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Abstract

Despite the growing prominence of online job portals, firms remain reluctant to hire outside traditional recruitment networks. We find that experimentally providing firms with a combination of advertising *and* the ability to verify an applicant's identity increases portal-based hiring by 68% and the likelihood of filling a vacancy by 11%. Advertising attracts more skilled applicants, while verification services allow employers to screen *unfamiliar* applicants. Portal-based hires are retained beyond the standard assessment period, suggesting they are well-suited to the vacancies. Firms assigned only advertising also attract more skilled applicants, but neither this intervention nor providing verification services alone increases hiring.

JEL Codes: J23, L86, M51, O12, O15
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Firms across the developing world report difficulties recruiting skilled workers (Abebe, Caria and Ortiz-Ospina, 2021). Yet, they rely heavily on traditional recruitment networks.[1] Network-based hiring can provide valuable information on worker attributes such as ability, trustworthiness, conscientiousness, or interest in a job, even as it may limit the quantity or quality of potential employees (Chandrasekhar, Morten and Peter, 2020). Online job portals allow firms to expand their recruitment networks, but remain heavily underutilized: under 2% of firms report using the internet for recruitment in urban India, the setting of our study.[2] As firms consider using job portals to hire outside their traditional networks, they may both struggle to attract interest from skilled candidates unfamiliar with their business, and be themselves reluctant to hire unfamiliar candidates whose reliability they cannot assess (Autor, 2009).

In this paper, we use a field experiment to investigate whether providing firms with services that allow them to attract and screen 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. At the outset, just 12% of (control) firms posting vacancies on QuikrJobs reported 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*, provided premium advertising to vacancies for 10 days which prioritized their ordering in search results and increased promotional alerts to job seekers. The second treatment, *Verification*, provided firms with access to verified background information on applicants to their vacancy. Once a job seeker applied to a vacancy in the experiment, they were offered the opportunity to verify their identity using government-issued documents.[3] The verification outcomes were then privately revealed to firms randomly assigned to receive this information. Finally, we implemented a third treatment, *Joint*, that gave firms access to the *Scale* and *Verification* treatments simultaneously.

Firms in the *Joint* treatment are 67.8% or 8.2 percentage points (p.p.) more likely to hire workers through the portal relative to control. The *Joint* treatment doubles the number of applications to a vacancy (55 applications) relative to control, leaves the average skill-level of applicants unchanged, but attracts more skilled candidates; we construct a skills

[1] We define traditional 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, Iversen and Torsvik, 2021).

[2] Authors' calculation using data from the National Sample Survey 2015-16 (National Sample Survey Office, 2018).

[3] 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.

index to show that the top-ranked applicant to a *Joint* vacancy is 0.33 standard deviations more skilled than the top-ranked applicant to a *Control* vacancy.[4] Combined with access to verification information, these changes lead to a significant increase in employer engagement on the portal as gauged through "clicks" that are required to initiate contact with applicants. Using click data from the portal, we find that firms in the *Joint* treatment more than double the number of unique applicants with whom they engage (6.2 profiles vs 2.5 in control).

Overall, *Control* firms successfully hire workers for 76.7% of their vacancies, two-thirds of whom continue to be sourced through traditional networks. *Joint* firms do not compensate for increased hiring on the portal by reducing hiring through traditional networks. *Joint* firms fill significantly more (10.7%, 8.2 p.p.) vacancies than firms in *Control*. In addition, at the time of the six month follow-up survey, *Joint* firms are 76% (11.4 p.p.) more likely to currently employ a worker hired through the portal, relative to control. This result suggests that portal-based hires are stable matches retained well-beyond the standard two-month probationary period and that the interventions successfully induced *Joint* employers to hire beyond their traditional networks.

In contrast to the *Joint* treatment, we find small, insignificant impacts on hiring for the *Scale* and *Verification* treatments. Relative to the *Joint* treatment, the *Scale* treatment results in near identical changes to the number and composition of applicants, but employer engagement with portal applicants is significantly lower. The *Scale* treatment increases employer engagement by 67.5% relative to control (4.2 applicants vs 2.5), but this effect is *less than half* the magnitude of the analogous *Joint* treatment effect. Perhaps as a consequence, we do not find that *Scale* firms increase their likelihood of portal-hiring, relative to control. Moreover, we are able to reject that the *Joint* hiring effect is equal to the *Scale* hiring effect (*p*-value$=0.07$), suggesting that advertising alone is not a sufficient condition to increase hiring through the portal.

Unlike the *Scale* and *Joint* treatments, the *Verification* treatment does not influence the size or composition of applicant pools relative to *Control* vacancies. This allows us to focus solely on the effects of identity verification services. We do not find any significant effects on employer engagement or portal-hiring for vacancies assigned to the *Verification* treatment. Since, in contrast, the relative impacts of the *Scale* and *Joint* treatments suggest that verification services are *pivotal* in inducing hiring through the portal, the absence of effects for the *Verification* treatment imply that the value of verification services may depend on the size and composition of applicant pools observed by employers.

Larger applicant pools, however, may impose a significant burden on an employer's recruitment capacity. Consequently, employers may value verification information because it allows them to identify bona fide candidates and streamline portal-based recruitment. Successfully passing verification may be a signal of applicant trustworthiness, a trait valued in customer-facing positions. Alternatively, uploading verification information may signal an applicant's interest in a vacancy or their conscientiousness, which employers may otherwise

[4]The skills index is a normalized index that aggregates an applicant's education level, language skills, job skills, certifications, experience, and the completeness of their profile.

have difficulty discerning from a resumé. By combining advertising and verification services, the *Joint* treatment allows employers to leverage larger applicant pools to successfully hire through the portal and expand beyond their traditional recruitment networks.

