EC9C0 Topics in Development Economics

Week 3: Workers
Lecture 5

Stefano Caria

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Announcement

On Thursday this week, we will work together on writing a referee report for Vyborny et al. (2024) Why don't jobseekers search more?.

Plan

- Descriptive evidence on workers in low and middle income countries (LMIC)
- The accumulation of human capital
- Search and matching
- Labor market beliefs

Roadmap

Descriptive evidence

The accumulation of human capital

Search and matching

Beliefs

Reading

Bandiera et al. (2022)'s Jobs of the World: a key resource to do your own exploration

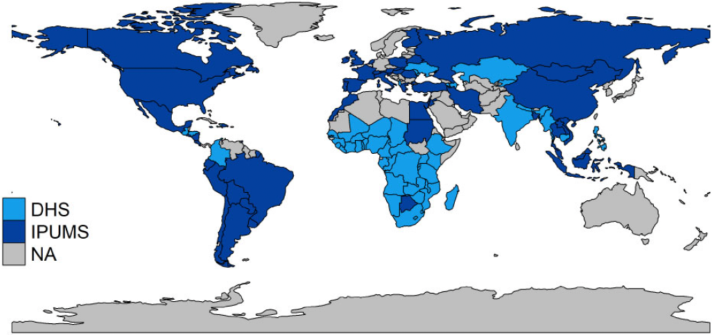


FIGURE 1. Countries in JWD.

1. Poor countries have average-to-high employment rates; low labor productivity is the issue

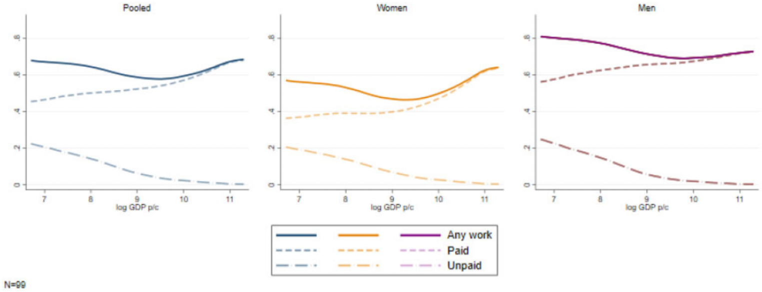


FIGURE 3. Paid and unpaid work against log GDP per capita by gender.

From Bandiera et al. (2022)

In poor countries, the poor are more likely to work than the rich; in rich countries, the reverse is true

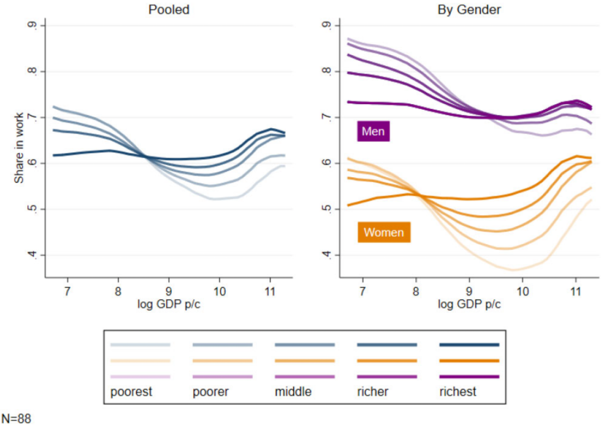
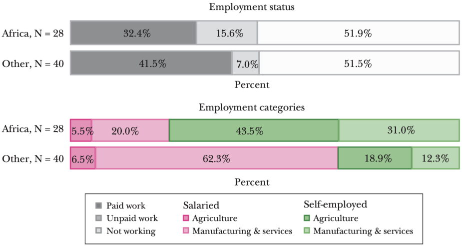


FIGURE 4. Share in work against log GDP per capita by gender and wealth.

From Bandiera et al. (2022)

Youth employment, however, is an issue

Figure 2
Occupational Structure of the 18–24 Year-Old Population



Source: Demographic and Health Surveys and IPUMS, harmonized via the Jobs of the World Project.
Note: Regional aggregates for the 18–24 year-old population in 68 low-income countries (28 countries from Africa and 40 countries from the rest of the world) constructed from the latest sample available for each country in the set of Demographic and Health Surveys and IPUMS censuses that contain the relevant labor outcomes for our exercise. The top panel plots the relative shares of three "extensive margin" categories: fraction of individuals aged 18–24 (i) working for pay, (ii) in unpaid work, and (iii) not working. The bottom panel plots the relative shares of four employment categories (defined according to sector and type of work), restricting the sample to working individuals (paid and unpaid). Regional averages are computed using countries' population size as weights; for the unweighted version, see Figure A2 in the online Appendix. For figures that disaggregate these results by gender, see Figure A3 in the online Appendix.

