

Meet Your Future

Experimental Evidence on the Labor Market Effects of Mentors

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Africa Youth Un(der)employment Challenge

- ▶ 420 million young people in Africa today
- ▶ 140 million are unemployed; 130 million are underemployed [[AfDB 2018](#)]
- ▶ Consequences for well-being of millions, countries' economic growth and world-wide development

Supply-Side Information Frictions are Relevant in Low-Income Settings

- ▶ How to find out about vacancies [Jensen 2012; Beam 2016; Groh et al. 2016; Abel et al. 2019; Abebe et al. 2021; Bandiera et al. 2022]
- ▶ Search process [Abebe et al. 2021; Carranza et al. 2021; Bassi and Nasamba 2021]
- ▶ Overly optimistic beliefs about their labor market prospects [Spinnewijn 2015; Mueller et al. 2021, Potter 2021; Abebe et al. 2021; Banerjee and Sequeira 2021; Bandiera et al. 2022]

Meet Your Future: Tailored, Relevant, Credible, and Low-Cost Information

Research Question: Can connecting young jobseekers with experienced workers improve their labor market trajectories?

Methodology: Experimentally generate mentorship relationships between skilled youth and successful workers in their sector of training

Data: 6 survey rounds spanning 3 years and audio recordings of the mentoring sessions

Main Findings: The program improved participants career trajectories

- ✗ Not via job referrals nor by building search capital
- ✓ Via info that corrects overoptimism and raises perceived returns to experience

Policy: Cost effective and scalable program with an estimated IRR of 300%

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Setting and Experimental Design

Ugandan Urban Labor Markets

5 Vocational Training Institutes

- ▶ Post-secondary 2-year course in one of 13 occupations [▶ Relevance](#)
- ▶ Common tool used to upskill youth [\[Alfonsi et al. 2020\]](#)

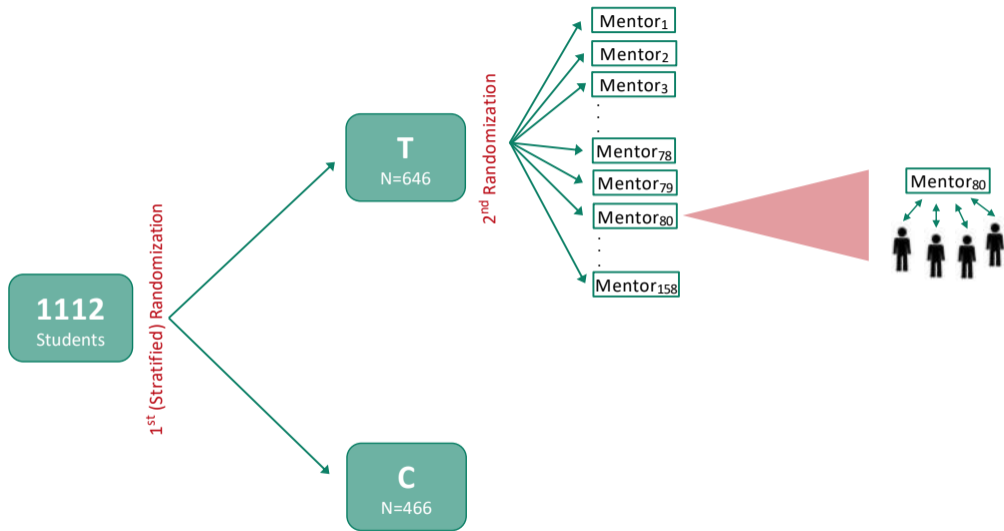
1112 Students

- ▶ 20 years old on average
- ▶ Pervasive overoptimism about entry wages and poor knowledge of wage dynamics [▶ Details](#)

158 Mentors

- ▶ 25 years old on average
- ▶ Successful alumni of the same VTIs and courses [▶ Digitization](#) [▶ Selection](#)

Experimental Design



- ▶ Stratification
- ▶ PAP
- ▶ 12\$
- ▶ Timeline

Impacts on Labor Market Outcomes

In the Short Run Treated Students Work More While Earning the Same

$$Y_{i,s,t} = \beta_0 + \beta_1 T_i + X_i' \delta + \lambda_s + \epsilon_{i,s,t}$$

	Out of the Labor Force (1)	Days Worked Last Month (2)	Hours Practicing Technical Skills (3)	Total Earnings Last Month (4)	First Job Duration (5)
MYF Treatment	-.057*** (.019) [.003]	1.267** (.540) [.010]	17.234*** (5.041) [.002]	1.900 (2.081) [.078]	18.469*** (5.150) [.002]
Control Mean	.21	16.15	52.15	11.35	81.18
Treatment Effect (%)	-26.57	7.85	33.05	16.73	22.75
N	934	934	838	933	833

Notes: ITT estimates: OLS coefficients, clustered se in parentheses.

- ▶ At 3 months treated students are 27% less likely be out of the labor force, work more and spend more time practicing technical skills
- ▶ No differences in earnings nor job quality
- ▶ Initial matches are more stable

Labor Market Trajectories Get Steeper in the Medium Run

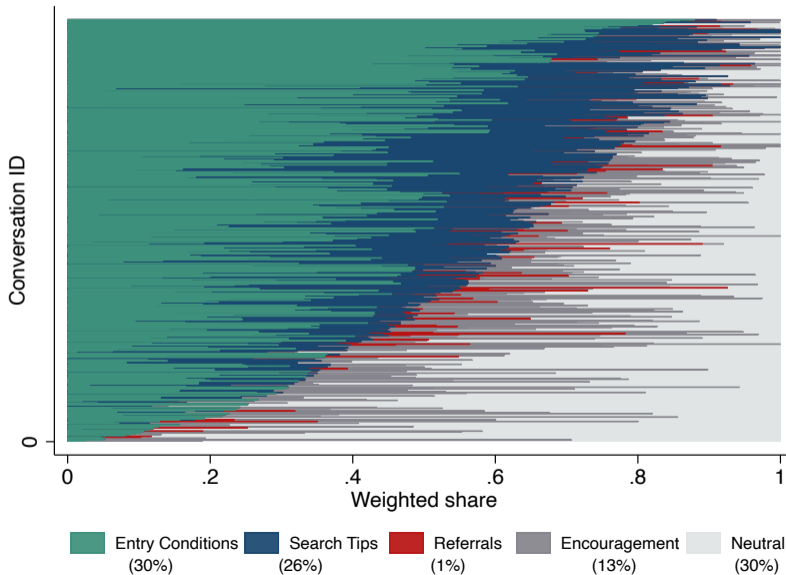
	Transitions		Medium Run	
	Internship to Job Transition Within Firm (1)	Internship to Job Transition Between Firms (2)	Out of the Labor Force (3)	Total Earnings Last Month (USD) (4)
MYF Treatment	.041** (.019)	.076** (.033)	-.025 (.022)	6.149* (3.601)
Control Mean	.18	.37	.26	34.84
Treatment Effect (%)	22.87	20.70	-9.46	17.65
N	934	934	916	916

Notes: ITT estimates: OLS coefficients, clustered se in parentheses.

