Returns to Work Experience: An Experimental Approach

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Abstract

This paper estimates the returns to short term work experience in a developing country setting. I exploit an experiment that randomized individuals' outside options of employment during a recruitment process resulting in exogenous variation in acquired (short-term) work experience. I find positive (albeit statistically insignificant) impacts on the intensive margin: average employment across 8 months following the intervention. I find relatively large impacts on the extensive margin: average daily wages are approximately \$3.6 - \$5 higher representing a 50 – 70 percent increase in daily wages for those receiving the short term work experience. The wage impacts seem to be relatively persistent across the 8 months following the intervention. The results are concentrated among those of lower ability, suggesting that the mechanism for these effects is driven by skills acquired during the period of work experience. In contexts with high unemployment these results suggest large feedback effects from the acquisition of (short term) work experience. They also suggest a role for labor interventions that include work experience as part of the program.

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1. Introduction

Unemployment is high in many African countries and particularly high among urban male youth (World Bank, 2009). Increasing rates of urbanization and the demographic youth bulge is leading to increasing pressure on labor markets as labor force participation is rising. Employment programs are aimed at achieving multiple goals from reducing poverty, as well as to reduce the risk of social instability. To achieve these goals, many employment intervention programs exist. Puerto (2007) and Rother (2006) both provide extensive reviews of employment interventions targeted at youth in Africa.

An extensive literature examines job training programs in developed countries (Katz, 1994; Fay, 1996, Martin 1998 and Kluve 2006). The evidence of job training programs is somewhat mixed, meta-analyses suggest that the impacts are quite modest and sometimes negative (Heckman et al. 1999; Betcherman et al. 2007; Card et al. 2009). There is considerably less research conducted in transition (Planas and Jacob, 2010) and developing economies (Aedo and Nunez, 2004; Card et al., 2007; Attanasio et al. 2008). In recent work, Blattman, Fiala and Martinez (2012) evaluate the Ugandan *Youth Opportunities Program* and provide experimental evidence in a developing setting that suggests high returns. However, this program is in many ways akin to a cash transfer program, more research is needed on the impact of labor market programs in Africa.

Given rising unemployment, and rising interest in employment interventions in Africa, understanding returns to short term work experience is important for understanding the potential value of labor market policy interventions that encourage work-experience/internships/ and volunteer work.

Measuring the effect of past work experience on current employment, wages and labor market perceptions are typically fraught with difficulty. There are many unobserved factors that jointly determine both previous work experience and current employment, wages and labor market perceptions. Due to the inability to adequately control for all the omitted variables estimates it is difficult to estimate the causal effect of experience. For example, one omitted variable is perseverance. Someone who is more likely to persevere in looking for work is both more likely to have some work experience and is likely to earn better. As such, estimating work experience would in this case be confounding the effect of perseverance and previous work experience. There are many omitted variables in this context – ability, presentability, motivation. Many studies try to control as broadly as possible for these factors to the extent they can.

In this paper, I exploit random variation in (short term) work experience that is not typically available to a researcher. In an experimental study, individuals received a randomized probability of a guaranteed short term job. While I am not explicitly testing the impact of a job training program per se, the returns to the short term work experience obtained offers important insights to the design of such programs in developing countries.

The paper finds the following key results. First, there is no statistically significant impact of short term work experience on employment status (on average during the 8 months following the intervention). The estimated coefficient is positive suggesting a 7 percentage point increase in employment. Similarly individuals are not induced to search more for work and are no more (or less) likely to hold multiple concurrent jobs. Second, I do find that individuals earn a return to the short term work experience – they earn approximately \$3.6 - \$5 more per day. This is a large return, as it suggests a 50 to 70 percent increase in daily wages attributable to the short term work experience acquired. This return to work experience persists across the 8 month period following the short term work experience (although it is higher in the first 3 months following the acquired work experience). Thirdly, I find that the estimated returns to work experience are larger among those who perform worst on a numeracy and literacy test, and that the estimated returns for these individuals persist across the 8 month period more so than for those of “higher ability”. This suggests that in the short term all types benefit from the work experience acquired, but high ability types are able to catch up in the absence of receiving the short term work experience.

The paper proceeds as follows: Section 2 describes the setting and the experimental variation that is exploited. Section 3 presents the empirical strategy and Section 4 discusses the results. Section 5 discusses various underlying mechanisms and Section 6 concludes.

2. Setting

2.1. Malawian Labor Markets

Malawi is one of the poorest, least developed countries and has one of the highest internal migration rates in Africa (HDR, 2009). Currently it has widespread employment, higher in the urban areas. Given little growth in labor market opportunities, the average urban Malawian is likely to suffer increasing unemployment rates. The integrated household survey (a nationally representative dataset) shows that in 2004/05 only 56.7 percent of urban residents did any income generating tasks in the past week and only worked for approximately 24.3 hours.

2.2. Experimental variation

This paper exploits experimental variation from a randomized control trial conducted in urban Malawi discussed in-depth in Godlonton (2012). In the experiment, job trainees in a recruitment process (for a real job) were offered randomized probabilities of an alternative job. Individuals were assigned a 0-, 1-, 5-, 50-, 75- or 100-percent chance of alternative employment (stratified by ability and prior experience with the recruiter). The alternative employment offered the same terms (duration and wage) as the standard wage offer of the recruiter. Individuals were still able to "earn" a job through the recruitment process by performing well during the job training. Once the recruitment process was completed, the realizations of the probability of employment were determined. For individuals assigned a 1-, 5-, 50- or 75 percent chance of an alternative job; draws were conducted. For example, if they were assigned a 75 percent chance of an alternative job, they were required to draw a token from a bag. The bag included 75 red tokens and 25 green tokens. If they drew a red token then they were received the option to get an alternative job. Similar draws were conducted by each individual for each of these uncertain treatment groups. For individuals assigned a 0-percent chance, they knew with certainty they were not eligible for the alternative job, while those assigned a 100-percent chance knew with certainty they were eligible for the alternative job. Thus, the alternative job probabilities assigned serve as a valid instrument for work experience. This unusual random allocation of work experience allows a unique opportunity to measure the causal effect of past work experience on future employment and earnings as it avoids common concerns such as: omitted variable biases and endogeneity concerns.

