

# The effect of peer earnings information on wage expectations

Design and pre-analysis plan

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## **Abstract**

How do secondary school graduates' wage expectations react to different types of new information? In this study, we ask this question by tracking the evolution of earnings expectations over a randomised control trial which exposes individuals to different information treatments over the period. The RCT is conducted with a large sample of Mozambican secondary school leavers from technical and vocational education institutes who are part of an on-going tracer study as they transition from school to the labour market.

# 1 Key information

Country	Mozambique
Status	On-going
Trial start date	02/10/2019 (baseline)
Intervention start date	06/04/2020 (first SMS)
Intervention end date	22/09/2020 (final SMS)
Trial end date	01/12/2020
No. participants	1,622
No. treatment arms	4

## 2 Background

UNU-WIDER, in partnership with the Ministry of Economics and Finance, the Ministry of Labour and Social Security and the University of Eduardo Mondlane in Mozambique, is conducting a tracer study of graduates of Technical and Vocational schools in the provinces of Maputo City, Maputo Province, Tete, Cabo Delgado and Nampula. The study has two phases. The first phase, which has been completed, is a baseline survey (October/November 2019) that captures the students' cognitive abilities, their family background, their expectations and aspirations. The second phase of the study involves tracking the same students as they transition to the labour market. They will be followed for one full year after graduation (January - December 2020, the 'trial period') through quarterly phone interviews.

By tracking TVET finalists for one year after graduation, the knowledge gathered on the transition process for young people into the economy is hoped to generate empirical insights and policy recommendations for the Ministry of Labour as well as the Ministry of Science, Technology and Professional Education (who hold responsibility for TVET institutions) on relevant issues such as labour market mobility, over- and under- qualification, youth unemployment, labour formality and informality, impediments in the job search process and employment security for recent school leavers. One metric which will be tracked is their wage expectations, and how they change over time.

The planned RCT (outlined below) on wage expectations will be embedded within the ongoing tracer study and, as such, will leverage the data collection process already planned (in progress) under the latter observational study. Through these phone surveys, the students actual earnings,

as well as any changes to their expected earnings, will be tracked over time. The survey also collects a wide range of other employment information for each participant, including their current work status, type of work undertaken, conditions of employment (e.g., with/without a contract), and the number of hours worked.

The RCT aims to contribute to the recent literature on job search concerning the process by which individuals update their wage expectations over time. The existing literature suggests changes in expectations can be usefully studied in terms of ‘updating toward the signal’ (UTS) ([Chambers and Healy, 2012](#)), which simply proposes that existing (prior) beliefs are combined with new information to form updated (posterior) beliefs. This broad framework has been applied in various domains where uncertainty prevails, including risk perceptions (?) and price expectations ([Armantier et al., 2016](#); [Cavallo et al., 2017](#)), and lends its self to be studied in an experimental setting.

Concretely, the RCT will track the evolution of Mozambican TVET graduates’ evolution of earning expectations after three different information treatments, each which provide them with information about their peers’ earnings: the average realized wage across all surveyed graduates; average salaries among graduates who had attended the same school type (public/private); and average salaries for students in their same field of training (and hence, area of work). This allows us to study the magnitude of adjustments to wage beliefs in response to different types of information, as well as any heterogeneity in updating responses, such as between job seekers versus those already in work.

This RCT combines elements of the information experiment of [Wiswall and Zafar \(2015\)](#) who provided US students with information on average earnings of different population segments, and a longitudinal data set-up similar to that analysed in [Conlon et al. \(2018\)](#). It is also inspired by [De Paola et al. \(2001\)](#) and [Stinebrickner and Stinebrickner \(2014\)](#), who find contextually relevant information is more effective in influencing job seeker’s beliefs, as well as [Kriechel and Pfann \(2006\)](#), who suggest that job seekers learn from their peers’ labour market experiences, we randomly allocated students to alternative information treatment groups.

## 3 Experimental design

### 3.1 Set-up

The experiment will focus on how individuals update their wage expectations in response to different types of information about the actual income distribution. The primary research questions is therefore: how do TVET graduates revise their own-wage expectations in response to new information about the earnings of their peers?

