Mobile phones for labor market intermediation: A multi-treatment experimental design

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Abstract

This paper investigates the causal impacts of integrating mobile phone technologies into traditional public labor-market intermediation services on employment outcomes. By providing faster, cheaper and up-to-date information on job vacancies via SMS, mobile phone technologies might affect both the rate at which offers arrive and the probability of receiving a job offer. Yet, in contrast to agricultural or fishing markets where the speed of information matters, in labor markets the scope of information might be more important due to the lack of homogeneity of workers and firms. We therefore implement a social experiment with multiple treatments that allows us to investigate both the role of information channels (digital versus non-digital) and information sets (short [public] versus enhanced [public/private]). The results show positive and significant short-term effects on employment. Yet, it is not the technology by itself that leads to these effects. Rather, it is the enhanced set of information about job opportunities, transmitted through digital channels, which drives the positive impacts. As for potential matching efficiency gains, the results suggest no (statistically) significant effects associated with either information channels or information sets.

JEL classification codes: I3, J2.
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1. Introduction

Information, though often costly or incomplete in reality, is central to the functioning of markets (e.g., Stigler 1961). Labor market transactions are not an exception as workers and firms must dedicate resources and time to meet in the marketplace. Given the costly nature of job searches, it has been long emphasized that the role of labor market intermediaries (LMIs), such as public employment offices and temporary help agencies, can reduce search costs and adverse selection problems (Autor 2001). Yet, despite their potential contribution to the functioning of the labor market, these institutions remain relatively understudied (Autor 2009).

The unprecedented expansion of Information and Communication Technologies (ICT) in the last two decades has enabled and shaped the existence of a new array of labor market intermediaries, such as online job boards, social media sites, and e-recruiting firms, which have invigorated research in this area. Evidence, largely based on U.S. data, has shown how the diffusion of the Internet has allowed new labor market intermediaries to offer information access to a larger pool of individuals at much lower costs (Stevenson 2009, Nakamura et al. 2009, Bagues and Sylos 2009). It still remains unclear, however, whether access to the Internet has positively affected the duration of unemployment spells. While Kuhn and Skuterud (2011) showed that Internet job searches were effective in reducing unemployment durations, Kroft and Pope (2009) and Kuhn and Skuterud (2004) reports no effects. Evidence for developing countries is nonexistent.

While this promising research has addressed the impacts of Internet access on search behavior and unemployment spells, nothing is yet known about the role of mobile phone technologies on the efficiency of the labor markets. In fact, mobile phone technologies have not been yet incorporated formally in the evaluation of labor market intermediation. The aim of this study is to provide evidence, analysis and insights on the causal impacts of (digital) public labor-market intermediation in a developing-country setting.

Unlike the Internet, mobile phones have become the most rapidly-adopted technology in developing countries due to the fact that the costs associated with the installation of mobile phone towers is relatively low (Jensen 2010). Recent statistics for mobile phone penetration indicate that 8 of 10 people in the world had a subscription in 2011, up from 1 in 10 in 2000 (World Bank 2012). Not surprisingly, credible non-experimental studies of fishermen in India (Jensen 2007) and farmers in Niger (Aker 2010), Uganda (Muto and Yamano 2009), and India (Goyal 2010) have shown how access to mobile phone service is associated with increases in arbitrage, declines in price dispersion and increases in the number of markets over which farmers trade.

While there is a great deal of narrative evidence in regard to the promise of mobile phone technology fostering economic development, well-identified empirical studies are scarce (Chong 2011, World Bank 2012). A distinctive feature of this study is its experimental design. We use as a case study the public LMI system in Peru, a country that adopted an innovative e-government initiative in labor intermediation.[1] We implement a social experiment with multiple treatments as part of regular (non-experimental) public labor intermediation services. This approach minimizes considerable empirical difficulties due to 'unobserved' factors associated with participation and the endogenous placement of mobile phones.

This study addresses four specific and related topics of interest. First, we exploit unique data to analyze the determinants of digital job search in Peru by considering both Internet and mobile-phone channels. Second, we evaluate the overall (digital and non-digital) effectiveness of public LMI on reducing unemployment spells and improving the match quality of workers to jobs.

[1] Peru's mobile infrastructure reached a substantial coverage of 87 mobile phone subscriptions per 100 inhabitants, with 80 percent of them classified as prepaid subscriptions (ECLAC 2009).

Evidence in this area is mixed, highly dependent on the research design and corresponds mainly to developed countries where concerns about the efficiency of unemployment insurance systems have led to a stream of studies in this field (e.g., Bishop 1993, Ashenfelter et al. 2005, Meyer 1995).

Third, we compare the effectiveness of digital versus non-digital labor market intermediation within the public system. By providing faster, better and cheaper access to information, mobile phone technologies might help poorly functioning markets to work better as jobseekers can access relevant, up-to-date information on job vacancies via SMS. Yet, in contrast to fishing or agricultural markets in which the speed of access to information matters, the technology by itself might not be enough to efficiently connect workers to jobs.

Four, we analyze whether it is the technology or the set of information available to jobseekers that matters most. In contrast to agricultural markets where there is a certain degree of homogeneity to the commodities being exchanged, the potential gains of improving the scope of information, rather than its speed, might be more dramatic due to the lack of homogeneity of workers and firms. We then compare the impacts of short (public) versus enhanced (public/private) information sets available to jobseekers while holding fixed the information technology.

From June 22, 2009 to September 1, 2009, the experimental sample was selected at the initial registration filing for the normal inflow of applicants into Lima. Jobseekers 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).

From a theoretical standpoint, the improvement of access to information via mobile phone service might affect the efficiency of labor market intermediation through several channels. Economic theory predicts that the larger the cost of search, the less extensive will be the searches undertaken by workers at a given wage distribution (e.g., Stigler 1962). A direct effect of introducing mobile phones in labor market intermediation is a direct fall in the costs of search as workers can access relevant, up-to-date information on job vacancies via SMS. A second channel through which improved information via mobile phones affects the labor markets is via better arbitrage of prices (wages), which might lead to higher wages being offered to workers (Grossman and Stigler 1976). Information in the labor market is, after all, capital that is produced at the lower cost of search and, thus, yields higher returns than what would have been received in its absence. A third channel through which improved information via mobile phones affects the labor markets is by speeding the clearing of the labor market. Mobile phones allow information to travel instantly and at lower costs. Standard search models predict that both the rate at which offers arrive and the probability of receiving a job offer will increase as a result of search costs decreasing (Mortensen 1986). A fourth channel is by better matching workers to jobs due to enhancements in search and coordination tasks (Aker and Mbiti 2010).

At the same time, some countervailing factors might affect the relevance of mobile phone service in labor intermediation. The rise in the number of potential matches because of reduced search costs would increase the minimum wage a worker will accept or the minimum productivity an employer will accept (Pissarides 2000, Boone and Van Ours 2004). Moreover, the fall in search costs may also lead to a fall in match quality due to an excess of applications of unemployed people who belong to groups with chronic problems of employability (Lang 2000), or the emergence of crowding-out effects from traditional search methods. If the introduction of mobile phone technology exacerbates adverse selection in labor intermediation, matching in the labor markets would rely more on personal connections than on formal intermediation mechanisms (Casella and Hanaki 2010). Furthermore, there are some mitigating concerns about the effectiveness of mobile phone technology in developing countries due to the lack of human capital and due to the language barriers between the users of the technology and the technology itself (Chong 2011). In all, the net effect of the introduction of mobile phone technologies on unemployment duration and match quality is an empirical question that will depend on the relative strengths of these channels.