2.3. Work Experience

The work experience acquired by those individuals who were eligible is short term constituting only 5 days of paid work. Individuals were engaged in many different types of research assistant work, including: archival research, data entry, and translation and transcription of qualitative interviews[2]. They received a standard letter of reference after completing their 5 days.

3. Data

This paper utilizes two types of data: i) Administrative records from the experiment and ii) Survey data (both Baseline, and Follow-up data collected 9 months after the acquired work experience).

Administrative Data:

Administrative data recording which participants drew an alternative job are used. That is, at the conclusion of the recruitment process in which the experiment was conducted individuals drew and the realization of the probabilistic job guarantees was made known. For example, and individual with a 1-percent chance of an alternative job would pick a token from a bag that contained 99 green tokens and 1 red token. If they picked the red token they were offered the alternative job. A similar procedure was followed for all the treatment arms 5-, 50-, and 75- percent chance of an alternative job. Those with a

[2] Individuals participating are relatively well-educated for Malawi in that they have completed secondary schooling.

100-percent chance were all offered an alternative job and those with a 0-percent chance were not. It is the realization of these draws that is taken from administrative records.

Survey Data:

Two survey datasets are used in the analysis. A baseline survey was conducted prior to the implementation of the experiment. This survey collected information on basic demographics, general education and work experiences as well as related perceptions; as well as mental and physical health. The baseline survey was self-administered by respondents. The baseline data consists of 268 men that participated in the experiment.

A follow-up survey was conducted 9 months following the implementation of the experiment. The follow-up survey was conducted telephonically and included an extensive module on job search, labor market perceptions (current and future likelihood of finding employment), current employment and employment experiences over the last 6 months, current and past wages as well as a mental health module.

Table 1 presents the finding rates at follow-up by treatment group. A total of 84.7 percent of the sample was successfully interviewed. While the finding rate was highest among those that had received the 75-percent job guarantee (92.9 percent) this finding rate is not statistically significant different (p=0.168) from the group with the lowest finding rate (81.1 percent in the group assigned a 0-percent chance of an alternative job).

Table 2 presents attrition by baseline characteristics and shows that there are not large observable differences between the sample found at follow-up and the baseline sample. Finding rates of the Ngoni's and those that had worked in the 6 months prior to baseline were slightly higher (significant at the 5 percent level and 10 percent level respectively). However, these differences are not large in magnitude and do not suggest large biases in the follow-up sample.

The resulting sample used in this paper is approximately 26 years old, 17.2 percent of which are married. Approximately 16.7 percent of the sample have at least one child, and of those that do have at least one child they have an average of 1.8 children. Respondents are relatively well educated for Malawi with an average of 13 years of education, but this is driven by the eligibility criteria of the recruiter which required individuals to have at a minimum completed their secondary school education. Despite being relatively well-educated for Malawi all these men were actively seeking work at the time of the baseline sample and they reported earnings of only approximately $218 per month over the last 3 months. Despite relatively low income, these individuals are financially responsible for many relatives or friends having assisted approximately 8 different people in the last month. (Table 2, Column 3)

Job uncertainty is rife in this population and similar when compared to large nationally representative household survey such as the Integrated Household survey (IHS) conducted by the World Bank and Malawi National Statistics Office. For instance respondents in the IHS in 2004 worked on average 5.7 months of the year which is similar to the 2.7 months (over the last 6 months) worked by respondents in the my baseline sample.

4. Empirical Strategy

If experience was randomly assigned across individuals, then we could estimate the average treatment effect of experience on employment, and wages using ordinary least squares. In this case, one would estimate the following regression equation:

$$y_i = \alpha + \beta_1 T_i + X_i' \delta + \varepsilon_i \qquad (1)$$

Where: y_i = employment (or wages) for individual i, T_i is a dummy indicator for whether or not the individual was randomly assigned work experience, X_i is a set of individual characteristics (including whether the individual has ever worked, as well as their: age, education and marital status).

However, in the current context assignment to receive work experience was not quite randomly determined. Individuals were randomly assigned to different probabilities of obtaining work experience. While this should be equivalent to random assignment to receiving work experience there may be concerns that violate this. As discussed in Section 3, individuals drew tokens to determine whether or not they received work experience. If individuals cheat to influence the outcome of their draw then the treatment would not directly map into random assignment of work experience.[3]

To enable a causal interpretation of the effect of work experience on employment and wages I implement an instrumental variables approach. I instrument for work experience using dummy variables for the probability of alternative employment assigned during the intervention. The identification assumption is that the treatment dummies (of the probability of alternative work) do not affect employment or wages independent of the work experience acquired. The system of equations then estimated is:

$$y_i = \alpha_0 + \beta_1 T_i + X_i'\delta + \varepsilon_i \qquad (2)$$

$$T_i = \pi_0 + \pi_1 T1 + \pi_2 T5 + \pi_3 T50 + \pi_4 T75 + \pi_5 T100 + X_i'\varphi + \varepsilon_i \qquad (3)$$

Given that the assignment to treatment status was conducted stratified by ability and prior work experience with the recruiter I include stratification cell fixed effects. The key coefficient of interest is β_1 and measures the effect of obtaining work experience on employment outcomes such as employment and wages.

