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Registered Report Stage 1: Proposal

# Meet Your Future: Job Search Efforts and Aspirations of Young Jobseekers

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**Abstract**
This study investigates the relative importance of several barriers to quality employment young jobseekers in developing contexts face when transitioning into a labor market characterized by high levels of informality and technological constraints: lack of information on labor market conditions, inability to communicate their own value, lack of connections, lack of motivation and liquidity constraints. The experimental setting is that of Vocational Training Institutes (VTI) in Uganda. We track 1115 VTI students over a period of 3 years to follow the evolution of their employment expectations and planned search strategy as they approach the labor market and start the search. Treated students are eligible to participate in the Meet Your Future Program, a highly tailored career-coaching program delivered by successful alumni who belong to their same VTI and course of study. A random sub-group of treated students receives a cash transfer to aid them in their search in addition to the program. We estimate the casual effect of these interventions on students' expectations, job search and labor market outcomes. Last, through detailed data on students' pre-intervention network and socioeconomic background we are able to evaluate the program's potential to increase equality of access to quality jobs.

**Proposed timeline of the Meet Your Future Project**

The overall duration of the project is 36 months. We conducted three pre-intervention interviews at the student level and three at the alum level. In January 2021, subjects were contacted again to confirm participation to the study as well as their contacts. The intervention was rolled out in February and March 2021. As part of the intervention, we conducted a Post-Interaction survey with treated students and an Alumni Check-in with the alumni selected to participate in the program. The first endline survey took place in May 2021. The second one will take place in February 2022.

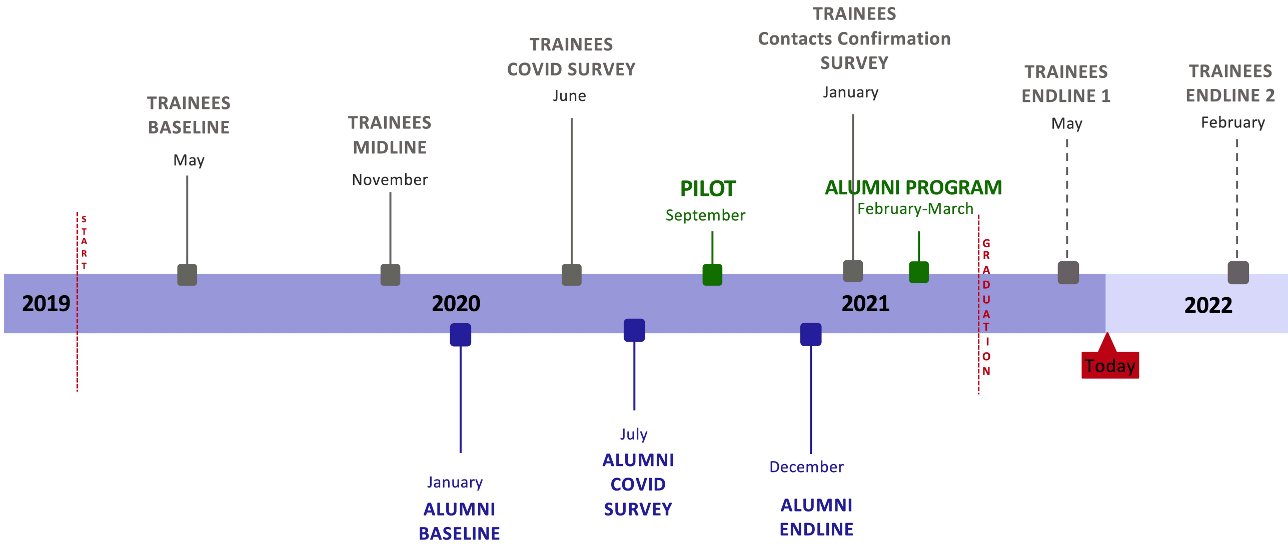


Figure 1a. Project Timeline

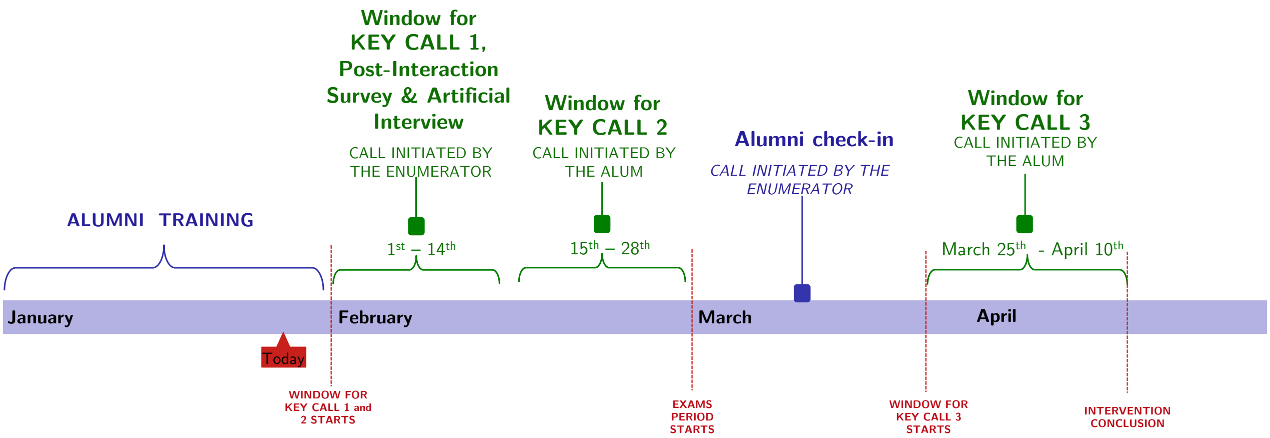


Figure 1b. Intervention Timeline - detail

# 1 Introduction

In highly informal labor markets, network connections are key for a successful job search. A solid network is essential for the efficient matching of workers with jobs, as it has the potential to solve the numerous frictions identified by the literature on job search in developing countries: mismatched expectations about wages and firms' requirements (Babcock et al., 2012; Abebe et al., 2017b), intention-behavior gaps and lack of motivation (Abel et al., 2017), over-optimism and suboptimal search effort (Spinnewijn, 2015), liquidity constraints (Abebe et al., 2017a), unawareness and inability to communicate own value and skills (Pallais, 2014; Bassi et al., 2020; Carranza et al., 2020). These barriers are magnified for young jobseekers who lack previous experience when taking their first steps into the labor market, and thus network connections are extremely valuable to them.

In this study, we evaluate the impact of exogenously expanding the network of a graduate student on their employment expectations, job-search strategy and labor market outcomes. In particular, we implement a field experiment involving 1115 students enrolled in their last year of education in five accredited Vocational Training Institutes (henceforth, VTIs) in Central and Eastern Uganda. Students are trained in a variety of sectors, including hairdressing, welding, electrical engineering, tailoring, and catering. A subset is randomly selected to participate in the Meet Your Future Program, a highly tailored coaching experience where students are matched with successful alumni who attended their same VTIs and course of study. The program involves a minimum of three phone conversations between the student and their matched alumni. During these conversations, students have the opportunity to ask questions, share doubts, fear and dreams. Alumni can support the students in several ways, which we classify into four main groups: provision of information on the status of the labor market; provision of tips and guidance for a successful job search; referral to potential employers; encouragement and motivation. The conversations took place in February and March 2021, around the time of graduation.

By combining information on students' engagement in the program with information on the frequency, content and form of the phone conversations, we first determine if and when the program successfully transformed an exogenous match into a close link. To our knowledge, this is the first field experiment to exogenously create new links between young jobseekers entering the job market for the first time and workers in their sector of interest. We then use a randomized controlled trial to evaluate whether furthering the formation of a valuable network by connecting recent graduates with alumni aligns their expectations, leads them to re-optimize their search, connects them to openings and eventually improves their labor market performance compared to control students.

To understand whether simultaneously relaxing liquidity constraints has the potential to magnify the effects of a network expansion, we unconditionally provide 40,000 UGX (~ $12) to a random subset of the MYF Program participants, with the recommendation that they use the money to finance their job search or contact the alumni.

Finally, we look at the equity effects of the program. Students from poorer socio-economic background face more binding liquidity constraints as well as are equipped at baseline with lower quality homophilic social networks which perpetuate inequality and reinforce economic disparities.

This study contributes to several strands of the literature. First, it contributes to the literature on job search frictions in developing countries. By analyzing the content of the phone conversations, we identify the labor market frictions that prevail in the population of interest and compare them to those previously identified in the literature. Second, this study speaks to the literature on job search assistance programs for young jobseekers. Evidence on their effectiveness in developing contexts is mixed (McKenzie, 2017). While they have more scope in contexts with greater search and matching frictions, they are also likely to be less effective if employers highly rely on their network for hiring or publicizing vacancies. Additionally, some studies highlight how relaxing one constraint is insufficient to trigger labor market responses if other constraints are not simultaneously relaxed. For instance, Groh et al. (2015) and Abebe et al. (2017a) find that reducing search costs by matching firms and jobseekers has limited consequences on employment because jobseekers have reservation wages which are too high. Other types of interventions, such as support with job search planning, instead proved effective at increasing employment in Ethiopia (Abebe et al., 2017b). The MYF Program we implement differs from previous efforts in one major way: it is highly tailored to each student's specific needs. This characteristic makes it capable of relaxing multiple constraints at the same time. Brooks et al. (2018) implement a similar program where young female entrepreneurs are matched with a mentor from the same community and leave the relationship completely unrestricted. We differ from them in two major ways. First, we analyze the population of students transitioning from the education system to the labor market. This is a critical passage with long-lasting consequences over the students' future working trajectories. Second, through close monitoring of the interactions between participants and intense data collection, we create a framework to analyze and to test what is helpful, how and for whom.

Last, coaching programs are often institutionalized by schools and universities in developed countries. These programs have greater potential in contexts characterized by a high degree of labor market informality and a high reliance on network connections to navigate the labor market. Rigorously evaluating the effectiveness of a career-coaching program in a high-stake setting where it is currently nonexistent has the potential to support the labor market transitions of many generations of students to come.

# 2 Background

## 2.1 The Ugandan Labor Market

In Uganda, the second youngest country in the world, the quick population growth within the last couple of decades paired with simultaneous heavy investments in human capital has resulted in an increase in schooling within the workforce. Unfortunately, these stellar trends have coincided with a period of slower economic growth which has meant slower growth in labor demand and insufficient creation of good jobs. The rates of youth unemployment and underemployment have risen steeply and returns to education have declined rapidly (World Bank, 2019). With such oversupply of labor, it is of fundamental importance to ensure that frictions do not prevent efficient allocation of skilled workers across the few available good jobs. At the same time, the high degree of labor market informality and lack of digital platforms by making information acquisition and applications for suitable jobs more costly make the risk of mismatches much higher in this context. In practice, the limited high-quality jobs are filled most commonly by those who already possess valuable network connections within the industry, connections that youth belonging to poorer or more remote households are less likely to have. Increasing equity in labor market access therefore becomes deeply interconnected to increasing its efficiency and maximizing the likelihood of matching the candidate with the highest potential to the position. In this context, we evaluate the impacts of providing a valuable source of information and connections to young jobseekers entering the labor market through linking skilled graduates with successful alumni. By reducing the cost to acquire information and connect to job openings, we aim to improve the quality of the matchings at first job and level the playing field across graduates from different socio-economic backgrounds.

## 2.2 Study Population

As in many other economies in East Africa, attempts to educate and skill the population have also taken place through vocational training and other skill transfers. In the early two thousand, the Ugandan government designed specific bodies to set rules for accreditation, assessment, certification, and inspection. As of today, the vocational sector is well established in Uganda: vocational training is a common route through which workers acquire skills, and SME firm owners are familiar with recruiting trainees from VTIs. It is also a common tool used by NGOs to promote the transition of secondary scholars from disadvantaged backgrounds into practical tertiary training. It is within this context of vocational training that the sample of our students makes the school-to-work transition.

Specifically, we survey the population of students that enrolled in the National Certificate (NC) Program in 2019 in five VTIs across Eastern and Central Uganda[1]. Our sample is representative of the population of Ugandan youth enrolled in practical tertiary training[2]. The NC is a two-years program aimed at teaching students a specific trade. The course includes theoretical and practical classes and, at the end of it, students receive a certificate of skill ownership with national validity.

The 1115 students in our sample are trained in 13 specific skills: motor-mechanics, plumbing, catering, tailoring, hairdressing, construction, electrical engineering, welding, machining and fitting, teaching/ECD,

[1] We selected VTIs with a long-lasting history of collaboration with BRAC Uganda, our implementing partner, which pre-selected them based on their reputation, infrastructures and equipment, teachers' educational attainment and teacher-students ratio.

[2] There is no shortage of VTIs in Uganda, and as in other low-income contexts, there are concerns over a long tail of low-quality training providers existing in equilibrium. It is not obvious the results would replicate in one of these low-quality providers.

agriculture, accounting and secretarial studies.  As shown in Table A.1, these sectors constitute a source of stable employment for young workers in Uganda: around 16% of employed workers aged 20-30 work in them (a percentage that more than doubles if we exclude those involved exclusively in agriculture). Students' distribution across field of study and treatment arms is described in Table A.2.
As shown in table A.3 at baseline the students are on average 20 years old, 40% of them are female, and most of them are single, Christian and have no children. The sample is relatively heterogeneous in terms of socio-economic background, which we proxy using information on households' asset ownership, urban or rural location and household of origin main source of income, which is divided between subsistence agriculture (33%), commercial agriculture (15%), wage job (33%) and a family business (19%). About 40% of the students worked before the VTI, mostly in unskilled wage or casual occupations. When asked about plans for the future, almost 60% of the students reported their intention to look for a job, 15% to start their own business, and 27% to pursue further education before entering the labor market. The latter percentage is around halved towards the end of the training when we re-elicit their intentions. Finally, in the three pre-intervention survey rounds we asked the students to name up to 9 people (four at baseline, up to four more at midline and up to one more during the covid survey) to whom the students would ask for support, broadly defined, when looking for a job. We obtained information of 4,932 network members (of which 4,896 are unique) whose main characteristics are reported in Table A.7. 62% of the network members are male, on average they are 37 years old and have completed 12 years of education. 81% of them were working when the students were interviewed, most of which in full time jobs. Despite the overall high quality of this group of people, there is enough heterogeneity which becomes evident when we compare measures of network quality between students with high and low SES. Table A.8 shows that poorer and richer students have networks that are similar in size (4.4 members on average) and composition (88% of the members coming from the original community, including family members, friends, neighbors, etc., and 12% coming from the VTI, including VTI friends and teachers). However, students with low SES have a lower share of network members with secondary education (difference of 12pp), able to provide students with a job (12pp difference), to be currently working (9pp difference) and to be earning above the median in the sample of alumni (14pp difference). This evidence supports the view that a valuable employment network comes with solid economic background, and that relying on word of mouth and network connections for demand and supply of labor to match perpetuate existing inequalities.

## 2.3 Transition into the Labor Market

To gather information about how the transition into the labor market generally evolves for the young graduates that leave the VTIs and inform the project design we (i) surveyed 246 trainees from two renowned VTIs in Uganda; (ii) conducted numerous focus groups (FDGs) with VTIs' managers, teachers, current students, and alumni; (iii) collected and digitized hard copies of phone contacts[3] for 1,368 alumni, of which we successfully contacted and surveyed 714[4]. The rich set of information collected consistently points toward three major challenges students face during the transition into the labor market, as well as to the greater impact of these challenges upon students belonging to a lower socioeconomic status.

First, students are overall "poorly prepared to face the outside" i.e., they lack information about labor market conditions and hold misaligned expectations. In Figure A.2. we show that students' expected wages after graduation are significantly higher than the alumni's average wage at their first job at baseline, one year into the program, and in the midst of the first lockdown. In Figure A.3. we show the time required to search for a job as expected by the students across three points of time and learn that the students not only overestimate their wage at first job, but they also underestimate the required time when compared to the average time spent on the job search following graduation of the alumni in the sample. At baseline students underestimated the time required by over half. Even when surveyed during the Covid-19 pandemic in June and July 2020, when job market prospects were relatively grim, the students still underestimated the time

[3] One example of the digitized material is shown in Figure A.1.

[4] The attrition from the initial sample of 1,368 alumni contacts is largely attributed to the quality of the information which was collected by the VTIs at the time of each student's graduation. Due to the written nature and manual entry of the records, the digitization process was not only prone to error, but much of the data was not recent as telephone SIM cards were required to be registered in 2016 which led many Ugandans to change phone numbers. Of the 714, 657 were successfully interviews in all three survey rounds.

required by an average of four weeks. Taken together, and abstracting for their believes' evolution over time, we interpret this as evidence for optimism over wages and arrival rates.

When confronted with the possibility of meeting successful alumni, the students in the pilot study came up with numerous questions on how to job-search, which challenges to expect, how to find customers and input providers, how much capital they would need and how to obtain it, what to expect about working conditions, such as pay, hours, and benefits. Students declared to be interested in hearing alumni's personal experiences to figure out what are the necessary steps required to build a successful career. Similar information gaps, and more, were identified during the FGDs conducted with alumni when we asked what they wish they had known before starting to look for their first job. The most recurring answers across courses were: important documents' formatting and organization, dress code, attitude for interviews, and dropping the application to the right person. Overall, we understood that alumni are a precious source of information and advice that could benefit students and whom they would be interested in hearing from.

Second, jobs seekers and firms are not using formal channels to find jobs. Indeed, over 60% of the respondents identified network connections with friends and/or relatives as one of the main channels they plan to use to look for a job. When we look at the alumni sample, 61% of them found a job through this channel, proving that the relevance of the channel is widely understood by the students. And rightly so: suggestive evidence shows that more connected alumni performed better than less connected ones in their first steps in the labor market as well as four years down the road. As shown in Table A.4 alumni with at least one relative who works at or owns a business in their sector of training find a job significantly earlier, are less likely to work in casual occupations as first activity following graduation as well as pre Covid-19 (which corresponds to on average 4 years into the labor market) and are significantly more satisfied of their career. This comes from the fact that in highly informal labor markets network connections are primary determinants of what information, opportunities and support young jobseekers have access to, and eventually of their success in the labor market. In the words of an alum who participated in our focus group discussions, for a young jobseeker making her first steps in the labor market *"first and foremost you must have friends, in this era one cannot get a job without having friends that connect you to deals"*.

This acknowledged importance of a network explains why we find that 20% of the students identify limited access to valuable network connections as one of the main challenges they will face when transitioning to the job market (Figure A.4). Unsurprisingly, it is the poorer students who feel they lack network connections: when we analyze students' perceived challenges by their asset index[5] we observe that students with worse SES are 7 percentage points significantly more likely to say that one of the main challenges they will face is "lack of connections".

This worry is well grounded, as displayed in Table A.8 for students and confirmed again in the alumni sample, where we find additional suggestive evidence that valuable relationships come with a solid economic background (Table A.6). What we can additionally do in the sample of alumni with respect to the sample of students is to obtain evidence, although suggestive, that lack of a connections likely play an important role in perpetuating inequality in the labor market, as alumni with low SES and poor network have worse labor market outcomes (Table A.5). Connections, which develop around existing social hierarchies and reinforce economic disparities, also translate into access to information, guidance, support, and opportunity. Consequently, a lack of connections can serve as a barrier to increasing inclusivity of poor people in higher quality jobs.

Third, when students were asked about which challenges, they expected to face when looking for their first job, many bring up the lack of economic resources to finance the search process or to invest in a new business: 43% of the students mentioned "lack of money for transportation" or "lack of money to finance the job search" (all in the category "money for job search" in Figure A.4).

In conclusion, most students are poorly informed about labor market conditions, lack expansive networks to leverage in the job search process, and face liquidity constraints. Additionally, these three challenges are harder to overcome for those who belong to households of a lower socio-economic status. With this project, we provide insights into the effectiveness of a career-coaching program performed by "the future you", a successful alumnus of the VTIs, and we investigate the program's potential to smooth the transition from the education system into the labor market and increase equality of access to quality jobs.

[5] Built with information on the assets present in the household where they grew up, we use it as a proxy for their social economic status.

### 2.4 Covid-19 in Uganda

Lockdowns in East Africa in response to the Covid-19 pandemic have been among the most stringent on the continent and consequently the region boasts the lowest cases. This is also true in Uganda, where schools were closed as of March 20th and other non-essential businesses and public transport were shut down for over two months beginning April 1st. The decisive action to shut down businesses not deemed most essential helped the country cope with the virus, but it is predicted that Eastern Africa will be the hardest hit region with respect to labor market impacts.

From the data collected on the alumni, we find that as a result of total lockdown measures in Uganda about 40% of businesses were forced to temporarily close and about 71% of wage employed alumni were temporarily laid off when surveyed in June and July of 2020. In December, six months after total lockdown measures were lifted and only a public mask mandate and nighttime curfew were left in place, almost 80% of the alumni who had been laid off during the total lockdown had returned to work. This relatively high rate of reintegration back into the labor market among these young alumni suggests that the current context with respect to finding jobs was less grim at the time of graduation than it had been in the summer of 2020[6]. While the data suggests that the labor market was beginning to recover in Uganda six months after the total lockdown, the state of the market in March 2021 is unclear for young entrants as there exists the possibility that these firms are simply replacing the skilled workers who were previously laid off in March and April of 2020. However, if it is the case that jobs are even more scarce for our graduates now, ensuring productive matches and access to information for all has the potential to be even more important than in pre Covid-19 times.

Anecdotal evidence from within Uganda on increased prices of transportation and income shocks across households reinforces the data collected on current labor market conditions and speaks to the salience of our project's T2 cash transfer, especially with regards to the additional cost of job searches borne by graduates.

# 3 Research Design

### 3.1 Intervention and Treatment Groups

As part of our intervention, we administer two treatments: the Meet Your Future Program (T1) to 30% of the sample and the Meet Your Future Program with Mobile Money (T2) to another 30% of the sample. The remaining 40% is a pure control group.

<u>T1: Meet Your Future Program (MYF)</u>

Students assigned to receive this treatment will be matched with “the future you”, a successful alum who graduated from their same VTI and in their same course of study. In particular, the research team will facilitate three conversations on the phone. During these phone calls, students have the chance to ask questions, share their doubts, fears, and dreams. These interactions are unrestricted: no specific topic coverage is required. Each student-alum pair is free to discuss what they find most interesting and useful for the student’s transition from the education system into the labor market. In this way, the coaching is tailored to each student’s specific needs. We anticipate each conversation to revolve around general as well as student-specific topics.

The first phone call, which we call Key Call 1, takes place approximately one month before graduation.[7] It is a conference call between the student, the alum and the enumerator who initiates and records the conversation. Prior to Key Call 1, the enumerator contacts the alumni and students to find a common availability. Treated students learn about the existence of the MYF program during this phone call with the enumerator. During the call, following the initial introduction, the enumerator remains silent, listens to the conversation, and compiles a survey (the Artificial Survey – more detail available in Section 4.1) to identify

[6] As we write this version of the manuscript, Covid-19 cases in Uganda are roaring once more and stricter measures are likely to be ahead. From the Endline 2 survey we will be able to gather and include findings on how students’ labor market conditions as of Endline 1, changed following the second lockdown.

[7] Students graduating in ECD have an earlier graduation date, which implies that for them the program is administered around their graduation and after.

the topics covered as well as to characterize the *form* of the conversation. At the end of Key Call 1, the student remains connected with the enumerator to answer a brief survey, the Post Interaction Survey, to record the student's main take-aways and feelings immediately following the first interaction with the alum.

The second and third phone calls, which we call Key Calls 2 and 3, take place two weeks prior to and two weeks following graduation. They are initiated by the alum and are private conversations between the alum and the student. Alumni are required to send a text after the completion of each of these Key Calls to confirm they took place and we double check this information with the students during Endline 1. We also encourage students and alumni to interact beyond these three Key Calls, if they wish. Alumni are required to take notes of the frequency, duration, content and means (in person, phone call, video-call, WhatsApp messages, SMS, email, etc.) of any additional interaction that takes place over the two months duration of the program.

The alumni taking part in the program have been previously selected and trained by the research team. To select the alumni that will administer the intervention, we defined a set of rules to ensure the overall quality of the coaching as well as to ensure replicability. From a sample of 657 alumni, we exclude 90 alumni that did not provide their availability for the MYF program or never worked in the occupation of training. To select the most successful alumni among the remaining ones, we assign a score to a set of relevant characteristics and rank them based on their total score. The characteristics considered are: (i) accessibility, (ii) quality of first and current jobs, (iii) general labor market indicators, (iv) school performance, and (v) soft skills. The full list of variables we use in the selection and their corresponding scores are in Table 1.

We rank alumni based on their total score. Our goal is to match students with alumni who attended their same VTI and course of study. For this reason, we select the N highest ranked alumni for each VTI-training area combination, where N is a function of the number of treated students in each VTI-training area.[8] There are 12 out of 57 combinations of VTI-training areas for which we have slightly less alumni than we need. In these cases, we select the highest ranked alumni graduated from the training areas in question that have not been yet assigned, regardless of the VTI[9]. After the selection, we end up with a sample of 171 alumni. Each alum is assigned one to five treated students at random. Each alum is assigned students belonging to the same treatment arm. The specific number of students in each combination of VTI-training area-treatment arm is determined based on the exact number of students assigned to each alum. When forming groups, we maximize the number of groups with three, four or five students per alum[10,].

Alumni are trained by the research team prior to the start of the program. During the training, the alumni get to know their duties as career-coaches and program ambassadors and are guided through the different ways in which they could help the students:

- Share information about general labor market features [Information];
- Provide tips for a successful job search [Strategy];
- Refer the student to potential employers [Referral];
- Encourage the students to do their best and put in the effort [Motivation].

They are also reminded that they can interact with the students as many times as they wish, and that during their interactions with each student they are free to discuss whatever they think would be most useful for that student to learn. To thank them for their two months long participation in the program, conditional upon the completion of the three Key Calls and the Alumni Check-In (see Section 4.1 for details), alumni are provided ~$40 as well as reimbursements of the airtime incurred to make the phone calls. The facilitation does not depend on students' success in the labor market.

Table 1. Alumni Ranking Procedure

| Characteristic | Score |
|---|---|
| ***Accessibility*** | +1 |
| Alum has smartphone | +1 |
| ***Quality of first and current job*** | |
| First job: wage-employed or self-employed | +1 |
| First job: earnings above median | +1 |

[8] The number of required alumni in a specific VTI-training area increases by one every five treated students.

[9] However, in these cases we try to match students with alumni who graduated from another school but in the same urban area.