Bandiera et al. 2022b

2. Underlying these patterns are profound differences in (i) sectoral composition, (ii) urbanization, (iii) education

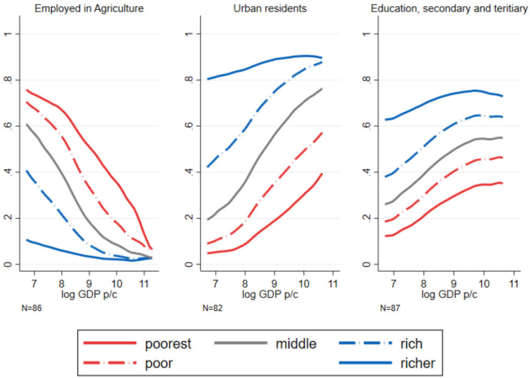


FIGURE 2. Inequality within and across countries.

From Bandiera et al. (2022)

And (iv) self-employment and informality are widespread

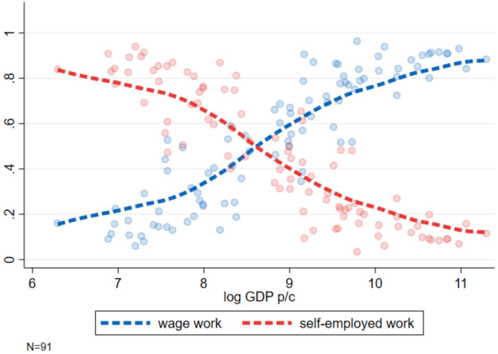


FIGURE 6. Share in self-employed work and wage work against log GDP per capita.

From Bandiera et al. (2022)
On informality, see Ulyssea et al 2023.

3. Earnings are low, and grow slowly

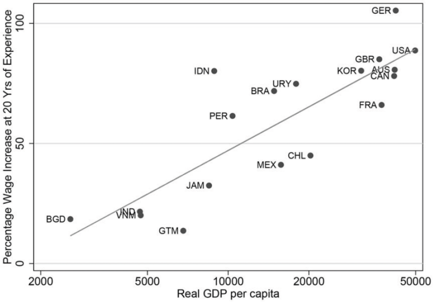
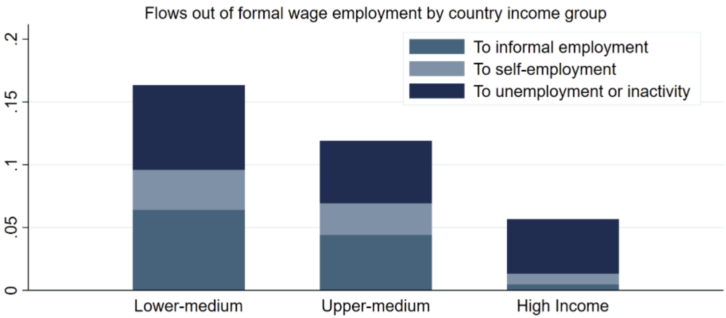


FIG. 3.—Percentage wage increase at 20–24 years of experience by GDP per capita. This figure plots the heights of the cross-sectional experience-wage profiles by 20–24 years of potential experience relative to 0–4 years of potential experience against GDP per capita at PPP in 2011. Experience-wage profiles are for full-time males working in the private sector and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. For each country and year, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers with less than 5 years of experience. The experience-wage profiles used in the figure are the unweighted average wage ratios by experience across all years.

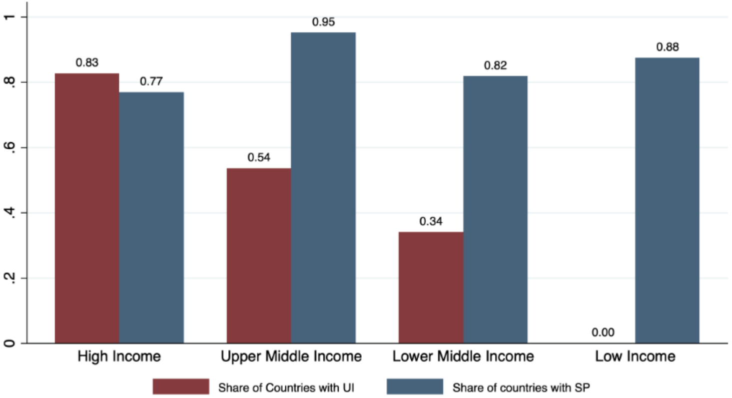
From Lagakos et al. (2018)

4. Job instability is high



Data from Donovan et al. (QJE 2023) (caveat: no low-income country)

