Meet Your Future

Experimental Evidence on the Labor Market Effects of Mentors

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Africa's Youth Un(der)employment Challenge

- 420 million young people in Africa today
  - 1/3 unemployed; 1/3 underemployed [AfDB 2018]
- Efficient allocation of human capital is critical for:
  - Individual well-being
  - Economy-wide process of economic development
- Main policy response: skills building programs
  - Generate human capital and promote employment but overall placement rates are low [Alfonsi et al. 2020; Bandiera et al. 2022]

Supply-Side Information Frictions Play a Crucial Role

- Poor knowledge of the job search process [Jensen 2012; Beam 2016; Groh et al. 2015; Alfonsi et al. 2020; Abebe et al 2021]
- Overly optimistic beliefs about their career prospects [Spinnewijn 2015; Mueller et al. 2021, Potter 2021; Banerjee and Sequeira 2023; Bandiera et al. 2022; Chakravorty et al. 2021; Jones and Santos 2022]

→ Prolong exit from unemployment

So far:

- Standard, non-personalized information treatments proved ineffective for most...
- ...and backfired for others who over-revised downward becoming discouraged

$\rightarrow$ How can we provide tailored and credible information to overoptimistic job seekers in low-income settings, withouth leading to discouragement effects?

This Paper: Tailored, Relevant, Credible and Low-Cost Information

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- Random assignment to MYF to establish causal impacts of a mentor on jobseekers' labor outcomes
- Randomization to a mentor (plus job search model) to test mechanisms

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Data:

- Students: 6 survey rounds spanning 3 years
- Mentors: 4 survey rounds spanning 2 years
- Audio recordings of the mentorship sessions

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Policy: Cost effective and scalable program ▸ IRR

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]

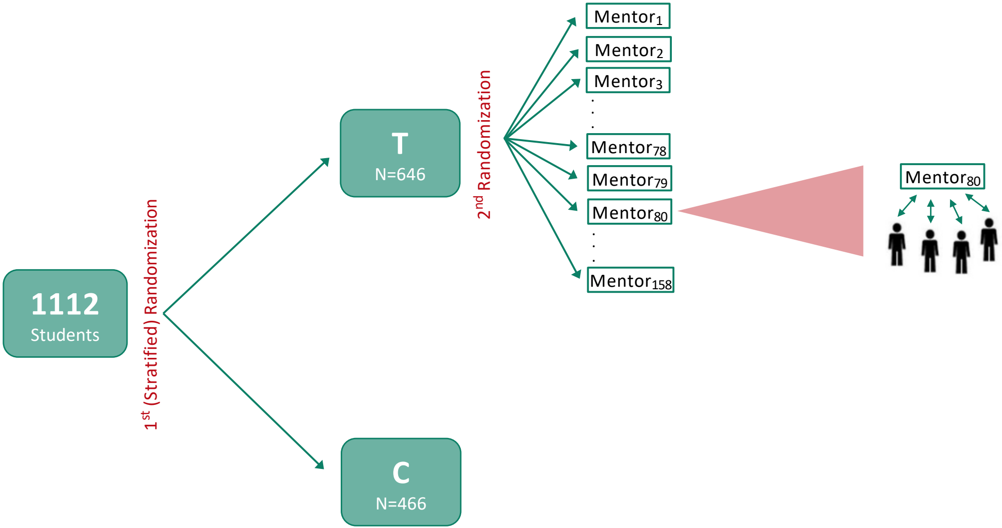
1112 Students

- 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***	1.267**	17.234***	1.900	18.469***
	(.019)	(.540)	(5.041)	(2.081)	(5.150)
	[.003]	[.010]	[.002]	[.078]	[.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

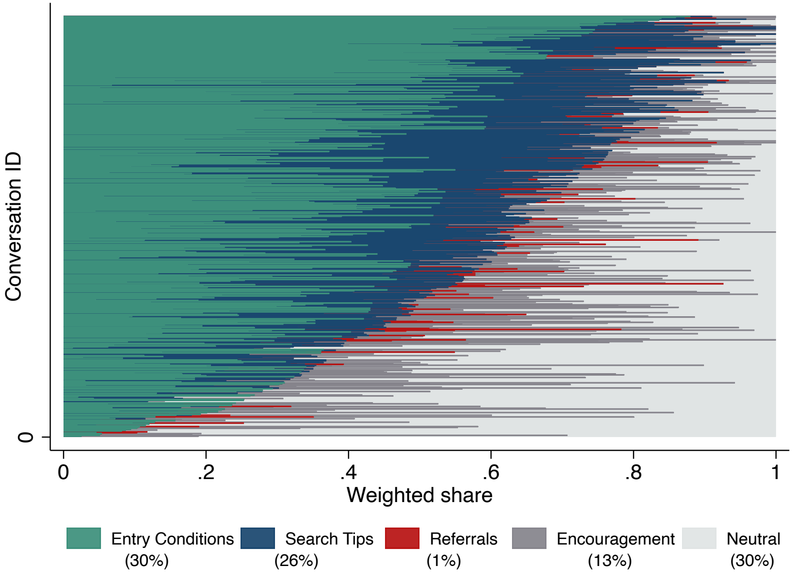
	Transitions		Medium Run	
	Internship to Job Transition Within Firm	Internship to Job Transition Between Firms	Out of the Labor Force	Total Earnings Last Month (USD)
	(1)	(2)	(3)	(4)
MYF Treatment	.041**	.076**	-.025	6.149*
	(.019)	(.033)	(.022)	(3.601)
Control Mean	.18	.37	.26	34.84
Treatment Effect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

