Development Economics 1

Lecture 4: Workers

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In yesterday's lecture we introduced a framework that suggests that matching efficiency and productivity can be two key levers to boost employment in LMICs.

We also looked at the emerging evidence on matching frictions.

Today, we will investigate whether labour market policy can boost productivity and raise employment.

We will focus in particular on interventions designed to increase productive skills.

A key distinction will be between general and specific skills:

- General skills re equally productive across employers
- Specific skills are mostly valuable with a specific employer

Roadmap

What are the returns to skills in LMICs?

Is the provision of skills inefficient?

Reading

A training experiment by Alfonsi et al 2020

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. VT likely to focus on general skills; FT on firm-specific skills (but not exclusively).
4. Three endline surveys (24, 36 and 48 months after treatment).

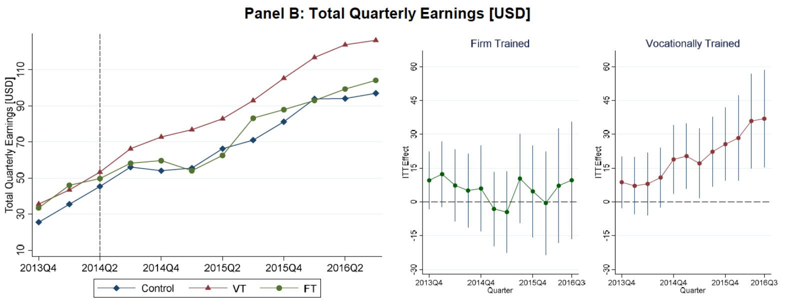
Strong impacts on employment of both VT and FT

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)

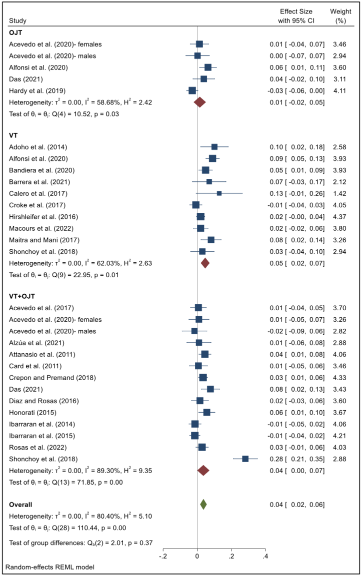
	Any paid work in the last month	Number of months worked in the last year	Hours worked in the last week	Total earnings in the last month [USD]	Labor market index	Worked in sector of training/matching in the last month
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Trained	.063	.518	-.196	1.89	.105	.045
	(.025)	(.259)	(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



Agarwal et al 2024 meta-analysis finds similar results

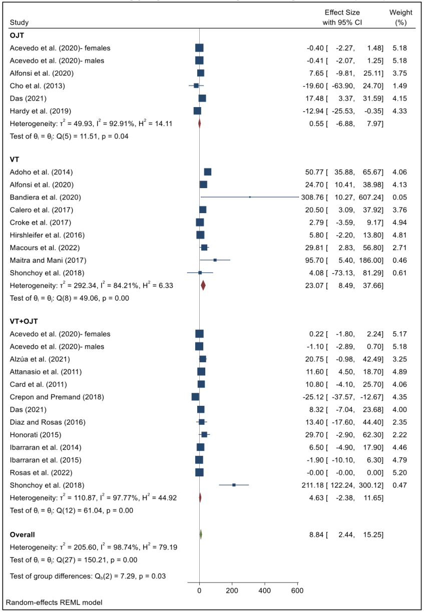
Figure 7: Effect of skills training program on employment including McKenzie (2017) studies



Notes: See notes in Figure 3 for studies reviewed in this article. For papers in our review, we use the latest follow-up for consistency with McKenzie (2017)'s approach. Diaz and Rosas (2016) have two estimates (administrative and survey data). We use the employed estimate from the survey data (they only have wage employed estimate from the administrative data).

VT increases earnings by approx 25 %

Figure 8: Effect of skills training program on earnings including McKenzie (2017) studies



Notes: See notes on Figure 5 for details on studies covered in this article. For papers from our review, we use the latest follow-up for consistency with McKenzie (2017)'s approach.