[10] Eventually we have: 30 groups with 5 students per alum; 29 with 4 students per alum, 19 with 3 students per alum, 5 with 2 students per alum and 5 "groups" with just one student per alum.

| | |
|---|---|
| First job: sector same as sector of training | +1 |
| Current job: wage-employed or self-employed | +1 |
| Current job: earnings above median | +1 |
| Current job: sector same as sector of training | +1 |
| ***General labor market indicators*** | |
| Graduated between 2014 and 2018 | +1 |
| Longest unemployment spell below median | +1 |
| ***Education*** | |
| A or A+ in DIT Exam; graduated with honor in UBTEB exam[11] | +1 |
| ***Soft Skills*** | |
| Alum strongly agrees/agrees they generate enthusiasm | +1 |
| Alum strongly disagrees they generate enthusiasm | +1 |

To design our intervention and refine each survey tool and protocol, we piloted a small-scale version of the program with 30 students and 10 alumni from a sixth VTI (which is not part of the intervention) between October and December 2020. All pilot participants completed the program and provided highly positive feedback about its usefulness.

T2: Meet Your Future Mobile Money (MM-MYF)

Students assigned to this treatment arm receive 40,000UGX (~$12) through mobile money upon graduation. The cash transfer is unconditional. However, students are recommended by SMS to use such funding to facilitate the kickoff of their careers and are required to report to BRAC how they spent them (the SMS text is available in Appendix A).

### 3.2 Assignment to treatment

The strong implementation capacity of our local partner BRAC Uganda, as well as the collaboration with the VTI's principals, allows for the randomization of the applicants into the program. The randomization is private, that is, only the research team is privy to the process. We assign students to three randomly selected groups and to treatment eligibility as follows:

Table 2. Assignment to treatment

| Group | Intervention | N | % of sample |
|---|---|---|---|
| 1 | Control | 442 | 40 |
| 2 | T1 | 334 | 30 |
| 3 | T1+T2 | 339 | 30 |

The identification strategy for our RCT relies on the hypothesis that the three groups are identical, on average, in all observable and unobservable characteristics. To support this hypothesis, we check for balance across treatment arms over available characteristics likely to correlate with the outcomes of interest. The experimental design is balanced in nearly all the variables of interest, as shown in Tables A.2, Table A.3 and Table A.9. The randomization we perform is stratified at the student level. In this section we describe how we choose the "strata variables", the set of variables along which we stratify the randomization, and the "balance variables", the set of variables for which we require no imbalance. We set specific imbalance goals to make the re-randomization process as transparent as possible. All strata and balance variables will be included in all treatment regressions. In all our choices, we followed the principles highlighted in Bruhn and McKenzie (2009) and Athey and Imbens (2017).

Choice of the strata variables

First, we decide to stratify by VTI, as the implementation of the treatment could vary at the school level.[12] Second, we decide to stratify by a measure of "risk of attrition" to reduce the possibility of selective attrition. The variable we use is *hard_to_find*, an indicator for whether the student has not been successfully

[11] These measures allow to flag the top 15% of both exams' participants.

[12] We use indicators for schools in a similar way as Bruhn and McKenzie (2009) suggest using indicators for different geographic areas which are possibly subject to different shocks affecting the way in which interventions are administered.

interviewed in three out of the three pre-intervention survey rounds. Third, we choose to stratify along dimensions that are likely to be correlated with our outcomes of interest based on economic theory and existing data. To identify these variables, we perform two sets of analyses.

i. Within the sample of students, we check how a pre-determined set of students' characteristics correlate with employment indicators before the beginning of their course in the VTI and during the lockdown. We believe that the ability to find a job in the past, as well as having some work experience, could be positively correlated with the ability of finding a job after school completion.
ii. Within the sample of alumni, we check how a set of alumni's characteristics correlate with the following set of labor market outcomes a) earnings at their first job, b) their most recent employment status and earnings.

The variables we correlate with the outcomes above are: indicator for male student/alum; indicator for ownership of a smartphone; indicator for agriculture as household's main source of income (rather than wage or self-employment in non-agricultural activities); asset index; scholarship status; caretakers' educational attainment; indicators for each of the VTIs; indicators for each of the training areas.

These correlation analyses (whose results are available upon request) reveal the following:

- The indicator for male is highly and positively correlated with labor market outcomes in both samples of students and alumni;
- The indicator for smartphone ownership is highly and positively correlated with labor market outcomes in both samples.

The remaining variables display weaker or inconsistent correlation patterns. To sum up, we decide to stratify along the following four dimensions and obtain a total of 5x2x2x2=40 strata[13]:

Table 3. Strata Variables

| Strata variable name | Description | Motivation |
|---|---|---|
| Vti | Categorical variable with 5 levels corresponding to the 5 VTIs in our sample | Potentially correlated with treatment implementation |
| Male | Indicator for whether student's gender is male | Positively correlated with labor market outcomes |
| Hard_to_find | Indicator for not reaching the student in all pre-intervention survey rounds | To reduce the risk of having differential attrition by treatment status |
| Wa_sp | Indicator for smartphone ownership | Negatively correlated with labor market outcomes; to reduce the risk of having differential attrition by treatment status |

<u>Choice of the balance variables</u>

We decide to replicate the randomization procedure until we achieve balance on a pre-determined characteristic that we believe could be highly correlated with the outcomes of interest: a dummy for whether the student has ever worked (either before beginning the course or during the lockdown). We ex-ante define the procedure that determines whether the randomization should be replicated. For any given treatment assignment:

a. We regress *ever_worked* on indicators for control group, treatment 1 and treatment 2 groups, and we record the p-value from the Wald (F)-test that the coefficients of all indicators are jointly equal.
b. We use t-tests to test whether the difference in means among 1) students assigned to the first and second treatment groups and 2) students assigned to the first and third treatment groups are statistically different from zero and we record the two-corresponding p-values.
c. We reject the treatment assignment if any p-value from Wald or t-test is below 0.3 and 0.1, respectively.

In practice, we achieve balance after one randomization, therefore, we do not replicate the randomization.

[13] We generate strata using the *egen group* function in STATA. The command we implement on STATA to generate strata is the following: *egen strata=group(vti male hard_to_find wa_sp).* The variable obtained this way has 3 missing values, and is missing whenever any of the strata variables are missing. We randomly assign these 3 observations to the existing strata so that the final *strata* variable has no missing observations.

### 3.5 Replicability and Cost Effectiveness

Replicability and cost effectiveness have been an important goal while designing the intervention, given the interest expressed by involved VTIs as well as the BRAC Youth Empowerment Program. For this reason, the intervention is relatively easy and inexpensive to replicate.

In its current form, the hardest step in setting up the Meet Your Future Alumni Program consists of obtaining the contacts of the alumni for a cohort with two to five years of experience in the labor market, as VTIs are unaccustomed to tracking their alumni. However, once the program is set up, tracking methods become less costly. For instance, students might be systematically asked for updated contact information. They can also be made aware of and inducted into the alumni program prior to graduation. The algorithm proposed to select the alumni is easy to replicate, as it is based on accessible survey and administrative information. Once alumni have been selected and schools' administrators instructed on how to make random matches, the implementation of the intervention is straightforward. Moreover, institutionalizing the intervention at the school level will make its implementation easier. Indeed, the first interactions between students and alumni will be facilitated by the schools with no need for an enumerator to attend, further reducing the cost of this intervention which is already relatively low. We estimated a per alum cost of: ~$5 for a half-day training (includes a snack, a face mask, a hand sanitizer, stationary and a venue); ~$15 for airtime (which is the equivalent of 70 hours of talking time) and an overall ~$40 facilitation to thank them for participating in the Alumni training, the Alumni Check-In and for conducting the Key Calls. Considering that an alum is matched to an average of 3.9 students, the cost per student is ~$15. The per student cost is relatively low and makes up a minute proportion of the fees paid for these programs ($650 - $800). Given the institutions providing need-based scholarships already allocate large amounts of funding to pay for the training of these students, it would behoove them to invest this additional small amount which is expected to amplify returns by a great deal and make a difference in employment outcomes. This additional investment is especially poignant for students belonging to disadvantaged economic backgrounds for who the program is expected to make the largest difference.

The costs discussed are exclusive of the administrative costs. While the airtime and training costs are likely to stay the same (it is likely the schools will not need to rent a venue and hopefully face masks and hand sanitizers will not be needed forever), we foresee the facilitation to be needed only for the first 2-3 years of the program. Once the alumni program is institutionalized and students who benefitted from it during the initial years are themselves asked to be ambassadors, we believe that the monetary compensation will not be needed or could be effectively reduced.

Similarly, the difficulty in gathering contact information from the students to set up the Mobile Money intervention would be greatly lessened if the program were to be institutionalized such that schools could collect and update this information in an organized manner. Once the contact information is available, sending money and communicating with students about their suggested use can easily and cheaply be automatized[14]. A rigorous evaluation of the program cost-effectiveness will be conducted before disseminating any policy suggestion.

With this study we focus on the supply side of the labor market and look at viable and cost-effective ways to improve jobs to students matching, job satisfaction and equality in access to quality jobs, while keeping labor demand factors fixed. If the program has positive effects on these outcomes, scaling it up will neither create distortions on the local labor markets, nor will the potential effects dissipate. For what concerns the experiment study, as we are currently implementing the program in 5 out of 715 accredited VTIs only in Central and Eastern Uganda (1270 nation-wide)[15], the advantage for treated students will likely not come at the expense of the control group. Indeed, treated students represent a tiny fraction of the cohort of jobseekers, and the urban labor markets in which they are most likely transitioning into are among the biggest in the country (Kampala and Jinja) suggesting that negative treatment effects are unlikely.

[14] We used Telerivet Software for broadcasting SMS.

[15] As of 2017-2018, the total number of VTI in the Central and Eastern regions, both formal and informal, accredited either by the DIT (493, of which 383 located in the Central region, and 110 located in the Eastern region) or UBTEB (291, of which 196 in the Central region, and 95 in the Eastern region) or both (69, of which 50 in the Central region, 19 in the Eastern one) was 715. However, this is likely to be an upper bound: 33 VTIs (8 in Eastern Region, 25 in Central region) that appear in a 2015 list do not appear in what seems to be an updated version of such list in 2017. Additionally, the overlap between UBTEB and DIT accredited VTI could be refined. These are the results from an exact matching. The lower bound is 460 (should all the UBTEB and DIT overlap and should those 33 have closed down).

# 4. Hypotheses and Theory of Change

We collected a rich dataset, which will be used to test several hypotheses. Subsection 4.1 concerns impacts on our primary outcomes, as well as heterogeneity of impacts. Subsection 4.2 concerns the process and mechanisms that can explain the impacts, or lack of therefore, on the primary outcomes. Details on how outcomes are measured follow in Section 5.

## 4.1 Impacts on primary outcomes

*Hypothesis 1: Matching students with a successful alum from the same VTI and course of study will (i) align students' expectations, and improve their (ii) job search strategy and (iii) labor market outcomes.*

Alumni represent a network connection which is orthogonal to the students' existing network, as well as a source of information, advice and motivation. For this reason, we anticipate the following treatment effects:

(i) Impact on labor market expectations:

a. We expect treated students to internalize the information on available opportunities and labor market conditions obtained by alumni and readjust their expectations about how long it takes to find a job and earnings at first job, for themselves and for members of their class.

(ii) Impact on search strategy:

a. We expect that the number and the type of job opportunities treated students are aware of and apply to will expand compared to the control group. Concretely, this means more resources devoted to job search: higher index of search intensity and a higher index of search broadness.
b. We expect treated students to internalize their alumni's advice, tips and suggestions and improve their job search efficacy index.
c. We expect treated students to receive a higher number of interviews and job offers than control students.

(iii) Impact on labor market outcomes:

a. We expect treated students to work, earn and apply their newly acquired skills more than control students in the four weeks preceding Endline 1 and Endline 2.
b. Conditional on finding a job, we expect treated students to find better jobs than control students, to have higher career and job satisfaction and lower turnover.

*Hypothesis 2: Receiving cash on top of the career coaching program will magnify the effects of the MYF treatment on students' (i) job search strategy and (ii) labor market outcomes with respect to students only receiving the alumni program.*

(i) Impact on search strategy: the cash transfer, paired with the MYF program, will relax students' job-search budget constraint and allow them to get closer to their *new* unconstrained optimum. Concretely, this means an even higher index of search intensity and of search broadness as compared to students in T1.

(ii) Impact on labor market outcomes:

a. Following the stronger effects on search intensity and broadness we expect treated students who received cash to work, earn and apply their newly acquired skills even more than students in T1 in the four weeks preceding Endline 1 and Endline 2.
b. Conditional on finding a job, we expect treated students who received cash to find better jobs than treated students who did not receive cash to have higher career and job satisfaction and lower turnover.

Additionally, we will investigate the presence of heterogeneous effects for relevant sub-groups of students. Sub-groups are identified by categorical variables capturing characteristics at baseline. When characteristics are continuous, we create subgroups by separating individuals below and above the median level of the characteristic. These characteristics are:

- Gender. Women have lower labor force participation rates in general and their sectors of training appear to be hit harder by the Covid-19 shock. We expect effects to be greater for women, whom previous research has shown are more likely to get discouraged while searching and have harder time seeking support from their network members.
- Previous work experience: dummy for whether the student has ever worked before graduation. We expect people with work experience to have a smaller treatment effect.
- Raven's scores at baseline. We expect higher ability people to have a larger treatment effect.
- Locus of Control from the World Value Survey. We expect people with and external LOC to have a smaller treatment effect, as they may not value the program.
- Disadvantaged socio-economic background. Effects are larger for economically disadvantaged students with (i) worse employment network pre-intervention; (ii) lower asset index; (iii) from rural households.

### 4.2 Process analysis and mechanisms

We envision a 3-step process through which the coaching program can lead to broader information sets, realigned expectations, improved strategy to find a job, better labor market outcomes and higher job-satisfaction:

1. The three Key Calls between the student and the alum matched to her take place.
2. During each interaction the alum is engaged and provides a combination of:
    (i) Generic information about the job market [Information];
    (ii) Tips for a successful job search [Strategy];
    (iii) Contacts for specific openings/potential employers [Referral];
    (iv) Motivation and encouragement [Motivation];

   Of a reasonable standard and quality to which, on average, students would not have access to otherwise.
3. The student values the inputs shared by the alum and is inspired by him/her to land a good job.

The program may fail to have an impact on expectations and job-seeking behavior, and consequently labor market outcomes, if any of these steps does not occur. Indeed, we expect the impact of the coaching program on the primary outcomes will be (1) lower for students with fewer and shorter interactions with their alum; (2) greater for students who participate to engaging interactions and the alum provides a combination of (i) - (iv) and (3) e lower for students who do not value the inputs shared and/or are not inspired by the alum. At the same time, the occurrence of each of these steps is likely to be endogenous and prone to self-selection. For this reason, every analysis on these process outcomes should be treated as descriptive only (e.g. students may decide to never speak with an alum because they already have a job waiting for them, or not to use the cash transfer for job search because they are facing more urgent monetary needs). As part of this exploratory analysis, we will investigate the determinants of the process outcomes among students' and alumni's characteristics. To further inform process understanding we will treat the process outcomes as left-hand side variables so to examine whether heterogenous effects are similar in process outcomes to those in primary outcomes. More specifically, we will predict, with pre-treatment variables, the process outcomes. We will then interact the predicted outcome measures with treatment status to examine whether those who engage in more process changes are also those who have larger treatment effects.

We envision a 2-steps process through which receiving the cash transfer can affect job search strategy/strategy to set up a business, labor market outcome and job-satisfaction.

i. Student receives the cash transfer and autonomously decides how to spend it;
ii. Student spends the funds on career-related activities.

The effect of the cash transfer on primary outcomes will be smaller for students without full disposal of the money received and for those who do not use the entire transfer for purposes related to job search and career launch. As before, such process outcomes are at risk of endogeneity and their analysis is to be considered purely exploratory. We will focus on looking at predictors for the success of these two steps and analyze how they correlate with the main effects on the primary outcomes.

*Hypothesis 3: The training and the mobile money will be more effective in labor markets with strong labor demand.*

In our study we do not directly observe labor demand dynamics. To better interpret our findings (or the lack of thereof), we will provide evidence on the conditions of the economy, overall and by sector. We will do so using:

- The rich set of data collected right before the Covid-19 outbreak (when the economy was in a good state), two months and six months following the end of the total lockdown (when the economy was in a good state), from our 714 alumni in their role of recent graduates, young entrepreneurs and workers;
- The "COVID-19, Firm Dynamics and Market Structure in Urban Uganda" Project of which members of this research team are Co-PIs. This study combines four rounds of pre-COVID panel data on more than 4,000 firms with two new rounds of surveys to collected during the crisis and one year following the onset of it on SMEs in the same occupations in which the students on the Meet Your Future projects are trained.

Leveraging these unique panels, we will create a sector specific index about the status of the economy as the jobseekers approach the market using the following information:

- The change in the share of employed alumni by sector between pre- and post- pandemic to evaluate trade-specific consequences of the pandemic.
- An indicator for whether the distribution of search time and earnings differs between the samples of alumni and students.
- An indicator for whether absence of jobs is reported as the main obstacle to find a job by 50% or more of students in the sector.
- Firms' expansion patterns and hiring levels by sectors.

The status of the economy will be classified as "good" or "bad" if these indicators convey the same information. While the process analysis shall be seen as exploratory, Hypothesis 3 can be tested based on exogenous variation.

# 5. Survey Instruments and Outcome Variables

## 5.1 Data collection and processing

For the data collection, the research team trains and hires, through BRAC Uganda, professional enumerators that routinely work in research projects involving interviews both in person and over the phone. Enumerators are selected after the training based on their performance on a test, where the score is indicative of the enumerators' understanding of the survey tool. All surveys are conducted through Survey Solutions using the Computer Assisted Personal Interviewing Software (CAPI), where consistency checks were built into the program. Additionally, random back-checks were performed to verify the quality of the data. The observed coherence in the correlation analyses we conducted on both pre-intervention datasets reassures us that the quality of the data is high.

The two key data sources for this study are the students' surveys and the alumni surveys. As schools keep updated administrative data on the population of enrolled students, students' lists were easy to obtain soon after the establishment of a partnership with the schools. Conversely, schools do not systematically store former students' contacts. For this reason, we collected and digitized the alumni's contacts that were available in the VTIs registries. We chose cohorts of alumni that have been in the labor market for 2 to 5 years, with the goal of selecting alumni with enough experience in the labor market, yet of similar age to current students. Given that many of the contacts from previous students had not been updated in years, of the ~1400 names and contacts digitized, 657 were eventually tracked down and surveyed three times.

On top of the students' and alumni's surveys, which we administer to the entire samples of students and alumni, we collect post-intervention surveys, one for treated students and one for selected alumni that are operating the coaching. The goal is to obtain real time information about how the interactions went and what do students and alumni think about each other.

We use Key Call 1 voice recordings and data collected by the enumerators listening to Key Call 1 (what we call "Artificial Survey") to characterize the one-to-one interactions between the alumni and the students. Thanks to these two sources of information, we track not only the content - what inputs are shared - but also the *form* of the conversations. Findings from different areas of social psychology, communication, and sociology have long confirmed that a sense of we-ness and shared identity emerges because of both the content of social interactions (what is being said both verbally and nonverbally) and because of a strong influence by the form of interaction: disruptions in conversational flow, speaking at a similar pace, mimicking the emotions of one's interaction (Koudenburg et al., 2017). This is important under a policy perspective as it makes innovative (alumnus-students) pedagogic methods comparable to the standard ones in terms of involvement and participation. See Table 6 for more details on each data collection activity.

## 5.2 Outcomes of interest

We define four domains of outcomes of interest: (i) job search strategy; (ii) expectations; (iii) labor market outcomes and (iv) existence and strength of network connection. The first three are primary outcomes of interest while those in domain (iv) are secondary outcomes that we use for exploratory analysis. The outcomes within each domain, as well as their measurement, are described below.

*Domain 1: Job search strategy / Strategy to start up a business:*

We characterize the search strategy through several indicators:

i. Index of search intensity (hours per day, days per week and number of applications submitted, savings devoted to starting up a career);
ii. Index of search broadness (search/fundraise methods, geographical scope of search, sector);
iii. Index of search efficacy (interviews/applications and offers/applications, used CV during search) - only for students planning to look for wage employment.

*Domain 2: Students' expectations about own performance in the labor market:*

We elicited point estimates or full distributions depending on what worked best in the piloting phase. When necessary, we help respondents answer unconventional questions via visual scales. We provide monetary incentives that reward accuracy of the prediction. These data include: (i) Expected time to first employment for the respondent and for the classmates; (ii) Expected earnings at first employment as in Attanasio et al. (2011) and their evolution is mapped through 4 different data points (5 for the treatment group): baseline, midline 1, midline 2, contacts confirmation survey and, for the treatment group, the Post Interaction survey.

*Domain 3: Labor Market Outcomes:*
Our primary outcomes in this domain are:

1. Labor Market Index: an index that measures labor market performance. We build the index following Anderson (2008), so accounting for the covariance structure in components, and we normalize by the standard deviation of the index in the control group to ease interpretation. The index combines:
    i. A dummy for whether the individual has worked at all in the last 4 weeks;
    ii. The number of days worked in the last 4 weeks: this will be coded as zero for individuals who have not worked;
    iii. The total monthly income from work in the last 4 weeks: this will be coded as 0 for individuals who have not worked and will be top-coded at the 99th percentile of the earnings distribution conditional on working, to reduce influence of outliers;
2. Number of hours spent applying newly acquired skills in occupation of training in the 30 days preceding the survey: we designed an innovative survey module to track how much time the respondent spent performing each of a set of detailed typical trade-specific tasks a list we compiled by combining information from focus groups discussions with the alumni and resources from the O*NET Program (e.g., if the respondent was trained in motor-mechanics, she is asked whether she had mend a tire tube in the last 4 weeks, and if so how many times and how long it takes on average to conduct such task once);
3. Matching Quality Index, measured as:
    a. Self-reported job satisfaction through the widely used formula “All things considered, how satisfied are you with your career as a whole on a scale of 0 to 10?”;
    b. Employer-reported satisfaction with the employee;
    c. Dummy for whether the individual is working in the sector of training, conditional on being working;
    d. Ability to keep the job/firm running for at least 3 months.

For students who look for wage employment, conditional on employment, we will explore the quality of the employment landed. We will look at formality (whether the job was obtained with an interview as in Abebe et al. 2017a; existence of a contract as in Abebe et al., 2017b), and employment type (trainee, casual, temporary or permanent as in Franklin, 2017 and Abebe et al., 2017a). For students who look to start their own business, conditional on their business being operative, we will explore the business’s solvency, formality, value of equipment and size. Since this last analysis conditions on an endogenous outcome, these conditional outcomes are strictly suggestive.

*Domain 4: Characteristics of the new network connection:*
We define a jobseekers’ employment network as the set of people (i) she can reach out to; (ii) she thinks can be helpful for her career (iii) prone to provide help. To characterize whether a new network link is formed and what its strength is, we use:

i. <u>Engagement Index</u>: measuring student engagement level during the first interaction (See Appendix B for details). We build a flatly weighted index following Kling, Liebman and Katz (2007). The index has 4 components:
    a. *Mutual engagement* from the Artificial Survey measured on a 0-10 scale where 0 means not at all (e.g., the conversation was characterized by many brief and unexpected/awkward silence) and 10 means extremely smooth;
    b. *Relative engagement* from the Artificial Survey measured on a 0-10 scale where 0 means the alum never talked compared to the student and 10 means the opposite;
    c. *Student engagement* from the Post Interaction Survey.
    d. *Alum’s perception* of student’s interest in the program from the Alumni Check-In.

ii. <u>Identification Index</u>: to measure student identification with the alum we produce an 8-question index drawing from Rubin et al. (1985), Cohen (2001) and Igartua (2010) questions which required no adaptation to the context (See Appendix B for details).

iii. Usefulness Index: Self-reported student's evaluation of the project. We use a total of 7 questions in this index (See Appendix B).

iv. Frequency and duration of interactions: we use a dummy for whether more interactions followed the first one; a dummy for whether the student and alum ever connected outside the program; the overall number of interactions; and their average duration.

v. Type and amount of support provided: we put extensive effort into tracking whether and to what extent a mechanism is activated for a given alum-student dyad. Specifically, for each dyad we can observe whether the alum: shared information about general labor market features [Information]; provided tips for a successful job search [Strategy]; referred the student to potential employers [Referral]; encouraged the students to do their best [Motivation]. To do so, we cross check the recordings of Key Call 1 (which will be analyzed through text analysis with the list of topics compiled in the Artificial Survey by the enumerator while listening to Key Call 1 (see List of Topics in Appendix A). Moreover, we use the Students Post Interaction Survey to identify what inputs were shared with the student that the student would not have had access to otherwise, as well as the Alumni Check-in and students' Endline 1 and 2 to gather info on Key Call 2, 3 and any other following interactions.

Table 6. Surveys

| Survey | Sample | Stage | Date | Key information collected | Mode |
|---|---|---|---|---|---|
| **Students** | | | | | |
| Baseline | 1115 students | Completed | May 2019 | Demographics; Time preferences; Risk aversion; Raven's test; Savings: amount, purpose, intention to save in the future; Detailed information about 4 employment network members: level of education, employment status, frequency of interactions, how they can help finding a job; Life worries and self-esteem; Expectations about own performance in the labor market; Plan on how to job search/start-up a business. | In person |
| Midline 1 | 1115 students | Completed | Nov 2019 | Savings: amount, purpose, intention to save in the future; Updated detailed information about four employment network members; Life worries and self-esteem; Expectations about own and class-level performance in the labor market; Plan on how to job search/start-up a business. | In person |
| Midline 2 - "Covid-19 survey" | 1115 students | Completed | Jun 2020 | Time use during school closure (due to Covid-19); Labor market outcomes; Life worries and self-esteem, Expectations about own and class-level performance in the labor market; Plan on how to job search/start-up a business; Savings; Migration. | Phone |
| Contacts Confirmation survey | 1115 students | Completed | Jan 2021 | Updated contacts; Expectations about own and class-level performance in the labor market. | Phone |
| Post-Interaction Survey | 673 treated students | Completed | Feb 2021 | Survey to record the student's main take-aways and feelings immediately following the first interaction with the alum (Key Call 1). Contains questions on: engagement in the conversation, topics of discussion, identification and connection with the alum, main take-always, plans for future interactions. | Phone |
| Endline 1 | 1115 students | On-going | May 2021 | Job search and Labor market outcomes. Content and frequency of additional interactions with alum. | Phone |
| Endline 2 | 1115 students | Not started | Feb 2022 | Job search and Labor market outcomes. Content and frequency of additional interactions with alum. | Phone |
| **Alumni** | | | | | |
| Baseline | 657 alumni | Completed | Jan-Feb 2020 | Demographics, characteristics of first job (how did they find it, in how much time, wages/profits) and, if different, of current job. Availability to participate to the study. | Phone |
| Follow-up 1 - "Covid-19 survey" | 657 alumni | Completed | Jul 2020 | Labor market outcomes, Covid-19 impacts, time use during total lockdown, district of current residence, economic outlook and expected own labor market prospects. Availability to participate to the study. | Phone |
| Follow-up 2 | 674 alumni | Completed | Dec 2020 | Labor market outcomes, Covid-19 impacts on livelihoods, district of current residence, economic outlook and expected own labor market prospects. Availability to participate to the study. Updated contacts information. | Phone |
| Alumni Check-In | 171 alumni | Completed | Mar 2021 | Content and duration of each Key Call 2; additional interactions (whether they took place, who initiated them, duration, mode and content). 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. | Phone |
| **Interactions Characterization** | | | | | |
| Artificial Survey and Recordings | 673 students-alumni pairs | Completed | Feb-Mar 2021 | During Key Calls 1 the enumerators listens and keeps track of mutual & relative engagement levels, conversation pace, topics of discussions. Recordings will be used to confirm the information collected in the Artificial Survey | Phone |

# 6 Analysis

## 6.1 Missing Values, Outliers and Questions with Limited Variation

In cases where covariates are missing but outcomes are available, we will follow an approach based on Lin and Green (2016): If a covariate is missing for no more than 10 percent of observations, then we will recode the covariate to the overall mean. If a covariate is missing for more than 10 percent of observations, then we will recode the covariate to the overall mean and add in indicator equal to one for observations with the missing covariate.

