Extended Abstract: "Soft Skills and Hiring"

PRELIMINARY RESULTS

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Abstract

We provide the first experimental evidence on how using more information about job applicants' soft skills in firms' hiring decisions affects both firm and workseeker outcomes. Partnering with the largest recruitment agency in South Africa, we randomize the criteria used to shortlist job applicants for job listings at partner firms. We test whether including measures of soft skills in candidate ranking leads to better firm-worker matches, more inclusive hiring, and improved labor market trajectories for workseekers.

1 Introduction

Developing country labor markets often suffer from inefficiencies that contribute to high turnover and persistently high unemployment, especially among youth [9]. A significant factor is information frictions: firms have limited information about prospective workers' skills, particularly "soft" skills that are difficult to observe but correlate with productivity [2, 5]. This lack of information can lead to lower productivity, wages, and higher worker turnover [7].

In South Africa, these information frictions are highly relevant. The unemployment rate exceeds 30% [3], and firms express a willingness to pay for information about applicants' soft skills [1, 8]. High turnover rates [6, 14] further exacerbate the problem.

We provide the first experimental evidence on how using more information about job applicants' soft skills in firms' hiring decisions affects both firm and workseeker outcomes. Partnering with the largest recruitment agency in South Africa, we randomize the criteria used to shortlist job applicants for job listings at partner firms. We test whether including measures of soft skills in candidate ranking leads to better firm-worker matches, more inclusive hiring, and improved labor market trajectories for workseekers.

2 Experimental Design

We partner with a South Africa-based non-profit social enterprise. Our research partner operates an online job search and matching platform that helps match young workseekers to entry-level work and training opportunities. In particular, the platform uses an algorithm based on hiring criteria such as education, work experience, and distance from the posted job to rank applicants to each vacancy. Employers then select candidates to interview and hire based on this ranked list. Using a sample of job postings from the platform's partner firms, we explore the effects of including information about job applicants' soft skills in the candidate ranking algorithm.

We have already randomized a sample of over 1000 job postings for our study. We plan to continue randomizing job postings through the end of 2024, meaning that the final sample size will depend on the rate of posting on the platform.

The randomization and data collection process for each job posting is as follows:

1. Platform staff members share a pre-filtered applicant list with the research team. This list includes only the applicants who meet baseline requirement for the job as specified by the employer (e.g., located within 10 miles of the job).

2. The job posting is randomly assigned to either the control group or the treatment group.

3. The research team ranks the candidate list according to the algorithm specified by the assignment from step 2.

    (a) Candidate lists for job postings assigned to the control group are ranked using the platform's traditional algorithm, which is based on education, work experience, and distance from the job.

    (b) Candidate lists for job postings assigned to the treatment group are ranked using an algorithm that is based on the criteria listed above as well as a measure of the candidate's soft skills.

4. The research team shortens the ranked list to either the top 20 applicants by rank or the top n*4 applicants by rank (whichever is greater), where n is the target number of hires listed by the employer (e.g., n would be equal to four if a retailer posted a job ad looking to hire four cashiers).

5. This ranked shortlist is sent to the employer, with a note at the top of the list explaining that the applicants are ranked according to their expected fit with the job.

6. After the shortlist is shared with the employer, we conduct a short-term survey with the shortlisted applicants, as well as applicants who would have been shortlisted, to measure interviews, offers, and employment at the job for which they applied, as well as employment, wages, promotions, job satisfaction, turnover, and job search more broadly.

7. We also survey the employer about their hiring decisions for the job they posted, as well as post-hiring outcomes for any hired applicants, subsequent hiring, and branch-level performance.

8. Finally, we conduct a second round of follow-up interviews with the applicants surveyed in step 6 to measure longer-term labor market outcomes.

Our soft skill measure uses a weighted average of Behavioural Activation [12], Grit [10], and Growth Mindset [11] scales. These scales are self-administered on the platform and must be completed by applicants in order to apply to job ads included in the study.

Assignment to treatment and control groups is conducted in real time as applicant lists are received by the research team, based on pre-generated sequences of random assignments stratified within blocks. The timing of job postings depends on employer demand and is therefore not uniform. The randomization and treatment stage of the experiment started in November 2022 and is planned to finish in the first half of 2024. Outcome data collection started in January 2023 and is planned to finish in the first half of 2025.

3 Data

3.1 Workseeker Surveys

We conduct surveys with:

- **Shortlisted Applicants**: To measure interviews, job offers, employment status, wages, job satisfaction, turnover, and job search behavior.
- **Counterfactual Shortlisted Applicants**: Those who would have been shortlisted under the alternative ranking scheme, allowing us to estimate the effect of being shortlisted.

Surveys are conducted within a few months of shortlisting and again at least twelve months later to capture both short-term and longer-term outcomes, as described in Section 2 above.