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

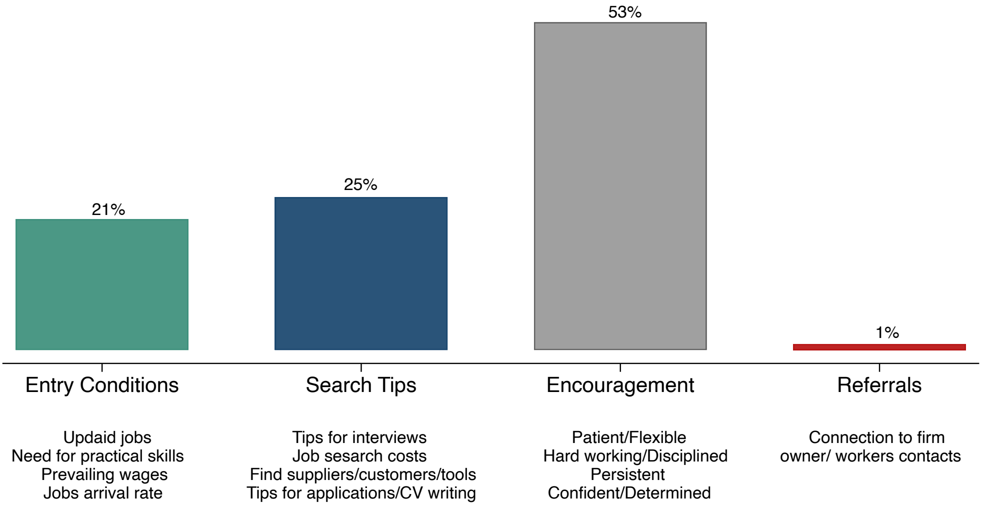
- More stable matches set them on a steeper job ladder
- 1 year later, treated students earn 18% more ▸ QTEs ▸ Cumulative earnings

Mechanisms

Conversation Content: Info on Entry Conditions, Few Job Referrals



Students Main Takeaway



▸ Micro-topics ▸ Micro- takeaways ▸ Over time

Framework

McCall 1970 with distorted beliefs, Cortés et al. 2023

- **Set-up:** Utility maximizing agents whose behavior follows a reservation wage strategy

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  - Those who search draw a wage offer w_t with probability λ from $F(w) \sim N(\mu, \sigma)$

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  - If they accept, they earn w_t, in t and $w_{t+1} + \omega$ thereafter, where ω represents a constant experience premium you mature after your first spell

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- **Distorted beliefs:** The jobseeker acts based on a perceived probability distribution $\hat{F}(w) \sim N(\hat{\mu}, \sigma)$ and an expected experience premium $\hat{\omega}$

Framework

Predictions

Prediction 1: Search tips and job referrals, by increasing the probability of receiving an offer ($\lambda \uparrow$), lead to an increase in the reservation wage ($w_R \uparrow$) and in the search cutoff ($c^* \uparrow$)

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Prediction 2: Information on entry conditions rectifies optimistic beliefs, ($\hat{\mu} \downarrow$) leading to a decrease in the reservation wage ($w_R \downarrow$) and in the search cutoff ($c^* \downarrow$)

Prediction 3: Encouragement and confidence over a positive future outlook lead to a decrease in the reservation wage ($w_R \downarrow$) and an increase in the cutoff search strategy ($c^* \uparrow$) by upward shifting beliefs over the future value of the first job ($\hat{\omega} \uparrow$)

Direct Measures of Intermediate Outcomes:

- Entry Conditions ✓ → Revise down expectations over immediate prospects ▸ Table
  → Reservation wages drop 32% ▸ Table
  → 13% higher willingness to accept unpaid job
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- Search Tips ✗ → Treated students are not better at searching

Conclusions

- 1:1 mentoring with experienced workers improves labor market outcomes
  $\rightarrow$ Take-away: Cost-effective and scalable with large effects on career trajectory

- Mentors' impacts mediated by info about entry-level jobs and encouragement
  - Importance of credible source of personalized information
  - Importance of balancing "bad news" with hope for better future outcomes

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Next 1: Determinants of jobseekers' overoptimism?

Next 2: Meet Your Past: what are the effects of the program on mentors?

Thank you!

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Additional Slides

Job Search Behavior and Reservation Wages

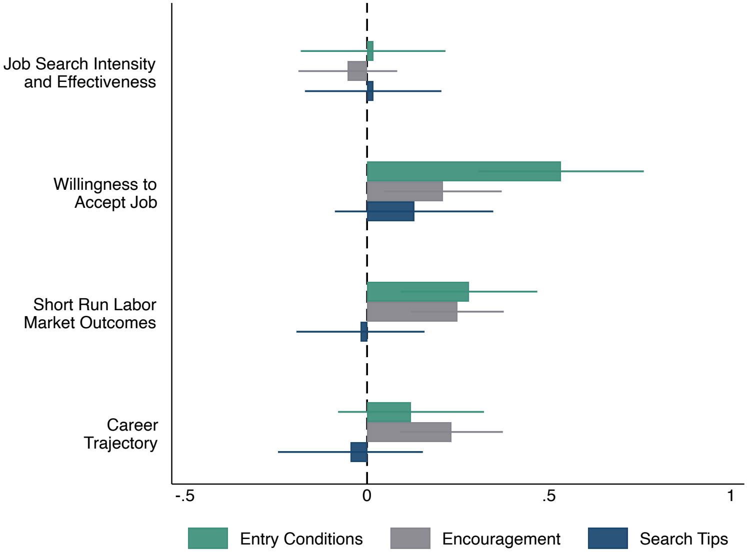
	Willingness to Accept a Job			Job Search			Search Duration
	Reservation Wage (1)	Would Accept Unpaid Job (2)	Refused Job Offer | Searched (3)	Search Efficacy Index (4)	Search Intensity Index (5)	Started Job Search (6)	Search Duration | Searched (7)
MYF Treatment	-11.581***	.071**	-.057**	-.056	.018	.029**	-8.525**
	(3.357)	(.031)	(.026)	(.059)	(.068)	(.014)	(4.053)
	[.004]	[.052]	[.052]	[.128]	[.293]	[.052]	[.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 Back

Learning How Each Topic of Conversation Affects Outcomes

- Goal: $Y_i = \beta_0 + \beta_1 Info_i + \beta_2 Enc_i + \beta_3 Search_i + X_i' \delta + \epsilon_i$
- 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

