Econometrica Supplementary Material

SUPPLEMENT TO "TACKLING YOUTH UNEMPLOYMENT: EVIDENCE FROM A LABOR MARKET EXPERIMENT IN UGANDA"

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APPENDIX A

A.1. *Attrition*

TABLE A.V presents evidence on the correlates of worker attrition. Attrition is low, with only 13% of workers attriting by the 48-month endline. Focusing on attrition between baseline and endline, Column 1 shows that: (i) attrition is uncorrelated to treatment assignment; (ii) worker characteristics do not predict attrition in general, but workers that score higher on a cognitive ability test are more likely to attrit. Column 2 shows there to be little evidence of heterogeneous attrition across treatments by baseline cognitive scores. Any bias that might arise from selective attrition on unobservables cannot be signed a priori. Tracked workers would be negatively selected if attriters are more likely to find employment themselves, or they would be positively selected if attriters are least motivated to find work and remain attached to the labor market. To account for attrition, we weight our ITT estimates using inverse probability weights (IPWs). We also show the robustness of the main treatment impacts when using conditional Lee bounds (Lee (2009)).

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TABLE A.I

BASELINE BALANCE ON WORKER CHARACTERISTICS. MEANS, ROBUST STANDARD ERRORS FROM OLS REGRESSIONS IN PARENTHESES. p-VALUE ON t-TEST OF EQUALITY OF MEANS WITH CONTROL GROUP IN BRACKETS. p-VALUE ON F-TESTS IN BRACES[a]

	Number of Workers (1)	Age [Years] (2)	Married (3)	Has Child(ren) (4)	Currently in School (5)	Ever Attended Vocational Training (6)	Cognitive Test Score (7)	F-Test of Joint Significance (8)
All Workers	1714	20.0	0.040	0.118	0.016	0.036	0.561	
		(0.198)	(0.016)	(0.024)	(0.008)	(0.018)	(0.043)	
T1: Control	451	20.1	0.027	0.102	0.011	0.042	0.560	
		(0.211)	(0.016)	(0.025)	(0.009)	(0.020)	(0.047)	
T2: Firm Trained	283	20.1	0.040	0.121	0.018	0.038	0.554	{0.999}
		(0.139)	(0.014)	(0.024)	(0.009)	(0.015)	(0.037)	
		[0.970]	[0.271]	[0.260]	[0.576]	[0.897]	[0.640]	
T3: Vocationally Trained	390	20.0	0.056	0.127	0.018	0.032	0.529	{0.849}
		(0.134)	(0.014)	(0.022)	(0.008)	(0.013)	(0.033)	
		[0.781]	[0.056]	[0.339]	[0.553]	[0.461]	[0.573]	
T4: Vocationally Trained + Matched	307	20.0	0.030	0.123	0.029	0.038	0.603	{0.878}
		(0.146)	(0.012)	(0.023)	(0.011)	(0.015)	(0.037)	
		[0.975]	[0.128]	[0.075]	[0.248]	[0.792]	[0.772]	
T5: Untrained, Matched	283	20.0	0.047	0.122	0.007	0.027	0.568	{0.937}
		(0.148)	(0.015)	(0.024)	(0.007)	(0.014)	(0.037)	
		[0.429]	[0.084]	[0.201]	[0.468]	[0.359]	[1.00]	
F-test of joint significance		{0.933}	{0.243}	{0.449}	{0.445}	{0.752}	{0.974}	

[a]All data are from the baseline survey to workers. Column 1 reports the number of workers assigned to each treatment. Columns 2 to 7 report the mean value of each worker characteristic, derived from an OLS regression of the characteristic of interest on a series of dummy variables for each treatment group. All regressions include strata dummies and a dummy for the implementation round. The excluded (comparison) group in these regressions is the Control group. Robust standard errors are reported in parentheses throughout. The variable in Column 7 is a dummy equal to 1 if the applicant scored at the median or above on a cognitive test administered with the baseline survey. The test consisted of six literacy and six numeracy questions. Column 8 reports the p-values from F-tests of joint significance of all the regressors from an OLS regression where the dependent variable is a dummy variable taking value 0 if the worker is assigned to the Control group, and it takes value 1 for workers assigned to treatment group j (with j going from 2 to 5) and the independent variables are the variables in Columns 2 to 7. Robust standard errors are also calculated in these regressions. The p-values reported in the last row are from the F-test of joint significance of the treatment dummies in each column regression where the sample includes all workers.

TABLE A.II

EXTERNAL VALIDITY. MEANS, STANDARD DEVIATIONS IN PARENTHESES[a]

	Number of Individuals (1)	Age [Years] (2)	Gender [Male = 1] (3)	Married (4)	Currently in School (5)	Years of Education (6)	Ever Attended Vocational Training (7)	Has Worked in the Last Week [Yes = 1] (8)	Has Had Any Wage Employ-ment in the Last Week (9)	Has Done Any Casual Work in the Last Week (10)	Total Earnings From Wage Employment in the Last Month [USD] (11)
A. Baseline, aged 18–25	1608	20.1	0.567	0.038	0.014	9.77	0.037	0.362	0.142	0.156	2.60
		(1.86)	(0.496)	(0.190)	(0.116)	(2.06)	(0.189)	(0.481)	(0.350)	(0.363)	(9.74)
Uganda National Household Survey 2012/13:											
B. All, aged 18–25	4696	21.1	0.465	0.395	0.309	7.42	0.062	0.681	0.293	0.512	9.13
		(2.32)	(0.499)	(0.489)	(0.462)	(3.65)	(0.241)	(0.466)	(0.455)	(0.500)	(28.2)
C. Labor Market Active, aged 18–25	3456	21.4	0.475	0.448	0.207	6.96	0.064	0.902	0.389	0.679	12.2
		(2.33)	(0.499)	(0.497)	(0.405)	(3.50)	(0.245)	(0.297)	(0.489)	(0.467)	(32.0)

[a]We report mean and standard deviation of the characteristics of individuals from three samples: (i) those individuals in our baseline sample aged 18–25; (ii) individuals aged 18–25 and interviewed in the Uganda National Household Survey 2012/13 (UNHS) conducted by the Ugandan Bureau of Statistics; (iii) individuals aged 18–25 and interviewed in the UNHS who self-report being active in the labor market (either because they are employed or are actively seeking employment). The UNHS was fielded between June 2012 and June 2013. Our baseline survey was fielded between June and September 2012. In the UNHS, respondents are considered to have attended vocational training if the highest grade completed is post-primary specialized training/diploma/certificate or post-secondary specialized training/diploma/certificate. In the baseline survey, questions on employment status did not refer to work activities performed in the last week, but to work activities performed at the time of the survey. Therefore, for the baseline survey, the variable "Has worked in the last week" corresponds to the worker being "Currently employed or involved in a work activity". Similarly, Columns 8–10 for the baseline survey are based on the most recent activity performed by the individual, conditional on him/her saying to be currently employed or involved in a work activity. For UNHS, the outcomes in Columns 8–10 are based on the main activity performed in the week before the survey. In Column 9, casual work includes occupations that are casual in nature, as well as agricultural occupations. In Column 10, workers who report doing no wage employment in the past month (or only did unpaid work in the last month) have a value of zero for total earnings.