How much do these interventions cost? McKenzie 2017

Table 1: Summary of Vocational Training Program Impacts

Country	Study	Population	Sample Size	Attrition	Time Frame	Impacts on: Employment	Formal Employment	Earnings	Formal Earnings	Monthly income	Cost
Turkey	Hirshleifer et al. (2016)	Unemployed	5,902	6%	1 year	2.0	2.0	5.8	8.6	US$11.5	US$1700
						[−0.5, 4.4]	[−0.4, 4.4]	[−2.3, 13.8]	[−0.5,17.7]		
		Unemployed		0%	2.5 years	n.r	−0.1	n.r	−0.8	−US$3	
							[−3.3, 1.5]		[−7.9, 6.3]		
Argentina	Alzúa et al. (2016)	Low-income Youth	407	0%	18 months	n.r.	8.0	n.r.	64.9	US$83	US$1722
							[0.7, 15.3]		[17.1, 112.7]		
		Low-income Youth		0%	33 months	n.r.	4.3	n.r.	23.1	US$45	
							[−3.6, 12.1]		[−15.3, 61.5]		
Colombia	Attanasio et al. (2011)	Low-income Youth	4,350	18.5%	14 months	4.5	6.4	11.6	27.1	US$12.8	US$750
						[1.0, 8.0]	[3.2, 9.6]	[4.5, 18.7]	[12.8, 41.3]		
	Attanasio et al. (2017)	Low-income		0%	up to 10 years	n.r.	4.2	n.r.	13.6	US$17.7	
		Youth					[1.8, 6.6]		[5.5, 21.8]		
Dominican Republic	Card et al. (2011)	Low-income Youth	1,556	38%	12 months	0.7	2.2	10.8	n.r.	US$10	US$330
						[−4.6, 6.0]	[−2.3, 6.7]	[−4.2, 25.7]			
	Ibarrarán et al. (2014)	Low-income	5,000	20%	18 to 24 months	−1.3	1.8	6.5	n.r.	US$8.5	US$700
		Youth				[−4.8, 2.2]	[−0.3, 3.9]	[−4.8, 17.9]			
	Ibarrarán et al. (2015)	Low-income Youth	5,000	34%	6 years	−1.4	2.6	−1.9	n.r.	−US$2.3	US$700
						[−4.4, 1.6]	[−0.5, 5.5]	[−10.0,6.3]			
	Acevedo et al. (2017)	Low-income Youth	2,779	17.6%	3 years	0.7	n.r.	n.r. (a)	n.r.	n.r.	n.r.
						[−4.0, 5.3]					
India	Maitra and Mani (2017)	Low income Women	658	25%	18 months	8.1	n.r.	95.7	n.r.	US$7.2	US$39
						[2.2, 14.0]		[5.6, 186.0]			
Kenya	Honorati (2015)	Low-income Youth	2,100	23%	14 months	5.6	n.r	29.7	n.r.	US$47.5	US$1150
						[0.9, 10.3]		[−2.9, 62.3]			

A job-ladder model to understand the persistence of VT effects

- Workers have treatment status T and general human capital ϵ, which can be increased by T.
- Jobs pay $w = r * \epsilon$, with r drawn from $F(r)$ (wage-posting)
- When unemployed, job opportunities arrive at rate λ_0 (random search)
- When employed, job opportunities arrive at rate λ_1 (on-the-job search)
- Jobs are destroyed at rate δ
- Interest/discount rate ρ
- Model is entirely partial equilibrium (firms play no role)

The value functions

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

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

U (V) is the value of unemployment (employment). $R(\epsilon, T)$ is the reservation wage. $F(r)$ has maximum $\bar{r}$

Identification I

Need to estimate ϵ, λ_0, λ_1, δ, $F(r)$

Allow separate values for (i) control, (ii) FT compliers, (iii) FT non-compliers, (iv) VT compliers, (v) VT non compliers.

Assume $\epsilon = s^{\alpha}$

They observe s (a sector-specific skill score) for every individual at endline.

α can be recovered by estimating:

$$ln(w_{ij}) = \gamma_0 + \alpha ln(s_i) + \sum_k \gamma_k T_{ik} + u_{oj} \tag{1}$$

Then recover $\hat{r}_{ij} = w_{ij}/s_i^{\hat{\alpha}}$ and $F(r)$ (using a condition that relates $G(r|\epsilon)$ to $F(r)$) .

Identification II

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)

Panel A: Parameter Estimates (Monthly)	Control	Non-Compliers: Firm Trained	Non-Compliers: Vocationally Trained	Compliers: Firm Trained	Compliers: 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 there are positive returns, why are people not investing in these skills themselves?