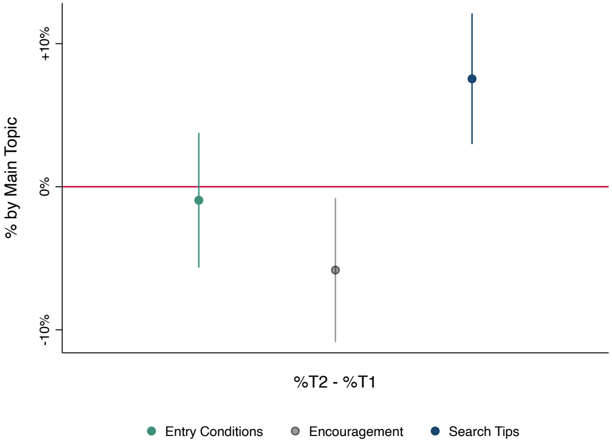


▸ Table

▸ Mentors matter

▸ Demographics

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



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

An Ineffective Cash Transfer

	Transitions		Medium Run	
	Retained post Internship	Internship to Job Transition	Out of the Labor Force at 1 Year	Total Earnings Last Month at 1 Year
	(1)	(2)	(3)	(4)
T1 (MYF)	.06**	.11**	-.06*	10.84**
	(.02)	(.04)	(.03)	(4.19)
T2 (MYF+Cash)	.02	.01	.01	1.95
	(.03)	(.04)	(.03)	(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

▸ Search and Willingness to Accept ▸ Short Run

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, G^2LIC|IZA, CAS & IRLE @UCB

APPENDIX

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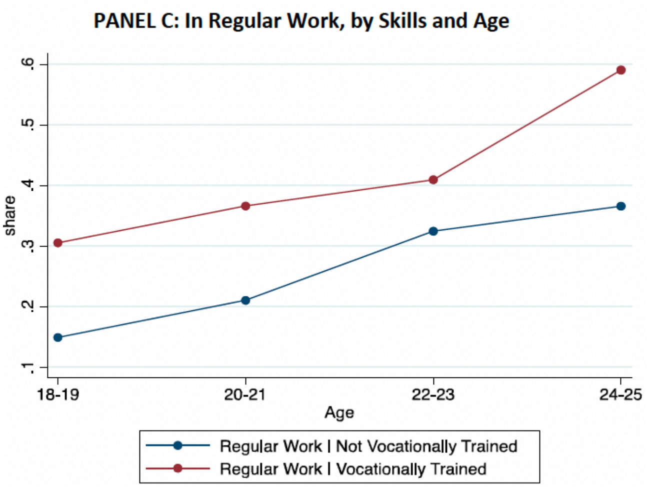
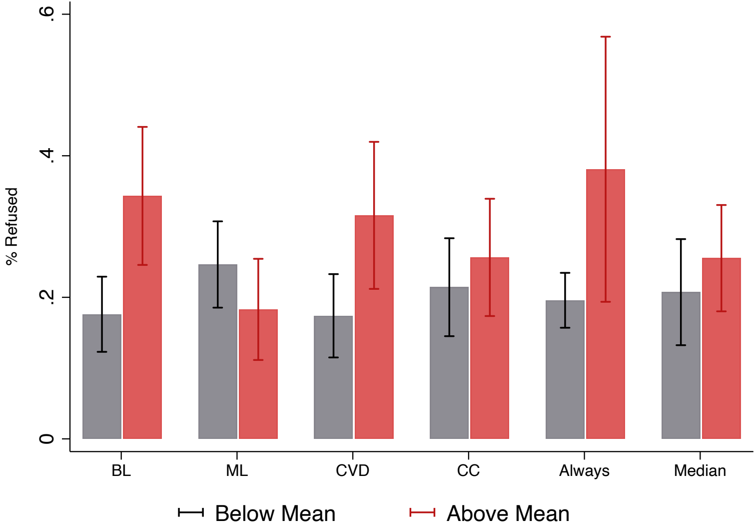
Jobs and Skills by Age



Source: Bandiera et al. 2022

Back

Optimism Leads to More Refusals



Back

High Take-Up and Engagement with the Program

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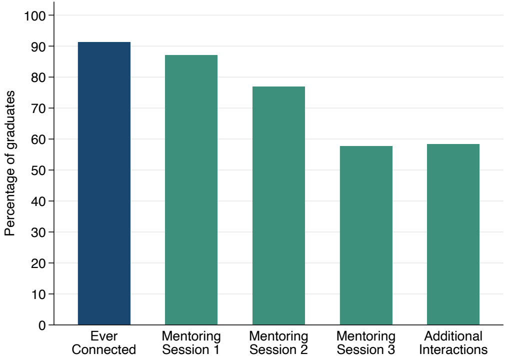
- Average # interactions: 6.8
- Average total interaction time = 3.2h
- More interactions among mentor-mentees closer in age and from same VTIs



▸ Details ◂ Back

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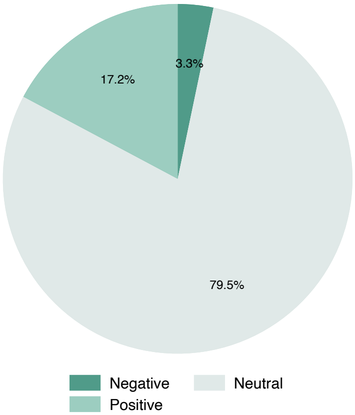
- More interactions among mentor-mentees closer in age and from same VTIs
- High satisfaction, identification and transportation across all student-mentor pairs confirm with the text data
- Neutral or positive sentiment

Details



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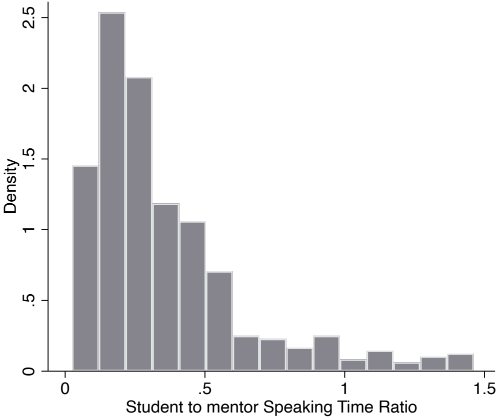
- Conversations led by the mentors but engaged students



