precursor to hiring using click data. Consistent with the portal hiring effects, we find evidence suggesting that the *Joint* treatment generates a complementarity that induces greater employer engagement relative to the sum of *Scale* and *Verification* treatments (p-value=0.05). In addition, our results suggest that the gains in employer engagement with applicants in the *Joint* treatment are concentrated among relatively lower-skilled individuals who may only be preferable to the outside option after successful verification is revealed to employers (see Appendix B.5).

6.5 Alternative Interpretations of the Role of Verification

We view our results as being *most* consistent with identity verification providing valuable information on applicant trustworthiness. However, we consider two alternative interpretations. First, verification may instead provide a signal of applicant interest in a job. If so, *Joint* employers may even reduce recruitment effort by weeding out uninterested applicants. However, we find that employers increase overall recruitment effort by contacting *more* portal applicants and leaving time spend on other recruitment methods unchanged (see Table 1, columns 4-6, and Appendix B.4). Second, verification may *only* provide information on applicant ability. In this case, we would expect higher-skilled applicants to differentially benefit.

Rather, we find that differences in employer engagement between *Joint* and *Scale* are stronger for relatively lower-skilled applicants (Appendix B.5).

7 Conclusion: External Validity and Verification at Scale

What do our findings reveal more generally about hiring frictions in an urban labor market? The frictions we study are not specific to our context: difficulty locating suitable candidates is a commonplace concern for firms across the developing world and many are to hire outside their networks because of inadequate screening mechanisms (Abebe et al., 2021b; Caria and Falco, 2022; Cullen et al., 2022; Hardy and McCasland, 2022). The proliferation of online job portals—22 in India alone at the time of writing—represent a technological advance that can greatly expand recruitment networks, but under 2% of firms across urban India report using the internet to hire workers. The challenges our interventions overcome are not unique to QuikrJobs and appear a generic consequence of hiring beyond traditional networks: across a number of job portals firms cite concerns about the trustworthiness of candidates (Cappelli, 2001; Fountain, 2005).

Our sample firms are well-positioned to benefit from portals—they have already posted on a portal, are larger than the average firm in urban India, and are more likely to have a hired employee (See Appendix A.2). While this may make our sample firms more responsive to our treatments, it also suggests that our treatment effects maybe are underestimated relative to the average Indian firm. We view our results as showing the promise of online job portals and the necessity of providing ancillary services in fulfilling that promise. Given the rapid proliferation of government-supported digital identity systems in lower-income countries (Gelb and Metz, 2017), identity verification technologies could serve as a low-cost, scalable screening tool for improving labor market matching. Employers value screening services and are willing to pay to access them: an incentive-compatible willingness to pay exercise with 115 sample employers, we find that 89% are willing to pay a positive amount to access this information on the portal (see details in Appendix A.6). We focused on identity verification due to our study setting of low-wage retail and service work, however, future work can explore the benefits of incorporating a wider range of verifiable information with more heterogeneous groups of firms.

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Table 1: Recruitment Pools and Employer Engagement

	Applications	Skills Index		Application Clicks		Interviews
	(1) Number	(2) Mean	(3) Maximum	(4) Any	(5) Number	(6) Any
Verification (V)	2.040	0.022	-0.011	0.027	-0.090	0.022
	(2.179)	(0.019)	(0.040)	(0.033)	(0.767)	(0.062)
Scale (S)	25.794***	-0.010	0.314***	0.067*	1.688**	0.056
	(2.506)	(0.021)	(0.038)	(0.035)	(0.776)	(0.066)
Joint (J)	30.128***	-0.006	0.332***	0.126***	3.685***	0.129**
	(2.723)	(0.016)	(0.036)	(0.033)	(0.996)	(0.062)
N Vacancies	1719	1682	1685	1719	1719	-
N Firms	-	-	-	-	-	550
Control Mean	25.239	-0.037	0.994	0.349	2.499	0.503
Test p-val: J=V	0.000	0.108	0.000	0.003	0.001	0.075
Test p-val: J=S	0.130	0.836	0.602	0.092	0.045	0.248

Notes: This table shows impacts on applications and employer engagement. Data for columns 1–5 come from the portal's administrative data and data for column 6 comes from the long version of the firm follow-up survey. Column 1 shows the number of applications, top coded at the 99th percentile. Columns 2–3 consider the mean and the maximum of the 'skills index' at the vacancy level, respectively. The skills index is generated at the applicant level using the approach specified in Anderson (2008) and then summarized at the vacancy level. It includes: whether an applicant has an undergraduate or higher educational degree; has English-language skills; has job category-specific skills, certifications, or expertise; shares resume; shares ID details for verification; and number of total attributes in an applicant's profile. The sample in columns 2–3 restricts to only those 1,685 vacancies that receive at least 1 application; column 2 has fewer observations due to some outlier corrections. Columns 4–5 report on application clicks by employers to access contact details on the portal; column 4 is an indicator for whether the employer clicked on any application and column 5 shows the number of unique applications the employer clicked on. Column 6 reports an indicator for whether the employer interviewed any portal-sourced applicant. Regressions include strata fixed effects and for column 6, additionally include controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table 2: Hiring and Employee Composition

	Any Hire for Posted Vacancy?		Employee Composition at Follow-Up
	(1) via Portal	(2) All Methods	(3) via Portal
Verification (V)	0.009	0.044	0.030
	(0.035)	(0.043)	(0.037)
Scale (S)	0.012	0.026	0.005
	(0.038)	(0.046)	(0.040)
Joint (J)	0.082**	0.082**	0.114***
	(0.039)	(0.042)	(0.041)
N Firms	794	794	794
Control Mean	0.121	0.767	0.150
Test p-val: J=V	0.048	0.340	0.039
Test p-val: J=S	0.072	0.194	0.010

Notes: This table examines impacts on hiring and employee composition, using data from follow-up surveys. The dependent variables in columns 1-2 consider whether any hires were made since vacancy posting. Column 1 reports the estimated effect on making any hire via the portal; column 2 reports hires overall, viz. through all possible recruitment methods. The dependent variable in column 3 reports whether there was an employee working at the firm in the month prior to the follow-up survey who was hired via the portal. If a firm has multiple vacancies in the experiment, we use the treatment status assigned to the first vacancy in this table. Regressions include strata fixed effects and controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table 3: Heterogeneous Effects by Firm Size and Job Type

	Dependent variable: # Application Clicks			
	Employer Type		Job Type	
	(1) Small Firm (0-9 employees)	(2) Large Firm (10+ employees)	(3) Trust-sensitive Vacancy	(4) Not Trust-sensitive Vacancy
Verification (V)	-0.877	0.000	-0.564	-0.473
	(0.612)	(0.597)	(0.785)	(0.534)
Scale (S)	0.809	2.606***	1.335	1.735**
	(0.804)	(0.801)	(0.917)	(0.708)
Joint (J)	2.759***	3.382***	3.609***	2.611***
	(0.901)	(0.822)	(1.105)	(0.716)
N Vacancies	830	889	645	1074
Control Mean	2.340	2.028	2.481	1.984
Test p-val: J=V	0.000	0.000	0.000	0.000
Test p-val: J=S	0.039	0.431	0.050	0.301