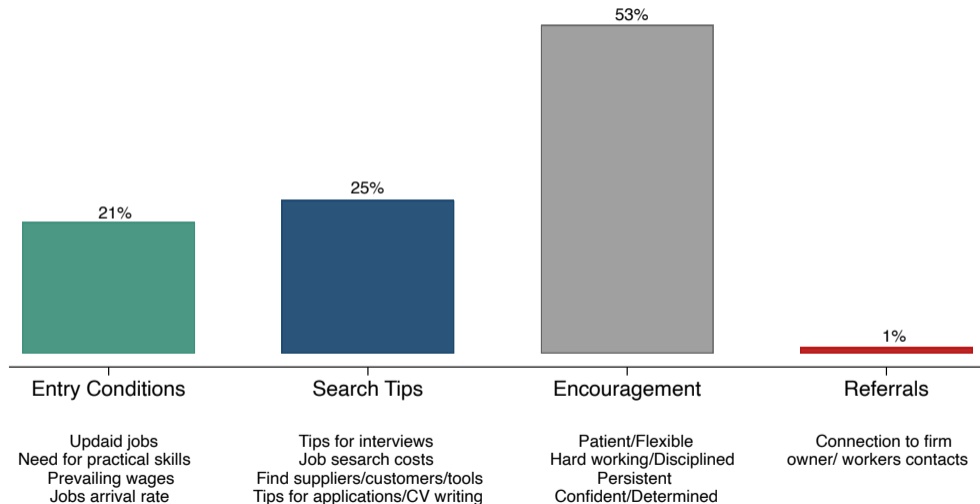
- ▶ More stable matches set them on a steeper job ladder
- ▶ 1 year later, treated students earn 18% more ▶ QTEs ▶ Cumulative earnings

Mechanisms

Conversation Content: Info on Entry Conditions, Few Job Referrals



Students Main Takeaway



Combining Direct Measures of Intermediate Outcomes with a Mentor IV Design We Find:

- ▶ **Job Referrals** ✗ → 7.4% received or were offered a referral
→ 2.6% found job via mentor, results hold without them
- ▶ **Search Tips** ✗ → Treated students are not better at searching
- ▶ **Entry Conditions** ✓ → Reservation wages down by 30%
→ 13% higher willingness to accept an unpaid job
→ Reject 27% fewer job offers
→ Results driven by the most optimistic
- ▶ **Encouragement** ✓ → More likely to start job search
→ Less likely to get discouraged and drop out of labor force
→ Mentors giving encouragement drive medium run results

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Conclusions

- ▶ A mentorship program able to provide credible and relevant information to young job seekers improves employment outcomes, career trajectories, and education-career synergies
- ▶ Not by changing the fundamentals of the search problem, rather, the way young and overly optimistic jobseekers perceive it
- ▶ Our findings highlight:
 - ▶ Role of distorted beliefs as an important channel by which info frictions decrease earnings and career advancement
 - ▶ Importance of balancing bad news with hope for better future outcomes to prevent *discouragement*, dropout and human capital wastage

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Additional Slides

Job Search Behavior and Reservation Wages

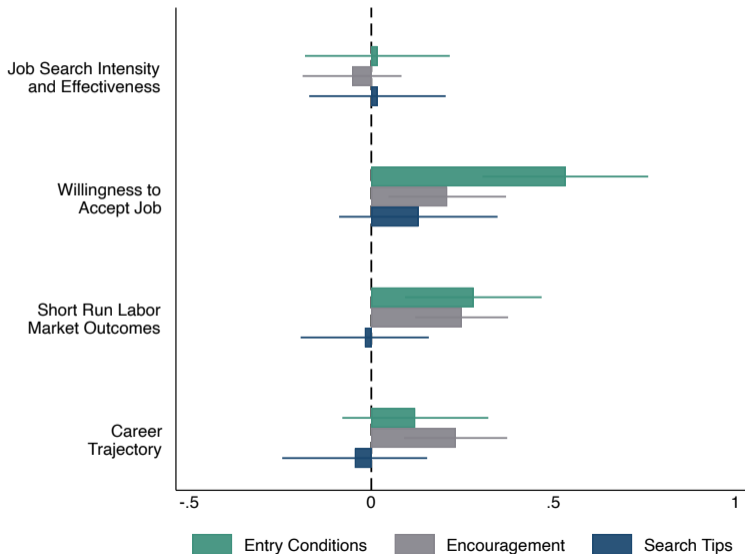
	Willingness to Accept a Job			Job Search		Search Duration	
	Reservation Wage (1)	Would Accept Unpaid Job (2)	Refused Job Offer Searched (3)	Search Efficacy Index (4)	Search Intensity Index (5)	Started Job Search (6)	Search Duration Searched (7)
MYF Treatment	-11.581*** (3.357) [.004]	.071** (.031) [.052]	-.057** (.026) [.052]	-.056 (.059) [.128]	.018 (.068) [.293]	.029** (.014) [.052]	-8.525** (4.053) [.052]
Control Mean	36.76	.54	.21	.04	-.01	.93	28.28
Treatment Effect (%)	-31.50	13.09	-27.24	-157.94	-161.15	3.10	-30.14
N	737	739	745	934	934	934	885

- ▶ Treated students revise their reservation wages down by 30%, are more willing to accept an unpaid job and reject fewer job offers [▶ Pathways analysis](#)
- ▶ They search for a shorter time. However, they are neither better at searching nor search more intensively
- ▶ Results are driven by the over-optimistic students [▶ Het](#)

Learning How Each Topic of Conversation Affects Outcomes

- ▶ **Goal:** $Y_i = \beta_0 + \beta_1 \text{Info}_i + \beta_2 \text{Enc}_i + \beta_3 \text{Search}_i + X_i' \delta + \epsilon_i$
- ▶ **Identification issue:** Non guided conversations
- ▶ **Solution:** Leverage the second randomization and instrument the conversation content with 158 mentor indicators
- ▶ **Assumptions:** Relevance; Exclusion Restriction

Mentors Providing Entry Conditions Info and Encouragement Drive Results

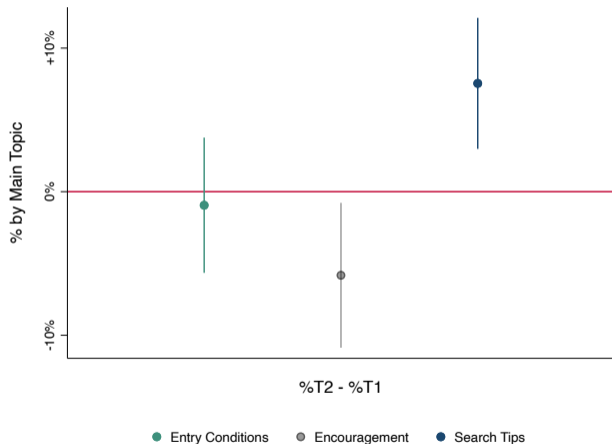


▶ Table

▶ Mentors matter

▶ Demographics

Cash Makes the Mentors Give More Actionable Search Tips Crowding Out Encouragement



- ▶ Students who received the cash transfer received less encouragement and more actionable search tips

An Ineffective Cash Transfer

	Transitions		Medium Run	
	Retained post Internship (1)	Internship to Job Transition (2)	Out of the Labor Force at 1 Year (3)	Total Earnings Last Month at 1 Year (4)
T1 (MYF)	.06** (.02)	.11** (.04)	-.06* (.03)	10.84** (4.19)
T2 (MYF+Cash)	.02 (.03)	.01 (.04)	.01 (.03)	1.95 (3.80)
Control Mean	.18	.41	.26	34.84
T1 Effect (%)	32.69	27.38	-22.77	31.10
T2 Effect (%)	13.57	3.10	2.45	5.61
N	934	844	916	916
T1=T2	0.28	0.08	0.12	0.02

- ▶ The cash transfer had no differential impacts in the short run but attenuated the effects at 1 year

Conclusions

- ▶ Connecting young jobseekers with experienced workers is effective at improving labor market outcomes
- ▶ Not by changing the fundamentals of the search problem, rather, the way it is perceived
- ▶ MYF is a cost effective and scalable program with an estimated IRR of 300%

Next: Why are young jobseekers overly optimistic?

MYF Dream Team

Research Assistants

- ★ Pedro De Souza Ferreira
- ★ Ottavia Anna Veroux

URAP students

- ★ Elena Kiryakova
- ★ Yash Dave
- ★ Hao Wang

Interns

- ★ Nicola Lipari
- ★ Cristina Perricone
- ★ Matteo Giugovaz
- ★ Marco Vicini
- ★ Elvin Bora
- ★ Yannik Stuka
- ★ Matilde Casamonti
- ★ Carmelita Gatto
- ★ Paola Giannattasio

Enumerators

- ★ Sylvia Ssenyonjo
- ★ Lillian Ahirwe
- ★ Christine Akumu
- ★ Mariam Nakaziba
- ★ Elisabeth Nassuna
- ★ Benedict Kole
- ★ Caroline Busingye
- ★ Jackson Nsibo
- ★ Vivian Nshemerirwe
- ★ Moreen Mugaba
- ★ Winnifred Nabukeera
- ★ Nanziri Juliet
- ★ Nyakato Brenda

Funders: IDRC via CEGA, J-PAL PPE, G²LIC|IZA, CAS & IRLE @UCB

Thank you!

