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

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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 applicant identity increases portal-based hiring by 68 percent and the likelihood of filling a vacancy by 11 percent. Advertising attracts more skilled applicants, while verification enables the screening of unfamiliar applicants. Portal-based hires are retained beyond the standard assessment period, suggesting that they are well suited to the vacancies. Firms assigned only advertising also attract more skilled applicants, but providing neither advertising nor verification alone increases hiring. (*JEL* D22, J23, J24, J63, M51, O15)

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 percent of firms report using the

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

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 percent of (control) firms posting vacancies on QuikrJobs reported successfully hiring through the portal and, overall, 23 percent 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 ten 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 percent or 8.2 percentage points (pp) 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 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 versus 2.5 in control).

Overall, *Control* firms successfully hire workers for 76.7 percent of their vacancies, two-thirds of whom continue to be sourced through traditional networks. *Joint*

[2] Authors' calculation using data from the National Sample Survey 2015–2016 (National Sample Survey Office 2018).

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

[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.

firms do not compensate for increased hiring on the portal by reducing hiring through traditional networks. *Joint* firms fill significantly more (10.7 percent, 8.2 pp) vacancies than firms in *Control*. In addition, at the time of the six-month follow-up survey, *Joint* firms are 76 percent (11.4 pp) 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 percent relative to control (4.2 applicants versus 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 sufficient 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 have difficulty discerning from a résumé. 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, Tekleselassie, and Witte (2021), who offer subsidized vacancy

[5] Examples of worker-level interventions include signaling skills through reference letters or skill certifications (e.g., Abel, Burger, and Piraino 2020; Bassi and Nansamba 2022; Carranza et al. 2022) and subsidizing search costs through transport subsidies, job fairs, or direct matching (e.g., Beam 2016; Abebe et al. 2021; Bandiera et al. 2023). Some of these interventions increase employment, particularly for disadvantaged job seekers.

posting services to small Ethiopian firms and find that it *reduces* the likelihood of any hire by 17 percent. The authors suggest that 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 percent of small Ghanaian firms are willing to employ apprentices screened through a government program for up to two years (Hardy and McCasland 2023). 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 percent. 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]

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 percent 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 eight million job seekers and two million jobs with an average monthly salary of ₹17,800 (US$252). Naukri.com is widely believed to be the largest online job platform in India and commands nearly 75 percent of web traffic for online platforms (Info Edge 2022). Though QuikrJobs has a much smaller share of the Indian online recruitment market, it is widely believed

[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 percent 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 percent 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, Kostøl, and Vigtel 2020; Pries and Rogerson 2022).

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 five-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 it may also purchase premium advertising services described in Section IC. 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; 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 online Appendix A.2). The posted jobs are typically for full-time positions, offering an average minimum monthly salary of ₹12,847 (US$182.50) and requiring less than one year of experience (see online Appendix C.1).

Over two-thirds of these firms report recruitment-related constraints as a key barrier to their growth (see online Appendix A.3, Table A3). While the primary concern cited by these firms is a difficulty finding applicants with suitable technical skills, 53 percent 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 percent 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 percent of Ethiopian firms (Hensel, Tekleselassie, and Witte 2021) and 16 percent of French firms (Le Barbanchon, Ronchi, and Sauvagnat 2023) are unable to fill their vacancies. Though a qualitatively different market, we also note that 50–70 percent of vacancies on online job task platforms (e.g., Upwork.com) remain unfilled (Horton 2017; Leung 2016).

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 online Appendix A.3, Figure A3b). When employers were asked *why* they want identity verification, 81 percent report that it builds trust in applicants—that is, it provides reassurance that applicants are honest, are 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 percent or 100 percent 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 email 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 percent did so within 90 days of posting a vacancy.

Scale.—Vacancies assigned to this treatment received free access to premium advertising services that increased 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 ₹599 (US$8.50). A vacancy granted access to this service was ordered at the top of applicant search results, displayed with a "Gold" badge (see online 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 ten 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 received identity verification results at no cost for either 50 percent or 100 percent of their applicants on the portal for the entire time the vacancy was active on the portal. This service was

[9] See online 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, and 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.

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"), did not pass verification ("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 online Appendix A.4, Figure A4.2. Over the course of the experiment, 20 percent of job seekers submitted their ID details for verification and 89 percent of those who submitted passed verification.

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

II. Data Sources and Empirical Strategy

A. *Timeline and 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 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, and so forth.

