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EVIDENCE FROM MONGOLIA

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Abstract

We applied behavioural science in labour market policy, the job placement service by the Labour and Welfare Office of Ulaanbaatar, Mongolia. We replicated the personalized message treatment implemented in the UK by Sanders and Kirkman (2019). Individuals have different attitudes towards message ads. We randomly assigned 4,674 job-seeking citizens registered at the district-level office into four groups and sent them different messages, simple, personalized and success-wishing. Young unemployed are more likely to respond to public messages than personalized private messages, while individuals aged 41-65 are more responsive to messages with personal information.

Keywords: Labor market, Employment, Field experiment, Personalization, Mongolia.

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1. Introduction

Numerous experimental studies in behavioural economics have demonstrated that people behave differently from what the standard theories of human behaviour dictate. For example, people engage in irrational behaviour such as systematic errors, avoidance of complexities, and procrastination (Babcock et al., 2012, Dohmen, 2014, DellaVigna, 2009) .

These behaviours have a direct impact on individual decisions. For example, it is common for an unemployed person to assume that he will get the same salary as his previous job, to overestimate his chances of getting a job, and to compare his job search with his previous job. It is sometimes unrelated to the current market conditions, and the unemployed citizen risks losing the opportunity to get a job. There is also a tendency for the unemployed to delay their job search and make little or no effort. Although diligent job searching benefits the individual in the long run, it is counterproductive due to the behavioural tendency to procrastinate (Laibson, 1997, O'Donoghue & Rabin, 2015) . Avoiding problems can lead to avoiding employment services such as job placement and skills training.

Chetty (2015) argued that applying the findings of behavioural economics to public policy can be an important contribution to improving policy effectiveness. Considering these characteristics is also important for the outcome of labor market policies, as they influence decisions about searching for work, entering a job, or participating in employment support programs (Babcock et al., 2012). A large body of research has applied behavioural concepts to labor market policy. These studies mainly apply behavioural concepts to three labor market contexts: employers, the unemployed, and employment services.

Empirical studies that have applied behavioral approaches to employment promotion policies have mainly been conducted in developed countries. There are very few examples of use in developing countries. The British Behavioral Research Team's (The BI Team) studies that tested behavioral methods in the labour market were mainly conducted using examples of employment promotion policies in Great Britain, Australia, and Singapore (Briscese & Tan, n.d.). Also, in the manual, which combines the examples of the perspective approach issued by the Organisation for Economic Cooperation and Development (OECD) in the social and economic policies of OECD member countries and partner countries, the behavioral approach is used in the United Kingdom, Canada, the Netherlands, and Singapore.

Briscese & Tan report that pilot studies applying behavioural approaches to the labour market have been successful both on the small scale of early trials and on a larger scale. This proves that the results of the experiments carried out by the BI team, using the example of other countries in similar programs, are likely to be high. Also, applying behavioural approaches to the labor market is suitable for implementation in developing countries because it can achieve high cost-effectiveness results.

In this study, we present the results of a randomised control trial implemented to test the effectiveness of mobile text messaging for unemployed people registered at the Labor and Welfare Office of Songinkhairkhan district of Ulaanbaatar, the capital city of Mongolia. We replicated the design tested in the UK (Sanders & Kirkman, 2019).

We randomly assigned more than 4,674 unemployed citizens registered at the district office into four groups. Four different messages were sent to these groups. The different content of the messages had varying effects on citizen participation. For example, messages with content wishing for success increased the participation of citizens over 45 years of age, while the participation of citizens under 45 years of age was not affected.

In the next section, we discussed the literature review on the application of behavioural science and digital technology to labour market policy. Subsequent sections discussed the context, intervention, data, and empirical strategy. In the final section, we concluded.

2. Literature review

Our study belongs to two strands of literature – the effects of technology and behavioral treatments on labor market outcomes. There are many international experiences of using behavioral concepts combined with modern technology in the labour market. Text messages are used for job placement (Dammert et al., 2015, Field et al., 2023), social insurance services (Cruces et al., 2020), and labour market information delivery (Jones & Santos, 2022), and the use of mobile text messaging to improve job fair attendance (Sanders & Kirkman, 2019).