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APPENDIX

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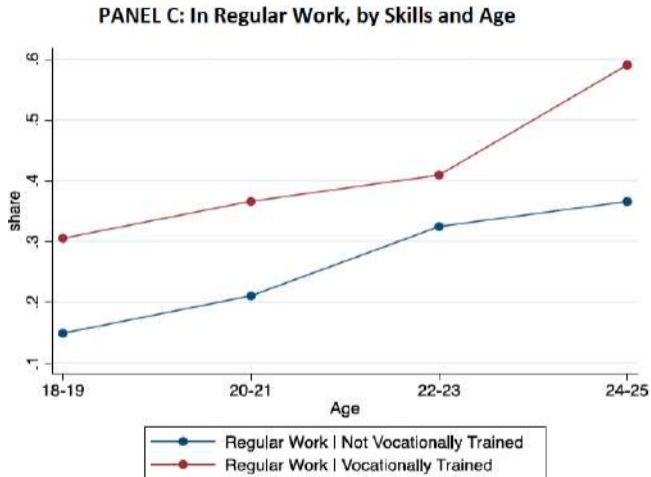
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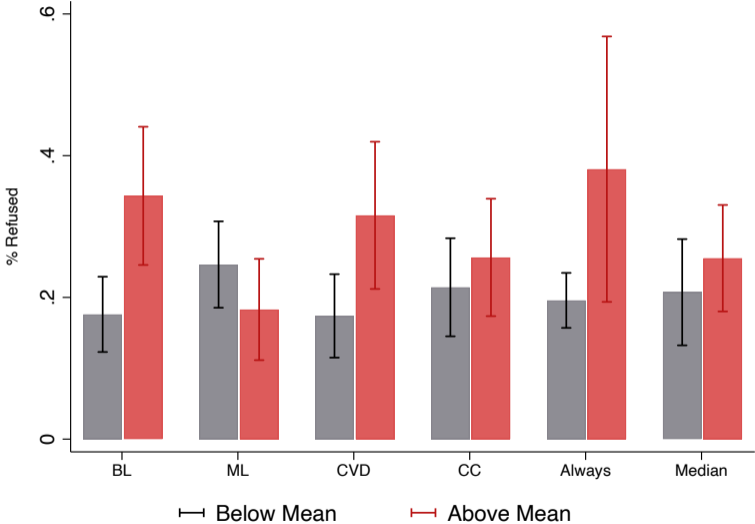
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Jobs and Skills by Age



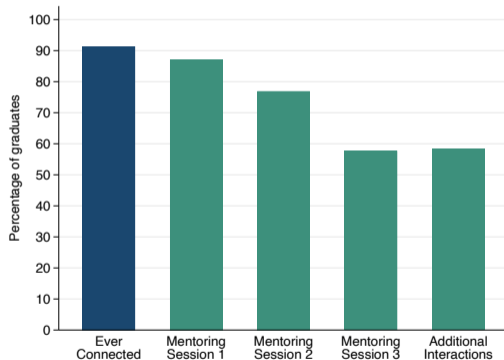
Source: [Bandiera et al. 2022](#)

Optimism Leads to More Refusals



High Take-Up and Engagement with the Program

- ▶ Treatment take up: 91%
- ▶ Average # interactions: 6.8
- ▶ Average total interaction time = 3.2h
- ▶ More interactions among mentor-mentees closer in age and from same VTIs



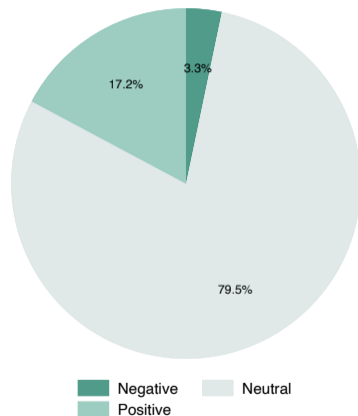
▶ Details

◀ Back

High Take-Up and Students Engagement with the Program

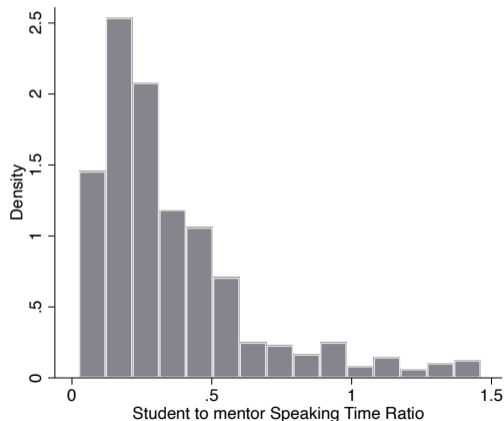
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- ▶ High satisfaction, identification and transportation across all student-mentor pairs confirm with the text data
- ▶ Neutral or positive sentiment

▶ Details



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- ▶ Neutral or positive sentiment
- ▶ Conversations led by the mentors but engaged students



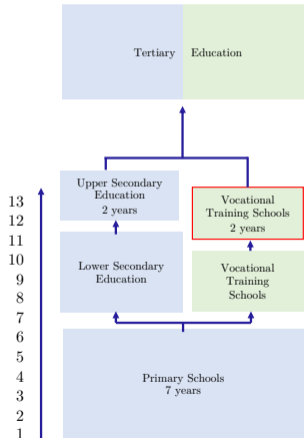
Setting

History of the VTI Industry in Uganda

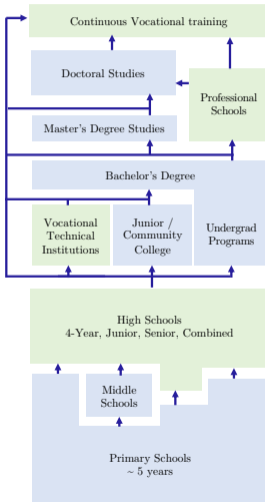
- ▶ Renewed awareness of vocational education critical role in national development
- ▶ After decades of alienation (colonial and post-colonial education policies did not prioritize productive skills acquisition)
- ▶ The Ugandan VTI system traces back to the 1940's when WWII camps were converted to re-train demobilized soldiers and youth to attain skills for survival
- ▶ In 1968 the Government came up with a strategy of strengthening vocational training schemes
- ▶ The idea did not take off for another 36 years when Uganda's Parliament enacted a much broader and decisive legal framework under the BTVET Act in 2008
- ▶ Determination of: institutional and legal regime, scope and levels of different programmes, the roles of different providers, the establishment of the Uganda Business and Technical Examinations Board

Comparing Education Systems: Uganda, US, Germany

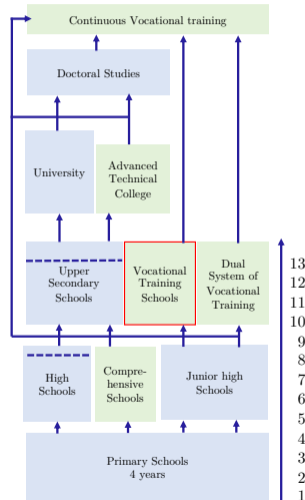
Ugandan Educational System



US Educational System



German Educational System

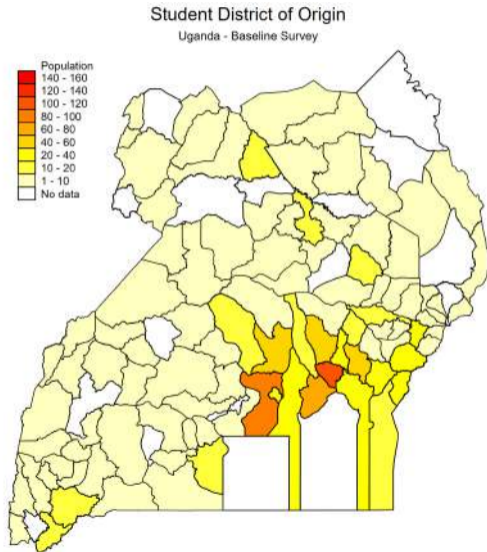


Locations - Students

◀ Back

▶ Location of Origin

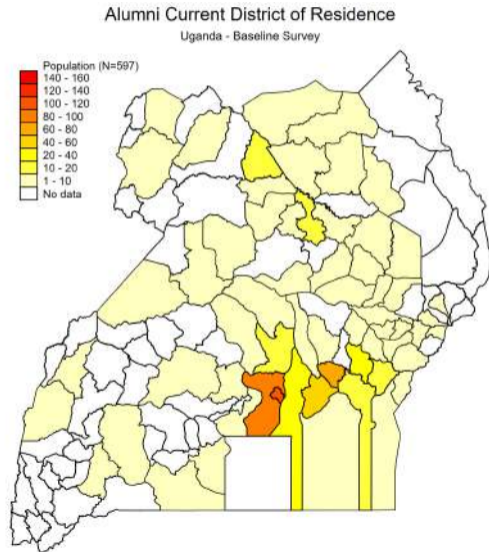
- ▶ 84% comes from Central or Eastern Uganda
- ▶ 56% comes from a rural area (far from town)
- ▶ 72% have either Kampala or Jinja as preferred location where to search (94% if we consider up to the third preference)