We plan to convert monetary outcomes into USD PPP and trim the top 1% of the distribution by survey round of variables that are particularly sensitive to the existence of outliers, such as "minimum expected wage", "expected number of weeks to have a fully operative business", etc. We will also look at untrimmed values and check that our results are not sensitive to the 1% trimming by repeating the analysis with the full distribution with different trimming procedures. In order to limit noise caused by variables with minimal variation, questions for which 95% of observations have the same value within the relevant sample will be omitted from the analysis and will not be included in any indicators or hypothesis tests.

## 6.2 Estimation of Average Treatment Effects

Our main treatment effects specification to capture the impact of the MYF Program on outcomes domains (i), (ii) and (iii) and test Hypothesis 1 and 2 is the following OLS specification:

$$Y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_i^{'}\delta + \varepsilon_i$$

$Y_i$ is the outcome of interest for student *i* measured at Endline 1 or Endline 2. For outcome variables measured at both rounds (e.g. career satisfaction, time spent conducting occupation-related tasks etc.) we will pool the samples and cluster the standard errors at the respondent level.

$T1_i$ is a treatment indicator that takes value 1 for students in MYF only; $T2_i$ is a treatment indicator that takes value 1 for students in MM-MYF (MYF + cash transfer). The omitted category is "control students"; $X_i$ is a vector including (i) the strata and balance variables listed in Section 3.2[16], (ii) baseline outcome when available to increase power, and (iii) individual covariates measured at baseline which we will condition on to improve statistical power (McKenzie 2012); these covariates will be selected from the baseline data on the basis of their ability to predict the primary outcomes[17]. $\varepsilon i$ is the error term. When available, we will control for baseline level of outcomes (e.g. for students' wellbeing). The equation is estimated using Ordinary Least Squares estimators. Errors are robust to heteroskedasticity. Estimation is performed over the entire sample of students.

Given our randomized design, $(\beta_1+\beta_2)/2$ measures the Average Treatment Effect on the Treated of the Meet Your Future with and without the cash transfer altogether. $\beta_1$ measures the ATT of the MYF Program without the additional cash transfer on Y and $\beta_2$ measures the ATT of the MM-MYF. We interpret $\beta_2 - \beta_1$ as the additional effect of receiving the cash transfer. We plan to report results from two additional approaches for our primary outcomes measured in both Endline 1 and Endline 2. Due to the nature of the tracking activity, there will be some respondents surveyed as part of Endline 1 that are not surveyed in Endline 2 or that did not provide usable data in Endline 2. In order to maximize sample size, we also consider specifications, which include all respondents surveyed as part of either Endline 1 and Endline 2, making use of the most recent data that we have from each student. We denote this as Approach 2. Our specification for Approach 2 mirrors that of Approach 1, but brings in an indicator for the Endline round from which the data comes from.

$$Y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_i^{'}\delta + \mu I(\text{endline1}) + \varepsilon_i$$

[16] These variables are: an indicator for male, an indicator for student's ownership of a smartphone, student's VTI, an indicator for whether the student was not successfully interviewed in three out of three pre-intervention survey rounds, an indicator for whether the student has ever worked before graduation (either before enrolling in the VTI or during the lockdown).

[17] We adapt the post-double-selection approach set forth in Belloni et al. (2014)

## 6.3 Estimation of Treatment Effects – Intention To Treat (ITT)

To estimate the treatment effects on outcomes domains (i), (ii), and (iii) and to test Hypothesis 1 and 2, we use an intention-to-treat specification that takes noncompliance into account. In particular: $Z_{it}$ indicates assignment to treatment t, $T_{it}$ indicates treatment status when treatment considered is t=1,2. We estimate the first stage, obtain fitted values of $T_i$, and use them in the second stage regression:

$$T_i = \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \gamma X_i + \varepsilon_i$$

$$Y_i = \beta_0 + \beta_1 \check{T}_{1i} + \beta_2 \check{T}_{2i} + \gamma X_i + \varepsilon_i$$

The equations are estimated using Ordinary Least Squares estimators. Errors are robust to heteroskedasticity. Estimation is performed over the entire sample of students.

## 6.4 Treatment Effects – Heterogeneity

We will test the heterogeneity of treatment effects along a pre-determined set of (i) students' characteristics $S_i$, (ii) alumni's characteristics and (iii) student-alum pair's characteristics $S_{ij}$. In particular, we will use the following specification to run heterogeneity analysis on hypotheses 1 and 2. To investigate whether the treatment effect differs along each of these dimensions, we estimate the following regression using Ordinary Least Squares estimators over the sample of treated students (T1 and T2). Errors are robust to heteroskedasticity.

$$Y_i = \alpha + \beta T_i + \gamma T_i * S_i + X_i' \delta + \varepsilon_i$$

$X_i$ includes $D_i$. $(\beta+\gamma)$ is the ATT for individuals with $S_i$=1. $\beta$ is the ATT for individuals with $S_i$=0. When analyzing heterogeneities that involve alumni's characteristics or student-alum pair's characteristics, we will include alumni fixed-effects.

## 6.5 Multiple hypothesis testing

On top of the uncorrected estimates the main tables will also present additional p-values that account for multiple testing. Since the analysis tests multiple hypotheses within each domain of outcomes, it is appropriate to control for the possibility that some true null hypotheses will be falsely rejected. Within each of the three domains of pre-specified primary outcomes, the analysis will compute the False Discovery Rate (FDR) adjusted q-values (analogue to the standard p-value) that control the expected proportion of rejections that are Type I errors over the primary outcomes within a domain. Within the first domain we have 9 q-values for the three primary outcomes (three outcomes times three pairwise comparisons per outcome). Similarly, we have 6 q-values for the two primary outcomes in the second domain and nine for the three primary outcomes in the third domain. Q-values will be calculated at each follow-up round and presented in separate summary tables of impacts on the primary and secondary outcomes.

## 6.6 Network Link Formation – Dyadic Regression

To explore which links are more likely to form, the data are analyzed dyadically, that is, the characteristics of both the student and the alum in each pair are considered in tandem. This allows assessment of whether network ties between students and alumni with similar characteristics (homogamy) are more likely to form than are network ties between dissimilar students and alumni, or whether particular characteristics of students or alumni—independent of their counterpart—are more strongly associated with link formation. Following Fafchamps and Gubert (2007), we estimate a dyadic regression model of the form:

$$L_{ij} = 1 \text{ if } B(d_{ij}) - C(d_{ij}) + e_{ij} > 0$$
$$L_{ij} = 0 \text{ otherwise}$$

Where $L_{ij}$ denotes the existence of a strong link between student i and alum j, and $d_{ij}$ represents the cultural distance between i and j. The benefits and costs of the link are denoted $B_{ij}$ and $C_{ij}$ respectively. $e_{ij}$ is a residual effect. A link is established if benefits exceed costs. Links in our setting can only be unidirectional, i.e. $L_{ij} = L_{ji}$

for every i and j. The symmetry condition that follows from the unidirectionality allows us to specify the regression as:

$$L_{ij} = \beta_0 + \beta_1(z_i - z_j) + \beta_2(z_i + z_j) + \gamma w_{ij} + u_{ij}$$

Where $z_i$ and $z_j$ are characteristics of student i and alum j thought to influence the likelihood of $L_{ij}$, a link between them. Coefficient $\beta_1$ measures the effect of differences in attributes on $L_{ij}$, while $\beta_2$ captures the effect of the combined level of $z_i$ and $z_j$ on $L_{ij}$. For $\beta_2$ to be identified, individuals must not have the same number of links, which is true in our setting as the alumni will have multiple links (see Fafchamps and Gubert 2007 for details). Estimation is performed over the sample of students assigned to the MYF Alumni program (students in T1 and T2).

## 6.7 Attrition, take up and non-compliance with treatment assignment

All the VTIs in our sample are boarding schools: over 90% of the students live there[18]. For these reasons, attrition rates for in person surveys are low (8.8%). At baseline we successfully interviewed 1105 out of the 1372 students in the lists provided[19]. Between baseline and midline, attrition was limited to students who dropped out of school or who had not yet returned from the break in between terms. However, following the Covid-19 pandemic, the temporary closure of schools and their dorms, and the consequent shift to interviews on the phone, attrition rates have gone up (Table 4). With the program conducted over the phone, an extensive effort to collect a wide array of best contacts has been made to maximize take up. We have an average of 3.4 contacts per student, including both best contacts in the VTI and outside of the VTI so that we are able to reach the students irrespective of their physical location when the program rolls out. To reduce attrition, we are currently running a Contacts Confirmation Survey to confirm these contacts one more time. For this reason, we anticipate lower attrition rates for the two endline surveys. To reduce attrition further, we will devote extra effort and resources toward contacting respondents that are not found at first attempt. This includes contacting teachers and the school office to obtain further information. All data will be probability-reweighted to reflect this intensive tracking.

Table 4. Attrition (Pre- Assignment to Treatment)

| **Survey** | **N successfully interviewed** | **Attrition rate** |
|---|---|---|
| Baseline | N=1105 | - |
| Midline 1 | N=970 | 8.8% |
| Midline 2 – "Covid-19 survey" | N=812 | 27% |

To account for the attrition that took place prior to the assignment to treatment, we stratify the randomization on an indicator, *hard_to_find,* which we expect will predict both program take-up and attrition at endline. All the estimation will be run on the "Baseline sample" (N=1115) as well as on the sample of those for which *hard_to_find*=0, i.e. those successfully interviewed at Baseline, Midline 1 and Midline 2. Additionally, we will investigate whether attrition is correlated with treatment status. We will do so by running the following regression:

$$A_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_s'\delta + \varepsilon_i$$

Where $A_i$ is an indicator of whether individual i attrits from the study by not responding to or being able to be contacted for Endline 1 or 2, $T_i$ are the two treatment indicators, and $X_s$ are all the randomization strata dummies. Conditional on the strata, the randomization is performed at the individual level. We therefore use Huber-white standard errors. If treatment status is found not to significantly affect attrition at the 5 percent significance level, estimation will proceed without any adjustment for attrition.

If attrition is found to be related to treatment status, we postulate that attrition will be higher for the control group and we will use IPW as well as employ Lee bounds on our treatment estimates.

[18] Under regular circumstances the exact figure ranges from 90% for one VTI, 95% for two of them and 99% for the remaining two.
[19] The 10 more students missing to reach 1115 were added to the sample at midline.

On top of these standard approaches, we will follow McKenzie (2021) and leverage our "hard_to_find", variable to learn about selection. Such variable tags respondents that were not always found across the numerous pre-intervention survey rounds and contact-confirmations surveys, under the assumptions that hard to find respondents are more similar to attritors than respondents that are easy to interview. Although our characterization of "hard to find" respondents differs from the standard measures used in the literature, such as the number of call attempts it takes to reach a respondent, it is easier to collect and readily available in most field studies, and has the potential to be as informative. In our paper, we will assess whether hard to find respondents have systematically different outcomes from easy to find respondents and, if so, we will use this information to refine our IPW and sensitivity bounds.

We expect non-compliance (more specifically defiers) to be virtually nonexistent given the on-phone nature of the intervention. Key call 1 is organized by our enumerators, who will put in touch through a conference call the student-alum pair. Following Key call 1, interactions will take place without the presence of a moderator. Alumni are instructed during the training to call and interact separately and independently with each of their matched students and only with them, and kindly decline requests to interact advanced by other students. Similarly, should they decide to meet in person with the student, they are to meet only with that student. This will be facilitated by the impossibility for the alumni to visit the students in the VTIs due to Covid-19 related measures. Should non-compliance arise, our treatment effect will be an underestimate of the real treatment effect. On top of this, we anticipate negligible non-compliance from students assigned to T1 and T2 as well. Survey data collected during the pilot of the intervention (available upon request) suggest that both students and alumni (approximately 30 students and 10 alumni) found the program useful and interesting. No one refused participation. Finally, students assigned to the Mobile-Money intervention will just receive the transfer on their phone.

### 6.8 Statistical power

Our students' sample includes 1115 students enrolled in the National Certificate Program in 2019 in five VTIs across Eastern and Central Uganda. We exclude from this sample 257 students who were originally on the lists provided by the schools, but that we were never able to interview in any of the three pre-intervention surveys. Our alumni's sample contains 657 alumni from the same schools and training areas. To define our sample frame, we identified 5 VTIs interested in testing our version of an alumni program with their students. Previous collaboration with BRAC Uganda, as well as interest in the study results suggest they represent an ideal experimental setting in which the successfulness of the program will be favored.

In Table 5 we show the Minimum Detectable Effects (MDEs) we anticipate being able to detect. These calculations are based on a two-sided hypothesis test with a 5% significance level and 80% power. Issues to consider while calculating statistical power are compliance (take-up) and attrition. As we believe compliance is not a major concern in this context, we calculate MDEs in scenarios with no attrition, with a 15% attrition uncorrelated with treatment and with full compliance and 20% attrition in the control group and 10% attrition in the two treatment groups.

For our primary outcomes in domain (ii) (see Section 4.2) we use data collected in the students' baseline. For our primary outcomes in domain (i) and (iii) we cannot rely on pre-intervention data, as search strategy and labor market outcomes are still un-realized for our respondents. For these outcomes, when possible, power calculations are based on the alumni surveys from this project and a sample of 700 VTI graduates from Alfonsi et al. (2020). This procedure is subject to the caveat that our alumni sample is likely to be positively selected with higher averages and/or smaller standard deviations in labor market outcomes. In turn, this implies higher MDEs compared to those we would have were data on the entire population of alumni in our VTIs available. Similarly, the sample from Alfonsi et al. (2020) is not identical to that of our soon to be graduates. Participants in that project were disadvantaged youth at baseline who undertook a sponsored six months training and not the two years National Certificate training.

Based on our power calculations we can detect effects between around 3 and 8 percentage points for outcome sin Domain 1, 15 and 20pp for outcomes in Domain 2 and 1.5 and 15% for outcomes in Domain 3.

Taken into consideration the gains in power that will come from the combination of (i) strata fixed effects, (ii) using post-double-selection lasso for selecting the controls, (iii) the addition of baseline values and (iv) the fact that many of our primary outcomes are indexes, we believe we will have enough power to test our main hypothesis of interest.

**Table 5. MDEs**

| **T1 vs C** | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | C | T1 | MDE of T1 | % Mean | MDE of T1 | % Mean | MDE of T1 | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 442 | 334 | 36073,72 | 8,5% | 39125,38 | 9,2% | 39019,38 | 9,2% |
| Expected earnings - Minimum | 3,55 | 1,21 | 442 | 334 | 0,25 | 7,0% | 0,27 | 7,5% | 0,27 | 7,5% |
| Expected earnings - Maximum | 5,40 | 0,93 | 442 | 334 | 0,19 | 3,5% | 0,21 | 3,8% | 0,20 | 3,8% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 442 | 334 | 0,40 | 6,6% | 0,43 | 7,1% | 0,43 | 7,1% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 442 | 334 | 0,63 | 20,3% | 0,69 | 22,0% | 0,69 | 22,0% |
| Broadness of search - number of methods | 2,12 | 1,57 | 442 | 334 | 0,32 | 15,1% | 0,35 | 16,4% | 0,35 | 16,3% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 442 | 334 | 0,09 | 12,6% | 0,10 | 13,6% | 0,10 | 13,6% |
| Earnings at first job | 276553,67 | 197678,00 | 442 | 334 | 40201,99 | 14,5% | 43602,88 | 15,8% | 43484,75 | 15,7% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 442 | 334 | 0,14 | 1,1% | 0,16 | 1,2% | 0,16 | 1,2% |
| Course satisfaction | 1,26 | 0,53 | 442 | 334 | 0,11 | 8,5% | 0,12 | 9,3% | 0,12 | 9,2% |

| **T2 vs T1** | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | T1 | T2 | MDE of T2 | % Mean | MDE of T2 | % Mean | MDE of T2 | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 334 | 339 | 38367,35 | 9,0% | 41627,51 | 9,8% | 40438,93 | 9,5% |
| Expected earnings - Minimum | 3,55 | 1,21 | 334 | 339 | 0,26 | 7,4% | 0,28 | 8,0% | 0,28 | 7,8% |
| Expected earnings - Maximum | 5,40 | 0,93 | 334 | 339 | 0,20 | 3,7% | 0,22 | 4,0% | 0,21 | 3,9% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 334 | 339 | 0,43 | 7,0% | 0,46 | 7,6% | 0,45 | 7,4% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 334 | 339 | 0,68 | 21,6% | 0,73 | 23,5% | 0,71 | 22,8% |
| Broadness of search - number of methods | 2,12 | 1,57 | 334 | 339 | 0,34 | 16,1% | 0,37 | 17,4% | 0,36 | 16,9% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 334 | 339 | 0,10 | 13,4% | 0,11 | 14,5% | 0,10 | 14,1% |
| Earnings at first job | 276553,67 | 197678,00 | 334 | 339 | 42758,11 | 15,5% | 46391,35 | 16,8% | 45066,75 | 16,3% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 334 | 339 | 0,15 | 1,2% | 0,17 | 1,3% | 0,16 | 1,2% |
| Course satisfaction | 1,26 | 0,53 | 334 | 339 | 0,11 | 9,1% | 0,12 | 9,9% | 0,12 | 9,6% |

**Table 5. MDEs (continued)**

| **T1&T2 pooled vs C** | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | C | T1&T2 pooled | MDE of T1&T2 pooled | % Mean | MDE of T1&T2 pooled | % Mean | MDE of T1&T2 pooled | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 442 | 673 | 30450,81 | 7,2% | 33026,19 | 7,8% | 33276,56 | 7,8% |
| Expected earnings - Minimum | 3,55 | 1,21 | 442 | 673 | 0,21 | 5,9% | 0,23 | 6,4% | 0,23 | 6,4% |
| Expected earnings - Maximum | 5,40 | 0,93 | 442 | 673 | 0,16 | 3,0% | 0,17 | 3,2% | 0,17 | 3,2% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 442 | 673 | 0,34 | 5,6% | 0,37 | 6,0% | 0,37 | 6,1% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 442 | 673 | 0,54 | 17,2% | 0,58 | 18,6% | 0,59 | 18,8% |
| Broadness of search - number of methods | 2,12 | 1,57 | 442 | 673 | 0,27 | 12,7% | 0,29 | 13,8% | 0,29 | 13,9% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 442 | 673 | 0,08 | 10,6% | 0,08 | 11,5% | 0,08 | 11,6% |
| Earnings at first job | 276553,67 | 197678,00 | 442 | 673 | 33935,59 | 12,3% | 36805,71 | 13,3% | 37084,73 | 13,4% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 442 | 673 | 0,12 | 0,9% | 0,13 | 1,0% | 0,13 | 1,0% |
| Course satisfaction | 1,26 | 0,53 | 442 | 673 | 0,09 | 7,2% | 0,10 | 7,8% | 0,10 | 7,9% |

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# Appendix A – Intervention Details

### Assignment to T1

This is how enumerators communicate to the students their assignment to the program and encourage them to take part to it in a phone call following this script:
*Dear student, this is NAME from the Meet Your Future Research Team. I am very glad to inform you that you have been selected to participate to the Meet Your Future Program organized by BRAC Uganda in partnership with your VTI. As part of this program you will have the opportunity to interact with an older student, an alumnus or an alumna, who graduated from your same school and training area. We have selected this alum based on their success in their profession. We believe this is a great opportunity for you to ask questions and receive advice from someone with previous experience in the labor market who has a similar history to yours, and this is why we call this person "the Future You". This program comes at no cost and is totally free. With your permission, we are going to organize three phone calls between you and the alum during the next 2 months. I am here today to organize the first one. Are you available on XXX at XXX? We suggest you keep your phone with you and do not miss scheduled appointments. We know that starting your working life is not an easy task, but "the Future You" is there to help. We recommend you prepare a list of questions to make the most out of this experience: you may be interested in receiving advice about various aspects of the job search process or the process to set up a business: which material to prepare for job applications, prevailing wages in a specific occupation and time needed to usually find employment are just examples of possible topics around which to prepare your questions. We look forward to having you on-board!*

### Assignment to T2

We communicate to the students their assignment to T2 through the following SMS:
*Hello, this is the Meet Your Future research team. We have just sent 40,000 UGX to your phone number/to your best contact phone number. This money is a gift from BRAC research team for your personal use. You are free to use the money as you want. As we know looking for a job and setting up a business are expensive activities, we suggest you use it to finance your search of a job, to set up your business, or to contact the alum you have been assigned to receive extra support. Please keep track of how you use this money, as you will be asked this information in the future.*

## Logbook – Example

# 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.**

ADDITIONAL INTERACTIONS

**Student's 1 name:**

| DATE | DURATION (in minutes) | MEAN OF COMMUNICATION (sms, whatsapp, in person, phone) | WHO INITIATED IT (alum or student) | REASON/MAIN TOPICS |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |

**Student's 2 name:**

| DATE | DURATION (in minutes) | MEAN OF COMMUNICATION (sms, whatsapp, in person, phone) | WHO INITIATED IT (alum or student) | REASON/MAIN TOPICS |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |

**If you have other interactions with the student on top of the 3 KEY CALLS, please use this form to keep track of them. For each of them write down the day in which each interaction took place, how long each one lasted, the mean of communication used (for example sms, whatsapp, phone call, meeting in person), who started the interaction, and up to 3 main topics discussed between you and the student.**

## List of Topics

### A: Useful connections you can make for the students

| | |
|---|---|
| A1 | Employers you know in which the student could be hired if you refer him/her, that is, if you make a connection |
| A2 | Someone you know that could help the student finding a job |
| A3 | A provider of raw materials and/or tools that you know, and you can suggest the student to contact |
| A4 | A client that you know and that the student could contact once his/her business is operative |

### B: Tips for an effective job search/ business start up

| | |
|---|---|
| B1 | Recommended locations where to look for jobs/start a business, or locations to avoid |
| B2 | How to make a good impression at job interviews. Examples: good manners, what to wear, no slang, etc. |
| B3 | How many job applications to do |
| B4 | When to turn down a job opportunity |
| B5 | Tips on how to write a CV |
| B6 | Which material to prepare for job applications |
| B7 | Which aspects of the job offer can be bargained over and negotiation with employers |
| B8 | The importance of accumulating savings during the training |
| B9 | How to create a network of input providers |
| B10 | How to create a network of clients/customers |
| B11 | Where to find basic equipment/tools |
| B12 | How to manage the accounting of the firm |
| B13 | How to obtain a loan to set up a business/buy tools and materials |

### C: Information on the status of the labor market

| | |
|---|---|
| C1 | Specific existing job vacancies or firms that accept candidacies from someone like the student |
| C2 | How much it generally takes to find a job in the occupation of training |
| C3 | What are the wages in the market in the occupation of training |
| C4 | Possibility of finding a job/working in occupations unrelated to the occupation of training |
| C5 | How common it is to accept an unpaid job or a job where you have to pay the owner |
| C6 | Average cost of one job application |
| C7 | How much money is generally spent on transportation costs during the job search phase |
| C8 | Which practical skills are needed to find a job in the occupation of training |
| C9 | What types of positions/contractual arrangements are usually available after the training |
| C10 | Women's condition, discrimination and rights in the job place |
| C11 | Amount of resources needed to start up business in the occupation of training |
| C12 | How much it takes generally to have an operative business from scratch in the occupation of training |
| C13 | What are the profits for a young business in the occupation of training |

### D: Alum personal experience

| | |
|---|---|
| D1 | The wage you were given during your first job |
| D2 | The profits you made during the first month of operation of your first business |
| D3 | How much time it took to find your first job/ to start up your first business |
| D4 | How you found your first job/set up your first business |
| D5 | Who helped you finding your first job/setting up your first business |
| D6 | The way in which you overcame an obstacle when looking for your first job/setting up your first business |
| D7 | An unexpected challenge you had to face when looking for your first job/setting up your first business |
| D8 | That time you failed, but then found the strength to go on |
| D9 | The wages/profits in your current job |
| D10 | How you found the current job/set up your current business |
| D11 | Who helped you finding current job/setting up your current business |

### E: Encouragement for the student

| | |
|---|---|
| E1 | The importance of not losing hope and not giving up |
| E2 | The importance of being patient and waiting for results to come |
| E3 | The importance of resilience, the ability to recover after failure |

| | |
|---|---|
| E4 | The importance of persisting and remaining focused on the goals |
| E5 | The importance of finding the way in which each one is special and valuable |

# 8 Appendix B – Indexes details

### Engagement Index

The index has 4 components:

<u>Mutual engagement</u>

*[Extract from the Artificial Survey observed by the enumerator]*

**Q:** On a scale from 0 to 10 how smooth, efficient, and mutually engaging was the flow of the conversation?

<u>Relative engagement</u>

*[Extract from the Artificial Survey observed by the enumerator]*

**Q:** On a scale from 0 to 10 how much did the alum talk compared to the student?

<u>Student engagement (Connection Index)</u>

*[Extract from the Post Interaction Survey self-reported by the student]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q0.1:** You felt at ease asking questions and talking about personal issues and goals
**Q0.2:** The alum seemed to care about your personal experience
**Q0.3:** Speaking with the alum made you comfortable, as if you were with a friend
**Q0.4:** The alum can provide you valuable support in your career
**Q0.5:** The alum seems prone to provide help

<u>Alum's perception</u> of student's interest in the program from the Alumni Check-In.