Four main findings emerge. First, Internet and mobile phone job search channels seem to be complements, fueled by the substantial growth of small Internet Café shops (‘*cabinas de Internet*’) across most neighborhoods. Jobseekers with past labor-market experience and high expectations on future job gains are more prone to use both digital channels when searching for jobs. In contrast to Internet-based search, the use of mobile phones for job purposes is more related to disadvantaged men and migrants. Second, setting aside the distinction between digital and non-digital channels, we found a short-term statistically significant employment impact of 6 percentage points for the government-sponsored LMI. Third, by comparing digital versus non-digital channels and short versus enhanced information sets in a multiple treatment framework we find that it is not the technology by itself that causes these positive impacts. Indeed, it is the enhanced set of information about job opportunities, transmitted through digital means, which drives the positive employment results. In contrast to fish and agricultural markets, the scope and extent of information sets seems to be more relevant in the labor market. Fourth, independently of the information set and information channel, we do not find (statistically) impacts of public intermediation on job matching efficiency. This result can be explained by the ‘information-only’ intermediary nature of mobile phones.

This study speaks directly to the recent literature on digital labor market intermediation that is largely based on observational data for developed countries. Several studies in this area showed how the diffusion of the Internet has allowed information on labor market opportunities to travel instantly and at a lower costs (Stevenson 2009, Nakamura et al. 2009), leading to a reallocation of search effort among various job search activities (Stevenson 2009, Kuhn and Mansour 2011), and as a result, to more diversified job search behavior (Kroft and Pope 2010, Cahuc and Fontaine 2009). By providing the first experimental evidence on the role of mobile phone technologies in connecting workers to jobs, we expand this literature in important ways.

We contribute to the understanding of how the new 'information economy' (Freeman 2002) is shaping new labor market institutions in developing countries. E-government initiatives are transforming the way governments interact with citizens and organize their operations; yet, there are no formal evaluations of their effectiveness. By documenting the impacts of mobile phone technologies on job search outcomes, our findings contribute to an emerging body of empirical literature that reports how the development and use of mobile phone services has brought new possibilities for economic development. In this regard, a number of recent studies have addressed the impacts of mobile phones in agriculture (e.g., Aker and Fefchamps 2013, Goyal 2010), health (e.g., Dammert et al. 2013a, Pop-Eleches 2011), institutions (e.g., Yañez-Pagans and Machicado 2010), and financial markets (e.g., Karlan et al. 2010).

This study is organized as follows. Section 2 presents a background discussion about the public intermediation system in Peru; sections 3 develops a theoretical search model with endogenous effort in both public and private search channels, section 4 discusses the research design, treatment and treatment groups; section 5 analyzes the data and the baseline equivalence; section 6 analyzes the determinants of digital job search; section 7 reports the empirical results; and section 8 concludes.

2. Background: Public employment services in Peru

Prior to 1996, the Peruvian Public Employment Services operated as a centralized intermediation office, hosted at the headquarters and regional branches of the Ministry of Labor and Social Promotion, with the aim of connecting workers to jobs. The employer-employee matching process was highly bureaucratic and done manually case-by-case without any regard for the automatization of the data collection and dissemination of the information. Not surprisingly, the job intermediation process was inefficient and costly. The average time it took for a worker to complete the registration process was 4 days after completing a battery of aptitude, knowledge, and psychometric tests (Ministry of Labor, 1998). As a result, only 3 percent of active jobseekers used the public employment services in 1996, and in particular, they were those with chronic problems of employability (Chacaltana and Sulmont 2003).[2]

In 1996, the Peruvian government launched an ambitious e-government initiative aimed to modernize the role of the public employment agencies. With technical and financial support from the Swiss government and the European Union, a new National Information System (SIL) was put into place to support the adoption and design of e-government procedures, lower the administrative burden, and to improve the efficiency of the intermediation process. Bureaucratic processes were replaced by simpler and time-saving protocols, the compilation and dissemination of information changed from manual to automated matching algorithms, centralized labor-market institutions were replaced with decentralized offices through partnerships with not-for-profit institutions such as NGOs and vocational schools, and more caseworkers were hired and trained in labor-market intermediation (MTPS 1998, 1999, ICA 2005).

[2] The duration of unemployment for jobseekers using the public employment services was around 11 weeks, while for those using other job search strategies was 7 weeks.

This active labor-market initiative started its operations in 1998 with the introduction of CIL-PROEMPLEO, an LMI institution that offers three complementary services: intermediation, information, and low-cost reemployment services. On the intermediation front, bureaucratic practices was greatly simplified as participation only requires individuals and firms to register in-person at any labor mediation office by filling a simple application form and answering a short standard labor-market survey.[3] This information is subsequently uploaded to SILNET, a customized informatics system of job intermediation available only through an intranet. SILNET has simplified enormously the search costs in time and effort for both firms and workers. The registration process, for instance, went from 4 days prior to 1998 to less than an hour (MTPS 1999). The computer software analyzes and matches workers' skills and experience with job openings. Once a suitable match is found, the jobseeker is contacted in person, by telephone or e-mail, if available, in order to pick-up a letter of presentation from the Ministry of Labor with details about the job vacancy. It is worth noticing that job matches are based only on job opportunities generated from firms that have previously signed up on CIL-PROEMPLEO.

The information component aims to provide relevant information to both registered workers and firms in topics such as wages by types of occupation, basic regulatory framework, demand in specific occupations, training opportunities, occupational profiles, etc. Registered jobseekers are also entitled to receive low-cost reemployment services such as workshops on writing CVs, interviewing skills, and job-search strategies. Unlike other experiences, particularly in developed

[3] The information collected from jobseekers include standard demographic variables, schooling, training participation, computing knowledge, foreign-language knowledge, driver's license, labor market experience, and current labor-market situation. Firms provide contact information (address, contact name, telephone, location, etc.), detailed description of the job vacancy (work schedules, salary, location, main responsibilities and tasks), and job requirements (education, experience, computing and language knowledge, years of experience, driver's license).

countries, participation in these services is voluntary given the absence of an unemployment insurance system in Peru.

Two years after the implementation of CIL-PROEMPLEO, the number of intermediated workers significantly increased. While in 1996, the total number of employee-employer intermediation was 10,275 at the national level, it jumped to 22,764 in 1998. The corresponding numbers for metropolitan Lima, which represents more than 55 percent of the total intermediation, were 7,914 and 12,682, respectively (Ministry of Labor 1999). All in all, the number of unemployed persons using the public intermediation system has increased significantly in the past decade from three percent in 1997 to 14 percent in 2007. Likewise, the number of job vacancies that has been offered through the public system has increased by five times from 12,707 in 1997 to 66,691 in 2007. According to administrative data, the average cost for each intermediated worker reaches US$ 25 dollars, which reflects a US$ 191 dollars per capita of social savings with respect to the cost of using private employment agencies (MTPS 1998).[4]

Administrative data also shows that the effective rate of intermediation was quite steady over time. As a percentage of the labor supply, CIL-PROEMPLEO was able to intermediate one-out-of-four workers, with small variations over time. As a percentage of the number of job vacancies, there is more variability ranging from 60 to 80 percent between 1998 and 2007. One potential explanation for this flattened profile is the relatively small number of job vacancies that are still advertised via the public intermediation system. Indeed, only 15 percent of firms located in metropolitan Lima were registered with CIL-PROEMPLEO in 2004 (Vera 2006).

A second wave of reforms in the operation of the Peruvian public intermediation system occurred in 2004 when the online version of CIL-PROEMPLEO started its operation in an effort to

[4] A common practice for private employment agencies in Peru is to charge each worker half of the monthly salary they would receive in the new job.

expand the adoption of information and communication technologies in the labor market.[5] In practice, this e-government innovation allows all registered jobseekers and firms online access to CIL-PROEMPLEO services, provided they have access to the Internet.[6] The main attribute of this online service is that workers and firms can upload their information and exchange suitable matches without the intervention of any caseworker. In 2005, one year after the full operation of this electronic version, 59,137 people used the online version, along with more than 5,000 firms that offered 32,000 job vacancies (MTPS 2006). There is no available data, however, on the rate of labor intermediation for this component as firms and workers exchange freely without the direct intervention of CIL-PROEMPLEO.