Locations - Alumni

◀ Back

- ▶ Location of Current Work (pre-Covid)
 - ▶ 87% work in Central or Eastern Uganda
 - ▶ 64% work in Kampala or Jinja metropolitan area



Sector Relevance and Gender Composition Nationwide

	(1)	(2)	(3)	(4)	(5)	(6)
	Young Adults UNHS			VTI Graduates UNHS		
	% All	% Female	% Male	% All	% Female	% Male
Food and hospitality	0.044	0.524	0.476	0.049	0.349	0.651
Tailoring	0.006	0.600	0.400	0.006	0.794	0.206
Electrical work	0.001	0.115	0.885	0.006	0.218	0.782
Motor-mechanics	0.011	0.072	0.928	0.016	0.041	0.959
Construction	0.037	0.004	0.996	0.035	0.016	0.984
Plumbing	0.001	0.000	1.000	0.003	0.000	1.000
Secretary and accounting	0.006	0.408	0.592	0.011	0.591	0.409
Teaching (pre-primary and primary)	0.024	0.470	0.530	0.171	0.495	0.505
Hairdressing	0.013	0.425	0.575	0.019	0.593	0.407
Machining and fitting	0.006	0.034	0.966	0.012	0.000	1.000
Retail	0.137	0.441	0.559	0.133	0.637	0.363
Agriculture	0.528	0.444	0.556	0.158	0.320	0.680
Other unskilled	0.099	0.153	0.847	0.141	0.204	0.796
Other skilled	0.086	0.270	0.730	0.240	0.380	0.620

Available Data - Students

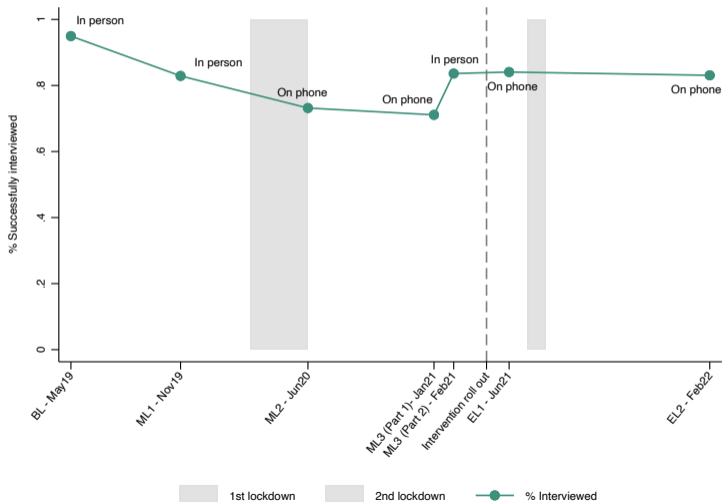
- ▶ Baseline
 - ▶ Demographics; Savings; Employment Network (4 people); Planned job search strategy; Labor market expectations; Raven's
- ▶ Midline
 - ▶ Planned job search strategy; Labor market expectations; Employment Network (+4 people); Savings; Risk and time preferences
- ▶ CVD Survey
 - ▶ Labor market expectations; Employment network; Livelihood; Migration; Time use
- ▶ CC and CC2 Survey
 - ▶ Drop-out status and Labor market expectations
- ▶ Post Interaction Survey - *collected for treated students immediately following CS1*
 - ▶ Engagement in the conversation, topics of discussion, identification and connection with the alum, main take-always, plans for future interactions
- ▶ Endline 1 and Endline 2
 - ▶ Job search and Labor market outcomes. Content and frequency of additional interactions with alum.

Available Data - Alumni

- ▶ Baseline
 - ▶ Demographics; First and Current job; Soft skills; Availability for program
- ▶ Follow-up 1, 2 and 3
 - ▶ Labor market outcomes during and after the Covid-19 shock [different paper]
- ▶ MYF Check-in - *collected for the 158 alumni involved in MYF*
 - ▶ For each student the alum is asked about: his/her identification with each student and a ranking between the students, each student's employability one and three months after the program and a ranking, the student's interest in the program.

Experimental Design

Despite Covid-19 Attrition Rates Were Satisfactory



LOGBOOK of _____

KEY CALLS

STUDENTS' NAMES and PHONE NUMBERS	KEY CALL 1	KEY CALL 2			KEY CALL 3		
	Date (day and month)	Date (day and month)	Duration (in minutes)	Three main topics of conversation	Date (day and month)	Duration (in minutes)	Three main topics of conversation

Please, use this logbook to keep track of the day and time of each KEY CALL. For KEY CALL 2 and 3 keep track of the duration of the conversation and of the 3 main topics you have discussed with the student. Remember the enumerator will ask you to tell him/her about the information in this logbook. Please, write clearly.

Logbook, example

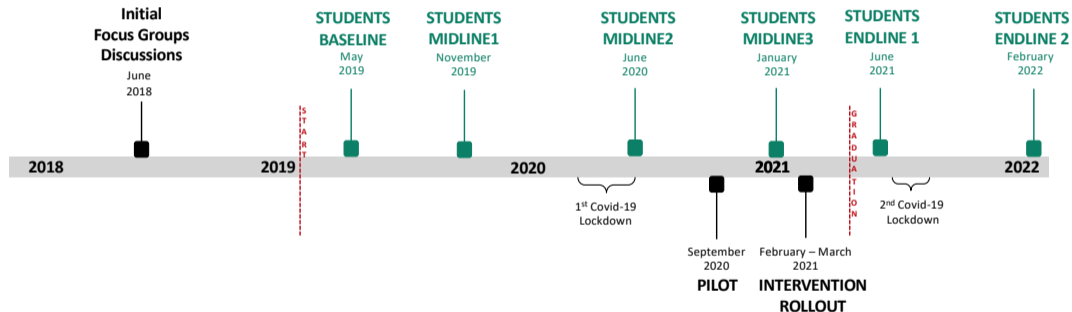
LOGBOOK of ASAPH MAKIKA

KEY CALLS

STUDENT'S NAME and PHONE NUMBERS	KEY CALL 1		KEY CALL 2			KEY CALL 3		
	Date (day and month) 2021	Date (day and month) 2021	Duration (in minutes)	Three main topics of conversation	Date (day and month) 2021	Duration (in minutes)	Three main topics of conversation	
BRIAN MWARITANA 0777 224 186	2/Feb 2021	2/March 2021	30	- How to go about studies - The Job market - Field and industrial training	15 th April 2021	11 mins	- Effective job search - Field & industrial training - General encouragement	
STEPHEN OSEGE 0775 049 987	9/Feb 2021	8/March 2021	15	- The Job market - How to find opportunities - Field & industrial training	7 th April 2021	Review	- Personal experience - Effective job search - The Labour Market	
BRETT IBRAHIM 0796 978 319 0701 723 716	10/Feb 2021	10/March 2021	25	- The Job world - General encouragement - Review Personal experience	13 th April 2021	10 mins	- The Labour Market - How to plan with savings - General encouragement	
AARON WATANGA 0784 850802 0457 916611	11/Feb 2021	5/March 2021	20	- Personal experience - Effective job search - General encouragement	14 th April 2021	10 mins	- The Labour Market - Possible opportunities - General encouragement	
NANDEGA HELEON 0786 4457407	2/March 2021	2	3	She repeated the discussion	—	—	—	

*Please, use this logbook to keep track of the day and time of each KEY CALL. For KEY CALL 2 and 3 keep track of the duration of the conversation and of the 3 main topics you have discussed with the student. Remember the enumerator will ask you to tell him/her about the information in this logbook. Please, write clearly.