Firm Surveys.—Firms were surveyed in person twice—once after vacancy posting ("baseline") and again roughly six 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 percent ($N = 794$ firms).[13]

[11] The actual cost of verification during the experiment was ₹25 (US$0.36) per individual.

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

[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 IIID.

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 ten 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 percent and 100 percent 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.

C. *Randomization Balance*

Online Appendix C.1 summarizes balance checks using pretreatment 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 of 42 comparisons are significantly different across groups at the 10 percent level, as one would expect to occur by chance.[16]

[14] Our qualitative conclusions are unchanged when we estimate a fully saturated model (see online Appendix C.7), as suggested by Muralidharan, Romero, and Wüthrich (2023).

[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 percent 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 online Appendix C.8).

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

Table 1—Recruitment Pools and Employer Engagement

	Applications	Skills index			Application clicks		Interviews
	Number (1)	Mean (2)	Maximum (3)	Minimum (4)	Any (5)	Number (6)	Any (7)
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	1,719	1,682	1,685	1,682	1,719	1,719	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 ninety-ninth 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 a higher education degree; has English language skills; has job category–specific skills, certifications, or expertise; shares résumé; and shares ID details for verification; as well as the 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 one application; column 2 has fewer observations due to some outlier corrections. Columns 5 and 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 the March 2020 COVID-19 lockdown. We report robust standard errors in parentheses.

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

[17] Specifically, it includes eight variables: whether an applicant has a higher education degree; has English language skills; reports job category–specific skills, certifications, and expertise; shares a résumé; and shares ID details for verification; as well as 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 online Appendix B.1 for treatment effects on the components of the skills index.

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*.

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 online Appendix Figure A4.2, panel B), these click data provide a useful proxy for employer engagement with applicants.

At the outset, just 34.9 percent of control group employers unlock the contact details for *any* application. Employers in the *Joint* treatment are 36.1 percent (12.6 pp) 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 also increase the *number* of unique applicants they click on (6.2 versus 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 percent (6.7 pp) 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-values < 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 percent (12.9 pp) 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 IVB.

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

Table 2—Hiring and Employee Composition

	Any hire for posted vacancy?		Employee composition at follow-up
	Via portal	All methods	Via portal
	(1)	(2)	(3)
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 and 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 (i.e., 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 the March 2020 COVID-19 lockdown. We report robust standard errors in parentheses.

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 percent of control firms report hiring from the portal. In comparison, 20.3 percent of *Joint* firms hire from the portal (column 1)—an increase of 67.8 percent (8.2 pp). Increased hiring from the portal does not result in substitution away from other recruitment methods and, instead, increases *overall* hiring—that is, whether or not a firm fills the posted vacancy across all recruitment methods—for the *Joint* group by 10.7 percent or 8.2 pp (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 pp) and not statistically distinguishable from *Control*. Though we are likely underpowered 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 percent (11.4 pp) 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-values $<$ 0.05).

As 83 percent of employers in our sample state that 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 online Appendix C.3). Further, we do not find evidence to suggest that there was differential attrition by treatment status when we compare the vacancy characteristics of attritees (see online Appendix C.4).

To allow for a more transparent comparison to the hiring effects discussed in Section IIIC, 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]

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.

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

[20] The inverse probability weighting predicts survey response using vacancy characteristics shown in online 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 online 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 treatment assignment and the outcome of interest, their inclusion provides an alternative way of adjusting for imbalances caused by attrition.

Table 3—Attrition Reweighted Estimates

	Any hire for posted vacancy?		Employee composition at follow-up
	Via portal	All methods	Via portal
	(1)	(2)	(3)
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 reweight observations to account for attrition using inverse probability weights, calculated from a probit regression that predicts survey response using vacancy characteristics listed in online Appendix C.1, our stratifying variables, and treatment indicators. The dependent variables in columns 1 and 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 the March 2020 COVID-19 lockdown. We report robust standard errors in parentheses.

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 percent 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 online 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 percent of employers in *Control* successfully recruit through the portal, while 51 percent 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 IIIB), or we are underpowered to detect small positive hiring effects.

[22] This figure reflects the fact that on average 20 percent of job seekers shared relevant details for verification and that 89 percent of those who did were successfully verified.

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 interpretations.

First, verification may provide employers with information on applicant trustworthiness. When asked why they value identity verification, 81 percent of employers stated that it builds trust in applicants (see online 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 résumé, 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 (online 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 online 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 2023; Hardy and McCasland 2023). The proliferation of online job portals represents a technological advance that can greatly expand recruitment networks, but under 2 percent 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 online 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 what the impacts could be for 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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