We primarily contribute to the literature on hiring frictions in lower-income countries. Whereas this literature has largely focused on worker-level interventions, our study instead examines a *firm*-level intervention.[5] The work closest to our own is Hensel et al. (2021), who offer subsidized vacancy posting services to small Ethiopian firms and find that it *reduces* the likelihood of any hire by 17%. The authors suggest this is because firms are induced to create more white-collar vacancies, which ultimately crowded out blue-collar hiring. In contrast, our interventions are assigned to *existing* vacancies.[6] Other firm-level interventions show mixed impacts on hiring: wage subsidies for Sri Lankan microenterprises increase hiring *only* during the subsidy period, but not afterwards (de Mel, McKenzie and Woodruff, 2019); on the other hand, 47% of small Ghanaian firms are willing to employ apprentices screened through a government program for up to two years (Hardy and McCasland, 2022). Our experiment shows that interventions that increase access to skilled candidates *and* provide screening services can significantly increase hiring through an online portal and a firm's overall success in filling a vacancy.

Second, our findings evidence the promise of internet-based technologies in addressing labor market frictions in the developing world. In India, Kelley, Ksoll and Magruder (2022) randomize text message job alerts and find that they *reduce* respondents' likelihood of being employed, likely due to overoptimistic beliefs about the number and types of jobs on the portal. In South Africa, Wheeler et al. (2022) show that training workers to use LinkedIn increases employment by 10%. Both of these papers target job-seeker search activity, whereas we focus on a firm-level intervention aimed at inducing hiring through a job portal.[7] We contribute to this literature by showing that a screening technology—identity verification— embedded directly on a job portal can increase employer engagement with unfamiliar applicants and induce hiring outside traditional networks.[8]

[5] Examples of worker-level interventions include: signaling skills through reference letter or skill certifications (e.g., Abel, Burger and Piraino, 2020; Bassi and Nansamba, 2022; Carranza et al., 2022), or subsidizing search costs through transport subsidies, job fairs or direct matching (e.g., Beam, 2016; Abebe et al., 2021; Bandiera et al., 2022). Some of these interventions increase employment, particularly for disadvantaged job-seekers.

[6] Algan, Crépon and Glover (2020) study hiring frictions in a high-income context, using an intervention that provides French firms with counselors to screen and invite applicants to posted vacancies, leading to a 7% increase in hires. While their hiring impact is comparable to our own, their setting is substantially more mediated.

[7] Horton (2017) shows that recommending workers to employers on an online labor market increases hiring by 20% for high-skilled vacancies, but has no effect on low-skilled vacancies.

[8] Our findings are consistent with macro evidence from high-income countries, which suggest that internet expansion and accompanying advances in screening technologies have improved labor market matching (Kuhn and Mansour, 2014; Bhuller, Kostol and Vigtel, 2021; Pries and Rogerson, 2022).

I. Context and Design

A. Online Recruitment and QuikrJobs

In India, the rapid expansion of low-cost mobile and internet-based technologies has led to substantial growth in the online search and recruitment industry. At least 22 job portals catered to the Indian market in 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 specializing in blue collar positions in the retail and service sectors. In 2019, QuikrJobs was active in over 1,000 cities, encompassing over 8 million job-seekers and 2 million jobs with an average monthly salary of Rs.17,800 (USD 252). Naukri.com is widely believed to be the largest online job platform in India and commands nearly 75% of web traffic for online platforms (InfoEdge, 2022). Though QuikrJobs has a much smaller share of the Indian online recruitment market, it is widely believed to be the leader in blue collar positions, which more closely resemble average urban incomes in India (Jha and Basole, 2022). Consistent with this specialization, a leading portal, Shine.com, advertised 300,000 jobs in a 5-month duration with an average salary more than twice that of QuikrJobs (Chiplunkar, Kelley and Lane, 2020).

An employer can post vacancies at no cost on QuikrJobs, though they may also purchase premium advertising services described in Section I.C. Job-seekers 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.

B. Hiring Frictions and Study Setting

Our study takes place in Bengaluru, a city of over 12 million people in the Indian state of Karnataka. We sample firms posting vacancies on the QuikrJobs portal and, consequently, our 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 typically 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 Appendix A.3, Table A3). While the primary concern cited by these firms is a difficulty finding applicants with suitable technical skills, 53% of firms report "trust-related" concerns about employee misbehavior. While the QuikrJobs portal provides access to larger recruitment networks, employer concerns about screening workers are likely exacerbated by the prospect of hiring workers outside traditional networks. These concerns may explain why just 35% of (control) employers initiate contact with an applicant on the QuikrJobs portal and nearly a quarter are unable to fill their vacancy.

Rather than an idiosyncratic feature of our study context, several papers suggest that firms provided with access to online job portals are unable to take advantage of expanded recruitment networks and struggle to fill their vacancies (Fountain, 2005). For example, even after receiving access to an online job portal, 32% of Ethiopian firms (Hensel et al., 2021) and 16% of French firms are unable to fill their vacancies (Le Barbanchon, Ronchi and Sauvagnat, 2023). Though a qualitatively different market, we also note that 50-70% of vacancies on online job task platforms (e.g. UpWork.com) remain unfilled (Horton, 2017; Leung, 2021).

To understand how employer engagement on the platform 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 (see Appendix A.3, Figure A3b). When employers were asked *why* they want identity verification, 81% report that it builds trust in applicants, viz. it provides reassurance that applicants are honest, less likely to steal or misbehave with customers, and are presenting truthful information on their profiles.

C. Experimental 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 treatments intended to increase the volume of applicants (*Scale*, n=367), provide employers with third-party verified information (*Verification*, n=467), a combination of the two services (*Joint*, n=470), or 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 treatment. We first describe the status-quo service received by the control group and then each of the treatments.

Control: Vacancies assigned to this group received neither our advertising nor our verification treatments. A regular posting on the platform is free. The vacancy is not prioritized in search results and job-seekers may receive information on this vacancy via email or text message based on location and occupational preferences. These vacancies stayed active for 90 days. These employers were free to purchase premium advertising, but only 12% did so

[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.

within 90 days of posting a vacancy.