Project Timeline, Data and Attrition



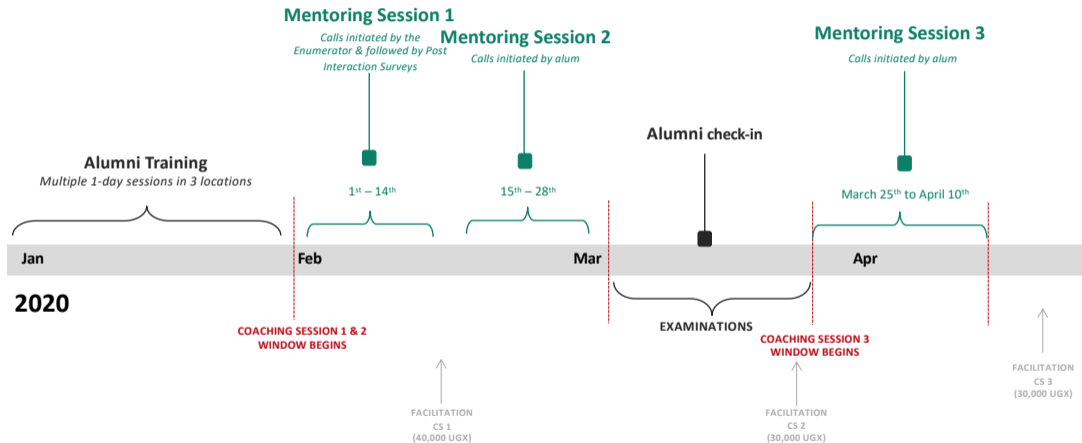
▶ Data: students

▶ Data: alumni

▶ Attrition

◀ Back

The MYF Program



The Mentors Training

- ▶ Mentors were guided through ways in which they could help the students by going through a long list of examples in each of the 4 categories
- ▶ They were explained the structure and admin of the program
- ▶ They were given logbooks and instructed on how to fill them
- ▶ Mentors are provided ~\$40 in three separate batches conditional on performing the three coaching sessions, as well as reimbursements of the airtime incurred to make the phone calls. The facilitation did not depend on students' success in the labor market

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The Mentors Training



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Alumni Sample Construction - Records digitization

A photograph of a handwritten ledger or record book. The page is titled "2012" at the top. It contains several columns of data, with many entries obscured by black redaction marks. The columns appear to contain names, dates, and other identifying information. The handwriting is in black ink on lined paper.

[← Back](#)

Mentors Selection

- ▶ Like most VTIs, none of our partners tracked their students' career developments or kept contact information
- ▶ We digitized schools' hard copies of registries containing contacts for the 2014-19 graduating cohorts
- ▶ We excluded 90 alumni that did not provide availability or never worked in the occupation of training
- ▶ We interviewed the rest of them (twice) and assigned scores to: (i) accessibility, (ii) quality of first and current jobs, (iii) labor market indicators, (iv) school performance, and (v) soft skills
- ▶ We matched students with the best alumni who attended their same VTI and course

Experimental Design

Pre-Registration and Peer Review

This study was:

1. Registered on the AEA Registry in 2019
2. Peer-reviewed based on the merits of its research question and methodological framework before empirical results realized
3. Accepted based on pre-results review at the Journal of Development Economics

[◀ Back](#)

Mentor-Mentee Closer in Age, from Same School and SES Talked More

- ▶ Data analyzed dyadically, i.e. mentors and students characteristics considered in tandem
- ▶ Because of the symmetry condition that follows from unidirectionality we specify [Fafchamps and Gubert 2007] dyadic regression model as:

$$SL_{ij} = \beta_0 + \beta_1|z_i - z_j| + \beta_2(z_i + z_j) + \gamma|w_{ij}| + u_i$$

- ▶ We observe three primary inhibitors: students and mentors from different VTIs, age gaps, and different socioeconomic status
- ▶ No statistically significant differences with mixed gender pairs, yet 86% of pairs are same gender

◀ Back

	Ever Connected (1)	Connected More Than Once (2)	Strong Link (3)
<i>Dyad has same:</i>			
Tribe	-0.18 (-0.67)	-0.16 (-0.57)	-0.24 (-1.43)
Primary Language	-0.27 (-0.96)	0.08 (0.23)	-0.28 (-1.33)
District of origin	0.06 (0.19)	0.06 (0.23)	0.38** (2.12)
VTI	0.66** (1.99)	0.67** (2.13)	0.35 (1.62)
Gender	-0.35 (-0.93)	-0.30 (-0.73)	-0.06 (-0.24)
<i>Sum of:</i>			
Age	0.04 (1.20)	0.07* (1.94)	0.03 (1.20)
Household Asset Index	-0.14 (-1.62)	-0.08 (-0.91)	-0.04 (-0.68)
<i>Difference in:</i>			
Age	-0.07* (-1.80)	-0.07* (-1.67)	-0.06* (-1.84)
Household Asset Index	-0.25* (-1.82)	-0.04 (-0.31)	-0.12 (-1.12)
N	603	602	603

How much is 12\$?

- ▶ Average \$ spent for one day of search = 4\$
- ▶ Short run control mean monthly income = 12.3\$ (SD = 54\$)
- ▶ At baseline 70% of students reported having no savings. Of those who saved, half had savings that amounted to less than 100,000 UGX (~27 USD)

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ITT Estimates: Savings and Job Search Expenditures

	Job Search Daily Expenditure (1)	Saving BL (2)	Saving ML1 (3)	Saving ML2 (4)	Saving ML3 (5)	Saving EL1 (6)	Savings Above EL1 (7)	Savings Amount EL1 (8)	Saving EL2 (9)
T1 (MYF)	-.241 (.730)	-.009 (.032)	.042 (.035)	.031 (.028)	.008 (.042)	-.028 (.047)	.007 (.057)	.545 (5.297)	-.009 (.046)
T2 (MYF+Cash)	-.257 (.499)	.031 (.042)	.008 (.047)	.026 (.028)	.037 (.043)	.071** (.034)	.103*** (.035)	7.566 (8.910)	-.038 (.043)
Control Mean	2.56	.33	.25	.26	.29	.41	.47	29.44	.50
Control SD	5.72	.47	.43	.44	.46	.49	.50	57.31	.50
T1 Effect (%)	-9.41	-2.75	16.86	11.77	2.63	-6.73	1.55	1.85	-1.71
T2 Effect (%)	-10.06	9.33	3.36	9.91	12.45	17.21	22.13	25.70	-7.57
N	697	1099	963	795	780	922	907	912	910
T1=T2	0.97	0.49	0.32	0.83	0.43	0.03	0.05	0.49	0.43

Randomization and Identification

Stratified (private) randomization at student level [\[Bruhn and McKenzie 2009\]](#)

- ▶ VTI: Potentially correlated with treatment implementation
- ▶ Hard to find: To reduce the risk of having differential attrition by treatment status
- ▶ Gender: Male positively correlated with labor market outcomes
- ▶ Indicator for smartphone ownership: strongly correlated with labor market outcomes and expected treatment take up

One balance variable [\[Athey and Imbens 2017\]](#)

- ▶ Ever worked pre intervention

Identification assumption: within each strata, T, and C do not differ on average in all observable and unobservable characteristics [◀ Back](#)