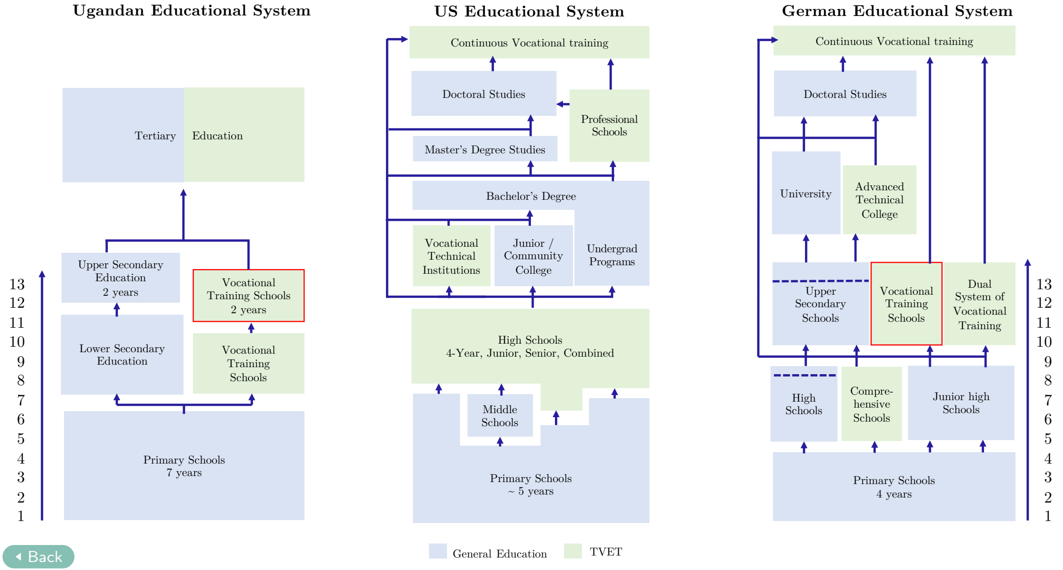
Setting

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

Back

Comparing Education Systems: Uganda, US, Germany



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Locations - Students

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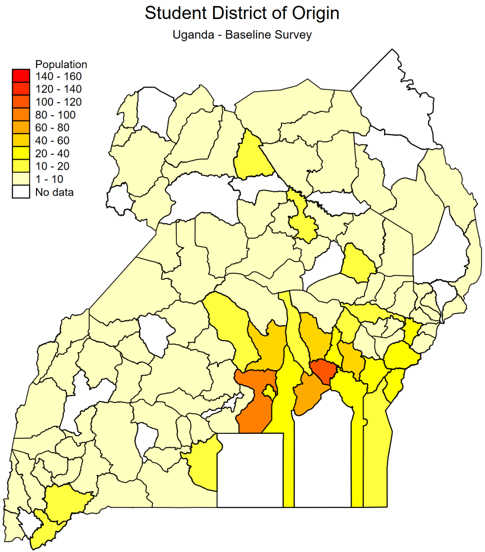
- Location of Origin
  - 84% comes from Central or Eastern Uganda
  - 56% comes from a rural area (far from town)
  - 72% have either Kampala or Jinja as preferred location where to search (94% if we consider up to the third preference)



Locations - Alumni

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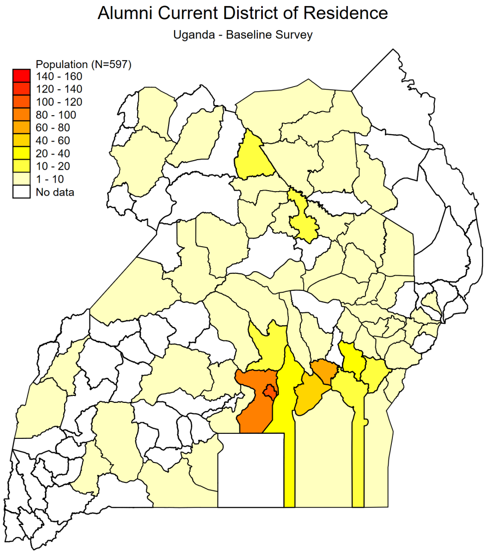
- Location of Current Work (pre-Covid)
  - 87% work in Central or Eastern Uganda
  - 64% work in Kampala or Jinja metropolitan area



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

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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.

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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.

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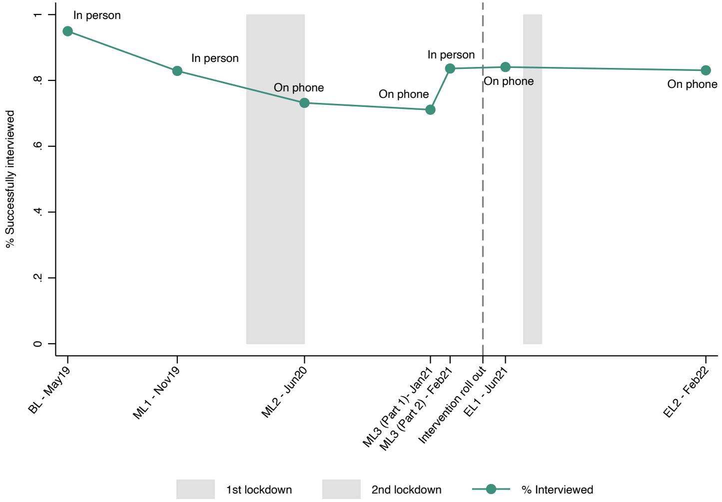
Experimental Design

Despite Covid-19 Attrition Rates Were Satisfactory



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Logbook

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.

