

Matsuda, Norihiko; Hayashi, Ryotaro

**Working Paper**

## The impact of an online job fair: Experimental evidence from Bangladesh

ADB Economics Working Paper Series, No. 689

**Provided in Cooperation with:**

Asian Development Bank (ADB), Manila

*Suggested Citation:* Matsuda, Norihiko; Hayashi, Ryotaro (2023) : The impact of an online job fair: Experimental evidence from Bangladesh, ADB Economics Working Paper Series, No. 689, Asian Development Bank (ADB), Manila,  
<https://doi.org/10.22617/WPS230227-2>

This Version is available at:

<https://hdl.handle.net/10419/298135>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by/3.0/igo/>

# THE IMPACT OF AN ONLINE JOB FAIR

EXPERIMENTAL EVIDENCE FROM BANGLADESH

*Norihiko Matsuda and Ryotaro Hayashi*

**NO. 689**

July 2023

**ADB ECONOMICS  
WORKING PAPER SERIES**



ADB Economics Working Paper Series

# The Impact of an Online Job Fair: Experimental Evidence from Bangladesh

Norihiko Matsuda and Ryotaro Hayashi

No. 689 | July 2023

Norihiko Matsuda (nmatsuda@fiu.edu) is an assistant professor of economics, Florida International University. Ryotaro Hayashi (rhayashi@adb.org) is a social sector economist, Human and Social Development Sectors Group, Asian Development Bank.

The *ADB Economics Working Paper Series* presents research in progress to elicit comments and encourage debate on development issues in Asia and the Pacific. The views expressed are those of the authors and do not necessarily reflect the views and policies of ADB or its Board of Governors or the governments they represent.



Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO)

© 2023 Asian Development Bank  
6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines  
Tel +63 2 8632 4444; Fax +63 2 8636 2444  
[www.adb.org](http://www.adb.org)

Some rights reserved. Published in 2023.

ISSN 2313-6537 (print), 2313-6545 (electronic)  
Publication Stock No. WPS230227-2  
DOI: <http://dx.doi.org/10.22617/WPS230227-2>

The views expressed in this publication are those of the authors and do not necessarily reflect the views and policies of the Asian Development Bank (ADB) or its Board of Governors or the governments they represent.

ADB does not guarantee the accuracy of the data included in this publication and accepts no responsibility for any consequence of their use. The mention of specific companies or products of manufacturers does not imply that they are endorsed or recommended by ADB in preference to others of a similar nature that are not mentioned.

By making any designation of or reference to a particular territory or geographic area, or by using the term “country” in this publication, ADB does not intend to make any judgments as to the legal or other status of any territory or area.

This publication is available under the Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO) <https://creativecommons.org/licenses/by/3.0/igo/>. By using the content of this publication, you agree to be bound by the terms of this license. For attribution, translations, adaptations, and permissions, please read the provisions and terms of use at <https://www.adb.org/terms-use#openaccess>.

This CC license does not apply to non-ADB copyright materials in this publication. If the material is attributed to another source, please contact the copyright owner or publisher of that source for permission to reproduce it. ADB cannot be held liable for any claims that arise as a result of your use of the material.

Please contact [pubsmarketing@adb.org](mailto:pubsmarketing@adb.org) if you have questions or comments with respect to content, or if you wish to obtain copyright permission for your intended use that does not fall within these terms, or for permission to use the ADB logo.

Corrigenda to ADB publications may be found at <http://www.adb.org/publications/corrigenda>.

Note:

In this publication, “\$” refers to United States dollars.

# CONTENTS

<b>TABLES AND FIGURES</b>	<b>iv</b>
<b>ACKNOWLEDGMENTS</b>	<b>vi</b>
<b>ABSTRACT</b>	<b>vii</b>
<b>ABBREVIATIONS</b>	<b>viii</b>
<b>1. INTRODUCTION</b>	<b>1</b>
<b>2. RESEARCH DESIGN</b>	<b>3</b>
Study Context: Labor Markets in Bangladesh	3
Intervention: Online Job Fair	3
Recruitment and Randomization	4
Data	5
Timeline	5
<b>3. DESCRIPTIVE STATISTICS</b>	<b>5</b>
Jobseekers	5
Participation in the Fair	5
<b>4. THE EFFECTS OF THE FAIR</b>	<b>7</b>
Matches through the Fair	7
Estimation Results	7
Mechanism and Discussions	10
<b>5. COST-EFFECTIVENESS</b>	<b>13</b>
<b>6. CONCLUSIONS</b>	<b>13</b>
<b>APPENDIXES</b>	
A. Additional Figures and Tables	15
B. Randomization and Attrition Balances between Treatment and Control Jobseekers	23
C. Robustness Checks: Estimation Results without Controls	25
D. Cost Breakdown and Comparison with an In-person Job Fair	27
<b>REFERENCES</b>	<b>29</b>

## TABLES AND FIGURES

### TABLES

1	Summary Statistics of Jobseekers	6
2	Effects of the Online Job Fair	8
3	Differences in Wages, Job Tenure, Skill-Match Quality, and Job Satisfaction between Employed Treatment and Control Jobseekers	9
A1	List of Job Titles	16
A2	Summary Statistics of Employers and Jobs	17
A3	What Types of Jobseekers Are More Likely to Participate	18
A4	Average Treatment Effects of the Fair on the Treated	19
A5	Additional Results on the Effects of the Job Fair	20
A6	Reasons Why Job Offers Were Declined	20
A7	Heterogeneity of the Effects by Baseline Employment Status	21
A8	Heterogeneity: Comparisons of Employed Treatment and Control Jobseekers by Baseline Employment Status	22
B1	Randomization Check: Balance between Treatment and Control Jobseekers	23
B2	Balance on Survey Attrition between Treatment and Control Jobseekers	24
C1	Robustness without Controls: Effects of the Online Job Fair	25
C2	Robustness without Controls: Differences in Wages, Job Tenure, Skill-Match Quality, and Job Satisfaction between Treatment and Control Jobseekers	26
D1	Cost Breakdown and Comparison between the Online Job Fair and a Counterfactual In-Person Fair	28

**FIGURES**

1	Job Fair Participation and Matches	7
2	Jobseekers' Experiences in the Fair	11
A1	Job Search Challenges for Jobseekers	15
A2	Online Job Fair	15
A3	Study Timeline	16



## **ACKNOWLEDGMENTS**

We are deeply indebted to Bdjobs.com, especially Kazi Latifur Rahman, Prokash Roy Chowdhury, and Mohammad Ali Firose, for their continuous strong support. We thank MOMODa Foundation, especially Md Enamul Haque and H. M. Masudur Rahman for their field data collection. We appreciate exceptional research assistance from Sandy Noboa Lindao and Md Rezwatul Hoque. We are grateful for comments from Takashi Yamano, Paul Vandenberg, and seminar participants at the Asian Development Bank (ADB). Special thanks to Md Saidur Rahman and Akihiro Shoji for their support in the field. This study is supported by ADB TA9402 (Developing Impact Evaluation Methodologies, Approaches, and Capacities in Selected Developing Member Countries [Subproject 3]). This study was approved by the Social and Behavioral Institutional Review Board of Florida International University (IRB-21-0353). The study is preregistered at the AEA registry (AEARCTR-0009002). The views of the authors do not necessarily represent those of ADB. All errors are our own.

## ABSTRACT

Online job fairs are a new labor market intervention. This paper provides the first experimental evidence on their impact by evaluating an online fair for information and communication technology jobs in Bangladesh. The fair generated a non-negligible number of job offers; however, over 90% of them were rejected, so no effect on employment probability or type was found. Interestingly, jobseekers lowered their reservation wages, kept their jobs longer, and ended up in worse skill-matched jobs. The reason is that jobseekers initially had overoptimistic expectations, but learned about market conditions at the fair, lowered their expectations, and became discouraged from job search. As a result, those who had already been employed kept their jobs longer, even if the jobs did not match their skills, and those who had initially been unemployed ended up with lower employment probabilities and lower skill-match quality.

**Keywords:** job fair, job matching, online search, youth employment, Bangladesh

**JEL codes:** O12, O15, J24, J64

## ABBREVIATIONS

ADB	Asian Development Bank
AEA	American Economic Association
ATE	average treatment effect on the treated
COVID-19	coronavirus disease
ICT	information and communication technology
ITT	intention-to-treat

# 1. INTRODUCTION

Search frictions in labor markets prevent jobseekers from learning about jobs and meeting with employers. To overcome the search frictions, various types of interventions exist such as information provision (Altmann et al. 2018; Belot, Kircher, and Muller 2019; Dammert, Galdo, and Galdo 2015); search subsidies (Banerjee and Sequeira 2022; Bryan, Chowdhury, and Mobarak 2014; Franklin 2018); recruitment services (Jensen 2012); and in-person job fairs (Abebe et al. 2022; Beam 2016).<sup>1</sup> Online job fairs are a new addition to this set of labor market interventions. They have become more common after the outbreak of the coronavirus disease (COVID-19) and are expected to grow and become a standard job matching program, according to data from the United States (Handshake Network Trends 2021).<sup>2</sup> Although online job fairs have obvious advantages such as affordability, accessibility, flexibility, and scalability, their effectiveness is still unknown. For example, the effectiveness may be weaker due to the lack of face-to-face interaction (Atkin, Chen, and Popov 2022; Startz 2021).

This paper provides the first experimental evidence on the effects of online job fair attendance on labor market outcomes. We partner with the largest online job portal in Bangladesh, Bdjobs.com, to conduct an online job fair for information and communication technology (ICT) jobs. The country is a good fit for our study because of high search frictions and spatial mismatches (Bryan, Chowdhury, and Mobarak 2014; Matsuda and Nomura 2022); the national development focus on digitizing the economy (General Economics Division 2020); and the rapid expansion of internet users.<sup>3</sup> The timing of the fair also fits well because it was when jobs recovered to the pre-pandemic level (Hayashi, Matsuda, and Rahman 2022), while the fear of contracting COVID-19 remained, preventing people from extensive job searches.<sup>4</sup>

The fair consisted of three components: job postings on the fair website; live sessions where employers made presentations and engaged in two-way communication with jobseekers; and job application. The fair lasted 3 days on weekdays, 9–11 November 2021. While these components are essentially the same as in-person fairs offer, the online fair has several unique advantages. First, because it is online and remote, there is no need for travel or transportation. This feature may be particularly beneficial for jobseekers with liquidity constraints (Abebe, Caria, and Ortiz-Ospina 2021; Baird, McKenzie, and Özler 2018); spatial constraints (Banerjee and Sequeira 2022; Franklin 2018); and mobility constraints (Borker 2021; Field and Vyborny 2022; Muralidharan and Prakash 2017). Second, it allows flexible participation. That is, jobseekers do not have to spend entire days but can browse job ads at their convenience and selectively attend live sessions.<sup>5</sup> The flexibility, along with the remoteness, may be especially important for time-constrained jobseekers (He, Neumark, and Weng 2021), including women who are disproportionately burdened with household work (Delecourt and Fitzpatrick 2021; Dinkelman 2011; Tas et al. 2022).

---

<sup>1</sup> For reviews of active labor market policies, see for example, Card, Kluve, and Weber (2018) and McKenzie (2017).

<sup>2</sup> Although, to our knowledge, data on online job fairs in developing countries do not yet exist, we conjecture that online job fairs will expand in developing countries too, because broadband networks are expanding (International Telecommunication Union 2022) and there is a need for low-cost means of matching.

<sup>3</sup> The proportion of people using the internet almost tripled between 2015 and 2021 (World Bank Open Data).

<sup>4</sup> When jobseekers were asked about their labor market challenges in our baseline survey, 51% of them agreed that they worried about COVID-19 infection (Figure A1).

<sup>5</sup> The session program was published in advance on the fair website.

The fair focused exclusively on ICT jobs at entry to junior levels for jobseekers with college education. This clear focus on the type and level of jobs aimed to maximize the fair's outcomes in terms of both match quantity and quality, while it also fitted the country's context, such as the importance of the ICT sector and the need to support educated youth in their transition to labor markets (ADB 2019a; General Economics Division 2020).