Earnings Expectations Over Immediate and Future Prospects

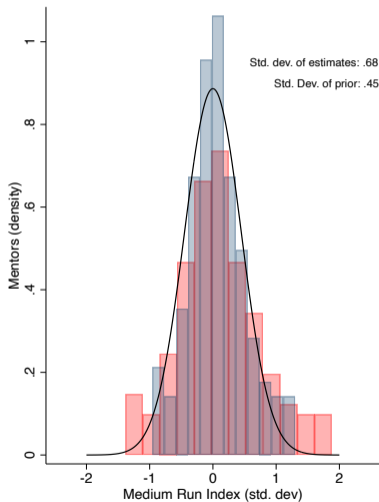
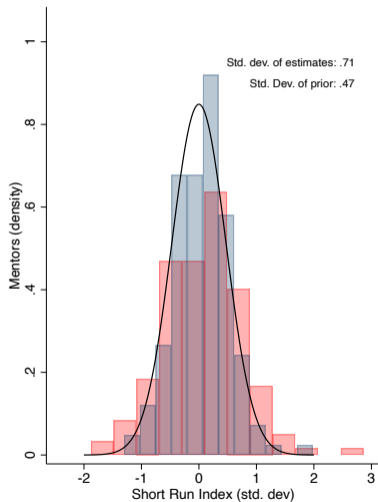
	Immediate Prospects (3 months)			Future Prospects (1 Year)		
	Expected Earnings Minimum (1)	Expected Earnings Maximum (2)	Expected Earnings T-Average (3)	Expected Earnings Minimum (4)	Expected Earnings Maximum (5)	Expected Earnings T-Average (6)
MYF Treatment	-7.943 (4.801)	-13.308*** (4.829)	-11.567* (6.765)	1.538 (3.973)	2.186 (4.957)	1.114 (4.561)
Control Mean	97.99	171.24	147.21	88.58	156.10	134.33
Control SD	75.08	74.94	97.23	54.49	68.65	77.79
T Effect (%)	-8.11	-7.77	-7.86	1.74	1.40	.83
N	926	883	926	922	879	909

Overoptimistic Students Drive Results on Reservation Wage and Willingness to Accept Job

	Reservation Wage (1)	Would Accept Unpaid Job (2)	Refused Job Offer Searched (3)	Search Duration Searched (4)
MYF Treatment	-11.58*** (3.36)	.07** (.03)	-.06** (.03)	-10.58** (4.90)
MYF Treatment				
× Feb expectations above mean	-23.52*** (5.99)	.14** (.06)	-.11 (.09)	-8.06 (8.32)
× Feb expectations below mean	1.43 (3.13)	.02 (.05)	-.06 (.06)	-5.85 (6.53)
Difference	-24.951	.116	-.052	-2.204
P-Value	.000	.131	.545	.835
Control Mean	36.76	.54	.21	33.94
Control SD	48.14	.50	.41	73.45
Treatment Effect (%)	-31.50	13.09	-27.24	-31.17
N	737	739	745	740

Mentors Heterogeneity Matters

$$Y_i = \gamma_{i1} + X_i' \delta + \mu_i$$



Mentors Providing Info and Encouragement Drive the Results on Labor Market Outcomes

$$Y_i = \beta_0 + \beta_1 \widehat{Info}_i + \beta_2 \widehat{Enc}_i + \beta_3 \widehat{Search}_i + X_i' \delta + \epsilon_i$$

	Mechanisms		Labor Market Outcomes	
	Search Behavior Index (1)	Willingness to Accept Job Index (2)	Short Run Impacts Index (3)	Medium Run Impacts Index (4)
Entry Conditions	.02 (.12)	.57*** (.15)	.28** (.11)	.11 (.12)
Encouragement	-.05 (.08)	.29*** (.11)	.25*** (.08)	.23*** (.09)
Search Tips	.02 (.11)	.10 (.15)	-.02 (.11)	-.05 (.12)
Control Mean	-.01	-.24	-.13	-.09
N	934	537	933	833
F-Test of joint significant (pval)	.47	.00	.04	.04
AP Partial F (pval)- Info	.00	.00	.00	.00
AP Partial F (pval)- Encouragement	.00	.00	.00	.00
AP Partial F (pval)- Search Tips	.00	.00	.00	.00
Sargan (pval)	.85	.77	.22	.10

Type of Support Provided, Job Search and Willingness to Accept a Job

Table 1/2

	Willingness to Accept a Job			Job Search		Search Duration	
	Started Job Search (1)	Search Efficacy Index (2)	Search Intensity Index (3)	Reservation Wage (4)	Would accept Unpaid Job (5)	Refused Job Offer Searched (6)	Search Duration Started (7)
Entry Conditions	-.04 (.05)	.07 (.11)	.05 (.10)	-21.83*** (5.74)	.13** (.06)	-.12** (.05)	-4.56 (6.66)
Encouragement	.02 (.03)	-.11 (.08)	-.01 (.07)	-11.26*** (4.17)	.09* (.05)	-.04 (.03)	-9.05** (4.54)
Search Tips	.03 (.05)	-.09 (.11)	.04 (.10)	-1.09 (5.63)	-.07 (.06)	.02 (.05)	-14.41** (6.32)
Control Mean	.78	.04	-.01	36.76	.54	.21	28.28
N Mentors	158	158	158	158	158	155	155
N	934	934	934	737	739	745	885
F-Test of joint significance (pval)	0.64	0.35	0.93	0.00	0.02	0.10	0.05
AP Partial F (pval)- Info	.00	.00	.00	.00	.00	.00	.00
AP Partial F (pval)- Encouragement	.00	.00	.00	.00	.00	.00	.00
AP Partial F (pval)- Search Tips	.00	.00	.00	.00	.00	.00	.00
Sargan (pval)	.54	.73	.42	.04	.06	.13	.97

Type of Support Provided and Labor Market Outcomes

Table 2/2

	Short Run Impacts				Transitions		Medium Run Impacts		
	Out of the Labor Force (1)	Days Worked Last Month (2)	Time Practicing Technical Skills (3)	Total Earnings Last Month (4)	First Job Duration (5)	Retained post Internship (6)	Internship to Job Transition (7)	Out of the Labor Force (8)	Total Earnings Last Month (9)
Entry Conditions	-.08* (.05)	1.73* (1.05)	13.92 (13.76)	6.34 (4.51)	17.94 (13.83)	.03 (.05)	.01 (.06)	-.02 (.05)	11.36* (6.09)
Encouragement	-.07** (.03)	1.14 (.71)	20.84** (9.40)	3.02 (3.07)	26.44*** (9.43)	.08** (.03)	.08* (.04)	-.04 (.04)	8.79** (4.25)
Search Tips	-.01 (.04)	.10 (.99)	1.67 (12.97)	-5.54 (4.23)	3.41 (13.02)	-.04 (.05)	.05 (.06)	-.00 (.05)	-2.13 (5.92)
Control Mean	.21	16.15	52.66	11.35	78.07	.18	.41	.26	34.84
N Mentors	158	158	158	158	158	158	157	157	157
N	934	934	934	933	929	934	844	923	916
F-Test of joint significance (pval)	0.08	0.22	0.15	0.17	0.04	0.05	0.28	0.72	0.07
AP Partial F (pval)- Info	.00	.00	.00	.00	.00	.00	.00	.00	.00
AP Partial F (pval)- Encouragement	.00	.00	.00	.00	.00	.00	.00	.00	.00
AP Partial F (pval)- Search Tips	.00	.00	.00	.00	.00	.00	.00	.00	.00
Sargan (pval)	.44	.01	.02	.06	.01	.07	.47	.26	.04

ITT Estimates: Willingness to Accept Job and Search by Treatment Arm

	Willingness to Accept a Job			Job Search		Search Duration	
	Reservation Wage (1)	Would Accept Unpaid Job (2)	Refused Job Offer Searched (3)	Search Efficacy Index (4)	Search Intensity Index (5)	Started Job Search (6)	Search Duration Searched (7)
T1 (MYF)	-13.42*** (3.89)	.08** (.04)	-.02 (.03)	-.10 (.07)	.01 (.08)	.03* (.02)	-11.60** (4.49)
T2 (MYF+Cash)	-9.74*** (3.59)	.07* (.04)	-.09** (.03)	-.02 (.08)	.03 (.07)	.03 (.02)	-5.61 (4.68)
Control Mean	36.76	.54	.21	.04	-.01	.93	28.28
T1 Effect (%)	-36.50	14.15	-10.42	-279.37	-75.11	3.37	-41.02
T2 Effect (%)	-26.50	12.03	-43.30	-42.91	-242.67	2.86	-19.84
N	737	739	745	934	934	934	885
T1=T2	0.27	0.79	0.04	0.31	0.69	0.74	0.17

- ▶ MYF only and MYF + Cash have the same effects on willingness to accept a job. Neither has an effect on job search intensity/efficacy

