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Informed job entry

Does labour market information speed job-taking in Mozambique?

Ricardo Santos, Sam Jones, and Gimelgo Xirinda*

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Abstract: High youth unemployment rates and long school-to-work transition times pose a threat to low-income countries' sustainable growth prospects. Using a randomized control trial experiment conducted in Mozambique, we find strong evidence that providing information on wages and unemployment reduces the time that university graduate job-seekers take to become employed, with different levels of efficacy depending on the type of information provided. This relatively low-cost mechanism can, therefore, reduce labour market frictions at the point of entry, contributing to a quicker intake of qualified human capital into economies where it is relatively scarce.

Key words: school-to-work, labour, information, randomized control trial

JEL classification: C41, J64, I23, O15

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* All authors: UNU-WIDER, Maputo, Mozambique; corresponding author: ricardo.santos@wider.unu.edu

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Information and requests: publications@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

To most young people, the moment of getting their first job out of school is a life-changing one. School-to-work transition (SWT) is seen as a rite of passage (Goodwin and O'Connor 2007), one of the changes involved in the transition to adulthood (Young et al. 2011). It is also fraught with uncertainty and longer than most would expect. With length come costs. Prolonged unemployment spells during youth can affect mental and physical health, linked to stress, depression, and illness later in life (Lundberg and Wuermli 2012). In addition, a prolonged period of unemployment waiting for the first job out of school or a first job that offers no opportunities for learning and growth can potentially hurt future productivity and function as a negative signal towards prospective employers (Filmer and Fox 2014; Kroft et al. 2013).

In this study we investigate how access to up-to-date information about labour market indicators can impact the duration of the SWT. With this purpose, we randomly assigned students to receive information via Short Message Service (SMS) about peer employment rates and the average wages of those employed. We established three different treatments, differentiating the peer reference groups from which the indicators were calculated: a first treatment branch with general information collected from all survey participants; a second differentiating information according to each specific university peer group; and a third differentiating information according to each specific study-area peer group.

The context is Mozambique, a low-income country (LIC). Not dissimilar to what is recorded in the Global North, many LICs struggle with high youth unemployment rates (Scelta et al. 2019), together with challenges of long SWT times (Nilsson 2019). While there is, therefore, ample research suggesting that this is a global phenomenon, Nilsson (2019: 746) finds that 'the lion's share of the evidence from school-to-work transitions is based on data from high-income countries, essentially from Europe and North America'. Furthermore, there are reasons to expect differences in nature and degree in the Global South. This is powerfully illustrated by Bridges et al. (2017), who found that in urban Tanzania the average duration of unemployment for new labour market entrants was above four years for those transitioning into self-employment and above five years for those that eventually became wage-employed. In Mozambique, Jones et al. (2020), using this study's survey data, estimate that one year after the end of their senior university year, 37% of students were unemployed, with only 32% having a steady job and 14% doing casual work,[1] percentages that changed to 23%, 45%, and 16%, respectively, by the end of the panel survey six months later.

The literature has long established the penalizing effect of unemployment duration on job attainment (Heckman and Borjas 1980; Schweitzer and Smith 1974). More recent evidence (Arulampalam et al. 2000) confirms what is now named the 'stigma effect' (per Berkovitch 1990), a stylized fact as stated by Unt and Täht (2020) and Lopes (2021). Furthermore, Krug et al. (2019) find evidence that some longer-term unemployed job-seekers are conscious of this stigma and, while reacting and intensifying their job-seeking efforts, do not have better chances to get employed. In light of this, there is a clear need to find and implement policies that may reduce job-seekers' unemployment time, particularly young entrants as they transition from school.

Information can be one valuable tool to help address long SWT times. It is considered an essential tool to improve markets' performance, particularly in developing settings where informational problems are seen as critical barriers to growth and development (Dammert et al. 2015). Some studies on how students react when receiving new information show they update expectations and adjust their behaviour. Wiswall and Zafar (2015) found that university students in the United States updated their wage expectations in response to further information. Using this study's survey data, Jones and Santos

[1] The remainder were found to be in internships (7%), still studying (3%), or inactive (7%).

(2020) found that university graduate job-seekers in Mozambique also update wage expectations when receiving peer-level information, with heterogeneous responses to the granularity and signal of the information received. Altmann et al. (2018) found that providing information to unemployed individuals via a brochure increased job finding among individuals with low re-employment prospects. Gee (2019) found that giving job-seekers information about the number of other applicants increased applications, with women responding more than men. Dammert et al. (2015) found that providing individuals with up-to-date information about vacancies via SMS increased employment in the short run. This paper seeks to contribute to this growing yet still scarce literature.

In this experimental duration study, where the success event is the attainment of the first job after university, we find significant and robust causal evidence that offering university students access to labour market information will lead to quicker entrance into the labour market. Focusing on the most robust evidence, we find particular effects of information regarding the entry salary of university graduates. We find that this acceleration of job intake does not appear to result in worse working conditions, either objectively or subjectively as perceived by job entrants. We also find a strong suggestion that this job-start acceleration results from a more active adoption of job-search strategies, particularly those found to be more effective in Mozambique: support of family and friends, job advert searches on TV and the media, and job advert searches on the internet.

The rest of the paper proceeds as follows. In Section 2 we present the survey and experiment designs. In Section 3 we briefly describe the underlying data and establish sample balance. In Section 4 we describe the survival analysis approach used, followed by Section 5 with the results and robustness checks. Section 5.2 presents a debate on the quality of jobs attained and strategies used for achieving them. Section 6 concludes.

2 Survey design

In March 2017 we started a longitudinal school-to-work survey of Mozambican university students, comprising students in their final year of undergraduate studies. The baseline survey was conducted at six of the largest universities, which jointly teach approximately three-quarters of Mozambican students. The universities were: Universidade Eduardo Mondlane (UEM), Universidade Pedagógica (UP), Universidade Politécnica (AP), and Universidade São Tomás de Moçambique (USTM) in their Maputo campuses; Universidade Católica de Moçambique (UCM) and Universidade Zambeze (UZ) in their Beira campuses. A total of 27 faculties participated, allowing us to survey students from 106 different courses; 2,174 finalists were surveyed at the baseline (1,024 women and 1,150 men). The courses were grouped into seven distinct study fields: (1) *Education*; (2) *Languages and Humanities*; (3) *Social Sciences*, *Management and Law*; (4) *Natural Sciences*; (5) *Engineering*, *Industry and Construction*; (6) *Agriculture*; and (7) *Health and Welfare*.[2] At the baseline, participants provided socio-demographic information, namely on their province of origin, age, gender, marital status, and on whether they already had children, the highest level of education and the most significant sector of work within their household. They also provided information on self-assessed knowledge of English and responded to simplified Raven's, verbal, and numeric skill tests and a locus of control questionnaire. Finally, they informed about whether they had a job before, had interned before, or had a job waiting.

[2] The survey baseline sample size for a theoretical proportion p of 50% respondents finding a job, with a confidence interval $(1-\alpha)$ of 95% and as per Cochran (1977), allows for error margins of 1.7% in the total sample, of up to 2.4% in each gender subsample, and up to 6.3% in the least represented study field. The implementation of both baseline and follow-up phone surveys is further explained in Jones et al. (2018, 2020).

Following the baseline and from March 2018, survey participants were tracked every quarter by telephone over 18 months (i.e. over six rounds) to the end of 2019. All phone primary and secondary numbers were tested in preparation for this follow-up phase. Of those surveyed in the baseline, 2,100 agreed to remain in the follow-up sample and participated in the survey experiment.

Starting from the second round of the follow-up phone survey, we conducted an experiment to investigate the effects of labour market information on job-seekers' beliefs, discussed in Jones and Santos (2020), and on labour market outcomes, most notably on unemployment duration for university graduates.