3. Some Theoretical Considerations

The model presented here is a (marginal) extension of a standard job-search model with endogenous search intensity (Mortensen, 1986) to illustrate the theoretical effects of policies that aim at changing the rate at which jobseekers are informed about job openings on search intensity and exit rate from unemployment. Previous related literature has studied the effect of job offer arrival rates on the exit rate from unemployment in the context of constant individual's search efforts and a single job search channel. For this particular case, Van den Berg (1994), shows minimal conditions on the wage offer distribution that ensure a positive effect on the exit rate associated with an increase in the job offer arrival rate. Fougère *et. al.* (2009) extended the model by considering two channels of job-search, public and private, with endogenous search effort only along the private channel. Results from this model suggest that an increase in the public job offer

[5] The service is free and accessible to anyone with a computer at http://www.empleosperu.gob.pe.
[6] It is estimated that 34 percent of registered jobseekers make use of this electronic version of the program (MTPS 2006).

arrival rate has only a positive effect on the exit rate as long as the wage offer distributions in both channels are assumed to be identical; otherwise, the direction of the effect is ambiguous.

We extended the model by considering two job search channels, public and private, with endogenous search efforts in both search channels. In contrast to Fougère *et. al.* (2009), we consider that the job offer arrival rate via the public channel is endogenous since the features of the public labor intermediation services we are studying suggest that individuals need to allocate a complementary search effort to make effective a job offer. In this study, the job offer arrival rate depends on the individual's search effort, the type of technology employed by the public labor mediation services, and the set of information used to match individuals to jobs. We consider an unemployed individual who does not receive any UI benefits and is actively searching for a job using both private and public labor intermediation services. Unemployed individuals using public intermediation services are contacted and informed about job openings according to a Poisson process with endogenous rate $s_1\lambda_1(\tau,\xi)$ that depends on the search intensity effort s_1 and the overall channel-specific search efficiency λ_1, which in turn depends on the technology used to convey the information τ and the set of information employed to match job openings ξ. We assume that the overall channel-specific search efficiency level can be improved with information communication technologies $\lambda_{1,\tau} > 0$, and by employing a broader set of information on job openings $\lambda_{1,\xi} > 0$ to match individuals to jobs. The arrival rate of effective job offers is defined as $q_1 s_1\lambda_1(\tau,\xi)$ where q_1 is the probability that a job contact via public mediation service leads to a job offer.

Likewise, unemployed individuals using private job-search methods are informed about job openings at rate $s_2\lambda_2$, which depends on the search intensity effort s_2 and an overall constant channel-specific search efficiency level λ_2. The arrival rate of effective job offers is defined as $q_2 s_2 \lambda_2$ where q_2 is the probability that a job contact via private job-search leads to an effective job offer. Job offers along this two channels of search are characterized as random draws from wage offer distributions $F_1(w)$ and $F_2(w)$, respectively.[7] Search intensity effort is costly and can be summarized by the cost function $c(s_1, s_2)$ with increasing and convex arguments such that $c_{s_i} > 0, c_{s_i s_i} > 0, c_{s_i s_j} > 0, c_{s_i s_i} c_{s_i s_j} - c^2_{s_i s_j} > 0$. In the absence of UI benefits as it is the case here, let z be the value of leisure and r the discount rate. An optimal search strategy is a choice of an intensity of search effort and reservation wage w^*. Let U and $W(w)$ denote the present discounted value of income when unemployed and employed, respectively. The present-discounted value from unemployment U satisfies the bellman equation

$$rU = \underset{s_1, s_2 \geq 0}{Max}\left[z - c(s_1, s_2) + q_1 s_1 \lambda_1(\tau, \xi)\int_0^\infty \max[0, W_1(x) - U]dF_1(x) + q_2 s_2 \lambda_2 \int_0^\infty \max[0, W_2(x) - U]dF_2(x) \right] \qquad (1)$$

By applying the reservation wage property $U = W(w^*) = w^*/r$ to equation (1), we can state that the reservation wage, w^*, is solution to

$$w^* = \underset{s_1, s_2 \geq 0}{Max}\left[z - c(s_1, s_2) + \frac{q_1 s_1 \lambda_1(\tau, \xi)}{r}\int_{w^*}^\infty (x - w^*)dF_1(x) + \frac{q_2 s_2 \lambda_2}{r}\int_{w^*}^\infty (x - w^*)dF_2(x) \right] \qquad (2)$$

The first order conditions for optimal search intensities efforts s_1^* and s_2^* equates its marginal return and cost, and can be written as

[7] We do not make any assumption regarding the distributions functions *F_1 and F_2* .

$$\left.\begin{array}{ll} s_1: & -c_{s_1} + \dfrac{q_1\lambda_1(\tau,\xi)}{r}\displaystyle\int_{w^*}^{\infty}(x-w^*)dF_1(x) = 0 \\ s_2: & -c_{s_2} + \dfrac{q_2\lambda_2}{r}\displaystyle\int_{w^*}^{\infty}(x-w^*)dF_2(x) = 0 \end{array}\right\} \tag{3}$$

The exit rate from unemployment for an individual that use public labor intermediation services as well as alternative private job-search methods is defined as

$$\gamma = q_1 s_1 \lambda_1(\tau,\xi)[1-F_1(w^*)] + q_2 s_2 \lambda_2[1-F_2(w^*)] \tag{4}$$

The theoretical effect of policies that may affect the rate at which unemployed individuals are informed about job openings (e.g., SMS technology) on the exit rate from unemployment is defined as

$$\frac{d\gamma}{d\tau} = \lambda_1(\tau,\xi)a_1\frac{\partial s_1}{\partial\tau} + s_1 a_1\frac{\partial\lambda_1(\tau,\xi)}{\partial\tau} + \lambda_2 a_2\frac{\partial s_2}{\partial\tau} + [s_1\lambda_1(\tau,\xi)\frac{\partial a_1}{\partial w^*} + s_2\lambda_2\frac{\partial a_2}{\partial w^*}]\frac{\partial w^*}{\partial\tau} \tag{5}$$

where $a_i = q_i[1-F_i(w^*)]$. By construction we know that the overall search efficiency level λ_1 can be improved by information technology (e.g., SMS) used to convey information on job opportunities to unemployed individuals $\partial\lambda_1(\tau,\xi)/\partial\tau > 0$. Then, a comparative static exercise (available under request), suggest that the search effort allocated to the public job-search channel increases with the technology that improves the rate at which unemployed individuals are contacted and informed about job openings, $\partial s_1 / \partial\tau > 0$.

The intuition for this result suggest that as long as the SMS technology improves the overall search efficiency in the public search channel, those using this channel will tend to allocate higher search efforts to it. Conversely, it is expected that individuals' search efforts allocated to alternative private search channels will be crowed-out since $\partial s_2 / \partial\tau < 0$. Further, as the technology improves the rate at which individuals are informed about job openings, we expect a more patient unemployed individual waiting to consider a better wage offer, as the increase in the reservation wage suggest, $\partial w^* / \partial \tau > 0$. Hence, the sign of expression (5) is uncertain, and clearly hinges on the magnitudes of the reservation wage response to policy and the crowding-out effect on private job-search effort. This uncertainty only has been resolved in models with a single job-search channels and constant job offer arrival rate (Van den Berg, 1994) or models with two job-search channels and an endogenous job offer arrival rate in only one channel (Fougère et. al. , 2009). Yet here with endogenous job offers arrival rates in both search channels, finding conditions to tell the direction of expression (5) is not clear. Therefore, we have to turn to an empirical approach to gain additional insights.