Our randomization was across jobseekers, using an oversubscription design. After Bdjobs.com advertised the fair, interested jobseekers filled out an online application form, from which we identified 2,556 jobseekers eligible for the study. Randomly selected 1,280 treatment jobseekers were invited to the fair, while the other 1,276 control jobseekers did not receive any intervention. We conducted two follow-up surveys, approximately 2 months and 1 year after the fair.

As direct outcomes of the fair, 139 jobseekers were interviewed and 45 job offers were made, but only 4 offers were accepted. Our estimation finds no statistically significant effects on the probability or type of employment at either the first or second endline survey. Interestingly, the fair reduced reservation wages while it did not affect aspired future wages. Our estimation also finds that treatment jobseekers kept their jobs longer than control jobseekers even though their skills were less frequently used and less well matched to their current jobs than the skills of control jobseekers were.

Further analyses provide interpretations of these estimation results. Qualitative analyses of the reasons for rejecting job offers and the experience of the fair clearly show that jobseekers initially had overoptimistic expectations about wages, working conditions, and the availability of skill-matched jobs, but developed more realistic views at the fair and lowered their expectations. According to a heterogeneous analysis, treatment jobseekers who were initially unemployed ended up with lower employment probabilities and lower skill-match quality than the control jobseekers who were initially unemployed, because lowered expectations discouraged the treatment jobseekers from job search. Treatment jobseekers who had already been employed had more or less the same probability of being employed at endline as the control jobseekers, because both the treatment and control jobseekers engaged in on-the-job search. However, the treatment jobseekers were more likely to stay in skill-mismatched jobs than the control jobseekers.

The rather disappointing result that the online job fair was ineffective in improving employment outcomes should not be interpreted as implying a unique flaw of online job fairs. The underlying cause of the ineffectiveness is overoptimistic expectations. Even if the fair had been conducted in person, the employment effect would likely have been the same in the presence of overoptimistic expectations, as has been the case for other job matching interventions (Abebe et al. 2022; Bandiera et al. 2022; Groh et al. 2015). Therefore, a policy implication from this study is to educate jobseekers about labor markets.

This paper contributes to the literature on job matching interventions. While recent studies examine new interventions such as text messaging about the labor markets (Dammert, Galdo, and Galdo 2015; Jones and Santos 2022; Kelley, Ksoll, and Magruder 2022), algorithmic search advice (Horton 2017; Dhia et al. 2022), and online professional networking (Wheeler et al. 2022), there are no studies on online job fairs. In-person fairs are studied by Abebe et al. (2022) in Ethiopia and Beam (2016) in the Philippines, and a matching event (which is similar to a job fair) is evaluated in a developed country, the Netherlands, by Van der Klaauw and Ziegler (2022). In Jordan, Groh et al. (2015) examine a customized job intermediation service for university-educated youth. All of these studies except Van der Klaauw and Ziegler (2022) find that the interventions are ineffective in generating direct hires because of jobseekers' overoptimism (Abebe et al. 2022) and misaligned preferences regarding job types (Groh et al. 2015) and locations (Beam 2016). Our paper adds a similar finding from an online job fair in Bangladesh to these previous studies.

This paper also adds to the growing body of studies that demonstrate jobseekers' overoptimism. Their overoptimism is found in both developing countries (Abebe et al. 2022; Alfonsi, Namubiru, and Spaziani 2022; Bandiera et al. 2022; Banerjee and Sequeira 2022; Jones and Santos 2022) and developed countries (Krueger and Mueller 2016; Mueller, Spinnewin, and Topa 2021; Van der Klaauw and Ziegler 2022). Abebe et al. (2022); (Alfonsi, Namubiru, and Spaziani 2022); Banerjee and Sequeira (2022), and Van der Klaauw and Ziegler (2022) find that moderating overoptimism encourages job search and offer acceptance; on the other hand, Bandiera et al. (2022) find that moderating overoptimism discourages job search and leads to worse employment outcomes in the long run. Our paper adds to the latter, since we find that moderating it discourages job search and results in lower skill-match quality. The uniqueness of our study is that the overoptimism is found even when jobs are tightly matched to jobseekers' preferred sector (i.e., ICT jobs) and levels (entry/junior-level jobs for college-educated workers), whereas the existing studies find the overoptimism when broader types and levels of jobs and jobseekers are matched to each other.

Finally, the paper relates to a nascent literature on online job portals. The portals are growing across the world with great potential (Afridi et al. 2022; Hensel, Tekleselassie, and Witte 2021; Jones and Sen 2022; Fernando, Singh, and Tourek 2022). They can not only facilitate job postings and application, but also provide additional features such as skill assessment (Yamauchi et al. 2018) and workplace information disclosure (Leibbrandt and List 2018; Matsuda et al. 2022; Ward 2022). By collaborating with an online job portal, our study demonstrates that an online fair can be another add-on to portals.

## 2. RESEARCH DESIGN

### **Study Context: Labor Markets in Bangladesh**

Bangladesh achieved annual economic growth of 7.9% in fiscal year 2019, the highest in Asia and the Pacific. However, this recent growth was largely led by the ready-made garment industry (ADB 2019b). The country needs new engines for economic growth, so the Government of Bangladesh has started to invest in the ICT industry (General Economics Division 2020) and implemented programs that foster ICT firms and train ICT skills.

The ICT sector is also important for youth employment. Every year 2.2 million young people enter the workforce but face challenging transition from school to work. According to a recent study (ADB 2019a), only 42% of college graduates with ICT-related degrees find a job within a year of graduation, and there are significant geographic differences in job placement rates. There is a need to strengthen job placement services.

### **Intervention: Online Job Fair**

The online job fair was implemented by Bdjobs.com, the country's largest online job portal with about 1 million active jobseekers and 10,000 firms. In partnership with the Asian Development Bank (ADB) and the research team, Bdjobs.com developed an online job fair program and conducted two small-scale pilots prior to the fair evaluated in this study.

The fair had three components: job postings, live sessions, and application. On the fair website employers posted job ads, and jobseekers browsed them. Both the website and job ads became available about 10 days before the fair days, so jobseekers had enough time to review the job ads in advance. On the fair days, employers held live online sessions in which they explained their businesses, job positions, career paths, etc., and took and answered questions from jobseekers. Recorded videos of the sessions were made available on the fair website. Jobseekers were able to submit applications through the website before, during, and on the day after the fair. Figure A2 presents screenshots of the fair.<sup>6</sup> The fair was held on 3 weekdays. It was free for both jobseekers and employers.<sup>7</sup>

The fair focused entirely on ICT jobs (i.e., jobs requiring ICT skills) at entry to junior levels (requiring zero to 6 years of work experience) for workers with tertiary education. Accordingly, the participating jobseekers had strong interest in ICT jobs and ICT skills, as presented in the next section.

### Recruitment and Randomization

Bdjobs.com recruited 110 employers by reaching out to those that were using its portal and to the Bangladesh Association of Software and Information Services. Summary statistics of employers and jobs are presented in Appendix Table A2. Ninety-four percent of them (or 103 employers) were located in Dhaka city. In terms of firm size, 54% were small (10–49 full-time employees); 22% micro (1–9 employees); 10% medium (50–99 employees); 10% large (100–999 employees); 4% mega (1,000 or more employees). Although all employers advertised ICT jobs, 86% (or 95 employers) operated in the ICT sector; the remaining 14% (15 employers) were in non-ICT sectors such as professional services, manufacturing, and trade.

Each employer posted exactly one job ad, so there were a total of 110 job ads.<sup>8</sup> Due to logistical and scheduling constraints, 41 employers held live sessions. The mean number of vacancies per job was 3.2, and the total number of vacancies was 350 (Appendix Table A2). The mean minimum years of experience required was 0.8 years, and the mean maximum years of experience was 2.5 years. Most of the jobs (85%) required a college degree or higher.

To recruit jobseekers, Bdjobs.com advertised the fair on its portal website. They also sent emails to their users with 0–6 years of experience and students in ICT-related universities and vocational training programs. The emails included a link through which interested jobseekers could submit an application form for the fair. Based on the information provided in the form, we identified eligible jobseekers for the study. The eligibility criteria were that a jobseeker had completed or was currently enrolled in tertiary education, had access to a digital device (e.g., computer, tablet, and smartphone) and the internet to attend the fair, and had a free account on Bdjobs.com.<sup>9</sup> The number of eligible jobseekers was 2,556.

Of the 2,556 eligible jobseekers, 1,280 were randomly selected as treatment jobseekers who were invited to the fair. The remaining 1,276 were control jobseekers who did not receive any intervention. The randomization was at the jobseeker level and stratified by geographic divisions. After the randomization, Bdjobs.com informed treatment jobseekers, via email, phone, and push notifications, that they were selected for the fair and instructed them to register online for the fair. We examine the balance of baseline characteristics between treatment and control jobseekers and find no statistically significant difference between them (Appendix Table B1).

<sup>6</sup> At the fair, we introduced a job preference signaling mechanism. It was essentially identical to the signaling mechanism in the economist job market by the American Economic Association (Coles et al. 2010). We applied a randomization method to test the mechanism as a pilot study. It was separately registered (AEARCTR-0009003).

<sup>7</sup> Although our fair was free for employers, in-person job fairs organized by Bdjobs.com usually charge fees for employers, while they are always free for jobseekers.

<sup>8</sup> Appendix Table A1 presents what their job titles were like.

<sup>9</sup> If a jobseeker did not have an account when filling out the application form, he or she was redirected to the Bdjobs.com account sign-up page after submitting the form.

## Data

We collected baseline data on jobseekers through the fair’s application form. It asked about demographics, employment, and job search. Employer baseline data was collected through an online survey form, which was completed by 104 of the 110 participating employers.

At endline, we conducted interview surveys of all jobseekers over the phone twice, approximately 2 and 11 months after the fair. The response rate was 94% in the first endline survey and 81% in the second one. The response rates were not statistically significantly different between treatment and control jobseekers but were nearly equal (Appendix Table B2). For employers, we conducted an in-person survey about 2 months after the fair. The response rate was 81%.

Additionally, we use the administrative data of Bdjobs.com and the fair. The former includes basic information about jobseekers and employers. The latter includes information on fair registration and job applications.

## Timeline

The timeline of the study is illustrated in Appendix Figure A3. The fair was held on 9–11 November 2021. The recruitment of jobseekers and employers started in late September. On 30 October, Bdjobs.com published the fair website, including job ads, and began communicating with treatment jobseekers. From 30 October to 12 November (i.e., one day after the fair) registered jobseekers could submit job applications, which employers could review at any time, even after 12 November.

# 3. DESCRIPTIVE STATISTICS

## Jobseekers

Summary statistics of jobseekers are presented in Table 1. Eighty-eight percent of them were male, and the mean age was 25 years, and 21% were married. They were highly educated: 94% had a college diploma or higher degree.<sup>10</sup> Seventy-seven percent had previously taken ICT-related training courses. When asked to rank 14 industries based on their preference, 95% ranked ICT first and 3% ranked second. So they were very interested in ICT jobs. While 62% of jobseekers were employed, the mean years of experience was only 1.45 years, and 18% had never worked before.

## Participation in the Fair

Panel (a) of Figure 1 shows jobseekers’ participation in the fair. Of 1,280 treatment jobseekers, 878 (or 69%) registered for the fair,<sup>11</sup> and 713 (56%) applied for at least one job. The mean number of applications conditional on applying was 8.6.

<sup>10</sup> The remaining 6% were studying at college.

<sup>11</sup> This take-up rate is slightly higher than the in-person fairs in Ethiopia (Abebe et al. 2022), which uses an oversubscription design and has a take-up rate of 60%.