TABLE A.III

THE MINCERIAN RETURNS TO VOCATIONAL TRAINING, BY SECTOR[a]

	Worker Is Skilled: Self-Reported VTI Attendance			
	Share of Firms in Sector (1)	% Workers Skilled in Sector (2)	Coefficient and SE From Worker Wage Regressions [USD] (3)	Coefficient and SE From Worker log(wage) Regressions [USD] (4)
All Sectors		**31.0%**	**26.2**	**0.515**
			(3.15)	(0.045)
Manufacturing				
Welding	14.57%	24.9%	34.5	0.381
			(6.40)	(0.084)
Motor-mechanics	9.80%	23.5%	16.1	0.294
			(9.41)	(0.153)
Electrical wiring	6.37%	41.9%	27.3	0.486
			(7.60)	(0.189)
Construction	4.38%	28.8%	11.5	0.289
			(9.39)	(0.170)
Plumbing	3.08%	49.1%	60.9	0.719
			(19.0)	(0.281)
Services				
Hairdressing	39.64%	29.2%	22.9	0.444
			(5.97)	(0.069)
Tailoring	14.96%	41.6%	15.9	0.898
			(9.76)	(0.182)
Catering	7.20%	40.2%	26.8	0.330
			(11.6)	(0.109)

[a]The data used are from the Census of firms, which includes 2309 firms and 6306 workers. A worker is defined as skilled if he/she was reported as having attended formal vocational training at any point in the past. Coefficients and standard errors in Columns 3 and 4 are from a regression of workers' total earnings in the last month (or the logarithm of workers' total earnings in the last month) on a dummy for being a skilled worker (as defined above). Control variables in these regressions include: employee's age and age squared, gender, tenure and tenure squared, firm size, BRAC branch dummies, and firm sector dummies. Robust standard errors are reported. All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD. The top 1% wages and capital stock values are excluded.

On the IPWs, we proceed as follows. At each survey wave t, we define a dummy s_{it} such that we observe (y_{it}, x_{it}) for observations for which $s_{it} = 1$. We then first estimate a probit of s_{it} on z_{it} for each post-intervention survey wave separately, where z_{it} includes: (i) $\mathbf{x}_{i0}$: the vector of baseline covariates used as controls throughout in (1); (ii) strata and implementation round dummies; (iii) $\mathbf{z}_{i0}$, baseline measures excluded from regression analysis: dummies for orphan, anyone in household has a phone, willing to work in multiple sectors, and; (iv) the survey team the respondent was assigned to in each survey round ($Team_{it}$). The underlying assumption is that conditional on z_{it}, y_{it} is independent of s_{it}. $\hat{p}_{it}$ are fitted probabilities from this regression using survey wave t, and so at a second stage, we weight our OLS ITT estimates with weights $1/\hat{p}_{i1}$, $1/\hat{p}_{i2}$, $1/\hat{p}_{i3}$.

A.2. *Beliefs About the Returns to Vocational Training*

An explanation for why workers do not themselves invest in vocational training is that they have incorrect beliefs about the returns to such investments. We assess this using information collected from workers at baseline over their expected probability of finding

TABLE A.IV

CHARACTERISTICS OF APPRENTICESHIPS[a]

A. Availability	
Worker received on-the-job training at the current firm	0.498
Duration of on-the-job training [months]	10
B. Payments	
In the first month of training, the worker:	
Was paid	0.198
Was unpaid	0.515
Was paying the firm owner	0.288
Earnings (conditional on > 0) [US$] (median)	39.2 (40.1)
Amount worker was paying to owner (conditional on > 0) [US$] (median)	51.9 (33.3)
C. Trainers	
Who was mainly involved in training the worker:	
Firm owner only	0.457
Other employees only	0.091
Firm owner as well as other employees	0.452

[a]The data are from the first firm follow-up, and the sample is restricted to those workers employed in Control firms. The sample includes 955 workers employed in 332 firms. All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD. The top 1% monetary values are excluded.

work, and their expected earnings conditional on employment, if they received vocational training. This is shown in Table A.VIII. Columns 1 and 2 show that: (i) at baseline, workers expect their employment probability to be 57% (that is optimistic given baseline employment rates of 40%); (ii) workers expect their likelihood of finding work to rise by 30pp or 53%, if they receive vocational training. This is also optimistic given the ATE impact on the extensive margin being closer to 31%.

In terms of earnings, Column 3 of Table A.VIII reports worker beliefs at baseline, over the average monthly earnings given their current skill set (assuming they were employed). These correspond to just under $60. We then asked workers what they expected their maximum and minimum monthly earnings to be if they received vocational training (and the likelihood they would be able to earn more than the midpoint of the two). Fitting a triangular distribution to their beliefs, we derive an expected earnings from vocational training. This is shown in Column 4: on average, workers report earnings would more than double, so a greater than 100% return. This is double the Mincerian returns shown in Table A.III, which are themselves upwards biased. Combining both margins, we see that workers expect the returns to vocational training to be nearly 200%, many times more than the ATE estimate of returns, at 42%.

A.3. *Robustness Checks*

To conduct robustness checks, we first combine multiple labor market outcomes into the same index shown in Column 5 of Table III. Column 1 of Table A.IX repeats the baseline ITT estimates as a point of comparison. In addition to the ITT estimates, we also report conditional Lee bounds on the treatment effects (where we use the convention that the bound is underlined if it is statistically different from zero).[1]

[1]We bound the treatment effect estimates using the trimming procedure proposed by Lee (2009). The procedure trims observations from above (below) in the group with lower attrition, to equalize the number of

TABLE A.V

ATTRITION. OLS REGRESSION COEFFICIENTS, ROBUST STANDARD ERRORS IN PARENTHESES[a]

	Worker Attrited by Endline	
	With covariates (1)	Heterogeneous (2)
T2: Firm Trained	−0.000	0.002
	(0.026)	(0.035)
T3: Vocationally Trained	−0.018	0.022
	(0.024)	(0.034)
T4: Vocationally Trained + Matched	−0.011	−0.012
	(0.027)	(0.036)
T5: Untrained, Matched	0.013	0.014
	(0.027)	(0.035)
High Score on Cognitive Test at Baseline [Yes = 1]	0.045	0.061
	(0.018)	(0.032)
T2: Firm Trained × High Cognitive Score		−0.005
		(0.051)
T3: Vocationally Trained × High Cognitive Score		−0.071
		(0.047)
T4: Vocationally Trained + Matched × High Cognitive Score		0.001
		(0.051)
T5: Untrained, Matched × High Cognitive Score		−0.002
		(0.053)
Mean of outcome in T1 Control group	0.134	0.134
Strata and Implementation round dummies	Yes	Yes
Other baseline characteristics	Yes	Yes
Test of joint significance of baseline characteristics		
F-statistic	2.35	1.57
p-value	0.071	0.196
Test of joint significance of Treatment × High Score interactions		
F-statistic		0.79
p-value		0.529
Number of observations (workers)	1561	1561

[a]Data are from baseline, first, second, and third follow-up of applicants to the vocational scholarships. Standard errors adjusted for heteroscedasticity are reported in parentheses. Other baseline characteristics include: age at baseline, a dummy for whether the worker was married at baseline, a dummy for whether the worker had any children at baseline, and a dummy for whether the worker was employed at baseline. The variable High Score on Cognitive Test at Baseline is a dummy = 1 if the applicant scored at the median or above on the cognitive test administered with the baseline survey.

Columns 2 and 3 split the labor market index by gender. Women have been found to benefit more from some training interventions, although this finding is far from universal (McKenzie (2017)). We generally find larger ITT impacts on men. Columns 4 and 5 split treatment effects by sector: we generally find larger labor market impacts in manufacturing. Given the correlation between gender and sector (manufacturing sectors tend to be

observations in treatment and control groups. It then re-estimates the program impact in the trimmed sample to deliver the lower (upper) bounds for the true treatment effect. The bounding procedure relies on the assumptions that treatment is assigned randomly and that treatment affects attrition in only one direction so there are no heterogeneous effects of the treatment on attrition/selection, in line with the evidence in Table A.V. As Lee (2009) discussed, using covariates to trim the samples yields tighter bounds. The covariates we use are the strata dummies.