### Usefulness Index

*[Extract from the Post Interaction Survey that follows Key Call 1]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q1.1**: Connecting and talking with the alum today has been useful for you
**Q1.2**: You learnt from the alum useful things that you wouldn't learn at school from teachers or from your family and community about how to start my career
**Q1.3**: You had the opportunity to ask all the **questions** you cared about
**Q1.4**: The time was not enough to talk about all the **topics** you cared about
**Q1.5**: You were engaged in the conversation

### Identification Index

*[Extract from the Post Interaction Survey that follows Key Call 1]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q2.1**: During the conversation you realized you and the alum have a lot of things in common
**Q2.2**: During the conversation you were able to understand the alum's problems and concerns he/she had when starting his/her working life/ moved from the VTI to the work force
**Q2.3**: While listening, you felt you are going through the same things the alum went through
**Q2.4**: When the alum told you about his/her successes you felt joy, when he/she told you about her/his failures, you felt sad
**Q2.5**: You found the alum's personal story relevant to your daily life

# 9 Appendix C – Appendix Tables

Table A1. Relevance of Sectors of Training

| | MYF | UNHS | UNPS |
|---|---|---|---|
| Electrical work | 20.38 | 0.20 | 0.31 |
| Motor-mechanics | 17.95 | 0.84 | 0.82 |
| Tailoring | 13.11 | 0.72 | 0.82 |
| Plumbing | 11.58 | 0.22 | 0.21 |
| Catering/Food service | 9.96 | 2.59 | 1.59 |
| Teaching | 7.90 | 3.21 | 3.50 |
| Construction | 7.27 | 2.75 | 2.73 |
| Secretary/Accountant/Business Mgmt | 4.31 | 0.70 | 0.46 |
| Welding | 2.60 | 0.32 | 0.36 |
| Hairdressing | 2.51 | 1.33 | 1.13 |
| Matching &fitting | 1.35 | 1.40 | 0.93 |
| Agriculture | 0.81 | 55.24 | 65.75 |
| Carpentry | 0.27 | 0.79 | 0.46 |
| Retail | - | 14.19 | 8.08 |
| Transports | - | 4.38 | 3.60 |
| N | 1114 | 9422 | 1944 |

*Notes: The three columns of the table show the percentage of the overall working population between 20-30 years old employed in each sector. The data in the second column comes from the Uganda National Household Survey 2016/2017 (UNHS), a national representative survey conducted by the Ugandan Bureau of Statistics (UBOS). Instead, the data in the third columns comes from the Uganda National Panel Survey 2018/2019 (UNPS), a survey conducted by the Ugandan Bureau of Statistics in partnership with the World Bank, representative at the household level.*

Table A2. Students' distribution across field of study

| Training Area | C | T1 | T2 | t-test C – T1 | C – T2 | T1 – T2 | F-test |
|---|---|---|---|---|---|---|---|
| Motor-mechanics | 0.15 | 0.22 | 0.19 | -0.07** | -0.04 | 0.03 | 3.16** |
| | (0.02) | (0.02) | (0.02) | | | | |
| Plumbing | 0.14 | 0.07 | 0.12 | 0.07*** | 0.02 | -0.05** | 5.00*** |
| | (0.02) | (0.01) | (0.02) | | | | |
| Catering and hotels | 0.11 | 0.09 | 0.10 | 0.02 | 0.01 | -0.01 | 0.38 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Tailoring | 0.13 | 0.15 | 0.12 | -0.02 | 0.01 | 0.03 | 0.64 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Hairdressing | 0.02 | 0.02 | 0.03 | 0.00 | -0.01 | -0.01 | 0.54 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Construction | 0.07 | 0.08 | 0.07 | -0.01 | 0.00 | 0.01 | 0.25 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Electrical wiring | 0.23 | 0.17 | 0.20 | 0.05* | 0.02 | -0.03 | 1.59 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Welding | 0.02 | 0.03 | 0.03 | -0.01 | 0.00 | 0.00 | 0.21 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Carpentry | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 1.15 |
| | (0.00) | (0.00) | (0.00) | | | | |
| Taeaching/ECD | 0.08 | 0.08 | 0.09 | 0.00 | -0.01 | -0.01 | 0.15 |
| | (0.01) | (0.01) | (0.02) | | | | |
| Agriculture | 0.00 | 0.01 | 0.01 | -0.01 | 0.00 | 0.00 | 0.68 |
| | (0.00) | (0.01) | (0.01) | | | | |
| Machining and fitting | 0.01 | 0.02 | 0.02 | -0.01 | -0.01 | 0.00 | 0.58 |
| | (0.00) | (0.01) | (0.01) | | | | |
| Secretary | 0.02 | 0.03 | 0.02 | 0.00 | 0.00 | 0.01 | 0.33 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Accounting and business management | 0.01 | 0.03 | 0.02 | -0.02* | 0.00 | 0.02 | 1.88 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Observations | 442 | 333 | 339 | | | | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups.
***. **. and * indicate significance at the 1. 5. and 10 percent critical level.

Table A3. Students' baseline characteristics

| | C | T1 | T2 | t-test C – T1 | C – T2 | T1 – T2 | F-test |
|---|---|---|---|---|---|---|---|
| Age | 19.87 | 19.85 | 19.83 | 0.02 | 0.04 | 0.02 | 0.04 |
| | (0.09) | (0.12) | (0.11) | | | | |
| Male | 0.60 | 0.60 | 0.59 | 0.00 | 0.01 | 0.01 | 0.05 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Single | 0.91 | 0.89 | 0.88 | 0.02 | 0.02 | 0.01 | 0.70 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Christian | 0.82 | 0.84 | 0.83 | -0.02 | -0.02 | 0.01 | 0.43 |
| | (0.02) | (0.02) | (0.02) | | | | |
| HH assets index | -0.30 | 0.61 | -0.37 | -0.90* | 0.08 | 0.98* | 2.30 |
| | (0.31) | (0.39) | (0.34) | | | | |
| Trainee has a scholarship | 0.20 | 0.22 | 0.20 | -0.02 | -0.01 | 0.02 | 0.31 |
| | (0.02) | (0.02) | (0.02) | | | | |
| *Main source:* | | | | | | | |
| - Subsistence agriculture | 0.33 | 0.31 | 0.30 | 0.01 | 0.02 | 0.01 | 0.25 |
| | (0.02) | (0.03) | (0.03) | | | | |
| - Commercial agriculture | 0.15 | 0.14 | 0.16 | 0.01 | -0.01 | -0.01 | 0.14 |
| | (0.02) | (0.02) | (0.02) | | | | |
| - Wage job | 0.33 | 0.36 | 0.34 | -0.03 | -0.01 | 0.02 | 0.41 |
| | (0.02) | (0.03) | (0.03) | | | | |
| - Family Business | 0.19 | 0.18 | 0.19 | 0.01 | 0.00 | -0.01 | 0.07 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Rural | 0.56 | 0.55 | 0.51 | 0.01 | 0.06 | 0.05 | 1.33 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Ever worked before VTI | 0.38 | 0.41 | 0.38 | -0.03 | 0.00 | 0.03 | 0.40 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Expected weeks to first job | 5.28 | 5.89 | 5.80 | -0.61 | -0.52 | 0.09 | 0.36 |
| | (0.43) | (0.62) | (0.70) | | | | |
| Expected average wage post-training (in USD) | 151.00 | 166.00 | 152.00 | -14.60 | -0.58 | 14.04 | 0.55 |
| | (7.45) | (13.59) | (11.97) | | | | |
| Plan after VTI: entering the labor market | 0.73 | 0.66 | 0.69 | 0.06* | 0.04 | -0.03 | 1.73 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Plan after VTI: pursue further education | 0.27 | 0.33 | 0.30 | -0.06* | -0.04 | 0.02 | 1.51 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Observations | 442 | 333 | 339 | | | | |

*Notes:* Conversion rate: 3600 UGX = 1 USD. The value displayed for t-tests are the differences in the means across the groups. ***. **. and * indicate significance at the 1. 5. and 10 percent critical level

Table A4. Alumni and pre Covid-19 job characteristics and employment network

| | NO Relatives in trade of training | Relatives in trade of training | t-test |
|---|---|---|---|
| Months to first work activity | 4.51 | 3.53 | 0.98* |
| | (0.45) | (0.37) | |
| First job earnings (USD) | 83.97 | 74.59 | 9.38 |
| | (6.04) | (4.36) | |
| Post-VTI: wage/self-empl | 0.76 | 0.73 | 0.03 |
| | (0.03) | (0.02) | |
| Post-VTI: casual occupations | 0.03 | 0.01 | 0.03*** |
| | (0.01) | (0.00) | |
| Pre Covid-19 earnings (USD) | 108.03 | 103.02 | 5.01 |
| | (5.96) | (5.13) | |
| Pre Covid-19: wage/self-empl | 0.73 | 0.80 | -0.08** |
| | (0.03) | (0.02) | |
| Pre Covid-19: casual occupations | 0.07 | 0.04 | 0.04** |
| | (0.02) | (0.01) | |
| Career Satisfaction | 7.66 | 8.25 | -0.59*** |
| | (0.13) | (0.11) | |
| Observations | 294 | 425 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A5. Alumni first and pre Covid-19 job characteristics and SES

| | HH Asset Index Below Median | HH Asset Index Above Median | t-test |
|---|---|---|---|
| Months to first work activity | 4.27 | 3.56 | 0.71 |
| | (0.42) | (0.38) | |
| First job earnings (USD) | 70.26 | 84.93 | -14.68** |
| | (4.57) | (5.25) | |
| Post-VTI: wage/self-empl | 0.77 | 0.72 | 0.05 |
| | (0.02) | (0.02) | |
| Post-VTI: casual occupations | 0.02 | 0.01 | 0.01 |
| | (0.01) | (0.01) | |
| Pre Covid-19 earnings (USD) | 105.32 | 104.66 | 0.67 |
| | (5.81) | (5.25) | |
| Pre Covid-19: wage/self-empl | 0.73 | 0.81 | -0.07** |
| | (0.02) | (0.02) | |
| Pre Covid-19: casual occupations | 0.07 | 0.03 | 0.04** |
| | (0.01) | (0.01) | |
| Career Satisfaction | 7.58 | 8.36 | -0.79*** |
| | (0.13) | (0.11) | |
| Observations | 355 | 364 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A6. Alumni network and SES

| | HH Asset Index Below Median | HH Asset Index Above Median | t-test |
|---|---|---|---|
| Has relatives working/owning firm in trade of training | 0.54 | 0.64 | -0.11*** |
| | (0.03) | (0.03) | |
| Has VTI friends working/owning firm in trade of training | 0.93 | 0.96 | -0.03* |
| | (0.01) | (0.01) | |
| Has friends working/owning firm in trade of training | 0.90 | 0.93 | -0.04* |
| | (0.02) | (0.01) | |
| Has other network members working/owning firm in trade of training | 0.66 | 0.77 | -0.11*** |
| | (0.03) | (0.02) | |
| Observations | 355 | 364 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A7. Students' network overall characteristics

| | Obs. | Mean | St.dev. | Min | Median | Max |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Male | 4849 | 0.62 | 0.49 | 0 | 1 | 1 |
| Age | 4499 | 37.06 | 12.61 | 14 | 35 | 85 |
| Completed years of education | 4932 | 12.32 | 2.75 | 0 | 14 | 14 |
| No education | 4364 | 0.01 | 0.11 | 0 | 0 | 1 |
| Completed primary education | 4364 | 0.95 | 0.22 | 0 | 1 | 1 |
| Completed secondary education | 4364 | 0.63 | 0.48 | 0 | 1 | 1 |
| Currently working | 4866 | 0.81 | 0.39 | 0 | 1 | 1 |
| Months worked in last year | 4173 | 9.49 | 4.09 | 0 | 12 | 12 |
| Part time job | 3697 | 0.13 | 0.34 | 0 | 0 | 1 |
| Full time job | 3697 | 0.83 | 0.38 | 0 | 1 | 1 |
| Casual daily labor | 3697 | 0.04 | 0.21 | 0 | 0 | 1 |
| Earnings below 500,000 UGX | 2011 | 0.50 | 0.50 | 0 | 0 | 1 |
| Earnings above 500,000 UGX | 2011 | 0.50 | 0.50 | 0 | 1 | 1 |

*Notes:* the table shows summary statistics for the sample of network members mentioned by the students in the various survey rounds.

Table A8. Students' network quality and SES

| | HH assets index below mean | HH assets index above mean | t-test (1)-(2) |
|---|---|---|---|
| Number of network members | 4.39 | 4.49 | -0.09 |
| | (0.04) | (0.05) | |
| Share from community of origin | 0.87 | 0.88 | -0.01 |
| | (0.01) | (0.01) | |
| Share from VTI | 0.12 | 0.11 | 0.01 |
| | (0.01) | (0.01) | |
| Share providing job | 0.43 | 0.55 | -0.12*** |
| | (0.01) | (0.02) | |
| Share currently working | 0.77 | 0.86 | -0.09*** |
| | (0.01) | (0.01) | |
| Share earning above median | 0.15 | 0.29 | -0.14*** |
| | (0.01) | (0.01) | |
| Share with no edu | 0.01 | 0.01 | 0.01 |
| | (0.00) | (0.00) | |
| Share with primary edu | 0.83 | 0.85 | -0.02 |
| | (0.01) | (0.01) | |
| Share with secondary edu | 0.50 | 0.62 | -0.12*** |
| | (0.01) | (0.01) | |
| Share working in same sector | 0.10 | 0.11 | -0.01 |
| | (0.01) | (0.01) | |
| Observations | 670 | 433 | |

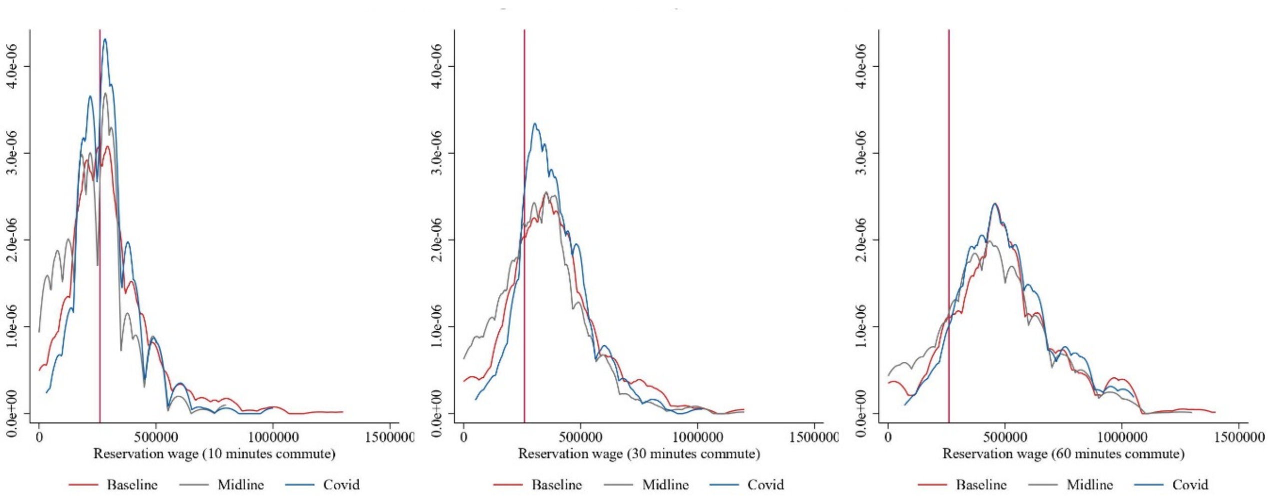
*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A9. Students' network quality balances across treatment arms

| | C | T1 | T2 | t-test C-T1 | C-T2 | T1-t2 | F-test |
|---|---|---|---|---|---|---|---|
| Number of network members | 4.37 | 4.53 | 4.39 | -0.15** | -0.02 | 0.13 | 2.26 |
| | (0.05) | (0.06) | (0.06) | | | | |
| Share from community of origin | 0.88 | 0.88 | 0.87 | 0.00 | 0.00 | 0.00 | 0.01 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share from VTI | 0.12 | 0.11 | 0.12 | 0.00 | 0.00 | 0.00 | 0.02 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share providing job | 0.47 | 0.48 | 0.47 | 0.00 | 0.00 | 0.01 | 0.03 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Share currently working | 0.80 | 0.81 | 0.81 | -0.01 | -0.01 | 0.00 | 0.33 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share earning above median | 0.20 | 0.20 | 0.22 | 0.01 | -0.02 | -0.03 | 0.83 |
| | (0.01) | (0.01) | (0.02) | | | | |
| Share with no edu | 0.01 | 0.01 | 0.02 | 0.00 | -0.01 | -0.01 | 1.25 |
| | (0.00) | (0.00) | (0.00) | | | | |
| Share with primary edu | 0.83 | 0.83 | 0.86 | -0.01 | -0.03* | -0.03 | 2.01 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share with secondary edu | 0.55 | 0.54 | 0.56 | 0.01 | -0.01 | -0.02 | 0.38 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Share working in same sector | 0.09 | 0.10 | 0.11 | -0.01 | -0.01 | -0.01 | 0.59 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Observations | 442 | 334 | 339 | | | | |

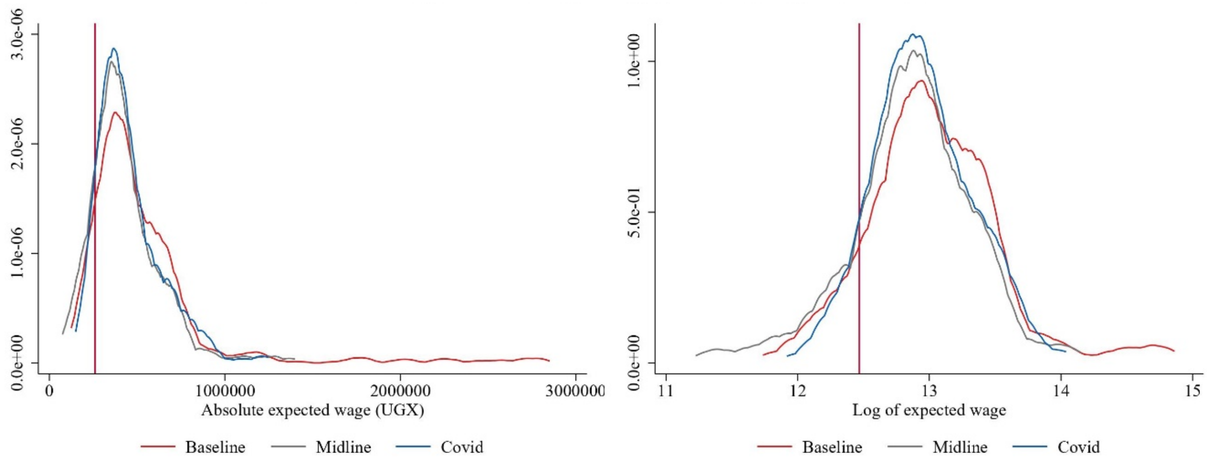
*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Figure A.1. Students' reservation wage by commuting time



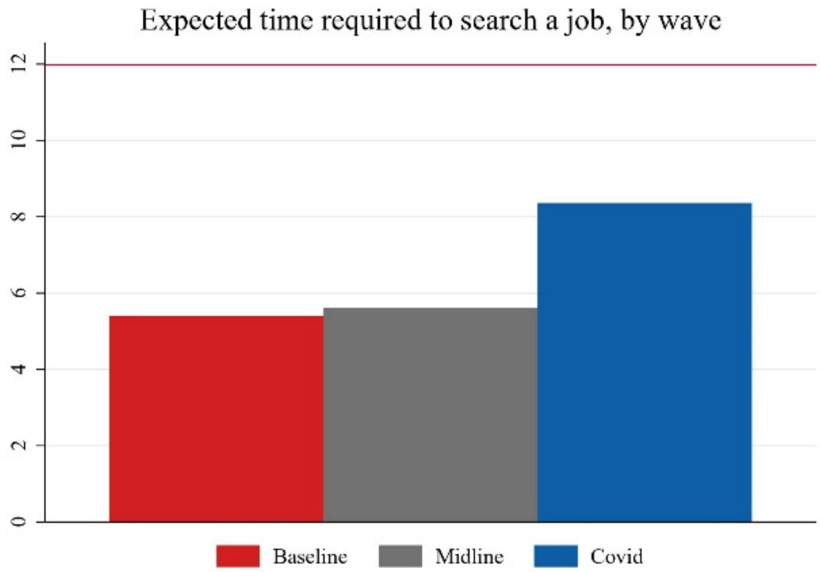

*Note: the red vertical line represents the alumni's average wage at first job*

Figure A.2. Students' expected wage post-training (absolute value and log)




*Note: the red vertical line represents the alumni's average wage at first job*

Figure A.3. Students' expected time required for job search




*Note: the horizontal vertical line represents the alumni's average search time for first job following graduation.*

Figure A.4. Expected challenges students will face reported by students

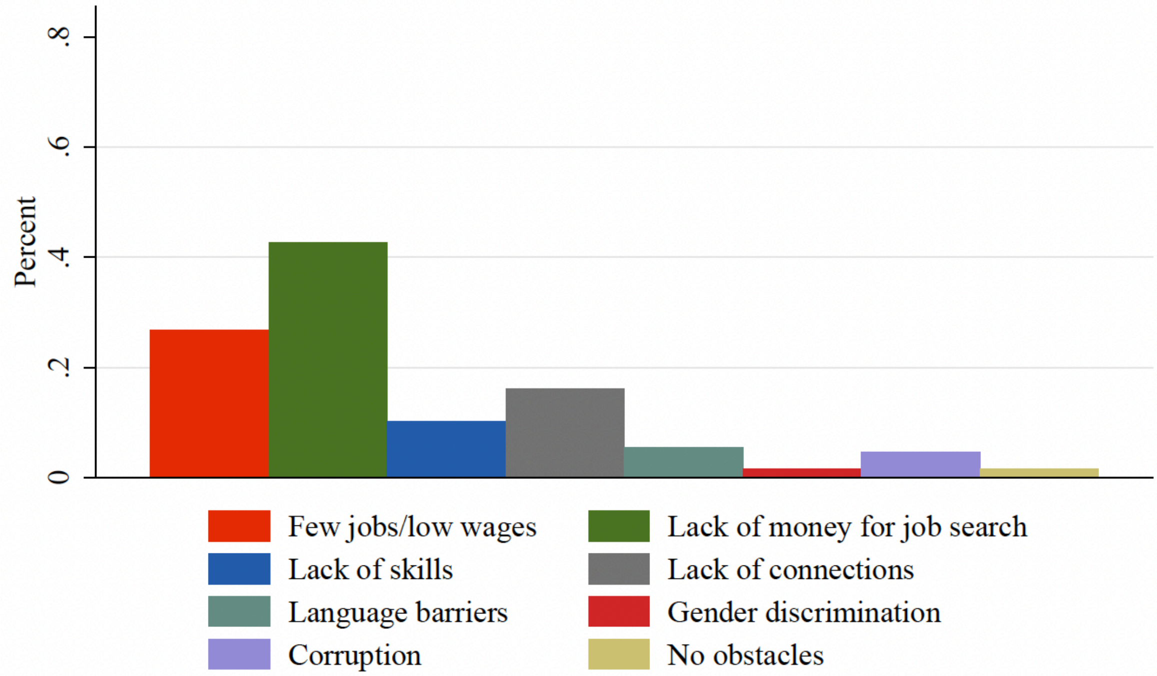
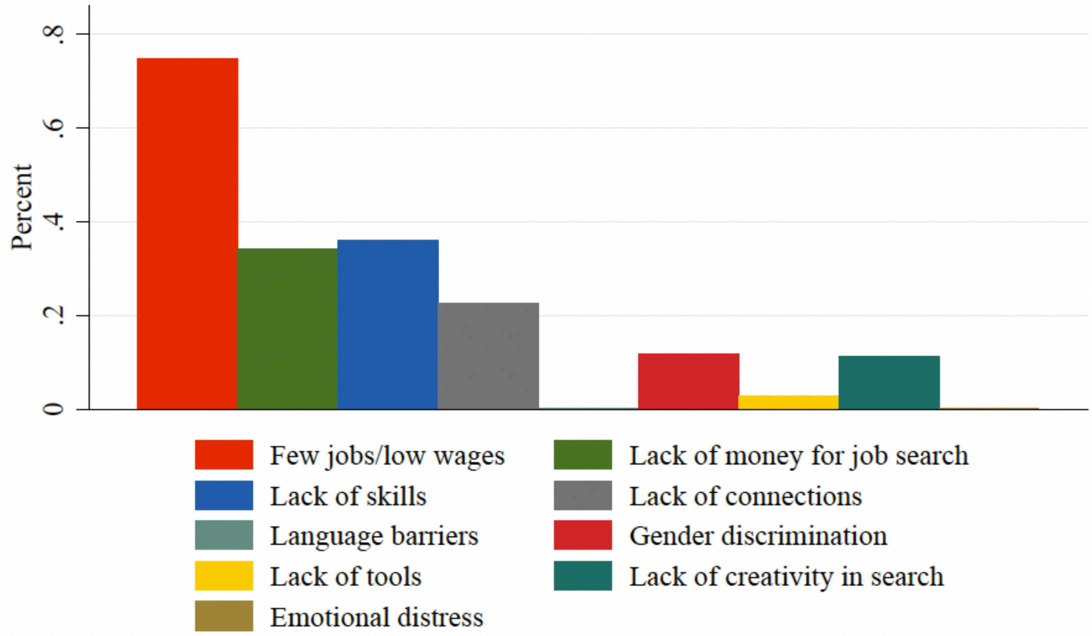



Figure A.5. Expected challenges students will face reported by alumni



# 9 Administrative information

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**Institutional Review Board:** Necessary approvals are in place. This study has been reviewed and approved by three entities: by the University of California at Berkeley's Committee for the Protection of Human Subjects (under Protocol ID 2019-09-12569); in Uganda, by the Mildmay Uganda Research Ethics Committee (under Proposal Reference Number #REC REF 0206-2019); in Uganda, by the Uganda National Council for Science and Technology (under the study reference number SS338ES).

**Declaration of interest:** The authors state that they have no competing conflicts.

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Manuscript File Click here to view linked References

*Journal of Development Economics*

Registered Report Stage 1: Proposal

# Meet Your Future: Job Search Efforts and Aspirations of Young Jobseekers

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**Keywords:** job search, employment network, vocational education, youth unemployment, expectations
**JEL codes:** D84, J24, J64, O15
**Study pre-registration:** AEARCTR-0004310 (https://doi.org/10.1257/rct.4310-1.0)

**Abstract**
This study investigates the relative importance of several barriers to quality employment young jobseekers in developing contexts face when transitioning into a labor market characterized by high levels of informality and technological constraints: lack of information on labor market conditions, inability to communicate their own value, lack of connections, lack of motivation and liquidity constraints. The experimental setting is that of Vocational Training Institutes (VTI) in Uganda. We track 1115 VTI students over a period of 3 years to follow the evolution of their employment expectations and planned search strategy as they approach the labor market and start the search. Treated students are eligible to participate in the Meet Your Future Program, a highly tailored career-coaching program delivered by successful alumni who belong to their same VTI and course of study. A random sub-group of treated students receives a cash transfer to aid them in their search in addition to the program. We estimate the casual effect of these interventions on students' expectations, job search and labor market outcomes. Last, through detailed data on students' pre-intervention network and socioeconomic background we are able to evaluate the program's potential to increase equality of access to quality jobs.