Scale: Vacancies assigned to this treatment receive free access to premium advertising services that increase their visibility through time-limited, "top-of-page" placement. This is the most popular paid service the portal offers to employers to expand their applicant pools; the usual cost of this service at the time of the experiment was Rs.599 (USD$8.5). A vacancy granted access to this service was ordered at the top of applicant search results, displayed with a "Gold" badge (see Appendix A.4, Figure A4.1), and promoted via emails and text messages to job seekers registered on the portal. These promotional features remained active for the first 10 days following the posting, after which the vacancy transitioned to "regular" status for the next 80 days, unless an employer purchased any paid service on their own.

Verification: Vacancies assigned to this treatment receive identity verification results at no cost for either 50% or 100% of their applicants on the portal for the entire time the vacancy was active on the portal. This service was newly introduced for the experiment and not available on the portal otherwise.[11] Applicants to *all* vacancies in the experimental sample received an identity verification request, which asked them to submit details from government-issued identification (ID).[12] 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 for vacancies assigned to treatment 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 A.4, Figure 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.

Joint: Vacancies assigned to this treatment received access to both the *Scale* and *Verification* treatments described above. *Joint* vacancies received promotional advertising for 10 days and verification services were available for as long as the vacancy was active on the portal.

II. Data Sources & Empirical Strategy

A. Timeline & Data Sources

Our experiment ran on the portal from November 2018 to January 2020. Firms posting eligible vacancies were surveyed once immediately after doing so (December 2018-February 2020) and six months later (June 2019-July 2020). We now describe the data sources used in

[11] The actual cost of verification during the experiment was Rs.25 (USD 0.36) per individual.

[12] 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.

our empirical analyses in more detail (Fernando, Singh and Tourek, 2023b).

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).[13] 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 and employee composition. In the long version (589 firms), we additionally collected details about the recruitment process and worker-level details for up to 10 new hires.

B. Empirical Strategy

Our main specification compares outcomes across treatment groups using OLS:

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

where i denotes a vacancy or a firm and s denotes randomization strata. 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. Throughout our analysis, we pool together the 50% and 100% verification cells to improve power.[14]

We report vacancy-level results when using administrative data and firm-level results when using survey data. A subset of firms had multiple vacancies assigned to an experimental condition, but our results are robust to their exclusion and to adjusting for within-firm spillovers.[15] For our firm-level results, we use the treatment status of the first vacancy posted by the firm, as subsequent behavior is endogenous to this status.

[13] Phone-based surveying proved to be an inadequate substitute for in-person surveying in our setting. We discuss attrition in greater detail in Section III.D.

[14] Our qualitative conclusions are unchanged when we estimate a fully saturated model (see Appendix C.7), as suggested by Muralidharan, Romero and Wüthrich (2019).

[15] In general, only one vacancy per firm was assigned to an experimental condition. However, a firm with multiple users on the platform may have had multiple vacancies assigned to varying treatments. Overall, 94% of firms have a single vacancy and our vacancy-level results are both robust to clustering standard errors at the firm-level and restricting the sample to the first vacancy assigned to a treatment (see Appendix C.8).

C. 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.[16]

III. Results

A. Effects on the Quantity and Composition of Applicants

Using the portal's administrative data, we find that vacancies in the *Joint* treatment arm receive 55 applications on average, more than doubling the 25 applications received on average by *Control* (Table 1, column 1). Vacancies assigned to the *Scale* treatment receive 51 applications on average, an increase that is statistically indistinguishable from *Joint*. In contrast, the *Verification* treatment does not influence the number of applications received relative to *Control*. These impacts are consistent with the intended design: advertising attracts more applicants to vacancies, but verification, which was requested from candidates *after* their application, does not.

To understand whether the treatments also influence applicant composition, we construct a "skills index", which incorporates applicants' self-reported qualifications and the completeness of their profile.[17] For vacancies assigned to both the *Joint* and *Scale* treatments, we do not find a change in the *mean* of the skills index (column 2), but the *maximum* of the skills index is significantly higher (column 3) and the minimum is significantly lower (column 4).[18]

In sum, the premium advertising common to the *Joint* and *Scale* treatments resulted in a mean-preserving spread to the distribution of skills observed by these employers relative to *Control*. While the average applicant to *Control* and *Joint* vacancies are similarly skilled, *Joint* vacancies received more applicants from the tails of the distribution and, consequently, their best applicant ranked higher on the skills index. The effects for *Scale* vacancies are again similar to that of the *Joint* treatment, suggesting that these two treatments led to virtually identical applicant pools for employers.

Finally, we note that the average, maximum, and minimum of the skills index corresponding to vacancies assigned to the *Verification* treatment are indistinguishable from those assigned to *Control*.

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

[17] Specifically, it includes the following eight variables: whether an applicant has a higher educational degree; has English-language skills; reports job category-specific skills, certifications, and 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). See Appendix B.1 for treatment effects on the components of the skills index.

[18] See Appendix B.2 for additional results on the skill composition of applicants.

B. Effects on Employer Engagement

Our primary measure of employer engagement relies on administrative data tracking clicks on the portal. As an employer can only contact an applicant by clicking to unlock their contact details (see Appendix 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 *Joint* treatment are 36.1% (12.6 p.p.) more likely to unlock contact information for at least one applicant (column 5). This extensive margin response is accompanied by a large intensive margin increase (column 6): *Joint* employers increase the *number* of unique applicants they click on (6.2 vs 2.5 in control).

Meanwhile, employers in the *Scale* treatment also increase engagement with applicants significantly, though less so than in the *Joint* treatment. They are 19.2% (6.7 p.p.) more likely to unlock contact information for at least one applicant and click on a total of 4.2 applications. The magnitude of impacts are significantly higher in *Joint* than in *Scale* (p-value < 0.1), suggesting that *Joint* employers increase the *intensity* of their engagement with applicants and value the additional information provided by identity verification services.