And insurance against job loss limited



Data from Gerard, Gonzaga & Naritomi (forthcoming)
UI = Unemployment Insurance; SP = Severance Pay

5. The search for (formal) wage employment is costly and time consuming

Table 3: Job search behaviour and costs

Paper	Country	Proportion searching	Search costs among active jobseekers	Search hours
Abebe et al. (2021b)	Ethiopia	75% (past 6 months) 50% (past week)	16% of overall expenditure	-
Alfonsi et al. (2022)	Uganda	93%	40% of earnings[10]	-
Caria et al. (2023)	Jordan	43% of Syrian refugees 57% of Jordanians	38.4% of expenditure for Syrian refugees - 39.2% of expenditure for Jordanians	4.16 hours (past week) for Syrian refugees 5.79 hours (past week) for Jordanians
Carranza et al. (2022)	South Africa	97% (past week)	18.6% of earnings (past week) at endline	17 hours (past week)

From Caria, Orkin et al 2024

6. Reliance on social networks is widespread

Social networks are widely used to

- gather information about vacancies;
- obtain referrals to specific employers.

In several labor markets, about half of jobseekers use social networks for either of these two purposes.

See Caria, Orkin et al 2024 for relevant references.

One of the most common question policy makers in LMICs have is: how can I raise employment and wages, especially among the youth and women.

What answers can we give to these policy makers?

Roadmap

Descriptive evidence

The accumulation of human capital

Search and matching

Beliefs

Reading

Alfonsi et al 2020

Design

1. A sample of 1,700 young individuals who applied to a training program
2. Individual randomization into control, vocational training (VT), and firm-provided training (FT)
3. Three endline surveys (24, 36 and 48 months after treatment).

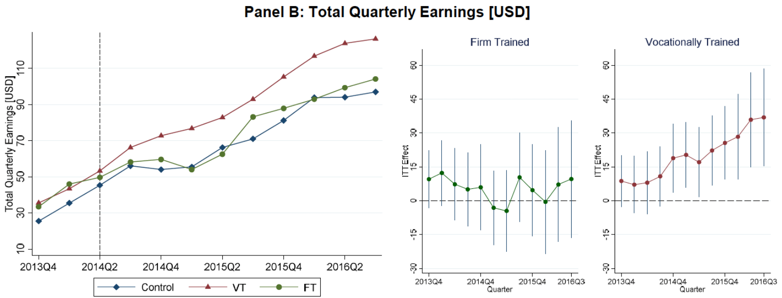
Strong impacts on employment of both VT and FT

Table 3: ITT Estimates, Labor Market Outcomes

OLS IPW regression coefficients and robust standard errors in parentheses
Bootstrap p-values in braces: unadjusted p-values (left) and Romano and Wolf [2016] adjusted p-values (right)

	Any paid work in the last month	Number of months worked in the last year	Hours worked in the last week	Total earnings in the last month [USD]	Labor market index	Worked in sector of training/matching in the last month
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Trained	.063	.518	-.196	1.89	.105	.045
	(.025)	(.259)	(2.27)	(2.20)	(.051)	(.015)
	{.016 ; .046}	{.049 ; .126}	{.945 ; .945}	{.408 ; .601}	{.043 ; .043}	{.005 ; .005}
Vocationally Trained	.090	.879	3.76	6.10	.170	.112
	(.020)	(.207)	(1.84)	(1.80)	(.041)	(.013)
	{.001 ; .001}	{.001 ; .001}	{.043 ; .126}	{.001 ; .005}	{.001 ; .001}	{.001 ; .001}
Mean Outcome in Control Group	.438	4.52	28.2	24.7	.003	.067
Control for Baseline Value	Yes	No	Yes	Yes	Yes	Yes
P-values on tests of equality:						
Firm Trained = Vocationally Trained	[.255]	[.134]	[.059]	[.048]	[.169]	[.000]
N. of observations	3,256	3,256	2,057	3,115	3,256	3,256

But impacts of VT much more persistent



A job-ladder model to understand this persistence

- Workers have treatment status T and employment type ϵ.
- Jobs pay $r * \epsilon$, with r drawn from $F(r)$.
- When unemployed, job opportunities arrive at rate λ_0
- When employed, job opportunities arrive at rate λ_1
- Jobs are destroyed at rate δ

The value functions

$$\rho U(\varepsilon, T) = \lambda_0(T) \int_{R(\varepsilon,T)}^{\bar{r}} [V(x, \varepsilon, T) - U(\varepsilon, T)]\, dF(x). \tag{2}$$

$$\rho V(r, \varepsilon, T) = r\varepsilon + \delta(T)\, [U(\varepsilon, T) - V(r, \varepsilon, T)] + \lambda_1(T) \int_{r}^{\bar{r}} [V(x, \varepsilon, T) - V(r, \varepsilon, T)]\, dF(x). \tag{3}$$

Identification

Assume $\epsilon = s^{\alpha}$: s is measured skills, and α estimated from a wage equation.