4. Research design, treatment, and treatment groups

A primary concern in the literature of labor-market intermediation is the role of 'selection on unobservables' that has plagued non-experimental empirical studies (e.g., Meyer 1995, Kuhn and Skuterud 2004). In this setting, adverse selection is a key issue since public employment services seems to be populated with unemployed individuals with chronic problems of employability (e.g., Autor 2001 and Thomas 1997).[8] Moreover, the introduction of mobile phone technology in labor market intermediation might tend to exacerbate selection issues due to endogeneity problems associated with technology adoption and participation (Heeks 2010).

A distinctive feature of this study is its experimental design with multiple treatments that minimizes considerable empirical difficulties associated with both self-selection in labor intermediation and the endogenous placement of mobile phones. Early in 2009, we signed a formal agreement of cooperation with the Ministry of Labor and Social Promotion. This agreement

[8] Thomas (1997), for example, shows that the positive relationship between public employment services use and unemployment spell duration is biased because of the lack of control for the timing of unemployment.

allowed us access, in real time, to the SILNET intranet system. The field experiment was implemented as part of the regular (non-experimental) public intermediation services, which affords us three main advantages. The experimental sample is formed exclusively with new registered users of the public employment system and that greatly minimizes 'selection on unobservables' issues. Second, new registered users are not aware of 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). Finally, we automatically gained access to administrative baseline data. On the other hand, due to institutional restrictions we were only allowed to leave the control group individuals out of intermediation for three months after registration in the LMI system, and thus, we were only able to measure short-run treatment effects.

The random assignment was carried out on a daily basis (excluding weekends and holidays) from June 22, 2009, to September 1, 2009. The experimental sample was selected at the initial registration filing for the normal inflow of applicants into Lima after excluding registered individuals who do not own mobile phones or hold occupations with very high turnover rates; i.e., unskilled persons. The treatment consisted of three months of subsidized job search assistance in which individuals' labor profiles were matched with available job vacancies. The matching algorithm was able to map specific job requirements (e.g., gender, age, schooling level, prior experience, and skills) to individuals' profiles. Jobseekers were contacted immediately when a positive match was found.

We randomly assigned new registered users of CIL-PROEMPLEO into three different groups: non-digital treatment group, digital treatment group, and control group, following a random allocation of 30, 40, and 30 percent, respectively. The non-digital treatment group was subject to the standard CIL-PROEMPLEO intermediation practices. To avoid any disruption (or caseworker bias) the names of selected members in this group were kept away from case workers. In contrast to this treatment group, the digital treatment group was exposed to a technological innovation aimed to reduce job search costs. Jobseekers assigned to this group 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 non-digital and digital treatment groups is that the former is contacted in-person or by phone following the standard protocols from CIL-PROEMPLEO, while the latter is electronically contacted via text messages. 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.[9] It is worth mentioning that the experimental design provided evidence only on subsidized job search assistance and does not incorporate elements of job search requirements, i.e., enforcement and verification, because of the absence of an unemployment insurance system in Peru. In other studies that combine both aspects, it is more challenging to identify what aspects of the experiments induced the change in outcomes (Meyer 1995, Black et al. 2004, Ashenfelter 2005). Finally, control group individuals were removed temporarily from the information system for a period of three months.

In contrast to recent studies that has credited the technology (mobile phones) with significant increases in arbitrage, declines in price dispersion and increases in the number of markets over which farmers trade in developing countries (e.g., Aker 2010, Jensen 2007), it is not clear that jobseekers will shorten their unemployment spells by having access to faster and cheaper labor-market information. As shown in the previous section uncertain effects of technology-driven

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

search efficiency improvement on unemployment spells emerges because patient jobseekers could wait for a better wage offer or because of crowding-out effects in the alternative private search channel. Therefore, we turned to the experimental data to compare the employment effects of digital versus non-digital experimental treatment groups relative to a control group.

Furthermore, a key feature of CIL-PROEMPLEO is that registered jobseekers can be intermediated only with job vacancies from firms that signed up on the public intermediation system. This attribute could be inefficient as the majority of job vacancies in Lima are advertised through alternative channels such as newspaper ads, job boards or private employment agencies (Vera 2006).[10] Therefore, to test whether it is the technology by itself or the set of information available to jobseekers that matters most, we implemented a second set of randomization that manipulates the size of the information sets available to jobseekers while holding fixed the (information) technology.

Within the digital treatment group, individuals were randomly assigned into two different groups: short-digital treatment group and enhanced-digital treatment group. The former is matched only with job-opportunities generated within the CIL-PROEMPLEO system, i.e., the public information set, while the latter is matched with both CIL-PROEMPLEO vacancies as well as job opportunities posted on alternative channels such as national newspapers ads and not-for-profit private employment agencies, i.e., public/private information sets. The allocation ratio was 1:1.5 for both groups. Thus, the comparison of these short- and enhanced-digital treatment groups allows one to test the impact of expanding the set of information available to jobseekers while holding fixed the information technology.

[10] According to a 2003 survey of formal firms located in metropolitan Lima, advertisement of job vacancies is mainly done via newspaper ads (54 percent).

In total, 1,280 individuals were randomly assigned from June 22 to September 1, 2009 to four different groups, of which 354 corresponded to the control group (D^{c}), 344 to the standard non-digital treatment group (D^{T1}), 188 to the short-digital group (D^{T2}) and 303 to the enhanced-digital treatment group (D^{T3}). By comparing the treatment impacts across these different experimental groups we are able to evaluate the overall impact of CIL-PROEMPLEO on the employment status of registered participants, evaluate the effectiveness of adopting digital technology (i.e., SMS) in labor-market intermediation, and test the impact of expanding the set of information available to jobseekers while holding fixed the information technology. We acknowledge that our sample represents a particular subset of the unemployed population, so external validity of the findings should be taken with caution.

5. Data and baseline equivalence

The baseline dataset contains information for 1,189 individuals, which implies an attrition rate of 7 percent relative to the original sampling design.[11] This feature adds to the quality of the dataset used in this study since attrition bias is common in these types of settings. A critical step in the estimation of the causal treatment effects is to analyze the effectiveness of randomization in balancing the distribution of covariates across all treatment groups. Table 1 depicts baseline socio-demographic and labor-market information for all experimental groups, collected from administrative sources at the initial registration filing, and complemented with information from a customized labor survey implemented right after the registration process. Columns 1 to 4 show descriptive statistics for each one of the four experimental groups, while columns 5 and 6 show the

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

p-values for the t-test (treatment versus control) and the F-test of equality of means across all four experimental groups.

Panel A shows that the average individual in our sample has completed a high-school education, is younger than 30 years old, and single. There is a slight disproportion in the rate of enrollment by gender, as 55 percent of registered users are men. Only 30 percent of users have offspring, which indicates the average user of the public intermediation is relatively young. Moreover, an analysis of household indicators reveal that the average individual in this data have access to basic infrastructure and own household assets. The p-values for all variables, except for age, do not reject the null hypothesis of the equality of means across all experimental groups.

Panel B reports basic statistics for a rich set of baseline labor-market characteristics. The unemployment spells for all groups is statistically balanced (94 days), which constitutes an important piece of information since the reliability of several non-experimental studies in this area has been questioned because they exploited only variation of intermediation usage without controlling for the timing and duration of the unemployment spell (see for instance Thomas 1997). Moreover, 80 percent of the sample has previous job experience, mainly in the private sector, while 12 percent are considered as a discouraged worker. The average monthly income and weekly hours of work are 520 soles and 35 hours, respectively. Around one fourth of the sample had fringe benefits including health insurance, accident insurance, and pension plans, while 50 and 16 percent worked as white- and blue-collar workers, respectively. The p-value of the F-test for the equality of means is above 0.05 for all variables except for the share of people who had worked under formal contracts.