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 7). In contrast, employers in the *Scale* treatment are not significantly more likely to conduct an interview relative to *Control*.

Unlike the *Scale* and *Joint* treatments however, the *Verification* treatment alone does not change engagement significantly. This lack of impact suggests that the value of verification services may depend on the size and composition of the applicant pool, a proposition we consider in more detail in Section IV.B.

Collectively, our results demonstrate that employers in the *Joint* treatment significantly increase their effort in recruiting applicants from the portal.

C. Effects on Hiring and Retention

In Table 2, we compare hires at the firm-level across the treatment groups 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.). Increased hiring from the portal does not result in substitution away from other recruitment methods and, instead, increases *overall* hiring—i.e. whether or not a firm fills the posted vacancy across all recruitment methods—for the *Joint* group by 10.7% or 8.2 p.p. (column 2).

In contrast, the effects of the *Scale* and *Verification* treatments on hiring through the portal are both quantitatively smaller than the *Joint* treatment (< 1.2 p.p.) and not statistically distinguishable from *Control*. Though we are likely under-powered to detect small positive portal-hiring effects from the unitary treatment arms, we *are* able to reject that the *Joint* hiring effect is equal to the analogous *Scale* (p-value $= 0.07$) and *Verification* (p-value $= 0.05$) effects on portal-based hiring.

Increased hiring by *Joint* firms also has a dramatic effect on the *composition* of their employees at the time of the follow-up survey. *Joint* firms are 76% (11.4 p.p.) more likely than *Control* firms to report that a current employee was sourced from the portal (column 3). We can reject equality between this estimate and the analogous estimates corresponding to the unitary treatment arms (p-value < 0.05). 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, this change in employee composition also reveals that portal hires were good matches retained well beyond the standard assessment period.

We observe limited information about the characteristics of hired workers but note that workers hired on the portal, relative to those hired through traditional networks, are more likely to be female and Muslim, though we do not find that our treatments significantly influenced the share of new hires belonging to either of these groups.[19]

Collectively, our effects suggest that access to advertising *and* verification services on the portal meaningfully induced employers to hire beyond their traditional networks and, in so doing, enabled firms to fill vacancies that may have otherwise remained unfilled.

D. Survey Attrition

Disruptions to our survey operations caused by the COVID-19 pandemic greatly affected our follow-up survey response rates. In this section, we assess the importance of survey attrition in influencing estimates based off these data. We first note that there are no significant differences in survey completion rates between the treatment arms and control (see Appendix C.3). Further, we do not find evidence to suggest there was differential attrition by treatment status when we compare the vacancy characteristics of attritees (see Appendix C.4).

To allow for a more transparent comparison to the hiring effects discussed in Section III.C., in Table 3 we report the analogous hiring effects adjusted for attrition. In particular, we reweight observations according to the inverse probability of survey response predicted by baseline characteristics, thereby increasing the weight on surveyed firms who are more likely to be attritees.[20] We do not find that the reweighted estimates substantively differ from those reported in Table 2 and, collectively, our evidence suggests that survey attrition does not pose a threat to the internal validity of our results.[21]

[19]See Appendix B.5 for descriptive statistics of portal and network hires. Appendix B.6 shows that our treatments do not influence the composition of workers hired along these dimensions, though we are likely under-powered to detect these treatment effects.

[20]The inverse probability weighting predicts survey response using vacancy characteristics shown in Appendix C.1, the stratifying variables, and treatment indicators using a Probit model. We use the inverse of the predicted values as weights, increasing the importance of observations more likely to exit our sample.

[21]In Appendix C.5, we show that our hiring results are robust to the inclusion of controls selected by the double LASSO algorithm (Belloni, Chernozhukov and Hansen, 2014). As these controls are highly predictive of

IV. Discussion

A. Spillover Effects

We note that the assignment of vacancies to premium advertising—the *Scale* and *Joint* treatments—may influence the prominence of other posted vacancies. Vacancies in these treatment groups may influence the search rankings of vacancies both within and outside the experimental sample. However, as our experimental vacancies account for less than 1% of vacancies during this period, it is perhaps unsurprising that we do not find evidence of spillover effects either within or outside our experimental sample (see Appendix C.6).

B. Mechanisms Underlying *Joint* Hiring Effects

In contrast to the *Joint* hiring effects, neither the *Verification* treatment nor the *Scale* treatment resulted in detectable hiring effects. These results are at once indicative of a complementarity between treatments and suggest why the unitary treatment arms may not be sufficient for inducing hiring effects.

We first note that just 12% of employers in *Control* successfully recruit through the portal, while 51% hire candidates through traditional networks. Employers in the *Verification* treatment receive as many applications (27) as those in *Control* but, additionally, receive verified information on approximately 5 candidates.[22] As this information likely benefits marginal applicants who would not have otherwise been preferred to traditional networks, the quantity of verified applicants may not have been sufficient to induce employer engagement (as suggested by Section III.B.), or we are under-powered to detect small positive hiring effects.

In contrast, the *Scale* treatment doubles applications to a vacancy, providing employers with access to more skilled applicants. While this treatment increases employer engagement relative to *Control*, it is significantly lower than in *Joint*. Consequently, though *Scale* employers benefit from larger applicant pools, they may struggle to process this volume of applications if they are unable to identify bona fide applicants. Alternatively, even if they were to process these applicants, they may find that an applicant's observable skills are a poor proxy for unobservable attributes (e.g. trustworthiness or conscientiousness) that are especially relevant to their vacancy. We next consider the evidence in support of each of these explanations.

C. The Role of Identity Verification

Our results suggest that identity verification can serve as a valuable screening tool for employers. But precisely what information verification conveys is consistent with a number of

treatment assignment and the outcome of interest, their inclusion provides an alternative way of adjusting for imbalances caused by attrition.

[22]This figure assumes the 20% of applicants upload verification and 89% of those who do are successfully verified.

interpretations.