4.1 Impact across time

To assess the persistence of effects across time, I use the restrospective work calendar history data collected at follow-up and construct a monthly panel data set of job search, employment and wages in each month controlling for time. In this case, there are 9 observations per individual – one for each

[3] This is of limited concern in the current context as many measures were adopted to reduce this. Also, the realization of the fraction of individuals getting alternative jobs is similar to the expected distribution. For example, 73.1 percent of individuals assigned to the 75 percent treatment group received a job; exactly 50 percent of the 50-percent treatment group received a job. Four percent of those in the 1-percent treatment group were successful, and 11.6 percent of the 5 percent treatment group. This may be due to cheating, or due to small sample sizes.

month following the experiment. Therefore, in these specifications, the standard errors are clustered by individual.

4.2 Heterogeneity of impacts

I also explore the heterogeneity of the impacts of the work experience by various baseline characteristics to try to determine the particular mechanism driving the observed effects. To do this I interact the indicator variable of whether the individual received an alternative job with the baseline characteristic of interest and instrument with the set of treatment dummies interacted with the same baseline characteristic. I implement the following set of equations:

$$y_{it} = \alpha_0 + \beta_1 T_i + \beta_2 Base_i + \beta_3 (T_i * Base_i) + X_i' \delta + \varepsilon_{it} \tag{4}$$

$$T_i = \pi_0 + \pi_1 T1 + \pi_2 T5 + \pi_3 T50 + \pi_4 T75 + \pi_5 T100 + X_i' \varphi + \varepsilon_i \tag{5}$$

$$(T_i * Base_i) = \pi_6 + \pi_7 (T1 * Base_i) + \pi_8 (T5 * Base_i) + \pi_9 (T50 * Base_i) + \pi_{10} (T75 * Base_i) + \pi_{11} (T100 * Base_i) + X_i' \gamma + \varepsilon_i \tag{6}$$

where: $Base_i$ is a measure from baseline including an individuals' ability score, whether they had previous work experience.

5. Results

This section first presents the first stage results. I then present the results of receiving work experience on job search, employment and concurrent number of jobs held. Then I discuss the impact of the short term work experience on the number of hours worked and average daily wages.

5.1 First Stage:

Table 3 presents the first stage estimates. The outcome variable is an indicator for whether an individual received work experience. These are regressed on the set of dummy variables indicating which treatment group the individual had been assigned. Individuals that had been assigned a 0-percent job probability should have no chance of receiving an alternative job and they are used as the omitted category in all regression analyses. Also, it is clear that the treatments roughly predict the expected job probability outcome. For example, we can see that 73 percent of the participants assigned to the 75-percent job probability group did in fact obtain work. For those in the 1 and 5 percent treatment groups, they are slightly more likely (4.2 and 11.6 percent) to have actually obtained work. (Table 3, Column 1) Unsurprisingly, the treatment dummies serve as good instruments for whether the individuals obtained work experience. Controlling for additional covariates does not alter the results in any substantive manner.

5.2. Returns to Experience: Extensive Margin

Table 4 presents the impact of the work experience on job search, employment, and concurrent number of jobs held. The job search variable is defined as the fraction of the past 8 months that the individual actively looked for work (whether or not they were employed). Similarly, the employment variable used is the fraction of the past months that the individual was employed. The measure of concurrent work is constructed as the average number of concurrent jobs held over the last 8 months. Table 4 presents the intention-to-treat results. Columns 1 through 3 show that on average in the 8 months following the intervention, there is no impact on job search; employment (Columns 4-6) and number of concurrent jobs held (Columns 7-9). Although the effects are not statistically significant, the sign of the coefficients suggest that individuals may have more actively sought work and found employment. The OLS results are presented in Appendix Table 1 and are consistent with these results.

5.3. Returns to Experience: Intensive Margin

Table 5 presents the impact of the short term work experience on the number of hours worked in an average week and the average daily wage. To measure the average number of hours worked in an average week measures the average number of hours worked in a week over the last 8 months. Similarly, the average daily wage is an average of daily wages by month across the 8 month period.

Table 5 Columns 1 through 3 suggest that individuals receiving the short term work experience worked approximately 4 more hours per week on average across this time period. However, this result is not statistically significant. Interestingly, Columns 4 through 6 indicate that those who received the short term work experience benefitted in the form of an increase in the average daily wage. Recall that Table 4 indicated a slight increase in employment coefficients (albeit not statistically significant). To determine whether the average daily wage effects are driven by this employment difference, I drop all individuals who were unemployed and present the results in Table 5 Columns 7 – 9. These results indicate larger returns although the coefficient is no longer statistically significant at the 10 percent level which is understandable given the low power to detect in this case.

This impact of the work experience on the daily wage is quite large. The estimated effect suggests a $3.6 - $5 increase in the daily wage. Given that the average daily wage in the sample of those who did not receive an alternative job and were employed is approximately $7, the estimated effects suggest a 50 to 70 percent return. The increase in the number of hours worked translates only into an 18 percent increase. These results taken together suggest that while some of the increased earnings may be driven by an increase in the number of hours worked, a large fraction is not. This may suggest that the work experience enabled individuals to acquire higher paying work in the 8 months following this experience relative to those who did not receive this work opportunity.

Appendix Table 3 presents the OLS regression results which are broadly consistent with the results presented here. The estimated coefficients are however, smaller and not statistically significant.