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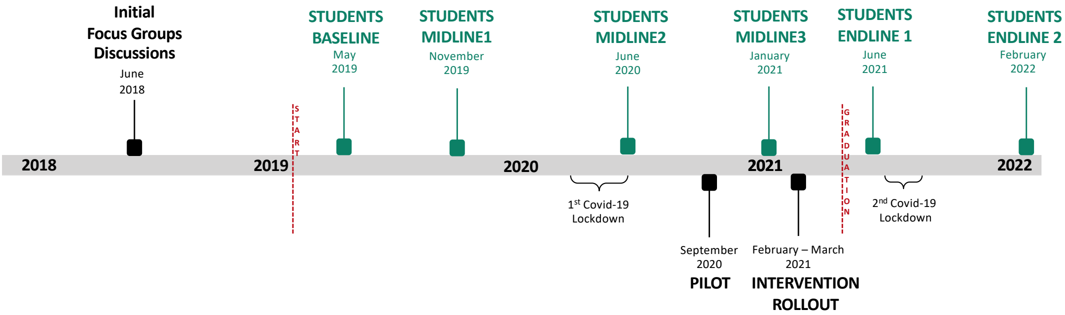
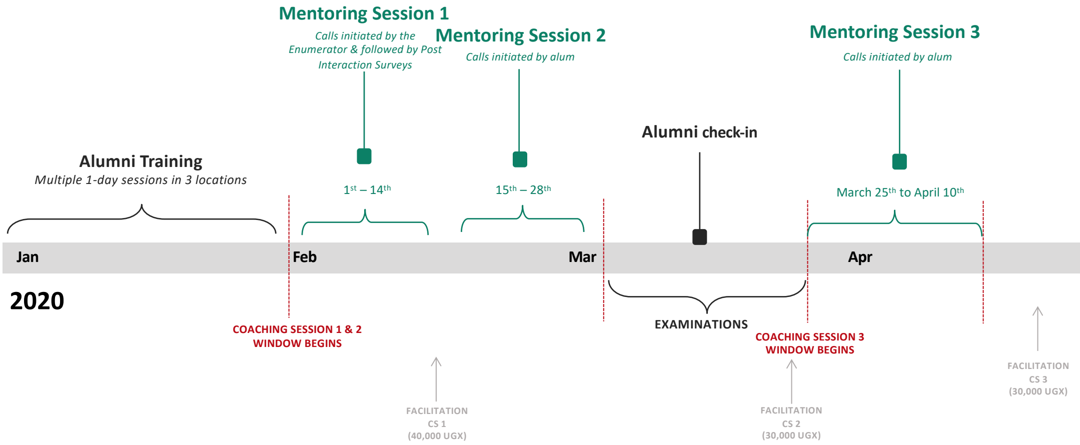
Project Timeline, Data and Attrition



▸ Data: students ▸ Data: alumni ▸ Attrition ◂ Back

The MYF Program



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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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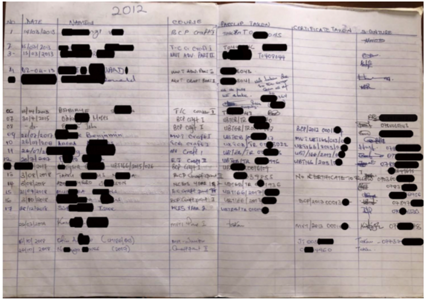
Alumni Sample Construction - Records digitization



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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

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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

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

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

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

- 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

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	Ever Connected (1)	Connected More Than Once (2)	Strong Link (3)
Dyad has same:			
Tribe	-0.18	-0.16	-0.24
	(-0.67)	(-0.57)	(-1.43)
Primary Language	-0.27	0.08	-0.28
	(-0.96)	(0.23)	(-1.33)
District of origin	0.06	0.06	0.38^{**}
	(0.19)	(0.23)	(2.12)
VTI	0.66^{**}	0.67^{**}	0.35
	(1.99)	(2.13)	(1.62)
Gender	-0.35	-0.30	-0.06
	(-0.93)	(-0.73)	(-0.24)
Sum of:			
Age	0.04	0.07^{*}	0.03
	(1.20)	(1.94)	(1.20)
Household Asset Index	-0.14	-0.08	-0.04
	(-1.62)	(-0.91)	(-0.68)
Difference in:			
Age	-0.07^{*}	-0.07^{*}	-0.06^{*}
	(-1.80)	(-1.67)	(-1.84)
Household Asset Index	-0.25^{*}	-0.04	-0.12
	(-1.82)	(-0.31)	(-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 ($\sim$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	-.009	.042	.031	.008	-.028	.007	.545	-.009
	(.730)	(.032)	(.035)	(.028)	(.042)	(.047)	(.057)	(5.297)	(.046)
T2 (MYF+Cash)	-.257	.031	.008	.026	.037	.071**	.103***	7.566	-.038
	(.499)	(.042)	(.047)	(.028)	(.043)	(.034)	(.035)	(8.910)	(.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	-13.308***	-11.567*	1.538	2.186	1.114
	(4.801)	(4.829)	(6.765)	(3.973)	(4.957)	(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

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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***	.07**	-.06**	-10.58**
	(3.36)	(.03)	(.03)	(4.90)
MYF Treatment				
× Feb expectations above mean	-23.52***	.14**	-.11	-8.06
	(5.99)	(.06)	(.09)	(8.32)
× Feb expectations below mean	1.43	.02	-.06	-5.85
	(3.13)	(.05)	(.06)	(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

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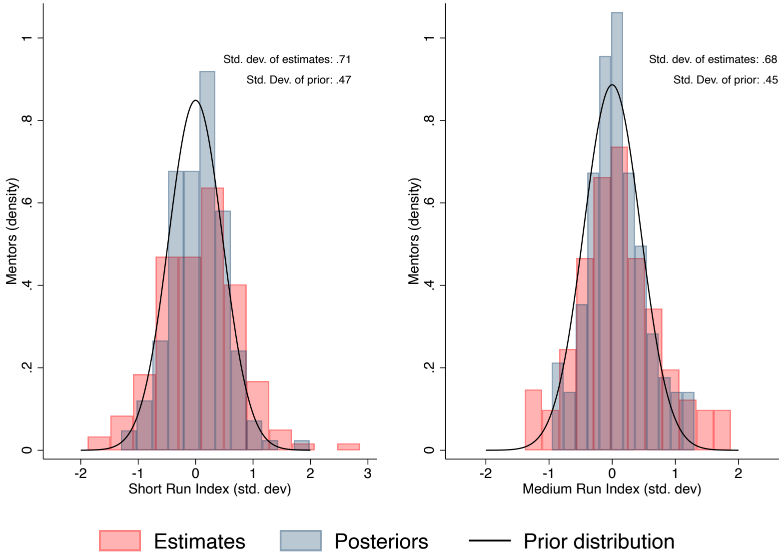
Mentors Heterogeneity Matters