Notes: This table examines how employer engagement with applications on the portal varies by firm size and job type. Employer engagement is measured by the number of unique applications clicked on by employers in the portal administrative data, top coded at 99th percentile to deal with outliers. Column 1 restricts the sample to small firms, defined as reporting fewer than 10 employees, whereas column 2 focuses on large firms, defined as reporting 10 or more employees. Column 3 restricts the sample to 'trust-sensitive' vacancies in the sample; a vacancy is coded as 'trust-sensitive' if the job description mentions cash or merchandise delivery or collections, customer interactions, or trust. Column 4 reports results for vacancies *not* coded as 'trust-sensitive.' Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

FOR ONLINE PUBLICATION

Hiring Frictions and the Promise of Online Job Portals: Evidence from India

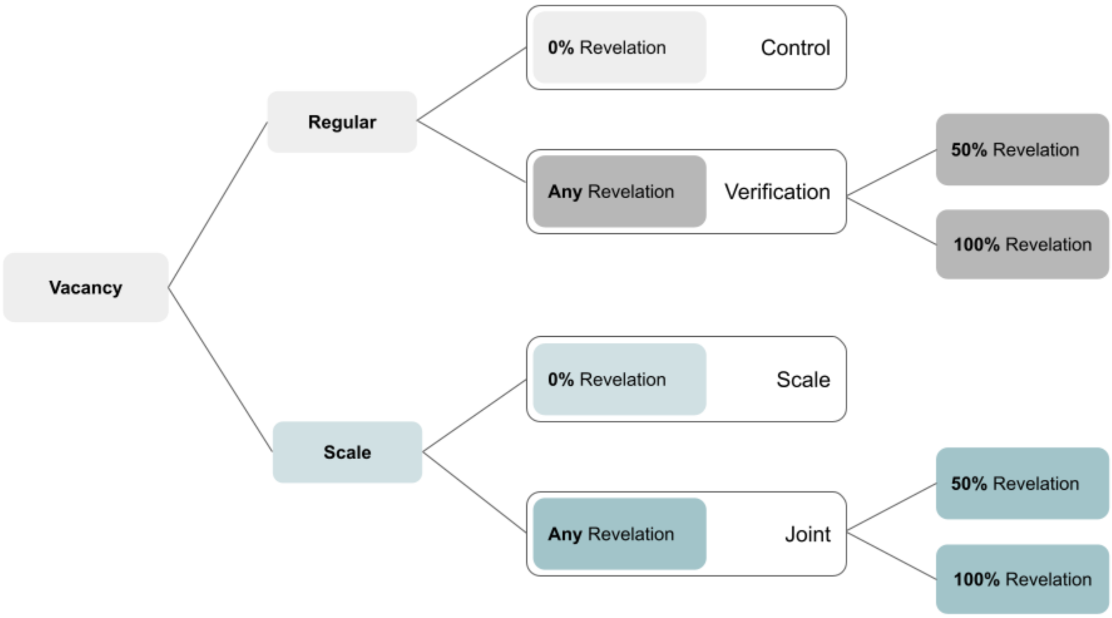
A. Nilesh Fernando, Niharika Singh, and Gabriel Tourek

Table of Contents

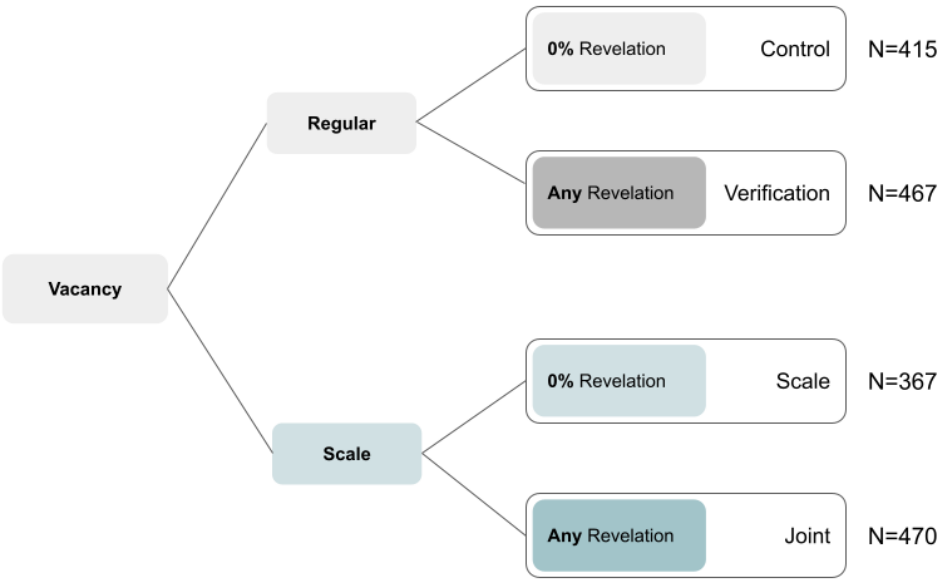
Appendix A Experimental Design and Data

Appendix A.1 Experimental Design

Panel A: Design



Panel B: Sample Sizes for Main Specification



Notes: This figure shows the experimental design. Panel A shows the experimental groups: vacancies are assigned to *Control*, *Verification*, *Scale*, or the *Joint* treatment. For vacancies in the *Verification* and *Joint* treatments, either 50% or 100% of applicant verification outcomes are revealed to employers. Panel B shows the sample sizes for the different groups for the main specification which pools together the 50% and 100% verification cells into 'Any revelation.'

Appendix A.2 Comparison of Study Sample to Firm Census

Table A2: Comparison of Sample Firms with Urban-area Firms in Economic Census 2013-14

	(1) Study Sample	(2) Census Urban Karnataka	(3) Census Bengaluru
Panel A: Sector of Operation			
Wholesale & retail trade, transport, accommodation & food service	29.92%	54.36%	n/a*
Professional, technical & admin	13.42%	3.76%	
Information & communication	13.08%	1.17%	
Education, human health & social work	11.04%	4.53%	
Manufacturing, mining & others	9%	23.46%	
Real estate	8.53%	0.85%	
Other services	7.28%	5.84%	
Financial & insurance activities	4.32%	2.02%	
Construction & utilities	3.41%	2.01%	
Agriculture, forestry & fishing	0%	2.00%	
Panel B: Other Firm Attributes			
Located within HH premises	8.62%	18.35%	8.50%
Located outside HH premises	91.38%	81.65%	91.49%
Establishments with at least 1 hired person	98.01%	44%	52.83%
Establishments with less than 8 persons	37.73%	95.8%	94.30%

Notes: This table compares sample firms to a population census of firms, the Economic Census 2013-14, conducted by the Indian government. Data on the study sample comes from firm surveys. Census statistics are compiled by the authors from the annual report for the Economic Census 2013-14 for the Karnataka region. Panel A shows the sector of operation. Panel B shows additional firm attributes.