TABLE A.VI

TAKE-UP OF TREATMENTS[a]

	Vocational Training		Matching and Firm Training			
Sample of Workers:	All Workers	Offered Training	All Workers	Invited to Interview	Met at Least One Firm	Worker Received a Job Offer
Outcome:	% Workers Offered Training	% Workers Trained	% Workers Invited to Interview	% Workers That Met at Least One Firm	% Workers Who Received a Job Offer	% Workers Hired
	(1)	(2)	(3)	(4)	(5)	(6)
T3: Vocationally Trained	**97.9**	73.8	–	–	–	–
T4: Vocationally Trained + Matched	**95.4**	63.1	**12.7**	74.4	58.6	23.5
T2: Firm Trained	–	–	**50.5**	80.4	90.4	66.4
T5: Untrained, Matched	–	–	**19.1**	85.2	34.8	18.8

[a]The data used are from the tracker survey and process reports. The tracker survey was collected in July–August 2013, at the end of the main round of vocational training. Process reports were collected during the implementation of the firm-level interventions (September 2013–February 2014). In Columns 1 and 3, the sample includes all workers assigned to the respective treatment groups. In Column 1, only workers that were traced and successfully informed about the treatment offer are considered as having been offered treatment. In Column 2, the sample includes those workers who could be traced and were offered the treatment by BRAC staff, and the percentage of workers who took up training includes the workers who completed the 6 months vocational training. For Matching and Firm Training (Column 3), the treatment offer is defined as firms having invited the worker for an interview (so those workers matched to firms that were not interested in the program are not included, as they were not offered treatment). In Column 4, the sample includes workers who were invited for an interview; in Column 5, it includes those workers who met with at least one firm; in Column 6, the sample includes workers who received an offer to start at the firm. In Column 6, the percentage of workers who took up treatment is calculated as the percentage of workers who accepted the offer received by the firm, and so started work/training at the firm.

TABLE A.VII

COMPLIANCE WITH THE FIRM TRAINING TREATMENT. OLS REGRESSION COEFFICIENTS, ROBUST STANDARD ERRORS IN PARENTHESES IN ALL COLUMNS EXCEPT COLUMN 4 WHERE STANDARD ERRORS ARE CLUSTERED AT THE FIRM LEVEL. DEPENDENT VARIABLE: WORKER STARTED TRAINING AT THE FIRM ASSIGNED TO IN THE FT TREATMENT[a]

	Worker Characteristics (1)	Worker and Program Characteristics (2)	Worker, Program, and Firm Characteristics (3)	Firm Fixed Effects (4)
Female	0.011	−0.132	−0.108	0.019
	(0.065)	(0.092)	(0.094)	(0.138)
Age	0.013	0.006	0.002	0.004
	(0.017)	(0.017)	(0.017)	(0.023)
Any child	0.017	0.039	0.073	0.058
	(0.092)	(0.089)	(0.084)	(0.120)
High education	−0.070	−0.043	−0.030	−0.013
	(0.058)	(0.058)	(0.059)	(0.086)
High cognitive test score	−0.081	−0.067	−0.064	0.047
	(0.057)	(0.056)	(0.054)	(0.089)
Employed	−0.063	−0.068	−0.035	−0.079
	(0.060)	(0.065)	(0.066)	(0.158)
Ideal job is wage employment	−0.103	−0.070	−0.079	−0.032
	(0.060)	(0.061)	(0.060)	(0.100)
High risk attitude	−0.054	−0.066	−0.080	−0.040
	(0.053)	(0.050)	(0.048)	(0.070)
High patience	0.086	0.107	0.100	0.099
	(0.055)	(0.054)	(0.052)	(0.089)
Employed in August 2013	0.075	0.071	0.060	0.066
	(0.071)	(0.069)	(0.066)	(0.117)
Second round		0.278	0.251	0.147
		(0.085)	(0.086)	(0.132)
Matched to more than one firm		−0.040	0.002	−0.288
		(0.075)	(0.077)	(0.187)
Average firm size of matched firms			0.000	
			(0.020)	
Average log profit per worker of matched firms			−0.119	
			(0.052)	
Average log capital per worker of matched firms			−0.023	
			(0.057)	
Mean of dep. var. in control	0.244	0.244	0.244	0.244
p-value: worker covariates	0.065	0.156	0.194	0.976
p-value: firm covariates			0.002	
Region of application dummies	Yes	Yes	Yes	Yes
Sector of match dummies	No	Yes	Yes	No
BRAC branch of match dummies	No	Yes	Yes	No
Firm fixed effects	No	No	No	Yes
Adjusted R-squared	0.083	0.177	0.213	0.143
Observations	259	259	259	417

[a]We report OLS regression coefficients and robust standard errors (in parentheses) in all columns except in Column 4 where standard errors are clustered at the firm level. Data are from the first follow-up worker survey and from the matching surveys, which are used to construct compliance measures. Compliance is defined as having started training at the firm. The sample includes workers assigned to Firm Training. The regression in Column 4 is run on a data set at the match level. So the data set includes all the scheduled assignments between workers and firms in FT. The p-values reported at the bottom of each column are from join F-tests of significance of the worker and firm covariates, as indicated in the table. Risk attitudes and patience are measured with hypothetical survey questions. All variables termed as “High” correspond to dummies equal to 1 if the worker had a value of the underlying variable on or above the sample median at baseline.

TABLE A.VIII

WORKER EXPECTATIONS. MEANS, STANDARD DEVIATIONS IN PARENTHESES. ALL AMOUNTS IN 2012 USD[a]

	Expected Probability of Finding a Job in the Next 12 Months		Average Expected Monthly Earnings (Triangular Distribution)	
	With Current Skill Set (1)	If Received VT (2)	With Current Skill Set (3)	If Received VT (4)
All Workers (Baseline Interview)	0.567 (0.288)	0.867 (0.144)	57.8 (46.9)	118 (71.5)
N. of observations	1611	1589	1243	1411

[a]The data used are from the baseline and first three follow-up worker surveys. Columns 1 to 4 report the mean and standard deviation (in parentheses) of the average expected probability of finding a job and the average monthly earnings (assuming a triangular distribution of expected earnings) with the current skill set (Columns 1 and 3), or if the worker were to receive vocational training (Columns 2 and 4). This is based on all workers interviewed at baseline (across all treatments). All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD. The top 1% values of each variable are excluded from the analysis.

male dominated), it is hard to definitively separate out whether the impacts are driven by gender or sector. Fourth, we consider impacts in labor markets outside of Kampala, where 81% of workers reside: the result in Column 6 largely replicates the main findings.

Finally, we examine the sensitivity of the treatment effects to the timing of labor market entry. To do so, we exploit the fact that we have two batches of vocationally trained workers; the majority of trainees from the first round of applicants started training in January 2013. For logistical reasons, a second round of randomized-in applicants received vocational training between October 2013 and April 2014 (and so receive their training at the same time as when the apprenticeships are being implemented). In Column 7, we allow the impacts of vocational training to differ by the first and second batch of trainees; we see no evidence that workers in the second batch have different outcomes as measured by the labor market index.[2]

In Columns 2 to 7, in most cases the Lee bounds remain significantly different from zero.

Finally, the final two columns show the robustness of the main results to dropping all covariates except baseline outcomes, randomization strata, and survey wave fixed effects, and to additionally not using IPWs.

A.4. *Likelihood*

We assume all random events (λ_0, λ_1, δ) are realizations of Poisson processes, so the residual durations are exponentially distributed. As unemployed workers are always assumed to be made job offers they accept, the unemployment spell hazard is λ_0. There

[2]To further examine this concern, we also estimated employment rates in August 2013 (when VT workers were graduating from the VTIs and the FT treatment was being rolled out); we find no significant differences in employment rates between workers assigned to the FT, VT, and control groups at that point. Moreover, recall that in terms of compliance with the FT treatment, the results in Table A.VII already showed that being employed in August 2013 does not predict compliance (so workers that might have found jobs earlier are no less likely to still take up the FT treatment). This is robust to alternative specifications for compliance (Columns 1 to 4 of Table A.VII). Finally, descriptive evidence from the process reports collected just prior to the FT intervention shows that in the great majority of cases, workers were interested and willing to start training at the FT firms, so that selection is mostly on the firm side. Only a handful of workers reported not being interested in meeting a firm because they already had a job.