**Proposed timeline of the Meet Your Future Project**

The overall duration of the project is 36 months. ~~The field activities observe the following timeline.~~ We conducted three pre-intervention interviews at the student level and three at the alum level. In January 2021, subjects were contacted again to confirm participation to the study as well as their contacts. The intervention was rolled out in February and March 2021. As part of the intervention, we conducted a Post-Interaction survey with treated students and an Alumni Check-in with the alumni selected to participate in the program. The first e~~E~~ndline survey~~s~~ ~~will take~~ took place in May 2021. The second one will take place in February~~ and March~~ 2022.

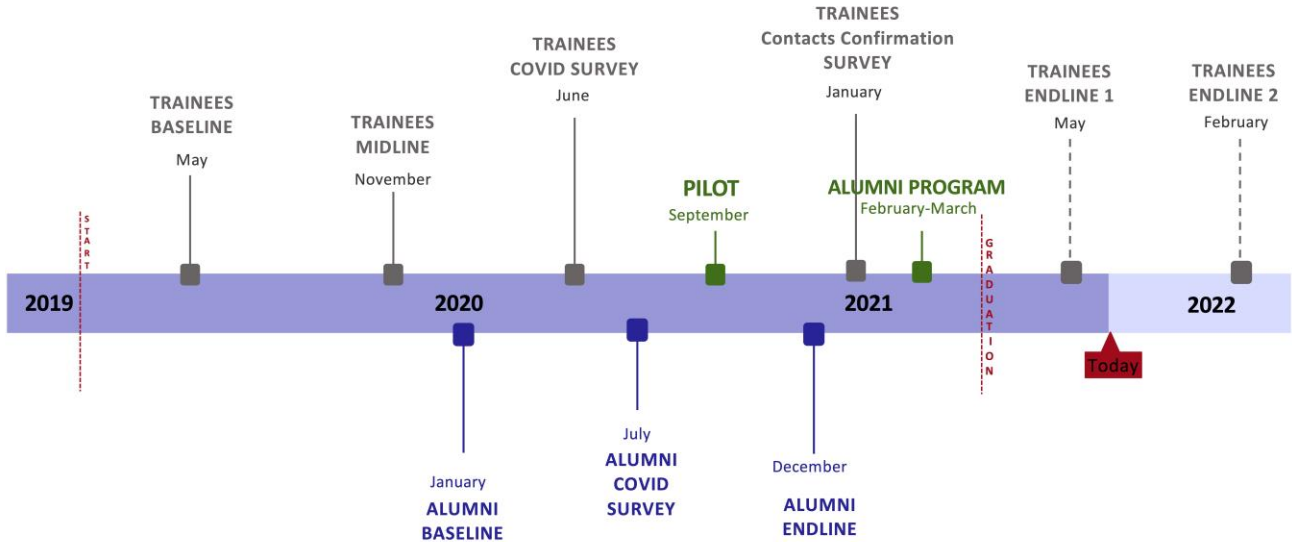


Figure 1a. Project Timeline

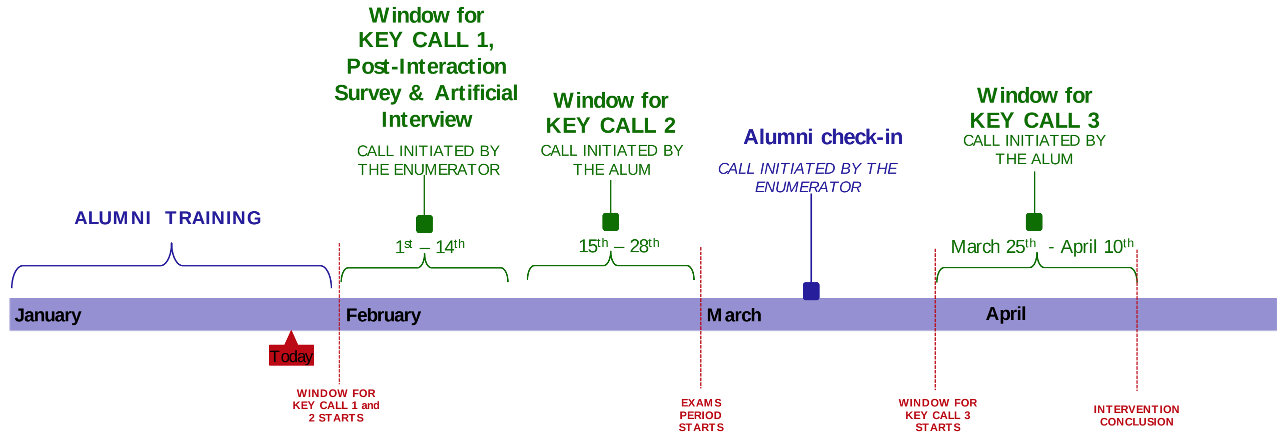


Figure 1b. Intervention Timeline - detail

# 1 Introduction

In highly informal labor markets, network connections are key for a successful job search. A solid network is essential for the efficient matching of workers with jobs, as it has the potential to solve the numerous frictions identified by the literature on job search in developing countries: mismatched expectations about wages and firms' requirements (Babcock et al., 2012; Abebe et al., 2017b), intention-behavior gaps and lack of motivation (Abel et al., 2017), over-optimism and suboptimal search effort (Spinnewijn, 2015), liquidity constraints (Abebe et al., 2017a), unawareness and inability to communicate own value and skills (Pallais, 2014; Bassi et al., 2020; Carranza et al., 2020). These barriers are magnified for young jobseekers who lack previous experience when taking their first steps into the labor market, and thus network connections are extremely valuable to them.

In this study, we evaluate the impact of exogenously expanding the network of a graduate student on their employment expectations, job-search strategy and labor market outcomes. In particular, we implement a field experiment involving 1115 students enrolled in their last year of education in five accredited Vocational Training Institutes (henceforth, VTIs) in Central and Eastern Uganda. Students are trained in a variety of sectors, including hairdressing, welding, electrical engineering, tailoring, and catering. A subset is randomly selected to participate in the Meet Your Future Program, a highly tailored coaching experience where students are matched with successful alumni who attended their same VTIs and course of study. The program involves a minimum of three phone conversations between the student and their matched alumni. During these conversations, students have the opportunity to ask questions, share doubts, fear and dreams. Alumni can support the students in several ways, which we classify into four main groups: provision of information on the status of the labor market; provision of tips and guidance for a successful job search; referral to potential employers; encouragement and motivation. The conversations took place in February and March 2021, around the time of graduation.

By combining information on students' engagement in the program with information on the frequency, content and form of the phone conversations, we first determine if and when the program successfully transformed an exogenous match into a close link. To our knowledge, this is the first field experiment to exogenously create new links between young jobseekers entering the job market for the first time and workers in their sector of interest. We then use a randomized controlled trial to evaluate whether furthering the formation of a valuable network by connecting recent graduates with alumni aligns their expectations, leads them to re-optimize their search, connects them to openings and eventually improves their labor market performance compared to control students.

To understand whether simultaneously relaxing liquidity constraints has the potential to magnify the effects of a network expansion, we unconditionally provide 40,000 UGX (~ $12) to a random subset of the MYF Program participants, with the recommendation that they use the money to finance their job search or contact the alumni.

Finally, we look at the equity effects of the program. Students from poorer socio-economic background face more binding liquidity constraints as well as are equipped at baseline with lower quality homophilic social networks which perpetuate inequality and reinforce economic disparities.

This study contributes to several strands of the literature. First, it contributes to the literature on job search frictions in developing countries. By analyzing the content of the phone conversations, we identify the labor market frictions that prevail in the population of interest and compare them to those previously identified in the literature. Second, this study speaks to the literature on job search assistance programs for young jobseekers. Evidence on their effectiveness in developing contexts is mixed (McKenzie, 2017). While they have more scope in contexts with greater search and matching frictions, they are also likely to be less effective if employers highly rely on their network for hiring or publicizing vacancies. Additionally, some studies highlight how relaxing one constraint is insufficient to trigger labor market responses if other constraints are not simultaneously relaxed. For instance, Groh et al. (2015) and Abebe et al. (2017a) find that reducing search costs by matching firms and jobseekers has limited consequences on employment because jobseekers have reservation wages which are too high. Other types of interventions, such as support with job search planning, instead proved effective at increasing employment in Ethiopia (Abebe et al., 2017b). The MYF Program we implement differs from previous efforts in one major way: it is highly tailored to each student's specific needs. This characteristic makes it capable of relaxing multiple constraints at the same time. Brooks et al. (2018) implement a similar program where young female entrepreneurs are matched with a mentor from the same community and leave the relationship completely unrestricted. We differ from them in two major ways. First, we analyze the population of students transitioning from the education system to the labor market. This is a critical passage with long-lasting consequences over the students' future working trajectories. Second, through close monitoring of the interactions between participants and intense data collection, we create a framework to analyze and to test what is helpful, how and for whom.

Last, coaching programs are often institutionalized by schools and universities in developed countries. These programs have greater potential in contexts characterized by a high degree of labor market informality and a high reliance on network connections to navigate the labor market. Rigorously evaluating the effectiveness of a career-coaching program in a high-stake setting where it is currently nonexistent has the potential to support the labor market transitions of many generations of students to come.

# 2 Background

## 2.1 The Ugandan Labor Market

In Uganda, the second youngest country in the world, the quick population growth within the last couple of decades paired with simultaneous heavy investments in human capital has resulted in an increase in schooling within the workforce. Unfortunately, these stellar trends have coincided with a period of slower economic growth which has meant slower growth in labor demand and insufficient creation of good jobs. The rates of youth unemployment and underemployment have risen steeply and returns to education have declined rapidly (World Bank, 2019). With such oversupply of labor, it is of fundamental importance to ensure that frictions do not prevent efficient allocation of skilled workers across the few available good jobs. At the same time, the high degree of labor market informality and lack of digital platforms by making information acquisition and applications for suitable jobs more costly make the risk of mismatches much higher in this context. In practice, the limited high-quality jobs are filled most commonly by those who already possess valuable network connections within the industry, connections that youth belonging to poorer or more remote households are less likely to have. Increasing equity in labor market access therefore becomes deeply interconnected to increasing its efficiency and maximizing the likelihood of matching the candidate with the highest potential to the position. In this context, we evaluate the impacts of providing a valuable source of information and connections to young jobseekers entering the labor market through linking skilled graduates with successful alumni. By reducing the cost to acquire information and connect to job openings, we aim to improve the quality of the matchings at first job and level the playing field across graduates from different socio-economic backgrounds.

## 2.2 Study Population

As in many other economies in East Africa, attempts to educate and skill the population have also taken place through vocational training and other skill transfers. In the early two thousand, the Ugandan government designed specific bodies to set rules for accreditation, assessment, certification, and inspection. As of today, the vocational sector is well established in Uganda: vocational training is a common route through which workers acquire skills, and SME firm owners are familiar with recruiting trainees from VTIs. It is also a common tool used by NGOs to promote the transition of secondary scholars from disadvantaged backgrounds into practical tertiary training. It is within this context of vocational training that the sample of our students makes the school-to-work transition.

Specifically, we survey the population of students that enrolled in the National Certificate (NC) Program in 2019 in five VTIs across Eastern and Central Uganda[1]. Our sample is representative of the population of Ugandan youth enrolled in practical tertiary training[2]. The NC is a two-years program aimed at teaching students a specific trade. The course includes theoretical and practical classes and, at the end of it, students receive a certificate of skill ownership with national validity.

The 1115 students in our sample are trained in 13 specific skills: motor-mechanics, plumbing, catering, tailoring, hairdressing, construction, electrical engineering, welding, machining and fitting, teaching/ECD,

[1] We selected VTIs with a long-lasting history of collaboration with BRAC Uganda, our implementing partner, which pre-selected them based on their reputation, infrastructures and equipment, teachers' educational attainment and teacher-students ratio.

[2] There is no shortage of VTIs in Uganda, and as in other low-income contexts, there are concerns over a long tail of low-quality training providers existing in equilibrium. It is not obvious the results would replicate in one of these low-quality providers.

agriculture, accounting and secretarial studies. As shown in Table A.1, these sectors constitute a source of stable employment for young workers in Uganda: around 16% of employed workers aged 20-30 work in them (a percentage that more than doubles if we exclude those involved exclusively in agriculture). Students' distribution across field of study and treatment arms is described in Table A.2.

As shown in table A.3 at baseline the students are on average 20 years old, 40% of them are female, and most of them are single, Christian and have no children. The sample is relatively heterogeneous in terms of socio-economic background, which we proxy using information on households' asset ownership, urban or rural location and household of origin main source of income, which is divided between subsistence agriculture (33%), commercial agriculture (15%), wage job (33%) and a family business (19%). About 40% of the students worked before the VTI, mostly in unskilled wage or casual occupations. When asked about plans for the future, almost 60% of the students reported their intention to look for a job, 15% to start their own business, and 27% to pursue further education before entering the labor market. The latter percentage is around halved towards the end of the training when we re-elicit their intentions. Finally, in the three pre-intervention survey rounds we asked the students to name up to 9 people (four at baseline, up to four more at midline and up to one more during the covid survey) to whom the students would ask for support, broadly defined, when looking for a job. We obtained information of 4,932 network members (of which 4,896 are unique) whose main characteristics are reported in Table A.7. 62% of the network members are male, on average they are 37 years old and have completed 12 years of education. 81% of them were working when the students were interviewed, most of which in full time jobs. Despite the overall high quality of this group of people, there is enough heterogeneity which becomes evident when we compare measures of network quality between students with high and low SES. Table A.8 shows that poorer and richer students have networks that are similar in size (4.4 members on average) and composition (88% of the members coming from the original community, including family members, friends, neighbors, etc., and 12% coming from the VTI, including VTI friends and teachers). However, students with low SES have a lower share of network members with secondary education (difference of 12pp), able to provide students with a job (12pp difference), to be currently working (9pp difference) and to be earning above the median in the sample of alumni (14pp difference). This evidence supports the view that a valuable employment network comes with solid economic background, and that relying on word of mouth and network connections for demand and supply of labor to match perpetuate existing inequalities.

### 2.3 Transition into the Labor Market

To gather information about how the transition into the labor market generally evolves for the young graduates that leave the VTIs and inform the project design we (i) surveyed 246 trainees from two renowned VTIs in Uganda; (ii) conducted numerous focus groups (FDGs) with VTIs' managers, teachers, current students, and alumni; (iii) collected and digitized hard copies of phone contacts[3] for 1,368 alumni, of which we successfully contacted and surveyed 714[4]. The rich set of information collected consistently points toward three major challenges students face during the transition into the labor market, as well as to the greater impact of these challenges upon students belonging to a lower socioeconomic status.

First, students are overall "poorly prepared to face the outside" i.e., they lack information about labor market conditions and hold misaligned expectations. In Figure A.2. we show that students' expected wages after graduation are significantly higher than the alumni's average wage at their first job at baseline, one year into the program, and in the midst of the first lockdown. In Figure A.3. we show the time required to search for a job as expected by the students across three points of time and learn that the students not only overestimate their wage at first job, but they also underestimate the required time when compared to the average time spent on the job search following graduation of the alumni in the sample. At baseline students underestimated the time required by over half. Even when surveyed during the Covid-19 pandemic in June and July 2020, when job market prospects were relatively grim, the students still underestimated the time

[3] One example of the digitized material is shown in Figure A.1.

[4] The attrition from the initial sample of 1,368 alumni contacts is largely attributed to the quality of the information which was collected by the VTIs at the time of each student's graduation. Due to the written nature and manual entry of the records, the digitization process was not only prone to error, but much of the data was not recent as telephone SIM cards were required to be registered in 2016 which led many Ugandans to change phone numbers. Of the 714, 657 were successfully interviews in all three survey rounds.

required by an average of four weeks. Taken together, and abstracting for their believes' evolution over time, we interpret this as evidence for optimism over wages and arrival rates.

When confronted with the possibility of meeting successful alumni, the students in the pilot study came up with numerous questions on how to job-search, which challenges to expect, how to find customers and input providers, how much capital they would need and how to obtain it, what to expect about working conditions, such as pay, hours, and benefits. Students declared to be interested in hearing alumni's personal experiences to figure out what are the necessary steps required to build a successful career. Similar information gaps, and more, were identified during the FGDs conducted with alumni when we asked what they wish they had known before starting to look for their first job. The most recurring answers across courses were: important documents' formatting and organization, dress code, attitude for interviews, and dropping the application to the right person. Overall, we understood that alumni are a precious source of information and advice that could benefit students and whom they would be interested in hearing from.

Second, jobs seekers and firms are not using formal channels to find jobs. Indeed, over 60% of the respondents identified network connections with friends and/or relatives as one of the main channels they plan to use to look for a job. When we look at the alumni sample, 61% of them found a job through this channel, proving that the relevance of the channel is widely understood by the students. And rightly so: suggestive evidence shows that more connected alumni performed better than less connected ones in their first steps in the labor market as well as four years down the road. As shown in Table A.4 alumni with at least one relative who works at or owns a business in their sector of training find a job significantly earlier, are less likely to work in casual occupations as first activity following graduation as well as pre Covid-19 (which corresponds to on average 4 years into the labor market) and are significantly more satisfied of their career. This comes from the fact that in highly informal labor markets network connections are primary determinants of what information, opportunities and support young jobseekers have access to, and eventually of their success in the labor market. In the words of an alum who participated in our focus group discussions, for a young jobseeker making her first steps in the labor market *"first and foremost you must have friends, in this era one cannot get a job without having friends that connect you to deals"*.

This acknowledged importance of a network explains why we find that 20% of the students identify limited access to valuable network connections as one of the main challenges they will face when transitioning to the job market (Figure A.4). Unsurprisingly, it is the poorer students who feel they lack network connections: when we analyze students' perceived challenges by their asset index[5] we observe that students with worse SES are 7 percentage points significantly more likely to say that one of the main challenges they will face is "lack of connections".

This worry is well grounded, as displayed in Table A.8 for students and confirmed again in the alumni sample, where we find additional suggestive evidence that valuable relationships come with a solid economic background (Table A.6). What we can additionally do in the sample of alumni with respect to the sample of students is to obtain evidence, although suggestive, that lack of a connections likely play an important role in perpetuating inequality in the labor market, as alumni with low SES and poor network have worse labor market outcomes (Table A.5). Connections, which develop around existing social hierarchies and reinforce economic disparities, also translate into access to information, guidance, support, and opportunity. Consequently, a lack of connections can serve as a barrier to increasing inclusivity of poor people in higher quality jobs.

Third, when students were asked about which challenges, they expected to face when looking for their first job, many bring up the lack of economic resources to finance the search process or to invest in a new business: 43% of the students mentioned "lack of money for transportation" or "lack of money to finance the job search" (all in the category "money for job search" in Figure A.4).

In conclusion, most students are poorly informed about labor market conditions, lack expansive networks to leverage in the job search process, and face liquidity constraints. Additionally, these three challenges are harder to overcome for those who belong to households of a lower socio-economic status. With this project, we provide insights into the effectiveness of a career-coaching program performed by "the future you", a successful alumnus of the VTIs, and we investigate the program's potential to smooth the transition from the education system into the labor market and increase equality of access to quality jobs.

[5] Built with information on the assets present in the household where they grew up, we use it as a proxy for their social economic status.

### 2.4 Covid-19 in Uganda

Lockdowns in East Africa in response to the Covid-19 pandemic have been among the most stringent on the continent and consequently the region boasts the lowest cases. This is also true in Uganda, where schools were closed as of March 20th and other non-essential businesses and public transport were shut down for over two months beginning April 1st. The decisive action to shut down businesses not deemed most essential helped the country cope with the virus, but it is predicted that Eastern Africa will be the hardest hit region with respect to labor market impacts.

From the data collected on the alumni, we find that as a result of total lockdown measures in Uganda about 40% of businesses were forced to temporarily close and about 71% of wage employed alumni were temporarily laid off when surveyed in June and July of 2020. In December, six months after total lockdown measures were lifted and only a public mask mandate and nighttime curfew were left in place, almost 80% of the alumni who had been laid off during the total lockdown had returned to work. This relatively high rate of reintegration back into the labor market among these young alumni suggests that the current context with respect to finding jobs was less grim at the time of graduation than it had been in the summer of 2020[6]. While the data suggests that the labor market was beginning to recover in Uganda six months after the total lockdown, the state of the market in March 2021 is unclear for young entrants as there exists the possibility that these firms are simply replacing the skilled workers who were previously laid off in March and April of 2020. However, if it is the case that jobs are even more scarce for our graduates now, ensuring productive matches and access to information for all has the potential to be even more important than in pre Covid-19 times.

Anecdotal evidence from within Uganda on increased prices of transportation and income shocks across households reinforces the data collected on current labor market conditions and speaks to the salience of our project's T2 cash transfer, especially with regards to the additional cost of job searches borne by graduates.

# 3 Research Design

### 3.1 Intervention and Treatment Groups

As part of our intervention, we administer two treatments: the Meet Your Future Program (T1) to 30% of the sample and the Meet Your Future Program with Mobile Money (T2) to another 30% of the sample. The remaining 40% is a pure control group.

<u>T1: Meet Your Future Program (MYF)</u>

Students assigned to receive this treatment will be matched with “the future you”, a successful alum who graduated from their same VTI and in their same course of study. In particular, the research team will facilitate three conversations on the phone. During these phone calls, students have the chance to ask questions, share their doubts, fears, and dreams. These interactions are unrestricted: no specific topic coverage is required. Each student-alum pair is free to discuss what they find most interesting and useful for the student’s transition from the education system into the labor market. In this way, the coaching is tailored to each student’s specific needs. We anticipate each conversation to revolve around general as well as student-specific topics.

The first phone call, which we call Key Call 1, takes place approximately one month before graduation.[7] It is a conference call between the student, the alum and the enumerator who initiates and records the conversation. Prior to Key Call 1, the enumerator contacts the alumni and students to find a common availability. Treated students learn about the existence of the MYF program during this phone call with the enumerator. During the call, following the initial introduction, the enumerator remains silent, listens to the conversation, and compiles a survey (the Artificial Survey – more detail available in Section 4.1) to identify

[6] As we write this version of the manuscript, Covid-19 cases in Uganda are roaring once more and stricter measures are likely to be ahead. From the Endline 2 survey we will be able to gather and include findings on how students’ labor market conditions as of Endline 1, changed following the second lockdown.

[7] Students graduating in ECD have an earlier graduation date, which implies that for them the program is administered around their graduation and after.

the topics covered as well as to characterize the *form* of the conversation. At the end of Key Call 1, the student remains connected with the enumerator to answer a brief survey, the Post Interaction Survey, to record the student's main take-aways and feelings immediately following the first interaction with the alum.

The second and third phone calls, which we call Key Calls 2 and 3, take place two weeks prior to and two weeks following graduation. They are initiated by the alum and are private conversations between the alum and the student. Alumni are required to send a text after the completion of each of these Key Calls to confirm they took place and we double check this information with the students during Endline 1. We also encourage students and alumni to interact beyond these three Key Calls, if they wish. Alumni are required to take notes of the frequency, duration, content and means (in person, phone call, video-call, WhatsApp messages, SMS, email, etc.) of any additional interaction that takes place over the two months duration of the program.

The alumni taking part in the program have been previously selected and trained by the research team. To select the alumni that will administer the intervention, we defined a set of rules to ensure the overall quality of the coaching as well as to ensure replicability. From a sample of 657 alumni, we exclude 90 alumni that did not provide their availability for the MYF program or never worked in the occupation of training. To select the most successful alumni among the remaining ones, we assign a score to a set of relevant characteristics and rank them based on their total score. The characteristics considered are: (i) accessibility, (ii) quality of first and current jobs, (iii) general labor market indicators, (iv) school performance, and (v) soft skills. The full list of variables we use in the selection and their corresponding scores are in Table 1.

We rank alumni based on their total score. Our goal is to match students with alumni who attended their same VTI and course of study. For this reason, we select the N highest ranked alumni for each VTI-training area combination, where N is a function of the number of treated students in each VTI-training area.[8] There are 12 out of 57 combinations of VTI-training areas for which we have slightly less alumni than we need. In these cases, we select the highest ranked alumni graduated from the training areas in question that have not been yet assigned, regardless of the VTI[9]. After the selection, we end up with a sample of 171 alumni. Each alum is assigned one to five treated students at random. Each alum is assigned students belonging to the same treatment arm. The specific number of students in each combination of VTI-training area-treatment arm is determined based on the exact number of students assigned to each alum. When forming groups, we maximize the number of groups with three, four or five students per alum[10,].

Alumni are trained by the research team prior to the start of the program. During the training, the alumni get to know their duties as career-coaches and program ambassadors and are guided through the different ways in which they could help the students:

- Share information about general labor market features [Information];
- Provide tips for a successful job search [Strategy];
- Refer the student to potential employers [Referral];
- Encourage the students to do their best and put in the effort [Motivation].

They are also reminded that they can interact with the students as many times as they wish, and that during their interactions with each student they are free to discuss whatever they think would be most useful for that student to learn. To thank them for their two months long participation in the program, conditional upon the completion of the three Key Calls and the Alumni Check-In (see Section 4.1 for details), alumni are provided ~$40 as well as reimbursements of the airtime incurred to make the phone calls. The facilitation does not depend on students' success in the labor market.

Table 1. Alumni Ranking Procedure

| **Characteristic** | **Score** |
|---|---|
| ***Accessibility*** | +1 |
| Alum has smartphone | +1 |
| ***Quality of first and current job*** | |
| First job: wage-employed or self-employed | +1 |
| First job: earnings above median | +1 |

[8] The number of required alumni in a specific VTI-training area increases by one every five treated students.

[9] However, in these cases we try to match students with alumni who graduated from another school but in the same urban area.

[10] Eventually we have: 30 groups with 5 students per alum; 29 with 4 students per alum, 19 with 3 students per alum, 5 with 2 students per alum and 5 "groups" with just one student per alum.

| | |
|---|---|
| First job: sector same as sector of training | +1 |
| Current job: wage-employed or self-employed | +1 |
| Current job: earnings above median | +1 |
| Current job: sector same as sector of training | +1 |
| ***General labor market indicators*** | |
| Graduated between 2014 and 2018 | +1 |
| Longest unemployment spell below median | +1 |
| ***Education*** | |
| A or A+ in DIT Exam; graduated with honor in UBTEB exam[11] | +1 |
| ***Soft Skills*** | |
| Alum strongly agrees/agrees they generate enthusiasm | +1 |
| Alum strongly disagrees they generate enthusiasm | +1 |

To design our intervention and refine each survey tool and protocol, we piloted a small-scale version of the program with 30 students and 10 alumni from a sixth VTI (which is not part of the intervention) between October and December 2020. All pilot participants completed the program and provided highly positive feedback about its usefulness.