First, verification may provide employers with information on applicant trustworthiness. When asked why they value identity verification, 81% of employers stated that it builds trust in applicants (see Appendix A.3). In contexts similar to our own (Bassi and Nansamba, 2022; Caria and Falco, 2022), employers value trustworthiness in light of concerns about employee malfeasance and theft. Since trustworthiness can be difficult to discern from the skills reported on a resumé, employers may interpret successful identity verification as a signal of applicant honesty.

Second, verification information may instead provide information on applicant ability. However, we find that the gains in employer engagement in the *Joint* treatment relative to *Scale* are concentrated among applicants with lower skills (Appendix B.4). The prior result may yet be consistent with verification signaling ability, if the ability in question is difficult to observe and its importance is elevated among vacancies requiring lower-skilled applicants. For example, employee conscientiousness (e.g. their punctuality or attention to detail) is likely to be valued in customer facing positions like retail—where it may be difficult to contract on effort—and may matter disproportionately among vacancies requiring relatively lower-skilled applicants.

Finally, verification may act as a "mini-ordeal" mechanism by revealing a costly signal of applicant interest. Given the low marginal cost of an application, employers may worry if applicants are bona fide, or even real persons as opposed to bots. As successful verification necessitates a series of steps that include the provision of government-issued identity documents, employers may view these candidates more favorably. Though a signal of applicant interest may reduce employer effort by helping them prioritize bona fide applicants, we instead find that it *increases* overall recruitment effort. *Joint* employers increase their engagement with portal applicants relative to those in *Scale* and do not compensate with a reduction in alternative recruitment methods (see Appendix B.3). The overall increase in recruitment effort for *Joint* relative to *Scale* is indicative of verification being a necessary condition in inducing employers to take advantage of expanded recruitment networks.

V. Conclusion: External Validity and Verification at Scale

The hiring 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 unable to hire outside their networks because of inadequate screening mechanisms (Abebe, Caria and Ortiz-Ospina, 2021; Caria and Falco, 2022; Cullen, Dobbie and Hoffmann, 2022; Hardy and McCasland, 2022). The proliferation of online job portals 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 are likely a generic consequence of hiring beyond traditional networks: across a number of job portals, firms cite concerns about the quality and responsiveness of candidates (Cappelli, 2001; Fountain, 2005; CareerPlug, 2020).

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 may be 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. We focused on identity verification due to our study setting of low-wage retail and service work. Future work may fruitfully explore the benefits of a wider range of verifiable information relevant to heterogeneous 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) Minimum	(5) Any	(6) Number	(7) Any
Verification (V)	2.101	0.022	-0.011	-0.075	0.027	-0.090	0.022
	(2.115)	(0.019)	(0.040)	(0.067)	(0.033)	(0.767)	(0.062)
Scale (S)	25.852	-0.010	0.314	-0.338	0.067	1.688	0.056
	(2.461)	(0.021)	(0.038)	(0.074)	(0.035)	(0.776)	(0.066)
Joint (J)	29.756	-0.006	0.332	-0.250	0.126	3.685	0.129
	(2.619)	(0.016)	(0.036)	(0.055)	(0.033)	(0.996)	(0.062)
N Vacancies/Firms	1719	1682	1685	1682	1719	1719	550
Control Mean	25.058	-0.037	0.994	-0.834	0.349	2.499	0.503
Test p-val: V=J	0.000	0.108	0.000	0.029	0.003	0.001	0.075
Test p-val: S=J	0.162	0.836	0.602	0.330	0.092	0.045	0.248

Notes: This table shows impacts on applications and employer engagement. Data for columns 1–6 come from the portal's administrative data and data for column 7 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 2–4 consider the mean, maximum, and minimum 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 2–4 restricts to only those 1,685 vacancies that receive at least 1 application; column 2 has fewer observations due to some outlier corrections. Columns 5–6 report on application clicks by employers to access contact details on the portal; column 5 is an indicator for whether the employer clicked on any application and column 6 shows the number of unique applications the employer clicked on. Column 7 reports an indicator for whether the employer interviewed any portal-sourced applicant. Regressions include strata fixed effects and for column 7, 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.

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: V=J	0.048	0.340	0.039
Test p-val: S=J	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.

Table 3: Attrition Reweighted Estimates

	Any Hire for Posted Vacancy?		Employee Composition at Follow-Up
	(1) via Portal	(2) All Methods	(3) via Portal
Verification (V)	-0.004	0.022	0.019
	(0.036)	(0.045)	(0.038)
Scale (S)	0.002	0.034	-0.003
	(0.039)	(0.046)	(0.041)
Joint (J)	0.068	0.071	0.101
	(0.040)	(0.043)	(0.042)
N Firms	794	794	794
Control Mean	0.121	0.767	0.150
Test p-val: V=J	0.045	0.249	0.042
Test p-val: S=J	0.083	0.395	0.014

Notes: This table assesses the robustness of our hiring and retention outcomes to attrition. We re-weight observations to account for attrition using inverse probability weights, calculated from a Probit regression that predicts survey response using vacancy characteristics listed in Appendix C.1, our stratifying variables, and treatment indicators. 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.

