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Digital labor-market intermediation and job expectations: Evidence from a field experiment

Ana C. Dammert[a,b], Jose Galdo[a,b], Virgilio Galdo[c,*]

[a] Carleton University, Canada

[b] IZA, Germany

[c] The World Bank, United States

HIGHLIGHTS

- This study analyzes how digital intermediation (SMS) affects job gain expectations.
- A distinctive feature of this study is its field experimental design with multiple treatments.
- Significant effects were found for those who received SMS based on a large information set.

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ABSTRACT

Subjective expectations are fundamental for understanding individual behavior. Yet, little is known about how individuals use new information to formulate and update their subjective expectations. In this study, we exploit data from a multi-treatment field experiment to investigate how job-market information sent to jobseekers via short text messages (SMS) influence subjective job gain expectations in Peru. Results show that jobseekers who received digital intermediation based on a large information set increased their before–after job gain expectations relative to the control group. Independently of the information channel, no significant effects were found when labor-market intermediation is based on a restricted (short) set of information.

1. Introduction

Understanding of the role of subjective expectations on economic behavior is central for economic modeling and policy design. While most progress in expectations literature pertains to its influence on a number of economic outcomes (see the surveys in Manski, 2004, and Delavande et al., 2011), little is known about how individuals use available information to formulate and update their subjective expectations. In fact, few studies have directly addressed the role of information on the formation of expectations (e.g., Luseno et al., 2003, Jensen, 2010, and Stinebrickner and Stinebrickner, 2012).

In the last decade, Information and Communication Technologies (ICT) have expanded at unprecedented rates in both developed and developing economies. In contrast to the Internet, mobile phones have become the most rapidly adopted technology in developing countries (Chong, 2011). Mobile phones allow information to travel instantly and at lower costs. Not surprisingly, a small but growing body of empirical literature has credited mobile phones with reductions in transaction costs and efficiency gains in developing settings (e.g., Jensen, 2007, Aker, 2010, and Goyal, 2010). So far, however, no study has addressed the link between digital information and subjective expectations.

This paper bridges these two streams of literature by investigating how information about job-market opportunities sent to jobseekers via short text messages (SMS) influence subjective ex-

* Correspondence to: Independent Evaluation Group, The World Bank, 1818 H St., NW Washington, DC 20433, United States. Mail Stop# MSC 9-006. Tel.: +1 2024588943.

E-mail addresses: ana_dammert@carleton.ca (A.C. Dammert), jose_galdo@carleton.ca (J. Galdo), vgaldo@worldbank.org (V. Galdo).

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pectations. By providing faster, better, and cheaper access to information, mobile phone technologies might influence job gain expectations, as searchers can access relevant, up-to-date information on job vacancies. From a theoretical perspective, job decisions are forward-looking and thus involve expectations. For instance, sequential search models that incorporate uncertainty about the wage distribution are based on expectations that depend on information signals coming from the wage offers individuals observe during their search time (e.g., Diagne, 2010).

As expectations could be merely proxying for other unobserved characteristics, a distinctive feature of this study is its field experimental design with multiple treatments. We use data from the Public Intermediation System in Peru, a country that adopted an innovative e-government initiative in labor intermediation. Searchers that signed up to receive public labor-market intermediation were randomly assigned to four treatment groups according to two information channels (i.e., digital and non-digital intermediation) and the scope of information they received (i.e., short (public) and enhanced (public/private) information sets).

This study finds that jobseekers subject to digital labor-market intermediation based on a large set of information show a positive and statistically significant change in their job gain expectations three months after signing up for public labor-market intermediation. This result suggests that the combination of digital technology and the scope of the information set matters rather than the technology by itself.

2. The intervention: institutions, treatment, and data

The experimental design was implemented as part of the regular (non-experimental) public intermediation system CIL-PROEMPLEO, which is run nationally for the Ministry of Labor in Peru and offers intermediation services, electronic information on the labor markets, and low-cost reemployment services to jobseekers who voluntarily sign up for these services.[1] CIL-PROEMPLEO aims to ease the labor-market functioning by decreasing search costs and improving the quality of employer/worker matches.[2] Since its introduction in 1998, the proportion of unemployed people in Peru who use the public intermediation program has increased substantially from 3% in 1997 to 18% in 2010 (Ministry of Labor 2012).