T2: Meet Your Future Mobile Money (MM-MYF)

Students assigned to this treatment arm receive 40,000UGX (~$12) through mobile money upon graduation. The cash transfer is unconditional. However, students are recommended by SMS to use such funding to facilitate the kickoff of their careers and are required to report to BRAC how they spent them (the SMS text is available in Appendix A).

## 3.2 Assignment to treatment

The strong implementation capacity of our local partner BRAC Uganda, as well as the collaboration with the VTI's principals, allows for the randomization of the applicants into the program. The randomization is private, that is, only the research team is privy to the process. We assign students to three randomly selected groups and to treatment eligibility as follows:

Table 2. Assignment to treatment

| Group | Intervention | N | % of sample |
|---|---|---|---|
| 1 | Control | 442 | 40 |
| 2 | T1 | 334 | 30 |
| 3 | T1+T2 | 339 | 30 |

The identification strategy for our RCT relies on the hypothesis that the three groups are identical, on average, in all observable and unobservable characteristics. To support this hypothesis, we check for balance across treatment arms over available characteristics likely to correlate with the outcomes of interest. The experimental design is balanced in nearly all the variables of interest, as shown in Tables A.2, Table A.3 and Table A.9. The randomization we perform is stratified at the student level. In this section we describe how we choose the "strata variables", the set of variables along which we stratify the randomization, and the "balance variables", the set of variables for which we require no imbalance. We set specific imbalance goals to make the re-randomization process as transparent as possible. All strata and balance variables will be included in all treatment regressions. In all our choices, we followed the principles highlighted in Bruhn and McKenzie (2009) and Athey and Imbens (2017).

Choice of the strata variables

First, we decide to stratify by VTI, as the implementation of the treatment could vary at the school level.[12] Second, we decide to stratify by a measure of "risk of attrition" to reduce the possibility of selective attrition. The variable we use is *hard_to_find*, an indicator for whether the student has not been successfully

[11] These measures allow to flag the top 15% of both exams' participants.

[12] We use indicators for schools in a similar way as Bruhn and McKenzie (2009) suggest using indicators for different geographic areas which are possibly subject to different shocks affecting the way in which interventions are administered.

interviewed in three out of the three pre-intervention survey rounds. Third, we choose to stratify along dimensions that are likely to be correlated with our outcomes of interest based on economic theory and existing data. To identify these variables, we perform two sets of analyses.

i. Within the sample of students, we check how a pre-determined set of students' characteristics correlate with employment indicators before the beginning of their course in the VTI and during the lockdown. We believe that the ability to find a job in the past, as well as having some work experience, could be positively correlated with the ability of finding a job after school completion.
ii. Within the sample of alumni, we check how a set of alumni's characteristics correlate with the following set of labor market outcomes a) earnings at their first job, b) their most recent employment status and earnings.

The variables we correlate with the outcomes above are: indicator for male student/alum; indicator for ownership of a smartphone; indicator for agriculture as household's main source of income (rather than wage or self-employment in non-agricultural activities); asset index; scholarship status; caretakers' educational attainment; indicators for each of the VTIs; indicators for each of the training areas.

These correlation analyses (whose results are available upon request) reveal the following:

- The indicator for male is highly and positively correlated with labor market outcomes in both samples of students and alumni;
- The indicator for smartphone ownership is highly and positively correlated with labor market outcomes in both samples.

The remaining variables display weaker or inconsistent correlation patterns. To sum up, we decide to stratify along the following four dimensions and obtain a total of 5x2x2x2=40 strata[13]:

Table 3. Strata Variables

| **Strata variable name** | **Description** | **Motivation** |
|---|---|---|
| Vti | Categorical variable with 5 levels corresponding to the 5 VTIs in our sample | Potentially correlated with treatment implementation |
| Male | Indicator for whether student's gender is male | Positively correlated with labor market outcomes |
| Hard_to_find | Indicator for not reaching the student in all pre-intervention survey rounds | To reduce the risk of having differential attrition by treatment status |
| Wa_sp | Indicator for smartphone ownership | Negatively correlated with labor market outcomes; to reduce the risk of having differential attrition by treatment status |

<u>Choice of the balance variables</u>

We decide to replicate the randomization procedure until we achieve balance on a pre-determined characteristic that we believe could be highly correlated with the outcomes of interest: a dummy for whether the student has ever worked (either before beginning the course or during the lockdown). We ex-ante define the procedure that determines whether the randomization should be replicated. For any given treatment assignment:

a. We regress *ever_worked* on indicators for control group, treatment 1 and treatment 2 groups, and we record the p-value from the Wald (F)-test that the coefficients of all indicators are jointly equal.
b. We use t-tests to test whether the difference in means among 1) students assigned to the first and second treatment groups and 2) students assigned to the first and third treatment groups are statistically different from zero and we record the two-corresponding p-values.
c. We reject the treatment assignment if any p-value from Wald or t-test is below 0.3 and 0.1, respectively.

In practice, we achieve balance after one randomization, therefore, we do not replicate the randomization.

[13] We generate strata using the *egen group* function in STATA. The command we implement on STATA to generate strata is the following: *egen strata=group(vti male hard_to_find wa_sp).* The variable obtained this way has 3 missing values, and is missing whenever any of the strata variables are missing. We randomly assign these 3 observations to the existing strata so that the final *strata* variable has no missing observations.

### 3.5 Replicability and Cost Effectiveness

Replicability and cost effectiveness have been an important goal while designing the intervention, given the interest expressed by involved VTIs as well as the BRAC Youth Empowerment Program. For this reason, the intervention is relatively easy and inexpensive to replicate.

In its current form, the hardest step in setting up the Meet Your Future Alumni Program consists of obtaining the contacts of the alumni for a cohort with two to five years of experience in the labor market, as VTIs are unaccustomed to tracking their alumni. However, once the program is set up, tracking methods become less costly. For instance, students might be systematically asked for updated contact information. They can also be made aware of and inducted into the alumni program prior to graduation. The algorithm proposed to select the alumni is easy to replicate, as it is based on accessible survey and administrative information. Once alumni have been selected and schools' administrators instructed on how to make random matches, the implementation of the intervention is straightforward. Moreover, institutionalizing the intervention at the school level will make its implementation easier. Indeed, the first interactions between students and alumni will be facilitated by the schools with no need for an enumerator to attend, further reducing the cost of this intervention which is already relatively low. We estimated a per alum cost of: ~$5 for a half-day training (includes a snack, a face mask, a hand sanitizer, stationary and a venue); ~$15 for airtime (which is the equivalent of 70 hours of talking time) and an overall ~$40 facilitation to thank them for participating in the Alumni training, the Alumni Check-In and for conducting the Key Calls. Considering that an alum is matched to an average of 3.9 students, the cost per student is ~$15. The per student cost is relatively low and makes up a minute proportion of the fees paid for these programs ($650 - $800). Given the institutions providing need-based scholarships already allocate large amounts of funding to pay for the training of these students, it would behoove them to invest this additional small amount which is expected to amplify returns by a great deal and make a difference in employment outcomes. This additional investment is especially poignant for students belonging to disadvantaged economic backgrounds for who the program is expected to make the largest difference.

The costs discussed are exclusive of the administrative costs. While the airtime and training costs are likely to stay the same (it is likely the schools will not need to rent a venue and hopefully face masks and hand sanitizers will not be needed forever), we foresee the facilitation to be needed only for the first 2-3 years of the program. Once the alumni program is institutionalized and students who benefitted from it during the initial years are themselves asked to be ambassadors, we believe that the monetary compensation will not be needed or could be effectively reduced.

Similarly, the difficulty in gathering contact information from the students to set up the Mobile Money intervention would be greatly lessened if the program were to be institutionalized such that schools could collect and update this information in an organized manner. Once the contact information is available, sending money and communicating with students about their suggested use can easily and cheaply be automatized[14]. A rigorous evaluation of the program cost-effectiveness will be conducted before disseminating any policy suggestion.

With this study we focus on the supply side of the labor market and look at viable and cost-effective ways to improve jobs to students matching, job satisfaction and equality in access to quality jobs, while keeping labor demand factors fixed. If the program has positive effects on these outcomes, scaling it up will neither create distortions on the local labor markets, nor will the potential effects dissipate. For what concerns the experiment study, as we are currently implementing the program in 5 out of 715 accredited VTIs only in Central and Eastern Uganda (1270 nation-wide)[15], the advantage for treated students will likely not come at the expense of the control group. Indeed, treated students represent a tiny fraction of the cohort of jobseekers, and the urban labor markets in which they are most likely transitioning into are among the biggest in the country (Kampala and Jinja) suggesting that negative treatment effects are unlikely.

[14] We used Telerivet Software for broadcasting SMS.

[15] As of 2017-2018, the total number of VTI in the Central and Eastern regions, both formal and informal, accredited either by the DIT (493, of which 383 located in the Central region, and 110 located in the Eastern region) or UBTEB (291, of which 196 in the Central region, and 95 in the Eastern region) or both (69, of which 50 in the Central region, 19 in the Eastern one) was 715. However, this is likely to be an upper bound: 33 VTIs (8 in Eastern Region, 25 in Central region) that appear in a 2015 list do not appear in what seems to be an updated version of such list in 2017. Additionally, the overlap between UBTEB and DIT accredited VTI could be refined. These are the results from an exact matching. The lower bound is 460 (should all the UBTEB and DIT overlap and should those 33 have closed down).

# 4. Hypotheses and Theory of Change

We collected a rich dataset, which will be used to test several hypotheses. Subsection 4.1 concerns impacts on our primary outcomes, as well as heterogeneity of impacts. Subsection 4.2 concerns the process and mechanisms that can explain the impacts, or lack of therefore, on the primary outcomes. Details on how outcomes are measured follow in Section 5.

## 4.1 Impacts on primary outcomes

# ~~4. Hypotheses and Theory of Change~~

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## ~~4.1 Impacts on primary outcomes~~

*Hypothesis 1: Matching students with a successful alum from the same VTI and course of study will (i) align students' expectations, and improve their (ii) job search strategy and (iii) labor market outcomes.*

Alumni represent a network connection which is orthogonal to the students' existing network, as well as a source of information, advice and motivation. For this reason, we anticipate the following treatment effects:

(i) Impact on labor market expectations:
   a. We expect treated students to internalize the information on available opportunities and labor market conditions obtained by alumni and readjust their expectations about how long it takes to find a job and earnings at first job, for themselves and for members of their class.

(ii) Impact on search strategy:
   a. We expect that the number and the type of job opportunities treated students are aware of and apply to will expand compared to the control group. Concretely, this means more resources devoted to job search: higher index of search intensity and a higher index of search broadness.
   b. We expect treated students to internalize their alumni's advice, tips and suggestions and improve their job search efficacy index.
   c. We expect treated students to receive a higher number of interviews and job offers than control students.

(iii) Impact on labor market outcomes:
   a. We expect treated students to work, earn and apply their newly acquired skills more than control students in the four weeks preceding Endline 1 and Endline 2.
   b. Conditional on finding a job, we expect treated students to find better jobs than control students, to have higher career and job satisfaction and lower turnover.

*Hypothesis 2: Receiving cash on top of the career coaching program will magnify the effects of the MYF treatment on students' (i) job search strategy and (ii) labor market outcomes with respect to students only receiving the alumni program.*

(i) Impact on search strategy: the cash transfer, paired with the MYF program, will relax students' job-search budget constraint and allow them to get closer to their *new* unconstrained optimum. Concretely, this means an even higher index of search intensity and of search broadness as compared to students in T1.

(ii) Impact on labor market outcomes:
   a. Following the stronger effects on search intensity and broadness we expect treated students who received cash to work, earn and apply their newly acquired skills even more than students in T1 in the four weeks preceding Endline 1 and Endline 2.

b. Conditional on finding a job, we expect treated students who received cash to find better jobs than treated students who did not receive cash to have higher career and job satisfaction and lower turnover.

Additionally, we will investigate the presence of heterogeneous effects for relevant sub-groups of students. Sub-groups are identified by categorical variables capturing characteristics at baseline. When characteristics are continuous, we create subgroups by separating individuals below and above the median level of the characteristic. These characteristics are:

- Gender. Women have lower labor force participation rates in general and their sectors of training appear to be hit harder by the Covid-19 shock. We expect effects to be greater for women, whom previous research has shown are more likely to get discouraged while searching and have harder time seeking support from their network members.
- Previous work experience: dummy for whether the student has ever worked before graduation. We expect people with work experience to have a smaller treatment effect.
- Raven's scores at baseline. We expect higher ability people to have a larger treatment effect.
- Locus of Control from the World Value Survey. We expect people with and external LOC to have a smaller treatment effect, as they may not value the program.
- Disadvantaged socio-economic background. Effects are larger for economically disadvantaged students with (i) worse employment network pre-intervention; (ii) lower asset index; (iii) from rural households.

## 4.2 Process analysis and mechanisms

We envision a 3-step process through which the coaching program can lead to broader information sets, realigned expectations, improved strategy to find a job, better labor market outcomes and higher job-satisfaction:

1. The three Key Calls between the student and the alum matched to her take place.
2. During each interaction the alum is engaged and provides a combination of:
   (i) Generic information about the job market [Information];
   (ii) Tips for a successful job search [Strategy];
   (iii) Contacts for specific openings/potential employers [Referral];
   (iv) Motivation and encouragement [Motivation];

   Of a reasonable standard and quality to which, on average, students would not have access to otherwise.
3. The student values the inputs shared by the alum and is inspired by him/her to land a good job.

The program may fail to have an impact on expectations and job-seeking behavior, and consequently labor market outcomes, if any of these steps does not occur. Indeed, we expect the impact of the coaching program on the primary outcomes will be (1) lower for students with fewer and shorter interactions with their alum; (2) greater for students who participate to engaging interactions and the alum provides a combination of (i) - (iv) and (3) e lower for students who do not value the inputs shared and/or are not inspired by the alum. At the same time, the occurrence of each of these steps is likely to be endogenous and prone to self-selection. For this reason, every analysis on these process outcomes should be treated as descriptive only (e.g. students may decide to never speak with an alum because they already have a job waiting for them, or not to use the cash transfer for job search because they are facing more urgent monetary needs). As part of this exploratory analysis, we will investigate the determinants of the process outcomes among students' and alumni's characteristics. To further inform process understanding we will treat the process outcomes as left-hand side variables so to examine whether heterogenous effects are similar in process outcomes to those in primary outcomes. More specifically, we will predict, with pre-treatment variables, the process outcomes. We will then interact the predicted outcome measures with treatment status to examine whether those who engage in more process changes are also those who have larger treatment effects.

We envision a 2-steps process through which receiving the cash transfer can affect job search strategy/strategy to set up a business, labor market outcome and job-satisfaction.

i. Student receives the cash transfer and autonomously decides how to spend it;
ii. Student spends the funds on career-related activities.

The effect of the cash transfer on primary outcomes will be smaller for students without full disposal of the money received and for those who do not use the entire transfer for purposes related to job search and career launch. As before, such process outcomes are at risk of endogeneity and their analysis is to be considered purely exploratory. We will focus on looking at predictors for the success of these two steps and analyze how they correlate with the main effects on the primary outcomes.

*Hypothesis 3~~4~~: The training and the mobile money will be more effective in labor markets with strong labor demand.*

In our study we do not directly observe labor demand dynamics. To better interpret our findings (or the lack of thereof), we will provide evidence on the conditions of the economy, overall and by sector. We will do so using:

- The rich set of data collected right before the Covid-19 outbreak (when the economy was in a good state), two months and six months following the end of the total lockdown (when the economy was in a good state), from our 714 alumni in their role of recent graduates, young entrepreneurs and workers;
- The "COVID-19, Firm Dynamics and Market Structure in Urban Uganda" Project of which members of this research team are Co-PIs. This study combines four rounds of pre-COVID panel data on more than 4,000 firms with two new rounds of surveys to collected during the crisis and one year following the onset of it on SMEs in the same occupations in which the students on the Meet Your Future projects are trained.

Leveraging these unique panels, we will create a sector specific index about the status of the economy as the jobseekers approach the market using the following information:

- The change in the share of employed alumni by sector between pre- and post- pandemic to evaluate trade-specific consequences of the pandemic.
- An indicator for whether the distribution of search time and earnings differs between the samples of alumni and students.
- An indicator for whether absence of jobs is reported as the main obstacle to find a job by 50% or more of students in the sector.
- Firms' expansion patterns and hiring levels by sectors.

The status of the economy will be classified as "good" or "bad" if these indicators convey the same information. While the process analysis shall be seen as exploratory, Hypothesis 3 can be tested based on exogenous variation.~~While the process analysis shall be seen as exploratory, Hypothesis 3 can be tested based on exogenous variation.~~

# 5. Survey Instruments and Outcome Variables

## 5.1 Data collection and processing

For the data collection, the research team trains and hires, through BRAC Uganda, professional enumerators that routinely work in research projects involving interviews both in person and over the phone. Enumerators are selected after the training based on their performance on a test, where the score is indicative of the enumerators' understanding of the survey tool. All surveys are conducted through Survey Solutions using the Computer Assisted Personal Interviewing Software (CAPI), where consistency checks were built into the program. Additionally, random back-checks were performed to verify the quality of the data. The observed coherence in the correlation analyses we conducted on both pre-intervention datasets reassures us that the quality of the data is high.

The two key data sources for this study are the students' surveys and the alumni surveys. As schools keep updated administrative data on the population of enrolled students, students' lists were easy to obtain soon after the establishment of a partnership with the schools. Conversely, schools do not systematically store former students' contacts. For this reason, we collected and digitized the alumni's contacts that were available in the VTIs registries. We chose cohorts of alumni that have been in the labor market for 2 to 5 years, with the goal of selecting alumni with enough experience in the labor market, yet of similar age to current students. Given that many of the contacts from previous students had not been updated in years, of the ~1400 names and contacts digitized, 657 were eventually tracked down and surveyed three times.

On top of the students' and alumni's surveys, which we administer to the entire samples of students and alumni, we collect post-intervention surveys, one for treated students and one for selected alumni that are operating the coaching. The goal is to obtain real time information about how the interactions went and what do students and alumni think about each other.

We use Key Call 1 voice recordings and data collected by the enumerators listening to Key Call 1 (what we call "Artificial Survey") to characterize the one-to-one interactions between the alumni and the students. Thanks to these two sources of information, we track not only the content - what inputs are shared - but also the *form* of the conversations. Findings from different areas of social psychology, communication, and sociology have long confirmed that a sense of we-ness and shared identity emerges because of both the content of social interactions (what is being said both verbally and nonverbally) and because of a strong influence by the form of interaction: disruptions in conversational flow, speaking at a similar pace, mimicking the emotions of one's interaction (Koudenburg et al., 2017). This is important under a policy perspective as it makes innovative (alumnus-students) pedagogic methods comparable to the standard ones in terms of involvement and participation.   See Table 6 for more details on each data collection activity.

## 5.2 Outcomes of interest

We define four domains of outcomes of interest: (i) job search strategy; (ii) expectations; (iii) labor market outcomes and (iv) existence and strength of network connection. The first three are primary outcomes of interest while those in domain (iv) are secondary outcomes that we use for exploratory analysis. The outcomes within each domain, as well as their measurement, are described below.

*Domain 1: Job search strategy / Strategy to start up a business:*

We characterize the search strategy through several indicators:

i. Index of search intensity (hours per day, days per week and number of applications submitted, savings devoted to starting up a career);
ii. Index of search broadness (search/fundraise methods, geographical scope of search, sector);
iii. Index of search efficacy (interviews/applications and offers/applications, used CV during search) - only for students planning to look for wage employment.

*Domain 2: Students' expectations about own performance in the labor market:*

We elicited point estimates or full distributions depending on what worked best in the piloting phase. When necessary, we help respondents answer unconventional questions via visual scales. We provide monetary incentives that reward accuracy of the prediction. These data include: (i) Expected time to first employment for the respondent and for the classmates; (ii) Expected earnings at first employment as in Attanasio et al. (2011) and their evolution is mapped through 4 different data points (5 for the treatment group): baseline, midline 1, midline 2, contacts confirmation survey and, for the treatment group, the Post Interaction survey.

*Domain 3: Labor Market Outcomes:*

Our primary outcomes in this domain are:

1. Labor Market Index: an index that measures labor market performance. We build the index following Anderson (2008), so accounting for the covariance structure in components, and we normalize by the standard deviation of the index in the control group to ease interpretation. The index combines:
    i. A dummy for whether the individual has worked at all in the last 4 weeks;
    ii. The number of days worked in the last 4 weeks: this will be coded as zero for individuals who have not worked;
    iii. The total monthly income from work in the last 4 weeks: this will be coded as 0 for individuals who have not worked and will be top-coded at the 99th percentile of the earnings distribution conditional on working, to reduce influence of outliers;
2. Number of hours spent applying newly acquired skills in occupation of training in the 30 days preceding the survey: we designed an innovative survey module to track how much time the respondent spent performing each of a set of detailed typical trade-specific tasks  a list we compiled by combining information from focus groups discussions with the alumni and resources from the O*NET Program (e.g., if the respondent was trained in motor-mechanics, she is asked whether she had mend a tire tube in the last 4 weeks, and if so how many times and how long it takes on average to conduct such task once);
3. Matching Quality Index, measured as:
    a. Self-reported job satisfaction through the widely used formula "All things considered, how satisfied are you with your career ~~choices~~ as a whole on a scale of 0 to 10?";
    b. Employer-reported satisfaction with the employee;
    c. Dummy for whether the individual is working in the sector of training, conditional on being working;
    d. Ability to keep the job/firm running for at least 3 months.

~~Labor market outcomes are self-reported but crosschecked by the enumerators at Endline 2: enumerators will meet students in their workplace and confirm that the information provided matches reality with the firm owner/ firm registries.~~ For students who look for wage employment, conditional on employment, we will explore the quality of the employment landed. We will look at formality (whether the job was obtained with an interview as in Abebe et al. 2017a; existence of a contract as in Abebe et al., 2017b), and employment type (trainee, casual, temporary or permanent as in Franklin, 2017 and Abebe et al., 2017a). For students who look to start their own business, conditional on their business being operative, we will explore the business's solvency, formality, value of equipment and size. Since this last analysis conditions on an endogenous outcome, these conditional outcomes are strictly suggestive.

*Domain 4: Characteristics of the new network connection:*

We define a jobseekers' employment network as the set of people (i) she can reach out to; (ii) she thinks can be helpful for her career (iii) prone to provide help. To characterize whether a new network link is formed and what its strength is, we use:

i. Engagement Index: measuring student engagement level during the first interaction (See Appendix B for details). We build a flatly weighted index following Kling, Liebman and Katz (2007). The index has 4 components:
    a. *Mutual engagement* from the Artificial Survey measured on a 0-10 scale where 0 means not at all (e.g., the conversation was characterized by many brief and unexpected/awkward silence) and 10 means extremely smooth;
    b. *Relative engagement* from the Artificial Survey measured on a 0-10 scale where 0 means the alum never talked compared to the student and 10 means the opposite;
    c. *Student engagement* from the Post Interaction Survey.
    d. *Alum's perception* of student's interest in the program from the Alumni Check-In.

ii. Identification Index: to measure student identification with the alum we produce an 8-question index drawing from Rubin et al. (1985), Cohen (2001) and Igartua (2010) questions which required no adaptation to the context (See Appendix B for details).

iii. Usefulness Index: Self-reported student's evaluation of the project. We use a total of 7 questions in this index (See Appendix B).

iv. Frequency and duration of interactions: we use a dummy for whether more interactions followed the first one; a dummy for whether the student and alum ever connected outside the program; the overall number of interactions; and their average duration.

v. Type and amount of support provided: we put extensive effort into tracking whether and to what extent a mechanism is activated for a given alum-student dyad. Specifically, for each dyad we can observe whether the alum: shared information about general labor market features [Information]; provided tips for a successful job search [Strategy]; referred the student to potential employers [Referral]; encouraged the students to do their best [Motivation]. To do so, we cross check the recordings of Key Call 1 (which will be analyzed through text analysis with the list of topics compiled in the Artificial Survey by the enumerator while listening to Key Call 1 (see List of Topics in Appendix A). Moreover, we use the Students Post Interaction Survey to identify what inputs were shared with the student that the student would not have had access to otherwise, as well as the Alumni Check-in and students' Endline 1 and 2 to gather info on Key Call 2, 3 and any other following interactions.

Table 6. Surveys

| Survey | Sample | Stage | Date | Key information collected | Mode |
|---|---|---|---|---|---|
| **Students** | | | | | |
| Baseline | 1115 students | Completed | May 2019 | Demographics; Time preferences; Risk aversion; Raven's test; Savings: amount, purpose, intention to save in the future; Detailed information about 4 employment network members: level of education, employment status, frequency of interactions, how they can help finding a job; Life worries and self-esteem; Expectations about own performance in the labor market; Plan on how to job search/start-up a business. | In person |
| Midline 1 | 1115 students | Completed | Nov 2019 | Savings: amount, purpose, intention to save in the future; Updated detailed information about four employment network members; Life worries and self-esteem; Expectations about own and class-level performance in the labor market; Plan on how to job search/start-up a business. | In person |
| Midline 2 - "Covid-19 survey" | 1115 students | Completed | Jun 2020 | Time use during school closure (due to Covid-19); Labor market outcomes; Life worries and self-esteem, Expectations about own and class-level performance in the labor market; Plan on how to job search/start-up a business; Savings; Migration. | Phone |
| Contacts Confirmation survey | 1115 students | Completed | Jan 2021 | Updated contacts; Expectations about own and class-level performance in the labor market. | Phone |
| Post-Interaction Survey | 673 treated students | Completed | Feb 2021 | Survey to record the student's main take-aways and feelings immediately following the first interaction with the alum (Key Call 1). Contains questions on: engagement in the conversation, topics of discussion, identification and connection with the alum, main take-always, plans for future interactions. | Phone |
| Endline 1 | 1115 students | On-going | May 2021 | Job search and Labor market outcomes. Content and frequency of additional interactions with alum. | Phone |
| Endline 2 ~~(Endline 3)~~ | 1115 students | Not started | ~~March~~ Feb 2022 | Job search and Labor market outcomes. Content and frequency of additional interactions with alum. | Phone~~In person~~ |
| **Alumni** | | | | | |
| Baseline | 657 alumni | Completed | Jan-Feb 2020 | Demographics, characteristics of first job (how did they find it, in how much time, wages/profits) and, if different, of current job. Availability to participate to the study. | Phone |
| Follow-up 1 - "Covid-19 survey" | 657 alumni | Completed | Jul 2020 | Labor market outcomes, Covid-19 impacts, time use during total lockdown, district of current residence, economic outlook and expected own labor market prospects. Availability to participate to the study. | Phone |
| Follow-up 2 | 674 alumni | Completed | Dec 2020 | Labor market outcomes, Covid-19 impacts on livelihoods, district of current residence, economic outlook and expected own labor market prospects. Availability to participate to the study. Updated contacts information. | Phone |
| Alumni Check-In | 171 alumni | Completed | Mar 2021 | Content and duration of each Key Call 2; additional interactions (whether they took place, who initiated them, duration, mode and content). 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. | Phone |
| **Interactions Characterization** | | | | | |
| Artificial Survey and Recordings | 673 students-alumni pairs | Completed | Feb-Mar 2021 | During Key Calls 1 the enumerators listens and keeps track of mutual & relative engagement levels, conversation pace, topics of discussions. Recordings will be used to confirm the information collected in the Artificial Survey | Phone |

# 6 Analysis

## 6.1 Missing Values, Outliers and Questions with Limited Variation

In cases where covariates are missing but outcomes are available, we will follow an approach based on Lin and Green (2016): If a covariate is missing for no more than 10 percent of observations, then we will recode the covariate to the overall mean. If a covariate is missing for more than 10 percent of observations, then we will recode the covariate to the overall mean and add in indicator equal to one for observations with the missing covariate.