5.4. Persistence of impacts

Figure 1 plots the estimated return to the short term work experience across time – this figure plots the estimated treatment effects by month using the instrumental variable approach. Evidently, across all months there appears to be a positive return to acquiring the work experience. The low return in October and January requires further exploration. While the initial return appears to be higher, this figure does suggest that across time while the impact may depreciate over time, it is not eliminated 9 months after receiving the work experience.

Table 6 further builds on this figure. This table presents regression results for three key outcomes of interest: job search; employment status; and average daily wage. For these regressions the retrospective work calendar history is used to construct a panel data set in which I observe each individual 9 times. These results suggest that even in the short term there appears to be little impact on job search (Column 3). There appears to be short term significant impact on employment (Columns 6), that appears to get slightly stronger across time. Lastly, the average daily wage impact is relatively consistent across time – the interaction effect with time is basically zero.

6. **Mechanisms**

In this section I focus primarily on the estimated impact of the work experience on average daily wages. I explore how the impacts differ for different types of people. Lastly, I explore differences between those who did and did not receive the job to assist in determining what might be driving this impact using OLS regressions.

There are many reasons why we might expect that experience (even short term informal work experience) leads to increased employment and/or wages. These include: i) Skills acquisition; ii) Signaling; iii) Altered social networks. I try to tease apart these different potential theories to determine the combination of factors driving the observed impacts on wages.

Table 7 presents heterogeneous treatment effects by ability, and an indicator for whether individuals had any prior work experience. I focus on the results on number of hours worked in the last week and the average daily wage as the two key outcomes of interest.

Columns 1 and 3 show that the return to work experience is largest for those at the bottom end of the ability distribution. For example, individuals at the 25th percentile of the ability distribution are estimated to work 8 hours more per week if they received the work experience compared to those who did not; while those at the 75th percentile are estimated to work approximately the same number of hours. In terms of the average daily wage earned, this same pattern is observed. Individuals at the 25th percentile of the ability distribution earn approximately $6.8 more if they received the work experience compared to those who did not, while the estimated impact for those at the 75th percentile is $1.9. This is suggestive evidence in favour of a skills acquisition hypothesis. These individuals who were least likely to have the skills are the ones who benefit the most. Figure 2 plots the average return from the IV regression by month for individuals scoring below the 25th percentile and those above the 25th percentile. This graph illustrates that the return to experience is concentrated in the first month for the "higher" ability types and may in fact be negative afterwards (although the confidence intervals suggest it is not statistically significant). The returns to those of "lower" ability although higher initially do not decline considerably over time.

Table 8 columns 2 and 4 present the results of the heterogeneity of the return by prior work experience. I find that the impacts do not differ by whether the respondent had ever worked. A large fraction of the sample report having ever worked. This therefore, might not be the best test and a better measure might be whether or not the individual has ever held a research assistant position. This requires further analysis.

Lastly, I examine reduced form impacts of receiving the work experience on a number of outcomes that may shed light on how individuals who received the job are accessing employment that is better paid. Table 8 columns 1 and 2 show individuals are more likely to have heard of work from someone they met during the recruitment process, they are no more likely to have actually secured employment through this extended network. Individuals' job related social networks grew as did their access to information about job opportunities, but this not translating into better employment outcomes.

Notably, individuals that received work experience were more likely to have worked in a research position in the last 9 months. This is consistent with a skills acquisition hypothesis – individuals gained work experience as a research assistant and then secure similar employment.

Individuals receiving work experience were also more likely to report using a letter of reference in employment applications. This might support a signaling hypothesis. Employers use the letter of reference from a reputable organization to assume that these individuals are of higher quality.

7. Conclusion

This paper sought to estimate the impact of temporary work experience on short term and medium term employment and wage effects. I find no statistically significant impact of short term work experience on employment status (8 months following the intervention). Second, I do find that individuals earn a return to the short term work experience – they earn approximately $3.6 - $5 more per day. This is a large return, as it suggests a 50 to 70 percent increase in daily wages attributable to the short term work experience acquired. This return to work experience persists across the 8 month period following the short term work experience. Thirdly, I find that the estimated returns to work experience are larger among those who perform worst on a numeracy and literacy test, and that the estimated returns for these individuals persist across the 8 month period more so than for those of "higher ability". This suggests that in the short term all types benefit from the work experience acquired, but high ability types are able to catch up in the absence of receiving the short term work experience.

There are a number of important limitations to the analysis conducted. First, the population studied is relatively well educated for Malawi and constitutes only men. This paper can not say anything about how a similar intervention that offers women or less well-educated individuals' work experience would benefit. Also, the specific intervention is ill-defined. There is no current program in Malawi offering the specific intervention exploited. Moreover, the work experience acquired is temporary. How the returns would differ with longer exposure can not be addressed in this setting. Lastly, the general equilibrium effects of such a program are not estimated. Given the small size of this intervention, it is not possible to determine if and the extent such a program if rolled-out would have on those individuals not participating. It is not clear if non-participants would be crowded out of the labor market or whether the returns are driven by increases in wages earned through entrepeneurship activities which would result in a net increase in employment.

However, the results do shed light on the potential impact of short term training programs or employment programs that include work experience as a key component. It also suggests a role for such programs targeted not only at the poorest of the poor as there are large returns in the population studied. The urban poor are often neglected in development projects in low income countries that are substantively subsistence economies. This growing population will be of growing concern given current internal migration rates and solutions to growing unemployment problems need to be dealt with. Moreover, they are often responsible for a large number of financial dependents through which such programs could have large spillover effects in terms of net welfare.