TABLE A.IX

ROBUSTNESS CHECKS. DEPENDENT VARIABLE: LABOR MARKET INDEX. OLS REGRESSION COEFFICIENTS, IPW ESTIMATES IN COLUMNS 1 TO 7, ROBUST STANDARD ERRORS IN PARENTHESES. LEE (2009) BOUNDS IN BRACKETS[a]

	(1) All	(2) Women	(3) Men	(4) Services	(5) Manufacturing	(6) Non-Kampala	(7) Batches	(8) No Covariates	(9) No IPW, No Covariates
Firm Trained	0.105	0.070	0.135	0.027	0.167	0.189	0.106	0.106	0.115
	(0.051)	(0.077)	(0.067)	(0.080)	(0.067)	(0.056)	(0.051)	(0.051)	(0.050)
	[0.026; 0.122]	[0.067; 0.112]	[0.005; 0.129]	[0.022; 0.094]	[0.034; 0.147]	[0.097; 0.175]			
Vocationally Trained	0.170	0.134	0.196	0.117	0.214	0.198	0.179	0.170	0.179
	(0.041)	(0.061)	(0.055)	(0.065)	(0.053)	(0.044)	(0.045)	(0.041)	(0.040)
	[0.111; 0.204]	[0.137; 0.198]	[0.094; 0.208]	[0.094; 0.198]	[0.109; 0.202]	[0.145; 0.221]			
Vocationally Trained × Second Batch of Trainees							−0.050		
							(0.088)		
Mean Outcome in Control Group	0.003	−0.115	0.092	−0.109	0.081	−0.067	0.003	0.003	0.003
Control for Baseline Value	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-values on tests of equality:									
Firm Trained = Vocationally Trained	[0.169]	[0.362]	[0.338]	[0.222]	[0.460]	[0.869]	[0.146]	[0.175]	[0.180]
N. of observations	3256	1424	1832	1320	1925	2578	3256	3256	3256

[a]The data used are from the baseline and first three follow-up worker surveys. We report OLS regressions, where we use inverse probability weighting (Columns 1 to 8) and robust standard errors are reported in parentheses. We report Lee (2009) bounds in brackets, where we implement a conditional Lee Bounds procedure that is able to condition on strata dummies in Columns 1–3 and 6–9, and to condition on region dummies and a dummy for having a level of education at the median or above at baseline in Columns 4–5. The dependent variable is the Labor Market Index that is computed using the following variables: any paid work in the last month (dummy), months worked in the last year, hours worked in the last week, and total earnings in the last month. Total earnings are set to zero for workers with no earnings. The index is constructed following Anderson's (2008) approach. Manufacturing sectors are: motor-mechanics, plumbing, construction, electrical wiring, and welding. Service sectors are: hairdressing, catering, and tailoring. Workers are assigned to Manufacturing or Service sectors according to stated preferences over their ideal job, reported at baseline. In Column 6, we restrict the sample to labor markets outside of Kampala. All regressions include strata dummies, survey wave dummies, a dummy for the implementation round, and dummies for the month of interview. In Columns 1 to 7, we also control for the following baseline characteristics of workers: age at baseline, a dummy for whether the worker was married at baseline, a dummy for whether the worker had any children at baseline, a dummy for whether the worker was employed at baseline, and a dummy for whether the worker scored at the median or above on the cognitive test administered at baseline. Columns 1 and 4–9 further control for a complete set of strata dummies. Columns 2 and 3 further control for region dummies, and a dummy for having a level of education at the median or above at baseline. The weights for the IPW estimates are computed separately for attrition at first, second, and third follow-up. The instruments for the IPW estimates are whether the worker was an orphan at baseline, a dummy if anyone in the household of the worker reported having a phone at baseline, a dummy for whether the worker reported being willing to work in more than one sector at the time of their original application to the VTIs, and dummies for the survey team the worker's interview was assigned to in each of the three follow-up survey rounds. At the foot of each column, we report p-values on the null that the impact of the vocational training is equal to the impact of firm training (T2 = T3). All monetary variables are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD.

TABLE A.X

ALPHA. OLS REGRESSION COEFFICIENTS, ROBUST STANDARD ERRORS IN PARENTHESES[a]

	ln(Earnings in First Month of Employment)		
Sample:	All Treatments, U2J	All Treatments, U2J	All Treatments, U2J
Outcome Variable:	Actual Earnings	Actual Earnings	Actual Earnings
	(1)	(2)	(3)
ln(Skills Test Score)	0.263	0.245	0.279
	(0.149)	(0.163)	(0.273)
Vocationally Trained × ln(Skills Test Score)			−0.024
			(0.346)
Firm Trained × ln(Skills Test Score)			−0.021
			(0.428)
Baseline Controls	No	Yes	No
N. Observations	162	161	162

[a]The data are from the second and third follow-up survey of workers and include information on all job spells workers have been involved in starting from November 2015. The unit of observation for the analysis is the job spell. The table shows coefficients and standard errors (in parentheses) from an OLS regression of the logarithm of earnings in the first month of employment on the logarithm of the score obtained by the worker in a sector-specific skills test. The sample includes workers who transitiond from unemployment into employment. All regressions control for treatment dummies. In Column 2, we also control for age, gender, and education at baseline, as well as strata dummies. In Column 3, we add interactions of the logarithm of the skills test score with treatment dummies.

are two competing causes of job spell termination: workers can be laid off (at rate δ), or workers can make a JJ transition (at rate $\lambda_1 \bar{F}(r)$). Hence, the hazard rate of job spells with piece rate r is $(\delta + \lambda_1 \bar{F}(r))$. Thus, conditional on initial employment status ($e_i = 0$ or 1) and on an initial piece rate r_{i1}, the individual likelihood contributions are the following.

TABLE A.XI

EFFECT OF SKILLS ON EMPLOYMENT. DEPENDENT VARIABLE: =1 IF WORKER IS EMPLOYED IN NOVEMBER 2015. ROBUST STANDARD ERRORS IN PARENTHESES. UNIT OF OBSERVATION: WORKER SPELLS[a]

Worker sample:	All Treatments	All Treatments	Control Group	All Treatments
	(1)	(2)	(3)	(4)
Skills Test Score	0.001	0.001	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Vocationally Trained × Skills Test Score				0.001
				(0.001)
Firm Trained × Skills Test Score				0.001
				(0.002)
Baseline Controls	No	Yes	No	No
N. Observations	1289	1274	396	1289

[a]The data are from the second and third follow-up survey of workers and include information on all job spells workers have been involved in starting from November 2015. The unit of observation for the analysis is the job spell. The table shows coefficients and standard errors (in parentheses) from an OLS regression of a dummy equal to 1 if the individual was employed in November 2015 on the score obtained by the worker in a sector-specific skills test. The sample in Columns 1 and 2 includes individuals from all treatment groups, while the sample in Column 3 is restricted to workers in the Control group. The regressions in Columns 1, 2, and 4 control for treatment dummies. In Column 2, we also control for age, gender, and education at baseline, as well as strata dummies.