Also, assume the following about remaining parameters and use maximum likelihood:

$$\lambda_0 = \lambda_{00} + \sum_k \lambda_{0k} T_k,$$

$$\lambda_1 = \lambda_{10} + \sum_k \lambda_{1k} T_k,$$

$$\delta = \delta_0 + \sum_k \delta_k T_k,$$

Table 6: Baseline 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)

		Non-Compliers		Compliers	
Panel A: Parameter Estimates (Monthly)	**Control**	**Firm Trained**	**Vocationally Trained**	**Firm Trained**	**Vocationally Trained**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Average units of effective labor [USD]	2.31	2.28	2.35	2.65	2.58
Job destruction rate, δ	.027	.027	.026	.023	.023
	(.003)	(.006)	(.005)	(.007)	(.004)
Arrival rate of job offers if UNEMPLOYED, λ_0	.019	.019	.018	.020	.028
	(.002)	(.003)	(.003)	(.005)	(.003)
Arrival rate of job offers if EMPLOYED, λ_1	.038	.042	.054	.032	.039
	(.010)	(.019)	(.022)	(.022)	(.013)

Table 8: Counterfactual Analysis on Relative Importance of Mechanisms

	Unemployment			Earnings Conditional on Employment			Unconditional Earnings		
	Different Arrival Rates	Different Separation Rates	Different Skills	Different Arrival Rates	Different Separation Rates	Different Skills	Different Arrival Rates	Different Separation Rates	Different Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Baseline Levels									
Control		.589			64.0			26.3	
Firm Trained		.531			73.4			34.4	
Vocationally Trained		.456			74.4			40.5	
Panel B: FT=VT=Control									
Firm Trained	*21%*	*76%*	*0%*	*-39%*	*33%*	*100%*	*-10%*	*56%*	*54%*
Vocationally Trained	*72%*	*29%*	*0%*	*3%*	*27%*	*74%*	*51%*	*30%*	*29%*
Panel C: FT=VT									
Vocationally Trained	*110%*	*-9%*	*0%*	*-*	*-*	*-*	*137%*	*-11%*	*-15%*

Notes: The table reports OLS estimates from simulated data generated from the model. We run 10 simulations of the behavior of 50,000 workers followed over a period of 48 months. In each simulation, we randomly assign individuals to treatment in the same proportions as in our experiment. Workers are also randomly assigned to take-up their treatment in the same proportion as in the experiment. In each simulation we calculate treatment effects as the average monthly impact of FT and VT on employment and earnings across the 48 months from OLS regressions. We then aggregate estimates across the different simulations. Panel A shows mean unemployment rate, conditional and unconditional earnings in the baseline simulations, when we allow arrival rates λ_0 and λ_1, separation rates δ and the distribution of effective units of labor $h(\varepsilon)$ to vary across Control and treatment groups. Panel B shows percentage changes in treatment effects beween the baseline and the counterfactual simulations when we set the parameters indicated at the top of the table for individuals in the FT, VT groups to be the same as for the Control group. In Panel C we set the parameters of FT workers to be equal to those of VT workers. So, in Panel C the parameters of individuals in VT and Control remain the same as in the baseline simulation. In Columns 1, 4 and 7 we set arrival rates λ_0 and λ_1 to be equal across treatments. In Columns 2, 5 and 8 we set separation rates δ to be equal across treatments. In Columns 3, 6 and 9 we set the distribution of effective units of labor $h(\varepsilon)$ to be equal across treatments. The percentages in Panel B are calculated as the percentage change in FT and VT coefficients between baseline and counterfactual simulation. The percentages in Panel C are instead calculated as the percentage change in the difference between the VT and FT coefficients in the baseline and counterfactual simulations.

If returns are so high, why are people not investing already?

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Abebe et al. 2021

Two views of exclusion from labor markets: Search costs vs. Signal quality

Abebe et al. 2021 experimentally evaluate two programs:

1. a **job application workshop**
2. a **transport treatment**

The hypothesis is that treated subjects will search more *intensely* and *effectively*, leading to improved employment outcomes.

Design

1. A sample of 3,000 young individuals.
   - Good variation in education level, gender, distance from the city centre, etc..
2. Two endline surveys (8 months and 4 years after treatment) and fortnightly phone calls for 1 year.
   - Key to explore mechanisms.

The **Job Application Workshop**

It involves two components:

1. **Orientation for effective job applications**:
   CVs, cover letters, interviews and use of the certificates
2. **Standardised tests**: cognitive, linguistic and mathematical ability and work sample test.