The treatment consisted of three months of subsidized job search assistance in which individuals' labor profiles were matched with available job vacancies. The experimental sample was selected at the initial registration filing for the normal inflow of applicants in Lima after excluding registered individuals who do not own mobile phones or hold occupations with very high turnover rates, i.e., unskilled peons. The random assignment was carried out on a daily basis (excluding weekends and holidays) from June 22, 2009, to September 1, 2009. In total, 1280 job seekers were randomly allocated to one of four different groups: (1) short-non-digital treatment group, (2) short-digital treatment group, (3) enhanced-digital treatment group, and (4) a control group, following a random allocation of 30%, 15%, 25%, and 30%, respectively. In total, 40% of the sample was subject to digital labor-market intermediation.

The short-non-digital treatment group was subject to the standard CIL-PROEMPLEO intermediation practices. In contrast to this treatment group, the digital treatment groups 2 and 3 were exposed to a technological innovation aimed to reduce job search costs. Jobseekers assigned to these groups were informed about job-market opportunities that match their labor profile through digital services, i.e., delivery of SMS messages to their mobile phones. The difference between treatment groups 2 and 3 is given by the set of information available to them. According to CIL-PROEMPLEO regulations, job matches are based only on firms that signed up on the public intermediation system. Treatment group 3 relaxed this restriction by considering an enhanced set of information coming from job opportunities generated outside the CIL-PROEMPLEO system (e.g., job boards, national newspapers ads, and non-profit private employment agencies).[3] Independently of whether individuals belong to the short- or enhanced-digital treatment groups, the framing of the information sent to jobseekers via SMS follows a standard structure and is limited to the description of the occupation and contact information.[4] Finally, control group individuals were removed temporarily from the information system for a period of three months.[5]

Comparison of treatment groups 2 and 3 allows one to test the impact of expanding the set of information available to jobseekers while holding fixed the information technology. From a theoretical standpoint, however, more information does not automatically lead the updating of subjective (job) expectations. Information theory states that if individuals update their expectations (or change their behavior) in response to new information they receive, then that information has value to them. According to Hirshleifer and Riley (1992), the value of information is determined by three important factors – confidence, novelty, and ability and willingness to act based on updated beliefs – all of which involve different forces and trade-offs. Individuals process new information largely based on their prior beliefs. If job seekers, for instance, place strong confidence in their initial beliefs, more information is not necessarily more valuable, all else held constant. Evidence from behavioral economics, for instance, suggests that individuals who formulate their initial beliefs based on poor past experiences have difficulty interpreting subsequent new information, as initial expectations tend to anchor one's processing of information (Tversky and Kahneman, 1974), thus leading to the so-called cognitive confirmation bias, a state on which people tend to ignore new information altogether or misread it (Griffin and Tversky, 1992).

Moreover, the greater the confidence in the message, the greater its effect on the updating of the subjective probability distribution. In this regard, it is noteworthy to recall that public labor market intermediation systems are populated with individuals with chronic problems of employability (Autor, 2001).[6] As such, they could have developed strong initial beliefs given their relatively poor experience in the marketplace, a genuine distrust of information coming from public sources, or both. If that is the case, they will not update mechanically their initial expectations in response to more information.

On the other hand, if new information constitutes a novelty relative to the individual's initial expectations, then one expects

1 Unlike western developed economies, Peru does not have an Unemployment Insurance (UI) system. Thus, participation in SIL-PROEMPLEO is voluntary and unrelated to UI benefit reception.

2 Labor-market intermediaries are institutions that somehow interpose themselves in the employer–worker relationship to ease the functioning of the labor markets. Yet, despite their potential contribution to the functioning of the labor market, they remain relatively understudied (Autor, 2001).

3 According to the 2003 survey of formal firms located in Metropolitan Lima, the advertisement of job vacancies is mainly done via newspaper ads (54%) and personal contacts (43%).

4 A literal reproduction of an SMS message says: "*PROEMPLEO. Hostess wanted Restaurant Amador Av. La Mar* #3453 *Lince Tel* 3038145. *Contact*: *Elizabeth Bartra*".

5 All individuals in the sample were unaware of both their participation in an experiment and the exogenous manipulation of the economic (intermediation) environment. This minimizes potential bias induced by the presence of 'John Henry' effects or, more generally, 'Hawthorne' effects (List and Rasul, 2010).