3.2 Firm Surveys

Following shortlisting, we survey employers about:

- **Hiring Decisions**: Job offers made and applicants that accepted and started the job.
- **Employee Performance**: Assessments of hired applicants' performance and productivity.
- **Retention**: Data on employee turnover and reasons for separation.
- **Branch-Level Outcomes**: Subsequent hiring decisions and overall performance metrics.

3.3 Matching Platform Data

Supplementing our survey data, we access applicant data from our partner's job matching platform, including:

- **Job Search Behavior**: Number of applications submitted, jobs viewed, and days active on the platform.
- **Application Data**: Records of which applicants applied to which job listings.

4 Estimation Strategy

4.1 Hiring and Post-Hiring Outcomes

Our main analysis explores the effect of treatment on hiring and post-hiring outcomes at the job posting level, which is the unit of randomization. Our primary results estimate the impact of incorporating soft skills into candidate ranking using the following equation:

$$y_j = \alpha_0 + \alpha_1 T_j + \gamma X_j + \zeta_j + \epsilon_j \tag{1}$$

where:

- y_j: Outcome for job posting j (e.g., number of hires)
- T_j: Treatment assignment (1 if treatment group, 0 if control)
- X_j: Covariates selected using Post Double Selection Lasso [4]
- ζ_j: Randomization block fixed effects

Hiring outcomes include the number of interview invitations, the number of completed interviews, the number of job offers, and the number of accepted job offers for each job posting. Post-hiring outcomes include the total wage bill, retention, and measures of match quality such as worker surplus (as reported by workers) and employee performance (as assessed by firms).

4.2 Counterfactual Analysis: Individual-Level Outcomes

To better understand potential spillover or displacement effects, we also estimate the effect of being shortlisted for a job posting on job search behavior and on labor market beliefs and outcomes at the individual level. For these outcomes, we estimate average treatment effects by comparing mean outcomes between individuals who were shortlisted for a job posting and individuals who *would have been* shortlisted for the job posting if it had been assigned to a different treatment, adjusting for job posting fixed effects and the inverse odds ratio of shortlisting[1], as follows:

$$y_{ij} = \beta_0 + \beta_1 S_{ij} + \gamma X_{ij} + \phi_{ij} + \zeta_j + \epsilon_{ij} \tag{2}$$

where:

- y_{ij}: Outcome for applicant i for job listing j (e.g., employment status)
- S_{ij}: Shortlisting status (1 if *not* shortlisted, 0 if shortlisted)
- X_{ij}: Covariates selected using Post Double Selection Lasso
- ϕ_{ij}: The inverse odds ratio of being shortlisted for applicant i for job listing j
- ζ_j: Job posting fixed effects.

5 Results

Our preliminary results suggest that treatment boosts hiring by helping employers find more suitable candidates. **We caveat that these results may be subject to change as we are still in the process of conducting our short-term follow-up surveys and do not yet have data for the complete sample.** The results presented below reflect data for roughly 75% of the anticipated sample.

We first confirm that the treatment alters the applicant pool considered by employers, and thus ultimately hiring outcomes. In line with this expectation, treatment increases the average soft skills of shortlisted applicants by 0.5 standard deviations and of hired applicants by 0.27 standard deviations. The treatment also increases the raises the share of less experienced workers, as shortlisted applicants in the treatment group are about 7.5% less likely to have any formal work experience, and hired applicants are about 11% less likely, than the control group average.

Our preliminary main results, as shown in Table 1, indicate that our treatment increases hiring at all stages of the recruiting pipeline. In particular, treated job openings yield significantly more interview invitations (about one additional interview on average compared to a control mean of about 4.5) and more actual employment (about 0.5 additional workers accepting and starting jobs compared to a control mean of about 1) than control group job openings.

Looking at the preliminary composition of hires to treated job postings in Table 2, we see that treatment particularly boosts hiring for less experienced, and to some extent younger, workers. Thus, incorporating soft skills not only increases the total number of hires but may also help less experienced applicants gain a foothold in the labor market.

[1] We adjust for the probability that each applicant is shortlisted for a given job posting because this probability is not constant across applicants, and is positively correlated with skills. Specifically, because we introduced a third treatment arm at some points in the study (as discussed in Section **??** below), some applicants have a 2/3 probability of appearing on a shortlist while others have only a 1/3 probability, for job postings randomized under our three-arm protocol. Adjusting for this inverse odds ratio accounts for the variation in treatment

Table 1: Hiring Results (PRELIMINARY)

	Interview		Job offer		
	(1) invite	(2) attended	(3) received	(4) accepted	(5) started
Treatment	1.035***	0.856***	0.485*	0.396	0.445**
	(0.382)	(0.330)	(0.275)	(0.247)	(0.202)
Control mean	4.378	3.365	1.940	1.518	0.971
Observations	767	767	767	767	767
Controls	Yes	Yes	Yes	Yes	Yes
Randomization block FE	Yes	Yes	Yes	Yes	Yes