The cost of the intervention was 18.2 USD per person (excluding the cost of developing the tests).

The intervention was implemented by AA Commercial College.

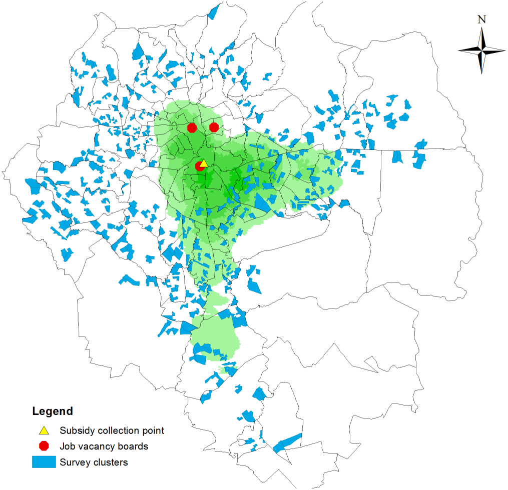
The **Transport Treatment**

- They offer a monetary reimbursement, available at a central location, 3 times per week, for an average of 16 weeks.

- Calibrated to cover the cost of a single return trip to the centre.
  - Median = \$ 1 , Max = \$ 1.50, Min = \$ 0.75.

The cost of the intervention was 19.8 USD per person.

They randomize at the level of geographical clusters



Conceptual framework: finding a 'good' job

Consider a labour market characterised by two frictions:

- Firms are uncertain about worker productivity;
- Workers have to do costly search to be matched to a vacancy.

Workers match with one vacancy every period t and are offered a job with probability S.

Employment rates will thus evolve according to:

$$E_t = 1 - (1 - S)^t$$

Conceptual framework: hiring in the market for ‘good’ jobs

What determines the probability of being hired S?

$$y_{if} = x_{if} + \varepsilon_{if}$$
$$x_{if} \sim \mathcal{N}(0,1)$$

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$$
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x_{if} &\sim \mathcal{N}(0,1) \\
\varepsilon_{if} &\sim \mathcal{N}(0,\sigma^2) \\
x_{if} \mid y_{if} &\sim \mathcal{N}\left(\frac{y_{if}}{1+\sigma^2}, \frac{\sigma^2}{1+\sigma^2}\right)
\end{aligned}
$$

Conceptual framework: hiring in the market for ‘good’ jobs

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x_{if} \,|\, y_{if} &\sim \mathcal{N}\left(\frac{y_{if}}{1+\sigma^2}, \frac{\sigma^2}{1+\sigma^2}\right)
\end{aligned}
$$

$$u(x) = -\exp(-rx)$$

Predictions: The Job Application Workshop

The firm will hire if and only if $y_{if} \geq 0.5r \cdot \sigma^2$.

The workshop will **decrease** σ^2 and thus increase hiring. This will:

1. Increase **permanent employment rates**;
2. Increase **expected match quality conditional on employment**, $\mathbb{E}(x_i \,|\, y_i > 0.5r\sigma^2)$.

Wages will also go up to reflect higher match quality, possibly with a delay.

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Predictions: the Transport Subsidy

The subsidy enables jobseekers to observe more vacancies.

This can be represented as 'speeding up time' by an amount α

$$E_t = 1 - (1 - S)^{\alpha t}$$

1. The subsidy will increase permanent employment rates;
2. but expected match quality will not change.

Predictions: the trajectory of the effects

Both treatments are effective for a limited period of time.

People in the control group continue to find job at the baseline rate and start catching up after the treatments stop.

This implies that:

1. Impacts on permanent employment rates will dissipate;
2. Impacts on match quality will persist: the jobs found by control group jobseeker do not have standard match quality.

Predictions: heterogeneity with respect to an observable covariate

$$\begin{pmatrix} x_{if} \\ z_i \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right).$$

Conditional on x_{if} and z_i, the probability of hiring is:

$$\Phi\left(-0.5r \cdot \sigma + \frac{x_{if}}{\sigma} + \frac{\rho\sigma}{1-\rho^2} \cdot z\right).$$

This probability is decreasing in σ if and only if:

$$-0.5r - \frac{x_{if}}{\sigma^2} + \frac{\rho}{1-\rho^2} \cdot z < 0.$$

A reduction in noise is valued by applicants who who have a **worse observable** (that is, lower z_i).

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Four predictions

1. Both intervention raise permanent employment rates. This effect is transitory.

2. This result is obtained through different mechanisms: the subsidy leads to more search and the workshop to more effective search.