Dammert et al. (2015) conducted a field trial that examined the impact of combining traditional recruitment services with modern mobile technology on employment. This study was conducted in Peru, one of the developing countries. They compared traditional recruitment services with electronic recruitment services aimed at reducing job search costs. Electronic information services differ from traditional services in that information about potential jobs that match the characteristics of the job seeker is sent to the job seeker's mobile phone via text message. The researchers concluded that electronic information services increased employment in the short term more than traditional services.

Field et al. (2023) implemented an experiment using a job search platform in Pakistan to test whether proactive phone calls can increase job applications by reducing psychological barriers to job search. They show that the experiment that reduces the psychological cost of initiating job applications increases applications by 600%.

Sanders & Kirkman (2019) experimentally examined the effects of several message types on participation in an employment service centre intervention. 1,224 active job seekers were randomly divided into four groups and sent four types of event announcements. The first is a message with a simple ad, the second is a message with a job seeker's name, the third is a message with a job specialist's name, and the fourth is a "you've been ordered, good luck" message. Success messages with the name of an employment specialist were the most effective when measuring the effectiveness of messages on jobseeker engagement.

According to international experience and project research, adopting electronic technologies in employment services has several benefits. Electronic technologies, such as text messaging, are inexpensive to extend the reach of employment interventions. Also, the timely delivery of suitable job information to job seekers will reduce job search costs.

Mobile phone technology can be considered as one of the foundation stones for technology-driven development, particularly for resource-constrained developing countries. Mobile subscriptions per 100 persons have increased by 2.8 times in OECD countries from 44 to 122, while in Sub-Saharan Africa, the increase was 51 times, from 1.7 to 87.6, between 2000 and 2022. Aker & Mbiti, 2010 highlight Sub-Saharan Africa’s low infrastructure investment, with only 29% of roads paved and fewer than three landlines per 100 people, making mobile phones a critical leapfrog technology.

Studies find that mobile phones "greatly reduce communication costs" and connect people quickly to information and markets (Jensen, 2007; Aker, 2010; Aker, 2015). This has important implications for job search: mobiles can broaden access to vacancy information, speed up search, and improve matches between workers and firms. A 2015 Pew survey found 68% of American adults owned a smartphone, and 28% of all adults (41% of smartphone owners) used a smartphone in a job search. Aker (2010) argues that mobile technology reduces search costs and enables more efficient worker-firm matches, like internet-driven technology Autor (2001). Indeed, a rigorous evaluation of introducing an SMS-based application connecting agricultural workers and employers in rural Tanzania illustrates that mobile technology can sharply lower search frictions (Jeong, 2021).

3. Context

Mongolia is a North East Asian country populated by 3.4 million people, 68.4% of whom are of working age. Rapid urbanisation, mining dependency, a persistent and high informal sector, and a large, well-educated youth share characterise its labour market.

Ulaanbaatar (UB), Mongolia's capital, houses half of the country’s population. The migration of herder families and youth to cities has driven this trend. Small firms in the commerce sector dominate labour demand, and about two-thirds of all firm-based jobs are in UB (Betcherman et al, 2022). Urban jobs tend to be in commerce, services, and public administration, whereas rural work is dominated by livestock herding and small-scale farming.

When we implemented the message experiment in 2022, the Mongolian economy was recovering from recessions, and so was its labour market. GDP growth was 4.8% after contracting by 4.6% in 2020 due to the pandemic. The unemployment rate declined from 7.9% to 6% between 2021 and 2022. The labour force participation rate increased by 1.3 percentage points in 2022 after declining from 65.4% to 61% between 2019 and 2021.

Another notable thing about 2022 is that a revised Labour Law came into effect. The revised version of the Labour Law overhaul sought to close regulatory gaps and strengthen worker protection. The reforms in the new law align with international standards and represent a policy strength (improving coverage and gender equity) (Betcherman et al. 2022). However, the report by Betcherman et al. notes potential drawbacks in the revised law. Extended leave provisions may raise employer costs or deter hiring, and informal workers still fall outside legal protection.