* Sector of operation is not available separately for the Bengaluru area in the annual reports.

Appendix A.3 Descriptive Evidence on Hiring Frictions

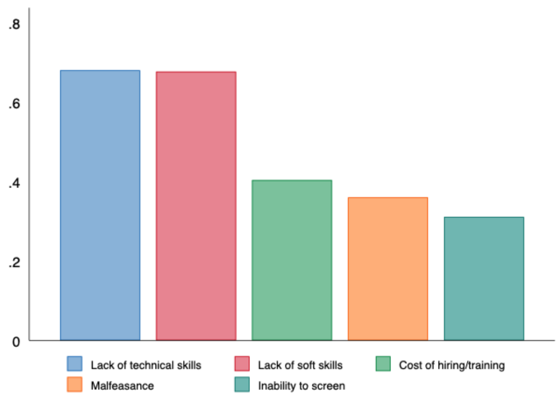
Table A3: Summary Statistics

	Mean		
	Overall	Small Firm (0-9 employees)	Large Firm (10+ employees)
N employees (Top coded 1%)	20.16	9.43	29.2
Mentions any constraint to growth	0.75	0.76	0.73
Mentions labor-related issues as constraint†	0.69	0.70	0.67
Mentions other non-labor issues as constraint†	0.34	0.34	0.35
Mentions trust-related recruitment issues⋆	0.53	0.57	0.50
Has dedicated HR staff	0.31	0.17	0.42
Reports using security equipment or personnel	0.59	0.48	0.68
Fraction of employees hired via networks	0.56	0.66	0.48
Pursuing network-based hiring for sample vacancy	0.84	0.87	0.80
Reports learning worker quality within 2 months	0.83	0.84	0.85

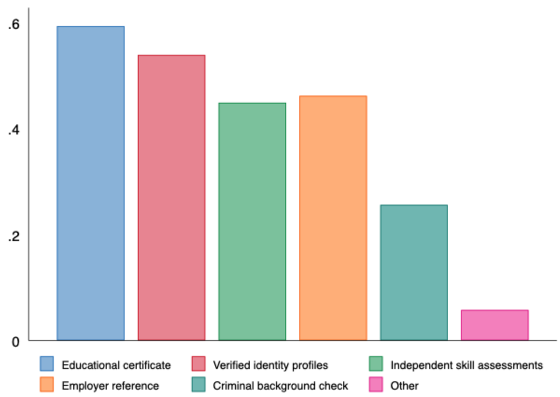
Notes: This table shows summary statistics on hiring frictions using data from baseline surveys with 915 firms. Within this set, there are 431 small firms, defined as reporting fewer than 10 employees, and 502 large firms, defined as reporting 10 or more employees.
† Labor-related issues include difficulty finding workers with technical or soft skills, concerns about employee behavior, screening difficulties, and cost of hiring and training new employees. Non-labor issues include lack of access to finance, low consumer demand, legal regulations, and economic policy uncertainty.
⋆ Trust-related issues include concerns about employee behavior and difficulty finding workers with required soft skills such as good behavior and communication.

Figure A3: Labor-related Constraints and Information Desired by Employers

(a) Breakdown of Labor-related Constraints



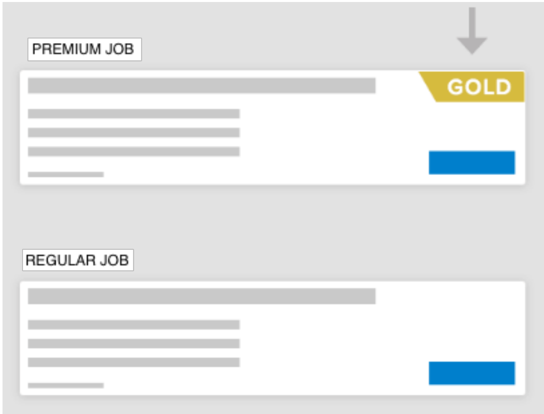
(b) Types of Job seeker Information Desired by Employers



Notes: Figure A3(a) reports labor-related issues shared by sample employers. The sample is restricted to only those employers (69%) who report any labor-related constraints. Soft skills are defined as skills relating to good behavior, communication, etc. Malfeasance is related to concerns about employee behavior, such as theft or crime. Figure A3(b) reports the types of additional job seeker information that employers would like to access on the portal. 98% of employers report wanting additional information. Data are from baseline surveys.

Appendix A.4 Treatment Visuals

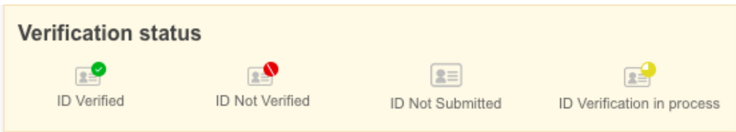
Figure A4.1: Comparison of vacancy with premium advertising services to a regular vacancy



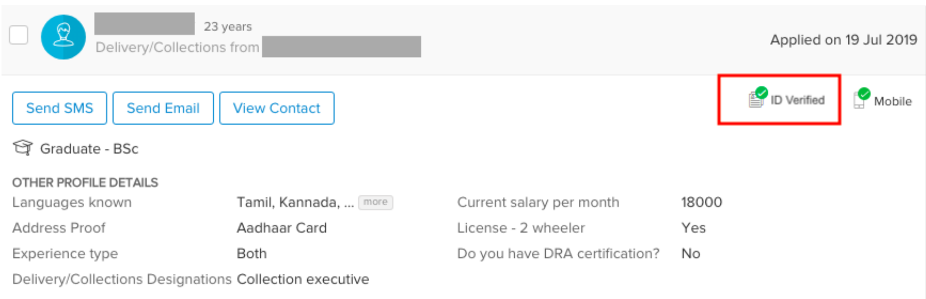
Notes: This figure depicts the visual difference between vacancies that receive premium advertising in the *Scale* and *Joint* treatments and those that do not in the control and *Verification* groups.

Figure A4.2: Verification Badges and Sample Applicant Profiles

Panel A: Verification Badges



Panel B: Sample of an Applicant Profile



Notes: Panel A shows the badges an employer receiving access to identity verification information may see on the profiles of their applicants. Panel B shows a sample application sent to an employer on the portal. The application includes an 'ID verified' badge, which indicates that the applicant successfully passed the verification request and applied to vacancy where the employer received access to identity verification information. To access an applicant's contact details, the employer must click on the blue buttons in the profile and the portal records these click actions.