Table 2: Demographics of Hired Applicants (PRELIMINARY)

	# hires					
	(1) female	(2) male	(3) exp.	(4) inexp.	(5) young	(6) old
Treatment	0.267	0.144*	0.134	0.268**	0.243*	0.169
	(0.197)	(0.078)	(0.148)	(0.133)	(0.126)	(0.139)
Relative effect size	0.260	0.295*	0.151	0.425**	0.315*	0.233
Control mean	1.026	0.490	0.888	0.630	0.771	0.724
Observations	767	767	767	767	767	767
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Randomization block FE	Yes	Yes	Yes	Yes	Yes	Yes

Finally, examining preliminary outcomes for counterfactual applicants at the individual level, we find that these applicants are less likely to be hired and have lower average wages than applicants who were actually shortlisted, as shown in Table 5. However, this is driven completely by shortlisted applicants who were actually hired, as shown in Table **??**. In other words, while our intervention changes who is hired to treated jobs (as expected), it does not appear to have any impact on employment or wages in jobs outside the experiment. Thus, as the intervention increases net employment, it is likely to have a net positive impact on employment and wages.

Table 3: Counterfactual Analysis (PRELIMINARY)

	Work					Expectations	
	(1) Any	(2) Wage	(3) Self-employed	(4) Hours	(5) Earnings	(6) Res. wage	(7) Wage exp.
Not shortlisted	-0.031***	-0.034***	-0.007	-0.666	-139.802	-169.781**	-155.004**
	(0.011)	(0.009)	(0.008)	(0.413)	(101.170)	(76.905)	(74.375)
Control mean	0.432	0.202	0.146	9.594	2128.318	6211.381	6646.718
Observations	8155	8155	8155	8103	8115	8144	8141
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Randomization block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Counterfactual Analysis Excluding Hired Applicants (PRELIMINARY)

	Work					Expectations	
	(1) Any	(2) Wage	(3) Self-employed	(4) Hours	(5) Earnings	(6) Res. wage	(7) Wage exp.
Not shortlisted	-0.009	-0.003	-0.014	0.025	-50.297	-123.203	-125.072
	(0.012)	(0.009)	(0.008)	(0.412)	(105.783)	(78.600)	(76.105)
Control mean	0.405	0.164	0.153	8.871	2033.217	6173.189	6626.892
Observations	7785	7785	7785	7779	7754	7789	7786
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Randomization block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

assignment probabilities for the same reasons that adjusting for the probability of selection into a sample accounts for sample selection bias [13].

References

[1] Martin Abel, Rulof Burger, and Patrizio Piraino. The value of reference letters: Experimental evidence from south africa. *American Economic Journal: Applied Economics*, 12(3):40–71, 2020.

[2] Achyuta Adhvaryu, Namrata Kala, and Anant Nyshadham. Returns to on-the-job soft skills training. *Journal of Political Economy*, 131(8):2165–2208, 2023.

[3] Statistics South Africa. *Quarterly labour force survey*. Statistics South Africa, 2023.

[4] Achim Ahrens, Christian Hansen, and Mark Schaffer. Pdslasso: Stata module for post-selection and post-regularization ols or iv estimation and inference. 2019.

[5] David H Autor and David Scarborough. Does job testing harm minority workers? evidence from retail establishments. *The Quarterly Journal of Economics*, 123(1):219–277, 2008.

[6] Chris Benner, Charley Lewis, and Rahmat Omar. The south african call centre industry: A study of strategy, human resource practices and performance. *Human Resource Practices and Performance (June 22, 2007)*, 2007.

[7] Christopher Blattman and Stefan Dercon. The impacts of industrial and entrepreneurial work on income and health: Experimental evidence from ethiopia. *American Economic Journal: Applied Economics*, 10(3):1–38, 2018.

[8] Eliana Carranza, Robert Garlick, Kate Orkin, and Neil Rankin. Job search and hiring with limited information about workseekers' skills. *American Economic Review*, 112(11):3547–3583, 2022.

[9] Kevin Donovan, Will Jianyu Lu, and Todd Schoellman. Labor market dynamics and development. *The Quarterly Journal of Economics*, 138(4):2287–2325, 2023.

[10] Angela Lee Duckworth and Patrick D Quinn. Development and validation of the short grit scale (grit–s). *Journal of personality assessment*, 91(2):166–174, 2009.

[11] Carol S Dweck. *Mindset: The new psychology of success*. Random house, 2006.

[12] Shelly L Gable, Harry T Reis, and Andrew J Elliot. Behavioral activation and inhibition in everyday life. *Journal of personality and social psychology*, 78(6):1135, 2000.

[13] James Heckman. Shadow prices, market wages, and labor supply. *Econometrica: journal of the econometric society*, pages 679–694, 1974.

[14] Rocco Zizzamia and Vimal Ranchhod. Measuring employment volatility in south africa using nids: 2008-2017. 2019.