New Bangladesh experiment by Bandiera et al.: take-up highly price sensitive

Table: Treatment Effects on Training Enrollment and Completion by Price

	Enrolled (1)	Completed (2)
Full price	0.021	0.017
	(0.015)	(0.012)
Discount 30pct	0.051***	0.041***
	(0.014)	(0.010)
Discount 70pct	0.124***	0.113***
	(0.014)	(0.013)
Pay if employed	0.198***	0.133***
	(0.015)	(0.012)
p-value for equality of treatment effects:		
	0.000	0.000
Control mean	0.000	0.000
Observations	8,932	8,932
R-squared	0.106	0.081

Standard errors are clustered by branch-trade. The dependent variables are indicators for enrolment in training (column 1) and training completion (2).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

New Bangladesh experiment by Bandiera et al.: returns at lower prices... are low

Table: Treatment Effects by Price

	Employed (1)	Work hrs (2)	Earnings (3)
Full price	0.031	2.084***	525.131**
	(0.020)	(0.717)	(224.802)
Discount 30pct	-0.015	0.564	43.397
	(0.022)	(0.810)	(196.833)
Discount 70pct	0.014	0.986*	164.240
	(0.013)	(0.587)	(170.314)
Pay if employed	-0.016	-0.717	-394.412**
	(0.017)	(0.677)	(174.890)
p-value for equality of treatment effects:			
	0.071	0.003	0.001
Endline control means by treatment:			
Full price	0.376	10.500	2711.955
Discount 30pct	0.409	13.238	3735.820
Discount 70pct	0.290	8.549	2156.150
Pay if employed	0.337	8.765	2202.736
Observations	6,802	6,802	6,802
R-squared	0.068	0.089	0.122

Standard errors are clustered by branch-trade. The dependent variables are an indicator for whether the respondent is currently employed in a salary/wage-based job (column 1), average weekly work hours over the past year (2) and average monthly earnings over the past year (3).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Roadmap

What are the returns to skills in LMICs?

Is the provision of skills inefficient?

Reading

A simple model by Acemoglu and Pischke (1999).

- Worker hired at time 0. General-skills training τ happens at time 0.
- At time 1, worker produces $f(\tau)$.
- Training costs $c(\tau)$.
- The wage at time 1 is $w(\tau)$.

- Perfect competition: $w(\tau) = f(\tau)$

$\rightarrow$ The firm will not pay for training as it will not be able to recoup the investment.

$\rightarrow$ The worker will choose tau^*, but may be credit-constrained.

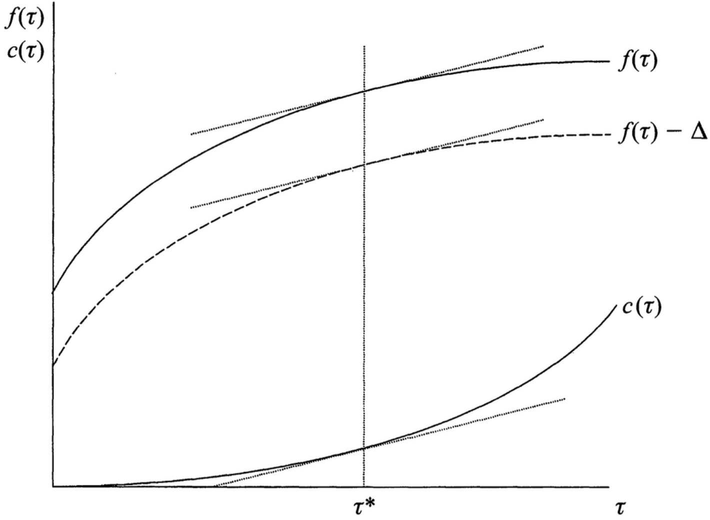


Fig. 1. *Training in Competitive Markets*

Imperfect competition makes firm-sponsored training possible

Two new features:

- Wages are below marginal product (firms have some monopsony power);
- Wage compression: $f(\tau) - w(\tau)$ grows with τ.

$\rightarrow$ The firm can recoup the initial investment in training.

$\rightarrow$ The firm increases its profits by providing training.