Appendix A.5 Timeline of Activities

The timeline of project activities is given below:

- Nov-2018 to Jan-2020: Sampling and interventions active on the QuikrJobs portal
- Dec-2018 to Feb-2020: Baseline firm surveys conducted in-person
- June-2019 to July-2020: Follow-up firm surveys conducted in-person until early March-2020 and then over the phone after COVID-19 pandemic

Appendix A.6 Willingness-to-Pay Exercise

During follow-up survey visits, a willingness-to-pay exercise for identity verification services was administered to a randomly selected 115 employers. Enumerators informed respondents that they would have a chance to purchase access to this service (via a coupon) for any future vacancy they post on the portal. Enumerators explained that the service would allow applicants to their vacancy to submit verification, and the verification outcome would then be revealed to them. They were told the market price for the service for one vacancy is around Rs.400 (USD 5.68), but that they would be able to purchase the service at market price or lower.

This exercise was conducted using the common Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). Respondents were asked to state their willingness to pay for the service between Rs.0 to Rs.400. The enumerator explained that they had a scratch card with a given price. If the price on the scratch card was higher than the respondent's bid, then the respondent could not buy the service at the time. If the scratch card price was equal or lower than their bid, then the respondent could purchase if they so wished. The approach thus incentivized truth-telling by the respondent.

We find that 89% of employers are willing to pay a positive amount to access this information on the portal. Among those willing to pay, the average bid price is Rs. 204 (USD 2.89). The cost of verification during the experiment was Rs. 25 (USD 0.36) per applicant. At scale, these costs are expected by our partner to be much lower (as low as Rs. 2 per verification). As such, it appears that the portal could easily cover the costs of verification by charging employers for the service.

Appendix B Additional Results

Appendix B.1 Applicant Attributes for Skill Index at the Vacancy Level

	Any applicants reporting X		Number of applicants reporting X		Fraction of applicants reporting X	
	(1) Control Mean	(2) Scale-C	(3) Control Mean	(4) Scale-C	(5) Control Mean	(6) Scale-C
Education: $\geq$ Bachelors	0.851	0.123***	8.990	9.885***	0.331	0.030**
		(0.020)		(1.141)		(0.013)
Language: English	0.959	0.032***	19.267	20.145***	0.731	0.009
		(0.010)		(2.059)		(0.013)
Report Skills	0.829	0.068***	12.316	13.077***	0.478	-0.018
		(0.016)		(1.539)		(0.014)
Report Certifications	0.545	0.098***	8.704	6.951***	0.225	-0.000
		(0.019)		(1.309)		(0.007)
Report Specific Expertise	0.901	0.085***	14.896	14.237***	0.516	-0.005
		(0.016)		(1.754)		(0.014)
Shared CV	0.737	0.161***	5.805	6.069***	0.210	-0.009
		(0.026)		(0.867)		(0.011)
Submitted ID information	0.629	0.200***	3.128	3.174***	0.099	0.015**
		(0.030)		(0.542)		(0.008)

Notes: This table shows how applicant attributes, X, vary between vacancies assigned to the *Control* and *Scale* treatment arms. The sample for these regressions is restricted to these *Control* and *Scale* vacancies. Attributes are self-reported on the portal by job seekers. Columns 1–2 focus on whether any applicant to a vacancy reports attribute X. Columns 3–4 show the number of applicants in a vacancy reporting attribute X, while columns 5–6 show the fraction of applicants in a vacancy doing the same. Columns 1, 3, and 5 reports the control mean at the vacancy level. Columns 2, 4, and 6 report coefficients from separate regressions of the attribute X on the indicator for the *Scale* treatment. Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix B.2 Distribution of Skills Index and Applications by Skills Index

	Within-vacancy Rank			Number of applications	
	(1) Top 5	(2) Minimum	(3) Bottom 5	(4) Below Median	(5) Above Median
Verification	0.029	-0.075	0.037	0.731	1.243
	(0.032)	(0.067)	(0.063)	(1.070)	(1.193)
Scale	0.341***	-0.338***	-0.263***	12.969***	12.656***
	(0.035)	(0.074)	(0.065)	(1.257)	(1.403)
Joint	0.362***	-0.250***	-0.247***	14.620***	14.483***
	(0.031)	(0.055)	(0.065)	(1.240)	(1.487)
N Vacancies	1685	1682	1685	1719	1719
Control Mean	0.539	-0.834	-0.597	12.694	12.446

Notes: This table shows additional measures of the skills index and how the number of applications vary by the skill index. The dependent variables in columns 1–3 are constructed by ranking each applicant, based on the skill index, for a given vacancy. Column 1 shows the mean of the skill index for the top 5 ranked applicants for each vacancy. Columns 2–3 examine the bottom of the distribution. Column 2 shows the index score of the lowest-ranked applicant, i.e., the minimum, while column 3 shows the mean of the index for the bottom 5 ranked applicants for each vacancy. Columns 4–5 show the number of applications by percentile thresholds (above/below median) of the skills index. The median is calculated using the applicant-level skills index for control vacancies. The dependent variables are then generated by counting the number of applications in a vacancy that fall below or above this median. Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix B.3 Applicant-level Effects of Revealing Verification Outcomes to Employers

	Employer Click	
	(1)	(2)
Revealed	-0.001	-0.001
	(0.004)	(0.004)
ID Verified	-0.014	-0.013
	(0.009)	(0.009)
Revealed * ID Verified	0.023*	0.023*
	(0.013)	(0.012)
R-Squared	0.42	0.45
No Revelation Mean	0.141	0.141
N Applications	14732	14727
Vacancy Fixed Effects	Y	Y
Applicant Controls	N	Y

Notes: This table shows how employer engagement varies by verification outcomes of applicants. The specification interacts revelation status by verification outcome. 'Revealed' is an indicator for whether the applicant's verification outcome was randomly selected to be revealed via a profile badge to the employer. 'ID Verified' takes on a value of 1 if the applicant passed verification. Our coefficient of interest is the interaction term, 'Revealed*ID Verified', which captures whether employers were differentially more likely to click on applicants who were revealed to have passed ID verification. The applicant sample comes from within-vacancy variation generated in the 50% revelation cells of the experiment; the dependent variable is whether the employer clicked to contact or access contact details of the application. The regression includes vacancy fixed effects and clusters standard errors at the vacancy level. Column 2 duplicates column 1, but includes applicant level controls available from the applicant profile information on the portal. Controls includes: number of days between vacancy posting and application; number of attributes in the profile and its square; gender; age; education; language skills; years of experience in occupation; current or previous employer; current monthly salary; any job-specific skills, certifications, or expertise; religion; or type of identity documents available. If a profile does not report a specific variable, it is coded as 0 for indicator variables, and assigned a value of -99 and tagged as missing using indicator variables for continuous variables in the regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix B.4 Investments in Alternate Recruitment Methods for Vacancy

	Applications		Interviews	
	(1) Any	(2) Number	(3) Any	(4) Number
Verification	0.054	2.104	0.041	1.051
	(0.051)	(3.707)	(0.054)	(1.443)
Scale	0.007	-1.334	-0.017	-0.076
	(0.055)	(2.926)	(0.059)	(1.298)
Joint	0.017	1.002	0.023	1.760
	(0.051)	(3.452)	(0.054)	(1.637)
N Firms	589	589	589	589
Control Mean	0.778	14.957	0.735	7.414