3. The workshop increases match quality and wages. The transport does not. This effect is permanent.

4. The workshop has strongest impacts for the most disadvantaged workers.

Estimation of impacts on endline job outcomes

Using baseline and endline face-to-face surveys, they estimate:

$$
\begin{aligned}
y_{ic} = \beta_0 + \beta_1 \cdot \texttt{transport}_{ic} + \beta_2 \cdot \texttt{workshop}_{ic} \\
+ \gamma_1 \cdot \texttt{spillover1}_{ic} + \gamma_2 \cdot \texttt{spillover2}_{ic} \\
+ \alpha \cdot y_{ic,pre} + \boldsymbol{\delta} \cdot \boldsymbol{x}_{ic0} + \mu_{ic}
\end{aligned}
$$

$\rightarrow$ They *correct standard errors* at the geographical cluster level.

$\rightarrow$They report false discovery rate q *values* for pre-specified families of outcomes (Benjamini et al., 2006).

Table: Employment outcomes

	2015			2018		
Outcome	Control mean (1)	Transport (2)	Workshop (3)	Control mean (4)	Transport (5)	Workshop (6)
Work	0.562	0.041	0.021	0.693	-0.063*	0.027
		(0.029)	(0.031)		(0.034)	(0.031)
		[0.397]	[0.666]		[0.305]	[1.000]
Hours worked	26.18	0.268	-0.254	28.26	-2.636*	0.144
		(1.586)	(1.562)		(1.486)	(1.404)
		[0.946]	[1.000]		[0.305]	[1.000]
Monthly earnings	1,145.0	4.8	71.4	1,533.7	27.1	308.8**
		(75.5)	(83.9)		(100.3)	(123.4)
		[0.946]	[0.656]		[0.715]	[0.087]
Permanent job	0.171	0.029	0.065***	0.307	-0.038	-0.011
		(0.018)	(0.020)		(0.025)	(0.028)
		[0.392]	[0.008]		[0.305]	[1.000]
Formal job	0.224	0.054***	0.051**	0.319	-0.006	-0.006
		(0.019)	(0.020)		(0.030)	(0.030)
		[0.033]	[0.029]		[0.715]	[1.000]
Job satisfaction	0.237	-0.001	0.025	0.574	-0.025	0.069*
		(0.027)	(0.027)		(0.036)	(0.036)
		[0.946]	[0.656]		[0.586]	[0.159]

Table: Employment outcomes

Outcome	Control mean (1)	Transport (2)	Workshop (3)	Control mean (4)	Transport (5)	Workshop (6)
	2015			2018		
Work	0.562	0.041 (0.029) [0.397]	0.021 (0.031) [0.666]	0.693	-0.063* (0.034) [0.305]	0.027 (0.031) [1.000]
Hours worked	26.18	0.268 (1.586) [0.946]	-0.254 (1.562) [1.000]	28.26	-2.636* (1.486) [0.305]	0.144 (1.404) [1.000]
Monthly earnings	1,145.0	4.8 (75.5) [0.946]	71.4 (83.9) [0.656]	1,533.7	27.1 (100.3) [0.715]	308.8** (123.4) [0.087]
Permanent job	0.171	0.029 (0.018) [0.392]	0.065*** (0.020) [0.008]	0.307	-0.038 (0.025) [0.305]	-0.011 (0.028) [1.000]
Formal job	0.224	0.054*** (0.019) [0.033]	0.051** (0.020) [0.029]	0.319	-0.006 (0.030) [0.715]	-0.006 (0.030) [1.000]
Job satisfaction	0.237	-0.001 (0.027) [0.946]	0.025 (0.027) [0.656]	0.574	-0.025 (0.036) [0.586]	0.069* (0.036) [0.159]

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Outcome	2015			2018		
	Control mean (1)	Transport (2)	Workshop (3)	Control mean (4)	Transport (5)	Workshop (6)
Work	0.562	0.041 (0.029) [0.397]	0.021 (0.031) [0.666]	0.693	-0.063* (0.034) [0.305]	0.027 (0.031) [1.000]
Hours worked	26.18	0.268 (1.586) [0.946]	-0.254 (1.562) [1.000]	28.26	-2.636* (1.486) [0.305]	0.144 (1.404) [1.000]
Monthly earnings	1,145.0	4.8 (75.5) [0.946]	71.4 (83.9) [0.656]	1,533.7	27.1 (100.3) [0.715]	308.8** (123.4) [0.087]
Permanent job	0.171	0.029 (0.018) [0.392]	0.065*** (0.020) [0.008]	0.307	-0.038 (0.025) [0.305]	-0.011 (0.028) [1.000]
Formal job	0.224	0.054*** (0.019) [0.033]	0.051** (0.020) [0.029]	0.319	-0.006 (0.030) [0.715]	-0.006 (0.030) [1.000]
Job satisfaction	0.237	-0.001 (0.027) [0.946]	0.025 (0.027) [0.656]	0.574	-0.025 (0.036) [0.586]	0.069* (0.036) [0.159]

Table: Employment outcomes

	2015			2018		
Outcome	Control mean (1)	Transport (2)	Workshop (3)	Control mean (4)	Transport (5)	Workshop (6)
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What about predictions 2-4?