ONLINE APPENDIX

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

A. Nilesh Fernando, Niharika Singh, and Gabriel Tourek

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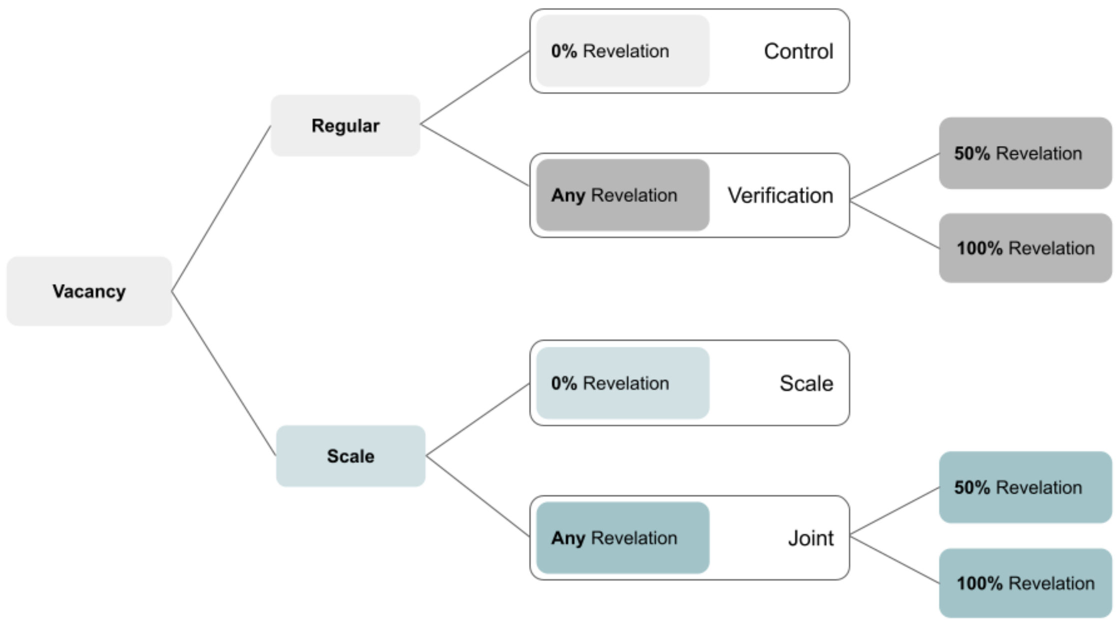
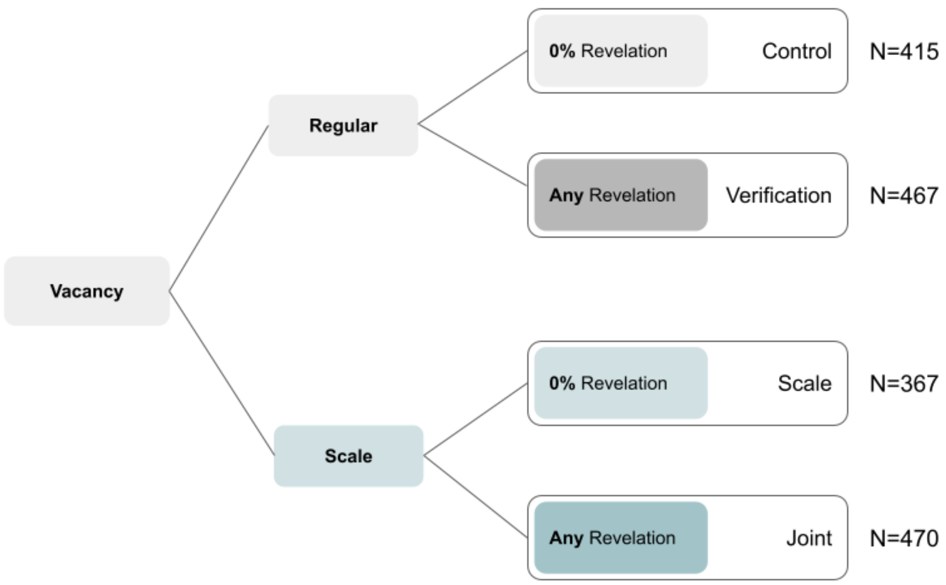
Appendix A Experimental Design and Data

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

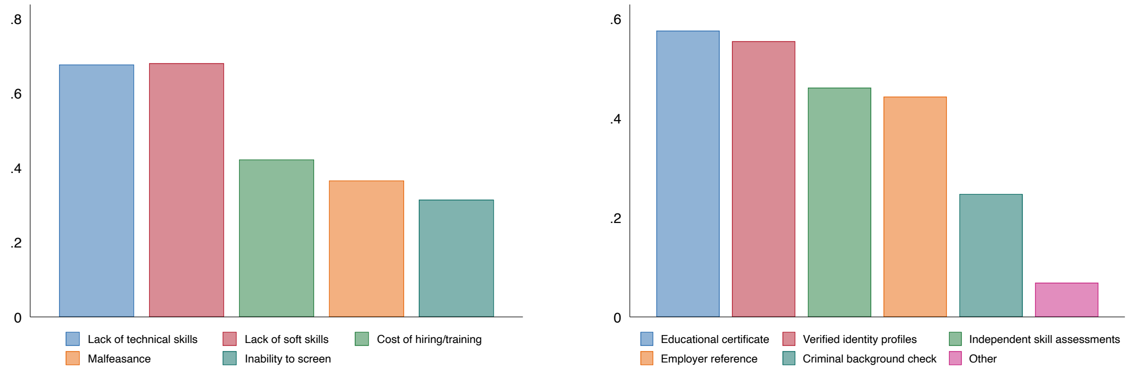
	Mean
N employees (Top coded 1%)	19.35
Mentions any constraint to growth	0.75
Mentions labor-related issues as constraint†	0.69
Mentions other non-labor issues as constraint†	0.34
Mentions trust-related recruitment issues⋆	0.53
Has dedicated HR staff	0.31
Reports using security equipment or personnel	0.59
Fraction of employees hired via networks	0.56
Pursuing network-based hiring for sample vacancy	0.84
Reports learning worker quality within 2 months	0.83
Reason for valuing ID verification: To build trust	0.81

Notes: This table shows summary statistics on hiring frictions using data from baseline surveys with 915 firms.
† 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