Notes: This table reports the effects on applications and interviews for the sample vacancy from alternative recruitment methods (i.e., excluding the portal in the experiment, but including networks, job fairs, employment agencies, other job portals, etc.). Data are from the long version of the follow-up survey. The dependent variables are as follows: whether any application was received (column 1); the number of applications received, top coded at the 99th percentile (column 2); whether any interview was conducted (column 3); and the number of interviews, top coded at 99th percentile (column 4). Regressions include strata fixed effects and controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix B.5 Employer Clicks by Skill Index of Applicants

	Number of Application Clicks by Percentile of Skills Index			
	(1) Upto 25th	(2) 25th to 50th	(3) 50th to 75th	(4) 75th to 100th
Verification	-0.197	-0.128	-0.014	0.248
	(0.185)	(0.230)	(0.208)	(0.237)
Scale	0.345*	0.279	0.530**	0.534**
	(0.196)	(0.228)	(0.234)	(0.218)
Joint	1.132***	0.823***	1.010***	0.720***
	(0.316)	(0.259)	(0.305)	(0.207)
N Vacancies	1719	1719	1719	1719
Control Mean	0.622	0.699	0.663	0.516

Notes: This table disaggregates the number of clicks employers made to obtain contact details for unique applications by percentiles of the skills index. The percentile thresholds are calculated using the applicant-level skills index for control vacancies and split the distribution into 4 bins. The dependent variables are then generated by counting the number of employer clicks based on the value of the skills index for each applicant and the associated percentile bin. Column 1 focuses on applicants up to the 25th percentile; column 2 on applicants between the 25th and 50th percentiles; column 3 on applicants between the 50th and 75th percentiles; and finally, column 4 on applicants between the 75th and 100th percentiles. Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix B.6 Hires through Traditional Recruitment Networks

	Any Hires via Networks		
	(1) Main Specification	(2) Adjusting for Sampling & Attrition	(3) Incl. PDS Lasso Selected controls
Verification	-0.009	0.005	-0.009
	(0.051)	(0.052)	(0.050)
Scale	-0.028	-0.012	-0.028
	(0.054)	(0.055)	(0.053)
Joint	-0.037	-0.024	-0.037
	(0.051)	(0.052)	(0.050)
N Firms	794	792	794
Control Mean	0.510	0.510	0.510

Notes: This table examines the impact on hiring via traditional recruitment networks, defined as family, friends, co-workers and their resulting referrals. The dependent variable is whether the firm reports making any hire via these networks since vacancy posting. Column 1 reports the effect for our main specification. Column 2 shows the effect after including vacancy-month and survey-month fixed effects and re-weighting to account for attrition using inverse probability weights, calculated from a probit regression that predicts attrition using vacancy characteristics listed in Table C.1. Column 3 shows the effect after adding controls using the post double selection lasso technique. The data for these measures come from follow-up surveys. If a firm has multiple vacancies in the experiment, then we use the treatment status of the first vacancy in this table. Regressions include strata fixed effects and controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C Robustness Tests

Appendix C.1 Summary Statistics and Balance for Vacancies

	Control Mean (1)	V-C (2)	S-C (3)	Joint-C (4)	N Vacancies (5)	Test: V=S (6)	Test: V=Joint (7)	Test: S=Joint (8)
Included company name	0.901	0.026	-0.001	0.023	1,719	0.182	0.891	0.220
		(0.019)	(0.022)	(0.020)				
Salary posted, minimum (Rs)	12,846.506	-342.389	-300.982	34.156	1,719	0.925	0.346	0.491
		(428.502)	(518.218)	(477.589)				
Salary posted, maximum (Rs)	18,577.947	-280.639	-593.296	-33.708	1,719	0.689	0.738	0.490
		(738.425)	(819.525)	(780.437)				
Experience required, minimum (years)	0.868	-0.000	-0.017	-0.130*	1,719	0.848	0.083	0.171
		(0.079)	(0.088)	(0.077)				
Experience required, maximum (years)	3.229	0.112	-0.096	-0.262	1,719	0.367	0.084	0.432
		(0.234)	(0.233)	(0.219)				
Is a full-time vacancy	0.906	0.033*	0.018	0.028	1,719	0.464	0.774	0.628
		(0.019)	(0.020)	(0.019)				
Character length of job posting	336.340	-11.072	16.697	-19.732	1,719	0.339	0.745	0.198
		(28.773)	(30.298)	(28.223)				
F-test p-value		0.533	0.987	0.408		0.624	0.150	0.297

Notes: This table describes the sample vacancies and shows balance tests across the experimental groups. Each row is a separate regression of a pre-treatment covariate on indicators for $Verification$ (V), $Scale$ (S), and $Joint$. Column 1 shows the control mean. Columns 2–4 show regression coefficients and standard errors in parentheses for differences between $Verification$, $Scale$, and $Joint$ vacancies to control vacancies, respectively. Column 5 shows the number of vacancies in the regression. Columns 6–8 show p-values from tests of equality between treatment groups. The last row shows F-test p-values from a joint test that the listed covariates jointly predict treatment status. To compute these joint tests, we restrict the regression to only the experimental groups under consideration. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.2 Balance on Firm Variables

	Control Mean	V-C	S-C	Joint-C	N Firms	Test: V=S	Test: V=Joint	Test: S=Joint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector: Retail trade, transport, food, & accommodation	0.328	-0.022	-0.032	-0.055	1,001	0.813	0.406	0.581
		(0.041)	(0.043)	(0.042)				
Sector: Information & communication	0.109	0.006	0.033	0.009	1,001	0.381	0.911	0.440
		(0.029)	(0.032)	(0.029)				
Sector: Professional, technical, & administrative	0.158	-0.016	-0.025	-0.014	1,001	0.782	0.928	0.727
		(0.031)	(0.034)	(0.033)				
Sector: Education, health, & social work	0.126	-0.013	-0.044*	-0.004	1,001	0.206	0.748	0.098
		(0.027)	(0.027)	(0.027)				
Firm age (years)	6.522	0.218	0.165	0.160	1,001	0.948	0.936	0.995
		(0.714)	(0.856)	(0.756)				
Has single establishment	0.671	-0.008	0.017	-0.041	914	0.577	0.447	0.209
		(0.044)	(0.047)	(0.045)				
Located on rented, outside HH premises	0.809	0.044	0.022	0.057	901	0.564	0.722	0.366
		(0.036)	(0.040)	(0.037)				
Firm type: Private Limited Company	0.394	-0.005	0.064	0.016	997	0.121	0.616	0.286
		(0.043)	(0.045)	(0.043)				
F-test p-value		0.811	0.409	0.553		0.553	0.928	0.641