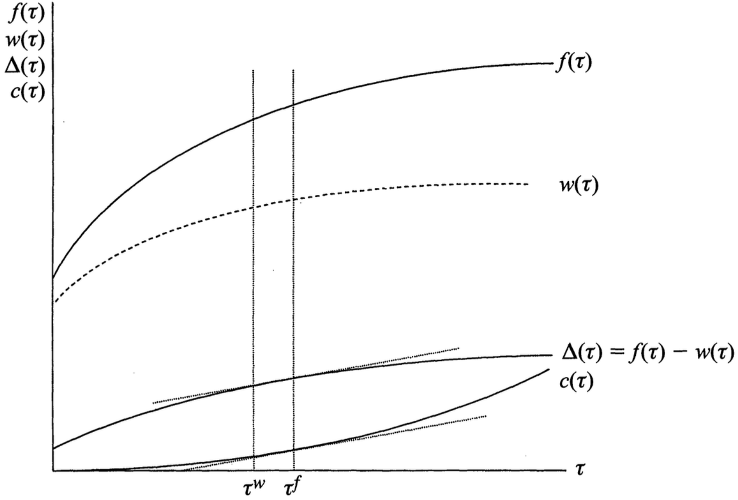


Fig. 2. *Training with a Compressed Wage Structure*

Abebe et al. 2025 study how turnover risk affects the demand for management training

We invite firms to send their *middle managers* to attend a management training program at AA School of Commerce.

We offer two types of incentives:

- A bonus for the middle manager: 1 month of pay after 12 months and 2 months of pay after 24 months;
- A subsidy of the cost of the training.

Firms (top managers) are then invited to apply for the program by nominating up to two middle managers.

We vary bonus conditionality to reduce expected turnover

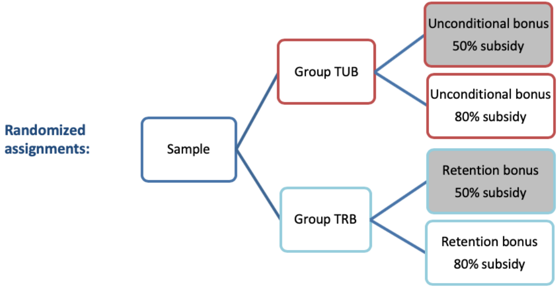
We vary the conditionality of the bonus:

- The *retention bonus* is conditional on staying at the firm;
- The *unconditional bonus* is not conditional on retention.

$\rightarrow$ Retention bonus designed to reduce expected turnover.

We also vary the amount of the subsidy: 50% or 80%.

We cross-cut the two interventions



Balance

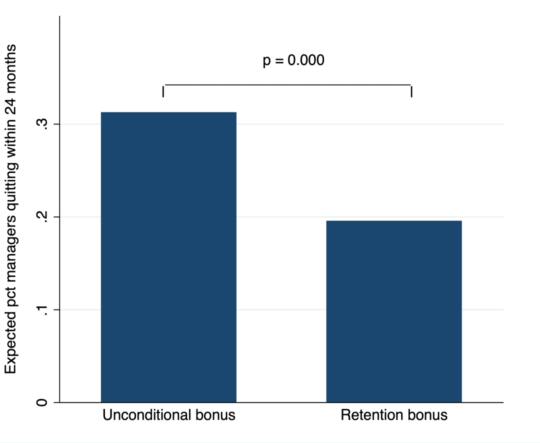
Examples of courses (cost is between 20 and 40 percent of monthly wage)

Logistics and Supply Chain Management Program Unit

ST-LSCM-01	Advanced Procurement Management	60 Hours
ST-LSCM-02	Inventory Management	40 Hours
ST-LSCM-03	Negotiation and Contract Management	40 Hours
ST-LSCM-04	Public Procurement	40 Hours
ST-LSCM-05	Operations Systems Change (Kaizen, BPR, TQM)	40 Hours
ST-LSCM-06	Import and Export Procedures	40 Hours
ST-LSCM-07	Office Kaizen	40 Hours
ST-LSCM-08	Value Chain Management	40 Hours
ST-LSCM-09	Global Supply Chain Management	40 Hours
ST-LSCM-10	Foreign Procurement	32 Hours
ST-LSCM-11	Disaster Relief Operations Management	32 Hours
ST-LSCM-12	Warehouse/Stores Management	40 Hours
ST-LSCM-13	Transport/Fleet Management	40 Hours
ST-LSCM-14	Customs Procedure	40 Hours
ST-LSCM-15	Property Management	40 Hours