For that purpose and in each survey round, we elicited detailed information about participants' work status—that is, whether they were working or not; if they were not working, whether they were looking to work (i.e. unemployed), whether they were studying, or whether they were neither studying nor looking for work (inactive); if they were working, whether they had taken an internship, casual work, or a steady job; in which sector of activity they were working; their perceptions of the quality of their work (including whether it was linked to their studies and they were looking or not for a different job) and self-reported objective job-quality indicators (whether it was a full-time and a permanent job, they had a written contract, and were registered in social security); and, finally, their wages.

We used the information from each prior round to design three distinct information treatments:

1. *General message:* summarized wage and employment information from the entire sample—for example, 'Survey results at Dec.1st: of all graduates in Mozambique (class of 2017), 59% are working and their average wage = 14,000 Mts/month.'
2. *University-specific message:* summarized wage and employment information from the subsample of participants that attended the same university as the recipient—for example, 'Survey results at Dec.1st: of all graduates from your university (class of 2017), 52% are working and their average wage = 24,000 Mts/month.'
3. *Field-specific message:* summarized wage and employment information from the subsample of participants in the same study field as the participant—for example, 'Survey results at Dec.1st: of all graduates from your area of studies (class of 2017), 50% are working and their average wage = 13,500 Mts/month.'

The information messages were sent by SMS at the beginning of each telephone survey round, excluding the first. As they were based on previous information up to the time the SMS was sent, the information contained in each SMS varied by survey round. Also, in the second and third types of messages, the information changed by individual according to the specific university they had attended or their field of study.

Regarding exposure to the treatments, individuals were randomly allocated directly after the baseline survey to one of five arms, distinguished by the type of information treatment they would receive. Specifically:

- The *control* group received no information messages.
- Group one (*general*) received the general (all-student) message in all relevant rounds.
- Group two (*university*) received the university-specific message in all relevant rounds.
- Group three (*field*) received the field-specific message in all relevant rounds.
- Group four (*mixed*) received the general message in the second round, the university-specific message in the third and fourth rounds, and the field-specific message in the following rounds.

Randomization across the five experimental arms was stratified by study field and gender, with a target of around 500 participants in the control group and 400 in each experiment arm.

The first row of Table 1 presents the initial allocation (undertaken after the baseline was concluded). The remaining rows show the number of responders over the follow-up rounds and by treatment arm, indicating very low attrition experienced throughout the survey (reaching a maximum of 12% in the last round). We also find minor differences in attrition across the arms, with a higher than average attrition (16.1%) in the control group, lower than average (7.8%) in the 'general information' treatment group, and average attrition levels among the remaining treatment groups. Overall, the realized experiment is well-powered.[3]

Table 1: Observations across survey rounds, by experimental arm

	Experimental arm						
Round	Cont.	Gen.	Uni.	Field	Mixed	Total	% base
Baseline	504	397	400	398	401	2,100	1.00
1	486	393	390	390	392	2,051	0.98
2	473	389	379	377	386	2,004	0.95
3	456	381	376	375	383	1,971	0.94
4	439	377	367	366	372	1,921	0.91
5	428	372	361	359	360	1,880	0.90
6	423	366	353	350	357	1,849	0.88

Note: cells report the raw number of observations by the experimental arm and round number; the final column gives the overall follow-up rate relative to the baseline sample.
Source: authors' calculations based on survey responses.

3 Descriptive statistics

Table 2 summarizes the participants' main characteristics along the experiment arms, indicating a balanced sample. The set of participants is relatively close to gender parity, with almost 45% female participants. The average age is close to 26 years, suggesting a delay of four years in achieving an undergraduate level of education, either due to late entry into primary school, grade repetition, or both, or a possible gap between secondary school and university. While nearly one-third of participants reported having children, only 12–16% are married. Meagre proportions of participants registered to have information on employment opportunities (around 20%) or had a job waiting (around 12%), despite more than half (around 60%) having had prior work experience.

Participant distribution by field of study and university is shown to be balanced across the experiment arms. Close to one-third of participants studied in the Education field, and almost half in Social Sciences. The remainder is distributed between Engineering, Health, Agriculture, Natural Sciences, and Languages and Humanities. Most participants studied at the leading national universities, UEM and UP. These are followed by the Beira campuses of UCM and UZ, and the two Maputo private universities of AP and USTM.

Tables 3 and 4 synthesize the different information sent to participants. Table 3 shows the percentage of survey participants working and their average wage, both of which increased throughout the 18 months of follow-up. The rate of working participants increased from around 34% to close to 60%, while the average wage of employed participants increased from about 10,000 to slightly above 14,000 meticais for each treatment group.

[3] Using the subsamples obtained in the last round, a t-test of differences in proportions between treatment and control groups (jointly) would be expected to detect a difference in response rates of around 7 percentage points with a power of 80% at the 5% significance level.

Table 2: Descriptive statistics

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
Age	26.11	25.63	25.84	25.83	26.18	0.783
	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	.
Female	0.44	0.44	0.45	0.45	0.44	0.995
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Married	0.15	0.13	0.12	0.16	0.14	0.516
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Has children	0.29	0.29	0.30	0.35	0.28	0.263
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had job before	0.62	0.61	0.61	0.58	0.60	0.921
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had internship before	0.49	0.49	0.53	0.53	0.50	0.941
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had a job waiting	0.15	0.12	0.12	0.12	0.10	0.545
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Education	0.31	0.30	0.32	0.32	0.30	0.885
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Language and Humanities	0.02	0.02	0.02	0.01	0.02	0.687
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Social Sciences	0.44	0.45	0.45	0.44	0.45	0.954
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Natural Sciences	0.04	0.04	0.04	0.04	0.04	1.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Engineering	0.08	0.08	0.08	0.08	0.08	0.997
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Agriculture	0.05	0.05	0.05	0.05	0.06	0.926
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	.
Health	0.06	0.06	0.06	0.06	0.06	0.983
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
UEM	0.36	0.36	0.35	0.34	0.34	0.988
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
UCM	0.08	0.10	0.09	0.09	0.09	0.849
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
UZ	0.11	0.11	0.10	0.09	0.11	0.975
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
USTM	0.05	0.05	0.07	0.06	0.03	0.061
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	.
UP	0.34	0.31	0.36	0.38	0.38	0.502
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
AP	0.06	0.07	0.03	0.04	0.04	0.254
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, N = 2,069; 'F-test' reports the probability that the means in the treatment arms jointly differ; abbreviations UEM–AP refer to universities (dummy variables); study fields are given in the second panel (dummy variables).

Source: authors' calculations based on survey responses.

Table 3: SMS information by round, averages

	Gen.		Uni.		Field	
Round	% working	Avg. salary	% working	Avg. salary	% working	Avg. salary
2	34.0	9.81	33.1	10.32	33.1	10.75
3	43.0	10.80	43.3	11.20	43.2	11.35
4	48.0	10.68	47.1	10.90	46.7	11.25
5	46.0	12.55	45.5	13.32	45.4	13.33
6	59.0	14.15	59.1	14.40	58.3	14.70

Note: average salary in thousand meticais.

Source: authors' calculations based on survey responses.

Table 4: Descriptive statistics: information treatments by arm

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
SMS employment info	0.00	38.35	38.43	38.50	38.47	0.168
	(0.00)	(0.39)	(0.43)	(0.43)	(0.42)	.
SMS salary info	0.00	9.67	9.83	9.85	9.76	0.318
	(0.00)	(0.10)	(0.11)	(0.11)	(0.11)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, N = 2,069; 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

This suggestion is reinforced in Table 4. It shows that the information received is statistically similar among the four experiment arms. If the information provided was statistically the same among all participants, the only difference in the information provided was the mention of the reference group from which it was sourced. It is, therefore, reasonable to assume that the reference group is the only statistically significant difference between information treatments. Descriptive statistics and sample balance statistics for all control correlates are presented in Tables A1–A4.