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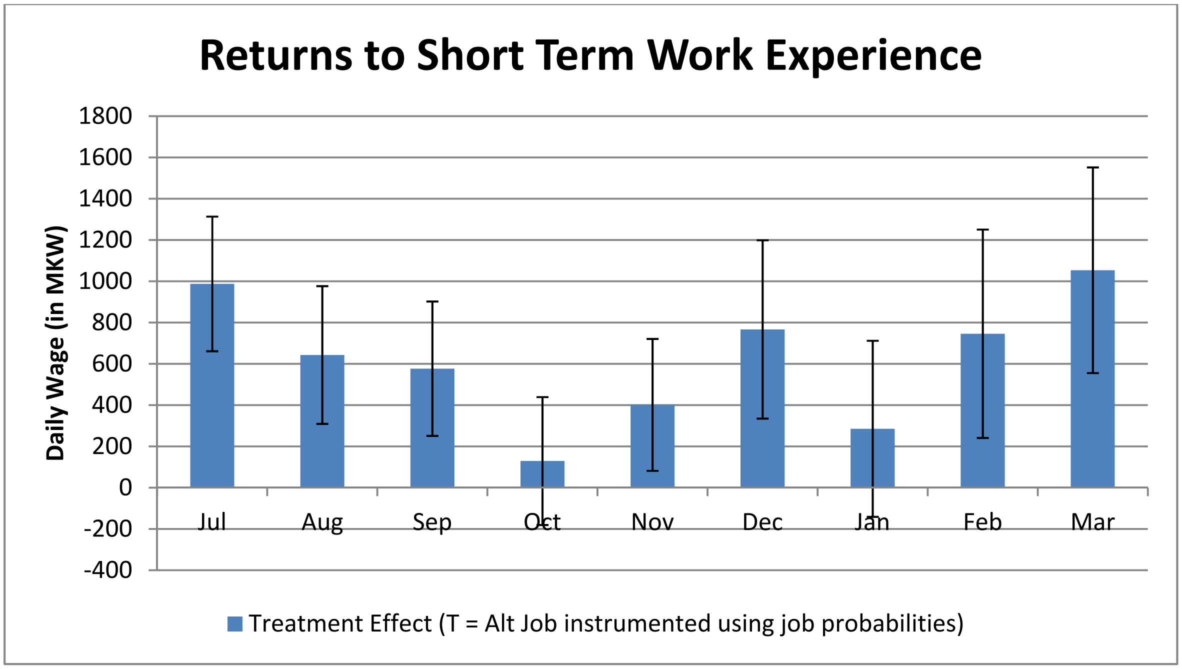

Figure 1: Average treatment effects by month

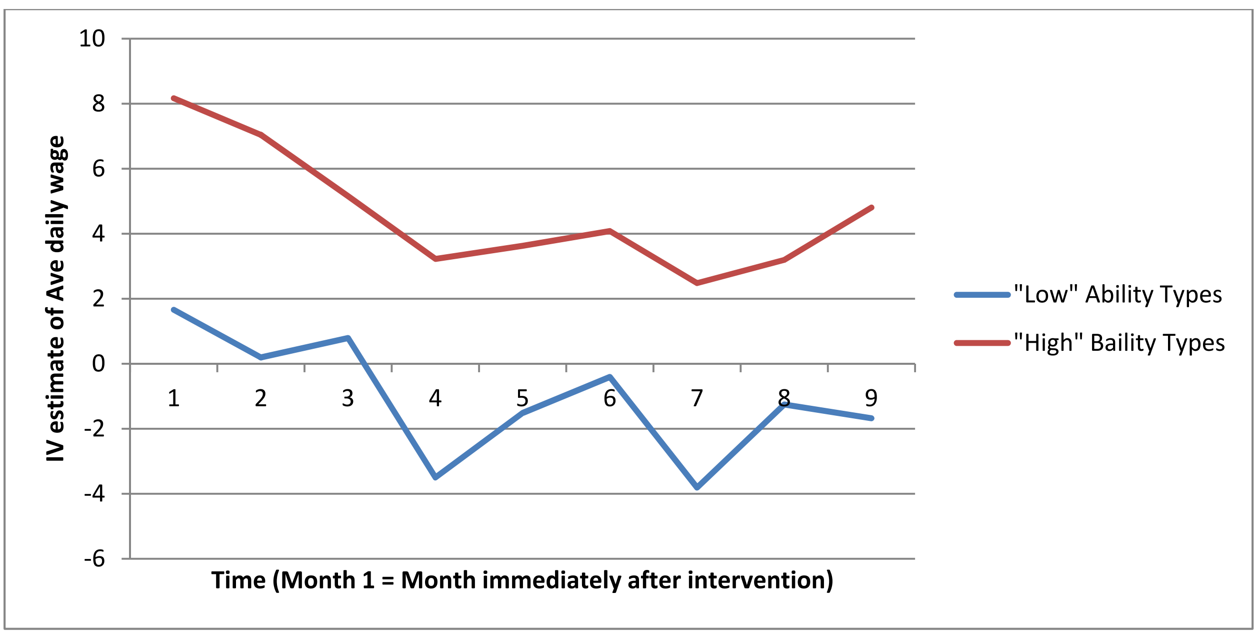

Figure 2: Average treatment effects by month and ability type

Table 1: Sample size and attrition

	N	Mean	SD
Treatment conditions:	(1)	(2)	(3)
0% Probability	53	0.811	0.395
1% Probability	56	0.857	0.353
5% Probability	52	0.827	0.382
50% Probability	54	0.852	0.359
75% Probability	28	0.929	0.262
100% Probability	25	0.840	0.374
Full sample:	**268**	**0.847**	**0.361**
p-value of F-test of joint significance:			
0% = 1% = 5% = 50% = 75% = 100%		0.827	

p-values of t-tests of pair-wise differences:

	1%	**5%**	**50%**	**75%**	**100%**
0%	0.510	0.826	0.564	0.168	0.745
1%		0.666	0.939	0.396	0.844
5%			0.724	0.233	0.882
50%				0.364	0.893
75%					0.376

Notes:

Individuals were assigned to one of the 6 treatment groups. If they received a 0-percent chance of an alternative (i.e. in 0% Probability treatment group) then they had no chance of receiving the alternative job. If they were assigned to the 1% Probability group then they had 1 percent chance of receiving an alternative job. Similarly for the 5-, 50-, 75- and 100 percent probability groups. There were twice as many assigned to the high probability groups as compared to the lower groups for budgetary purposes. The p-values denote the p-value associated with the F-test of whether the mean finding rate is the same in all treatment groups or in the case of the table the pair-wise t-test of differential finding rates.

Table 2: Sample and Attrition						
	Baseline N=268		**Follow-Up N=227**			
	Mean	SD	Mean	SD	**Difference**	
	(1)	(2)	(3)	(4)	(5)	
Demographics:						
Age	25.604	4.638	25.718	4.662	-0.114	
Married	0.172	0.378	0.172	0.378	0.000	
Any child?	0.164	0.371	0.167	0.374	-0.003	
Number of children	0.299	0.784	0.313	0.811	-0.014	
Number of fin dependents	7.959	9.355	8.264	9.406	-0.305	
Years of education	13.183	0.940	13.220	0.938	-0.037	
Income (USD, 3 months)	206.123	228.803	210.617	237.777	-4.494	
Ability score	-0.001	1.003	0.030	1.017	-0.031	
Tribe:						
Chewa	0.310	0.463	0.300	0.459	0.010	
Lomwe	0.108	0.311	0.110	0.314	-0.002	
Ngoni	0.164	0.371	0.181	0.386	-0.016	**
Tumbuka	0.190	0.393	0.189	0.393	0.001	
Other	0.201	0.402	0.198	0.400	0.003	
Education and Work:						
Ever worked?	0.869	0.338	0.863	0.344	0.006	
Ever worked with recruiter?	0.104	0.306	0.097	0.296	0.008	
Any work in last month	0.646	0.479	0.665	0.473	-0.020	
Any work in last 6 months	0.869	0.338	0.890	0.314	-0.020	*
Frac of 6 mths worked	2.657	2.176	2.727	2.175	-0.070	
Any job search last month	0.116	0.320	0.110	0.314	0.006	

Notes:

The baseline sample consists of 268 individuals who participated in the recruitment process and experiment discussed in Section 2, that is discussed in-depth in Godlonton (2012).The follow-up sample is the main sample used in this paper. The ability score is determined prior to the experiment conducted. It consists of a numeracy and literacy component, and has been standardized.

Table 3: First Stage: Job Guarantees Predict Work Experience

Dependent Variable:		**Got a job**	
	(1)	**(2)**	**(3)**
1% Job Guarantee	0.042	0.038	0.031
	[0.029]	[0.033]	[0.034]
5% Job Guarantee	0.116	0.114	0.108
	[0.050]**	[0.050]**	[0.052]**
50% Job Guarantee	0.5	0.499	0.484
	[0.075]***	[0.075]***	[0.076]***
75% Job Guarantee	0.731	0.714	0.703
	[0.088]***	[0.092]***	[0.094]***
100% Job Guarantee	1	1.002	1.002
	[.]	[0.013]***	[0.018]***
Age			-0.002
			[0.008]
Married			-0.014
			[0.090]
Ever worked			0.06
			[0.084]
Years of schooling			-0.007
			[0.027]
Constant	0	0.057	-0.012
	[.]	[0.104]	[0.419]
Observations	227	227	227
R-squared	0.53	0.54	0.55
Stratification cell FE's	No	Yes	Yes
F-stat (of instruments)	361.77	1257.4	717.86
Average of dep variable		0.276	

Notes:

The sample used here is the sample of 227 men found at follow-up.

The treatment group - 0 percent chance of alternative employment is the omitted category in these regressions.

The outcome variable "Got a job" is whether or not the individual received an alternative job (which is the measure of work experience used in this paper).

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously.

Table 4: Returns to Work Experience: Extensive Margin

Dependent Variable:	**% Months looked for work**			**% Months worked**			**Ave number concurrent jobs**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Got a job (IV using job	0.084	0.097	0.084	0.068	0.08	0.072	-0.016	-0.028	-0.023
probabilities)	[0.070]	[0.070]	[0.069]	[0.076]	[0.076]	[0.071]	[0.111]	[0.133]	[0.127]
Age			0.009			0.014			0.006
			[0.007]			[0.007]*			[0.012]
Married			-0.111			0.119			0.164
			[0.090]			[0.095]			[0.120]
Ever worked			0.082			0.074			-0.018
			[0.026]***			[0.030]**			[0.083]
Constant	0.601	0.843	-0.556	0.407	0.598	-0.827	0.514	0.634	0.726
	[0.030]***	[0.088]***	[0.422]	[0.033]***	[0.099]***	[0.457]*	[0.074]***	[0.118]***	[1.408]
Stratification cell FE's	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other covariates?	No	No	Yes	No	No	Yes	No	No	Yes
Observations	227	227	227	227	227	227	227	227	227
R-squared	0.01	0.04	0.09		0.1	0.18	0	0.16	0.18
Ave of dep variable (no job)		0.600			0.422			0.523	

Notes:

The regressions are IV estimates, whereby dummy indicators for the assigned job probability treatments (0-,1-,5-,50-,75- and 100-percent chance of alternative work) are used to instrument for the outcome of interest.