**Table 1: Summary Statistics of Jobseekers**

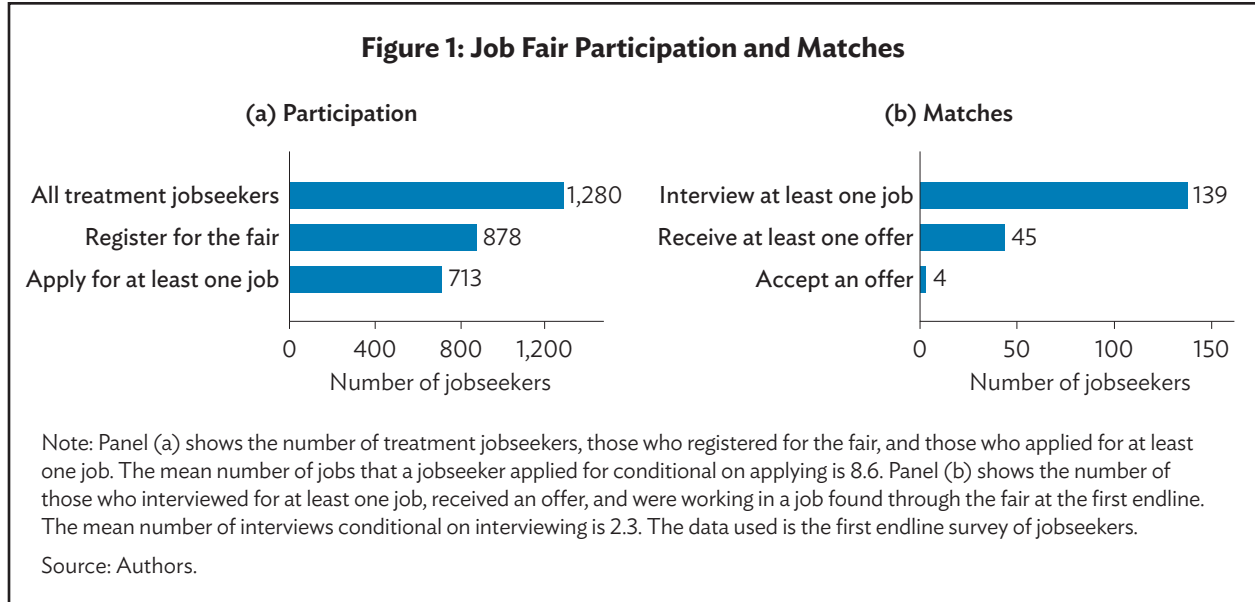
	Mean	SD	N
Male	0.88	0.33	2,556
Age	24.99	2.06	2,556
Married	0.21	0.41	2,519
Live in urban area	0.83	0.38	2,534
Highest education level attained			
Higher secondary school	0.06	0.24	2,556
Diploma	0.13	0.34	2,556
Bachelor	0.73	0.44	2,556
Master	0.07	0.26	2,556
Currently studying	0.23	0.42	2,528
Ever taken ICT-related training	0.77	0.42	2,524
Interest in ICT: Rank of ICT among 14 industries			
Top 1	0.95	0.22	2,556
Top 2	0.03	0.18	2,556
Top 3 or below	0.02	0.13	2,556
Work in last 4 weeks	0.62	0.48	2,556
Work full time (conditional on working)	0.76	0.43	1,483
Never worked	0.18	0.39	2,556
Years of experience	1.45	1.58	2,556
Look for jobs in last 4 weeks	0.85	0.36	2,556
Reservation wage (monthly, taka)	25,183.67	11,246.43	2,548

ICT = information and communication technology, N = observations, SD = standard deviation.

Notes: The other 13 sectors are finance and insurance; manufacturing; transportation; education; health; retail, wholesale, and trading; hotel, restaurant, and food services; construction; mining; agriculture, forestry, and fishing; professional, scientific, and technical activities; utilities (electricity, gas, water supply, and waste management); and entertainment, arts, and recreation.

Source: Authors.

We run regressions to understand what types of jobseekers were more likely to participate (Appendix Table A3). Those who were older, had ever taken ICT-related training, ranked ICT as their most preferred industry, and had applied for more jobs on Bdjobs.com in the last month before the fair were more likely to register for the fair and also to apply for at least one job at the fair. In addition, men were more likely than women to apply for a job, although they were not significantly more likely to register. Overall, at the extensive margin, the participation was positively correlated with how strongly a jobseeker looked for jobs and was attached to ICT jobs. At the intensive margin, those who had taken ICT-related training, ranked ICT as their most preferred industry, had shorter experience, and had applied for more jobs through Bdjobs.com submitted more applications in the fair.



## 4. THE EFFECTS OF THE FAIR

### Matches through the Fair

Panel (b) of Figure 1 presents job matches created directly through the fair. Of the 713 jobseekers who submitted applications, 17% (139 jobseekers) got interviews. The mean number of interviews conditional on interviewing was 2.3. In the end, 45 jobseekers (32% of the interviewed jobseekers) received an offer. However, only 4 jobseekers accepted them; the other 41 rejected. The rejection rate was 91%. This high rejection rate was surprising to us, especially given that these jobseekers had been informed of the type and level of jobs at the fair (i.e., ICT jobs at junior to entry levels) and that they were interested in and trained for these jobs.<sup>12</sup> We investigate the reason for the high rejection rate in section 4.3.

### Estimation Results

We estimate the effects of the fair for jobseekers using the following equation:

$$Y_i = \alpha + \beta T_i + \gamma X_{i0} + \delta_s + e_{it},$$

where  $Y_i$  is a labor market outcome of jobseeker  $i$ ;  $T_i$  is the treatment jobseeker dummy;  $X_{i0}$  is baseline characteristics, including baseline employment and job search variables;  $\delta_s$  is a randomization stratum fixed effect. Since the randomization is at the jobseeker level, we do not cluster the standard errors. The coefficient of interest is  $\beta$ , which shows the intent-to-treat (ITT) effect of the fair.

<sup>12</sup> Similarly high rejection rates are found in other studies. 81% of offers are rejected in Ethiopia (Abebe et al. 2022), 83% of jobs are either rejected or quickly quit in Jordan (Groh et al. 2015).

The estimated ITT effects are reported in Table 2.<sup>13</sup> All dependent variables except the number of jobs applied for (columns 6 and 14) are preregistered in the American Economic Association (AEA) registry.<sup>14</sup> As for employment, we do not find statistically significant effects on the probability or types of employment (such as wage, full-time, and formal employment) at either the first or second endline. For example, the point estimate of the ITT effect on the employment probability is 0 at the first and second endlines and -2 percentage points, and both of them are insignificant (columns 1 and 9). The essentially zero effect on employment at the first endline is somewhat consistent with the fact that only four hires were made directly through the fair. Regarding job search, the effect on the likelihood of looking for a job is zero at the first endline (column 5), but 4 percentage points and significant at the 10% level at the second endline (column 13). There is no significant effect on the number of jobs applied for (columns 6 and 14).

**Table 2: Effects of the Online Job Fair**

<i>Dependent Variables</i>	<b>Employed</b>	<b>Wage Job</b>	<b>Full Time Job</b>	<b>Formal Job</b>	<b>Looked for Jobs</b>	<b>No. of Jobs Applied</b>	<b>Log Reservation Wage</b>	<b>Log Aspired Wage</b>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker	0.00	-0.01	0.01	0.01	-0.00	-0.47	-0.06***	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.46)	(0.02)	(0.02)
Control mean	0.66	0.46	0.53	0.40	0.72	6.68	10.29	11.24
R-squared	0.27	0.29	0.28	0.23	0.05	0.03	0.40	0.21
Observations	2,363	2,363	2,363	2,360	2,363	2,360	2,341	2,295
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker	-0.02	-0.02	-0.02	-0.03	0.04*	0.38	-0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.46)	(0.02)	(0.02)
Control mean	0.84	0.63	0.72	0.58	0.55	5.18	10.35	11.36
R-squared	0.13	0.13	0.15	0.16	0.04	0.04	0.36	0.21
Observations	2,035	2,035	2,033	1,968	2,035	2,031	2,023	2,003

Notes: Wage job excludes day laborers, interns, probational employments, contractors, and freelancers. Formal job means employment based on a written, not oral, contract. Aspired wage is the wage desired to earn in 5 years. The controls are dummies for gender, age, marital status, living in an urban area, education levels, currently studying, having ever taken ICT-related training, the most preferred industry being ICT; employment-related variables at baseline (i.e., being employed, being employed full time, years of experience, looking for jobs, and log reservation wage); fixed effects for geographic divisions and endline survey interview weeks. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%.

Source: Authors.

<sup>13</sup> The regressions without controls, reported in Appendix Table C1, yield essentially the same results. In the appendix, we also report average treatment effects on the treated (ATETs) where the treatment variable is the fair registration dummy, which is instrumented by the treatment jobseeker dummy (Appendix Tables A4). Since the registration rate was 69%, the ATETs are about 1.45 times ( $=1/0.69$ ) as large as the ITT effects.

<sup>14</sup> The outcome variables that are preregistered but not included in the main text are reported in Appendix Table A5. The effects on these outcomes are insignificant.

Interestingly, we find a negative effect on reservation wages. Treatment jobseekers have lower reservation wages by 6% at the first endline and by 3%, albeit insignificant, at the second endline (columns 7 and 15). On the other hand, there is no significant effect on future wage aspired to earn in 5 years (columns 8 and 16). That is, while the fair reduced reservation wages, we find no evidence of the effect on long-term aspired wages. We discuss the mechanism behind these effects in section 4.3.

In Table 3, we delve into detailed employment outcomes by comparing the treatment and control jobseekers who are employed at endlines.<sup>15</sup> Monthly and hourly wages are not significantly different between treatment and control jobseekers at either the first or second endline (columns 1–2 and 9–10).<sup>16</sup>

Tenure in a current job is statistically significantly longer for treatment jobseekers than for control jobseekers by 2.7 months at the first endline and 2.4 months at the second endline (columns 3 and 11 in Table 3). In addition, treatment jobseekers' current jobs are less likely to have started after the fair than control jobseekers' jobs by 5 percentage points at the first endline and by 4 percentage points at the second endline (columns 4 and 12). These results mean that the fair made employed jobseekers keep jobs longer. We discuss the mechanism behind this effect in section 4.3.

**Table 3: Differences in Wages, Job Tenure, Skill-Match Quality, and Job Satisfaction between Employed Treatment and Control Jobseekers**

<i>Dependent Variables</i>	<b>Log Monthly Wage (taka)</b>	<b>Log Hourly Wage (taka)</b>	<b>Job Tenure (month)</b>	<b>Started After Fair</b>	<b>Skill Use (z-score)</b>	<b>Skill Fit (z-score)</b>	<b>Interest (z-score)</b>	<b>Job Satisfaction (z-score)</b>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker	0.02 (0.03)	0.01 (0.03)	2.68*** (0.96)	-0.05*** (0.02)	-0.03 (0.05)	-0.11** (0.05)	-0.01 (0.05)	-0.02 (0.05)
Control mean	9.80	4.71	16.73	0.21	0.00	0.00	-0.00	0.00
R-squared	0.26	0.23	0.22	0.14	0.04	0.07	0.04	0.03
Observations	1,457	1,455	1,578	1,578	1,578	1,578	1,577	1,576
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker	-0.02 (0.03)	-0.00 (0.03)	2.40*** (0.85)	-0.04* (0.02)	-0.09* (0.05)	-0.13*** (0.05)	-0.05 (0.05)	-0.03 (0.05)
Control mean	10.10	4.96	15.39	0.56	-0.00	-0.00	0.00	-0.00
R-squared	0.26	0.20	0.16	0.10	0.04	0.06	0.04	0.03
Observations	1,498	1,496	1,705	1,707	1,705	1,704	1,703	1,704

Notes: The estimation sample is the jobseekers who were employed at the time of the endline surveys. Started after fair is the dummy indicating that a current job started after the fair. Each of skill use, skill fit, interest and job satisfaction is based on a 5-Likert scale question and normalized to a z-score based on control jobseekers' standard deviation. The questions used were as follows: for skill use ("In your job, how often do you use your skills obtained from your previous education and professional experience?"); for skill fit ("How well do you think your skills match your current job?"); and for interest and job satisfaction ("How interesting is the job for you?"). The controls are the same as in Table 2. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%.

Source: Authors.