4 Method

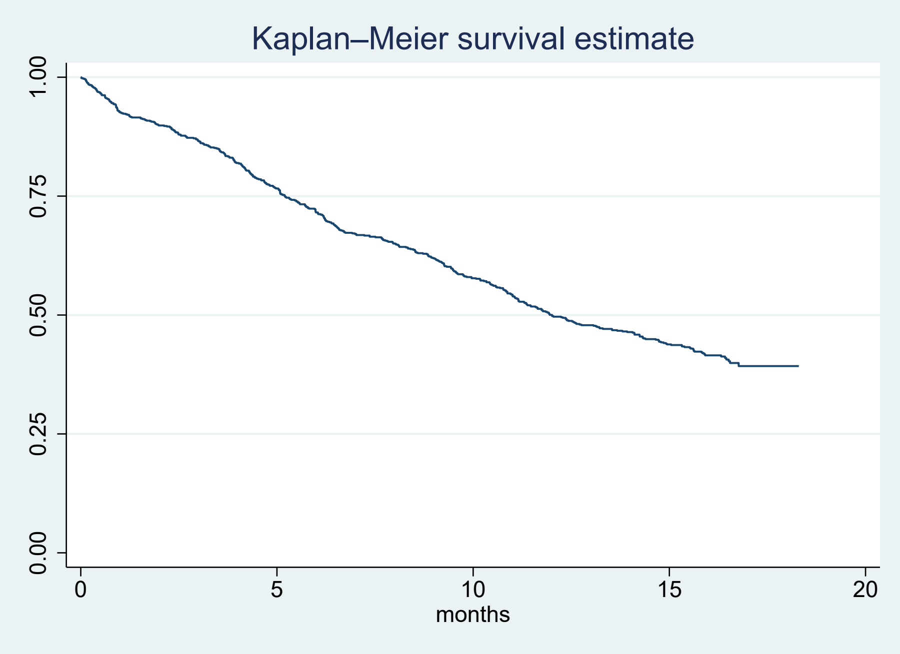
This study focuses on the time taken by young Mozambican graduates to find their first job out of university. It is, therefore, a time-to-event analysis adopting an empirical strategy akin to the one adopted in studies on the Spanish (Cordón-Lagares et al. 2022), German (Teichert et al. 2023), Taiwanese (Chuang 1999), and Italian labour markets (Sciulli and Signorelli 2011), or on nine European countries (Salas-Velasco 2007).[4] Here, survival time is a continuous variable corresponding to the duration between the first date of the follow-up survey and the event of finding a job, measured in months. In this study, that job can be with a permanent contract, fixed term, or casual/occasional.[5] Figure 1 depicts the estimated non-parametric Kaplan–Meier (KM) survival curve for the entire sample.

The figure shows a relatively stable pace of job entry and a slow intake. Three months after graduating, only around 10% of surveyed students had found a job, while it took about one year for half of the sample to be employed. Furthermore, by the end of the survey, one and a half years after graduation, 40% of the sample still hadn't found a job.

[4] This last study analyses SWT in Austria, Finland, France, Germany, Italy, the Netherlands, Norway, Spain and the UK.

[5] It does not include internships.

Figure 1: All sample



Source: authors' compilation based on survey responses.

In our empirical approach, we adopt a parametric Gompertz proportional hazard function formulation, $h(t)$:

$$\begin{aligned} h(t) &= h_o(t)\exp(X_i\beta), \text{ with} \\ h_o(t) &= \exp(a)\exp(\gamma t) \end{aligned} \tag{1}$$

where $h_o(t)$ denotes the baseline hazard—that is, the standard (positive) likelihood of finding the first job after graduation in time t, given that the participant had not found a job before. The Gompertz proportional hazard formulation is found to be suitable for modelling data with monotone hazard rates, as is evident in Figure 1.[6] The estimate of γ gives this monotonic transition rate into employment. A negative estimate indicates a hazard function decreasing in time.

The empirical model, in general terms, can be constructed as:

$$h(t) = \exp(\gamma t)\exp(a + X_i'\beta) \tag{2}$$

A proportional hazard function formulation assumes that the other parameters, other than γ, indicate an expectation of a proportional shift, up or down, of the hazard function.

For our analysis, we consider three increasingly complete formulations of the X_i matrix:

$$h(t) = \exp(\gamma t)\exp(a + Info_i\theta) \tag{3}$$

In the first, simplest formulation of Equation (3) we test a possible effect of having received labour market information, $Info$ (1 if the participant received an SMS with information on the share of survey participants working and their average wage), without testing for different reactions by participants to the type of information received.

As it aggregates all the differentiated information provided through the treatment SMS, this formulation averages out any possible differences in value attributed by treated participants to the information

[6] The Gompertz was selected as, in preliminary tests, it produced the lowest AIC scores. The alternative parametric distributions, exponential and Weibull, were used for robustness testing, discussed below. The exponential hazard function produced the lowest BIC score.

received. The following formulations seek to shed light on this:

$$h(t) = \exp(\gamma t)\exp(a + Gen_i\delta_1 + Uni_i\delta_2 + Field_i\delta_3) \tag{4}$$

In the second formulation, Equation (4), we differentiate the information treatment according to the typology. In this formulation, we consider three mutually exclusive covariates: *Gen* (1 if the participant received an SMS with information on the share of all participants working and their average wage); *Uni* (1 if the participant received an SMS with information on the share of participants from her university working and their average wage); and *Field* (1 if the participant received an SMS with information on the share of participants that completed studies in the same study field working and their average wage).

While this formulation has the potential to uncover possible differences in the attribution of informative value to the information received by treated participants, it still averages out the effects of the differentiated employment and wage statistics supplied to the treated participants. It also does not account for the different characteristics of participants.

$$\begin{aligned} h(t) = \exp(\gamma t)\exp(a + Gen_i\delta_1 + Uni_i\delta_2 + Field_i\delta_3) + \\ + Salary_{it}\delta_4 + Empl_{it}\delta_5 + \\ + Uni_i \times Salary_{it}\delta_6 + Field_i \times Salary_{it}\delta_7 + \\ + Uni_i \times Emp_{it}\delta_8 + Field_i \times Emp_{it}\delta_9 + X_i'\beta \end{aligned} \tag{5}$$

In the final formulation, Equation (5), we fully use the wealth of information provided to those participants who received treatment and of known individual characteristics at the baseline. We add, therefore, the following information treatment covariates: the salary information received by participant i immediately before time t, $Salary_{it}$, the information received by participant i on the share of their peers employed immediately before time t, $Empl_{it}$; interaction between salary and employment information and the reference group, specifically all university peers (Uni_i) or peers from the same field of study ($Field_i$). We centred the data on SMS *Salary* and *Employment* messages by transforming them into deviations from the sample mean.

The matrix of control correlates, X_i, encompasses the following variables characterizing the participants: age; gender (1 if female); whether the participant is married (1 if yes); whether the participant considers having information about potential jobs (1 if yes); whether they had a job waiting at the baseline (1 if yes); whether they had prior work experience; the highest level of education in the household; the most prevalent type of job in the household; the province of residency; university of graduation; study area; standardized grades in the Raven's test; the academic (literacy and numeracy) tests; locus of control; and self-assessed quality in English.

5 Results

We present the main results of our study in Table 5. In column (1) we present the results of the empirical model presented in Equation (3). In column (2) we offer the results of the model presented in Equation (4). In column (3) we present the complete model, as per Equation (5).