Mongolia operates a modest Active Labour Market Policy (ALMP) system under the Ministry of Family, Labour, and Social Protection. A network of Labour and Welfare Offices in 21 aimags, plus nine districts of Ulaanbaatar, and a few licensed private agencies provide counselling, job matching, and training. ALMP coverage remains very limited – only about 5.8% of the labour force in 2019, with total ALMP spending approximately 0.08% of GDP (Betcherman et al. 2022) – and programs disproportionately target self-employment grants. For instance, the largest ALMP (“Job Support Program”) channels roughly 60% of its funds into subsidies for micro-enterprise start-ups. In contrast, formal skills training occupies a much smaller role (Betcherman et al. 2022). Betcherman et al. (2022) suggest that ALMP in Mongolia needs to be reoriented and that overemphasis on subsistence self-employment should be reduced.

The personalised message treatment is used to increase job fair attendance. Our intervention, targeting unemployed individuals, was implemented to facilitate the employment of job seekers registered at a district-level Labour and Welfare Office. This intervention is significant in two key ways. First, it demonstrates the potential to scale up underutilised measures in employment promotion policy through the cost-effective and simple use of technology. Second, it contributes to the growing body of evidence on the use of technology and behavioural interventions in labour market policies in developing countries.

In this context, Mongolia’s relatively advanced mobile network infrastructure compared to other developing nations played a crucial role in successfully implementing the intervention and its potential scale-up. Mobile subscriptions per 100 persons increased by 22.6 times between 2000 and 2022, reaching 142, higher than the average worldwide and even in high-income countries.

4. Intervention

In 2024, five main promotion activities, Public Employment Services, Vocational Training, Financial Support for micro and small businesses, Employment Promotion for Disabled Citizens, and Support for Temporary Workplace, were implemented as part of the ALMP in Mongolia. Labour and Welfare Offices in aimags and districts of UB usually have 2-5 staff in the main office and one staff member responsible for labour and welfare issues at each *khoroo* branch.

Our treatment was conducted as part of the Public Employment Services, under which district staff conduct career counselling, job postings from employers, job placement services, and registration of new job vacancies. Public Employment Services covers the largest beneficiaries with the lowest budget among the ALMP. In 2024, the Public Employment Services served 68% (113,504 citizens) of the total ALMP beneficiaries with only 2% of the total ALMP budget.

On November 23, 2022, the Labour and Welfare Office of Songinokhairkhan district organised a day at Misheel Expo, one of the biggest event halls in UB, with the theme "Songinokhairkhan developed through hard work." During this day, job placement services were provided to more than 10 major employers for unemployed citizens. To attract unemployed citizens to this large-scale job fair, we sent an announcement via text message in cooperation with the district office. We sent four different messages as shown below.

Message 1	Message 2	Message 3	Message 4
You are invited to a job fair featuring major companies. The event will take place on Wednesday, November 23, from 10:30 AM to 3:00 PM at Misheel Expo.	Hello [**Name of job seeker**], You are invited to a job fair featuring major companies. The event will take place on Wednesday, November 23, from 10:30 AM to 3:00 PM at Misheel Expo.	Hello [**Name of job seeker**], You are invited to a job fair featuring major companies. Please come to Misheel Expo on Wednesday, November 23, between 10:30 AM and 3:00 PM. Check in with your district specialist, [**Name of specialist**], at the pavilion labeled “Employment and Welfare Service Center” to receive more information. You have been pre-registered for the event.	Hello [**Name of job seeker**], You are invited to a job fair featuring major companies. Please come to Misheel Expo on Wednesday, November 23, between 10:30 AM and 3:00 PM. Check in with your district specialist, [**Name of specialist**], at the pavilion labeled “Employment and Welfare Service Center” to receive more information. You have been pre-registered for the event. Wishing you success, [**Name of counsellor**]

Welfare Services Department (LWSD) of Songinokhairkhan district provided the individual-level administrative data of about 4,674 citizens without employment registered to the LWSD. We meticulously designed the study with robust statistical power to detect small effect sizes. The minimum detectable effect size in the study is a Cohen's h of 0.25.

A message was sent to the unemployed people two days before the day of 'Songinokhairkhan developed through hard work' organized by the district. A design for sending multiple messages with different content was determined based on several tests before sending.