<sup>15</sup> The estimation sample is those who are employed at endlines. Therefore, the estimation results may not show causal effects of the fair if the fair affects employment, although we do not find its employment effects. The estimation results without controls are very similar (Appendix Table C2).

<sup>16</sup> Hours worked are not significantly different.

Self-perceived skill-match quality is found to be lower among treatment jobseekers than among control jobseekers. At the first endline, the skill use score of treatment jobseekers is lower by 0.03 standard deviation (insignificant) than those of control jobseekers (column 5), and the skill fit score of treatment jobseekers is lower by 0.11 standard deviation (significant) according to column 6 in Table 3. At the second endline, the skill scores of treatment jobseekers are significantly lower by 0.09 standard deviation for skill use and 0.13 standard deviation for skill fit than those of control jobseekers (columns 13–14). Job interest and satisfaction scores are lower, though not significantly, for treatment jobseekers than for control jobseekers (columns 7–8 and 15–16). The reason that the skill-match quality is lower for treatment jobseekers may be that treatment jobseekers who lowered reservation wages became more likely to accept and/or retain skill-mismatched jobs, even though they did not become more interested in or satisfied with such jobs.

To summarize the estimation results, the fair did not affect employment probability or types. It did not affect job search after 2 months but seems to have increased the likelihood of searching for jobs after 1 year. It reduced reservation wages. Conditional on having been employed, treatment jobseekers keep their jobs longer than control jobseekers; however, the skills of treatment jobseekers are self-perceived to be less frequently used and less well matched to jobs than those of control jobseekers.

## Mechanism and Discussions

### Mechanism

Given that the fair generated only four hires, the insignificant effects on employment are understandable. What surprised us is that so many offers (41 out of 45) were rejected despite that ICT jobs matched the jobseekers' interest.<sup>17</sup> Why was the rejection rate so high? And why did the fair have negative effects on reservation wages and skill-match quality and a positive effect on job retention? Two qualitative analyses provide clues to these questions.

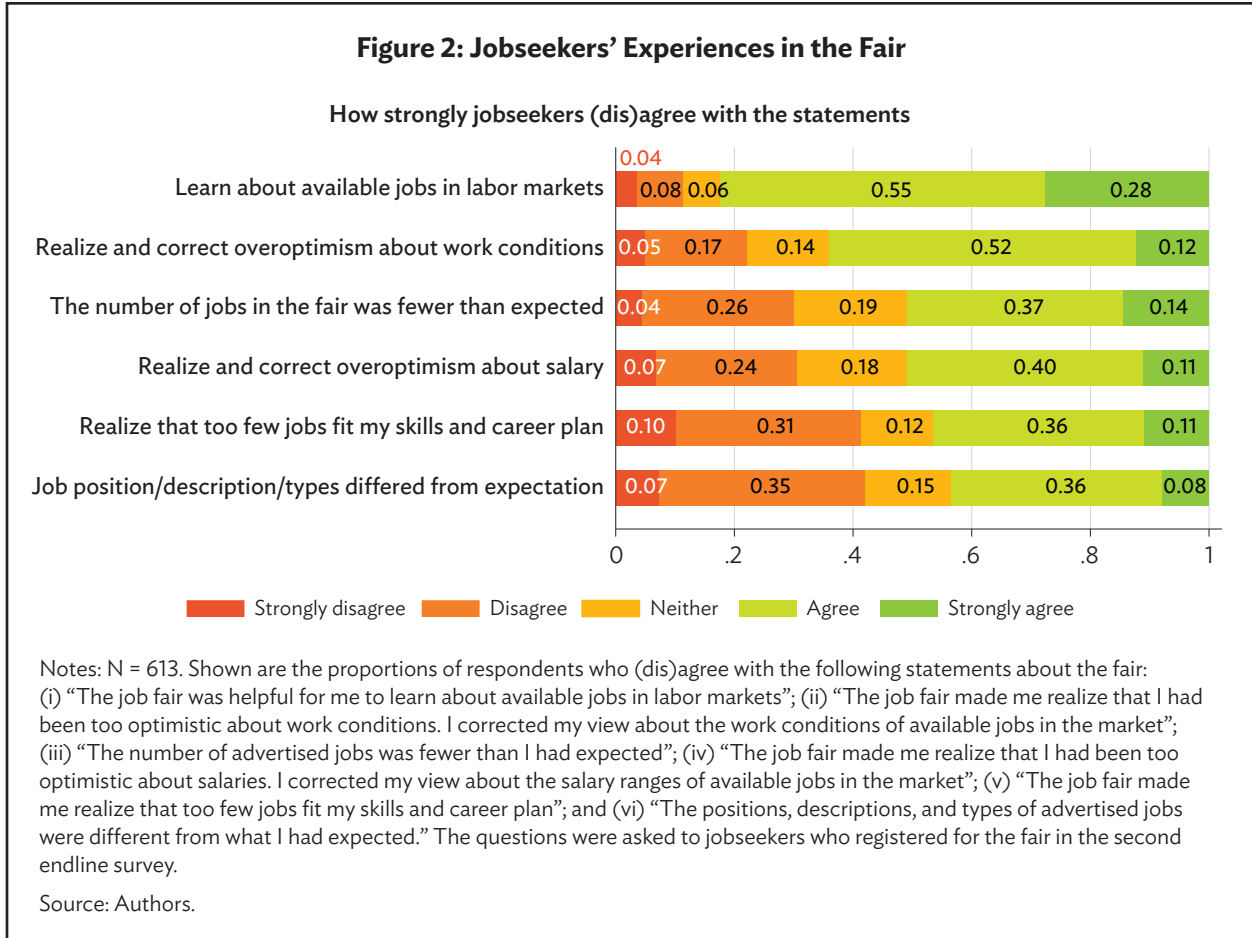
First, we find that jobseekers had overoptimistic expectations. Of the 41 jobseekers who rejected offers, 40 told why they did so in the first endline survey (Appendix Table A6). Most of the reasons were related to work compensation and conditions: low salary (mentioned by 12 jobseekers), distant job locations (9 jobseekers), and poor working conditions (4 jobseekers). Another common reason was that offered jobs did not match their skills or experience (8 jobseekers) even though these jobseekers had ICT skills.<sup>18</sup> It is worth emphasizing that they were interested in and trained for ICT jobs but turned down ICT jobs for low salaries, working conditions, and skill mismatches. Therefore, it is clear that their expectations regarding salaries, working conditions, and skill-match quality exceeded what was offered.<sup>19</sup>

Second, we find that jobseekers realized and corrected their overoptimism as a result of the learning in the fair. The second endline survey asked the treatment jobseekers who registered for the fair about their experiences in the fair (Figure 2). Overall, the fair was a good learning experience since 82% (12% disagree) of respondents agree (disagree) that the fair helped them learn about available jobs in labor markets. As for learning about salaries, 51% agree that they realized they were too optimistic about salaries and corrected their expectation. Sixty-four percent agree that they realized and corrected their overoptimism about working conditions. Regarding skill matches, 48% agree that they realized

<sup>17</sup> Ninety-five percent of jobseekers ranked ICT as the most preferred industry. They also self-selected into applying for the fair.

<sup>18</sup> Of the eight jobseekers, six had a bachelor's degree in computer science; the other two had a bachelor's degree in engineering. All had previously completed ICT-related training. Other reasons cited by jobseekers included "personal problems" (six jobseekers), "better opportunity" (two jobseekers), and "the offer was different from the advertised position" (two jobseekers).

<sup>19</sup> If they were not interested in or trained for ICT jobs, the results do not necessarily mean that they were overoptimistic. For example, if they were not interested in ICT jobs, they could only accept the jobs if the salaries were very high.



that too few jobs match their skills and career plan. This qualitative data directly shows that the fair led a majority of jobseekers to realize and correct their overoptimism about salaries, working conditions, and the availability of skill-matched jobs.

Taken together with the qualitative findings and estimation results, we interpret that jobseekers had overoptimistic expectations; however, they learned realistic views at the fair, lowered their expectations, and became discouraged from job search. Because of the lowered expectations, those who were already employed became more likely to keep their jobs, even skill-mismatched ones.

### Heterogeneous Effects for Those Who Were Already Employed and Those Who Were Not

Although our main estimation in Table 3 shows that the treatment jobseekers who were employed at baseline became more likely to keep their jobs (columns 3–4), it does not tell us much about what happened to those who were unemployed. To better understand the effects for each of those who were employed and unemployed, we conduct heterogeneity analysis across baseline employment status.

The estimation results are reported in Appendix Tables A7 and A8.<sup>20</sup> At the first endline, the effects are similar for those who were employed at baseline and those who were unemployed. Both jobseekers reduced reservation wages (column 7 in Appendix Table A7). At the second endline, the negative effect on employment is found for those who were unemployed at baseline: compared with control jobseekers who were unemployed at baseline, treatment jobseekers who were unemployed are 4 percentage points, albeit insignificantly, less likely to be employed, 6 percentage points significantly less likely to be employed in wage jobs, and 7 percentage points significantly less likely to be employed in full-time jobs (columns 9–11 in Appendix Table A7). This negative effect may be because the lowered expectations discouraged job search. The reason why the negative effect is not found for those who were already employed is most likely that they quit their jobs only when they found a new job (i.e., they engaged in on-the-job search). Treatment jobseekers who were unemployed at baseline are 7 percentage points more likely to look for a job at the second endline than the control jobseekers (column 5 in Appendix Table A7), probably because the former are more likely to be unemployed. Regarding skill-match quality, it appears that both treatment jobseekers who were employed at baseline and those who were unemployed have worse skill-matched jobs than control jobseekers (columns 13 and 14 in Appendix Table A8). In particular, treatment jobseekers who were unemployed at baseline have worse scores on skill use by 0.13 standard deviation (insignificant) and on skill fit by 0.25 standard deviation (significant) than the control jobseekers who were unemployed at baseline. They are also 0.18 standard deviation less interested in their jobs than the control jobseekers.

Overall, the heterogeneous analysis suggests that jobseekers who were unemployed at baseline end up with lower employment probabilities because the lowered expectations discourage their job search. Since they are more likely to accept skill-mismatched jobs, their jobs when they start working are more likely to mismatch their skills. For jobseekers who were employed at baseline, the discouragement by the lowered expectations makes them more likely to keep their jobs, even if the jobs mismatch their skills, and they do not face lower or higher employment probabilities because they engage in on-the-job search.

### **Why Overoptimism Exists and Why the Fair Made Jobseekers Realize It**

Why did jobseekers have overoptimistic expectations about labor market conditions? But why did the fair make them learn about labor markets and correct their overoptimism? An underlying cause for the overoptimism may be that the available information about salaries and working conditions is limited. For example, none of the 110 job ads at the fair included salary information. Only three job ads mentioned working conditions, but only slightly.<sup>21</sup> On Bdjobs.com, only 16.5% of job ads include salary information.<sup>22</sup> The reason why jobseekers' expectations are biased upward, rather than downward, may be twofold. First, the information available to jobseekers is heavily skewed upward. According to Bdjobs.com, the information about good compensation and working conditions at large firms tends to spread well among jobseekers. Similarly, university career fairs tend to showcase successful alumni and careers. Second, jobseeker's updating of labor market expectations may be asymmetric, responding more to positive than to negative information (Alfonsi, Namubiru, and Spaziani 2022). Because of the upward biased information and the asymmetric updating, the overoptimistic expectations may arise and persist.

<sup>20</sup> A difficulty in this heterogeneous analysis is that the baseline employment status has measurement errors. For many jobseekers, the baseline employment status according to the baseline data does not match the baseline employment status implied by the endline surveys. This may be because the baseline data was collected online through the job fair application form, where jobseekers might not have a strong incentive to answer truthfully. In contrast, the endline data was collected through interview surveys and may therefore be more accurate. As complementary information, we collected each jobseeker's employment history in the second endline survey, but not in the first endline. The heterogeneous analysis in Appendix Tables A7 and A8 is based on this employment history.

<sup>21</sup> Specifically, one job ad states, "Regular work time 8–12 hours. Double shifts must be on workload." Two job ads state "available for night shift."