The %months looked for work is computed using a retrospective calendar history, and is calculated as the number of months the individual actively sought work over the last 8 months, divided by 8. Similarly, % months employed is calculated as the number of months the individual was employed over the last 8 months, divided by 8.Lastly, the average number of concurrent jobs is the average of the total number of jobs held each month across the 8 month period.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Table 5: Returns to Work Experience: Intensive Margin

Dependent Variable:	**Avg hrs worked per week**			**Avg daily wage (incl. Unemployed)**			**Avg daily wage (excl. Unemployed)**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Got a job (instrumented)	4.094	4.531	4.175	3.622	3.946	3.636	4.867	5.472	4.994
	[3.095]	[3.119]	[2.966]	[1.697]**	[1.770]**	[1.607]**	[3.194]	[3.392]	[3.382]
Age			0.74			0.138			-0.056
			[0.333]**			[0.124]			[0.333]
Married			1.093			2.867			4.435
			[4.218]			[1.661]*			[4.515]
Ever worked			1.991			3.153			3.781
			[1.318]			[0.643]***			[1.444]***
Constant	15.815	30.156	-18.252	4.353	13.769	-35.038	12.625	7.045	-42.769
	[1.384]***	[5.045]***	[20.428]	[0.601]***	[7.391]*	[11.171]***	[1.312]***	[0.388]***	[19.988]**
Stratification cell FE's	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other covariates?	No	No	Yes	No	No	Yes	No	No	Yes
Observations	227	227	227	227	227	227	171	171	171
R-squared		0.09	0.15		0.05	0.21		0.05	0.12
Ave of dep variable (no job)		16.557			5.196			14.37	

Notes:

The regressions are IV estimates, whereby dummy indicators for the assigned job probability treatments (0-,1-,5-,50-,75- and 100-percent chance of alternative work) are used to instrument for the outcome of interest.

Ave hours worked per week is computed using a retrospective calendar history, and is calculated as the average number of hours worked per week on the individuals' main job by month. The average daily wage is also calculated using the restrospective job work history. The average daily wage is calculated as the average wage on the individual's main job in the last month. For Columns 4 through 6 - those who are unemployed are coded as 0's, whereas for Columns 7 through 9 they are coded as missing.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Table 6: Returns to Work Experience: Panel

Dependent Variable:	**Any job search**			**Employed**			**Avg daily wage**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Got a job (instrumented)	0.063	0.063	-0.102	0.093	0.093	0.17	3.636	3.636	3.643
	[0.066]	[0.066]	[0.094]	[0.066]	[0.066]	[0.089]*	[1.565]**	[1.565]**	[2.088]*
Age	0.008	0.008	0.008	0.013	0.013	0.013	0.138	0.138	0.138
	[0.007]	[0.007]	[0.007]	[0.007]*	[0.007]*	[0.007]*	[0.121]	[0.121]	[0.121]
Married	-0.100	-0.100	-0.100	0.112	0.112	0.112	2.867	2.867	2.867
	[0.085]	[0.085]	[0.085]	[0.091]	[0.091]	[0.091]	[1.618]*	[1.618]*	[1.618]*
Years of schooling	0.085	0.085	0.085	0.064	0.064	0.064	3.153	3.153	3.153
	[0.025]***	[0.025]***	[0.025]***	[0.028]**	[0.028]**	[0.028]**	[0.626]***	[0.626]***	[0.626]***
Time		0.006	-0.005		0.025	0.03		0.562	0.562
		[0.005]	[0.006]		[0.005]***	[0.006]***		[0.125]***	[0.142]***
Got a job X Time			0.033			-0.015			-0.001
			[0.013]**			[0.013]			[0.399]
Constant	-0.707	-0.735	-0.683	-0.848	-0.974	-0.997	-43.564	-46.373	-46.375
	[0.416]*	[0.416]*	[0.418]	[0.438]*	[0.439]**	[0.440]**	[8.721]***	[8.787]***	[8.907]***
Observations	2043	2043	2043	2043	2043	2043	2043	2043	2043
R-squared	0.05	0.05	0.04	0.09	0.11	0.11	0.1	0.12	0.12
Stratification cell FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ave of dep variable (no job)		0.609			0.411			5.229	

Notes:

The regressions are IV estimates, whereby dummy indicators for the assigned job probability treatments (0-,1-,5-,50-,75- and 100-percent chance of alternative work) are used to instrument for the outcome of interest.

Each month of the retrospective calendar history is used to determine whether the individual engaged in any job search that month, whether or not they were employed and what their average daily wage was. Time is defined by months, the first month after the experiment is coded as 1, the following month 2, up to 9.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Table 7: Heterogeneity in Impacts

Dependent Variable:	**Avg number of hrs**		**Avg daily wage (incl. Unemployed)**	
	(1)	**(2)**	**(3)**	**(4)**
Got a job	4.618	4.694	4.418	4.067
	[2.901]	[3.218]	[1.626]***	[1.802]**
Ability score X Got job	-5.697		-3.137	
	[2.532]**		[1.392]**	
Ability score	4.218		-1.199	
	[4.017]		[1.613]	
Ever worked X Got job		3.922		3.481
		[5.606]		[2.518]
Ever worked		0.795		1.139
		[2.598]		[0.982]
Ever worked with recruiter				
Ever worked with recruiter X Got job				
Constant	-28.709	-27.334	-22.448	-38.869
	[19.064]	[19.473]	[19.980]	[9.427]***
Stratification cell FE's	No	Yes	Yes	No
Other covariates?	Yes	Yes	Yes	Yes
Observations	227	227	227	227
R-squared	0.16	0.15	0.21	0.21
Ave of dep variable (no job)	16.557		5.196	

Notes:

The regressions are IV estimates, whereby dummy indicators for the assigned job probability treatments (0-,1-,5-,50-,75- and 100-percent chance of alternative work) are used to instrument for the outcome of interest.