The results of the 'Info Type' model of Equation (4), presented in column (2), already suggest the value of providing access to labour market information. While only with a 10% significance level, before considering the relative differences in information received and before adding individual controls, we find that those who received field-of-study-specific labour market information were 26% more likely to take a job than participants in the control group.

Table 5: Gompertz regressions: experiment

	(1) Simple	(2) Info Types	(3) Full Model
Analysis time when record ends			
Treated	1.05		
	(0.11)		
Gen.		0.86	1.07
		(0.11)	(0.17)
Uni.		1.03	1.06
		(0.13)	(0.14)
Field		1.26*	1.25*
		(0.15)	(0.17)
SMS salary info			1.43**
			(0.24)
SMS employment info			0.99
			(0.03)
Uni. × salary info			0.75*
			(0.13)
Field × salary info			0.74*
			(0.13)
Uni. × empl. info			1.04
			(0.03)
Field × empl. info			1.03
			(0.03)
Obs.	3,667	3,667	3,651
Log likelihood	–1,200.65	–1,196.16	–1,087.81
Gamma	–0.00	–0.01	–0.03
AIC	2,407.30	2,402.32	2,295.61
BIC	2,425.92	2,433.36	2,667.78
Individual controls	No	No	Yes

Note: significance: * 10%, ** 5%, *** 1%. Column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for both the reference groups and the information on peer salaries and peer employment. Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (p-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

Following the complete model, we find that, in each month of follow-up, for each 1,000 meticais above the average communicated salary communicated via SMS, the likelihood of job-taking among those receiving the general information was 42% higher than control survey participants. This information effect on job-taking was mitigated for those who received university- and field-specific information. By calculation, we find an estimate of 7.25% increase in the likelihood of job-taking for each 1,000 meticais above the average among those who received university-specific information. For those who received field-specific information we find an intrinsic 25% higher likelihood of job-taking, compared with those in the control group. However, the estimated increase in job-taking per 1,000 meticais above the average salaries communicated by SMS is lower when the information is field-specific: 5.82%. It should be recalled that, as shown in Table 3, the average salary that was communicated to treated participants increased in every round. To be more specific, we find that those who received general SMS messages only received above-average peer salary information immediately before the fifth survey round. Depending on the university, treated participants from this arm may have received above-average peer salary information immediately before the second or the third round, while participants from two universities only received this information immediately before the fifth or sixth rounds. Similarly, those who received field-specific salary information, having graduated from Natural Sciences, Engineering, Health, or Social Sciences, received above-average salary information at much earlier rounds than other colleagues. As university and field fixed effects are assumed in the complete model and treated participants were randomly and equally distributed, we infer that the causal effects occur despite and not because of the university and field that treated participants come from. We find no evidence that treated participants reacted to employment information.

Table 6: Gompertz regressions: controls

	(3) Full model
Analysis time when record ends	
Female	0.61***
	(0.06)
Has children	1.31*
	(0.22)
Sofala	0.45***
	(0.12)
UCM	2.28**
	(0.74)
UZ	2.17***
	(0.59)
UP	0.68**
	(0.12)
AP	0.66*
	(0.15)
Had job before	1.40***
	(0.14)
Had internship before	1.67***
	(0.19)
Limited English	1.35**
	(0.18)
Professional English	1.54**
	(0.31)
Fluent in English	2.17***
	(0.63)
Obs.	3,651
Log likelihood	–1,087.81
Gamma	–0.03
AIC	2,295.61
BIC	2,667.78
Individual controls	Yes

Note: significance: * 10%, ** 5%,*** 1%. Column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for both the reference groups and the information on peer salaries and peer employment. Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (*p*-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

We present interesting correlations in Table 6. While not causal, they are suggestive. The results suggest that in any given month, women participants may be 39% less likely to take a job than men. Participants with children, however, appear 32% more likely to do so. Participants residing in Sofala appear to be 66% less likely to find a job in any given month than those living in Maputo (the base category). This indication can be compensated by the suggestion that those who study at the Sofala campuses of UCM and UZ appeared to be twice as likely to take a job in any given month than those who studied at UEM (all other variables being equal). However, students who graduated from UP appear to be more likely to wait longer for a job.[7] Participants who had worked before were 40% more likely to find a

[7] It is essential to note that a significant proportion of UP graduates were employed while studying. These results apply, therefore, to the remaining UP students.

job at any given month of the survey, while those who had interned before were 67% more likely to do so. Knowledge of English significantly improved employability, with increasing efficacy the higher the proficiency: 35% more likely to get a job in any given month than the base for those with limited English, 54% more likely for those with professional proficiency in English, and 116% for those fluent in English.[8]

5.1 Robustness

While the results suggest a positive impact of providing labour market information to university graduate job-seekers, the literature warns of risks that such a result depends on the functional form of $h(t)$. This section discusses this possibility using the results presented in Table 7. Columns (1) and (2) present two alternative proportional hazard functions, exponential and Weibull.[9]

Column (3) presents a PH Gompertz approach to frailty. As explained by Hougaard (1995), a survival regression with frailty accounts for the effects of unobserved heterogeneity on participants' survival (in this case, the time to the first job after graduation). Reassuringly, the results assuming frailty barely change when compared to our primary model.

Table 7: Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Proportional hazards			Accelerated failure time			No attrition
	Exponential	Weibull	Gompertz with Frailty	Exponential	Weibull	Lognormal	
Analysis time when record ends							
SMS salary info	1.36*	1.37*	1.43**	0.74*	0.71*	0.51**	1.55**
	(0.22)	(0.23)	(0.23)	(0.12)	(0.13)	(0.15)	(0.29)
SMS employment info	0.98	0.99	0.99	1.02	1.01	1.02	0.99
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)
Gen.	1.01	1.06	1.16	0.99	0.93	0.57**	0.96
	(0.16)	(0.17)	(0.20)	(0.15)	(0.16)	(0.16)	(0.16)
Uni.	1.02	1.08	1.19	0.98	0.92	0.60**	0.97
	(0.14)	(0.16)	(0.19)	(0.13)	(0.15)	(0.14)	(0.14)
Field	1.18	1.25	1.40**	0.85	0.79	0.50***	1.15
	(0.16)	(0.18)	(0.22)	(0.11)	(0.12)	(0.11)	(0.16)
Uni. × salary info	0.78	0.77	0.75*	1.29	1.32	1.73*	0.68**
	(0.13)	(0.13)	(0.12)	(0.21)	(0.24)	(0.50)	(0.13)
Field × salary info	0.77	0.76	0.74*	1.30	1.34	1.75*	0.68**
	(0.13)	(0.13)	(0.12)	(0.22)	(0.25)	(0.51)	(0.13)
Uni. × empl. info	1.04	1.04	1.05	0.96	0.96	0.90**	1.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Field × empl. info	1.03	1.03	1.03	0.97	0.97	0.92*	1.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Obs.	3,651	3,651	3,651	3,651	3,651	3,651	3,267
Log likelihood	–1,091.11	–1,089.76	–1,100.26	–1,091.11	–1,089.76	–1,094.17	–953.84
AIC	2,300.22	2,299.52	2,296.51	2,300.22	2,299.52	2,308.33	2,025.67
BIC	2,666.19	2,671.68	2,594.24	2,666.19	2,671.68	2,680.50	2,385.08
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Columns present the complete model under different stochastic specifications; the model in column (1) assumes a PH Gompertz $h_0(t)$ function; in column (2) a PH Weibull function; in column (3) a PH exponential function with frailty; in column (4) an AFT (accelerated failure time) exponential failure function; in column (5) an AFT Weibull function; in column (6) an AFT lognormal function; in column (7) a PH exponential function with no attrition. Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (*p*-values) are calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

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[8] It should be remembered that knowledge of English was self-assessed by participants. This result suggests that, as far as employability is concerned, their assessment was valid.