Panel C reports novel information on ICT usage and job search strategies among jobseekers subject to public labor-market intermediation. The average number of search methods used by the sample is close to two. We find that 96 percent of the sample regularly use mobile phones, while 49 percent do so for job search purposes, and in particular, to contact prospective employers (57 percent), private (26 percent) and public (11 percent) labor-market intermediaries. Further, 84 percent of the sample has experience using the Internet, which is a relatively high percentage with respect to the population. Sixty-one percent of the sample used the Internet for job search purposes. Importantly, 4 out of 5 Internet-based searchers access the Internet from Internet café shops where for a small amount of money they can rent computers with online access. Only 25 percent of the sample access Internet from home. Moreover, the data show that on average our sample spent 0.9 hours-per-week on public search channels, which accounts for only 20 percent of the total weekly search time. This means that job search in Peru is mainly done outside of the public intermediation system since the weekly (average) number of hours devoted to active job search is 4.5. The p-value of the F-test for the equality of means does not reject the equality of means for all ICT-related variables.

In sum, the statistical analyses performed on a large set of personal and household covariates suggest that the sample of individuals assigned to all different groups were drawn from the same population. This gives credibility to the experimental design.

6. Determinants of digital job search in Peru

In this section, we use the baseline information to assess the determinants of digital labor-market intermediation for our sample of jobseekers irrespective of their treatment assignment. This analysis sheds light on the role of socio-demographic and labor-market characteristics on influencing digital job search, the complementarity between Internet and mobile-phone job search channels, and how previous exposure to digital technology affects digital job search.

Table 2 shows the marginal effects from a probit model that estimates the likelihood of digital job search conditional on a rich set of covariates. Each column corresponds to a different outcome of interest. In column 1, the dependent variable takes the value 1 for those individuals who have used either Internet or mobile phones for job search purposes, 0 otherwise, while columns 2 and 3 considers Internet and mobile phone job search channels separately. Standard errors are presented in parentheses.

By looking at Panel A in column 1, one is tempted to conclude that individuals' socio-demographic characteristics seems to play no role on the likelihood of (overall) digital job search in metropolitan Lima since no variable is statistically significant at the 5 percent level. Yet, a closer look at columns 2 and 3 reveals that indeed some personal characteristics matter depending on the digital technology used. Two variables emerge as statistically significant predictors for Internet job search: presence of siblings and poverty status, the former possibly associated with spillover effects from children's exposure to Internet at schools, and the latter associated with barriers to technology access due to income constrains. In fact, column 2 shows that the likelihood of using the Internet for job search purposes is almost 15 percentage points lower for poor households than that for non-poor ones, and 19 percentage points higher for individuals with offspring relative to those without them. The positive relationship between Internet job search and income is in line with international evidence for developed countries (e.g., Stevenson 2009). Column 3, on the other hand, shows that gender, schooling attainment, poverty and migration status of jobseekers matters for mobile phone job search channel. Men are 10 percentage points more likely to search for jobs using mobile phones than that for women, and an extra year of schooling is associated to 1.6 higher percentage points for mobile-phone job search. Likewise, the poor (and migrants) are 14 (and 9) percentage points more likely than non-poor (non-migrants) to use mobile phones during the job search process. Overall, these results suggest that poverty status is the main factor that differentiates the use of mobile phones from the Internet when selecting a job search channel. From a policy perspective, this result highlights the importance of mobile phones for vulnerable populations that cannot access to Internet in developing countries due to income barriers.

By turning our attention to Panel B, one observes that having previous job experience and being optimistic about future job-market prospects positively affects the likelihood of digital job search for both Internet and mobile phones channels. Those who had never worked show a 30-percentage point lower probability of digital job search with respect to those with previous job experience, while jobseekers that are optimistic about the probability of finding a job in the near future are 16 percentage points more likely to search for jobs using digital technologies. The former result suggests that past labor-market experiences have made workers more aware of the possibilities of digital technologies, while the latter reinforces the findings in Dammert et al. (2013b) that shows a causal link between digital labor intermediation and job gain expectations. This last evidence suggests a virtuous circle between digital labor-market intermediation and job gain expectations in developing settings, which matters because 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). Finally, no other labor-market variable such as the type of worker or job-quality attributes matter.

In Panels C and D, one observes how past exposure to Internet and mobile phones affect the likelihood of using them for job search purposes. The results show that digital experience does not matter for mobile-phones searchers. In fact, having computer and Internet literacy or owning a mobile phone for few months, three or more than five years, does not make any difference in the usage of mobile phones for job search purposes. On the contrary, Internet-based job search is greatly affected by the availability of a computer at home (likelihood increases by 52 percentage points), length of computer experience (22 percentage point increase for those who have used a computer for more than five years), and the existence of Internet cafe shops in the neighborhood (69 percentage points). Evidence on the first two variables is not surprising and it is in line with findings from other studies that are based on data from developed countries (e.g., Stevenson 2009, Autor 2001). The last variable, however, provides new insights on the growing importance of Internet cafes in developing settings. This type of business has blossomed in recent years, although its impacts on the marketplace are practically unknown. From a policy perspective, this result suggests that providing incentives for the expansion of this type of small business might improve the efficiency of the labor markets in countries where a home connection to Internet is still far from the norm in reality.

Finally, Panel E shows a positive correlation between Internet and mobile-phone search channels, which suggest a complementarity relationship between them. The likelihood of using cell phones for job search purposes is 40 percentage points higher for individuals who use the Internet for job search relative to those who do not, while it reaches 35 percent in the other direction.

In sum, this section has uncovered evidence on key covariates that affect the access and usage of digital job search channels in Peru. Poverty and the lack of availability of Internet cafes seems to be the main barriers for Internet-based job search, while the presence of offspring, a computer-at-home, labor-market experience and high expectations on job gain prospects are positively related to this activity. The use of mobile phones for job search purposes, on the other hand, seems to be more idiosyncratic with respect to Internet-based search, although it is clear that disadvantaged men and migrant individuals are more prone to use it. Only two variables have a consistent positive effect for both digital channels: labor-market experience and job gain expectations, variables that are usually overlooked in the analysis of digital job-search channels.

7. Empirical framework and results

To estimate the overall effectiveness of public labor intermediation in Peru we implement a standard parametric OLS regression for individual *i* in experimental (day) group *j*,

$$Y_{ij} = \beta_0 + \beta_1 D_i + X_{ij}'\beta_2 + \eta_j + \varepsilon_{ij} \qquad (6)$$

where Y_{ij} is the particular outcome of interest (employment), D_i denotes a treatment indicator that receives 1 for all individuals subject to labor intermediation independently of the information channel and information set they were assigned , 0 for those in the control group. X_{ij} denotes a set of socio-demographic and labor-market baseline covariates, while ε_{ij} is the error term. Given we have as many experimental sets as different days the experimental sampling lasted, we incorporate experimental group (date) fixed effects, η_j, to control for intra-day variation in the treatment allocation. The coefficient of interest is β_1 and represents an intent-to-treat parameter. The main outcome of interest is employment in the month of reference. In the context of our design, regression analysis is motivated by the availability of a rich set of baseline covariates that could reduce the size of the standard errors for the point estimates, the need to incorporate clustered standard errors due to intra-day variation in the random allocation, and a multiple treatment design that can be incorporated smoothly within this framework.[12]

[12] An alternative option would be to implement a standard parametric difference-in-differences model. Yet, the employment outcome in the baseline period refers to the week of reference, while the follow-up data captures monthly employment for each one the first months following treatment. One should not expect, however, to have different results given the strong balance in outcomes and covariates in the baseline period. In fact, we implemented an unrestricted difference-in-differences model (Lalonde 1986), which shows similar results. Table Appendix A1 reports

To evaluate the effectiveness of adopting digital technology in labor-market intermediation along with varying sets of information available to jobseekers, we expand equation (1) and implement the following complementary model,

$$Y_{ij} = \beta_0 + \beta_1 D_i^{T_1} + \beta_2 D_i^{T_2} + \beta_3 D_i^{T3} + X_{ij}'\beta_4 + \eta_j + \varepsilon_{ij} \qquad (7)$$

where D_i^{T1}, D_i^{T2} and D_i^{T3} denote treatment indicators for the non-digital, short-digital, and expanded-digital treatment groups, respectively. The base category is the control group. The coefficients β_1, β_2, and β_3 represent intent-to-treat parameters of interest. By comparing the magnitude and significance of β_1 and β_2 we are able to test the impacts of digital intermediation holding fixed the set of information, while by comparing β_2 and β_3 we test the impacts of expanding the set of information while holding fixed the information technology. Given the 3-month treatment duration, the follow-up survey asks individuals to respond on their employment status each month after assignment to treatment. Thus, we report three different estimates corresponding to the first, second and third month following the treatment assignment.