ITT Estimates: Short Run Labor Market Outcomes by Treatment Arm

	Out of the Labor Force (1)	Days Worked Last Month (2)	Hours Practicing Technical Skills (3)	Total Earnings Last Month (4)	First Job Duration (5)
T1 (MYF)	-0.05** (.02)	1.54** (.65)	22.71*** (7.16)	3.19 (2.55)	17.96** (7.40)
T2 (MYF+Cash)	-0.06** (.02)	1.00 (.63)	12.39** (5.59)	.67 (2.41)	18.92** (7.01)
Control Mean	.21	16.15	52.15	11.35	81.18
T1 Effect (%)	-22.90	9.56	43.55	28.11	22.13
T2 Effect (%)	-30.04	6.22	23.75	5.91	23.30
N	934	934	838	933	833
T1=T2	0.59	0.43	0.19	0.35	0.92

- ▶ Treatment effects on short run outcomes are equally strong for students who received MYF only and those who received MYF + Cash

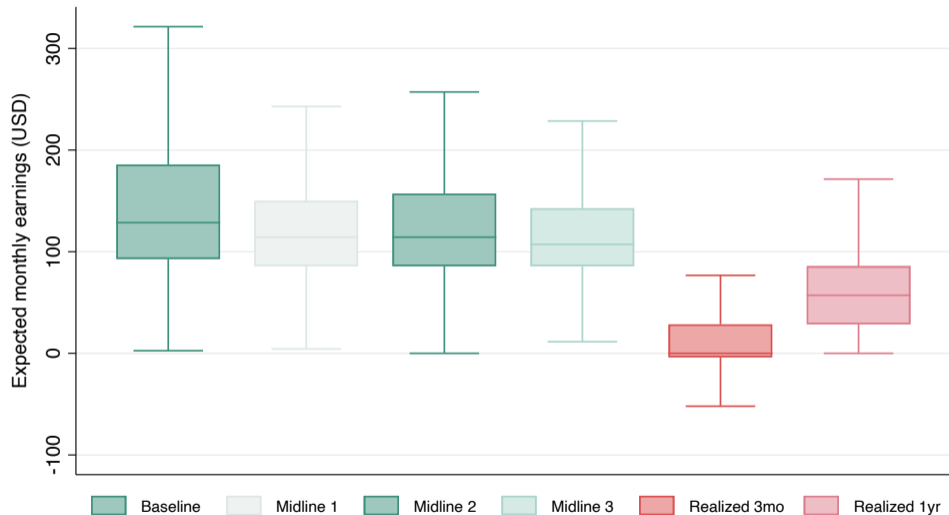
Decomposition of the Effect of MYF on Pathways to Employment

Reduced-form Estimates of the Effects of MYF on Pathways to Employment at 1 Year

	Unemp ↓ Unemp (1)	Unpaid ↓ Unemp (2)	Unpaid ↓ Paid (3)	Paid ↓ Unemp (4)	Paid ↓ Paid (5)
MYF Treatment	-.023 (.016)	-.024 (.030)	.056* (.032)	.005 (.024)	.015 (.029)
Control Mean	.07	.24	.26	.12	.22
T Effect (%)	-33.08	-9.84	21.52	3.85	6.89
N	844	844	844	844	844

- ▶ Each pathway is described by the combination of one of three possible statuses: unemployed; working for zero/negative wage; working for positive wage
- ▶ We report pathways with >5% of students
- ▶ Treated students are more likely to make the unpaid work to paid work transition

Overoptimism: Expected and Actual Earnings at First Job | Employment



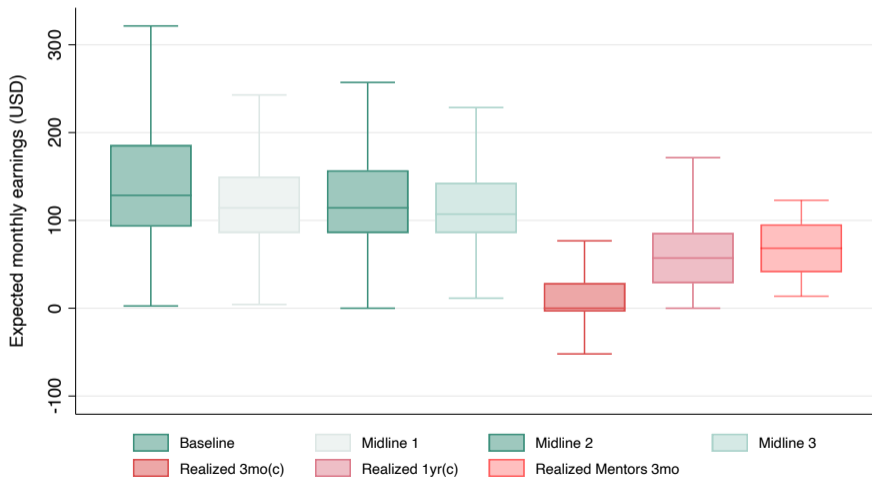
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Limited Knowledge of Labor Market Dynamics: Expected and Actual Job Ladders

		Expected			Actual		
		Paid	Unpaid	Unemp	Paid	Unpaid	Unemp
1 YEAR	Paid	52%	48%	42%	61%	55%	15%
	Unpaid	22%	25%	33%	3%	6%	3%
	Unemp	26%	28%	25%	36%	39%	82%
		Paid	Unpaid	Unemp	Paid	Unpaid	Unemp
3 MONTHS							

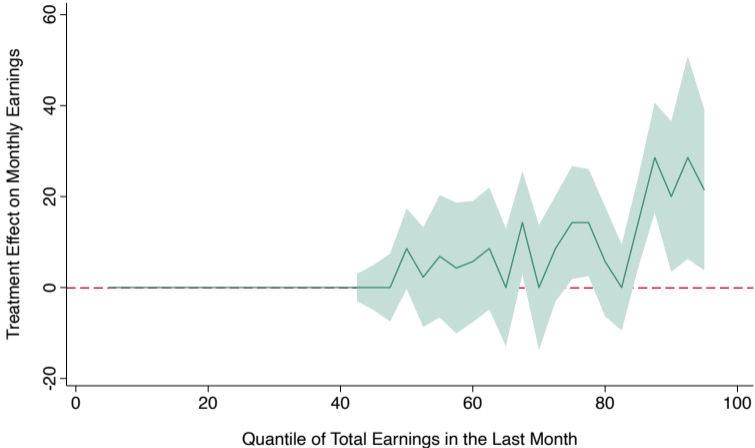
- ▶ Students undervalue unpaid initial job spells
- ▶ Underestimate the risks related to being unemployed for long

Overoptimism Also Using (Pre-Covid) Mentors Data



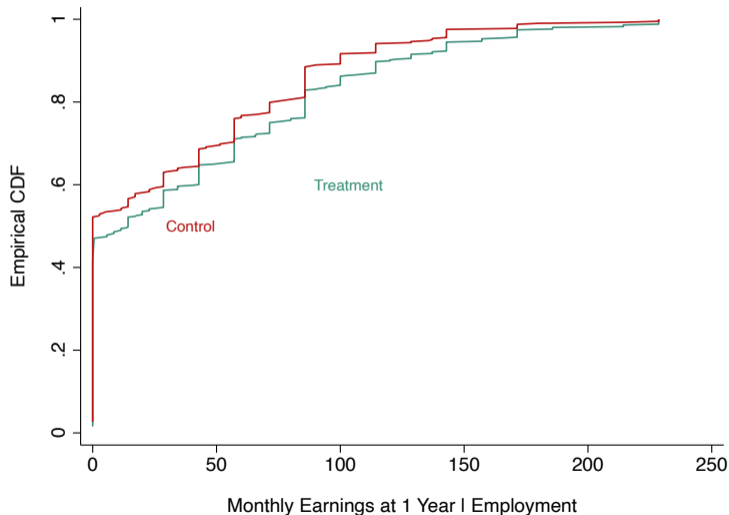
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Quantile Treatment Effects of MYF on Monthly Earnings