[9] The AIC statistic in column (3) of Table 6 is notably lower than those in columns (1) and (2) of Table 7. Therefore, we decided to use the Gompertz function as the preferred one.

Overall, the comparison between the estimates of the experiment full model, in column (3) of Table 6 and those in columns (1)–(3) of Table 7 points to the robustness of the effect of wage information on the time to the first job after graduation, suggesting that, in each month of follow-up, for each 1,000 meticais communicated via SMS the likelihood of job-taking among treated participants was 36–43% higher than among control survey participants.

Columns (4)–(6) present a different hazard function distribution typology. Rather than 'failure' odds ratios, the accelerated failure time (AFT) function coefficient estimates report the ratio of median survival times—that is, the proportional difference between the median survival time, by unit of the correlate, of those treated and those in the control group. As an example, the significant 0.57 estimate for general information on peers, in column (6), indicates that those who received the SMS general information were more likely to speed up job-taking, with an estimated 43% lower median time before first job out of university for this group in comparison to the control group. Again, the AFT regression estimates confirm the robustness of our results: there are beneficial effects of receiving information on entry wages of university graduates, namely on quicker uptake of a job after graduation.

Finally, column (7) presents the results of a Gompertz proportional hazard survival regression with only participants who did not drop from the panel before survival, to account for possible attrition bias. The results suggest that attrition did not significantly bias our results.

In summary, we find a robust indication that, after graduating from university, job entrants enter the labour market sooner by learning of higher salaries among their peers who have already found a job. Less robust results suggest that those who received university- and field-specific information of higher salaries found a job even earlier than those who received more general information.

5.2 Discussion

While the results of our trial indicate that, by accessing information on entry wages, university graduates are likely to find a job quicker, it is possible to assess whether that comes with a cost. More specifically, it could be argued that a trade-off exists between taking a job sooner and the quality of the job taken, objectively and subjectively perceived. We discuss this possibility in the following paragraphs. We also discuss the mechanism by which accessing job market information leads to a quicker job uptake, namely by adopting more effective job-seeking strategies.

On a possible trade-off between quicker job uptake and quality of job attained by treated participants

While there is causal evidence of quicker job uptake by those who received news of higher entry wages earned by their peers, summary statistics of objectively perceived work conditions in Table 8 suggest there is no evidence of significant differences. The average monthly salary stayed closely above 10,000 meticais among those in control (no information), general, and university-specific information arms, while significantly above, around 12,000 meticais for those that received field-specific information. Only close to one in three registered in Mozambique's national insurance (INSS), the contract type profile (around 55% occasional, 25% fixed term, and 20% indefinite duration) isn't significantly differentiated and around 60% of the jobs attained were full-time.

In Table 9 we find a suggestion that the subjective assessment of the attained job's quality may also not have been different. Only around half of jobs attained were considered related to the job-entrant's course, irrespective of treatment arm. There is a suggestion that a higher proportion, close to 30%, of those in the control group that found their first post-graduation job found it in the sector they desired to work in, close to 10% higher than among those in the treatment groups. Conversely, significantly higher proportions of treated job entrants chose to stop searching than those in the control group.

Table 8: Characteristics of first job attained after university: objective perception

	Experimental arm				
	Cont.	Gen.	Uni.	Field	F-test
Salary	10,402.20	10,153.38	10,822.68	12,191.84	0.411
	(1,062.86)	(881.94)	(784.82)	(858.80)	.
INSS	33.62	29.31	36.82	32.42	0.613
	(5.06)	(4.40)	(4.14)	(3.65)	.
Occasional	60.37	56.73	46.50	55.88	0.475
	(5.24)	(4.79)	(4.28)	(3.88)	.
Fixed term	23.11	30.60	28.02	19.72	0.475
	(4.52)	(4.45)	(3.85)	(3.11)	.
Indefinite duration	16.52	12.68	25.48	24.39	.
	(3.98)	(3.22)	(3.74)	(3.35)	.
Full-time	57.21	58.83	60.60	65.89	0.556
	(5.30)	(4.76)	(4.19)	(3.70)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on observations for each individual that found a job during the survey period, N = 498. 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

Table 9: Characteristics of first job attained after university: subjective perception

	Experimental arm				
	Cont.	Gen.	Uni.	Field	F-test
Desired sector	29.45	20.37	16.76	21.75	0.437
	(4.89)	(3.89)	(3.20)	(3.22)	.
Course related	53.49	51.23	50.09	53.04	0.178
	(6.00)	(5.10)	(4.86)	(4.19)	.
Not seeking	22.32	32.46	38.50	39.94	0.437
	(4.46)	(4.53)	(4.17)	(3.82)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on observations for each individual that found a job during the survey period, N = 498. 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

Labour market information and job-seeking strategies

In our survey we also enquired about the strategies adopted by job-seekers. These varied from the most formal, such as searching for vacancies in the media or on the internet, to more informal, such as direct contact with potential employers or resorting to family and friends. In the questionnaire, participants could indicate all the strategies used. Therefore, they were not mutually exclusive.

Using panel logit regressions with fixed effects for each strategy, Table 10 presents estimates of the different treatments' effects on the choice of the following job-searching strategies: through family and friends (column 2), direct contact with prospective employers (3), looking for job adverts on TV and in other media (4), looking on the internet (5), or choosing none of those strategies (1). It becomes evident that all those who received some labour market information were more likely to adopt at least one active job-search strategy. Those who received general information were 58% more likely to resort to family and friends, 35% more likely to look for jobs in the media, and 265% more likely to search for jobs on the internet than those in the control group. Those who received more specific information appear to have been slightly more likely to adopt those three strategies.[10]

[10] There is an indication that specific employment information, when received by those in the 'university' and 'field' treatment arms, slightly reduced their likelihood of using TV and media.

Table 10: Job-search strategies and information

Odds ratios	(1) No strategy	(2) Family and friends	(3) Direct contact	(4) TV and other media	(5) Internet
SMS salary info	0.88	1.02	0.93	0.88	0.93
	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)
SMS employment info	1.03	1.00	0.97	1.03*	1.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Gen.	0.78**	1.58***	0.96	1.35**	3.65***
	(0.09)	(0.19)	(0.13)	(0.18)	(0.45)
Uni.	0.76***	1.67***	0.89	1.32**	4.90***
	(0.08)	(0.18)	(0.11)	(0.15)	(0.56)
Field	0.84	1.86***	1.11	1.31**	3.58***
	(0.09)	(0.21)	(0.14)	(0.15)	(0.43)
Uni. × salary info	1.08	0.97	1.03	1.16	1.06
	(0.10)	(0.09)	(0.11)	(0.11)	(0.09)
Field × salary info	1.06	0.99	1.00	1.15	1.09
	(0.10)	(0.09)	(0.11)	(0.11)	(0.10)
Uni. × empl. info	0.99	0.99	1.02	0.97*	1.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Field × empl. info	1.00	1.00	1.01	0.96**	0.98
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Obs.	5,746	5,948	5,042	5,528	6,509
Individual controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Probit models are applied for adoption of each possible job-search strategy; in column (1), the dependent variable is binomial, taking a value of 1 if the participant adopted no job-search strategy; in column (2), if she resorted to support from friends and family; in column (3), if she resorted to direct contact with prospective employers; in column (4), if she searched for jobs through TV or other media; in column (5), if she searched for jobs through the internet. Selected coefficients shown are odds ratios. Robust standard errors are in parentheses.