1. Both intervention raise permanent employment rates. This effect is transitory.

2. This result is obtained through different mechanisms: the subsidy leads to more search and the workshop to more effective search.

3. The workshop increases match quality and wages. The transport does not. This effect is permanent.

4. The workshop has strongest impacts for the most disadvantaged workers.

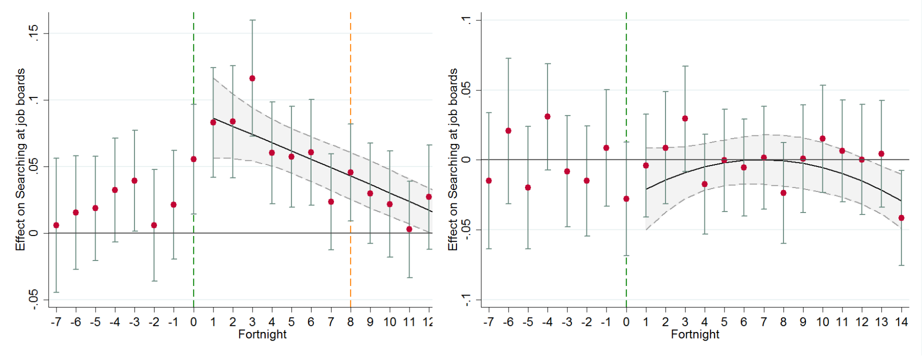
Prediction 2: we find impacts on search intensity and efficacy

They find that treated individuals:

1. search more intensely (only for the transport)
2. search more effectively

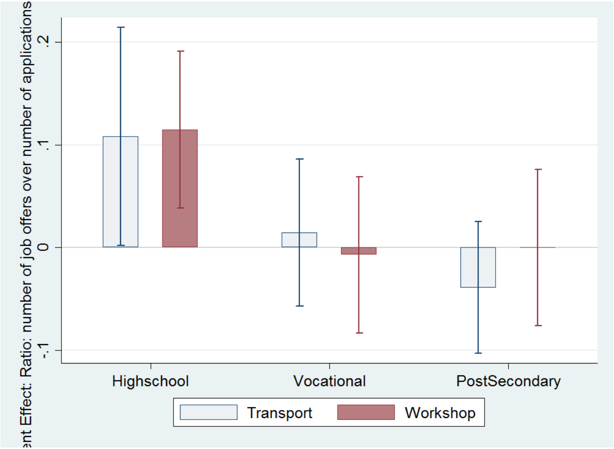
Also, evidence that effects of workshop are driven by higher return to skills.

Effects on **search at job boards**

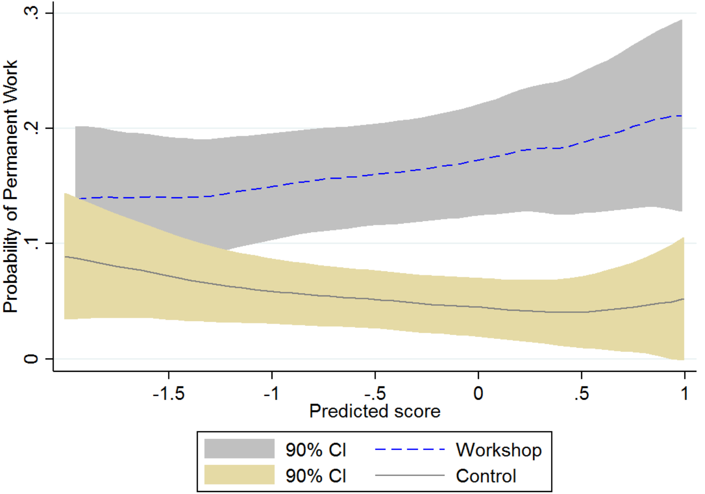


(a) Transport (b) Workshop

Endline effects on **search efficacy**: offers/applications



The workshop increases the returns to observable skills



Prediction 3: They find direct evidence of improved match quality

			ITT Estimates	
Outcome	Control mean	N	Transport Coeff	Workshop Coeff
Longest tenure (months)	11.845	1,739	0.294	1.197*
			(0.561)	(0.619)
Current job tenure (months)	21.326	1,383	0.199	-0.539
			(1.165)	(0.977)
Promoted in current job	0.190	1,383	0.022	0.006
			(0.025)	(0.023)
Uses skills in current job	0.323	2,016	0.032	0.082**
			(0.040)	(0.040)
Earnings conditional on working	2,209.3	1,383	195.0	370.4**
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Explaining the long-run earnings effect

They use *mediation analysis* to study whether the earning effects are indeed mediated by the gains in match quality.