Given the scarcity of reliable data on graduate wages, both in general as well as specifically for new labour market entrants, we used information on realized wages from prior rounds of the telephone survey to design three distinct information treatments. Namely:

- General message: summarises wage information from the entire sample – e.g., ‘Survey results at Dec.1st: of all TVET graduates in Mozambique (class of 2019), 59% are working and their average wage = 14,000 Mts / mes.’
- School type specific message: summarises wage information from the sub-sample of participants that attended the same school type as the recipient (public/private) – e.g., ‘Survey results at Dec.1st: of all graduates from public TVET institutions (class of 2019), 52% are working and their average wage = 24,000 Mts / month.’
- Field-specific message: summarises wage information from the sub-sample of participants in the same study field as the participant – e.g., ‘Survey results at Dec.1st: of all graduates from your area of studies (class of 2019), 50% are working and their average wage = 13,500 Mts / month.’

The messages are sent by SMS at the beginning of each telephone survey round, excluding the first. Note, the specific information contained in each SMS varied by survey round; and, in the second and third types of message, the information varied by individual according to the school type they had attended or their field of training. Mirroring variation in actual wages, this design provides for substantial variation in the underlying wage information received.

In terms of exposure to the treatments, directly after the baseline survey individuals were randomly-allocated to one of five experimental arms (including the control) and where the four treatment arms are distinguished by the type of messages they would receive. Specifically:

- Group one (general): received the general (all-student) message in all relevant rounds;
- Group two (school-type): received the school-type-specific message in all relevant rounds;
- Group three (field): received the field-specific message in all relevant rounds; and
- Group four (mixed): received the general message in round two, the school-type specific message in rounds three and four, and the field-specific message in rounds five and six.

## 3.2 Sample

The primary sample for the experiment is the baseline TVET sample (N = 1,639). This sample was collected across five provinces, Nampula, Tete, Maputo Cidade, Maputo and Cabo Delgado. Together, these provinces contain 60% of the population of TVET students in the country. Due to logistical constraints creating a need to work with larger class sizes during the surveying, our sample selection strategy was directly proportional to school size. As such, the sample is representative of finalists attending the largest TVET institutes in the 5 provinces. In sum, the survey was conducted in 20 technical schools – three community, six private and 11 public – and surveyed students across 50 different courses. More information on the sampling method and survey conducted, please refer to '*The school-to-work transition of Technical and Vocational students in Mozambique Baseline Report*' (Jones, Santos & Schnupp, 2019).

From this baseline sample we then removed (i) individuals who did not consent to participate in the follow-up telephone surveys, and (ii) individuals with duplicated phone numbers. This leaves us with a final available sample of 1,622 individuals. Table 2 gives a breakdown of the final available sample, by course type and province.

## 3.3 Randomization

Randomization across the five experimental arms was stratified by study field and gender, with a target of around 260 participants in the control group and 340 in each treatment arm. Table 2 gives a breakdown of the treatment arm allocations, by course type, province and school type.

Table 1: Description of realized sample

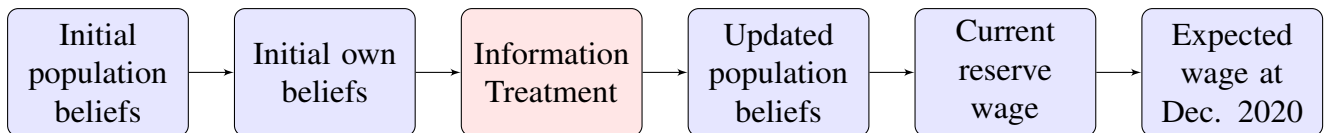
Province	Course type							
	Agriculture		Services		Industry		Total	
	No.	%	No.	%	No.	%	No.	%
Cabo Delgado	0	0.0	72	10.1	26	4.1	98	6.0
Maputo City	0	0.0	428	60.2	174	27.7	602	37.1
Maputo Prov.	136	48.2	42	5.9	142	22.6	320	19.7
Nampula	146	51.8	138	19.4	195	31.0	479	29.5
Tete	0	0.0	31	4.4	92	14.6	123	7.6
Total	282		711		629		1,622	