We plan to convert monetary outcomes into USD PPP and trim the top 1% of the distribution by survey round of variables that are particularly sensitive to the existence of outliers, such as "minimum expected wage", "expected number of weeks to have a fully operative business", etc. We will also look at untrimmed values and check that our results are not sensitive to the 1% trimming by repeating the analysis with the full distribution with different trimming procedures. In order to limit noise caused by variables with minimal variation, questions for which 95% of observations have the same value within the relevant sample will be omitted from the analysis and will not be included in any indicators or hypothesis tests.

## 6.2 Estimation of Average Treatment Effects

Our main treatment effects specification to capture the impact of the MYF Program on outcomes domains (i), (ii) and (iii) and test Hypothesis 1 and 2 is the following OLS specification:

$$Y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_i'\delta + \varepsilon_i$$

$Y_i$ is the outcome of interest for student *i* measured at Endline 1 or Endline 2. For outcome variables measured at both rounds (e.g. career satisfaction, time spent conducting occupation-related tasks etc.) we will pool the samples and cluster the standard errors at the respondent level.

$T1_i$ is a treatment indicator that takes value 1 for students in MYF only; $T2_i$ is a treatment indicator that takes value 1 for students in MM-MYF (MYF + cash transfer). The omitted category is "control students"; $X_i$ is a vector including (i) the strata and balance variables listed in Section 3.2[16], (ii) baseline outcome when available to increase power, and (iii) individual covariates measured at baseline which we will condition on to improve statistical power (McKenzie 2012); these covariates will be selected from the baseline data on the basis of their ability to predict the primary outcomes[17]. $\varepsilon i$ is the error term. When available, we will control for baseline level of outcomes (e.g. for students' wellbeing). The equation is estimated using Ordinary Least Squares estimators. Errors are robust to heteroskedasticity. Estimation is performed over the entire sample of students.

Given our randomized design, $(\beta_1+\beta_2)/2$ measures the Average Treatment Effect on the Treated of the Meet Your Future with and without the cash transfer altogether. $\beta_1$ measures the ATT of the MYF Program without the additional cash transfer on Y and $\beta_2$ measures the ATT of the MM-MYF. We interpret $\beta_2 - \beta_1$ as the additional effect of receiving the cash transfer. We plan to report results from two additional approaches for our primary outcomes measured in both Endline 1 and Endline 2. Due to the nature of the tracking activity, there will be some respondents surveyed as part of Endline 1 that are not surveyed in Endline 2 or that did not provide usable data in Endline 2. In order to maximize sample size, we also consider specifications, which include all respondents surveyed as part of either Endline 1 and Endline 2, making use of the most recent data that we have from each student. We denote this as Approach 2. Our specification for Approach 2 mirrors that of Approach 1, but brings in an indicator for the Endline round from which the data comes from.

$$Y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_i'\delta + \mu I(\text{endline1}) + \varepsilon_i$$

[16] These variables are: an indicator for male, an indicator for student's ownership of a smartphone, student's VTI, an indicator for whether the student was not successfully interviewed in three out of three pre-intervention survey rounds, an indicator for whether the student has ever worked before graduation (either before enrolling in the VTI or during the lockdown).

[17] We adapt the post-double-selection approach set forth in Belloni et al. (2014)

### 6.3 Estimation of Treatment Effects – Intention To Treat (ITT)

To estimate the treatment effects on outcomes domains (i), (ii), and (iii) and to test Hypothesis 1 and 2, we use an intention-to-treat specification that takes noncompliance into account. In particular: $Z_{it}$ indicates assignment to treatment t, $T_{it}$ indicates treatment status when treatment considered is t=1,2. We estimate the first stage, obtain fitted values of $T_i$, and use them in the second stage regression:

$$T_i = \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \gamma X_i + \varepsilon_i$$

$$Y_i = \beta_0 + \beta_1 \check{T}_{1i} + \beta_2 \check{T}_{2i} + \gamma X_i + \varepsilon_i$$

The equations are estimated using Ordinary Least Squares estimators. Errors are robust to heteroskedasticity. Estimation is performed over the entire sample of students.

### 6.4 Treatment Effects – Heterogeneity

We will test the heterogeneity of treatment effects along a pre-determined set of (i) students' characteristics $S_i$, (ii) alumni's characteristics and (iii) student-alum pair's characteristics $S_{ij}$. In particular, we will use the following specification to run heterogeneity analysis on hypotheses 1 and 2. To investigate whether the treatment effect differs along each of these dimensions, we estimate the following regression using Ordinary Least Squares estimators over the sample of treated students (T1 and T2). Errors are robust to heteroskedasticity.

$$Y_i = \alpha + \beta T_i + \gamma T_i * S_i + X_i^{'} \delta + \varepsilon_i$$

$X_i$ includes $D_i$. $(\beta+\gamma)$ is the ATT for individuals with $S_i$=1. $\beta$ is the ATT for individuals with $S_i$=0. When analyzing heterogeneities that involve alumni's characteristics or student-alum pair's characteristics, we will include alumni fixed-effects.

### 6.5 Multiple hypothesis testing

On top of the uncorrected estimates the main tables will also present additional p-values that account for multiple testing. Since the analysis tests multiple hypotheses within each domain of outcomes, it is appropriate to control for the possibility that some true null hypotheses will be falsely rejected. Within each of the three domains of pre-specified primary outcomes, the analysis will compute the False Discovery Rate (FDR) adjusted q-values (analogue to the standard p-value) that control the expected proportion of rejections that are Type I errors over the primary outcomes within a domain. Within the first domain we have 9 q-values for the three primary outcomes (three outcomes times three pairwise comparisons per outcome). Similarly, we have 6 q-values for the two primary outcomes in the second domain and nine for the three primary outcomes in the third domain. Q-values will be calculated at each follow-up round and presented in separate summary tables of impacts on the primary and secondary outcomes.

### 6.6 Network Link Formation – Dyadic Regression

To explore which links are more likely to form, the data are analyzed dyadically, that is, the characteristics of both the student and the alum in each pair are considered in tandem. This allows assessment of whether network ties between students and alumni with similar characteristics (homogamy) are more likely to form than are network ties between dissimilar students and alumni, or whether particular characteristics of students or alumni—independent of their counterpart—are more strongly associated with link formation. Following Fafchamps and Gubert (2007), we estimate a dyadic regression model of the form:

$$L_{ij} = 1 \text{ if } B(d_{ij}) - C(d_{ij}) + e_{ij} > 0$$
$$L_{ij} = 0 \text{ otherwise}$$

Where $L_{ij}$ denotes the existence of a strong link between student i and alum j, and $d_{ij}$ represents the cultural distance between i and j. The benefits and costs of the link are denoted $B_{ij}$ and $C_{ij}$ respectively. $e_{ij}$ is a residual effect. A link is established if benefits exceed costs. Links in our setting can only be unidirectional, i.e. $L_{ij} = L_{ji}$

for every i and j. The symmetry condition that follows from the unidirectionality allows us to specify the regression as:

$$L_{ij} = \beta_0 + \beta_1(z_i - z_j) + \beta_2(z_i + z_j) + \gamma w_{ij} + u_{ij}$$

Where $z_i$ and $z_j$ are characteristics of student i and alum j thought to influence the likelihood of $L_{ij}$, a link between them. Coefficient $\beta_1$ measures the effect of differences in attributes on $L_{ij}$, while $\beta_2$ captures the effect of the combined level of $z_i$ and $z_j$ on $L_{ij}$. For $\beta_2$ to be identified, individuals must not have the same number of links, which is true in our setting as the alumni will have multiple links (see Fafchamps and Gubert 2007 for details). Estimation is performed over the sample of students assigned to the MYF Alumni program (students in T1 and T2).

## 6.7 Attrition, take up and non-compliance with treatment assignment

All the VTIs in our sample are boarding schools: over 90% of the students live there[18]. For these reasons, attrition rates for in person surveys are low (8.8%). At baseline we successfully interviewed 1105 out of the 1372 students in the lists provided[19]. Between baseline and midline, attrition was limited to students who dropped out of school or who had not yet returned from the break in between terms. However, following the Covid-19 pandemic, the temporary closure of schools and their dorms, and the consequent shift to interviews on the phone, attrition rates have gone up (Table 4). With the program conducted over the phone, an extensive effort to collect a wide array of best contacts has been made to maximize take up. We have an average of 3.4 contacts per student, including both best contacts in the VTI and outside of the VTI so that we are able to reach the students irrespective of their physical location when the program rolls out. To reduce attrition, we are currently running a Contacts Confirmation Survey to confirm these contacts one more time. For this reason, we anticipate lower attrition rates for the two endline surveys. To reduce attrition further, we will devote extra effort and resources toward contacting respondents that are not found at first attempt. This includes contacting teachers and the school office to obtain further information. All data will be probability-reweighted to reflect this intensive tracking.

Table 4. Attrition (Pre- Assignment to Treatment)

| Survey | N successfully interviewed | Attrition rate |
|---|---|---|
| Baseline | N=1105 | - |
| Midline 1 | N=970 | 8.8% |
| Midline 2 – "Covid-19 survey" | N=812 | 27% |

To account for the attrition that took place prior to the assignment to treatment, we stratify the randomization on an indicator, *hard_to_find,* which we expect will predict both program take-up and attrition at endline. All the estimation will be run on the "Baseline sample" (N=1115) as well as on the sample of those for which *hard_to_find*=0, i.e. those successfully interviewed at Baseline, Midline 1 and Midline 2. Additionally, we will investigate whether attrition is correlated with treatment status. We will do so by running the following regression:

$$A_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + X_s{}'\delta + \varepsilon_i$$

Where $A_i$ is an indicator of whether individual i attrits from the study by not responding to or being able to be contacted for Endline 1 or 2, $T_i$ are the two treatment indicators, and $X_s$ are all the randomization strata dummies. Conditional on the strata, the randomization is performed at the individual level. We therefore use Huber-white standard errors. If treatment status is found not to significantly affect attrition at the 5 percent significance level, estimation will proceed without any adjustment for attrition.

If attrition is found to be related to treatment status, we postulate that attrition will be higher for the control group and we will use IPW as well as employ Lee bounds on our treatment estimates.

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[18] Under regular circumstances the exact figure ranges from 90% for one VTI, 95% for two of them and 99% for the remaining two.
[19] The 10 more students missing to reach 1115 were added to the sample at midline.

On top of these standard approaches, we will follow McKenzie (2021) and leverage our "hard_to_find", variable to learn about selection. Such variable tags respondents that were not always found across the numerous pre-intervention survey rounds and contact-confirmations surveys, under the assumptions that hard to find respondents are more similar to attritors than respondents that are easy to interview. Although our characterization of "hard to find" respondents differs from the standard measures used in the literature, such as the number of call attempts it takes to reach a respondent, it is easier to collect and readily available in most field studies, and has the potential to be as informative. In our paper, we will assess whether hard to find respondents have systematically different outcomes from easy to find respondents and, if so, we will use this information to refine our IPW and sensitivity bounds.

We expect non-compliance (more specifically defiers) to be virtually nonexistent given the on-phone nature of the intervention. Key call 1 is organized by our enumerators, who will put in touch through a conference call the student-alum pair. Following Key call 1, interactions will take place without the presence of a moderator. Alumni are instructed during the training to call and interact separately and independently with each of their matched students and only with them, and kindly decline requests to interact advanced by other students. Similarly, should they decide to meet in person with the student, they are to meet only with that student. This will be facilitated by the impossibility for the alumni to visit the students in the VTIs due to Covid-19 related measures. Should non-compliance arise, our treatment effect will be an underestimate of the real treatment effect. On top of this, we anticipate negligible non-compliance from students assigned to T1 and T2 as well. Survey data collected during the pilot of the intervention (available upon request) suggest that both students and alumni (approximately 30 students and 10 alumni) found the program useful and interesting. No one refused participation. Finally, students assigned to the Mobile-Money intervention will just receive the transfer on their phone.

### 6.8 Statistical power

Our students' sample includes 1115 students enrolled in the National Certificate Program in 2019 in five VTIs across Eastern and Central Uganda. We exclude from this sample 257 students who were originally on the lists provided by the schools, but that we were never able to interview in any of the three pre-intervention surveys. Our alumni's sample contains 657 alumni from the same schools and training areas. To define our sample frame, we identified 5 VTIs interested in testing our version of an alumni program with their students. Previous collaboration with BRAC Uganda, as well as interest in the study results suggest they represent an ideal experimental setting in which the successfulness of the program will be favored.

In Table 5 we show the Minimum Detectable Effects (MDEs) we anticipate being able to detect. These calculations are based on a two-sided hypothesis test with a 5% significance level and 80% power. Issues to consider while calculating statistical power are compliance (take-up) and attrition. As we believe compliance is not a major concern in this context, we calculate MDEs in scenarios with no attrition, with a 15% attrition uncorrelated with treatment and with full compliance and 20% attrition in the control group and 10% attrition in the two treatment groups.

For our primary outcomes in domain (ii) (see Section 4.2) we use data collected in the students' baseline. For our primary outcomes in domain (i) and (iii) we cannot rely on pre-intervention data, as search strategy and labor market outcomes are still un-realized for our respondents. For these outcomes, when possible, power calculations are based on the alumni surveys from this project and a sample of 700 VTI graduates from Alfonsi et al. (2020). This procedure is subject to the caveat that our alumni sample is likely to be positively selected with higher averages and/or smaller standard deviations in labor market outcomes. In turn, this implies higher MDEs compared to those we would have were data on the entire population of alumni in our VTIs available. Similarly, the sample from Alfonsi et al. (2020) is not identical to that of our soon to be graduates. Participants in that project were disadvantaged youth at baseline who undertook a sponsored six months training and not the two years National Certificate training.

Based on our power calculations we can detect effects between around 3 and 8 percentage points for outcome sin Domain 1, 15 and 20pp for outcomes in Domain 2 and 1.5 and 15% for outcomes in Domain 3.

Taken into consideration the gains in power that will come from the combination of (i) strata fixed effects, (ii) using post-double-selection lasso for selecting the controls, (iii) the addition of baseline values and (iv) the fact that many of our primary outcomes are indexes, we believe we will have enough power to test our main hypothesis of interest.

**Table 5. MDEs**

| T1 vs C | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | C | T1 | MDE of T1 | % Mean | MDE of T1 | % Mean | MDE of T1 | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 442 | 334 | 36073,72 | 8,5% | 39125,38 | 9,2% | 39019,38 | 9,2% |
| Expected earnings - Minimum | 3,55 | 1,21 | 442 | 334 | 0,25 | 7,0% | 0,27 | 7,5% | 0,27 | 7,5% |
| Expected earnings - Maximum | 5,40 | 0,93 | 442 | 334 | 0,19 | 3,5% | 0,21 | 3,8% | 0,20 | 3,8% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 442 | 334 | 0,40 | 6,6% | 0,43 | 7,1% | 0,43 | 7,1% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 442 | 334 | 0,63 | 20,3% | 0,69 | 22,0% | 0,69 | 22,0% |
| Broadness of search - number of methods | 2,12 | 1,57 | 442 | 334 | 0,32 | 15,1% | 0,35 | 16,4% | 0,35 | 16,3% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 442 | 334 | 0,09 | 12,6% | 0,10 | 13,6% | 0,10 | 13,6% |
| Earnings at first job | 276553,67 | 197678,00 | 442 | 334 | 40201,99 | 14,5% | 43602,88 | 15,8% | 43484,75 | 15,7% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 442 | 334 | 0,14 | 1,1% | 0,16 | 1,2% | 0,16 | 1,2% |
| Course satisfaction | 1,26 | 0,53 | 442 | 334 | 0,11 | 8,5% | 0,12 | 9,3% | 0,12 | 9,2% |

| T2 vs T1 | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | T1 | T2 | MDE of T2 | % Mean | MDE of T2 | % Mean | MDE of T2 | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 334 | 339 | 38367,35 | 9,0% | 41627,51 | 9,8% | 40438,93 | 9,5% |
| Expected earnings - Minimum | 3,55 | 1,21 | 334 | 339 | 0,26 | 7,4% | 0,28 | 8,0% | 0,28 | 7,8% |
| Expected earnings - Maximum | 5,40 | 0,93 | 334 | 339 | 0,20 | 3,7% | 0,22 | 4,0% | 0,21 | 3,9% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 334 | 339 | 0,43 | 7,0% | 0,46 | 7,6% | 0,45 | 7,4% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 334 | 339 | 0,68 | 21,6% | 0,73 | 23,5% | 0,71 | 22,8% |
| Broadness of search - number of methods | 2,12 | 1,57 | 334 | 339 | 0,34 | 16,1% | 0,37 | 17,4% | 0,36 | 16,9% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 334 | 339 | 0,10 | 13,4% | 0,11 | 14,5% | 0,10 | 14,1% |
| Earnings at first job | 276553,67 | 197678,00 | 334 | 339 | 42758,11 | 15,5% | 46391,35 | 16,8% | 45066,75 | 16,3% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 334 | 339 | 0,15 | 1,2% | 0,17 | 1,3% | 0,16 | 1,2% |
| Course satisfaction | 1,26 | 0,53 | 334 | 339 | 0,11 | 9,1% | 0,12 | 9,9% | 0,12 | 9,6% |

**Table 5. MDEs (continued)**

| **T1&T2 pooled vs C** | | | Count | | No attrition | | 15% Attrition | | 20% in C, 10% in T | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev | C | T1&T2 pooled | MDE of T1&T2 pooled | % Mean | MDE of T1&T2 pooled | % Mean | MDE of T1&T2 pooled | % Mean |
| ***Domain 1 - Labor market expectations*** | | | | | | | | | | |
| Expected earnings - Average (triangular) | 425391,44 | 177378,80 | 442 | 673 | 30450,81 | 7,2% | 33026,19 | 7,8% | 33276,56 | 7,8% |
| Expected earnings - Minimum | 3,55 | 1,21 | 442 | 673 | 0,21 | 5,9% | 0,23 | 6,4% | 0,23 | 6,4% |
| Expected earnings - Maximum | 5,40 | 0,93 | 442 | 673 | 0,16 | 3,0% | 0,17 | 3,2% | 0,17 | 3,2% |
| Expected probability to be working in 1m | 6,08 | 1,97 | 442 | 673 | 0,34 | 5,6% | 0,37 | 6,0% | 0,37 | 6,1% |
| ***Domain 2 - Job search behavior*** | | | | | | | | | | |
| Number of applications | 3,12 | 3,12 | 442 | 673 | 0,54 | 17,2% | 0,58 | 18,6% | 0,59 | 18,8% |
| Broadness of search - number of methods | 2,12 | 1,57 | 442 | 673 | 0,27 | 12,7% | 0,29 | 13,8% | 0,29 | 13,9% |
| ***Domain 3 - Labor market outcomes*** | | | | | | | | | | |
| Worked in last 4 weeks | 0,72 | 0,45 | 442 | 673 | 0,08 | 10,6% | 0,08 | 11,5% | 0,08 | 11,6% |
| Earnings at first job | 276553,67 | 197678,00 | 442 | 673 | 33935,59 | 12,3% | 36805,71 | 13,3% | 37084,73 | 13,4% |
| Earnings - Inverse hyperbolic transformation | 12,99 | 0,71 | 442 | 673 | 0,12 | 0,9% | 0,13 | 1,0% | 0,13 | 1,0% |
| Course satisfaction | 1,26 | 0,53 | 442 | 673 | 0,09 | 7,2% | 0,10 | 7,8% | 0,10 | 7,9% |

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# Appendix A – Intervention Details

### Assignment to T1

This is how enumerators communicate to the students their assignment to the program and encourage them to take part to it in a phone call following this script:

*Dear student, this is NAME from the Meet Your Future Research Team. I am very glad to inform you that you have been selected to participate to the Meet Your Future Program organized by BRAC Uganda in partnership with your VTI. As part of this program you will have the opportunity to interact with an older student, an alumnus or an alumna, who graduated from your same school and training area. We have selected this alum based on their success in their profession. We believe this is a great opportunity for you to ask questions and receive advice from someone with previous experience in the labor market who has a similar history to yours, and this is why we call this person "the Future You". This program comes at no cost and is totally free. With your permission, we are going to organize three phone calls between you and the alum during the next 2 months. I am here today to organize the first one. Are you available on XXX at XXX? We suggest you keep your phone with you and do not miss scheduled appointments. We know that starting your working life is not an easy task, but "the Future You" is there to help. We recommend you prepare a list of questions to make the most out of this experience: you may be interested in receiving advice about various aspects of the job search process or the process to set up a business: which material to prepare for job applications, prevailing wages in a specific occupation and time needed to usually find employment are just examples of possible topics around which to prepare your questions. We look forward to having you on-board!*

### Assignment to T2

We communicate to the students their assignment to T2 through the following SMS:

*Hello, this is the Meet Your Future research team. We have just sent 40,000 UGX to your phone number/to your best contact phone number. This money is a gift from BRAC research team for your personal use. You are free to use the money as you want. As we know looking for a job and setting up a business are expensive activities, we suggest you use it to finance your search of a job, to set up your business, or to contact the alum you have been assigned to receive extra support. Please keep track of how you use this money, as you will be asked this information in the future.*

## Logbook – Example

# 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.**

**ADDITIONAL INTERACTIONS**

**Student's 1 name:**

| DATE | DURATION (in minutes) | MEAN OF COMMUNICATION (sms, whatsapp, in person, phone) | WHO INITIATED IT (alum or student) | REASON/MAIN TOPICS |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |

**Student's 2 name:**

| DATE | DURATION (in minutes) | MEAN OF COMMUNICATION (sms, whatsapp, in person, phone) | WHO INITIATED IT (alum or student) | REASON/MAIN TOPICS |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |

**If you have other interactions with the student on top of the 3 KEY CALLS, please use this form to keep track of them. For each of them write down the day in which each interaction took place, how long each one lasted, the mean of communication used (for example sms, whatsapp, phone call, meeting in person), who started the interaction, and up to 3 main topics discussed between you and the student.**

## List of Topics

**A: Useful connections you can make for the students**

| | |
|---|---|
| A1 | Employers you know in which the student could be hired if you refer him/her, that is, if you make a connection |
| A2 | Someone you know that could help the student finding a job |
| A3 | A provider of raw materials and/or tools that you know, and you can suggest the student to contact |
| A4 | A client that you know and that the student could contact once his/her business is operative |

**B: Tips for an effective job search/ business start up**

| | |
|---|---|
| B1 | Recommended locations where to look for jobs/start a business, or locations to avoid |
| B2 | How to make a good impression at job interviews. Examples: good manners, what to wear, no slang, etc. |
| B3 | How many job applications to do |
| B4 | When to turn down a job opportunity |
| B5 | Tips on how to write a CV |
| B6 | Which material to prepare for job applications |
| B7 | Which aspects of the job offer can be bargained over and negotiation with employers |
| B8 | The importance of accumulating savings during the training |
| B9 | How to create a network of input providers |
| B10 | How to create a network of clients/customers |
| B11 | Where to find basic equipment/tools |
| B12 | How to manage the accounting of the firm |
| B13 | How to obtain a loan to set up a business/buy tools and materials |

**C: Information on the status of the labor market**

| | |
|---|---|
| C1 | Specific existing job vacancies or firms that accept candidacies from someone like the student |
| C2 | How much it generally takes to find a job in the occupation of training |
| C3 | What are the wages in the market in the occupation of training |
| C4 | Possibility of finding a job/working in occupations unrelated to the occupation of training |
| C5 | How common it is to accept an unpaid job or a job where you have to pay the owner |
| C6 | Average cost of one job application |
| C7 | How much money is generally spent on transportation costs during the job search phase |
| C8 | Which practical skills are needed to find a job in the occupation of training |
| C9 | What types of positions/contractual arrangements are usually available after the training |
| C10 | Women’s condition, discrimination and rights in the job place |
| C11 | Amount of resources needed to start up business in the occupation of training |
| C12 | How much it takes generally to have an operative business from scratch in the occupation of training |
| C13 | What are the profits for a young business in the occupation of training |

**D: Alum personal experience**

| | |
|---|---|
| D1 | The wage you were given during your first job |
| D2 | The profits you made during the first month of operation of your first business |
| D3 | How much time it took to find your first job/ to start up your first business |
| D4 | How you found your first job/set up your first business |
| D5 | Who helped you finding your first job/setting up your first business |
| D6 | The way in which you overcame an obstacle when looking for your first job/setting up your first business |
| D7 | An unexpected challenge you had to face when looking for your first job/setting up your first business |
| D8 | That time you failed, but then found the strength to go on |
| D9 | The wages/profits in your current job |
| D10 | How you found the current job/set up your current business |
| D11 | Who helped you finding current job/setting up your current business |

**E: Encouragement for the student**

| | |
|---|---|
| E1 | The importance of not losing hope and not giving up |
| E2 | The importance of being patient and waiting for results to come |
| E3 | The importance of resilience, the ability to recover after failure |

| | |
|---|---|
| E4 | The importance of persisting and remaining focused on the goals |
| E5 | The importance of finding the way in which each one is special and valuable |

# 8 Appendix B – Indexes details

## Engagement Index

The index has 4 components:

Mutual engagement

*[Extract from the Artificial Survey observed by the enumerator]*

**Q:** On a scale from 0 to 10 how smooth, efficient, and mutually engaging was the flow of the conversation?

Relative engagement

*[Extract from the Artificial Survey observed by the enumerator]*

**Q:** On a scale from 0 to 10 how much did the alum talk compared to the student?

Student engagement (Connection Index)

*[Extract from the Post Interaction Survey self-reported by the student]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q0.1:** You felt at ease asking questions and talking about personal issues and goals
**Q0.2:** The alum seemed to care about your personal experience
**Q0.3:** Speaking with the alum made you comfortable, as if you were with a friend
**Q0.4:** The alum can provide you valuable support in your career
**Q0.5:** The alum seems prone to provide help

Alum's perception of student's interest in the program from the Alumni Check-In.