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



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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	.57***	.28**	.11
	(.12)	(.15)	(.11)	(.12)
Encouragement	-.05	.29***	.25***	.23***
	(.08)	(.11)	(.08)	(.09)
Search Tips	.02	.10	-.02	-.05
	(.11)	(.15)	(.11)	(.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

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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	.07	.05	-21.83***	.13**	-.12**	-4.56
	(.05)	(.11)	(.10)	(5.74)	(.06)	(.05)	(6.66)
Encouragement	.02	-.11	-.01	-11.26***	.09*	-.04	-9.05**
	(.03)	(.08)	(.07)	(4.17)	(.05)	(.03)	(4.54)
Search Tips	.03	-.09	.04	-1.09	-.07	.02	-14.41**
	(.05)	(.11)	(.10)	(5.63)	(.06)	(.05)	(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

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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*	1.73*	13.92	6.34	17.94	.03	.01	-.02	11.36*
	(.05)	(1.05)	(13.76)	(4.51)	(13.83)	(.05)	(.06)	(.05)	(6.09)
Encouragement	-.07**	1.14	20.84**	3.02	26.44***	.08**	.08*	-.04	8.79**
	(.03)	(.71)	(9.40)	(3.07)	(9.43)	(.03)	(.04)	(.04)	(4.25)
Search Tips	-.01	.10	1.67	-5.54	3.41	-.04	.05	-.00	-2.13
	(.04)	(.99)	(12.97)	(4.23)	(13.02)	(.05)	(.06)	(.05)	(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

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

	Willingness to Accept a Job			Job Search			Search Duration
	Reservation Wage	Would Accept Unpaid Job	Refused Job Offer | Searched	Search Efficacy Index	Search Intensity Index	Started Job Search	Search Duration | Searched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T1 (MYF)	-13.42***	.08**	-.02	-.10	.01	.03*	-11.60**
	(3.89)	(.04)	(.03)	(.07)	(.08)	(.02)	(4.49)
T2 (MYF+Cash)	-9.74***	.07*	-.09**	-.02	.03	.03	-5.61
	(3.59)	(.04)	(.03)	(.08)	(.07)	(.02)	(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 willlingness to accept a job. Neither has an effecton job search intensity/efficacy

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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)	-.05**	1.54**	22.71***	3.19	17.96**
	(.02)	(.65)	(7.16)	(2.55)	(7.40)
T2 (MYF+Cash)	-.06**	1.00	12.39**	.67	18.92**
	(.02)	(.63)	(5.59)	(2.41)	(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

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

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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 $\downarrow$ Unemp (1)	Unpaid $\downarrow$ Unemp (2)	Unpaid $\downarrow$ Paid (3)	Paid $\downarrow$ Unemp (4)	Paid $\downarrow$ Paid (5)
MYF Treatment	-.023	-.024	.056*	.005	.015
	(.016)	(.030)	(.032)	(.024)	(.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 likley to make the unpaid work to paid work transition

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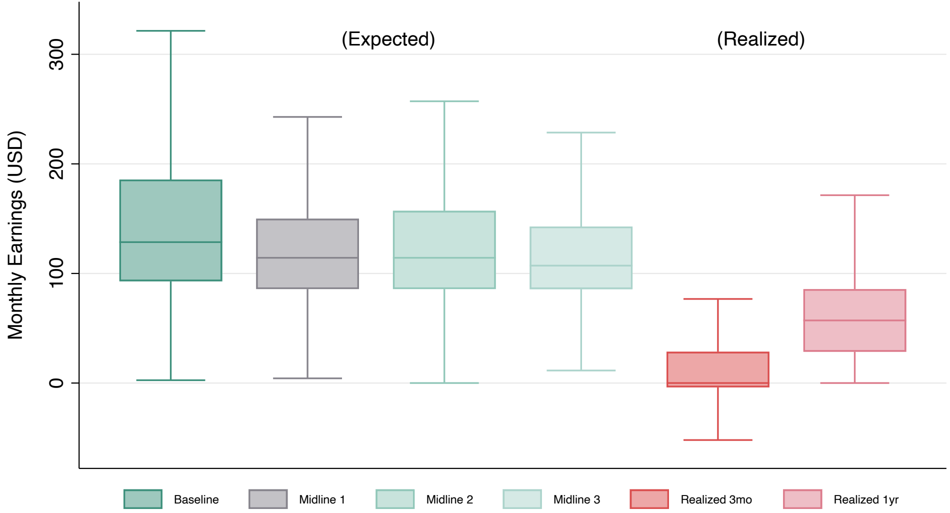
Overoptimism: Expected and Actual Earnings at First Job | Employment



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

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

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

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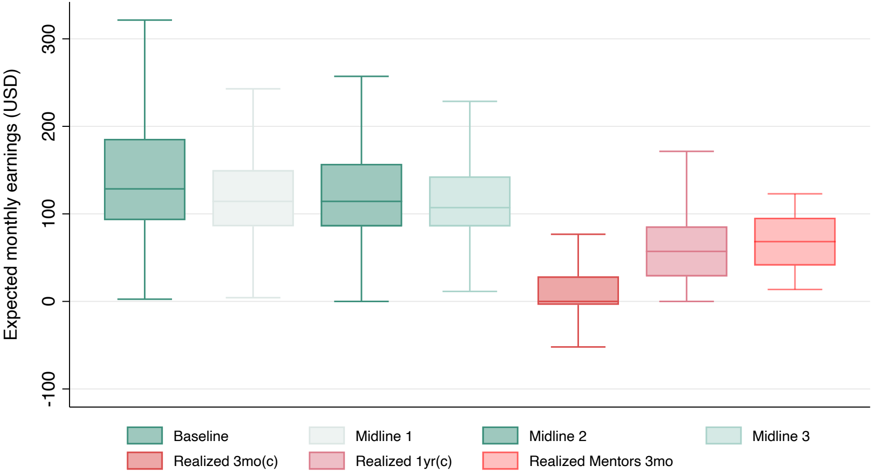
Overoptimism Also Using (Pre-Covid) Mentors Data