We worked closely with the district administration to ensure that the information, such as where the unemployed citizen should go and whom to meet, was included in the message. During the test period, about 140 text messages were sent to a number of more than 50 non-participating citizens.

5. Data and Balancing Tests

The research team carried out the “message ad” experiment in cooperation with the Labor and Welfare Services Department (LWSD) of Songinokhairkhan district. The study is based on the individual-level administrative data of about 4,674 citizens without employment registered in the LWSD. Administrative data of citizens without employment contains contact information, which includes home address and phone numbers. We sent one of the four intervention messages to 4320 eligible individuals who registered a valid phone number. The intervention messages are named as control, treatment 1, treatment 2, and treatment 3.

Baseline data from the unemployment register were used for the validity analysis of the test results. The quality of randomization and citizen participation was assessed using baseline indicators such as age, education, regional affiliation, and mobile phone operator of the unemployed. Mean covariate balancing tests for the three treatment messages are shown in Table 1. For all covariates, no systematic differences are observed between individuals in the treatment and control groups. The administrative data show that the typical non-working individual is 39 years old and a woman (67%). On average, they show high levels of formal education. Almost three-fifths had completed high school, and one-fifth had completed a college education. The baseline characteristics are broadly similar to those of individuals with no employment as reported in the 2022 labor force survey, which shows similar shares of women, age mean composition, and high education.

Table 1. Balancing Test Across Experimental Groups

	Control Mean	Treatment 1		Treatment 2		Treatment 3	
		Mean	p-value	Mean	p-value	Mean	p-value
Age in years	38.59	38.16	0.28	38.15	0.27	38.58	0.98
Gender (1=female)	0.67	0.68	0.46	0.67	0.94	0.66	0.64
Education							
Primary	0.05	0.06	0.53	0.06	0.57	0.05	0.86
Secondary	0.07	0.08	0.16	0.08	0.53	0.08	0.22
High school	0.60	0.56	0.06	0.58	0.38	0.58	0.38
Technical & Vocational	0.08	0.09	0.67	0.08	0.85	0.09	0.50
Bachelor or above	0.18	0.20	0.53	0.19	0.56	0.18	0.76
Mobile providers							
Mobicom	0.33	0.32	0.72	0.32	0.57	0.32	0.51
Unitel	0.51	0.53	0.43	0.56	0.03	0.55	0.09
District regions							
Tuv	0.36	0.36	0.88	0.37	0.58	0.35	0.59
Tolgoit	0.22	0.22	0.78	0.19	0.13	0.20	0.40
Unur	0.09	0.09	0.98	0.09	0.77	0.10	0.40
Bayankhoshuu	0.33	0.33	0.93	0.35	0.37	0.35	0.47
Newly registered	0.08	0.06	0.19	0.07	0.66	0.08	0.88

Source: Authors' calculations are from administrative data. Note: p-values from OLS models of treatment on each baseline covariate of interest. All values are expressed as proportions unless otherwise specified. Sample size varies across covariates and ranges from 1984 to 2050 for treatment 1, from 2000 to 2063 for treatment 2, and from 2021 to 2086 for treatment 3.

Most of them live in the Tolgoit and Bayankhoshuu regions, and more than half use the UNITEL mobile phone operators. LWSD carried out the registration of citizens without employment in early 2022 and extended the list with newly registered citizens in November, a few days before the message experiment. Unfortunately, there is no data on the exact registration date, and the employment status has not been updated. We created a variable to determine if an individual is newly registered or not. The majority of individuals (92.7%) in the administration data were early registrants, and only 7.3% were newly registered (Table 1).

In intervention 1 and 3, the p-values for coefficients of OLS models that regressed treatment status on covariates are above 0.05. The test results indicate that individuals in the control and treatment groups came from the same population. For intervention 2, p-values for all variables except unitel provider do not reject the equality of means between treatment groups.

The equality is rejected regarding mobile provider being Unitel. However, there are no significant difference in other interventions and they do not differ significantly in their failure rate. The attrition rate in this study was small. According to the message sending operator report, only 1 percent of the text messages failed to be received. As a result, 4278 participants received one of the four intervention messages successfully.