Notes: This table shows balance tests for firm-level variables across the experimental groups. Column 1 shows the control mean. Columns 2-4 show regression coefficients and standard errors in parentheses for differences between *Verification* (V), *Scale* (S), and *Joint* vacancies to control vacancies, respectively. Column 5 shows the number of firms in the regression. Columns 6–8 show p-values from tests of equality between treatment groups. Data come from baseline and follow-up surveys and variables are basic firm attributes that are unlikely to change due to treatment. Regressions include strata fixed effects. The last row shows F-test p-values from the joint test of orthogonality, which is computed by regressing the treatment variable on all covariates and strata fixed effects and testing whether they jointly predict treatment status. To compute these joint tests, we restrict the regression to only the experimental groups under consideration. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.3 Attrition

Of the 1,576 firms posting vacancies in the experiment, 65% were surveyed at least once, either during the baseline or the follow-up survey, and 50% were surveyed in the follow-up survey. We do not find significant differences in completion rates either between the treatment and the control group or between treatment groups across survey rounds. The one exception is the long version of the follow-up survey (column 5), where firms in the *Verification* treatment are 6.1% less likely to complete this survey. However, as our key hiring outcomes are collected in both the long and short versions of the follow-up survey, this difference should not affect our main results. We also do not find evidence of systematic differences in the vacancy characteristics of attritees across treatments (Table C.4). Nevertheless, for our survey-based outcomes, we implement robustness checks accounting for attrition using inverse probability weighting,[1] as well as for chance imbalance by adding controls using the post-double selection LASSO method (Belloni et al., 2013). Our results are qualitatively similar when implementing these adjustments (Table C.6).

	(1) Surveyed in any round	(2) Surveyed in both rounds	(3) Baseline	(4) Follow-up	(5) Follow-up (Long Version)
Verification	-0.003	-0.009	0.012	-0.025	-0.062*
	(0.034)	(0.036)	(0.035)	(0.036)	(0.035)
Scale	-0.008	-0.003	0.008	-0.019	-0.036
	(0.036)	(0.038)	(0.037)	(0.038)	(0.037)
Joint	-0.008	-0.022	0.013	-0.043	-0.045
	(0.035)	(0.036)	(0.036)	(0.036)	(0.035)
N Vacancies	1576	1576	1576	1576	1576
Control Mean	0.656	0.449	0.577	0.528	0.415

Notes: This table shows survey completion rates for firms in the experiment. The dependent variables are all indicators and measure whether a firm has completed: either the baseline or follow-up survey (column 1); both the baseline *and* follow-up surveys (column 2); the baseline (column 3); the follow-up (column 4); and only the long version of the follow-up survey (column 5). Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

[1] This procedure involves predicting attrition in the follow-up survey using the vacancy characteristics and then applying the inverse of the predicted probability as weights in the regression. We first predict attrition for the control group using a probit regression, and then use the resulting regression coefficients to predict attrition for the treatment groups.

Appendix C.4 Vacancy Characteristics of Attriters in Follow-up Survey

	Control Mean (1)	V-C (2)	S-C (3)	Joint-C (4)	N Vacancies (5)	Test: V=S (6)	Test: V=Joint (7)	Test: S=Joint (8)
Included company name	0.826	0.067*	0.055	0.051	780	0.716	0.592	0.918
		(0.035)	(0.038)	(0.036)				
Salary posted, min (Rs)	13,304.620	-386.876	-690.240	101.176	780	0.680	0.454	0.351
		(772.456)	(940.014)	(855.784)				
Salary posted, max (Rs)	19,106.511	520.258	-545.197	387.356	780	0.436	0.914	0.490
		(1338.425)	(1404.646)	(1302.638)				
Experience posted, min (years)	0.846	0.142	0.097	0.006	780	0.747	0.272	0.487
		(0.131)	(0.137)	(0.121)				
Experience posted, max (years)	2.973	0.743**	0.421	0.081	780	0.397	0.060	0.303
		(0.347)	(0.329)	(0.298)				
Is a full-time vacancy	0.908	0.007	0.020	0.008	780	0.684	0.983	0.689
		(0.031)	(0.031)	(0.030)				
Character length of job description	335.989	-16.491	78.690	7.481	780	0.039	0.550	0.133
		(45.180)	(51.167)	(47.119)				
F-test p-value		0.163	0.373	0.993		0.403	0.232	0.481

Notes: This table considers whether vacancy characteristics are systematically different across experimental groups for the sample of firms not surveyed in follow-up. Column 1 shows the control mean. Columns 2–4 show how attriters vary between treatment groups relative to control for each covariate. Column 5 shows the number of vacancies considered in the regression. Columns 6–8 report p-values from tests of equality of coefficients comparing treatment groups to each other. Regressions use robust standard errors and include strata fixed effects. The last row shows F-test p-values from the joint test of orthogonality, which is computed by regressing the treatment variable on all covariates and testing whether they jointly predict status. To compute these joint tests, we restrict the regression to only the experimental groups under consideration. Only the first vacancy posted by the firm in the sample is considered in this analysis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.5 Robustness Tests for Effects on Applications and Employer Engagement

	Applications	Skills Index		Application Clicks	
	(1) Number	(2) Mean	(3) Maximum	(4) Any	(5) Number
Panel A: Estimates Accounting for Sampling Variation					
Verification	-0.097	0.023	-0.032	0.010	-0.652
	(2.161)	(0.020)	(0.040)	(0.034)	(0.799)
Scale	25.855***	-0.008	0.319***	0.073**	1.700**
	(2.522)	(0.020)	(0.037)	(0.035)	(0.786)
Joint	27.289***	-0.005	0.304***	0.099***	2.987***
	(2.666)	(0.017)	(0.036)	(0.034)	(0.975)
N Vacancies	1719	1682	1685	1719	1719
Control Mean	25.239	-0.037	0.994	0.349	2.499
Panel B: Estimates using PDS Lasso Selected Controls					
Verification	3.388	0.019	-0.006	0.028	-0.093
	(2.108)	(0.018)	(0.038)	(0.032)	(0.757)
Scale	26.963***	0.004	0.334***	0.071**	1.699**
	(2.394)	(0.015)	(0.036)	(0.035)	(0.766)
Joint	30.739***	-0.010	0.335***	0.126***	3.683***
	(2.497)	(0.015)	(0.034)	(0.033)	(0.982)
N Vacancies	1719	1682	1685	1719	1719
Control Mean	25.762	-0.037	0.994	0.346	2.591

Notes: This table shows robustness for administrative outcomes related to applications and employer engagement shown in Table 1. Panel A modifies the main specification to include vacancy-month fixed effects in order to account for sampling variation during the experiment. Panel B considers a specification with additional controls selected using the post double selection Lasso technique. The dependent variables are: number of applications, top coded at 99th percentile (column 1); the mean of the skills index (column 2); the maximum of the skills index (column 3); whether the employer clicked on any application to access contact details (column 4); and the number of unique applications the employer clicked on for contact details (column 5). The sample in columns 2–3 restricts to only those 1,685 vacancies that receive at least 1 application; column 2 has fewer observations due to some outlier corrections. Regressions include strata fixed effects. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.6 Robustness Test for Hiring Effects