6 The unemployment spells for users of the public intermediation system in Peru are two-fold higher than that for non-users.

Table 1
Summary statistics by treatment status digital labor-market intermediation program, Lima 2009–2010.

Baseline variables	Treatment groups				p-value of F test
	Non-digital T_1 D^{T_1}	Digital T_2 D^{T_2}	Digital T_3 D^{T_3}	Control D^C	$[D^{T_1} = D^{T_2} = D^{T_3} = D^C]$
A. *Socio-demographic*					
Sex (1 = male)	0.57	0.52	0.55	0.54	0.65
Age	27.04	25.33	26.27	25.55	0.02
Years of schooling	12.15	12.09	12.06	11.94	0.76
Single	0.71	0.76	0.73	0.73	0.52
Have children	0.32	0.26	0.32	0.26	0.22
Number of children					
Migrant	0.27	0.29	0.26	0.25	0.75
Cement floor	0.66	0.69	0.69	0.66	0.80
Cement roof	0.80	0.74	0.75	0.74	0.20
Cement walls	0.91	0.88	0.89	0.89	0.64
Flush toilet	0.93	0.91	0.93	0.95	0.29
Safe water	0.94	0.90	0.93	0.94	0.39
Poverty index	0.06	−0.12	−0.01	0.02	0.66
B. *Last labor-market experience*					
Worked ever	0.81	0.80	0.82	0.82	0.95
Discouraged worker	0.11	0.14	0.13	0.13	0.65
Monthly income (in soles)	519. 82	484.97	490.60	562.00	0.60
Hours work per week	34.15	34.97	34.36	37.28	0.39
Had accident insurance	0.18	0.16	0.16	0.18	0.87
Had pension plan	0.25	0.26	0.21	0.22	0.66
Had health insurance	0.25	0.25	0.20	0.21	0.52
Last job matched with skills	0.32	0.33	0.27	0.31	0.62
C. *ICT usage*					
Use cell phone	0.95	0.95	0.96	0.97	0.43
Cell phone usage for job search	0.51	0.49	0.49	0.46	0.54
Use internet	0.83	0.85	0.84	0.83	0.86
Internet usage for job search	0.60	0.62	0.61	0.62	0.91
D. *Job gain expectations*					
Very optimistic	0.67	0.71	0.65	0.70	0.12
Somewhat optimistic	0.29	0.24	0.30	0.25	0.21
Only a little optimistic	0.04	0.04	0.05	0.05	0.78
Do not expect to find a job	0.00	0.01	0.00	0.00	0.86
N	345	188	303	354	

Notes: The test of equal means for the experimental sample is based on a regression with treatment indicators on the right-hand side: D^{T_1} refers to the short-non-digital treatment group, D^{T_2} to the short-digital treatment group, D^{T_3} to the enhance-digital treatment group, and D^C to the control group.

a strong updating effect. In our view, the distinctiveness between short (public) and enhanced (public/private) information sets involves a novelty factor since historically the (standard) public intermediation system has operated only with information from a limited group of (low-quality) firms. Finally, the value of the information also depends on individuals' ability and willingness to respond to the new information. In this regard, incentives and constraints affect how individuals react to information shocks. For instance, there are some mitigating concerns with regard to the effectiveness of digital information in developing countries due to the lack of human capital and language barriers between the users of the technology and the technology itself (Chong, 2011).

In all, the effect of more information on subjective expectations is ultimately an empirical question and depends on the relative strengths and forces of different attributes of information. From an empirical standpoint little is known about how individuals update their subjective expectations in real life in response to new information (see Manski, 2004; Delavande et al., 2011). Available evidence suggests that if individuals update expectations, they do it with a predictable bias towards optimism. In fact, empirical studies show that new valuable information is often read optimistically rather than objectively, since people underreact to negative information and overreact to positive information (e.g., Easterwood and Nutt, 1999; Hirshleifer and Shumway, 2003).