Ave hours worked per week is computed using a retrospective calendar history, and is calculated as the average number of hours worked per week on the individuals' main job by month. The average daily wage is also calculated using the restrospective job work history. The average daily wage is calculated as the average wage on the individual's main job in the last month. For Columns 4 through 6 - those who are unemployed are coded as 0's, whereas for Columns 7 through 9 they are coded as missing.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Table 8: Channels

Channel:	**Networks**		**Skill acquisition**	**Signalling**	**Expectations**
Dependent Variable:	**Heard about work?**	**Found employment?**	**Research position?**	**Used reference letter**	**Reservation wage (Month)**
	(1)	**(2)**	**(3)**	**(1)**	**(2)**
Got a job	0.169	0.009	0.181	0.274	-4.759
	[0.072]**	[0.038]	[0.071]**	[0.059]***	[30.919]
Constant	0.194	-0.137	-1.414	-0.042	-1,173.55
	[0.626]	[0.294]	[0.550]**	[0.409]	[320.635]***
Stratification cell FE's	Yes	Yes	Yes	Yes	Yes
Other covariates?	Yes	Yes	Yes	Yes	Yes
Observations	215	214	216	216	221
R-squared	0.1	0.06	0.16	0.2	0.24
Ave of dep variable (no job)	0.299	0.068	0.284	0.047	344.052

Notes:

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Appendix Table 1: Returns to Work Experience: Extensive Margin (OLS)

Dependent Variable:	% Months worked			% Months looked for work			Number jobs last month?		
	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(5)	(6)
Got a job (instrumented)	0.003	0.002	0.001	0.072	0.078	0.072	-0.064	-0.097	-0.092
	[0.055]	[0.054]	[0.051]	[0.049]	[0.050]	[0.049]	[0.085]	[0.107]	[0.104]
Age			0.014			0.009			0.006
			[0.007]**			[0.007]			[0.012]
Married			0.115			-0.112			0.16
			[0.095]			[0.090]			[0.120]
Ever worked			0.075			0.082			-0.017
			[0.030]**			[0.026]***			[0.083]
Constant	0.428	0.624	-0.823	0.605	0.849	-0.556	0.529	0.657	0.731
	[0.029]***	[0.106]***	[0.458]*	[0.027]***	[0.081]***	[0.421]	[0.068]***	[0.126]***	[1.406]
Stratification cell FE's	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other covariates?	No	No	Yes	No	No	Yes	No	No	Yes
Observations	227	227	227	227	227	227	227	227	227
R-squared	0	0.11	0.19	0.01	0.04	0.09	0	0.17	0.18
Ave of dep variable (no job)		0.600			0.422			0.523	

Notes:

The %months looked for work is computed using a retrospective calendar history, and is calculated as the number of months the individual actively sought work over the last 8 months, divided by 8. Similarly, % months employed is calculated as the number of months the individual was employed over the last 8 months, divided by 8.Lastly, the average number of concurrent jobs is the average of the total number of jobs held each month across the 8 month period.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.

Appendix Table 1: Returns to Work Experience: Extensive Margin

Dependent Variable:	**% Months worked**			**% Months looked for work**			**Number jobs last month?**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Got a job (instrumented)	0.111	0.13	0.117	0.119	0.137	0.118	-0.002	-0.012	-0.002
	[0.099]	[0.098]	[0.092]	[0.091]	[0.092]	[0.089]	[0.150]	[0.174]	[0.163]
Age			0.013			0.008			0.006
			[0.007]*			[0.007]			[0.012]
Married			0.122			-0.108			0.165
			[0.095]			[0.090]			[0.120]
Ever worked			0.079			0.088			-0.018
			[0.029]***			[0.026]***			[0.087]
Constant	0.402	0.582	-0.912	0.599	0.829	-0.64	0.509	0.629	0.726
	[0.033]***	[0.099]***	[0.448]**	[0.030]***	[0.099]***	[0.427]	[0.075]***	[0.122]***	[1.475]
Stratification cell FE's	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other covariates?	No	No	Yes	No	No	Yes	No	No	Yes
Observations	227	227	227	227	227	227	227	227	227
R-squared		0.09	0.18	0	0.03	0.09	0	0.16	0.17
Ave of dep variable (no job)		0.600			0.422			0.523	

Notes:

The regressions are IV estimates, whereby dummy indicators for the assigned job probability treatments (0-,1-,5-,50-,75- and 100-percent chance of alternative work) are used to instrument for the outcome of interest.

The %months looked for work is computed using a retrospective calendar history, and is calculated as the number of months the individual actively sought work over the last 8 months, divided by 8. Similarly, % months employed is calculated as the number of months the individual was employed over the last 8 months, divided by 8.Lastly, the average number of concurrent jobs is the average of the total number of jobs held each month across the 8 month period.

Stratification cell fixed effects are included as the randomization was conducted by stratifying on baseline ability and whether the individual had ever worked with the recruiter previously. The additional covariates controlled for in the regression include: age of respondent, marital status, any prior work experience and the number of years of schooling completed. *** denotes statistical significance at the 1 percent level, ** 5 percent level, and * 1 percent level. Robust standard errors are reported.