<sup>22</sup> According to Bdjobs.com, most employers do not want to disclose salary information.



The mechanism through which the fair led jobseekers to adjust their overoptimism may have been through the two-way interaction with employers in live sessions and interviews, which allowed jobseekers to ask directly about jobs, including compensation and working conditions. In addition, because the participating firms and their jobs were closely aligned with jobseekers' interests, and because these firms were relatively well-established and some well-known, the information obtained at the fair might be quite relevant and effective in adjusting their expectations.

## 5. COST-EFFECTIVENESS

One of the most attractive features of online job fairs is their low cost. There is no need for physical space, materials, or transportation. In our study, the total operational cost for the online fair was \$7,908, and the cost per participating jobseeker (specifically per registered jobseeker) was \$9.01. If the fair had been conducted in person, the costs would have been much higher at \$21,248 in total and \$24.20 per jobseeker (see Appendix D for the details). That is, conducting the fair online is 63% less expensive than conducting it in person. This comparison underestimates the cost advantage of the online fair in that it does not take into account the costs to jobseekers and employers, such as their transportation costs. Since their costs are likely to be much lower in the online fair than in an in-person fair, the cost advantage of the online fair is much greater than the 63% cost reduction implies.

## 6. CONCLUSIONS

This study estimates the impact of an online job fair. Contrary to our prior expectation, over 90% of job offers were declined, even though the focus of the fair was closely aligned with the interests and skill backgrounds of jobseekers. We find no effects on the probability or type of employment, but negative effects on reservation wages and skill-match quality and positive effect on job tenure. Together with qualitative analysis, we interpret that jobseekers were initially overoptimistic, but learned about labor market conditions at the fair, lowered their expectations, and became discouraged from job search. As a result, those who had already been employed stayed in their jobs longer, even if the jobs did not match their skills. Those who had been unemployed ended up facing a lower employment probability and also lower skill-match quality when they started working.

We would like to make two remarks about the effectiveness of online fairs. First, our finding does not mean that online job fairs are ineffective *per se*. The primary reason for the zero, or even negative, effects on labor market outcomes is the jobseekers' overoptimism. In the presence of the overoptimism, other matching interventions would have high rejection rates and zero employment effects, as found for in-person job fairs (Abebe et al. 2022) and job intermediation service (Groh et al. 2015). Therefore, online job fairs should not be dismissed for other interventions. Rather, our study implies the importance of educating jobseekers about labor markets and that online job fairs are cost-effective in doing so.



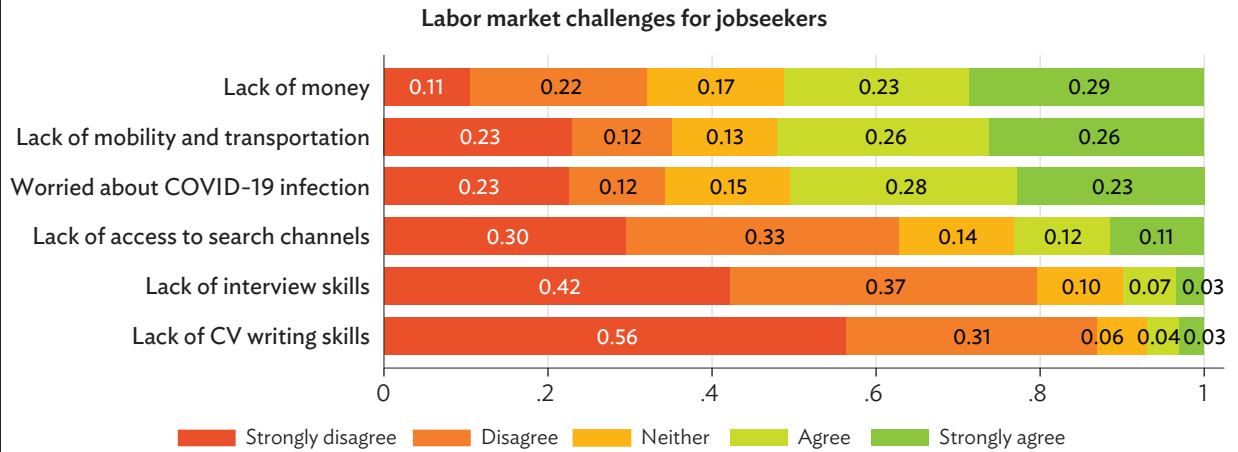
Second, the employment effect of online job fairs in Bangladesh may improve over time for several reasons. The online job fair program in this study was in its early stages, and Bdjobs.com has made improvements since then. Also, because online fairs were new, employers and jobseekers may not have been fully accustomed to our fair. As online fairs become more common, employers and jobseekers will use them more effectively. Finally, in our study, the number of participating jobseekers was cut in half because of the randomization, not because of capacity or logistical constraints. If the fair had been conducted as a regular event, the number of participating jobseekers could easily have been doubled. Then, the number of direct hires from the fair would have nearly doubled, although the effect on employment probability would be essentially the same.

We would like to mention one area for policy making and future research. Potentially, online job fairs can serve disadvantaged people uniquely well, such as people in remote areas and those who are too poor or too busy to attend in-person fairs. Also, online fairs can be beneficial for people with disabilities, who have limited job search options. To our pleasant surprise, building on our study experience, Bdjobs.com conducted an online fair for people with disabilities in collaboration with the Government of Bangladesh and the International Labour Organization (Business Standard 2022). If disadvantaged people are not overoptimistic, online fairs may already produce positive employment effects. Understanding the potential of online job fairs for them is left for future research.

# APPENDIXES

## A. ADDITIONAL FIGURES AND TABLES

**Figure A1: Job Search Challenges for Jobseekers**

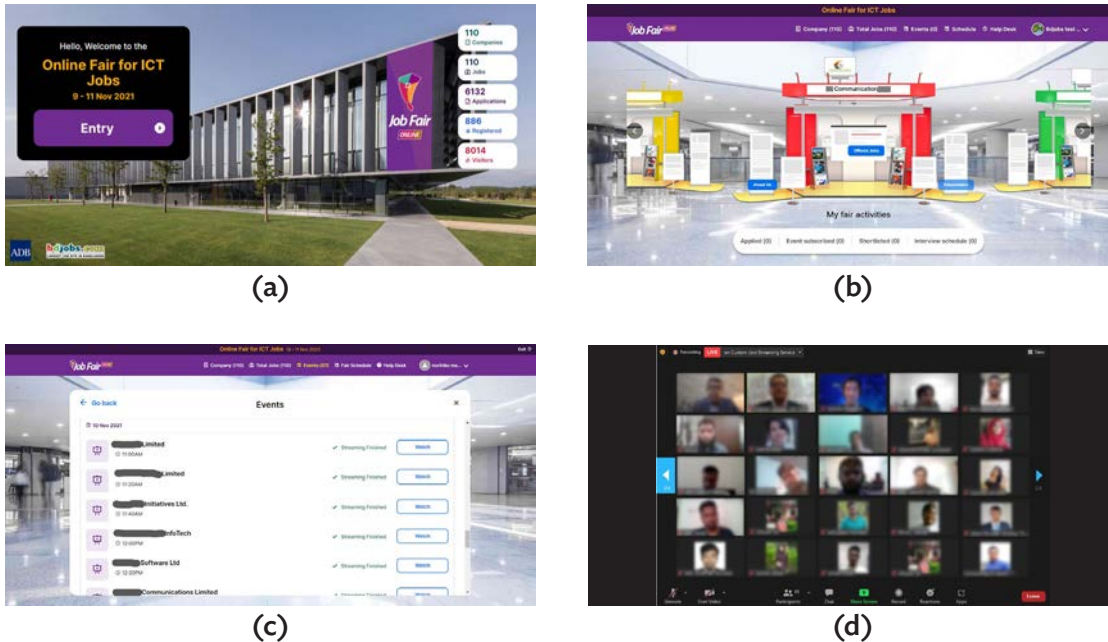


CV = curriculum vitae, COVID-19 = coronavirus disease.

Notes: N = 2,272; The figure is based on the job fair application form data at baseline.

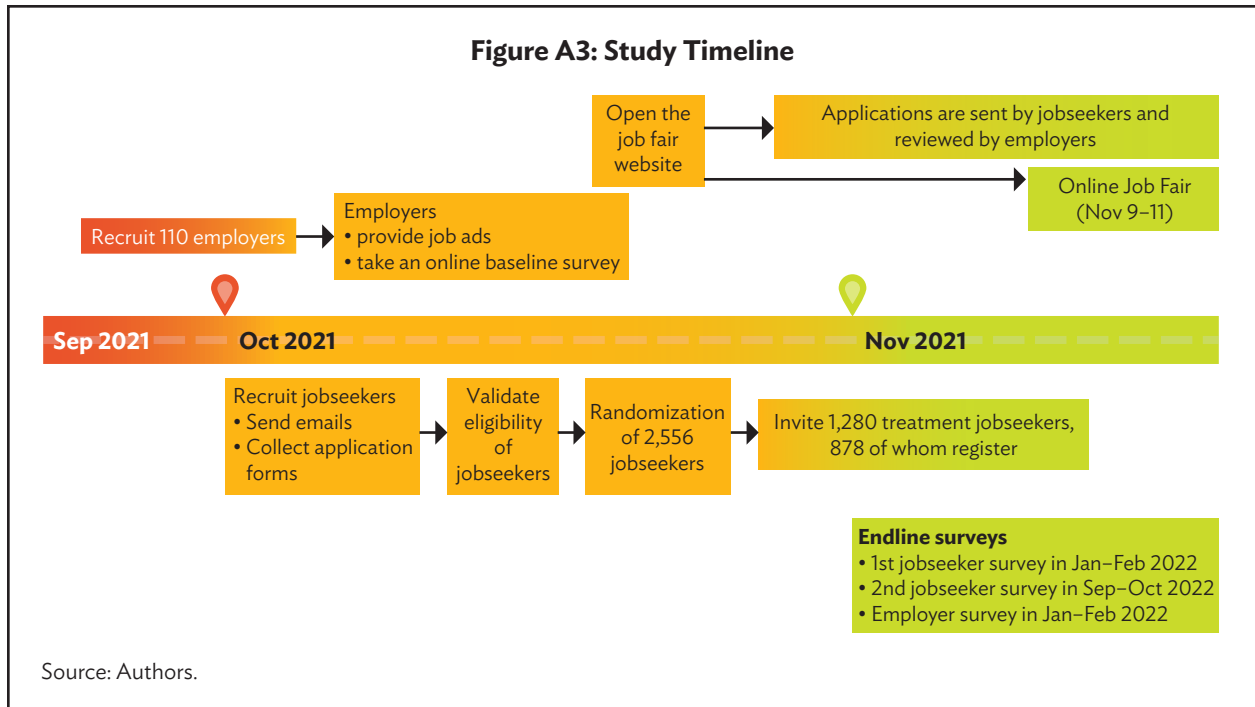
Source: Authors.

**Figure A2: Online Job Fair**



Notes: Panel (a) is the landing page of the fair. Panel (b) is a stall of employer, in which jobseekers find a job ad and a live session. Panel (c) is a list of live events. Panel (d) is a screenshot of a live session, which is blurred to protect identity.

Source: Bdjobs.com.



**Table A1: List of Job Titles**

Job Titles	N
Full stack developer	23
Web developer	12
Software developer/programmer	16
Programmer	10
Graphic designer	7
Digital marketing	6
IT sales/marketing executive	5
React developer	5
IT office administrator	4
App developer (android and ios)	4
IT executive	6
Flutter developer/programmer	4
IT assistant manager	1
Others	7
<b>Total</b>	<b>110</b>

IT = information technology.

Note: In this table, similar job titles are grouped together, so the exact job titles are different for some jobs.

Source: Authors.