They identify the 'average controlled direct effect' (Acharya et al. 2016) through sequential estimation:

$$ACDE(a; a'; m) = E[Y_i(a; m) - Y_i(a'; m)] \tag{1}$$

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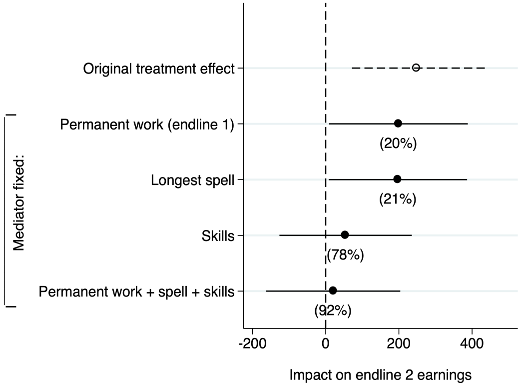
Most of the earning effect is mediated by match-quality proxies



Prediction 4: The workshop benefits the most disadvantaged

	Covariate = 0			Covariate = 1		
Baseline covariate	Control mean	Trans.	Works.	Control mean	Trans.	Works.
Tertiary Ed.n	826.4	15.1	470.9**	1,835.1	54.2	37.3
		(124.4)	(188.1)		(159.9)	(149.8)
		[1.000]	[0.034]		[1.000]	[0.993]
Male	1,181.9	-40.0	132.1	1,892.4	104.7	475.5*
		(110.0)	(116.4)		(179.3)	(245.1)
		[1.000]	[0.087]		[1.000]	[0.363]
Active searcher	1,442.2	3.1	351.9*	1,625.8	62.5	235.5
		(132.7)	(188.9)		(160.0)	(183.1)
		[1.000]	[0.050]		[1.000]	[0.663]
Ever perm. job	1,465.8	40.2	356.5***	1,975.7	-42.3	-288.7
		(104.7)	(136.7)		(367.8)	(350.3)
		[1.000]	[0.034]		[1.000]	[0.696]
Close to centre	1,468.8	41.8	406.2**	1,606.3	52.2	141.9
		(151.0)	(196.9)		(143.0)	(150.3)
		[1.000]	[0.042]		[1.000]	[0.696]
Pred. earnings	930.8	123.1	467.1***	2250.4	-226.4	-99.0
(above the median)		(115.5)	(170.3)		(227.8)	(224.1)

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→ Overall, the results are consistent with a simple framework focused on two frictions:

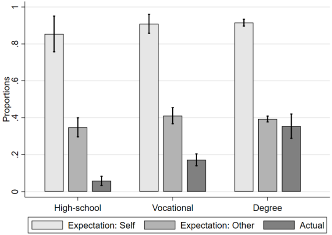
1. uncertainty about skills;
2. costly job search.

What about the impacts on the untreated?

Roadmap

Abebe et al 2024 show evidence of worker overconfidence

Figure 7: **Jobseekers' expectations of finding a job with a permanent contract in the next 12 months**



Note: 'Expectation: Self' refers to jobseekers' stated probabilities that they will be employed with a permanent contract in the next 12 months, as measured in our 2019 follow-up survey. 'Expectation: Other' refers to jobseekers' stated probabilities that others like them will be employed with a permanent contract in the next 12 months, as measured in our 2019 follow-up survey. 'Actual' refers to the actual proportion of jobseekers who found a job with a permanent contract, using our original survey data.

... but also of employer misperceptions

Appendix Figure B.2: **Distribution of employer beliefs by education**

PANEL A: BELIEFS ABOUT THE AVERAGE RAVEN'S TEST SCORE (LEFT: HIGH SCHOOL; RIGHT: TERTIARY)

Other papers with similar findings on the worker side:

- Banjeree and Sequiera
- Bassi et al
- Kiss et al.
- Alfonsi and Spaziani
- Chakravoty et al.

Roadmap

Descriptive evidence

The accumulation of human capital

Search and matching

Beliefs

Reading

- Bandiera et al. (2022). Economic Development and the Organisation Of Labour: Evidence from the Jobs of the World Project. Journal of the European Economic Association 20, no. 6 (2022): 2226-2270.

- Alfonsi et al 2020 Tackling youth unemployment: Evidence from a labor market experiment in Uganda. Econometrica 88, no. 6 (2020): 2369-2414.

- Abebe et al. 2021 Anonymity or distance? Job search and labour market exclusion in a growing African city. The Review of Economic Studies 88, no. 3 (2021): 1279-1310.