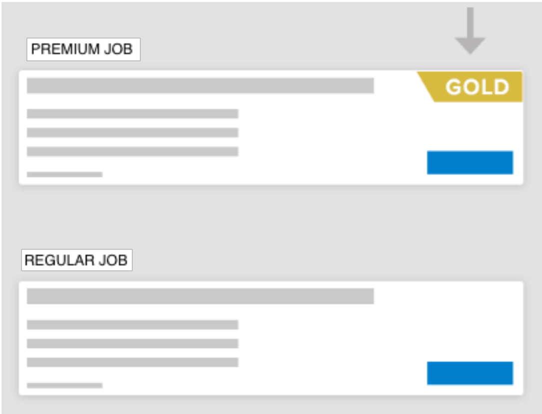
(b) Types of Job seeker Information Desired by Employers



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

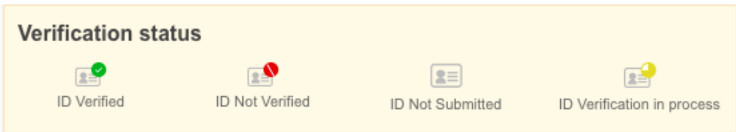
Figure A4.1: Comparison of vacancy with premium advertising services to a regular vacancy



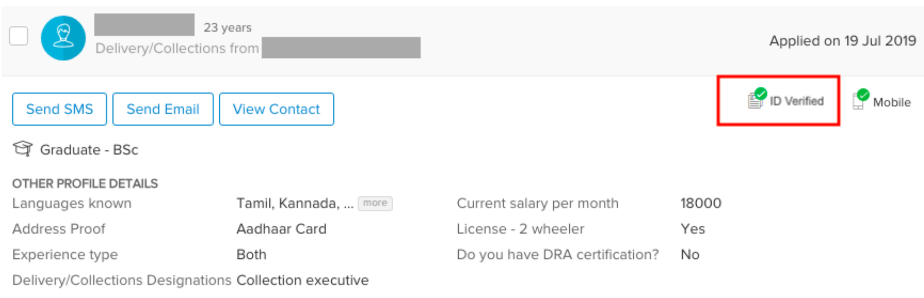
Notes: This figure depicts the visual difference between vacancies that receive premium advertising in the *Scale* and *Joint* treatments and those that do not in the control and *Verification* groups.

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 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	14.238	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.

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.

Appendix B.3 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.

Appendix B.4 Employer Clicks by Skill Index of Applicants

	Number of Application Clicks by Percentile of Skills Index			
	(1) Up to 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.

Appendix B.5 Descriptive Statistics of New Hires

	Hires via. Portal		Hires via. Networks	
	(1) Mean	(2) N	(3) Mean	(4) N
Female	0.44	101	0.30	317
Muslim	0.09	101	0.03	317
Permanent contract	0.82	88	0.86	295
Monthly salary	15932.05	78	15469.37	252

Notes: This table reports the characteristics of new hires made by all study firms after their vacancy was posted on QuikrJobs. Columns 1 & 2 restrict attention to new hires made through the QuikrJobs portal, while columns 3 & 4 refer to hires made through traditional networks. Whether or not an applicant is Muslim was coded using their given names. Where names are missing it was coded as a zero. The data used is at the worker-level and the sample sizes vary owing to non-response and whether it was collected in the short or long version of the follow-up survey.

Appendix B.6 Treatment Effects on the Composition of Hired Workers

	All Hires			Portal Hires		
	(1) % Female	(2) % Muslim	(3) % Permanent	(4) % Female	(5) % Muslim	(6) % Permanent
Verification (V)	-0.024	0.006	0.029	0.113	-0.117	-0.014
	(0.043)	(0.019)	(0.060)	(0.182)	(0.108)	(0.202)
Scale (S)	0.052	0.004	-0.062	0.064	-0.132	-0.216
	(0.047)	(0.022)	(0.060)	(0.181)	(0.092)	(0.200)
Joint (J)	0.004	0.005	0.053	-0.037	-0.085	-0.139
	(0.043)	(0.021)	(0.058)	(0.153)	(0.129)	(0.152)
N Firms	589	589	589	64	64	64
Control Mean	0.207	0.033	0.491	0.433	0.167	0.867
Test p-val: V=J	0.492	0.971	0.681	0.332	0.677	0.532
Test p-val: S=J	0.303	0.983	0.053	0.525	0.533	0.721

Notes: This table estimates treatment effects on the composition of hired workers at the firm-level. We collected information on up to 10 new hires in the long version of the follow-up survey. The dependent variables report the share of new hires that are female (columns 1 & 4), Muslim as coded by an employee's names where available (columns 2 & 5) and whether or not an employee is on a permanent contract (columns 3 & 6). If a firm did not hire a worker since vacancy posting or did not report a worker in the roster, the dependent variable is coded as 0 in columns 1-3. The estimates in columns 4-6 report restrict the sample to firms report any new hire via the portal. Regressions include strata fixed effects. We report robust standard errors in parentheses.

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. All regressions include strata fixed effects. 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.

Appendix C.2 Balance on Firm Variables

	Control Mean (1)	V-C (2)	S-C (3)	Joint-C (4)	N Firms (5)	Test: V=S (6)	Test: V=Joint (7)	Test: S=Joint (8)
Sector: Retail trade, transport, food, & accommodation	0.328	-0.023	-0.033	-0.055	1,001	0.809	0.411	0.591
		(0.041)	(0.043)	(0.042)				
Sector: Information & communication	0.109	0.006	0.033	0.009	1,001	0.380	0.918	0.435
		(0.029)	(0.032)	(0.029)				
Sector: Professional, technical, & administrative	0.158	-0.015	-0.023	-0.013	1,001	0.793	0.952	0.759
		(0.031)	(0.034)	(0.033)				
Sector: Education, health, & social work	0.126	-0.013	-0.045	-0.004	1,001	0.205	0.738	0.095
		(0.027)	(0.027)	(0.027)				
Firm age (years)	6.522	0.211	0.159	0.141	1,001	0.948	0.923	0.983
		(0.714)	(0.857)	(0.757)				
Has single establishment	0.671	-0.010	0.015	-0.042	914	0.584	0.452	0.215
		(0.044)	(0.047)	(0.045)				
Located on rented, outside HH premises	0.809	0.045	0.023	0.057	901	0.563	0.714	0.361
		(0.036)	(0.040)	(0.037)				
Firm type: Private Limited Company	0.394	-0.005	0.064	0.016	997	0.122	0.615	0.287
		(0.043)	(0.045)	(0.043)				
F-test p-value		0.811	0.409	0.549		0.553	0.932	0.637

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.