**Table A2: Summary Statistics of Employers and Jobs**

	Mean	SD	N
<b>Employer information</b>			
Dhaka (0/1)	0.94	0.25	110
Size: Number of full time employees			
Micro: 1–9	0.22	0.42	99
Small: 10–49	0.54	0.50	99
Medium: 50–99	0.10	0.30	99
Large: 100–999	0.10	0.30	99
Mega: 1,000 or more	0.04	0.20	99
Industry of employer's business			
ICT	0.86	0.34	110
Professional services	0.05	0.21	110
Manufacturing	0.04	0.19	110
Retail, wholesale, trading	0.01	0.10	110
Transportation	0.01	0.10	110
Finance	0.01	0.10	110
Education	0.03	0.16	110
<b>Job information</b>			
Number of vacancies	3.21	2.86	110
Minimum years of experience required	0.83	1.38	110
Maximum years of experience required	2.53	1.41	110
Minimum education level required			
Higher secondary	0.15	0.36	110
Diploma	0.13	0.33	110
Bachelor	0.65	0.48	110
Graduate	0.07	0.26	110
Maximum education level required			
Higher secondary	0.00	0.00	110
Diploma	0.05	0.23	110
Bachelor	0.70	0.46	110
Graduate	0.25	0.43	110

ICT = information and communication technology, N = observations, SD = Standard deviation.

Notes: The data used are the administrative data of the job portal and the fair and the employer baseline survey. Since each employer posted one job ad, the number of employers equals that of jobs.

Source: Authors.

**Table A3: What Types of Jobseekers Are More Likely to Participate**

	(1) Registered		(2) Applied (0/1)		(3) No. of Jobs Applied	
	Coef	S.E.	Coef	S.E.	Coef	S.E.
Male	0.054	(0.044)	0.100**	(0.045)	0.968	(0.771)
Age	0.016**	(0.008)	0.015*	(0.008)	0.016	(0.180)
Live in urban area	-0.006	(0.037)	0.004	(0.039)	-0.419	(0.819)
Education (omitted: higher secondary)						
Diploma	0.023	(0.072)	0.085	(0.072)	-1.275	(1.297)
Bachelor	0.019	(0.069)	0.118*	(0.068)	1.239	(1.344)
Master	0.050	(0.085)	0.090	(0.088)	-0.316	(1.542)
Currently studying	-0.014	(0.035)	-0.015	(0.037)	0.275	(0.769)
Ever taken ICT-related training	0.074**	(0.034)	0.085**	(0.034)	1.441***	(0.529)
Most preferred industry = ICT (0/1)	0.116*	(0.065)	0.236***	(0.063)	2.473***	(0.801)
Work in last 4 weeks	0.039	(0.043)	-0.013	(0.046)	-0.407	(0.897)
Work full time in last 4 weeks	-0.026	(0.038)	0.017	(0.041)	-0.414	(0.825)
Never worked	-0.039	(0.046)	-0.037	(0.047)	-0.747	(0.932)
Years of experience	-0.005	(0.011)	-0.006	(0.011)	-0.425**	(0.165)
Look for jobs in last 4 weeks	0.052	(0.041)	0.072*	(0.040)	0.354	(0.715)
Applied via Bdjobs in Oct 2021 (0/1)	0.131***	(0.031)	0.174***	(0.033)	0.684	(0.671)
No. of jobs applied via Bdjobs in Oct 2021	0.002**	(0.001)	0.003**	(0.001)	0.075***	(0.029)
Log reservation wage	0.031	(0.038)	-0.013	(0.039)	-0.679	(0.805)
Mean	0.69		0.56		4.79	
R-squared	0.06		0.09		0.04	
Observations	1,234		1,234		1,234	

ICT = information and communication technology, S.E. = Standard error.

Notes: The other controls are geographic division dummies. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%.

Source: Authors.

**Table A4: Average Treatment Effects of the Fair on the Treated**

<i>Dependent Variables</i>	<i>Employed</i>	<i>Wage Job</i>	<i>Full Time Job</i>	<i>Formal Job</i>	<i>Looked for Jobs</i>	<i>No. of Jobs Applied</i>	<i>Log Reservation Wage</i>	<i>Log Aspired Wage</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Registered for the fair	0.00 (0.02)	-0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	-0.00 (0.03)	-0.67 (0.66)	-0.09*** (0.02)	0.01 (0.03)
Control mean	0.66	0.46	0.53	0.40	0.72	6.68	10.29	11.24
R-squared	0.27	0.29	0.28	0.23	0.05	0.02	0.40	0.21
Observations	2,361	2,361	2,361	2,358	2,361	2,358	2,339	2,293
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Registered for the fair	-0.03 (0.02)	-0.03 (0.03)	-0.03 (0.03)	-0.04 (0.03)	0.06* (0.03)	0.55 (0.64)	-0.03 (0.02)	0.01 (0.03)
Control mean	0.84	0.63	0.72	0.58	0.55	5.18	10.35	11.36
R-squared	0.13	0.13	0.15	0.16	0.04	0.04	0.37	0.21
Observations	2,033	2,033	2,031	1,967	2,033	2,029	2,021	2,001

Notes: The estimation equation is  $Y_i = \alpha + \delta R_i + \gamma X_{i0} + \delta_s + e_{it}$ , where  $R_i$  is the fair registration dummy, which is instrumented by the treatment jobseeker dummy ( $T_i$ ). Reported in the table is the estimated  $\hat{\delta}$ . The controls are the same as in Table 2. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%. For other notes, see Table 3.

Source: Authors.

**Table A5: Additional Results on the Effects of the Job Fair**

<i>Dependent Variables</i>	<i>Job Finding Prospect</i>	<i>Life Satisfaction</i>	<i>Under-Qualified</i>	<i>Just-Qualified</i>	<i>Over-Qualified</i>
	(z-score)	(z-score)			
	(1)	(2)	(3)	(4)	(5)
<b>First Endline</b>					
Treatment seeker	0.05 (0.05)	-0.04 (0.04)	-0.01 (0.01)	-0.02 (0.02)	0.03 (0.02)
Control mean	0.00	0.00	0.03	0.76	0.22
R-squared	0.04	0.04	0.02	0.02	0.02
Observations	1,666	2,352	1,576	1,576	1,576
Sample used	Looking for jobs	All	Employed	Employed	Employed
	(6)	(7)	(8)	(9)	(10)
<b>Second Endline</b>					
Treatment seeker	-0.06 (0.04)	-0.04 (0.04)	0.00 (0.01)	-0.01 (0.02)	0.01 (0.02)
Control mean	0.00	-0.00	0.02	0.72	0.26
R-squared	0.03	0.04	0.02	0.02	0.02
Observations	1,950	2,032	1,702	1,702	1,702
Sample used	Employed	All	Employed	Employed	Employed

AEA = American Economic Association, ITT = intent to treat.

Notes: Reported here are the estimated ITT effects on the secondary outcomes that are preregistered in the AEA registry but not included in the main text of this paper. Job finding prospect in the first endline survey (column 1) is the percent chance that a jobseeker believes that s/he will have a full-time job within 6 months, while the one in the end endline survey (column 6) is the number of weeks a respondent believes that would take to get a full-time job if s/he start to look for a new job. Life satisfaction is based on a 5-Likert scale question asking about a jobseeker's satisfaction with his/her current life and normalized to a z-score based on control jobseekers' standard deviation. The controls are the same as in Table 2. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%.

Source: Authors.

**Table A6: Reasons Why Job Offers Were Declined**

<i>Reasons</i>	<i>Frequency</i>
Low salary	12
Long distance from home	9
Did not match skills or professional experience	8
Personal problem	6
Poor work conditions	4
Got better opportunity	2
Different from advertised position	2

Notes: The table is based on the following open-ended question in the first endline survey: "Why do you not work for the job despite that you received an offer?" which was asked to the 41 treatment jobseekers who turned down jobs they applied for through the fair, of which 40 treatment jobseekers answered. If a jobseeker mentioned multiple reasons, his/her answer is counted to multiple reasons in this table. Poor work conditions are specifically "too much workload," "long working hours," "problem with night shift," and "poor work environment."

Source: Authors.

**Table A7: Heterogeneity of the Effects by Baseline Employment Status**

<i>Dependent Variables</i>	<i>Employed</i>	<i>Wage Job</i>	<i>Full Time Job</i>	<i>Formal Job</i>	<i>Looked for Jobs</i>	<i>No. of Jobs Applied</i>	<i>Log Reservation Wage</i>	<i>Log Aspired Wage</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker × Baseline employed = 1	0.01 (0.02)	0.00 (0.02)	0.02 (0.02)	0.01 (0.03)	-0.02 (0.03)	-0.28 (0.60)	-0.08*** (0.02)	0.01 (0.03)
Treatment seeker × Baseline employed = 0	-0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.00 (0.03)	0.03 (0.03)	-0.25 (0.90)	-0.06** (0.02)	-0.02 (0.04)
P-value: Equal coefficients	0.76	0.83	0.45	0.88	0.24	0.98	0.49	0.53
Control mean: baseline emp = 1	0.82	0.61	0.66	0.53	0.69	5.88	10.36	11.25
Control mean: baseline emp = 0	0.42	0.23	0.32	0.22	0.78	8.04	10.16	11.18
R-squared	0.30	0.31	0.31	0.25	0.05	0.03	0.38	0.21
Observations	2,035	2,035	2,035	2,032	2,035	2,032	2,016	1,979
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker × Baseline employed = 1	-0.01 (0.01)	-0.00 (0.03)	0.01 (0.02)	-0.01 (0.03)	0.02 (0.03)	0.50 (0.58)	-0.03 (0.02)	-0.01 (0.03)
Treatment seeker × Baseline employed = 0	-0.04 (0.03)	-0.06* (0.03)	-0.07** (0.03)	-0.05 (0.03)	0.07** (0.04)	0.21 (0.77)	-0.02 (0.03)	0.04 (0.04)
P-value: Equal coefficients	0.31	0.20	0.07	0.31	0.24	0.77	0.83	0.34
Control mean: baseline emp = 1	0.94	0.69	0.78	0.64	0.56	5.07	10.41	11.40
Control mean: baseline emp = 0	0.70	0.53	0.63	0.48	0.54	5.34	10.26	11.29
R-squared	0.17	0.13	0.15	0.16	0.04	0.04	0.36	0.20
Observations	2,035	2,035	2,033	1,968	2,035	2,031	2,023	2,003

Notes: The p-value tests the equality of the coefficients on the treatment seeker dummy × baseline employed = 1 and the treatment seeker dummy × baseline employed = 0. The baseline employment dummy is based on questions about employment history asked in the second endline survey. The controls are the same as in Table 2. Robust standard errors are in parentheses. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%. For other notes, see Table 2.

Source: Authors.



**Table A8: Heterogeneity: Comparisons of Employed Treatment and Control Jobseekers by Baseline Employment Status**

<i>Dependent Variables</i>	Log Monthly Wage (taka)	Log Hourly Wage (taka)	Job Tenure (month)	Started After Fair	Skill Use (z-score)	Skill Fit (z-score)	Interest (z-score)	Job Satisfaction (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker × Baseline employed = 1	0.00 (0.03)	0.01 (0.03)	2.76** (1.18)	-0.07*** (0.02)	-0.04 (0.06)	-0.15** (0.06)	-0.02 (0.06)	0.01 (0.06)
Treatment seeker × Baseline employed = 0	0.09 (0.09)	0.03 (0.08)	3.27 (2.05)	-0.02 (0.05)	-0.02 (0.11)	-0.09 (0.12)	-0.02 (0.11)	-0.17 (0.12)
P-value: Equal coefficients	0.36	0.90	0.83	0.32	0.92	0.68	0.99	0.18
Control mean: baseline emp = 1	9.87	4.73	18.19	0.15	0.01	0.07	0.04	0.00
Control mean: baseline emp = 0	9.52	4.57	11.86	0.44	-0.08	-0.18	-0.07	-0.00
R-squared	0.28	0.23	0.23	0.19	0.04	0.07	0.04	0.04
Observations	1,274	1,272	1,367	1,367	1,367	1,367	1,367	1,366
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker × Baseline employed = 1	-0.01 (0.03)	-0.01 (0.03)	2.91** (1.13)	-0.05* (0.03)	-0.07 (0.06)	-0.08 (0.06)	0.01 (0.06)	0.02 (0.06)
Treatment seeker × Baseline employed = 0	-0.05 (0.05)	-0.00 (0.05)	0.50 (0.55)	0.00 (0.01)	-0.13 (0.09)	-0.25** (0.09)	-0.18** (0.09)	-0.13 (0.09)
P-value: Equal coefficients	0.44	0.93	0.06	0.08	0.53	0.11	0.08	0.16
Control mean: baseline emp = 1	10.14	5.00	20.37	0.35	0.03	-0.00	-0.01	-0.02
Control mean: baseline emp = 0	10.01	4.85	5.03	0.99	-0.07	0.00	0.03	0.04
R-squared	0.25	0.21	0.27	0.41	0.04	0.06	0.04	0.03
Observations	1,498	1,496	1,705	1,707	1,705	1,704	1,703	1,704

Notes: The p-value tests the equality of the coefficients on the treatment seeker dummy × baseline employed = 1 and the treatment seeker dummy × baseline employed = 0. The baseline employment dummy is based on questions about employment history asked in the second endline survey. The controls are the same as in Table 2. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%. For other notes, see Table 3.