Source: authors' calculations based on survey responses.

Figure 2 suggests that adopting different search strategies will likely translate into different job-entry speeds. In other words, the non-parametric Cox survival curves presented for each subgroup of participants, according to the job-search strategy adopted, suggests some distinctions in their efficacy. Unsurprisingly, the flattest survival curve, representative of the slowest attainment of the first job out of university, is that for those who did not adopt any active job-search strategies. It is followed by those who adopted direct contact strategies,[11] those who searched for jobs in the media,[12] and those who searched the internet.[13] By far the most effective job-search strategy in Mozambique appears to have been resorting to family and friends.[14] It is, notably, also the most informal and unequal of the strategies as it relies on graduates' social networks.

The evidence suggests a mechanism through which access to labour market information may trigger the adoption of active job-search strategies. Having received information on peer wages and employment, treated university graduates were more likely to adopt the most effective job-search strategies, reducing the time to their first job out of university.

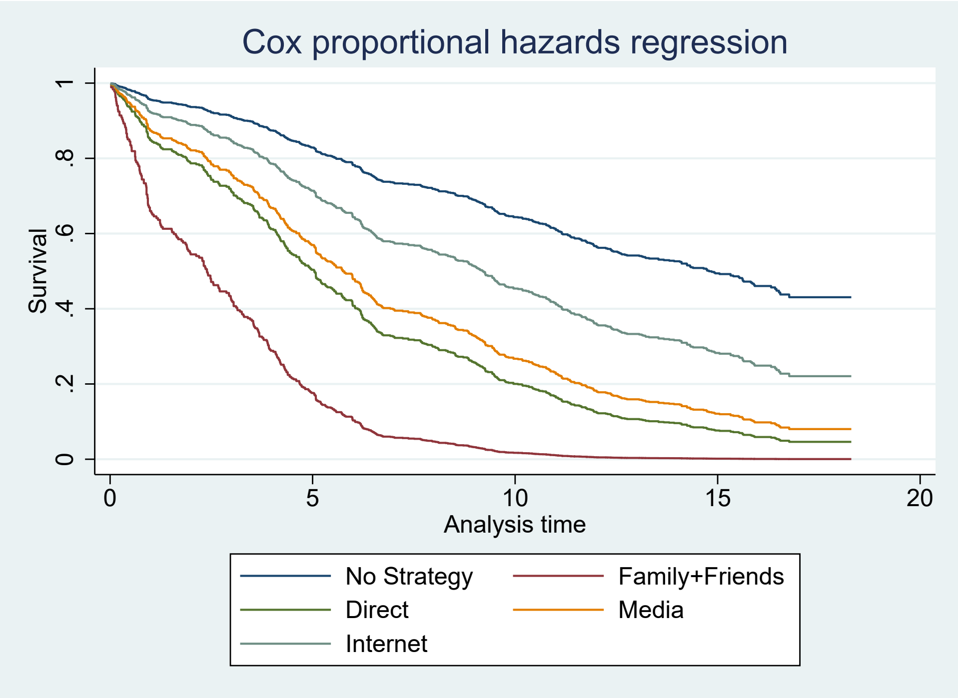
[11] Of which 28% also resorted to family and friends, 33% looked for jobs in the media, and 46% in the internet.

[12] Of which 37% also resorted to family and friends, 25% to direct contacts with employers, and 68% to internet searches.

[13] Of which 37% also resorted to family and friends, 29% to direct contacts with employers, and 57% to searching media adverts.

[14] Conjointly adopted with direct contacts with employers by 18%, and with searching adverts in the media by 32% and on the internet by 39% of participants who resorted to this very informal job-search strategy.

Figure 2: Survival curves by search strategy



Source: authors' calculations based on survey responses.

6 Conclusion

School-to-work transition is almost a rite of passage, one of the life changes that signals adulthood. Prolonged waiting time to attain the first job after university affects youth worldwide, hindering their physical and psychological well-being, stifling their learning, and inducing a 'stigma' that further reduces job-taking opportunities among those who stay unemployed the longest. Yet, while this is a global challenge, evidence for middle- and low-income countries is still relatively scarce, not only on the extent of it but even more so on measures that can reduce it.

In this paper we present the results of an information treatment on the SWT length for university graduates in an LIC, Mozambique. Treated participants received information on peer employment rates and the average wages of those employed. The information was differentiated into three types according to the reference group from whom the information was sourced: (1) general information collected from all survey participants; (2) information differentiated according to each specific university peer group; and (3) information differentiated according to each receiving participant's study-area peer group.

We conducted a survival analysis using a Gompertz proportional hazard function, where the success event is attainment of the first job after university for those participants who started the follow-up period without a job. We find significant and robust causal evidence that offering university students access to labour market information will lead to quicker first job attainment. Focusing on the most robust evidence, we find that in each month of follow-up, for each 1,000 meticais communicated via SMS, the likelihood of job-taking among treated participants was 36–43% higher than among control survey participants, regardless of the reference group the information was based on. In the discussion we find that this acceleration of job intake does not appear to result in worse job conditions, either objectively or subjectively perceived by job entrants.

We also find a strong suggestion that this job-intake acceleration results from a more active adoption of job-search strategies, particularly the ones found to be more effective in Mozambique. Those who received the most general information were 58% more likely to resort to family and friends, 35% more likely to look for jobs in the media, and 265% more likely to search for jobs on the internet than those in the control group. Those who received more specific information appear to have been slightly more likely to adopt those three strategies. The evidence suggests that the support of family and friends is by far the most effective strategy in Mozambique, followed by job advert searches on the internet and in the media. The strongly informal nature of the Mozambican labour market, translated into the apparent higher efficacy of the 'family and friends' channel, deserves further attention, as it has the makings of an inequality-producing mechanism.

In summary, we find significant and robust evidence of a causal benefit from allowing job-seekers access to (better) labour market information. The mechanism we used, relying on self-reporting from the panel itself, is relatively inexpensive and, we suggest, can be easily replicated and reproduced by university alum departments or, at the provincial and national levels, by labour market observatories or statistics bureaus.

The research design leads us to assume that, as participants were statistically similar on observables, the action of those primed by the information received, more than any labour supply effect, induced the faster matching. It also indicates that such a channel has limits and that measures at the employer level may need to be studied and proposed.

Nevertheless, the results of this study deserve particular attention and advise implementing access-to-information initiatives in low-income, low-information settings such as Mozambique. Further studies can confirm its validity in other settings and target groups.

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Appendix

Table A1: Baseline average characteristics across experimental arms: personal characteristics, field of study, and university

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
Age	26.11	25.63	25.84	25.83	26.18	0.783
	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	.
Female	0.44	0.44	0.45	0.45	0.44	0.995
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Married	0.15	0.13	0.12	0.16	0.14	0.516
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Has children	0.29	0.29	0.30	0.35	0.28	0.263
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had job before	0.62	0.61	0.61	0.58	0.60	0.921
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had internship before	0.49	0.49	0.53	0.53	0.50	0.941
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Had a job waiting	0.15	0.12	0.12	0.12	0.10	0.545
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Education	0.31	0.30	0.32	0.32	0.30	0.885
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Languages and Humanities	0.02	0.02	0.02	0.01	0.02	0.687
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Social Sciences	0.44	0.45	0.45	0.44	0.45	0.954
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Natural Sciences	0.04	0.04	0.04	0.04	0.04	1.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Engineering	0.08	0.08	0.08	0.08	0.08	0.997
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Agriculture	0.05	0.05	0.05	0.05	0.06	0.926
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	.
Health	0.06	0.06	0.06	0.06	0.06	0.983
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
UEM	0.36	0.36	0.35	0.34	0.34	0.988
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
UCM	0.08	0.10	0.09	0.09	0.09	0.849
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
UZ	0.11	0.11	0.10	0.09	0.11	0.975
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
USTM	0.05	0.05	0.07	0.06	0.03	0.061
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	.
UP	0.34	0.31	0.36	0.38	0.38	0.502
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
AP	0.06	0.07	0.03	0.04	0.04	0.254
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, N = 2,069. 'F-test' reports the probability that the means in the treatment arms jointly differ. Abbreviations UEM–AP refer to universities (dummy variables); study fields are given in the second panel (dummy variables).