## Usefulness Index

*[Extract from the Post Interaction Survey that follows Key Call 1]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q1.1**: Connecting and talking with the alum today has been useful for you
**Q1.2**: You learnt from the alum useful things that you wouldn't learn at school from teachers or from your family and community about how to start my career
**Q1.3**: You had the opportunity to ask all the **questions** you cared about
**Q1.4**: The time was not enough to talk about all the **topics** you cared about
**Q1.5**: You were engaged in the conversation

## Identification Index

*[Extract from the Post Interaction Survey that follows Key Call 1]*

For each statement, please tell me if you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree.

**Q2.1**: During the conversation you realized you and the alum have a lot of things in common
**Q2.2**: During the conversation you were able to understand the alum's problems and concerns he/she had when starting his/her working life/ moved from the VTI to the work force
**Q2.3**: While listening, you felt you are going through the same things the alum went through
**Q2.4**: When the alum told you about his/her successes you felt joy, when he/she told you about her/his failures, you felt sad
**Q2.5**: You found the alum's personal story relevant to your daily life

# 9 Appendix C – Appendix Tables

Table A1. Relevance of Sectors of Training

| | MYF | UNHS | UNPS |
|---|---|---|---|
| Electrical work | 20.38 | 0.20 | 0.31 |
| Motor-mechanics | 17.95 | 0.84 | 0.82 |
| Tailoring | 13.11 | 0.72 | 0.82 |
| Plumbing | 11.58 | 0.22 | 0.21 |
| Catering/Food service | 9.96 | 2.59 | 1.59 |
| Teaching | 7.90 | 3.21 | 3.50 |
| Construction | 7.27 | 2.75 | 2.73 |
| Secretary/Accountant/Business Mgmt | 4.31 | 0.70 | 0.46 |
| Welding | 2.60 | 0.32 | 0.36 |
| Hairdressing | 2.51 | 1.33 | 1.13 |
| Matching &fitting | 1.35 | 1.40 | 0.93 |
| Agriculture | 0.81 | 55.24 | 65.75 |
| Carpentry | 0.27 | 0.79 | 0.46 |
| Retail | - | 14.19 | 8.08 |
| Transports | - | 4.38 | 3.60 |
| N | 1114 | 9422 | 1944 |

*Notes: The three columns of the table show the percentage of the overall working population between 20-30 years old employed in each sector. The data in the second column comes from the Uganda National Household Survey 2016/2017 (UNHS), a national representative survey conducted by the Ugandan Bureau of Statistics (UBOS). Instead, the data in the third columns comes from the Uganda National Panel Survey 2018/2019 (UNPS), a survey conducted by the Ugandan Bureau of Statistics in partnership with the World Bank, representative at the household level.*

Table A2. Students' distribution across field of study

| Training Area | C | T1 | T2 | t-test | | | F-test |
|---|---|---|---|---|---|---|---|
| | | | | C – T1 | C – T2 | T1 – T2 | |
| Motor-mechanics | 0.15 | 0.22 | 0.19 | -0.07** | -0.04 | 0.03 | 3.16** |
| | (0.02) | (0.02) | (0.02) | | | | |
| Plumbing | 0.14 | 0.07 | 0.12 | 0.07*** | 0.02 | -0.05** | 5.00*** |
| | (0.02) | (0.01) | (0.02) | | | | |
| Catering and hotels | 0.11 | 0.09 | 0.10 | 0.02 | 0.01 | -0.01 | 0.38 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Tailoring | 0.13 | 0.15 | 0.12 | -0.02 | 0.01 | 0.03 | 0.64 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Hairdressing | 0.02 | 0.02 | 0.03 | 0.00 | -0.01 | -0.01 | 0.54 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Construction | 0.07 | 0.08 | 0.07 | -0.01 | 0.00 | 0.01 | 0.25 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Electrical wiring | 0.23 | 0.17 | 0.20 | 0.05* | 0.02 | -0.03 | 1.59 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Welding | 0.02 | 0.03 | 0.03 | -0.01 | 0.00 | 0.00 | 0.21 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Carpentry | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 1.15 |
| | (0.00) | (0.00) | (0.00) | | | | |
| Taeaching/ECD | 0.08 | 0.08 | 0.09 | 0.00 | -0.01 | -0.01 | 0.15 |
| | (0.01) | (0.01) | (0.02) | | | | |
| Agriculture | 0.00 | 0.01 | 0.01 | -0.01 | 0.00 | 0.00 | 0.68 |
| | (0.00) | (0.01) | (0.01) | | | | |
| Machining and fitting | 0.01 | 0.02 | 0.02 | -0.01 | -0.01 | 0.00 | 0.58 |
| | (0.00) | (0.01) | (0.01) | | | | |
| Secretary | 0.02 | 0.03 | 0.02 | 0.00 | 0.00 | 0.01 | 0.33 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Accounting and business management | 0.01 | 0.03 | 0.02 | -0.02* | 0.00 | 0.02 | 1.88 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Observations | 442 | 333 | 339 | | | | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups.
***. **. and * indicate significance at the 1. 5. and 10 percent critical level.

Table A3. Students' baseline characteristics

| | C | T1 | T2 | t-test C – T1 | C – T2 | T1 – T2 | F-test |
|---|---|---|---|---|---|---|---|
| Age | 19.87 | 19.85 | 19.83 | 0.02 | 0.04 | 0.02 | 0.04 |
| | (0.09) | (0.12) | (0.11) | | | | |
| Male | 0.60 | 0.60 | 0.59 | 0.00 | 0.01 | 0.01 | 0.05 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Single | 0.91 | 0.89 | 0.88 | 0.02 | 0.02 | 0.01 | 0.70 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Christian | 0.82 | 0.84 | 0.83 | -0.02 | -0.02 | 0.01 | 0.43 |
| | (0.02) | (0.02) | (0.02) | | | | |
| HH assets index | -0.30 | 0.61 | -0.37 | -0.90* | 0.08 | 0.98* | 2.30 |
| | (0.31) | (0.39) | (0.34) | | | | |
| Trainee has a scholarship | 0.20 | 0.22 | 0.20 | -0.02 | -0.01 | 0.02 | 0.31 |
| | (0.02) | (0.02) | (0.02) | | | | |
| *Main source:* | | | | | | | |
| - Subsistence agriculture | 0.33 | 0.31 | 0.30 | 0.01 | 0.02 | 0.01 | 0.25 |
| | (0.02) | (0.03) | (0.03) | | | | |
| - Commercial agriculture | 0.15 | 0.14 | 0.16 | 0.01 | -0.01 | -0.01 | 0.14 |
| | (0.02) | (0.02) | (0.02) | | | | |
| - Wage job | 0.33 | 0.36 | 0.34 | -0.03 | -0.01 | 0.02 | 0.41 |
| | (0.02) | (0.03) | (0.03) | | | | |
| - Family Business | 0.19 | 0.18 | 0.19 | 0.01 | 0.00 | -0.01 | 0.07 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Rural | 0.56 | 0.55 | 0.51 | 0.01 | 0.06 | 0.05 | 1.33 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Ever worked before VTI | 0.38 | 0.41 | 0.38 | -0.03 | 0.00 | 0.03 | 0.40 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Expected weeks to first job | 5.28 | 5.89 | 5.80 | -0.61 | -0.52 | 0.09 | 0.36 |
| | (0.43) | (0.62) | (0.70) | | | | |
| Expected average wage post-training (in USD) | 151.00 | 166.00 | 152.00 | -14.60 | -0.58 | 14.04 | 0.55 |
| | (7.45) | (13.59) | (11.97) | | | | |
| Plan after VTI: entering the labor market | 0.73 | 0.66 | 0.69 | 0.06* | 0.04 | -0.03 | 1.73 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Plan after VTI: pursue further education | 0.27 | 0.33 | 0.30 | -0.06* | -0.04 | 0.02 | 1.51 |
| | (0.02) | (0.03) | (0.03) | | | | |
| Observations | 442 | 333 | 339 | | | | |

*Notes:* Conversion rate: 3600 UGX = 1 USD. The value displayed for t-tests are the differences in the means across the groups. ***. **. and * indicate significance at the 1. 5. and 10 percent critical level

Table A4. Alumni and pre Covid-19 job characteristics and employment network

| | NO Relatives in trade of training | Relatives in trade of training | t-test |
|---|---|---|---|
| Months to first work activity | 4.51 | 3.53 | 0.98* |
| | (0.45) | (0.37) | |
| First job earnings (USD) | 83.97 | 74.59 | 9.38 |
| | (6.04) | (4.36) | |
| Post-VTI: wage/self-empl | 0.76 | 0.73 | 0.03 |
| | (0.03) | (0.02) | |
| Post-VTI: casual occupations | 0.03 | 0.01 | 0.03*** |
| | (0.01) | (0.00) | |
| Pre Covid-19 earnings (USD) | 108.03 | 103.02 | 5.01 |
| | (5.96) | (5.13) | |
| Pre Covid-19: wage/self-empl | 0.73 | 0.80 | -0.08** |
| | (0.03) | (0.02) | |
| Pre Covid-19: casual occupations | 0.07 | 0.04 | 0.04** |
| | (0.02) | (0.01) | |
| Career Satisfaction | 7.66 | 8.25 | -0.59*** |
| | (0.13) | (0.11) | |
| Observations | 294 | 425 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A5. Alumni first and pre Covid-19 job characteristics and SES

| | HH Asset Index Below Median | HH Asset Index Above Median | t-test |
|---|---|---|---|
| Months to first work activity | 4.27 | 3.56 | 0.71 |
| | (0.42) | (0.38) | |
| First job earnings (USD) | 70.26 | 84.93 | -14.68** |
| | (4.57) | (5.25) | |
| Post-VTI: wage/self-empl | 0.77 | 0.72 | 0.05 |
| | (0.02) | (0.02) | |
| Post-VTI: casual occupations | 0.02 | 0.01 | 0.01 |
| | (0.01) | (0.01) | |
| Pre Covid-19 earnings (USD) | 105.32 | 104.66 | 0.67 |
| | (5.81) | (5.25) | |
| Pre Covid-19: wage/self-empl | 0.73 | 0.81 | -0.07** |
| | (0.02) | (0.02) | |
| Pre Covid-19: casual occupations | 0.07 | 0.03 | 0.04** |
| | (0.01) | (0.01) | |
| Career Satisfaction | 7.58 | 8.36 | -0.79*** |
| | (0.13) | (0.11) | |
| Observations | 355 | 364 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A6. Alumni network and SES

| | HH Asset Index Below Median | HH Asset Index Above Median | t-test |
|---|---|---|---|
| Has relatives working/owning firm in trade of training | 0.54 | 0.64 | -0.11*** |
| | (0.03) | (0.03) | |
| Has VTI friends working/owning firm in trade of training | 0.93 | 0.96 | -0.03* |
| | (0.01) | (0.01) | |
| Has friends working/owning firm in trade of training | 0.90 | 0.93 | -0.04* |
| | (0.02) | (0.01) | |
| Has other network members working/owning firm in trade of training | 0.66 | 0.77 | -0.11*** |
| | (0.03) | (0.02) | |
| Observations | 355 | 364 | |

*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A7. Students' network overall characteristics

| | Obs. | Mean | St.dev. | Min | Median | Max |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Male | 4849 | 0.62 | 0.49 | 0 | 1 | 1 |
| Age | 4499 | 37.06 | 12.61 | 14 | 35 | 85 |
| Completed years of education | 4932 | 12.32 | 2.75 | 0 | 14 | 14 |
| No education | 4364 | 0.01 | 0.11 | 0 | 0 | 1 |
| Completed primary education | 4364 | 0.95 | 0.22 | 0 | 1 | 1 |
| Completed secondary education | 4364 | 0.63 | 0.48 | 0 | 1 | 1 |
| Currently working | 4866 | 0.81 | 0.39 | 0 | 1 | 1 |
| Months worked in last year | 4173 | 9.49 | 4.09 | 0 | 12 | 12 |
| Part time job | 3697 | 0.13 | 0.34 | 0 | 0 | 1 |
| Full time job | 3697 | 0.83 | 0.38 | 0 | 1 | 1 |
| Casual daily labor | 3697 | 0.04 | 0.21 | 0 | 0 | 1 |
| Earnings below 500,000 UGX | 2011 | 0.50 | 0.50 | 0 | 0 | 1 |
| Earnings above 500,000 UGX | 2011 | 0.50 | 0.50 | 0 | 1 | 1 |

*Notes:* the table shows summary statistics for the sample of network members mentioned by the students in the various survey rounds.

Table A8. Students' network quality and SES

| | HH assets index below mean | HH assets index above mean | t-test (1)-(2) |
|---|---|---|---|
| Number of network members | 4.39 | 4.49 | -0.09 |
| | (0.04) | (0.05) | |
| Share from community of origin | 0.87 | 0.88 | -0.01 |
| | (0.01) | (0.01) | |
| Share from VTI | 0.12 | 0.11 | 0.01 |
| | (0.01) | (0.01) | |
| Share providing job | 0.43 | 0.55 | -0.12*** |
| | (0.01) | (0.02) | |
| Share currently working | 0.77 | 0.86 | -0.09*** |
| | (0.01) | (0.01) | |
| Share earning above median | 0.15 | 0.29 | -0.14*** |
| | (0.01) | (0.01) | |
| Share with no edu | 0.01 | 0.01 | 0.01 |
| | (0.00) | (0.00) | |
| Share with primary edu | 0.83 | 0.85 | -0.02 |
| | (0.01) | (0.01) | |
| Share with secondary edu | 0.50 | 0.62 | -0.12*** |
| | (0.01) | (0.01) | |
| Share working in same sector | 0.10 | 0.11 | -0.01 |
| | (0.01) | (0.01) | |
| Observations | 670 | 433 | |

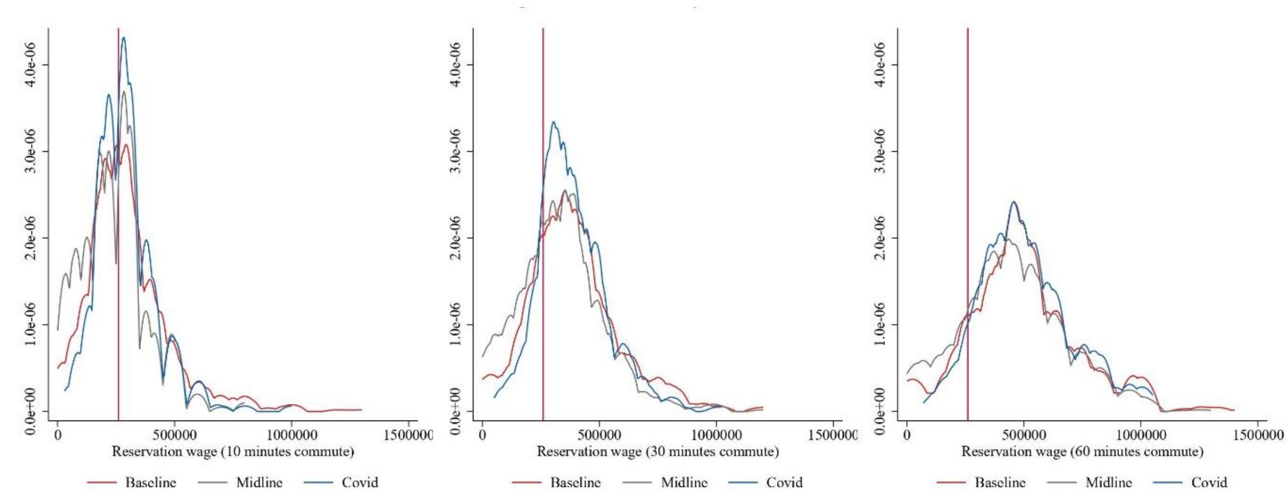
*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A9. Students' network quality balances across treatment arms

| | C | T1 | T2 | t-test C-T1 | C-T2 | T1-t2 | F-test |
|---|---|---|---|---|---|---|---|
| Number of network members | 4.37 | 4.53 | 4.39 | -0.15** | -0.02 | 0.13 | 2.26 |
| | (0.05) | (0.06) | (0.06) | | | | |
| Share from community of origin | 0.88 | 0.88 | 0.87 | 0.00 | 0.00 | 0.00 | 0.01 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share from VTI | 0.12 | 0.11 | 0.12 | 0.00 | 0.00 | 0.00 | 0.02 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share providing job | 0.47 | 0.48 | 0.47 | 0.00 | 0.00 | 0.01 | 0.03 |
| | (0.02) | (0.02) | (0.02) | | | | |
| Share currently working | 0.80 | 0.81 | 0.81 | -0.01 | -0.01 | 0.00 | 0.33 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share earning above median | 0.20 | 0.20 | 0.22 | 0.01 | -0.02 | -0.03 | 0.83 |
| | (0.01) | (0.01) | (0.02) | | | | |
| Share with no edu | 0.01 | 0.01 | 0.02 | 0.00 | -0.01 | -0.01 | 1.25 |
| | (0.00) | (0.00) | (0.00) | | | | |
| Share with primary edu | 0.83 | 0.83 | 0.86 | -0.01 | -0.03* | -0.03 | 2.01 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Share with secondary edu | 0.55 | 0.54 | 0.56 | 0.01 | -0.01 | -0.02 | 0.38 |
| | (0.01) | (0.02) | (0.02) | | | | |
| Share working in same sector | 0.09 | 0.10 | 0.11 | -0.01 | -0.01 | -0.01 | 0.59 |
| | (0.01) | (0.01) | (0.01) | | | | |
| Observations | 442 | 334 | 339 | | | | |

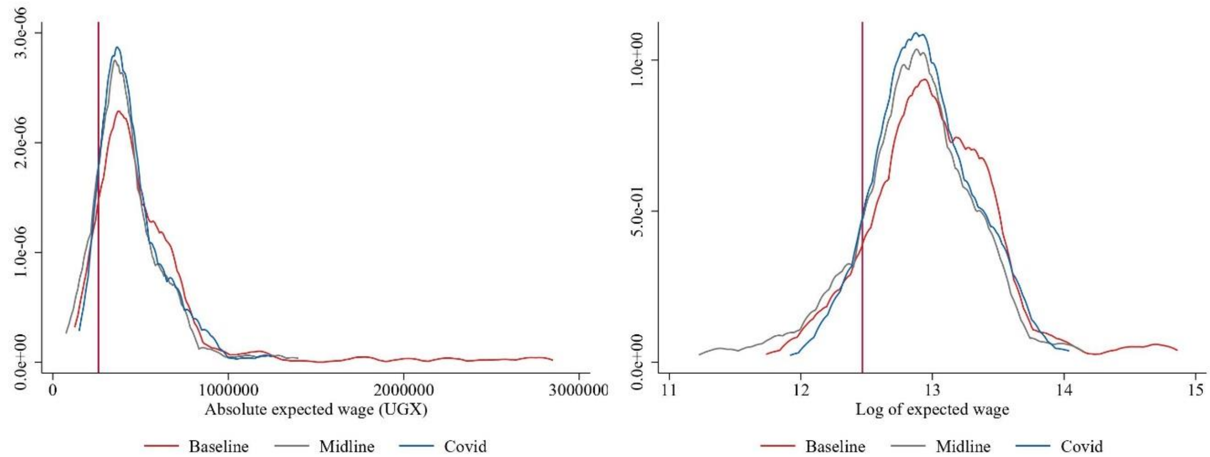
*Notes:* The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Figure A.1. Students' reservation wage by commuting time



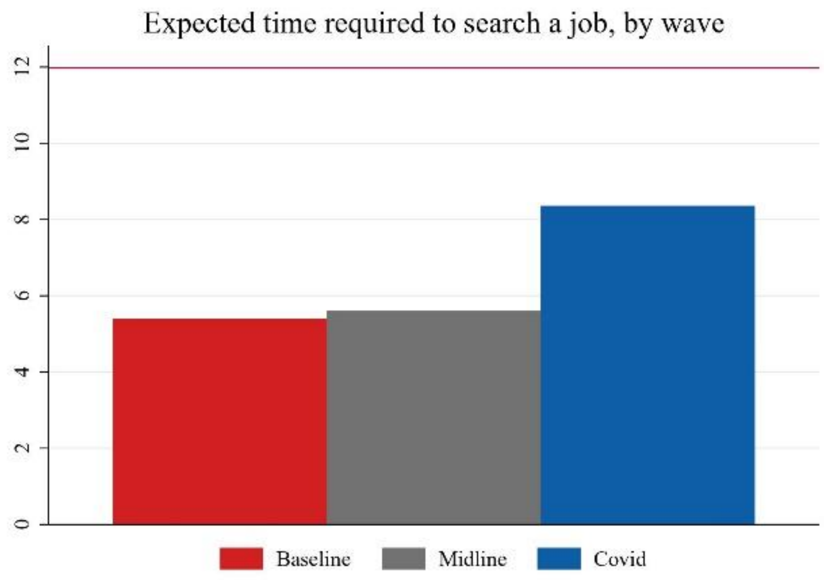

*Note: the red vertical line represents the alumni's average wage at first job*

Figure A.2. Students' expected wage post-training (absolute value and log)




*Note: the red vertical line represents the alumni's average wage at first job*

Figure A.3. Students' expected time required for job search




*Note: the horizontal vertical line represents the alumni's average search time for first job following graduation.*

Figure A.4. Expected challenges students will face reported by students

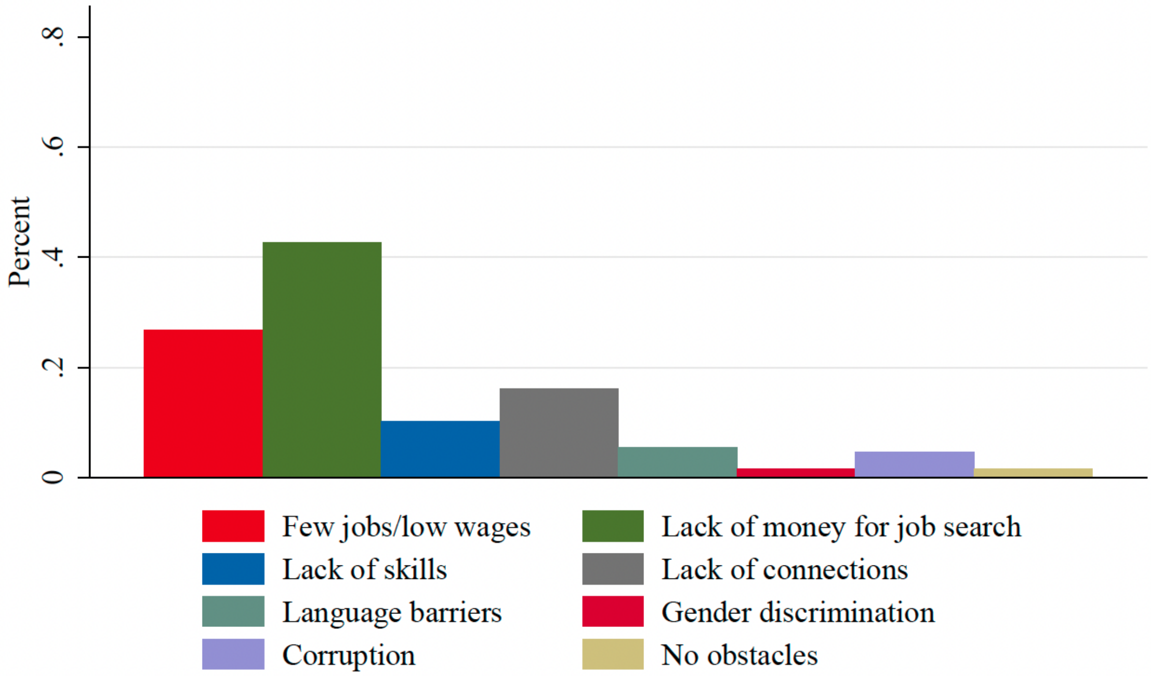
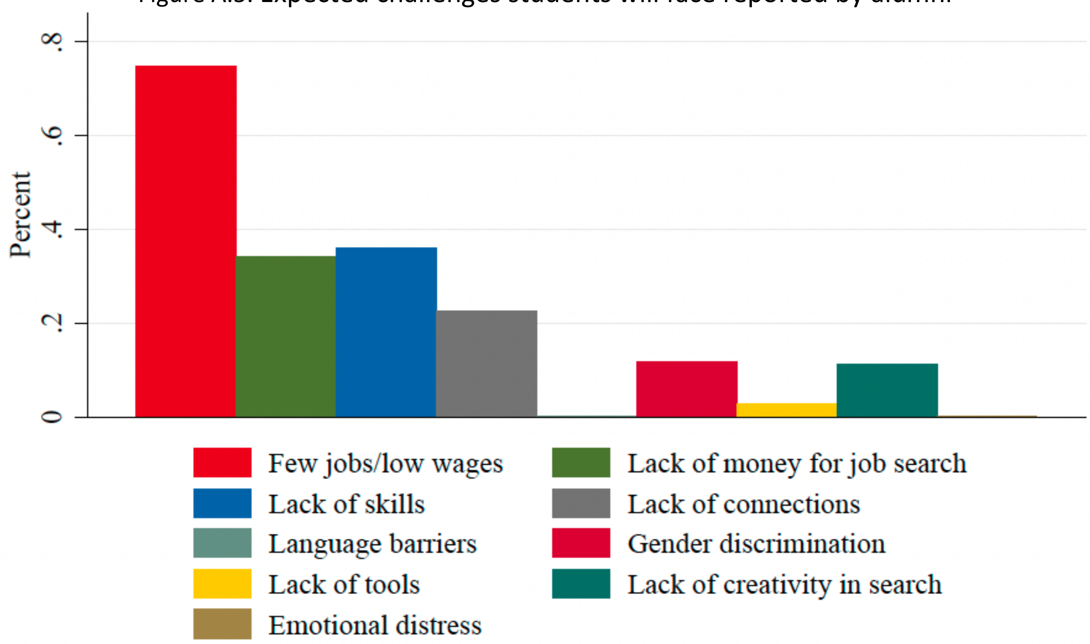



Figure A.5. Expected challenges students will face reported by alumni



# 9 Administrative information

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**Institutional Review Board:** Necessary approvals are in place. This study has been reviewed and approved by three entities: by the University of California at Berkeley's Committee for the Protection of Human Subjects (under Protocol ID 2019-09-12569); in Uganda, by the Mildmay Uganda Research Ethics Committee (under Proposal Reference Number #REC REF 0206-2019); in Uganda, by the Uganda National Council for Science and Technology (under the study reference number SS338ES).

**Declaration of interest:** The authors state that they have no competing conflicts.

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A CRediT author statement is not available at this time.

Declarations of interest: none

Livia Alfonsi