The outcome variable of the message interventions was measured by the number of unemployed people who attended the event.3 Table 2 reports average levels of attendance by treatment, and 95 percent confidence intervals around each. The control message performs slightly better than any of the treatment messages. As mentioned earlier, we applied the same intervention in Sanders and Kirkman (2019). However, the attendance rate has the reverse pattern to that in the UK.

Table 2. Average attendance and confidence intervals (CI) by treatment

	All registered citizens			Newly registered citizens		
	Average Attendance Rate	Lower Bound CI	Upper Bound CI	Average Attendance Rate	Lower Bound CI	Upper Bound CI
Control	5.473%	4.780%	6.166%	25.0%	20.25%	29.75%
Name	5.020%	4.334%	5.705%	27.69%	22.10%	33.28%
Advisor name	4.937%	4.263%	5.612%	23.94%	18.84%	29.04%
Reciprocity & Luck	4.915%	4.250%	5.580%	24.39%	19.62%	29.16%

Source: Authors' calculations from survey data. The sample consists of individuals aged from 18 to 65.

The newly registered citizens had a significantly higher attendance rate than the sample average. One-fourth of newly registered citizens attended the event, while only 3.6% of early registered citizens attended the event. As the SMS message experiment was conducted in November 2022, citizens who registered at the beginning of the year probably already had a job and did not attend the event.

[3] LWSD officers registered the attendance at the job fair event.

6. Empirical framework and findings

The study estimates two parameters of interest for the sample with complete survey information: intent-to-treat (ITT) and effective treatment-on-the-treated (TOT). We estimated the intent-to-treat parameter by a standard multivariate linear regression function of the form:

$$Y_i = \alpha + Z'_i\beta + X'_i\gamma + \varepsilon_i$$

where Y_i is the outcome of interest or the attendance of individual i, Z_i is a vector of treatment indicators (Z_{1i} takes 1 for the message with claimant name, Z_{2i} takes 1 for the message with advisor name, Z_{3i} takes 1 for the message with reciprocity and luck, and zero otherwise). X_i are baseline control variables such as gender, age, education, newly registered, and ε_i is the error term.

The 2SLS estimator estimates the effective treatment-on-the-treated parameter following an instrumental-variable approach in which actual messages (T) received is instrumented by treatment status variables (Z):

$$\begin{cases} Y_i = \alpha + T'_i\beta + X'_i\gamma + \varepsilon_i \\ T'_i = \delta Z_i + X'_i\gamma + \epsilon_i \end{cases}$$

We estimated ITT and TOT parameters using a model without control variables and a model with control variables. The ITT parameters were estimated by OLS, and the estimates are presented in **Table 3**. According to the OLS model without control variables (Column 1), there are small negative but imprecisely measured treatment effects. Column 2 shows the results for the model with control variables. The treatment effects are small negative and not significant, similar to Column 1. These results suggest that personalised messages do not improve, on average, the attendance in job fair events in Mongolia. But the message increased the attendance as the district officials emphasized that the participation of the citizens in the Expo event was higher than expected.

Table 3. ITT Estimates

	ITT: Attendance	
	(1)	(2)
Constant	0.052***	0.071***
	(0.007)	(0.023)
Name	-0.002	0.000
	(0.010)	(0.009)
Advisor Name	-0.004	-0.002
	(0.010)	(0.009)
Reciprocity and Luck	-0.005	-0.006
	(0.010)	(0.009)
Female		0.013*
		(0.007)
Age		-0.002**
		(0.001)
Bachelor education		-0.008
		(0.009)
Older than 40		0.040***
		(0.012)
Recently registered		0.220***
		(0.013)
N	4040	4040
R2 Adj.	-0.001	0.072

Source: Authors' calculations from survey data. *Note*: Standard errors in parentheses. ITT parameters were estimated by OLS models. ***p <0.01, **p<0.05, *p<0.1.

Model with control variables have some interesting results. Although attendance decreases with age, the attendance of individuals older than 40 is significantly higher (Column 2 of **Table 3**). Moreover, recently registered unemployeds have significantly higher attendance.

Table 4 presents the TOT parameters estimated by 2SLS. The actual messages received were instrumented by random assignment to treatment statuses (Message 2, Message 3, and Message 4). The ITT and TOT estimates are almost identical, as the non-compliance rate is very small.