Source: Authors.

## B. RANDOMIZATION AND ATTRITION BALANCES BETWEEN TREATMENT AND CONTROL JOBSEEKERS

**Table B1: Randomization Check: Balance between Treatment and Control Jobseekers**

	Treatment Mean	N	Control Mean	N	Diff: T-C Diff	p-value
Male	0.88	1,280	0.87	1,276	-0.01	(0.53)
Age	25.03	1,280	24.95	1,276	-0.08	(0.33)
Live in urban area	0.82	1,268	0.83	1,266	0.01	(0.65)
Married	0.21	1,263	0.21	1,256	0.01	(0.75)
Highest education level attained						
Higher secondary school	0.06	1,280	0.07	1,276	0.01	(0.56)
Diploma	0.13	1,280	0.14	1,276	0.02	(0.23)
Bachelor	0.74	1,280	0.72	1,276	-0.02	(0.30)
Master	0.07	1,280	0.07	1,276	-0.00	(0.72)
Currently studying	0.23	1,270	0.23	1,258	-0.01	(0.73)
Ever taken ICT-related training	0.78	1,260	0.77	1,264	-0.01	(0.74)
Interest in ICT sector (Rank among 14 sectors)						
Top 1	0.95	1,280	0.95	1,276	0.00	(0.67)
Top 2	0.03	1,280	0.04	1,276	0.00	(0.73)
Top 3 or below	0.02	1,280	0.01	1,276	-0.01	(0.22)
Work in last 4 weeks	0.63	1,280	0.62	1,276	-0.02	(0.43)
Job types						
Wage job	0.73	743	0.71	721	-0.03	(0.27)
Running non-agri business	0.00	743	0.01	721	0.00	(0.29)
Freelancer	0.16	743	0.18	721	0.01	(0.54)
Home tutor	0.07	743	0.08	721	0.02	(0.25)
Helping family business	0.03	743	0.02	721	-0.00	(0.57)
Work full time (conditional on working)	0.78	748	0.75	735	-0.03	(0.13)
Never worked	0.18	1,280	0.19	1,276	0.01	(0.66)
Years of experience	1.48	1,280	1.43	1,276	-0.05	(0.40)
Look for jobs in last 4 weeks	0.85	1,280	0.84	1,276	-0.01	(0.42)
No. of jobs applied for	6.73	1,076	6.85	1,052	0.12	(0.63)
Reservation wage (monthly, taka)	25,287.84	1,275	25,079.34	1,273	-208.50	(0.64)
Applied through Bdjobs in Oct 2021 (0/1)	0.51	1,280	0.51	1,276	0.00	(0.94)
No. of jobs applied through Bdjobs in Oct 2021	6.51	1,280	6.19	1,276	-0.32	(0.54)

ICT = information and communication technology, N = observations.

Note: The differences and p-values control for the randomization strata fixed effects.

Source: Authors.

**Table B2: Balance on Survey Attrition between Treatment and Control Jobseekers**

	(1) 1st Endline		(2) 1st Endline		(3) 2nd Endline		(4) 2nd Endline	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Treatment seeker	0.005	(0.010)	0.008	(0.010)	0.009	(0.016)	0.008	(0.016)
Male			0.016	(0.019)			0.057**	(0.028)
Age			0.004	(0.003)			0.003	(0.005)
Married			-0.004	(0.012)			0.006	(0.021)
Live in urban area			0.019	(0.014)			0.002	(0.022)
Education (omitted: higher secondary)								
Diploma			-0.017	(0.020)			0.004	(0.037)
Bachelor			-0.021	(0.019)			-0.014	(0.036)
Master			-0.028	(0.030)			-0.013	(0.051)
Currently studying			0.016	(0.013)			0.045**	(0.021)
Ever taken ICT-related training			0.005	(0.013)			0.025	(0.020)
Most preferred industry = ICT (0/1)			-0.008	(0.022)			-0.018	(0.036)
Work in last 4 weeks			0.036**	(0.016)			0.044*	(0.026)
Work full time in last 4 weeks			-0.002	(0.012)			-0.006	(0.022)
Never worked			0.006	(0.020)			0.038	(0.029)
Years of experience			0.009***	(0.003)			0.013**	(0.006)
Look for jobs in last 4 weeks			0.003	(0.014)			-0.001	(0.023)
Applied via Bdjobs in Oct 2021 (0/1)			0.004	(0.011)			0.027	(0.018)
No. of jobs applied via Bdjobs in Oct 2021			-0.000	(0.000)			-0.000	(0.001)
Log reservation wage			-0.037**	(0.016)			-0.075***	(0.024)
Control mean	0.94		0.94		0.80		0.80	
R-squared	0.00		0.02		0.01		0.02	
Observations	2,556		2,435		2,556		2,435	

ICT = information and communication technology, S.E. = standard error.

Notes: The dependent variables are the dummies for survey responses to the first endline (columns 1–2) and second endline (columns 3–4). The other controls are geographic division dummies. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%.

Source: Authors.

## C. ROBUSTNESS CHECKS: ESTIMATION RESULTS WITHOUT CONTROLS

**Table C1: Robustness without Controls: Effects of the Online Job Fair**

<i>Dependent Variables</i>	Employed	Wage Job	Full Time Job	Formal Job	Looked for Jobs	No. of Jobs Applied	Log Reservation Wage	Log Aspired Wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker	0.02 (0.02)	0.01 (0.02)	0.02 (0.02)	0.03 (0.02)	-0.01 (0.02)	-0.51 (0.46)	-0.05** (0.02)	0.01 (0.02)
Control mean	0.66	0.46	0.53	0.40	0.72	6.68	10.29	11.24
R-squared	0.03	0.05	0.04	0.04	0.02	0.01	0.04	0.04
Observations	2,398	2,398	2398	2,395	2,398	2,395	2,376	2,330
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)	0.04* (0.02)	0.29 (0.46)	-0.02 (0.02)	-0.00 (0.03)
Control mean	0.84	0.63	0.72	0.58	0.55	5.18	10.35	11.36
R-squared	0.01	0.03	0.03	0.04	0.03	0.02	0.05	0.04
Observations	2,067	2,067	2,065	1,998	2,067	2,063	2,055	2,033

Notes: The controls are fixed effects for residential divisions and survey interview weeks. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%. For other notes, see Table 2.

Source: Authors.

**Table C2: Robustness without Controls: Differences in Wages, Job Tenure, Skill-Match Quality, and Job Satisfaction between Treatment and Control Jobseekers**

<i>Dependent Variables</i>	Log Monthly Wage (taka)	Log Hourly Wage (taka)	Job Tenure (month)	Started After Fair	Skill Use (z-score)	Skill Fit (z-score)	Interest (z-score)	Job Satisfaction (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>First Endline</b>								
Treatment seeker	0.02 (0.04)	0.02 (0.03)	2.95*** (1.05)	-0.05*** (0.02)	-0.02 (0.05)	-0.11** (0.05)	-0.02 (0.05)	-0.02 (0.05)
Control mean	9.80	4.71	16.73	0.21	0.00	0.00	-0.00	0.00
R-squared	0.04	0.02	0.04	0.04	0.01	0.01	0.01	0.01
Observations	1,479	1,477	1,600	1,600	1,600	1,600	1,599	1,598
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<b>Second Endline</b>								
Treatment seeker	-0.02 (0.03)	0.00 (0.03)	2.32** (0.91)	-0.05* (0.02)	-0.08* (0.05)	-0.12** (0.05)	-0.04 (0.05)	-0.03 (0.05)
Control mean	10.10	4.96	15.39	0.56	-0.00	-0.00	0.00	-0.00
R-squared	0.05	0.03	0.02	0.01	0.01	0.02	0.01	0.01
Observations	1,523	1,521	1,732	1,734	1,732	1,731	1,730	1,731

Notes: The samples used are those who were employed at endlines. The controls are fixed effects for residential divisions and survey interview weeks. Robust standard errors are in parentheses. Significance levels: \*\*\*1%, \*\*5%, \*10%. For other notes, see Table 3.

Source: Authors.

## **D. COST BREAKDOWN AND COMPARISON WITH AN IN-PERSON JOB FAIR**

This section explains the cost breakdowns for the online fair and an in-person fair of the same size. We requested and discussed the cost breakdowns with Bdjobs.com. For comparison, we consider an in-person fair that accommodates the same number of jobseekers and employers as the online fair in this study. The duration of the in-person fair is set to be 1 day because in-person fairs, which may be more intensive, are typically held for 1 day only.

The total cost of the online fair is \$7,908, while that of the in-person fair is \$21,248. The cost per jobseeker is \$9.01 for the online fair and \$24.20 for the in-person fair. The online fair is 63% less expensive than the in-person fair. Note that only the operational costs are considered and compared here. If costs to jobseekers and employers, such as transportation, are included, the cost advantage of the online fair over the in-person fair is greater than the percentage difference of 63% indicates.

There are three caveats. First, because Bdjobs.com was involved not only in the implementation of the fair but also in research-related activities (e.g., asking employers to complete the online baseline survey), it is not very straightforward to separate out the implementation costs for the fair alone. Based on the amount of activities for the fair and the associated costs, the breakdowns were derived. We believe that they are more or less accurate. Second, both the online and in-person fairs considered here restrict the access to invited jobseekers only, which has a cost implication: communicating with jobseekers before the fair is much more expensive than in the case where a fair is open to all jobseekers. (However, this does not affect the cost comparison between the two fairs because both fairs are restricted to invited jobseekers. If they were open, costs would decrease by the same amount.) Finally, if the fairs were open to all jobseekers, the cost of recruiting jobseekers (such as advertising) would be more expensive. The reason is that the advertising would have to be more extensive to ensure that a minimum sufficient number of jobseekers participate. The more extensive advertising may, in turn, result in more jobseekers and possibly a lower cost per jobseeker. However, this increased recruitment cost does not affect the cost comparison between the online fairs and in-person fairs.