	Any Hire for Posted Vacancy?		Employee Composition at Follow-Up
	(1) via Portal	(2) All Methods	(3) via Portal
Panel A: Estimates after Accounting for Sampling Variation and Attrition			
Verification (V)	0.003	0.042	0.034
	(0.037)	(0.045)	(0.038)
Scale (S)	0.000	0.025	-0.010
	(0.040)	(0.047)	(0.041)
Joint	0.078*	0.078*	0.121***
	(0.041)	(0.044)	(0.043)
N Firms	792	792	792
Control Mean	0.121	0.767	0.150
Panel B: Estimates using PDS Lasso Selected Controls			
Verification	0.009	0.044	0.030
	(0.034)	(0.041)	(0.036)
Scale	0.012	0.026	0.005
	(0.037)	(0.045)	(0.039)
Joint	0.082**	0.082**	0.114***
	(0.038)	(0.041)	(0.040)
N Firms	794	794	794
Control Mean	0.121	0.767	0.150

Notes: This table shows robustness checks for the hiring effects presented in Table 2. Panel A shows effects after including vacancy-month and survey-month fixed effects and re-weighting to account for attrition using inverse probability weights, calculated from a probit regression that predicts attrition using vacancy characteristics listed in Table C.1. Panel B shows effects after adding controls using the post double selection lasso technique. The data for these measures come from follow-up surveys. The dependent variables in columns 1-2 consider whether any hires were made since vacancy posting. Column 1 only looks at hires via the portal; and column 2 considers any hires overall through all possible recruitment methods. The dependent variable in column 3 instead considers whether there was an employee working at the firm in the month prior to the survey who was hired via the portal. If a firm has multiple vacancies in the experiment, we use the treatment status assigned to the first vacancy in this table. Regressions include strata fixed effects and controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.7 Spillover Impacts of Increased Scale Exposure on Applications

The assignment of vacancies to the *Scale* and *Joint* treatments may influence vacancies—within and outside the experimental sample— by lowering their search rankings. At the outset, experimental vacancies account for under 1% of all vacancies, suggesting that spillover effects are unlikely to be a major concern. However, to test for such spillovers, we leverage administrative data on *all* vacancies posted in Bengaluru during the experiment and assess how daily variation in exposure to vacancies assigned premium advertising services impacts the number of applications received by other vacancies. We define exposure as the percentage of new vacancies on a given day for a given job category that experimentally receive access to advertising services. We do not find that an increase in exposure leads to a statistically significant difference in the number of applications received by other vacancies both within or outside the sample.

	# Applications (Sample vacancies)		# Applications (All vacancies)	
	(1)	(2)	(3)	(4)
Scale Exposure	-0.254	-0.305	0.033	-0.018
	(0.177)	(0.319)	(0.040)	(0.045)
Regular Vacancy			1.311	0.995
			(1.568)	(1.563)
Regular Vacancy * Scale Exposure			-0.277	-0.249
			(0.173)	(0.174)
R-Squared	0.21	0.55	0.17	0.19
N Vacancies	882	882	31763	31763
Depvar Mean	24.38	24.38	29.975	29.975
Posting Date FE	N	Y	N	Y

Notes: This table shows the effects of increased exposure to premium advertising on the number of applications received by regular vacancies. 'Scale exposure' is defined as the fraction of new vacancies that received access to the *Scale* and *Joint* treatments, i.e., premium advertising services, due to the experiment on the day of posting. The fraction is calculated separately for each day and job-category. Columns 1–2 consider how this increased exposure affected number of applications to regular vacancies within the experimental sample. Columns 3–4 expand the sample to include regular vacancies outside the experiment. Data outside the experiment does not track whether an employer purchased premium services on their own for a given vacancy. To overcome this issue, we code any vacancy with applications below the 90th percentile of the job-category specific distribution of applications received by *Scale* and *Joint* vacancies in the experiment as a 'regular' vacancy. Column 2 and 4 include posting date fixed effects. All regressions include job-category fixed effects and use robust standard errors. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.8 Effects on Main Outcomes by Revelation Saturation

	Applications	Application Clicks	Any Hire	Employee Composition
	(1)	(2)	(3)	(4)
	Number	Number	via Portal	Any hired via Portal
50% Verification	1.111	0.650	0.051	0.062
	(2.496)	(1.303)	(0.044)	(0.047)
100% Verification	2.991	-0.841	-0.040	-0.007
	(2.746)	(0.759)	(0.038)	(0.044)
Scale	25.808***	1.681**	0.012	0.005
	(2.507)	(0.777)	(0.038)	(0.040)
Joint, 50% Verification	28.010***	4.283***	0.093*	0.104*
	(3.354)	(1.141)	(0.051)	(0.055)
Joint, 100% Verification	31.846***	3.201**	0.074	0.122**
	(3.433)	(1.375)	(0.046)	(0.050)
N Vacancies	1719	1719	-	-
N Firms	-	-	794	794
Control Mean	25.239	2.499	0.121	0.150

Notes: This table reports treatment effects for the main outcomes separately by the 50% and 100% revelation saturation groups. Columns 1 and 2 rely on administrative data from the portal for the posted vacancy, whereas columns 3–4 use data from the follow-up survey. The dependent variables are as follows: the number of applications to the posted vacancy, top coded at the 99th percentile (column 1); the number of employer clicks on unique applications (column 2); whether any hire via the portal occurred since vacancy posting (column 3); and whether any employee working at the firm in the month prior to the survey was hired through the portal (column 4). Regressions include strata fixed effects and controls for survey version (long or short), survey method (in person or phone), or if surveyed after March 2020 Covid lockdown. We report robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Appendix C.9 Multiple Hypothesis Testing

	(1)	(2)	(3)	(4)	(5)
Outcome	Treatment	Coefficient	S.E.	Asymptotic p-value	WY p-value
Panel A: Employer Engagement					
Any clicks	Verification	0.027	0.033	0.420	0.806
Number of clicks	Verification	-0.090	0.767	0.906	0.915
Any interviews	Verification	0.032	0.062	0.604	0.842
Any clicks	Scale	0.067	0.035	0.058	0.249
Number of clicks	Scale	1.688	0.776	0.030	0.163
Any interviews	Scale	0.069	0.066	0.298	0.737
Any clicks	Joint	0.126	0.033	0.0002	0.003
Number of clicks	Joint	3.685	0.996	0.0002	0.004
Any interviews	Joint	0.143	0.062	0.022	0.139
Panel B: Hiring Outcomes					
Any hire - via Portal	Verification	0.009	0.035	0.793	0.975
Any hire - All methods	Verification	0.044	0.043	0.306	0.816
Composition - via Portal	Verification	0.030	0.037	0.419	0.878
Any hire - via Portal	Scale	0.012	0.038	0.750	0.975
Any hire - All methods	Scale	0.026	0.046	0.581	0.949
Composition - via Portal	Scale	0.005	0.040	0.897	0.975
Any hire - via Portal	Joint	0.082	0.039	0.035	0.197
Any hire - All methods	Joint	0.082	0.042	0.050	0.244
Composition - via Portal	Joint	0.114	0.041	0.006	0.048

Notes: This table reports asymptotic p-values and p-values adjusted for multiple hypothesis testing for employer engagement outcomes (Panel A) and hiring outcomes (Panel B). Columns 2–4 show the coefficients, the standard errors, and the asymptotic p-values from our main specification. Column 5 reports p-values adjusted using the Westfall-Young method using 5,000 simulations.