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.

	(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	-0.009	-0.022	0.013	-0.044	-0.045
	(0.035)	(0.036)	(0.036)	(0.036)	(0.035)
N Firms	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.

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

	Control Mean (1)	V-C (2)	S-C (3)	Joint-C (4)	N Firms (5)	Test: V=S (6)	Test: V=Joint (7)	Test: S=Joint (8)
Included company name	0.826	0.067	0.055	0.051	782	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	782	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	782	0.436	0.914	0.490
		(1338.425)	(1404.646)	(1302.638)				
Experience posted, min (years)	0.846	0.142	0.097	0.006	782	0.747	0.272	0.487
		(0.131)	(0.137)	(0.121)				
Experience posted, max (years)	2.973	0.743	0.421	0.081	782	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	782	0.684	0.983	0.689
		(0.031)	(0.031)	(0.030)				
Character length of job description	335.989	-16.478	78.541	6.376	782	0.039	0.566	0.127
		(45.188)	(51.164)	(46.892)				
F-test p-value		0.163	0.373	0.993		0.403	0.234	0.463

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 attritees vary between treatment groups relative to control for each covariate. 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.

Appendix C.5 Hiring Outcomes including Double-LASSO Controls

	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
	(0.034)	(0.041)	(0.036)
Scale (S)	0.012	0.026	0.005
	(0.037)	(0.045)	(0.039)
Joint (J)	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
Test p-val: V=J	0.042	0.327	0.033
Test p-val: S=J	0.064	0.181	0.008

Notes: This table shows robustness for our hiring and retention outcomes. We shows effects after adding controls using the post double selection LASSO technique (**?**). The dependent variables in columns 1-2 report whether any hires were made since vacancy posting. Column 1 only looks at hires via the portal; and column 2 reports any hires overall through all recruitment methods. The dependent variable in column 3 instead reports 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.

Appendix C.6 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)
Sample Vacancy			1.311	0.995
			(1.568)	(1.563)
Sample 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	24.385	24.385	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 the 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.

Appendix C.7 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	1.165	0.650	0.054	0.065
	(2.423)	(1.303)	(0.045)	(0.047)
100% Verification	3.055	-0.841	-0.042	-0.010
	(2.662)	(0.759)	(0.038)	(0.044)
Scale	25.865	1.681	0.012	0.005
	(2.462)	(0.777)	(0.038)	(0.040)
Joint, 50% Verification	27.962	4.283	0.093	0.104
	(3.296)	(1.141)	(0.051)	(0.055)
Joint, 100% Verification	31.212	3.201	0.073	0.122
	(3.254)	(1.375)	(0.046)	(0.050)
N Vacancies	1719	1719	-	-
N Firms	-	-	794	794
Control Mean	25.058	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.

Appendix C.8 Robustness Tests for Effects on Applications and Employer Engagement

	Applications	Skills Index			Application Clicks	
	(1) Number	(2) Mean	(3) Maximum	(4) Minimum	(5) Any	(6) Number
Panel A: Standard errors clustered at the firm level						
Verification (V)	2.101	0.022	-0.011	-0.075	0.027	-0.090
	(2.129)	(0.019)	(0.040)	(0.067)	(0.032)	(0.766)
Scale (S)	25.852	-0.010	0.314	-0.338	0.067	1.688
	(2.462)	(0.021)	(0.038)	(0.074)	(0.035)	(0.776)
Joint (J)	29.756	-0.006	0.332	-0.250	0.126	3.685
	(2.614)	(0.017)	(0.036)	(0.055)	(0.033)	(0.995)
N Vacancies	1719	1682	1685	1682	1719	1719
Control Mean	25.058	-0.037	0.994	-0.834	0.349	2.499
Test p-val: V=J	0.000	0.106	0.000	0.029	0.002	0.001
Test p-val: S=J	0.159	0.836	0.605	0.330	0.090	0.048
Panel B: Sample restricted to the first vacancy						
Verification (V)	2.207	0.013	-0.024	-0.085	0.030	0.090
	(2.222)	(0.020)	(0.042)	(0.073)	(0.035)	(0.839)
Scale (S)	25.448	-0.012	0.309	-0.353	0.053	1.074
	(2.556)	(0.022)	(0.039)	(0.079)	(0.037)	(0.742)
Joint (J)	29.200	-0.006	0.320	-0.263	0.121	3.563
	(2.743)	(0.017)	(0.037)	(0.062)	(0.035)	(1.070)
N Vacancies/Firms	1576	1544	1547	1544	1576	1576
Control Mean	25.405	-0.037	0.995	-0.834	0.354	2.521
Test p-val: V=J	0.000	0.296	0.000	0.043	0.009	0.003
Test p-val: S=J	0.197	0.771	0.752	0.364	0.066	0.016

Notes: This table reports tests probing the robustness of our main results to when multiple vacancies are assigned to experimental conditions for a single firm. For administrative outcomes related to applications and employer engagement shown in Table **??**. Panel A shows estimates after clustering standard errors at the firm level. Panel B restricts the sample to the first vacancy posted by all firms. The dependent variables are: number of applications, top coded at 99th percentile (column 1); the mean, maximum and minimum of the skills index (column 2-4); whether the employer clicked on any application to access contact details (column 5); and the number of unique applications the employer clicked on for contact details (column 6). The sample in columns 2–4 restricts to only those vacancies that receive at least 1 application; columns 2 and 4 have fewer observations due to some outlier corrections. Regressions include strata fixed effects. We report robust standard errors in parentheses.

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