Findings: The retention bonus reduces expected turnover

Figure: Expected turnover decreases by 1/3



But it does not affect demand for training

	Dep var: Application	
	(1)	(2)
Retention bonus	-.025 (0.028)	-.019 (0.040)
High subsidy	-.034 (0.029)	-.028 (0.041)
Retention bonus * high subsidy		-.011 (0.056)
Mean uncond. bonus, low subsidy	0.211	0.211
Obs.	598	598

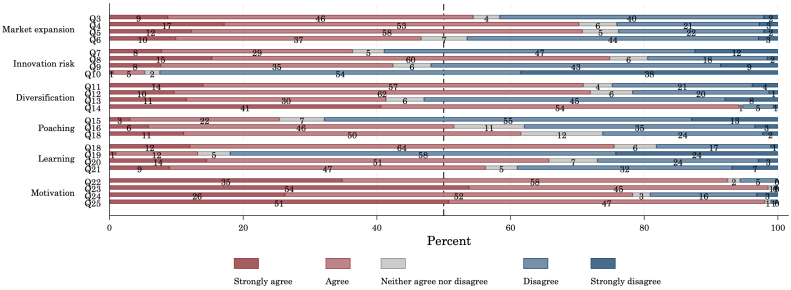
Are firms and/or workers simply uninterested?

- 88% of firms agree that 'This training will significantly increase this establishment's performance'.
- Firms estimate that the training program will increase market wages by 20 pct.
- Nominated managers do not take up the training, citing non-monetary costs as the main reason.

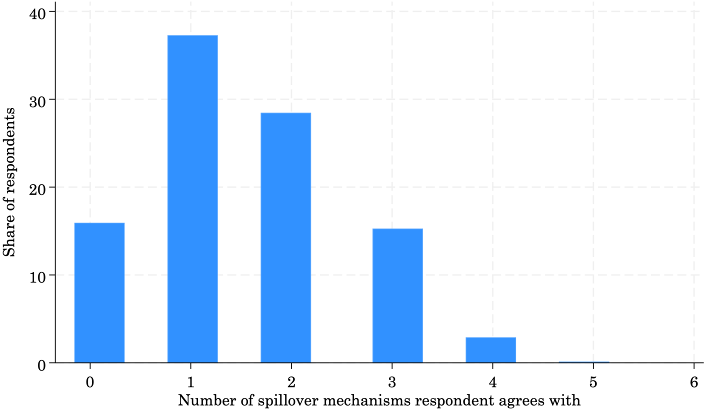
The positive spillover mental model

- We provide evidence that firms expect positive spillovers from competitors' adoption of new management practices.
- Under this mental model, poaching does not reduce (as much) the returns to training for the firm.
- Positive spillovers may arise from:
  - Direct observation
  - Poaching
  - Motivation contagion
  - Innovation risk (e.g. adoption of inferior practices)
  - Market expansion effects
  - Diversification

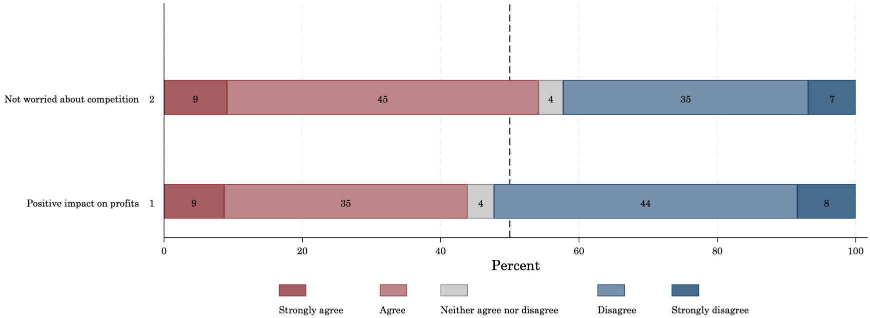
Direct evidence on the 6 mechanisms



85% of managers believe in at at least 1 mechanism



Almost 50% of managers believe competitors' upgrading will not affect their profits



Back

Mental models elicitation with DAGs

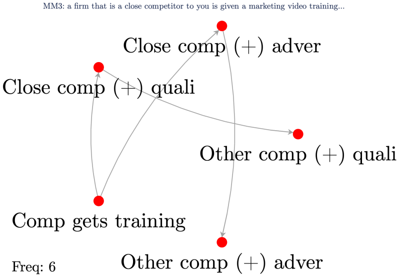
Mental models can be captured by *Directed Acyclical Graphs*.