Source: authors' calculations based on survey responses.

Table A2: Baseline average characteristics across experimental arms: household member's highest level of education and most significant sector of work

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
HH educ. - None formal	0.04	0.03	0.04	0.02	0.01	0.254
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
HH educ.—prim.	0.11	0.13	0.15	0.14	0.16	0.449
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH educ.—sec.	0.30	0.20	0.25	0.27	0.26	0.101
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH educ.—TVET	0.25	0.26	0.25	0.29	0.21	0.421
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH educ.—higher	0.30	0.36	0.31	0.28	0.34	0.303
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH educ.—other	0.01	0.02	0.01	0.00	0.01	0.388
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
HH job - Public	0.46	0.42	0.39	0.45	0.44	0.469
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH job—private	0.25	0.24	0.26	0.26	0.24	0.971
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH job—firm owner	0.00	0.03	0.02	0.01	0.02	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
HH job—agr. self empl	0.09	0.14	0.11	0.11	0.11	0.524
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH job—self	0.15	0.13	0.17	0.14	0.15	0.765
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
HH job—not known	0.05	0.04	0.05	0.03	0.04	0.866
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, *N* = 2,069. 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

Table A3: Baseline average characteristics across experimental arms: skills

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
Raven's test score	–14.40	–6.62	–11.22	–0.71	–9.64	0.577
	(2.30)	(2.06)	(2.14)	(2.05)	(2.12)	.
Verbal test score	–0.66	–9.00	–7.05	–11.03	1.43	0.320
	(2.38)	(2.07)	(2.13)	(2.08)	(2.06)	.
Numeric test score	–5.55	–17.77	–0.81	–1.06	–3.41	0.143
	(2.41)	(2.11)	(2.17)	(2.08)	(1.98)	.
Locus of control	–2.11	–3.37	2.13	4.78	–1.85	0.860
	(2.47)	(2.20)	(2.02)	(2.17)	(2.03)	.
Basic English	0.17	0.29	0.28	0.26	0.30	0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Limited English	0.17	0.26	0.26	0.25	0.22	0.028
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Professional English	0.04	0.07	0.06	0.10	0.09	0.028
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	.
Fluent in English	0.02	0.02	0.04	0.02	0.03	0.318
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
No skill in English	0.61	0.36	0.37	0.37	0.36	0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, *N* = 2,069. 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

Table A4: Baseline average characteristics across experimental arms: province or country of residence

	Experimental arm					
	Cont.	Gen.	Uni.	Field	Mixed	F-test
Cabo Delgado	0.00	0.01	0.01	0.00	0.00	0.738
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Gaza	0.00	0.02	0.02	0.02	0.03	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Inhambane	0.01	0.01	0.02	0.02	0.01	0.873
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Manica	0.01	0.00	0.01	0.00	0.01	0.066
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Maputo Cidade	0.44	0.46	0.46	0.51	0.46	0.610
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Maputo Província	0.34	0.29	0.30	0.28	0.31	0.515
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Nampula	0.00	0.01	0.01	0.01	0.01	0.216
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Niassa	0.00	0.00	0.00	0.00	0.00	0.910
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Sofala	0.16	0.18	0.17	0.15	0.16	0.889
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	.
Tete	0.01	0.01	0.00	0.00	0.01	0.288
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Zambezia	0.01	0.00	0.00	0.01	0.00	0.562
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
South Africa	0.00	0.00	0.00	0.00	0.00	0.908
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Tanzania	0.00	0.00	0.00	0.00	0.00	0.797
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Portugal	0.00	0.00	0.00	0.00	0.00	.
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.
Other country	0.00	0.00	0.00	0.00	0.00	.
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	.

Note: cells show means and mean standard errors (in parentheses) across different experimental arms of baseline variables, based on one observation for each individual observed at least once in the follow-up rounds, N = 2,069. 'F-test' reports the probability that the means in the treatment arms jointly differ.

Source: authors' calculations based on survey responses.

Table A5: Correlates of job-entry: Gompertz regressions, 1 of 4

	(1) Simple	(2) Info types	(3) SMS salary	(4) SMS employment	(5) Both
Analysis time when record ends					
Treated	1.05				
	(0.11)				
SMS salary info			1.29***		1.43**
			(0.09)		(0.24)
SMS employment info				1.05***	0.99
				(0.01)	(0.03)
Gen.		0.86	1.01	0.92	1.07
		(0.11)	(0.15)	(0.13)	(0.17)
Uni.		1.03	0.99	1.06	1.06
		(0.13)	(0.13)	(0.14)	(0.14)
Field		1.26*	1.16	1.29*	1.25*
		(0.15)	(0.15)	(0.17)	(0.17)
Uni. × salary info			0.83***		0.75*
			(0.06)		(0.13)
Field × salary info			0.84**		0.74*
			(0.06)		(0.13)
Uni. × empl. info				0.99	1.04
				(0.01)	(0.03)
Field × empl. info				0.98	1.03
				(0.01)	(0.03)
Obs.	3,667	3,667	3,651	3,651	3,651
Log likelihood	–1,200.65	–1,196.16	–1,095.77	–1,093.39	–1,087.81
AIC	2,407.30	2,402.32	2,305.53	2,300.79	2,295.61
BIC	2,425.92	2,433.36	2,659.09	2,654.34	2,667.78
Individual controls	No	No	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Note: column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for information of peer salaries only. The model in column (4) only accounts for information of peer employment. The most complete model is presented in column (5). Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (*p*-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

Table A6: Correlates of job-entry: Gompertz regressions, 2 of 4

	(1) Simple	(2) Info types	(3) SMS salary	(4) SMS employment	(5) Both
Analysis time when record ends					
Age			0.99	0.99	0.99
			(0.02)	(0.02)	(0.02)
Female			0.60***	0.61***	0.61***
			(0.06)	(0.06)	(0.06)
Married			1.18	1.20	1.21
			(0.28)	(0.28)	(0.29)
Has children			1.31*	1.35*	1.31*
			(0.22)	(0.22)	(0.22)
HH educ.—prim.			1.09	1.06	1.13
			(0.49)	(0.48)	(0.51)
HH educ.—sec.			1.15	1.13	1.19
			(0.50)	(0.49)	(0.51)
HH educ.—TVET			1.05	1.03	1.08
			(0.46)	(0.45)	(0.47)
HH educ.—higher			0.94	0.92	0.97
			(0.41)	(0.40)	(0.42)
HH educ.—other			1.22	1.11	1.31
			(0.72)	(0.69)	(0.78)
HH job—public			1.20	1.25	1.22
			(0.32)	(0.34)	(0.33)
HH job—private			1.27	1.30	1.26
			(0.34)	(0.35)	(0.34)
HH job—firm owner			1.35	1.39	1.33
			(0.57)	(0.58)	(0.56)
HH job—self			1.15	1.19	1.16
			(0.32)	(0.33)	(0.32)
HH job—not known			1.61	1.64	1.60
			(0.51)	(0.52)	(0.51)
Obs.	3,667	3,667	3,651	3,651	3,651
Log likelihood	–1,200.65	–1,196.16	–1,095.77	–1,093.39	–1,087.81
AIC	2,407.30	2,402.32	2,305.53	2,300.79	2,295.61
BIC	2,425.92	2,433.36	2,659.09	2,654.34	2,667.78
Individual controls	No	No	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for information of peer salaries only. The model in column (4) only accounts for information of peer employment. The most complete model is presented in column (5). Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (*p*-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