◀ Back

Empirical Distributions of Monthly Earnings in Treatment and Controls



Construction of Mentor Types

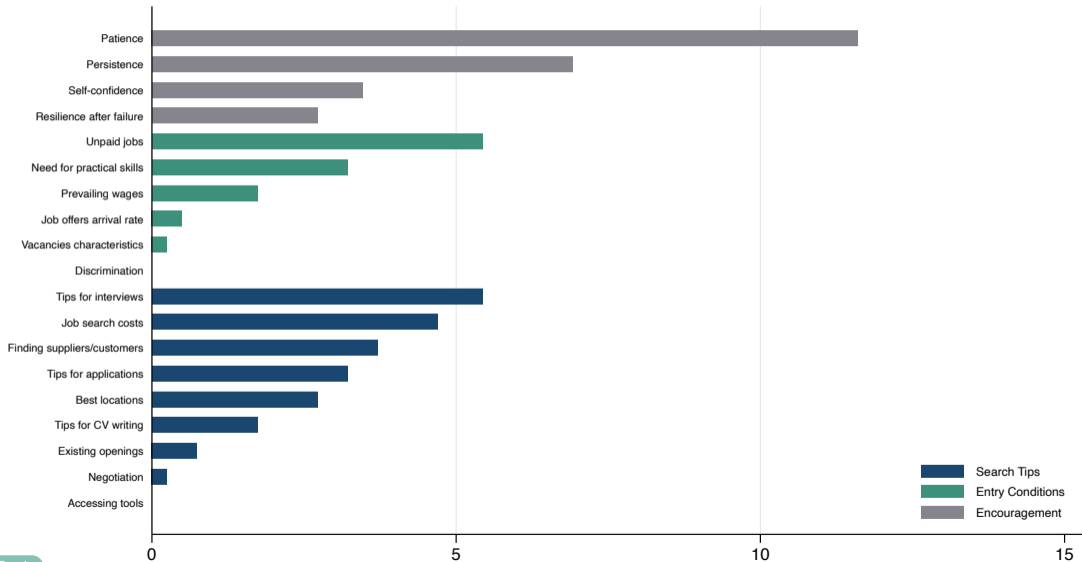
- ▶ Each mentor is randomly assigned to N students. Or, in other words, to a student i and the rest of the students $N - i$
- ▶ For each student i we use the leave-out mean of the topics discussed by the mentor with the $N - i$ to define a mentor type
- ▶ For example, the leave-out mean for the general information dummy tells us the number of times in which general information was the main topic discussed by the mentor with the $N - i$ students. It can be written as:

$$Info_{-i} = \sum_{i=1}^{N-1} Info_i$$

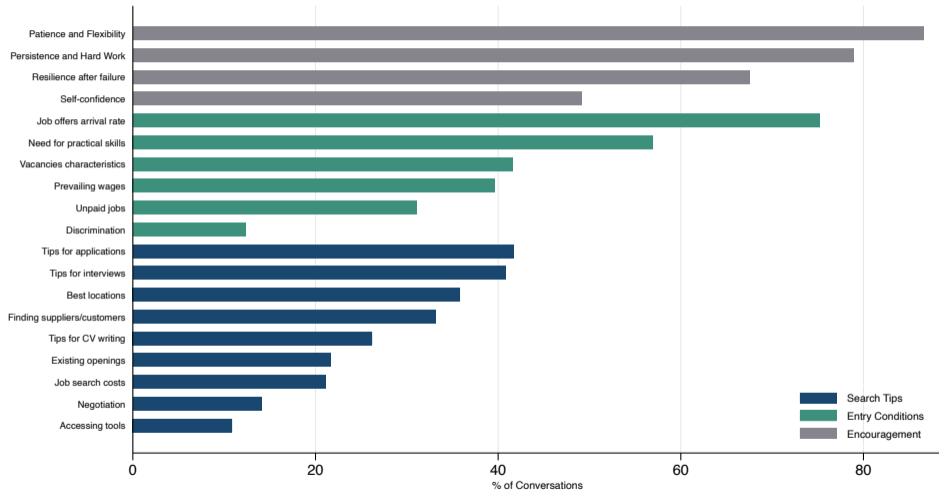
- ▶ Last, for each i the mean mentor type is built by taking the highest of the three leave-out means, that is:

$$\overline{Info}_i = 1 \quad \text{if} \quad Info_{-i} > Encouragement_{-i} \quad \text{and} \quad Info_{-i} > Search_{-i}$$

Understanding the Treatment: Students Main Takeaway in Detail



Understanding the Treatment: Micro-Topics in Detail



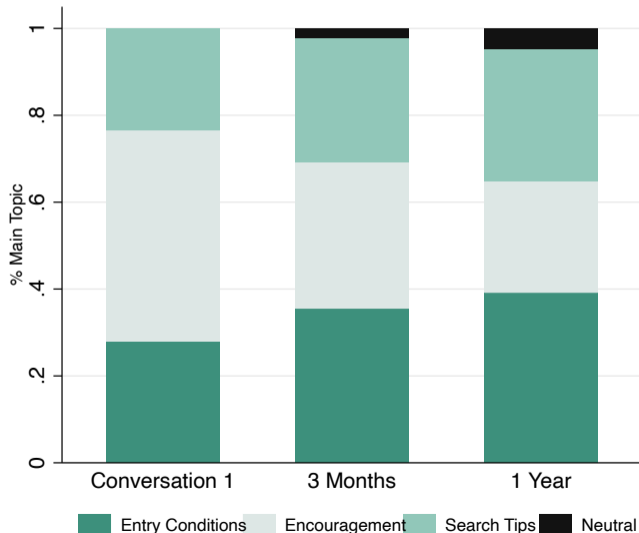
Understanding the Treatment: Main Takeaway Over Time

Frequency

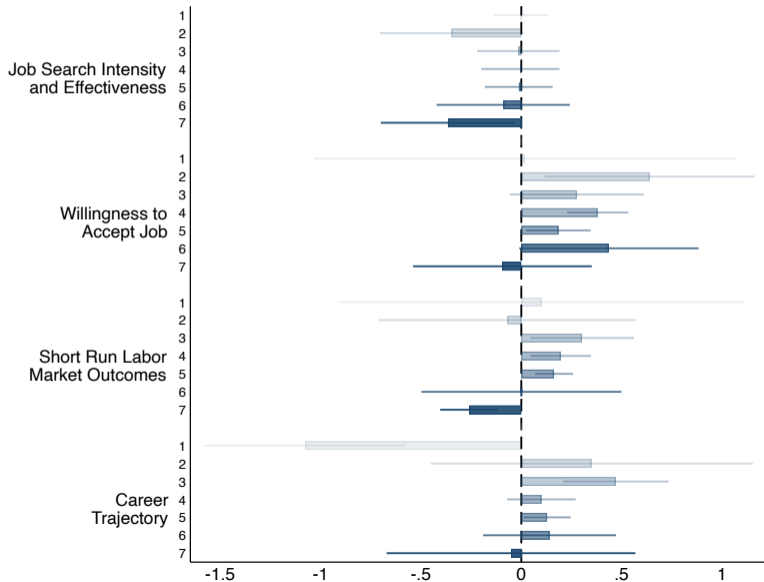
- ▶ Take-up: 91%
- ▶ Recording: 90%
- ▶ Talking at 3 months: 75%
- ▶ Talking at 1 year: 54%

Content Stability

- ▶ 41% exclusively General Info or Encouragement
- ▶ 7% exclusively Search Tips

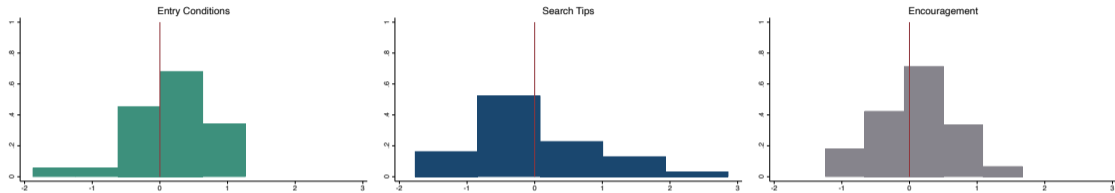


Mentors Heterogeneity by Number of Assigned Mentees



Mentors Heterogeneity by Type: FE Distributions

Panel A: Short Run Labor Market Index



Panel B: Career Trajectory Index