Appendix C.10 Expected Value of the Sample Maximum as Sample Size Increases

We show in this section that the expected value of the maximum of a sample increases with the size of the sample. This is a standard result in statistics.

Assume a vacancy receives n draws of ability, a, which is a random variable drawn from $F(a)$.[2] We assume the draws are independently and identically distributed. We define the maximum of these draws as a new random variable $Y = \max\{a_1, a_2, .., a_n\}$. The cumulative probability distribution, $F_Y(y)$, is the probability that the maximum is less than or equal to y. This can be written as:

$$F_Y(y) = P[(a_1 \leq y) \cap (a_2 \leq y) \cap ... \cap (a_M \leq y)] = \{F_a(y)\}^n$$

We can then compute the probability density function of the sample maximum, $F_Y(y)$ by taking the derivative, which gives us:

$$f_Y(y) = n\{F_a(y)\}^{n-1} f_a(y)$$

Then, the expected value is:

$$\int_{-\infty}^{\infty} y f_Y(y) dy$$

With a change of variables, where $z = \{F_a(y)\}^n$ and hence, $y = F^{-1}(z^{\frac{1}{n}})$, then:

$$\int_0^1 F_a^{-1}(z^{\frac{1}{n}}) dz$$

We consider the case where $F(a)$ is bounded.[3] Denote A as the maximum and note that $F_a^{-1}(1) = A$. As the number of applicant draws, n, increases, the above integral thus approaches A.

Appendix C.11 Complementarity Proof

Suppose firms (i) are hiring applicants (j) based on their ability (a_j) and their trust worthiness (θ_j), which are independently distributed. θ_j can take on two values: θ_H which is "honest" and θ_D which is "dishonest", with $\theta_H > \theta_D$. In *Scale* firms can perfectly identify ability, but cannot perfectly identify θ_j, so they instead look at the expected value of θ_j. The hiring happens if

$$a_j + \mathbb{E}[\theta_j] \geq c \tag{2}$$

where $c \in \mathbb{R}$ is the firm's outside option. In the *Joint* treatment the firms perfectly identify both a_j and θ, so the hiring happens if:

$$a_j + \theta_j \geq c \tag{3}$$

Theorem: If we assume:

- a_j is distributed with finite mean and variance

[2] We drop subscripts here for ease of notation.

[3] This is reasonable in our setting as the set of individuals searching on the portal at any given time will always be a subset of job seekers in the broader labor market.

- $f_a(x)$ (the p.d.f of a_j) is non-increasing (weakly decreasing)
- $\theta_H = -\theta_D$ with $Pr[\theta_j = \theta_H] = Pr[\theta_j = \theta_D]$. (This gives us $\mathbb{E}[\theta_j] = 0$ and $Pr[\theta_j = \theta_H] = 0.5$)
- Rule out corner solutions where either nobody will be hired or everyone will be hired, i.e. $\min(a_j) + \theta_H \geq c$ and $\max(a_j) + \theta_H \leq c$.

Proof: The probability of hiring in *Scale* is:

$$\begin{aligned} Pr[a_j + \mathbb{E}[\theta_j] \geq c] &= Pr[a_j \geq c] \\ &= \int_c^{\max(a_j)} f_a(x)dx \end{aligned}$$

and the probability of hiring in *Joint* is:

$$\begin{aligned} Pr[a_j + \theta_j \geq c] &= (Pr[\theta_j = \theta_H])Pr[a_j + \theta_H \geq c] + (Pr[\theta_j = \theta_D])Pr[a_j + \theta_D \geq c] \\ &= (0.5)Pr[a_j \geq c - \theta_H] + (0.5)Pr[a_j \geq c + \theta_H] \\ &= (\frac{1}{2})\int_{c-\theta_H}^{\max(a_j)} f_a(x)dx + (\frac{1}{2})\int_{c+\theta_H}^{\max(a_j)} f_a(x)dx \end{aligned}$$

Now, we are trying to show that:

$$Pr[a_j + \mathbb{E}[\theta] \geq c] \leq Pr[a_j + \theta_j \geq c]$$

which is equivalent to showing:

$$\int_c^{\max(a_j)} f_a(x)dx \leq (\frac{1}{2})\int_{c-\theta_H}^{\max(a_j)} f_a(x)dx + (\frac{1}{2})\int_{c+\theta_H}^{\max(a_j)} f_a(x)dx$$

$$\begin{aligned} \int_c^{c+\theta_H} f_a(x)dx + \int_{c+\theta_H}^{\max(a_j)} f_a(x)dx &\leq (\frac{1}{2})\int_{c-\theta_H}^{c} f_a(x)dx + (\frac{1}{2})\int_{c}^{c+\theta_H} f_a(x)dx \\ &+ (\frac{1}{2})\int_{c+\theta_H}^{\max(a_j)} f_a(x)dx + (\frac{1}{2})\int_{c+\theta_H}^{\max(a_j)} f_a(x)dx \end{aligned}$$

$$\int_c^{c+\theta_H} f_a(x)dx \leq \int_{c-\theta_H}^{c} f_a(x)dx$$

To show this, we use the fact that f_a is a non-increasing function, which then tells us that

$$\max_{x \in [c, c+\theta_H]} f_a(x) = f_a(c)$$

$$
\begin{aligned}
\implies \int_{c}^{c+\theta_H} f_a(x)dx &\leq \int_{c}^{c+\theta_H} f_a(c)dx \\
&= ((c+\theta_H)-c)f_a(c) \\
&= \theta_H f_a(c)
\end{aligned}
$$

We can also see that:

$$\min_{x\in[c-\theta_H,c]} f_a(x) = f_a(c)$$

$$
\begin{aligned}
\implies \int_{c-\theta_H}^{c} f_a(x)dx &\geq \int_{c-\theta_H}^{c} f_a(c)dx \\
&= (c-(c-\theta_H))f_a(c) \\
&= \theta_H f_a(c)
\end{aligned}
$$

$$\implies \int_{c}^{c+\theta_H} f_a(x)dx \leq \theta_H f_a(c) \leq \int_{c-\theta_H}^{c} f_a(x)dx$$

□