Table 4. TOT Estimates

	ITT: Attendance	
	(1)	(2)
Constant	0.052***	0.071***
	(0.007)	(0.023)
Name	-0.002	0.000
	(0.010)	(0.010)
Advisor Name	-0.004	-0.002
	(0.010)	(0.010)
Reciprocity and Luck	-0.006	-0.006
	(0.010)	(0.010)
Female		0.013*
		(0.007)
Age		-0.002**
		(0.001)
Bachelor education		-0.008
		(0.009)
Older than 40		0.040***
		(0.012)
Recently registered		0.220***
		(0.013)
N	4040	4040
R2 Adj.	-0.001	0.072

Source: Authors' calculations from survey data. *Note*: Standard errors in parentheses. TOT parameters were estimated by 2SLS that instrumented the message treatments (T) by randomly assigned treatment status (Z) of participants. ***p <0.01, **p<0.05, *p<0.1.

6.1. Heterogenous effects

According to the literature on labor market experimental studies, there is heterogeneity in the treatment impacts. We had the advantage of baseline data with individual socio-demographic characteristics such as gender, age, and education, which enabled us to examine heterogenous effects.

To account for the heterogeneity of effects across subgroups of participants, the estimation framework and model specification given in equations (1) and (2) are applied after interacting the treatment status variable with baseline covariates of interest: gender (men vs. women), age (18-40 vs. 41-65), and educational attainment (less than bachelor education vs. bachelor education).

Table 5 presents the main results of heterogenous impacts of messages. The models in Column (1) and Column (3) indicate absence of heterogenous impacts across gender and education groups. However, the model with the age group (Column 2) has different results.

Table 5. Heterogenous Impacts for Message Treatments

	Attendance		
	Gender (1)	Older than 40 (2)	BA education (3)
Constant	0.077**	0.081***	0.022
	(0.024)	(0.023)	(0.017)
Name	-0.011	-0.007	-0.004
	(0.016)	(0.012)	(0.010)
Advisor Name	-0.010	-0.017	0.000
	(0.016)	(0.012)	(0.010)
Reciprocity and Luck	-0.011	-0.022+	-0.008
	(0.016)	(0.012)	(0.010)
*Female*Name*	0.016		
	(0.020)		
*Female*Advisor Name*	0.012		
	(0.020)		
*Female*Reciprocity and Luck*	0.008		
*Older than 40*Name*		0.018	
		(0.019)	
*Older than 40*Advisor Name*		0.037+	
		(0.019)	
*Older than 40*Reciprocity and Luck*		0.041*	
		(0.019)	
*BA education*Name*			0.027
			(0.024)
*BA education*Advisor Name*			-0.009
			(0.024)
*BA education*Reciprocity and Luck*			0.015
			(0.024)
N	4040	4040	4040

Source: Authors' calculations from survey data. *Note*: Standard errors in parentheses. ITT parameters were estimated by OLS models with control variables. ***p <0.01, **p<0.05, *p<0.1.

The results highlight the heterogeneity of message add effects across age groups. Individuals have different attitudes towards message ads. Young unemployed are more likely to respond to public messages than to personalized private messages. In other words, adding personal information does not affect youth attendance.

On the other hand, individuals aged 41-65 are more responsive to messages with personal information. In particular, the group receiving the most informative message increased their attendance in response to the message with reciprocity and luck.

7. Conclusions

The objective of the study was to examine the effects of variations in text messages on attendance rates at an event by replicating the Sanders and Kirkman message experiment in the context of the Asian developing country, Mongolia. Mongolia has relatively advanced mobile network infrastructure compared to other developing nations, and a message can play a crucial role in employment promotion activities. The district officials emphasized that the participation of the citizens in the Expo event was higher than expected.

We took the advantage of baseline data of registered citizens without employment to examine the impact of message treatments. The results suggest that personalised messages do not improve, on average, the attendance at job fair events in Mongolia. However, message ads of job fair events are significantly more effective in a shorter period after the registration of unemployed citizens.

Individuals have different attitudes towards message ads. Young unemployed are more likely to respond to public messages than to personalized private messages, while individuals aged 41-65 are more responsive to messages with personal information.

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