7.1. Main results

Table 3 reports the OLS short-run impacts of public labor-market intermediation on employment status one, two and three months following the intervention. The upper panel shows the overall impacts (equation 6) without considering digital versus non-digital or short- versus enhanced-information sets treatment assignment. Clustered standard errors by date are shown in parentheses. Experimental results show that public labor-market intermediation has positive impacts on the employment status of job searchers. These effects are somewhat above 6 percentage

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these estimates. On the other hand, and because continuous data on unemployment spells are not available in the follow-up period, we cannot estimate complementary duration (hazard) models.

points and statistically significant at the 5 percent level for the first month following labor-market intermediation. This impact equals a 17 percent increase with respect to the baseline mean outcome. A comparison of columns 1 to 3 show that these positive effects are robust to the inclusion of a rich set of baseline covariates (column 2) and experimental groups fixed effects (column 3). This is expected given that randomization at the individual level have led the balance of baseline covariates between the treatment and control group individuals as shown in Table 1. The magnitude and statistical significance of the employment impacts lessens two and three months after treatment. Columns 4 to 6 show that the magnitude of the treatment effects reaches 5.5 percentage points and is statistically significant at the 10 percent level two months following the intervention. For the third month, no statistically significant impacts are observed (columns 7 to 9). Overall, Panel A in Table 3 shows positive and statistically significant short-run employment impacts for public labor-market intermediation in Peru, albeit these impacts are of lower magnitude with respect to the non-experimental evidence presented by Sulmont and Chacaltana (2003) in their analysis of earlier cohorts participating in the CIL-PROEMPLEO program.[13]

Two features related to this intervention might explain this profile for the employment impacts. First, due to institutional constraints, the control group individuals were left out of treatment for three months, and thus everyone in the sample was potentially subject to labor-market intermediation starting the fourth month. Thus, we are dealing with a short-term intervention in which the impacts of the third month of treatment might not be observed because of the timing of the intervention. Second, in general, users of the public labor-market intermediation are individuals

[13] Chacaltana and Sulmont (2003) used a sample of 153 individuals that were successfully intermediated in April 2001 as the treatment group. The comparison group comes from a representative employment survey from which 275 nonparticipant individuals, who were unemployed in April 2001, were drawn. Some outcomes of interest were measured and compared one year later using standard parametric matching techniques. The authors show significant gains in wages and employment for the treatment group, relative to the control one, one year later.

with above-average labor-market attachment problems (e.g., Autor 2001 and Thomas 1997), and thus, it is possible that those who were not able to get a job during the first two months after the start of the intervention are those particularly prone to having chronic problems of employability.

Panel B in Table 3 reports the intent-to-treat parameters following equation (7). Relative to the control group, the non-digital treatment group (D^{T1}) shows positive, but not significant treatment effects in months one (3.4 percentage points) and two (4 percentage points). On the contrary, the digital channel seems to explain the overall significant impacts we found for the public intermediation system. By looking closely at the last two rows in Table 3, one realizes that within the digital channel is the enhanced-digital treatment group (D^{T3}) which shows the strongest impacts in month one (8 percentage points) and month two (7 percentage points), both statistically significant at the 5 and 10 percent level, respectively. The magnitude of these impacts is equivalent to a slightly above 20 percent increase with respect to the baseline measure of employment. The short-digital treatment group (D^{T2}), on the other hand, has weaker impacts as it is statistically significant only at the 10 percent level in month one, while in month two it loses statistical relevance. Neither group shows significant impacts in month three. All of these findings are robust to the inclusion of a rich set of socio-demographic and labor-market baseline characteristics. Likewise, these results are robust to the inclusion of experimental date fixed effects and clustered standard errors.

How can one explain these results? According to information theory, the value of information is determined by three important factors—novelty, confidence, and ability and willingness to act based on the new information—all of which involve different forces and trade-offs (Hirshleifer and Riley 1992). 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. Thus, individuals in the enhanced-digital treatment group received on average, not only more information, but also qualitatively different information coming from firms that do not normally register with the public system, all of which makes more valuable the information received. Put differently, it is the value of the information generated by the novelty of the information, along the higher number of SMS received by jobseekers, which might explain the positive impacts on employment.

It is important to highlight that expanding the information set does not automatically translated into “better” outcomes since more information is not necessarily more valuable, all else held constant. One needs to recall that the typical user of the public labor market intermediation has above-average problems of employability, and therefore they could have developed strong initial beliefs about the value of the information, a genuine distrust of information coming from public sources, or both. If that is the case, they might not believe in the information or act automatically in response to more information. Evidence from behavioral economics, for example, suggests that individuals with poor past experiences have difficulty interpreting subsequent new information, ignore new information altogether or misread it as initial information expectations tend to anchor one’s processing of information (Griffin and Tversky, 1992).

In sum, these findings suggest that it is not the technology by itself that causes the positive effect of labor-market intermediation on employment. It is an enhanced set of information about job opportunities, transmitted through digital channels, which drives the positive employment results. Unlike agricultural or fishing markets where the speed of the information matters for the adjustment of price and quantities (e.g., Aker 2010, Jensen 2007), in the labor markets the scope and size of the information sent to jobseekers via SMS seems to matter most.

7.2 Heterogeneous Impacts

In this section, we analyze heterogeneous treatment impacts across three policy-relevant variables of interest: gender of participants, poverty status, and work experience. This analysis focuses on overall impacts rather than on particular treatments, since the latter might be asking too much from the data given the sample sizes. The gender dimension is important in its own, as a body of empirical evidence has shown strong gender gaps against women in the Peruvian market place (e.g., Ñopo 2012). The results reported in Table 4 shows negligible and not statistically significant impacts by gender. From a policy standpoint, this suggestive result shows that the public intermediation system is not reproducing inequalities against women in the marketplace.

Moreover, we address whether the public intermediation system has differential employment impacts depending on participants' previous job experience. This is policy relevant since adult jobseekers who have never worked are the most prone to fill the ranks of the inactive population. We define the discrete variable of interest as 1 for those who have never worked, 0 for otherwise. The results shown in the middle panel of Table 4 reveal statistically significant impacts from previous job experience. Jobseekers who have never worked shown a 16 percentage point difference in month one with respect to those who have work experience. This result reveals that a lack of labor-market experience constitutes a resilient barrier that is difficult to overcome by public labor-market intermediaries. No significant impacts were found for months two or three.

Finally, we analyze whether public labor-market intermediation is benefiting most the poor. For that purpose, we constructed a poverty index based on more than 15 variables related to house infrastructure (e.g., access to toilet, sewage) and household assets (e.g., computer, car) after combining the data using factor analytic methods. This continuous poverty index represents a proxy for long-run economic status. We use this index to define three categories: poor (first quartile), middle (second and third quartile), and high (fourth quartile). Results reported in the bottom of Table 4 show a well-defined pattern: there is a positive relationship between treatment and poverty status. In the first month, for example, where most of the employment impacts are observed, the point estimates associated to the poor (5 percentage points) are two times lower than those for the upper group (10 percentage points). This result suggests that those who are most in need do not benefit more from the public intermediation system. These differential impacts, however, are not statistically significant at the 5 percent level, and thus, we can only take this as suggestive evidence.