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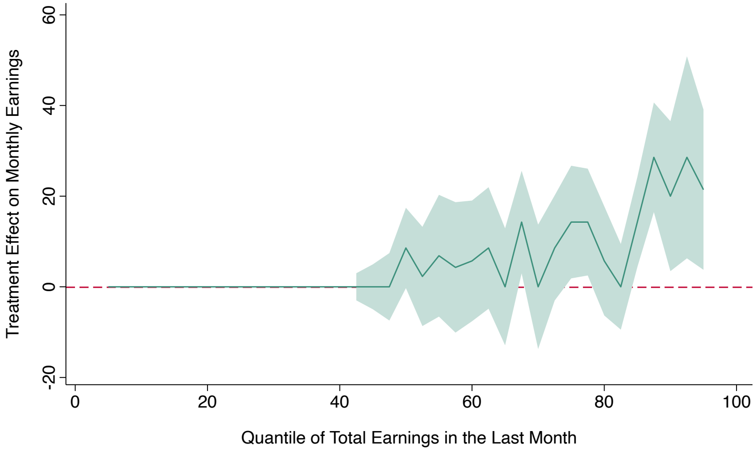
Quantile Treatment Effects of MYF on Monthly Earnings



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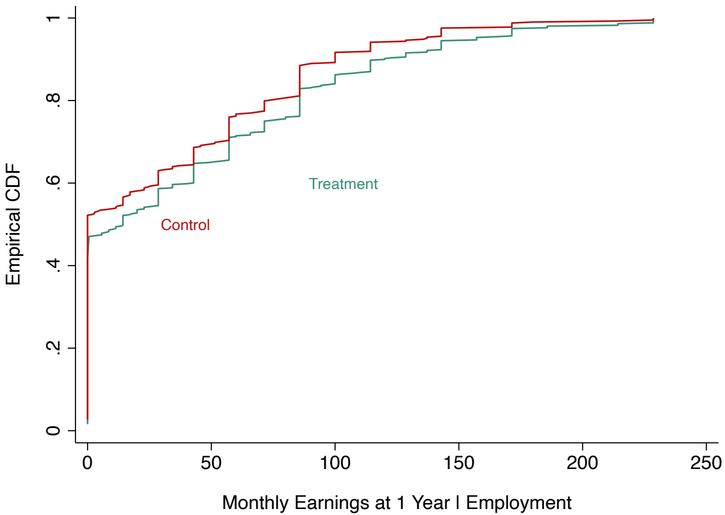
Empirical Distributions of Monthly Earnings in Treatment and Controls



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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:

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

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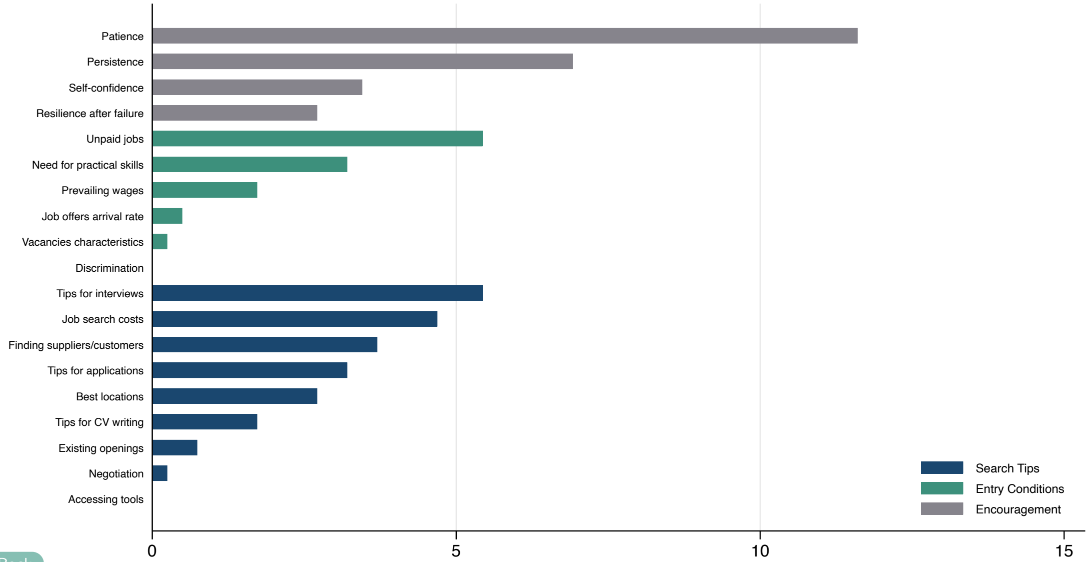
Understanding the Treatment: Students Main Takeaway in Detail



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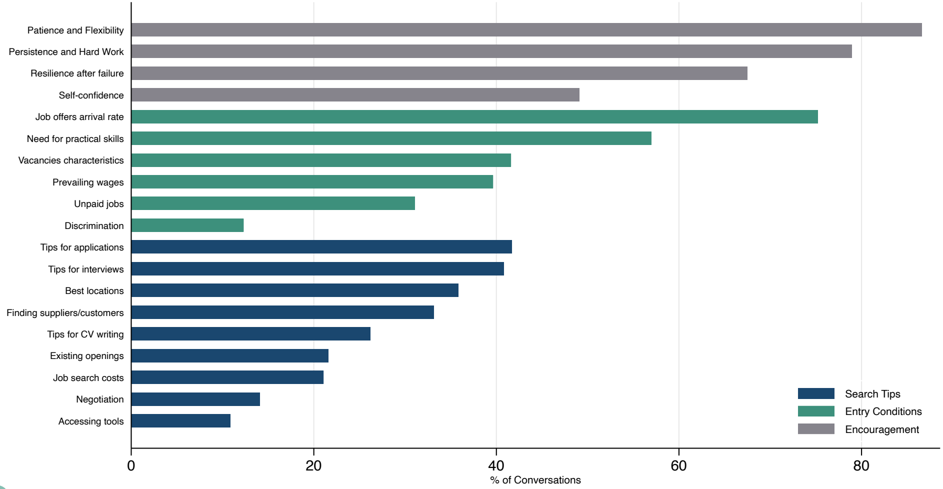
Understanding the Treatment: Micro-Topics in Detail