TABLE A.XII

ESTIMATES IN THE JOB LADDER SEARCH MODEL, WITH $F(r|T)$. TWO-STEP ESTIMATION PROCEDURE IN BONTEMPS, ROBIN AND VAN DEN BERG (2000). ASYMPTOTIC STANDARD ERRORS IN PARENTHESES. STEADY STATE: NOVEMBER 2015 (DATA FROM SECOND AND THIRD FOLLOW UP)[a]

		Non-Compliers		Compliers	
Panel C: Wages and Earnings	Control (1)	Firm Trained (2)	Vocationally Trained (3)	Firm Trained (4)	Vocationally Trained (5)
Average monthly OFFERED wages [USD]	44.1	47.6	41.5	41.7	46.8
Average monthly ACCEPTED wages [USD]	63.2	70.8	67.1	63.9	71.1
Impact on annual earnings [USD]		**37.4**	**19.1**	**49.7**	**150**
% Impact:		**12%**	**6.16%**	**16%**	**48%**

[a]The data set is a cross-section of workers, and for each worker it contains information on: spell type (employment, unemployment), spell duration (in months), earnings in employment spells (in USD), dates of transitions between spells and type of transition: (i) job to unemployment, (ii) unemployment to job, or (iii) job to job. Wages are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD. The data set contains at most two spells (and one transition) per individual. The data come from the second and third follow-up survey of workers, and the initial spell is identified as the (employment or unemployment) spell that was ongoing in November 2015. Spells are right-censored at the date of the third follow-up interview (which ended in December 2016). Spells are left-censored at 1 August 2014. Casual and agricultural occupations are coded as unemployment. Self-employment is coded as employment (but self-employment spells are assigned a separate spell). The estimation protocol follows the two-step procedure in Bontemps, Robin, and van den Berg (2000): in the first step, the G function is estimated nonparametrically from the data (so this is just the empirical CDF of observed wages for those workers that are employed in their first spell), and is then substituted into the likelihood function. In the second step, maximum likelihood is then conducted using information from both the first and second spells for each individual to recover the parameter estimates. In Panel C, average monthly offered and accepted wages are computed as the product of average offered and accepted piece rates, and average units of effective labor. We assume workers draw piece rates from the same offer distribution $F(r)$. $F(r)$ is the kernel density estimate of a weighted average of the distributions of offered piece rates across treatments—$F(r|T)$—where such distributions are obtained from their steady-state relationship with nonparametrically estimated $G(r|T)$. Weights are equal to the share of individuals in each treatment.

For type-ε employed workers in treatment group k:

$$l(\mathbf{x}_i|e_i=1,\varepsilon_i,T_k)=g(r_{1i}|T_k)\times\big(\delta+\lambda_1\bar{F}(r_{1i}|T_k)\big)^{(1-c_i)}e^{-(\delta+\lambda_1\bar{F}(r_{1i}|T_k))d_i}$$
$$\times\left(\frac{\delta}{\delta+\lambda_1\bar{F}(r_{1i}|T_k)}\right)^{\tau_{JU_i}}\times\left(\frac{\lambda_1\bar{F}(r_{1i}|T_k)}{\delta+\lambda_1\bar{F}(r_{1i}|T_k)}\right)^{\tau_{JJ_i}}, \qquad \text{(A.1)}$$

where λ_0, λ_1, and δ are parameterized as in (7) to (9) in the main text, and are therefore functions of the treatments, $g(\cdot)$ is the density of $G(\cdot)$, c_i is an indicator for right-censoring, d_i is the duration (in months) of the spell, τ_{JU_i} is an indicator for job-to-unemployment transition, and τ_{JJ_i} is an indicator for job-to-job transition.

For unemployed workers:

$$l(\mathbf{x}_i|e_i=0,\varepsilon_i,T_k)=\lambda_0^{1-c_i}e^{-\lambda_0 d_i}\times f(r_{0i}|T_k)^{1-c_i}, \qquad \text{(A.2)}$$

where $f(\cdot)$ is the density of $F(\cdot)$.

Given there is no selection into employment conditional on training status T, the generic likelihood contribution of an observation $\mathbf{x}_i$ given its type ε and treatment group T_k is given by

$$l(\mathbf{x}_i|\varepsilon_i,T_k)=\left(\frac{\lambda_0}{\delta+\lambda_0}(\mathbf{x}_i|e_i=1,\varepsilon_i,T_k)\right)^{e_i}\times\left(\frac{\delta}{\delta+\lambda_0}(\mathbf{x}_i|e_i=0,\varepsilon_i,T_k)\right)^{1-e_i}. \qquad \text{(A.3)}$$

TABLE A.XIII

HETEROGENEOUS IMPACTS ON SKILLS. 2SLS REGRESSION COEFFICIENTS, BOOTSTRAPPED STANDARD ERRORS IN PARENTHESES[a]

Dependent Variable: Sector-Specific Test Score (0–100)		
Heterogeneous Effects By:	Raven Matrices (1)	Patience (2)
Firm Trained × Below Median Trait	2.63	3.50
	(8.53)	(7.73)
Firm Trained × Above Median Trait	21.1	12.9
	(5.51)	(7.05)
Vocational Training × Below Median Trait	7.79	7.96
	(2.70)	(2.40)
Vocational Training × Above Median Trait	13.2	12.2
	(2.24)	(2.34)
Mean outcome in Control group	30.1	30.1
p-value FT × Low = FT × High	0.072	0.371
p-value VT × Low = VT × High	0.116	0.207
Observations	1485	1799

[a]The data used are from the baseline, second, and third follow-up worker surveys in all columns. We report 2SLS regression estimates, where treatment assignment is used as IV for treatment take-up. Treatment take-up is defined as a dummy equal to 1 if the worker (i) started firm training in FT or (ii) started vocational training in VT. Bootstrap standard errors are calculated using 1000 replications and reported in parentheses. All regressions control for strata dummies, survey wave dummies, a dummy for the implementation round, and dummies for the month of interview. We also control for the following baseline characteristics of workers: age at baseline, a dummy for whether the worker was married at baseline, a dummy for whether the worker had any children at baseline, a dummy for whether the worker was employed at baseline, and a dummy for whether the worker scored at the median or above on the cognitive test administered at baseline. At the foot of each column, we report p-values on the null that the impact of the vocational training is equal to the impact of firm training, by the various variables considered in each of the columns. Workers are divided into high/low Raven matrices using their score on the Raven Matrices test implemented at first follow-up. Workers are assigned to the High Raven group if they scored on or above the median of the Raven Matrices test. Workers are divided into high/low Patience using their answers to a series of questions about their willingness to wait to receive (hypothetical) monetary rewards at baseline. Workers are assigned to the High Patience group if they had a value of Patience on or above the median.

The likelihood is an explicit function of the transition parameters δ, λ_0, λ_1, and of both distributions $F(\cdot)$ and $G(\cdot)$. The empirical cross-sectional cdf of piece rates among employed workers at the initial sampling date provides a nonparametric estimator of $G(\cdot)$:

$$\hat{G}(r|T_k) = \frac{1}{\sum_i T_{ik}} \sum_i \mathbb{1}(r_{1i} \leq r) T_{ik}. \tag{A.4}$$

Under the steady-state assumptions, the relationship between $F(\cdot)$ and $G(\cdot)$ provides a nonparametric estimator of the piece rate sampling distribution F, for any given value of λ_1 and δ:

$$\hat{F}(r|T_k) = \frac{(\delta + \lambda_1)\hat{G}(r|T_k)}{\delta + \lambda_1 \hat{G}(r|T_k)}. \tag{A.5}$$

We use maximum likelihood to estimate the parameters δ, λ_0, and λ_1, and their asymptotic standard errors.

TABLE A.XIV

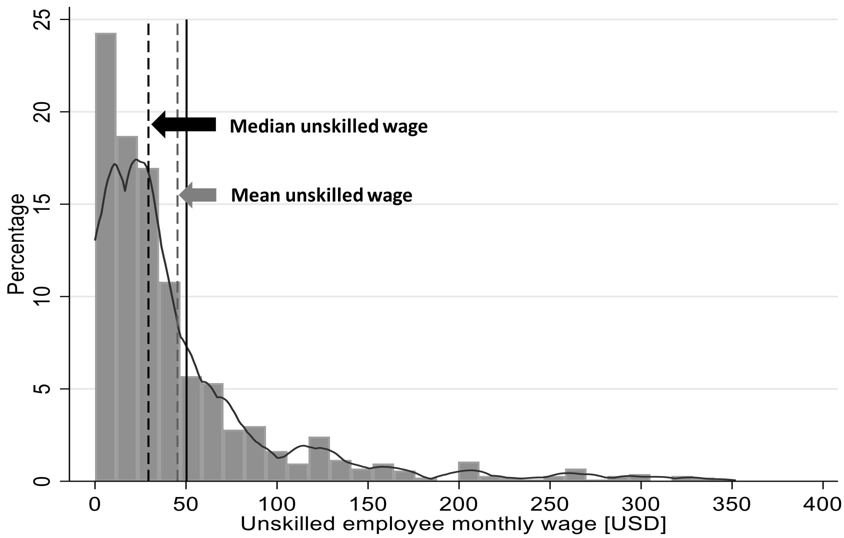
PARAMETER ESTIMATES OF THE JOB LADDER SEARCH MODEL. TWO-STEP ESTIMATION PROCEDURE IN BONTEMPS, ROBIN AND VAN DEN BERG (2000). ASYMPTOTIC STANDARD ERRORS IN PARENTHESES. STEADY STATE: NOVEMBER 2015 (DATA FROM SECOND AND THIRD FOLLOW UP)[a]