### 3.4 Hypotheses and outcomes

The primary null hypothesis is that exposure to information about actual average salaries does not alter individual wage expectations. Our three hypotheses are as follows:

1. Information on peers' earnings affects current beliefs about peers' earnings ( $w^h$  : belief about highest earnings among peers)
2. Information on peers' earnings affects current reserve wage ( $w^r$  : reserve wage)
3. Information on peers' earnings affects own-earnings beliefs ( $w^o$  : own expectations of salary as at December 2020)

Figure 1: Schematic representation of focus relationships



Consistent with the above scheme, in the baseline survey the students were asked a number of wage expectations questions, both for themselves (reserve wage, expected wage for first job, expected wage by Dec 2020) and for their estimations of the population distribution (minimum, average and maximum for a recent graduate from their course). They were also asked to give a full set of expectations for each type of work they were intending to do, either self-employed work (formal or informal) or as an employee. Most students (1,152) gave two sets of wage

Table 2: Experimental treatment allocation

	Treatment Groups											
	Control		Group 1		Group 2		Group 3		Group 4		Total	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Course type												
Agriculture	45	17.4	57	16.9	60	17.5	60	17.5	60	17.6	282	17.4
Services	113	43.6	148	43.9	150	43.7	150	43.9	150	44.0	711	43.8
Industry	101	39.0	132	39.2	133	38.8	132	38.6	131	38.4	629	38.8
Province												
Cabo Delgado	17	6.6	20	5.9	20	5.8	20	5.8	21	6.2	98	6.0
Maputo City	96	37.1	127	37.7	127	37.0	127	37.1	125	36.7	602	37.1
Maputo Prov.	50	19.3	66	19.6	68	19.8	68	19.9	68	19.9	320	19.7
Nampula	76	29.3	100	29.7	101	29.4	101	29.5	101	29.6	479	29.5
Tete	20	7.7	24	7.1	27	7.9	26	7.6	26	7.6	123	7.6
School type												
Private	89	34.4	137	40.7	133	38.8	114	33.3	127	37.2	600	37.0
Public	170	65.6	200	59.3	210	61.2	228	66.7	214	62.8	1,022	63.0
Total	259		337		343		342		341		1,622	

expectations, one for each type of work. 262 were not considering working for themselves, and 225 were not consider working as an employee.

In the phone rounds, students are asked the following questions on a quarterly basis, so that changes in expectations can be tracked over time:

- What do you think is the highest salary someone from your class (of 2019) is currently earning?
- What is the minimum salary you would accept now in order to work full time?
- How much do you think you will be earning by December 2020, per month?

The above questions match directly to the outcomes of interest  $(w^h, w^r, w^o)$ .

Note that reservation wages and the expected (future) wage are distinct concepts. Yet, despite both playing a role in the job search process, few empirical papers consider them in conjunction. Empirical literature on the updating process of the reservation wage primarily consider information relating to past experience, such as the duration of unemployment and previous wage offers.

However, future-oriented information is also likely to impact the reservation wage ([Brown and Taylor, 2013](#)). In our model, presented below, we will contribute to the limited literature in this space by considering how both the expected wage and the reservation wage evolve over time in response to new information.

### 3.5 Analysis Plan

Our proposed analysis follows the basic framework and empirical implementation of [Jones and Santos \(2020\)](#), using both static and dynamic specifications. For the static model, we will run simple differences-in-differences estimates, regressing each outcome of interest, observed in the first and final rounds, against exposure-to-treatment dummy variables. Note this is feasible since the SMS information treatments were only sent from rounds 2-4 only. Thus, our basic static specification, to be estimated via OLS, is:

$$w_{it} = \mu_i + \gamma_t + \beta \cdot \mathcal{I}(x_{it} \neq \emptyset) + \varepsilon_{it}$$

where  $\mathcal{I}(x_t \neq \emptyset)$  takes a value of one if individual  $i$  in round  $t$  received an SMS message and zero otherwise, meaning  $\beta$  will capture the average treatment effect on the treated (ATT) associated with receiving some peer wage information.