Table A7: Correlates of job-entry: Gompertz regressions, 3 of 4

	(1) Simple	(2) Info types	(3) SMS salary	(4) SMS employment	(5) Both
Analysis time when record ends					
Cabo Delgado			0.70	0.69	0.76
			(0.47)	(0.46)	(0.50)
Gaza			1.54	1.44	1.43
			(0.49)	(0.49)	(0.47)
Inhambane			0.96	1.06	0.97
			(0.36)	(0.38)	(0.35)
Manica			0.91	0.81	0.91
			(0.33)	(0.30)	(0.33)
Maputo Província			0.93	0.93	0.93
			(0.11)	(0.11)	(0.11)
Nampula			1.59	1.57	1.58
			(0.61)	(0.60)	(0.60)
Niassa			1.30	1.47	1.76
			(1.52)	(1.71)	(1.98)
Sofala			0.44***	0.43***	0.45***
			(0.12)	(0.12)	(0.12)
Tete			0.52	0.46	0.48
			(0.37)	(0.31)	(0.32)
Zambezia			0.24	0.25	0.25
			(0.22)	(0.23)	(0.23)
South Africa			0.00***	0.00***	0.00***
			(0.00)	(0.00)	(0.00)
Tanzania			0.00***	0.00***	0.00***
			(0.00)	(0.00)	(0.00)
Portugal			0.00***	0.00***	0.00***
			(0.00)	(0.00)	(0.00)
Languages and Humanities			0.66	0.74	0.71
			(0.21)	(0.24)	(0.23)
Social Sciences			0.78	0.96	0.90
			(0.15)	(0.20)	(0.19)
Natural Sciences			0.59**	0.75	0.69
			(0.14)	(0.18)	(0.17)
Engineering			0.59*	0.78	0.67
			(0.16)	(0.21)	(0.19)
Agriculture			0.66	0.76	0.74
			(0.18)	(0.22)	(0.21)
Health			0.55**	0.66	0.61*
			(0.16)	(0.19)	(0.18)
Obs.	3,667	3,667	3,651	3,651	3,651
Log likelihood	–1,200.65	–1,196.16	–1,095.77	–1,093.39	–1,087.81
AIC	2,407.30	2,402.32	2,305.53	2,300.79	2,295.61
BIC	2,425.92	2,433.36	2,659.09	2,654.34	2,667.78
Individual controls	No	No	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for information of peer salaries only. The model in column (4) only accounts for information of peer employment. The most complete model is presented in column (5). Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (p-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

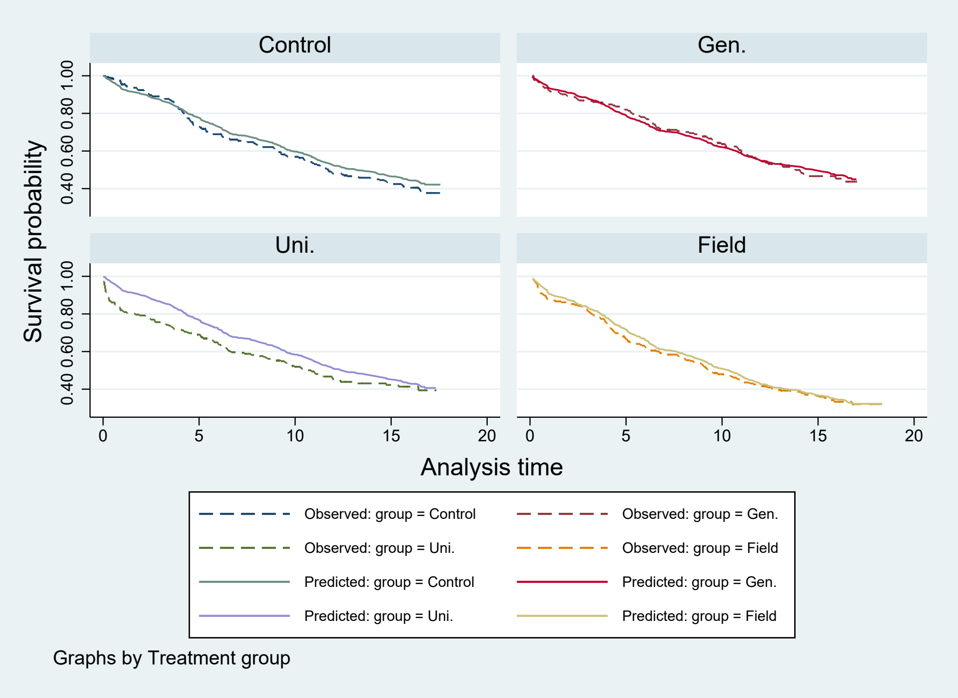
Table A8: Correlates of job-entry: Gompertz regressions, 4 of 4

	(1) Simple	(2) Info types	(3) SMS salary	(4) SMS employment	(5) Both
Analysis time when record ends					
UCM			2.07**	2.58***	2.28**
			(0.67)	(0.83)	(0.74)
UZ			2.04***	2.17***	2.17***
			(0.56)	(0.60)	(0.59)
USTM			1.03	1.15	1.16
			(0.19)	(0.22)	(0.22)
UP			0.71*	0.65**	0.68**
			(0.13)	(0.12)	(0.12)
AP			0.59**	0.75	0.66*
			(0.13)	(0.16)	(0.15)
Had job before			1.42***	1.40***	1.40***
			(0.14)	(0.14)	(0.14)
Had internship before			1.64***	1.68***	1.67***
			(0.19)	(0.20)	(0.19)
Had a job waiting			0.96	0.91	0.96
			(0.25)	(0.24)	(0.25)
Raven's test score			1.00***	1.00***	1.00***
			(0.00)	(0.00)	(0.00)
Verbal test score			1.00	1.00	1.00
			(0.00)	(0.00)	(0.00)
Numeric test score			1.00**	1.00*	1.00*
			(0.00)	(0.00)	(0.00)
Locus of control			1.00	1.00	1.00
			(0.00)	(0.00)	(0.00)
Basic English			1.22	1.20	1.20
			(0.16)	(0.16)	(0.16)
Limited English			1.35**	1.34**	1.35**
			(0.18)	(0.18)	(0.18)
Professional English			1.62**	1.50**	1.54**
			(0.31)	(0.30)	(0.31)
Fluent in English			2.12***	2.16***	2.17***
			(0.59)	(0.64)	(0.63)
Obs.	3,667	3,667	3,651	3,651	3,651
Log likelihood	–1,200.65	–1,196.16	–1,095.77	–1,093.39	–1,087.81
AIC	2,407.30	2,402.32	2,305.53	2,300.79	2,295.61
BIC	2,425.92	2,433.36	2,659.09	2,654.34	2,667.78
Individual controls	No	No	Yes	Yes	Yes

Note: significance: * 10%, ** 5%, *** 1%. Column (1) presents the simplest model, without controls nor accounting for differences in the information provided. The model in column (2) accounts for the different references used. The model in column (3) accounts for information of peer salaries only. The model in column (4) only accounts for information of peer employment. The most complete model is presented in column (5). Coefficients are hazard odds ratios. Standard errors, in parentheses, are calculated using the delta method. Significance (p-values) is calculated from the natural regression coefficients and standard errors.

Source: authors' calculations based on survey responses.

Figure A1: Goodness of fit



Source: authors' calculations based on survey responses.