- Nodes represent random variables.
- Directed links represent causal relations.

Many applications in philosophy, psychology, economics: Pearl 2000, Sloman 2005, Eliaz Spiegler 2020, Andre et al. 2022.

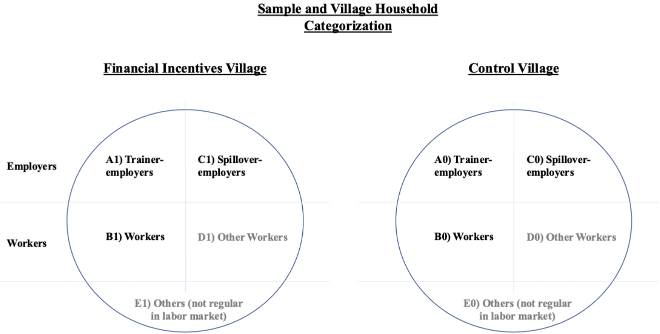
$\rightarrow$ We develop a simple app to have respondents sketch their own DAGs.

The most common DAGs: firms expect the training to affect quality and advertisement



Recent evidence from Cefala et al 2025 gives more support to the theory in a rural setting

(b) Categorization of village households



Results show evidence of imperfect appropriability

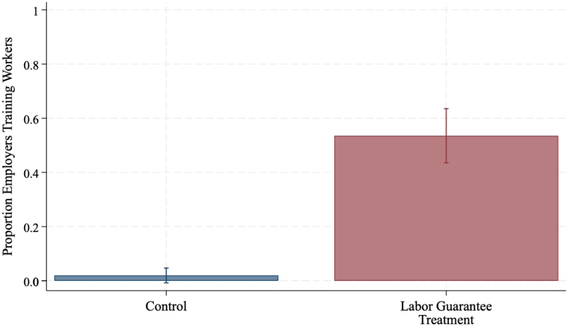
Table 5: Spillover Experiment: Hiring and technology adoption among spillover-employers

	Hiring (Any Worker)		Own Farm Adoption		
	Hired for Row Planting		At Least One Field	Bean Fields	All Fields
	(1)	(2)	(3)	(4)	(5)
Financial Incentives Treatment	1.31	3.04	0.10	0.13	0.09
	(0.32)	(1.17)	(0.03)	(0.03)	(0.02)
	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Dependent Variable Unit	Days	Days per ha	Binary	Share	Share
Control mean	2.14	6.34	0.76	0.40	0.29
Obs.	1466	1466	1466	1459	1465

Notes: This table shows the effect of living in a Financial Incentives village on spillover-employers' hiring of workers for different agricultural work during the planting season and spillover-employers' adoption of row planting on their farm fields. The sample is comprised of spillover-employers — employers in villages who in all treatment conditions were uninvolved in the village training event. The dependent variable in column 1 is the number of days spillover-employers hired any casual worker to do row planting or microdosage on their fields. The dependent variable in column 2 is the number of days per hectare spillover-employers hired any casual worker to do row planting or microdosage on their fields. The dependent variable in column 3 is an indicator variable for whether the employer used row planting and fertilizer microdosage on at least one of their farm fields. The dependent variable in column 4 is the share of bean fields that employers' row planted and used fertilizer microdosage on. The dependent variable in column 5 is the share of all fields (regardless of crop planted) that employers' row planted and used fertilizer microdosage on. Intent to treat estimates are shown. Standard errors are in parentheses and p-values are in brackets. Standard errors are clustered at the village level.

And that providing a job guarantee increases training

Figure 9: Labor Guarantee Experiment: Impact of the labor guarantee on trainer-employers' willingness to train



Roadmap

What are the returns to skills in LMICs?

Is the provision of skills inefficient?

Reading

(*) Acemoglu and Pischke (1999). ”Beyond Becker: Training in imperfect labour markets.” The Economic Journal 109, no. 453 (1999): 112-142.
Sections 2 and 3

(*) 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. 2025. Competition and Management Upgrading: Experimental Evidence from Ethiopia. No. w33886. NBER Working Paper, 2025.

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Agarwal et al 2024 . ”New evidence on vocational and apprenticeship training programs in developing countries.” In Handbook of Experimental Development Economics.