We will extend the specification to allow the  $\beta$ 's to vary across treatment arms; and we will add a limited set of time-varying variables, including: information on the current working status of the individual; the elapsed time (in months) between being contacted in each round, a dummy variable capturing whether the elicited wage expectation pertains to full-time work; and (for treated participants) the information received in the treatment messages regarding the share of peers in each specified group who are currently working.

The above static model will be run separately for each of the three outcomes noted above, representing reduced form specifications. However, following the scheme of [Figure 1](#), we also propose to estimate the following set of equations simultaneously (using an iterated SUR estimator, as in [Pagan, 1979](#)):

$$\begin{aligned} w_{it}^h &= \mu_i^h + \gamma_t^h + \beta^h \cdot \mathcal{I}(x_{it} \neq \emptyset) + \varepsilon_{it}^h \\ w_{it}^r &= \delta_1 w_{it}^h + \mu_i^r + \gamma_t^r + \beta^r \cdot \mathcal{I}(x_{it} \neq \emptyset) + \varepsilon_{it}^r \\ w_{it}^o &= \delta_3 w_{it}^r + \delta_2 w_{it}^h + \mu_i^o + \gamma_t^o + \beta^o \cdot \mathcal{I}(x_{it} \neq \emptyset) + \varepsilon_{it}^o \end{aligned}$$

The advantage of this system is that it should help identify the main channel(s) through which updating occurs.

For the dynamic analysis, we focus on the content of the message (the salary value transmitted) and presume changes in earnings beliefs in period  $t + 1$  partially reflect (new) public information about earnings (denoted  $x$ ):

$$w_{it+1} - w_{it} = \beta(x_{t+1} - w_{it}) + \theta\beta x_{t+1} + \nu_{it+1}$$

where the parameter  $\theta$  captures any variation in *how* the information signal is processed (as per [Wiswall and Zafar, 2015](#); [Jones and Santos, 2020](#)), and which is particularly important given we only track population beliefs about the highest earnings among peers ( $w^h$ ). In turn, this set-up implies an “update towards signal” model ([Chambers and Healy, 2012](#)):

$$w_{it+1} = w_{it} + \beta(x_{t+1} - w_{it}) + \theta\beta x_{t+1} + \nu_{it+1}$$

which constitutes our basic dynamic model.

As with the static analysis, we propose to run estimates of this form for each of the outcomes separately, as well as simultaneously. We also intend to follow [Jones and Santos \(2020\)](#) and extend the model to allow for unobserved private information ( $z$ ):

$$\Delta w_{it+1} = \beta(x_{it+1} - w_{it}) + \delta(\hat{z}_{it+1} - w_{it}) + \theta\beta x_{t+1} + \mu + \lambda_{t+1} + \xi_{it+1}$$

Finally, what has been laid out above assumes a homogeneous updating process. To account for potential cognitive biases and alternative updating heuristics, we will allow for heterogeneity in both the weight attributed to peer earnings news ( $\beta$ ) and information-processing parameter ( $\theta$ ). To do so, we will consider the following dimensions:

- initial uncertainty, as captured by the range of baseline expectations (from their max to min) as well as the difference between their wage estimates in the informal vs. formal sectors, and the length of time they expect to take to find work
- gender
- baseline expectations (high/low)
- academic and ravens test scores

- the credibility of the SMS wage information, indicated by the information provided about the proportion of peers in work
- the valence (sign) of the news, to allow for asymmetric updating

### **3.6 Power calculations**

Given the size of the experimental sample and the allocation into treatment arms, using an assumption that natural log of the expected wage in the control group equals 9.4 with a standard deviation of 0.7 (calculated from the baseline survey), the minimum detectable effect (at the 10% significance level) is 0.12 considering all treatment groups (combined). Or, for the smallest treatment group alone, the minimum detectable effect is a 0.14 log points. The former is about a three quarters the effect size found in [Jones and Santos \(2020\)](#).

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