**Table D1: Cost Breakdown and Comparison between the Online Job Fair and a Counterfactual In-Person Fair**

Setting:

- The number of invited jobseekers: 1,280
- The number of participating jobseekers: 878
- The number of participating firms: 110
- Job fair duration: 3 days for an online job fair; 1 day for an in-person job fair

Items	Online Job Fair			In-person Job Fair				
	Unit price (\$)	Unit	Amount (\$)	Notes	Unit price (\$)	Unit	Amount (\$)	Notes
<b>Platform preparation</b>								
Website setup	500.00	1 set	500.00		500.00	0 set	-	
<b>Venue</b>								
Rental	5,000.00	0 day	-		5,000.00	1 day	5,000.00	
Banner	1,000.00	0 set	-		1,000.00	1 set	1,000.00	
Firm stall, including personnel costs for setting up and logistics	80.00	0 set	-		80.00	110 sets	8,800.00	
<b>Communications with participants prior to the fair</b>								
Recruitment of jobseekers (advertisements, email, online notifications, etc.)	500.00	1 set	500.00		500.00	1 set	500.00	
Communications to participating jobseekers	2,730.00	1 set	2,730.00	1,280 jobseekers	2,730.00	1 set	2,730.00	1,280 jobseekers
Communication to participating employers	1,387.00	1 set	1,387.00	110 employers	1,387.00	1 set	1,387.00	110 employers
Managers	75.00	12 person days	900.00	3 persons x 4 days	75.00	12 person days	900.00	3 persons x 4 days
Staff	32.00	8 person days	256.00	2 persons x 4 days	32.00	8 person days	256.00	2 persons x 4 days
<b>Activities during the fair</b>								
Managers	75.00	9 person days	675.00	3 persons x 3 days	75.00	3 person days	225.00	3 persons x 1 days
Staff: moderators, coordinators	32.00	24 person days	768.00	6 persons x 4 days, including 1 prep day	32.00	8 person days	256.00	6 persons x 2 days, including 1 prep day
Staff: Help desk	32.00	6 person days	192.00	2 persons x 3 days	32.00	2 person days	64.00	2 persons x 1 days
Transportation	10.00	0 round trip	-		10.00	13 round trips	130.00	
			<b>Total cost 7,908.00</b>				<b>Total cost 21,248.00</b>	
			<b>Cost per jobseeker 9.01</b>				<b>Cost per jobseeker 24.20</b>	
			<b>Cost per firm 71.89</b>				<b>Cost per firm 193.16</b>	

Source: Authors.

## REFERENCES

- Abebe, G., A. S. Caria, and E. Ortiz-Ospina. 2021. The Selection of Talent: Experimental and Structural Evidence from Ethiopia. *American Economic Review*. 111 (6). pp. 1757–1806.
- Abebe, G., S. Caria, M. Fafchamps, P. Falco, S. Franklin, S. Quinn, and F. Shilpi. 2022. Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment. Working Paper.
- Afridi, F., A. Dhillon, S. Roy, and N. Sangwan. 2022. Social Networks, Gender Norms and Women's Labor Supply: Experimental Evidence Using a Job Search Platform. IZA Discussion Paper No. 15767. <https://ssrn.com/abstract=4294392>.
- Alfonsi, L., M. Namubiru, and S. Spaziani. 2022. Meet Your Future: Experimental Evidence on the Labor Market Effects of Mentors. Working Paper.
- Altmann, S., A. Falk, S. Jäger, and F. Zimmermann. 2018. Learning about Job Search: A Field Experiment with Job Seekers in Germany. *Journal of Public Economics*. 164. pp. 33–49.
- Asian Development Bank (ADB). 2019a. *Bangladesh: Computer and Software Engineering Tertiary Education in 2018—Tracer Study*. Manila.
- . 2019b. *Asian Development Outlook 2019: Strengthening Disaster Resilience*. Manila.
- Atkin, D., M. K. Chen, and A. Popov. 2022. The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley. *National Bureau of Economic Research Working Paper Series*. No. 31047. [https://www.nber.org/system/files/working\\_papers/w30147/w30147.pdf](https://www.nber.org/system/files/working_papers/w30147/w30147.pdf).
- Baird, S., D. McKenzie, and B. Özler. 2018. The Effects of Cash Transfers on Adult Labor Market Outcomes. *IZA Journal of Development and Migration*. 8 (1). pp. 1–20.
- Bandiera, O., V. Bassi, R. Burgess, I. Rasul, M. Sulaiman, and A. Vitali. 2022. The Search for Good Jobs: Evidence from a Six-Year Field Experiment in Uganda. Working Paper.
- Banerjee, A. V. and S. Sequeira. 2022. Spatial Mismatches and Imperfect Information in the Job Search. Centre for Economic Policy Research Press Discussion Paper. No. 14414. <https://cepr.org/publications/dp14414>.
- Beam, E. A. 2016. Do Job Fairs Matter? Experimental Evidence on the Impact of Job-Fair Attendance. *Journal of Development Economics*. 120. pp. 32–40.
- Belot, M., P. Kircher, and P. Muller. 2019. Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice. *Review of Economic Studies*. 86 (4). pp. 1411–1447.
- Borker, G. 2021. Safety First: Perceived Risk of Street Harassment and Educational Choices of Women. *Policy Research Working Paper*. No. 9731. Washington, DC: World Bank.
- Bryan, G., S. Chowdhury, and A. M. Mobarak. 2014. Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica*. 82 (5). pp. 1671–1748.



- Business Standard. 2022. Virtual Job Fair for Persons with Disabilities Kicks Off. <https://www.tbsnews.net/economy/corporates/virtual-job-fair-persons-disabilities-kicks-362653> (accessed 20 February 2023).
- Card, D., J. Kluge, and A. Weber. 2018. What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations. *Journal of the European Economic Association*. 16 (3). pp. 894–931.
- Coles, P., J. Cawley, P. B. Levine, M. Niederle, A. E. Roth, and J. J. Siegfried. 2010. The Job Market for New Economists: A Market Design Perspective. *Journal of Economic Perspectives*. 24 (4). pp. 187–206.
- Dammert, A. C., J. Galdo, and V. Galdo. 2015. Integrating Mobile Phone Technologies into Labor-Market Intermediation: A Multi-Treatment Experimental Design. *IZA Journal of Labor & Development*. 4 (1). p. 11.
- Delecourt, S. and A. Fitzpatrick. 2021. Childcare Matters: Female Business Owners and the Baby-Profit Gap. *Management Science*. 67 (7). pp. 4455–4474.
- Dhia, A. B., B. Crépon, E. Mbih, L. Paul-Delvaux, B. Picard, and V. Pons. 2022. Can a Website Bring Unemployment Down? Experimental Evidence from France. *National Bureau of Economic Research Working Paper Series*. No. 29914. [https://www.nber.org/system/files/working\\_papers/w29914/w29914.pdf](https://www.nber.org/system/files/working_papers/w29914/w29914.pdf).
- Dinkelman, T. 2011. The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review*. 101 (7). pp. 3078–3108.
- Fernando, A. N., N. Singh, and G. Tourek. 2022. Hiring Frictions and the Promise of Online Job Portals: Evidence from India. *Structural Transformation and Economic Growth Working Paper Series*. No. WP043.
- Field, E. and K. Vyborny. 2022. Women’s Mobility and Labor Supply: Experimental Evidence from Pakistan. *ADB Economics Working Paper Series*. No. 655. Manila: ADB.
- Franklin, S. 2018. Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies. *The Economic Journal*. 128 (614). pp. 2353–2379.
- General Economics Division. 2020. Eighth Five Year Plan July 2020–June 2025. Dhaka: Bangladesh Planning Commission, Government of the People’s Republic of Bangladesh.
- Groh, M., D. McKenzie, N. Shammout, and T. Vishwanath. 2015. Testing the Importance of Search Frictions and Matching through a Randomized Experiment in Jordan. *IZA Journal of Labor Economics*. 4. pp. 1–20.
- Handshake Network Trends. 2021. Who Wins with Virtual Recruiting? <https://joinhandshake.com/network-trends/virtual-recruiting/> (accessed 20 February 2023).
- Hayashi, R., N. Matsuda, and M. S. Rahman. 2022. Online Job Listings Rebounded Strongly after the Pandemic. Asian Development Blog. <https://blogs.adb.org/blog/online-job-listings-rebounded-strongly-after-pandemic> (accessed 20 February 2023).
- He, H., D. Neumark, and Q. Weng. 2021. Do Workers Value Flexible Jobs? A Field Experiment. *Journal of Labor Economics*. 39 (3). pp. 709–738.

- Hensel, L., T. Tekleelassie, and M. Witte. 2021. Formalized Employee Search and Labor Demand. IZA Institute of Labor Economics Discussion Paper Series. IZA DP No. 14839. <https://docs.iza.org/dp14839.pdf>.
- Horton, J. J. 2017. The Effects of Algorithmic Labor Market Recommendations: Evidence from a Field Experiment. *Journal of Labor Economics*. 35 (2). pp. 345–385.
- International Telecommunication Union. 2022. *Global Connectivity Report 2022*. Geneva, Switzerland.
- Jensen, R. 2012. Do Labor Market Opportunities Affect Young Women’s Work and Family Decisions? Experimental Evidence from India. *The Quarterly Journal of Economics*. 127 (2). pp. 753–792.
- Jones, S. and R. Santos. 2022. Can Information Correct Optimistic Wage Expectations? Evidence from Mozambican Job-seekers. *Journal of Development Economics*. 159. 102987.
- Jones, S. and K. Sen. 2022. Labour Market Effects of Digital Matching Platforms: Experimental Evidence from Sub-Saharan Africa. IZA Institute of Labor Economics Discussion Paper Series. IZA DP No. 15409. <https://docs.iza.org/dp15409.pdf>.
- Kelley, E. M., C. Ksoll, and J. Magruder. 2022. How Do Online Job Portals Affect Employment and Job Search? Evidence from India. Working Paper. <https://are.berkeley.edu/~jmagruder/KKM.pdf>.
- Krueger, A. B. and A. I. Mueller. 2016. A Contribution to the Empirics of Reservation Wages. *American Economic Journal: Economic Policy*. 8 (1). pp. 142–179.
- Leibbrandt, A. and J. A. List. 2018. Do Equal Employment Opportunity Statements Backfire? Evidence from a Natural Field Experiment on Job-Entry Decisions. *National Bureau of Economic Research Working Paper Series*. No. 25035.
- Matsuda, N., T. Fasih, S. Nomura, and E. O. Tas. 2022. Publicizing Female Friendliness in Job Advertisement: Evidence from Pakistan. Working paper.
- Matsuda, N. and S. Nomura. 2022. The Temptation of Social Networks under Job Search Frictions. SSRN 4235445.
- McKenzie, D. 2017. How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence. *The World Bank Research Observer*. 32 (2). pp. 127–154.
- Mueller, A. I., J. Spinnewijn, and G. Topa. 2021. Job Seekers’ Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias. *American Economic Review*. 111 (1). pp. 324–363.
- Muralidharan, K. and N. Prakash. 2017. Cycling to School: Increasing Secondary School Enrollment for Girls in India. *American Economic Journal: Applied Economics*. 9 (3). pp. 321–350.
- Startz, M. 2021. The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade. Working paper.
- Tas, E. O., T. Ahmed, N. Matsuda, and S. Nomura. 2022. Gender Impacts of COVID-19 on the Labor Market and Household Wellbeing in Pakistan. *Review of Economic Analysis*. 14 (2). pp. 221–252.
- Van der Klaauw, B. and L. Ziegler. 2022. A Field Experiment on Labor Market Speeddates for Unemployed Workers. *Journal of Human Resources*. 1021–11946R2.

Ward, G. 2022. Workplace Happiness and Job Search Behavior: Evidence from a Field Experiment. Working paper.

Wheeler, L., R. Garlick, E. Johnson, P. Shaw, and M. Gargano. 2022. LinkedIn (to) Job Opportunities: Experimental Evidence from Job Readiness Training. *American Economic Journal: Applied Economics*. 14 (2). pp. 101–25.

World Bank. World Bank Open Data. <https://data.worldbank.org/> (accessed on 14 June 2023).

Yamauchi, F., S. Nomura, S. Imaizumi, A. C. Areias, and A. R. Chowdhury. 2018. Asymmetric Information on Noncognitive Skills in the Indian Labor Market: An Experiment in Online Job Portal. *Policy Research Working Paper*. No. WPS 8378. Washington, DC: World Bank Group.



## **The Impact of an Online Job Fair**

*Experimental Evidence from Bangladesh*

This study examines the impact of an online fair for information and communication technology jobs in Bangladesh. The study found that there was no effect on employment probability since more than 90% of job offers generated were rejected. Jobseekers learned about market conditions at the fair. This led jobseekers to lower their labor market expectations and reservation wages. As a result, jobseekers who had been employed kept their jobs longer even if jobs did not match their skills. Those initially unemployed ended up with lower employment probabilities and lower skill-match quality.

### **About the Asian Development Bank**

ADB is committed to achieving a prosperous, inclusive, resilient, and sustainable Asia and the Pacific, while sustaining its efforts to eradicate extreme poverty. Established in 1966, it is owned by 68 members—49 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.