The baseline dataset contains information for 1189 individuals, which implies an attrition rate of 7% relative to the original sampling design.[7] Out of these data, 29%, 16%, and 25% correspond to treatment groups 1, 2, and 3, respectively, while the remaining 30% correspond to the control group. A critical step in the estimation of the causal treatment effects is an analysis of how effective the randomization was. Table 1 shows the mean baseline distribution for a large set of socio-demographic and labor-market variables across all treatment groups. Panel A shows that the average individual in our sample has completed high school education, is younger than 30 years old, and is single. There is a slight disproportion in the rate of enrollment by gender, as 55% of registered users are men. Only 30% of users have offspring, while one-fourth of them were not born in Lima. The p-value of F-test for the equality of means across all four randomized groups is above 0.05 for all variables except age.

Panels B and C show the mean distribution for baseline variables related to prior labor market experiences and ICT exposure. The data show that most individuals in the sample had previous job experience in the private sector, worked on average 35 h per week, and earned 560 soles per month. Less than one-third of them had fringe benefits, including health insurance and pension plans. Moreover, most jobseekers have used mobile phones and the Internet in general, while around half of the sample has used these electronic gadgets for job search purposes. The p-value of the F-test

[7] The rate of attrition was similar in all treatment groups and it is not statistically related to any particular socio-demographic variable.

for the equality of means is above 0.05 for all variables considered in these two panels.

Finally, Panel D shows the distribution of future job gain expectations. The baseline survey asks, "Are you optimistic you will find a job in the next three months?" with answers on a Likert scale of 'very optimistic', 'somewhat optimistic', 'only a little optimistic', or 'do not expect to find a job'.[8] Almost 68% of job seekers were very optimistic, while 26% and 5% were somewhat and only a little optimistic, respectively. Surprisingly, almost no one expects not to find a job. The p-value of F-test for the equality of means is above 0.05 for all of these categories. In sum, the statistical analyses suggest that the sample of individuals assigned to all of the different groups were drawn from the same population.

3. Empirical framework and results

The estimation framework is based on a standard difference-in-difference approach:

$$Y_{it+1} - Y_{it} = \beta_0 + \beta_1 D_i^{T_1} + \beta_2 D_i^{T_2} + \beta_3 D_i^{T_3} + X_{it}'\beta_4 + \varepsilon_{it} \qquad (1)$$

where $Y_{it+1} - Y_{it}$ is the before–after change in subjective expectations. Both Y_{it+1} and Y_{it} are expressed in binary form, with 'very optimistic' = 1 and ('somewhat optimistic', 'only a little optimistic', 'do not expect to find a job') = 0. $D_i^{T_1}$, $D_i^{T_2}$ and $D_i^{T_3}$ denote treatment indicators for the experimental groups 1, 2, and 3, respectively. The coefficients β_1, β_2, and β_3 represent intent-to-treat parameters of interest. The base category is the control group. X_{it} denotes a rich set of baseline covariates, while ε_{it} is the error term. The estimation sample is based on individuals who remain unemployed before and after the treatment as the survey design elicited subjective expectations only from them.

Table 2 presents estimates from the parametric model (1). Our estimates provide evidence that the enhanced-digital treatment intervention is positive and statistically related to before–after changes in subjective job gain expectations. Consider the parametric estimates in column 1. Although the parameters of interest across all treatment groups show a positive sign, only treatment group 3 reports statistically significant increases on job expectations relative to control group individuals. The point estimates for β_3 reach 14% points, or a 20% increase with respect to the baseline measure of job expectations. Controlling for a rich set of socio-demographic variables does little to change the estimates or their statistical significance, as is shown in column 2.

Because it is possible that previous labor-market experiences exert strong influence on future job expectations, in column 3 we also include a rich set of baseline labor-market characteristics. Results show a small increase in the magnitude of β_3 (17% points), which is statistically different from zero at the 5% level. In fact, columns 2 and 3 in Table 2 show that all baseline socio-demographic and labor-market variables are not statistically related to the outcome of interest, which adds evidence of the balancing property of the experimental design. Finally, as searchers were randomly allocated to four different groups on a daily basis following the normal inflow of applicants, we have as many experimental sets as different days the experimental sampling lasted. We therefore included in column 4 a date fixed effects to control for intra-day variation in the treatment allocation. The point estimates show slight variation with respect to results depicted in columns 2 and 3. Clustered standard errors by date report statistically significant impacts at the 5% level for the enhanced-digital treatment group.