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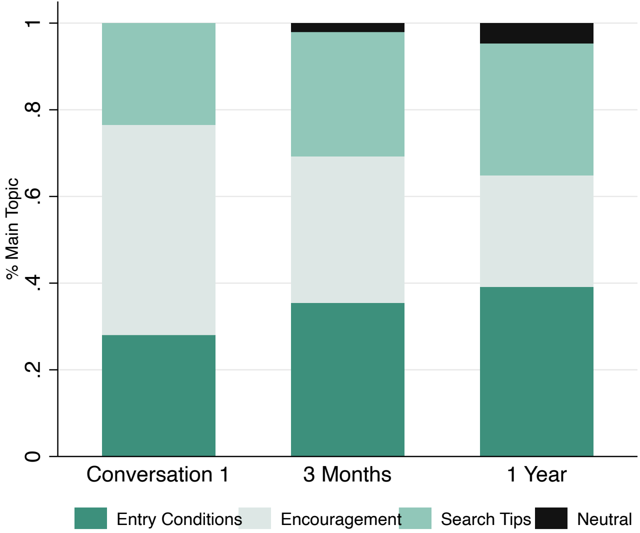
Understanding the Treatment: Main Takeaway Over Time

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



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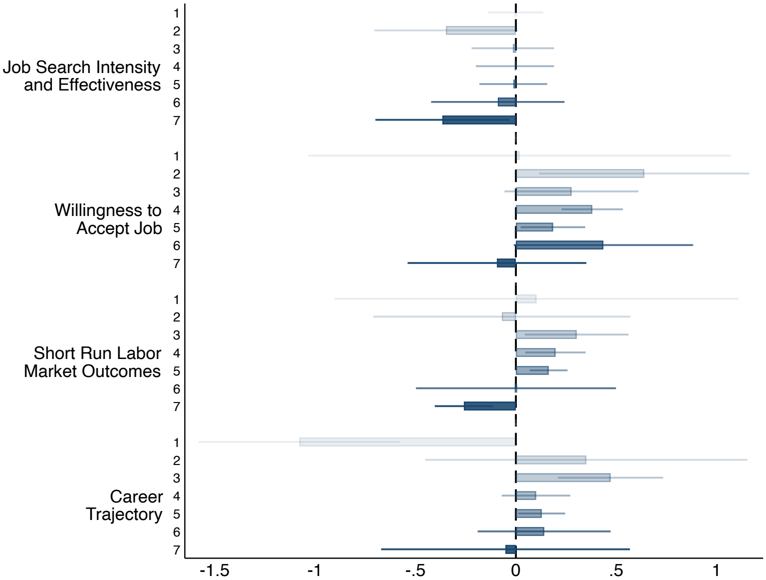
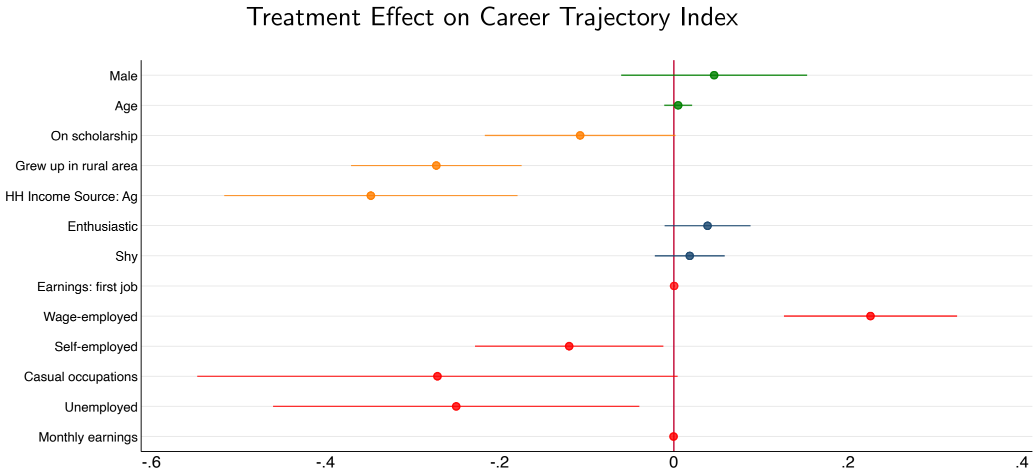
Mentors Heterogeneity by Number of Assigned Mentees



Mentors Heterogeneity by Demographics



- Wage-employed and high SES mentors are more effective

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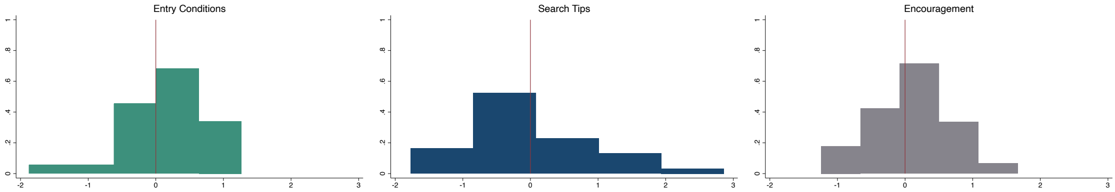
Mentors Heterogeneity by Type: FE Distributions

Panel A: Short Run Labor Market Index



Panel B: Career Trajectory Index