7.3 Job-matching Efficiency

The power of labor intermediation on matching efficiency has been discussed more than once in the literature since it is expected that efficiency gains are associated with formal intermediation mechanisms that breakdown traditional networks and geographic barriers (e.g., Freeman 2002). In this regard, Bagues and Sylos (2009), for instance, found that the monthly wages of graduates from universities that had a job board for their graduates increased by 3 percent compared to those who did not. Inspired by this line of inquiry, we considered two matching efficiency indicators as outcomes of interest: monthly earnings and matching skills. The latter is defined as a dummy variable that takes the value 1 when there is an alignment between job tasks and workers' qualifications, 0 otherwise. We use only the subsample of individuals who are successful in getting a job when estimating the impacts for these two variables. Panel A (B) in Table 5 shows the earnings (matching skills) treatment impacts. Within each panel, the first row corresponds to overall impacts of public intermediation, while rows 2-5 report the estimates for each one of the treatment groups, relative to the control group.

Some patterns emerge from this analysis. By looking at the first panel, we observe that the impacts for monthly earnings increase overtime, which suggest that those who become employed immediately and right after the intermediation begin to have lower reservation wages than those who got jobs later on. This result is consistent with standard predictions of theoretical search job models (e.g. Mortensen 1986). However, these point estimates are not statistically significant and thus they should be taken only as suggestive evidence. A second pattern we observe in this panel is that across all three months following treatment, the enhanced-digital treatment group shows the largest earnings impacts (30 soles, or 22 percent of the baseline earnings), while the short-digital treatment group shows the lowest. This suggestive evidence reinforces the previous discussion about the importance of the extent and scope of the information set in labor-market intermediation, as that seems to be more relevant than the transmission channel itself. The availability of a larger dataset or lengthier treatment duration would have helped us to provide more definitive results. From an international perspective, the empirical literature shows ambiguous effects for LMIs on matching efficiency, with some studies showing positive impacts on earnings (e.g., Bagues and Sylos 2009), and others a zero effect (e.g., Kroft and Pope 2009).

By looking at the lower panel, we observe no significant impacts of labor-market intermediation on job-matching skills for the overall program and for each particular treatment considered. One potential explanation is that, unlike the Internet, mobile phone intermediation does not necessarily improve the ability to screen applications, as it works as an 'information-only' intermediary channel. From an institutional standpoint, this result is not surprising given the high levels of underemployment by qualification that affects the Peruvian labor-market. According to Yamada (2010), the incidence of underemployment affects more than 60 percent of the work force. This apparent divorce between individuals' qualifications and job tasks is particularly manifest for those less successful in the marketplace. In short, three months of public intermediation is not enough to overcome this structural problem in the Peruvian labor-market.

7.4 Impacts on additional intermediate outcomes

Motivated by the complementarity between Internet and mobile-phone search channels uncovered in section 5, we investigate the causal impacts of digital labor-market intermediation on Internet-based search effort. The new outcome variable is defined as 1 for those who have used the Internet for search purposes within the three months following labor-market intermediation, 0 otherwise. Columns 1 and 2 in Table 6 show these results with clustered standard errors in parentheses. We observe a positive statistical relationship between mobile-phone labor market intermediation and Internet-based job search, which is explained by the enhanced-digital treatment group. On average, this particular treatment lead to an increase of 7.9 percentage points (13 percentage increase) in Internet-based job search results, a result that is statistically significant at the 10 percent level. Both the non-digital and short-digital treatment groups also show positive point estimates, although they are not statistically significant different from zero. This evidence reinforces the uncovered evidence that Internet and mobile-phone search channels are complements.

To analyze whether digital labor-market intermediation lead to crowding-out effects of traditional search channels, we analyzed the causal impact of digital intermediation on newspaper ads, friends and family referrals, among other traditional search channels, using the same parametric framework estimated over the sample of unemployed individuals who are actively looking for jobs in the week of reference.[14] The results reported in columns 3 and 4 in Table 6 show no evidence in this regard. The intent-to-treat parameters are not statistically significantly different from zero for all treatment groups. In contrast to evidence from developed countries that show how the lengthy penetration of Internet has led to a reallocation of search effort among various job search activities (Stevenson 2009, Kuhn and Mansour 2011), we do not find similar evidence for our short-length digital treatment intervention.

8. Conclusion

This study exploited a multi-treatment experimental design implemented as part of the regular (non-experimental) public intermediation system in Peru to investigate the extent to which public labor-market intermediation influences employment and job matching efficiency. Particular attention was given to investigate the interaction between the speed (digital/non-digital channels) and the scope of information (small/enhanced sets), given countervailing forces emerging from standard theoretical employment search models. This study showed that public labor-market intermediation causes positive and statistically significant employment impacts equivalent to 6 percentage points, relative to control group individuals. This positive effect, however, dissipated three months later, timing that coincides with the beginning of labor-market intermediation for the control group.

An important finding reported in this study is that, in the labor markets, the scope and novelty of the information travelling through digital means seems to be more important than the speed of information itself. Indeed, the use of an enhanced-information set that combines information from public and private sources involved a novelty factor since historically the

[14] In contrast to the Internet-based outcome, traditional search methods in the follow–up survey were asked only for the week of reference and only to the subsample of unemployed people.

standard public intermediation system has operated only with information from a limited group of (low-quality) firms. As for potential matching efficiency gains, the results suggest no statistically significant effects associated with information channels or sets. Overall, we reported (statistically) weaker impacts for SMS technologies in the labor market relative to previous studies that mainly focused on agricultural markets and outputs.

From a policy standpoint, this research has shown the feasibility and value of integrating new information technologies in the old, traditional labor-market intermediation services. That is perhaps the main policy contribution of this research as it highlights how traditional LMIs can take advantage of the rapid expansion of mobile phone technologies and catch-up themselves by using SMS applications as a delivery platform. A particular lesson emerging from this study is that the Peruvian public intermediation system could improve its efficiency if the restriction to operate based on a limited set of firms that have previously signed up to the system is relaxed. In this regard, jobseekers could benefit more if the public LMI operator also incorporated information generated outside the system, such as from online job boards and newspapers ads.

Booming mobile phone connectivity in developing countries offers a unique opportunity to counteract the Internet access gap against vulnerable populations. In this regard, this research has shown that both Internet and mobile phone search channels are complements, although disadvantaged men and migrants are more prone to use the latter for job search purposes. Likewise, particular attention should be given to those who lack labor-market experience as the analysis of determinants of digital job search in Peru show that this particular group of jobseekers disproportionally uses the Internet or cell phones less for job search purposes. Now, more than ever, mobile phone technologies might constitute an effective tool to lessen the global digital divide and empower vulnerable groups with access to tailored content-value information services.