		Control (1)	Firm Trained (2)	Vocationally Trained (3)
Panel A: Parameter Estimates (Monthly)				
Average units of effective labor [USD]		2.31	2.37	2.50
Job destruction rate, δ		0.027	0.026	0.024
		(0.003)	(0.005)	(0.004)
Arrival rate of job offers if UNEMPLOYED, λ_0		0.019	0.019	0.024
		(0.002)	(0.003)	(0.003)
Arrival rate of job offers if EMPLOYED, λ_1		0.038	0.037	0.042
		(0.010)	(0.015)	(0.012)
Panel B: Competition for Workers and Unemployment				
Interfirm competition for workers		1.41	1.44	1.77
	% Impact:		**2.1%**	**25%**
Unemployment rate		0.589	0.575	0.502
	% Impact:		**−2.3%**	**−15%**
Unemployment duration (months)		52.8	52.4	42.2
	% Impact:		**−0.78%**	**−20%**
Employment duration (months)		36.8	38.6	41.8
	% Impact:		**5.0%**	**14%**
Panel C: Wages and Earnings				
Average monthly OFFERED wages [USD]		43.1	44.3	46.7
Average monthly ACCEPTED wages [USD]		62.6	64.7	71.7
Impact on annual earnings [USD]			**21.4**	**12.0**
	% Impact:		**6.9%**	**39%**

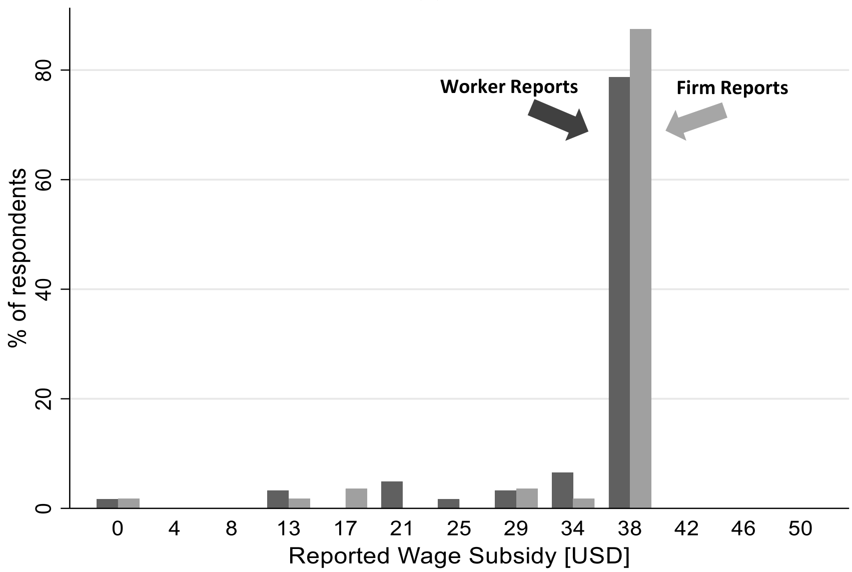
[a]The data set is a cross-section of workers, and for each worker it contains information on: spell type (employment, unemployment), spell duration (in months), earnings in employment spells (in USD), dates of transitions between spells and type of transition: (i) job to unemployment, (ii) unemployment to job, or (iii) job to job. Wages are deflated and expressed in terms of August 2012 prices, using the monthly consumer price index published by the Uganda Bureau of Statistics. Deflated monetary amounts are then converted into August 2012 USD. The data set contains at most two spells (and one transition) per individual. The data come from the second and third follow-up survey of workers, and the initial spell is identified as the (employment or unemployment) spell that was ongoing in November 2015. Spells are right-censored at the date of the third follow-up interview (which ended in December 2016). Spells are left-censored at 1 August 2014. Casual and agricultural occupations are coded as unemployment. Self-employment is coded as employment (but self-employment spells are assigned a separate spell). The estimation protocol follows the two-step procedure in Bontemps, Robin, and van den Berg (2000): in the first step, the G function is estimated nonparametrically from the data (so this is just the empirical CDF of observed wages for those workers that are employed in their first spell), and is then substituted into the likelihood function. In the second step, maximum likelihood is then conducted using information from both the first and second spells for each individual to recover the parameter estimates. As shown in Panel A, we estimate separate parameters for Control and Treatment groups, but we pool together compliers and non-compliers. Outputs in Panel B are derived from the model and computed as functions of the estimated parameters: (i) interfirm competition for workers $= \lambda_1/\delta$; (ii) unemployment rate $= \delta/(\delta+\lambda_0)$; (iii) unemployment duration $= 1/\lambda_0$; employment duration $= 1/\delta$. In Panel C, average monthly offered and accepted wages are computed as the product of average offered and accepted piece rates, and average units of effective labor. We assume workers draw piece rates from the same offer distribution $F(r)$. $F(r)$ is the kernel density estimate of a weighted average of the distributions of offered piece rates across treatments—$F(r|T)$—where such distributions are obtained from their steady-state relationship with nonparametrically estimated $G(r|T)$. Weights are equal to the share of individuals in each treatment. For each treatment, we then re-invert $F(r)$ using estimated parameters and steady-state relationships to obtain $G(r|T)$ under the assumption that workers draw piece-rates from the same offer distribution.

A.5. *Robustness of the Model Estimates*

In the baseline model, the distribution from which piece rate offers are drawn $F(\cdot)$ does not depend on treatment T: rather, all workers draw from this distribution, but once hired, workers are realized to be of higher type-ε, and paid a higher wage (at the same



(a)



(b)

FIGURE A.1.—(a) Wage distribution of unskilled workers at baseline. (b) Worker-firm wage subsidy splits. *Notes*: The top graph shows the distribution of unskilled workers' wages at baseline. The solid line is drawn in correspondence to the total amount of wage subsidy under the Firm Training treatment, and the dashed line indicates the median (unskilled) wage at baseline. A kernel density estimate of the distribution of wages is also shown. The lower histogram shows the reported monthly earnings of workers hired through the Firm Training treatment, where the first bar is always the worker's self-reported wage, and the second bar is what the firm reports paying the worker.

piece rate r). We now allow $F(\cdot)$ to also depend on compliance and treatment T. This enables us to investigate, in a very reduced form way, whether across treatments, workers search differently across firms in the economy who might then draw from different piece

Append Firm Owner's Photo Here

brac

Branch: ____________

CONTRACT

Small Firm Expansion and Job Creation Program: Mentorship

I ______________________________**(Firm Owner)** owner of____________________________**(Business Name)**

In _____________________________**(Village/Area)** in _________________________________**(Sub-County)**

Of ______________________________**(County)** and _____________________________________**(District)**

hereby promise that I will conduct training for the undersigned trainee regularly as per the following terms:

1. I am bound to provide a training course on ______________________ (trade type) for the duration of six month, starting ___/ ___ / 2013
2. I will refund the full allocation given by BRAC for training cost should I fail to provide the training.
3. BRAC Uganda will provide 30,000 UGSH monthly to supplement training costs. I expect no other payments from BRAC, Uganda.
4. I will attend monthly meetings and training sessions as per the schedule provided the Job Placement Officer (JPO) or ELA Staff.
5. I will keep track of the trainee's attendance in the attendance register provided by the JPO/ELA.
6. I will abide by the decisions of BRAC Uganda regarding changes to the schedule, content of training, or assignment of trainee.
7. I agree provide honest information to BRAC Uganda. I understand that falsifying documents, deceiving BRAC staff or bearing false witness will result in the immediate termination of the contract.
8. I commit to try my best to ensure to good quality skill development for the trainee through this training.
9. I confirm that I am physically able to conduct and compete the training.