These results tell a consistent story: It is not the technology itself that causes a (statistically) significant effect on job gain expectations, but rather, it is an enhanced set of information about labor-market opportunities transmitted through digital means which explains our findings. In our view it is the value

Table 2
Impacts of digital labor market intermediation on job gain expectations labor-market intermediation program, Lima 2009–2010.

Dependent var: expect_{t+1}–expect_t	(1)	(2)	(3)	(4)
Non-digital treatment (D^{T_1})	0.015	0.032	0.035	0.037
	(0.070)	(0.071)	(0.072)	(0.103)
Short-digital treatment (D^{T_2})	0.026	0.037	0.035	−0.006
	(0.084)	(0.085)	(0.085)	(0.104)
Enhance-digital treatment (D^{T_3})	0.144**	0.154**	0.173**	0.179**
	(0.072)	(0.073)	(0.074)	(0.077)
Age	–	−0.007	−0.008	−0.008
	–	(0.004)	(0.005)	(0.006)
Male	–	−0.029	−0.037	−0.055
	–	(0.055)	(0.056)	(0.059)
Migrant	–	0.039	0.034	0.034
	–	(0.066)	(0.067)	(0.072)
Single	–	0.078	0.076	0.131
	–	(0.098)	(0.098)	(0.098)
Years of schooling	–	−0.002	−0.003	0.000
	–	(0.011)	(0.011)	(0.011)
Has children	–	0.045	0.064	0.083
	–	(0.0135)	(0.141)	(0.136)
Number of children	–	0.036	0.031	0.033
	–	(0.072)	(0.076)	(0.069)
Poverty index	–	0.009	0.007	0.014
	–	(0.016)	(0.001)	(0.023)
Worked ever	–	–	−0.021	−0.034
	–	–	(0.090)	(0.096)
Discouraged worker	–	–	0.005	0.005
	–	–	(0.068)	(0.096)
Had accident insurance	–	–	−0.038	−0.032
	–	–	(0.101)	(0.139)
Had pension plan	–	–	0.181	0.211
	–	–	(0.155)	(0.188)
Had health insurance	–	–	−0.114	−0.090
	–	–	(0.156)	(0.178)
Had no formal contract	–	–	−0.041	−0.006
	–	–	(0.081)	(0.086)
Last job matched with skills	–	–	0.083	0.070
	–	–	(0.067)	(0.078)
R^2	0.01	0.02	0.04	0.148
N	386	386	386	386

Notes: Standard errors in parentheses. Estimates based on a parametric differences-in-difference estimator. D^{T_1} refers to the short-non-digital treatment group, D^{T_2} to the short-digital treatment group, and D^{T_3} to the enhance-digital treatment group. Base category is the control group. Column (4) includes date fixed effects and clustered standard errors by day. The estimation sample is based on unemployed individuals before and after the intervention.
** statistically significant at the 5% level.

8 Manski (2004) provides a detailed analysis of Likert scales with respect to more sophisticated subjective probabilities. Likert scales do not allow, for instance, for answers in a cardinal scale and thus cannot be used to calculate the moments of a distribution of interest.

of the information generated by the complementarity between the novelty of the (public/private) information and the higher number of messages received that might explain this relative gain in job expectations.[9] These results matter because subjective job expectations are a meaningful predictor of subsequent work status (Stephens, 2004) and are associated with job search effort (Diagne, 2010) and wage growth (Campbell et al., 2007).[10]

4. Conclusion

This study exploits a multi-treatment experimental design implemented as part of the regular (non-experimental) public intermediation system in Peru to investigate the extent to which digital labor-market intermediation influences subjective job gain expectations. Application of a standard difference-in-difference estimator reveals that jobseekers who received digital intermediation based on a large information set increase their before–after job gain expectations relative to the control group. Independent of the information channel, no significant effects were found when labor-market intermediation is based on a restricted (short) set of information. An extended analysis about the role of digital labor-market intermediation and the scope of information sets on unemployment spells and job search effort is the next step for us.

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[9] We acknowledge that evaluating the impacts of each information attribute separately would improve our understanding of the causal channels. In this regard, a nice extension of this paper would consider proxy variables for each information attribute that could be incorporated via interaction terms in Eq. (1).

[10] In fact, data only from the control group (to isolate the effect from the treatment information) also confirm the positive relationship (0.15) between baseline job gain expectations and future work realizations even after controlling for numerous socio-demographic and labor-market characteristics.