I here by sign the promissory note with full conciseness after reading, fully understanding and accepting the conditions, without any influence from any one.

____
Firm Owner's Full Name

____
Trainee's Full Name

____
Firm Owner's Signature

____
Trainee's Signature

____
Date

____
Date

____
JPO / ELA Staff Signature

____
Date

Worker ID

Firm ID

FIGURE A.2.—Firm-provided training contract.

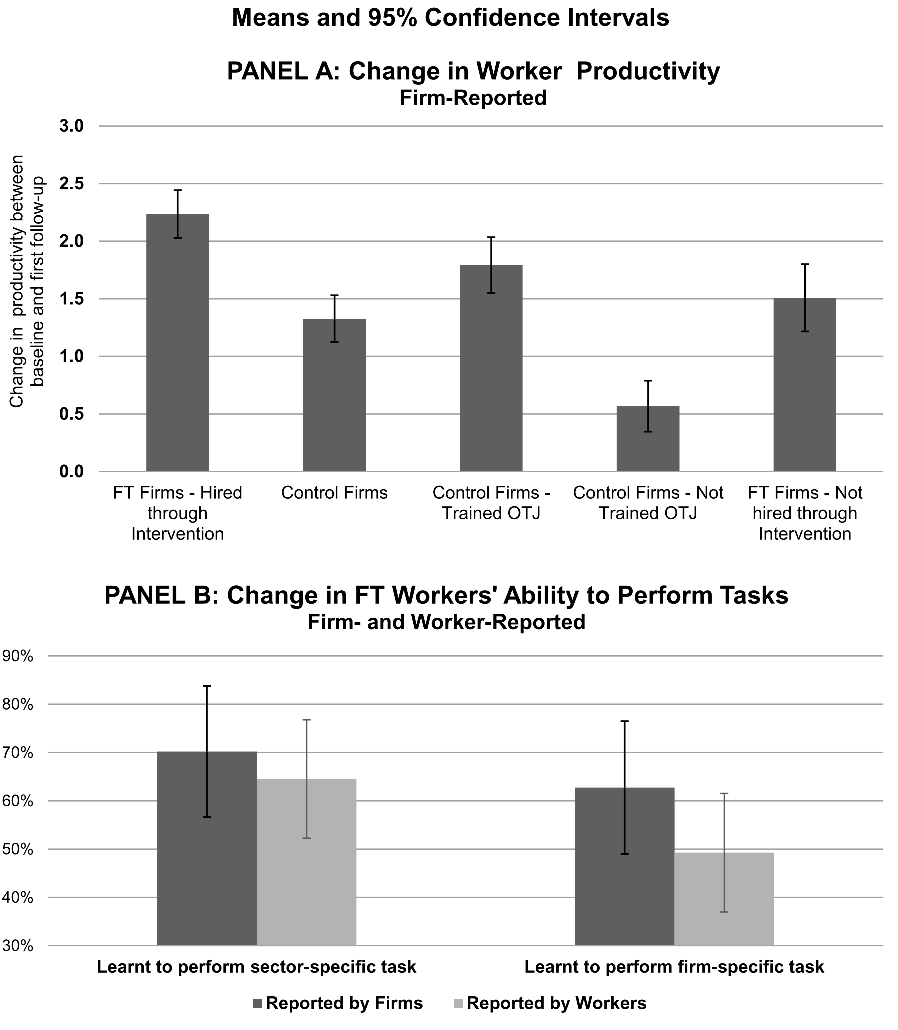


FIGURE A.3.—Change in worker productivity between recruitment and first follow-up. *Notes*: The data used are from the first follow-up survey of firms and workers. In the firm data, the unit of observation is the employee, and the sample only includes workers hired between 4 and 6 months prior the survey. In Panel A, the sample Control Firms—trained OTJ includes workers in Control firms who received on-the-job training; the sample FT Firms—Not hired through Intervention includes all workers hired in firms assigned to the Firm Training treatment, but not directly through the intervention; the sample FT Firms—Hired through Intervention includes workers hired through the Firm Training intervention only. For each worker, the respondent (i.e., the firm owner in most cases) was asked to rate the employee's productivity at recruitment and at the time of the interview (or at the time when the worker left the firm) on a scale from 1 to 5. The average productivity growth of workers across the different samples is shown in Panel A. In Panel B, we identified a specific task for each of the study sectors and asked the respondent (i.e., the firm owner or the worker) whether the worker was able to perform that task when he joined the firm and at follow-up (or at the time when the worker left the firm). For firm-specific tasks, respondents were asked to identify a task considered particularly important for the firm, and were then asked whether the worker was able to perform that task when he joined the firm and at follow-up (or at the time when the worker left the firm). Panel B shows the percentage of workers who learned how to perform the task between baseline and follow-up (or between baseline and the time when the worker left the firm) for workers in the firm training intervention who took up the treatment. The dark gray bars report the learning rate as reported by firms; the light gray bars report the learning rate as reported by workers.

1. MOTOR-MECHANICS		
1	*multiple-choice* What are you advised to do when servicing the engine by changing oil?	A. Top up lubricating oil B. Replace oil filter C. Over hand engine D. Over hand cylinder head **Correct Answer: B**
2	*multiple-choice* What immediate remedy can you give to a vehicle with a problem of excessive tyre wear in the center more than other parts?	A. Increase tyre pressure B. Reduce tyre pressure C. Inflate pressure D. Remove the vehicle tire **Correct Answer: B**
3	*multiple-choice* If a customer reports to you that his/her vehicle charging system works at lower rate, how can you help him?	A. Replacing the charging system B. Adjusting the alternator tension C. Replacing alternator housing D. Renewing wire insulator **Correct Answer: B**
4	*multiple-choice* Which of the following set of systems or component call for mechanical adjustment during general vehicle service?	A. Tyres, cooling system, master cylinder B. Break shoes, alternator, and valve clearance C. Distributor, radiator, propeller shaft D. Tank, crank shaft, Turbo charger **Correct Answer: B**
5	*multiple-choice* What solution would you give a customer with a vehicle engine producing blue smoke?	A. Top up lubricant B. Time the engine C. Replace piston rings D. Remove carbon deposits **Correct Answer: C**
6	*matching* What should you do to stop the following vehicle troubles?	1 Battery over charging — A Leaking fuel tank 2 Engine over heating — B Renew regulator 3 Lubricant leakage — C Reduce oil to the correct level 4 Smoke in exhaust — D Renew piston rings 5 Engine fails to start — E Charge the battery **Correct Answer: 1B, 2A, 3C, 4D, 5E**
7	*order* When changing engine oil, in which order should you perform the following steps?	A. Drain oil through drain plug B. Remove oil filter cup C. Run engine to check leaks D. Fill new oil through filler cup to level E. Remove oil filter F. Warm up the engine **Correct Answer: B, E, A, D, F, C**

FIGURE A.4.—Sector skills test for motor-mechanics.

rate distributions. An alternative interpretation of this extension is a set-up in which even once a worker is hired, their skills are not perfectly observable to the firm, as in a model of statistical discrimination where skill certificates are just a signal of unobserved worker ability.

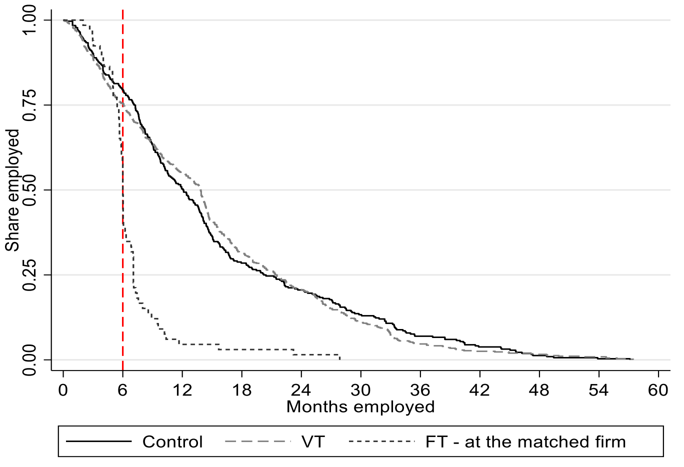


FIGURE A.5.—Survival analysis for employment. *Notes*: The figure plots survival functions for the first employment spell. For Firm Trained workers, we plot the survival function for workers who started training at the matched firm. For Control and Vocationally Trained workers, we plot survival functions in the first non-casual and non-agricultural employment spell in the post-training period (since August 2013).

Table A.XII shows these results: only Panel C changes from the baseline model because we no longer impose a common $F(\cdot)$ across groups. By allowing for treatment-specific piece rate offer distributions, we see differences in terms of offered wages, especially for complier FT workers. The mean offered wage is \$42 allowing for $F(r|T)$, while it was \$49 in our baseline model that assumed $F(r)$. For VT workers, the means are far more similar (\$47 vs. \$48). To understand what might drive this, recall the earlier results on FT compliance showed that firm characteristics predict whether a worker is taken on and trained by a firm offered a wage subsidy. Moreover, negatively selected firms (those with lower profits per worker) are more likely to hire the worker when offered a wage subsidy. These results suggest this *initial* match with a low productivity firm as part of the FT treatment might have *persistent* impacts on the wage offers these FT workers receive in steady state. This hysteresis shows up in the annual earnings impacts: these are 16% for FT workers, far lower than the baseline estimate of 31% (for VT workers, the estimate of 48% is more similar to the baseline estimate of 55%). Indeed, the gap in earnings impacts of FT compliers and FT non-compliers narrows considerably (16% vs.12%), while the earnings gap is stable between VT compliers and VT non-compliers. This kind of persistence might be suggestive of directed search of workers, and is something we study in greater detail in ongoing work (Bandiera, Bassi, Burgess, Rasul, Sulaiman, and Vitali (2019)).

We also conducted robustness checks examining how the estimates and simulated steady-state impacts change with alternative $\widehat{\alpha}$ estimates: recall this parameter relates to how worker skills map to worker productivity or type. The baseline results set $\widehat{\alpha} = 0.263$ from Column 1 of Table A.X. We can also take the lowest and highest values of $\widehat{\alpha}$ from this table. Doing so reveals a qualitatively similar pattern of results. In particular, for both low and high $\widehat{\alpha}$: VT workers have significantly higher job offer arrival rates than FT workers when unemployed. The bottom line is that, for low $\widehat{\alpha}$, the steady-state earnings impacts are 30% for FT and 54% for VT; for high $\widehat{\alpha}$, these are 32% and 56%, respectively. As we would expect, a higher $\widehat{\alpha}$ translates into larger earnings impacts because skills translate into higher productivity and wages.

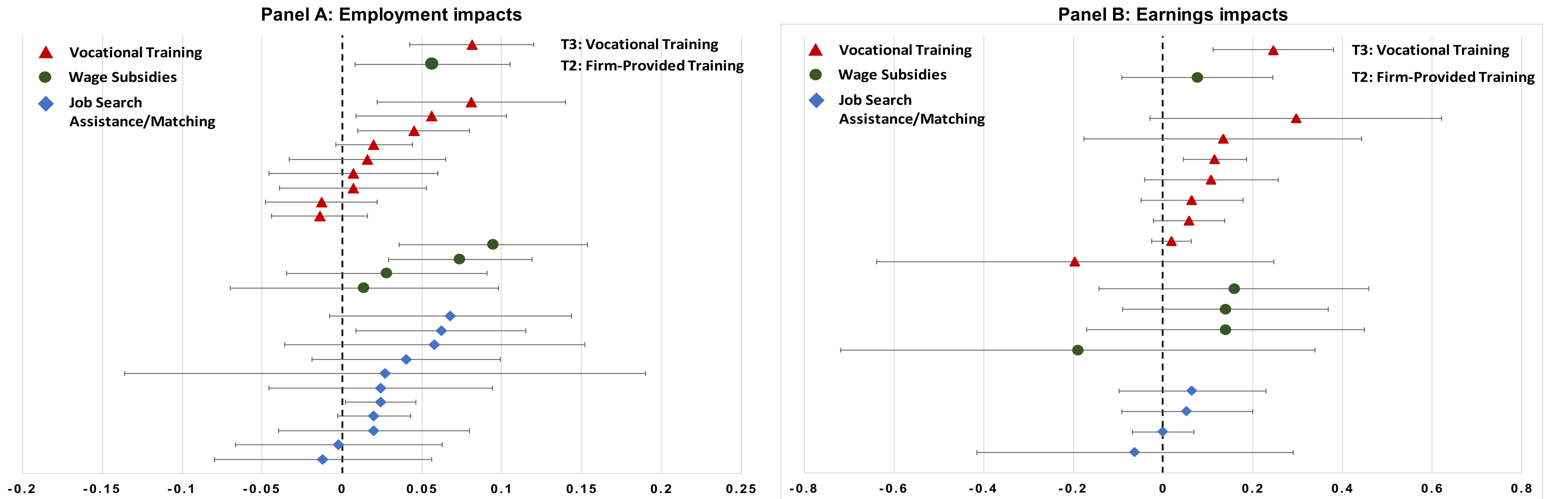


FIGURE A.6.—Comparison of treatment impacts to meta-analysis by McKenzie (2017). *Notes*: The figures compare the treatment impacts from this study to the treatment impacts reported in the meta-analysis by McKenzie (2017). The green estimates correspond to wage subsidy programs, the blue estimates to vocational training programs, and the red estimates to job search and matching assistance programs. Panel A reports treatment impacts (ITT) on the probability of paid employment, together with 95% confidence intervals. The estimates from our study are taken from Column 2 of Table IV, where we use as outcome variable "Any wage employment in the last month". Alongside our estimates, Panel A further reports 22 estimates of treatment impacts taken from Tables 1, 3, and 4 of McKenzie (2017). These correspond to all the available program estimates for this outcome reported in McKenzie (2017), a part from the estimate from Galasso, Ravallion, and Salvia (2004), which is omitted as no standard error is provided, and the estimate from Groh, Krishnan, Mckenzie, and Vishwanath (2016) with time frame 6 months, as that is estimated while the wage subsidy was still ongoing (while our estimates for T2: FT and all the other estimates for wage subsidy programs reported in the figure refer to the period after the wage subsidy ended). Panel B reports treatment impacts (ITT) on earnings, in terms of percentage increase relative to the earnings level of the Control group, together with 95% confidence intervals. The estimates from our study are taken from Column 4 of Table V, where we use as outcome variable "Total earnings in the last month". Alongside our estimates, Panel B further reports 15 estimates of treatment impacts taken from Tables 1, 3, and 4 of McKenzie (2017). These correspond to all the available program estimates for this outcome reported in McKenzie (2017), apart from the estimate from Groh et al. (2016) with time frame six months, as that is estimated while the wage subsidy was still ongoing (while our estimates for T2: FT and all the other estimates for wage subsidy programs reported in the figure refer to the period after the wage subsidy ended), and the estimate from Maitra and Mani (2017), which is excluded as that is very large relative to all the other estimates: Maitra and Mani (2017) estimate a treatment impact on earnings of 0.957, with confidence interval [0.056; 1.86]. However, this corresponds to only a $2.40 monthly increase in earnings in absolute terms, and so the large treatment impact is due to the women in their sample having extremely low earnings to begin with.

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