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Table 1: Summary Statistics by Treatment Status
Digital Labor-Market Intermediation Program, Lima 2009-2010

Baseline Variables	Treatment Groups Non-digital T1 D^{T1}	 Digital T2 D^{T2}	 Digital T3 D^{T3}	 Control D^{C}	p-value of t-test *Treatment=Control*	p-value of F test $[D^{T1}=D^{T2}=D^{T3}=D^{C}]$
A. Socio-Demographic						
sex (1=male)	0.57	0.52	0.55	0.54	0.62	0.65
age	27.04	25.33	26.27	25.55	0.01	0.01
years of schooling	12.15	12.09	12.06	11.94	0.36	0.76
single	0.71	0.76	0.73	0.73	0.82	0.46
have children	0.32	0.26	0.32	0.26	0.14	0.22
number of children	0.55	0.39	0.55	0.45	0.24	0.12
migrant	0.27	0.29	0.26	0.25	0.48	0.75
access to flush toilet	0.93	0.91	0.93	0.95	0.11	0.29
access to safe water	0.94	0.90	0.93	0.94	0.40	0.39
poverty index	0.06	-0.01	-0.02	0.03	0.68	0.64
B. Last Labor-Market Experience						
worked ever	0.81	0.80	0.82	0.82	0.91	0.97
discouraged worker	0.11	0.14	0.13	0.13	0.85	0.85
unemployment duration (days)	75	105	104	99	0.60	0.22
montly income (in soles)	526	485	491	556	0.29	0.66
hours work per week	34.15	34.97	34.36	37.28	0.18	0.39
had accident insurance	0.18	0.16	0.16	0.18	0.61	0.87
had pension plan	0.25	0.26	0.21	0.23	0.90	0.70
had health insurance	0.25	0.25	0.20	0.21	0.64	0.52
had formal contract	0.76	0.73	0.63	0.66	0.21	0.02
white-collar worker	0.48	0.52	0.46	0.56	0.19	0.45
blue-collar worker	0.17	0.12	0.19	0.14	0.35	0.27
C. Digital technologies and job search						
number of search methods	1.69	1.56	1.68	1.67	0.90	0.72
number of hours-week job search	5.68	5.18	5.48	5.68	0.63	0.79
number of hours-week in public channels	0.77	1.01	0.80	0.82	0.90	0.65
number of hours-week in private channels	4.90	4.01	4.67	4.84	0.52	0.28
use cell phone	0.95	0.95	0.96	0.97	0.14	0.43
use cell phone for job search	0.51	0.49	0.49	0.46	0.37	0.79
cell phone to contact prospective employers	0.55	0.57	0.57	0.60	0.39	0.83
cell phone to contact public LMIs	0.09	0.11	0.13	0.12	0.74	0.65
cell phone to contact private LMIs	0.27	0.28	0.25	0.24	0.47	0.85
use internet	0.83	0.85	0.84	0.84	0.98	0.86
use internet for job search	0.60	0.62	0.61	0.62	0.63	0.91
acess internet from home	0.24	0.29	0.24	0.20	0.12	0.30
access internet from internet cafes	0.74	0.70	0.74	0.79	0.13	0.35
access internet from work	0.02	0.01	0.01	0.01	0.83	0.62
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^{T1} refers to the short-non-digital treatmeng group, D^{T2} to the short-digital treatment group, D^{T3} to the enhance-digital treatment group, and D^{T4} to the control group.

Table 2: Determinants of Digital Job Search, Probit Marginal Estimates (Baseline Data)
Labor-Market Intermediation Program, Lima 2009-2010

	Marginal Effects		
	Digital internet+cell phones	Internet	Cell phones
A. Socio-Demograhic Characteristics			
gender (1=men, 0=women)	0.023	-0.026	0.097***
	(0.028)	(0.036)	(0.032)
age	-0.003	0.000	-0.004
	(0.002)	(0.003)	(0.003)
single	0.032	0.064	-0.038
	(0.047)	(0.063)	(0.053)
has children	0.105*	0.188**	-0.006
	(0.058)	(0.081)	(0.076)
number of children	-0.028	-0.076*	-0.000
	(0.029)	(0.041)	(0.036)
migrant	0.065	0.062	0.087*
	(0.043)	(0.061)	(0.053)
years from migration	-0.000	-0.000	-0.000
	(0.003)	(0.004)	(0.003)
years of schooling	0.007	0.004	0.016**
	(0.048)	(0.007)	(0.006)
poor	0.007	-0.145**	0.141***
	(0.048)	(0.063)	(0.054)
less poor	-0.036	-0.095*	0.066
	(0.041)	(0.052)	(0.047)
B. Labor-market Characteristics			
worked under formal contract	0.021	0.038	-0.014
	(0.038)	(0.050)	(0.043)
had pension plan	0.084	0.048	0.006
	(0.071)	(0.101)	(0.089)
had health insurance	0.007	0.077	0.023
	(0.078)	(0.095)	(0.088)
worked as blue-collar	-0.009	0.000	-0.011
	(0.035)	(0.047)	(0.039)
never work	-0.283***	-0.134**	-0.293***
	(0.047)	(0.054)	(0.042)
job gain expectations (1=high, 0=otherwise)	0.162***	0.159***	0.075**
	(0.031)	(0.038)	(0.034)

continue.....

Table 2: Determinants of Digital Job Search, Probit Marginal Estimates (Baseline Data)
(continued)

C. Cell phones Experience			
Up to one year	0.097**	0.105*	0.097*
	(0.036)	(0.054)	(0.050)
Between one and three years	0.043	0.023	0.025
	(0.029)	(0.039)	(0.036)
D. Internet Experience			
Has computer at home	0.279***	0.521***	-0.124
	(0.032)	(0.033)	(0.084)
use computer less than three years	0.005	0.148**	-0.092
	(0.060)	(0.067)	(0.069)
use computer between three and five years	-0.031	0.046	-0.053
	(0.063)	(0.072)	(0.071)
use computer more than 5 years	0.117**	0.220***	-0.010
	(0.052)	(0.063)	(0.070)
Internet café in the neighborhood	0.331***	0.688***	-0.066
	(0.073)	(0.055)	(0.081)
Internet café one block away from neighboohood	0.095**	0.062	0.067
	(0.040)	(0.052)	(0.051)
Internet café one to three blocks away from neighborhood	0.016	0.005	0.021
	(0.043)	(0.053)	(0.053)
Internet café is 12 o 24 months old	0.007	0.086	-0.083
	(0.063)	(0.070)	(0.070)
Internet café is more than 24 months old	-0.029	0.032	0.007
	(0.047)	(0.057)	(0.053)
E. Complementary between digital search channels			
cell phone job search	-----	0.349***	------
	-----	(0.033)	------
internet job search	------	------	0.393***
	------	------	(0.035)
N	1188	1188	1188

Notes: Standard errors in parentheses. Marginal effects from probit estimates using baseline data. The 'digital' outcome is defined as 1 for those who use Internet or cell phones for job search activities, 0 otherwise.
*** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.

Table 3: Labor market intermediation on employment outcome
Labor-Market Intermediation Program, Lima 2009-2010

	Month # 1			Month # 2			Month # 3		
Dep variable: employment									
Overall Treatment	0.066**	0.063**	0.062**	0.056*	0.054*	0.055*	0.003	0.001	-0.002
	(0.032)	(0.032)	(0.027)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)	(0.033)
Type of Treatment									
non-digital treatment (D^{T1})	0.041	0.035	0.034	0.046	0.042	0.040	-0.018	-0.027	-0.034
	(0.039)	(0.038)	(0.035)	(0.038)	(0.038)	(0.036)	(0.038)	(0.038)	(0.044)
short-digital treatment (D^{T2})	0.081*	0.088*	0.083*	0.057	0.061	0.060	0.034	0.033	0.034
	(0.046)	(0.046)	(0.042)	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.045)
enhance-digital treatment (D^{T3})	0.086**	0.079**	0.081**	0.067*	0.064*	0.069*	0.008	0.005	0.008
	(0.040)	(0.039)	(0.032)	(0.039)	(0.039)	(0.037)	(0.039)	(0.039)	(0.035)
N	1118	1118	118	1118	1118	118	1118	1118	118
Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Experimental Groups FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Standard errrors in parenthesis. Estimates based on a parametric cross-sectional estimator. The treatment indicator takes the value 1 for those benefiting from labor-market intermediation, 0 otherwise. Socio-demographic covariates include age, gender, marital status, poverty index, whether individual has children, number of children, whether individual is migrant, number of years since migration, years of schooling. Labor-market covariates include whether individual worked ever, an indicator for dicouraged worker, whether individual had access to pension plan in last job, health insurance in last job, accident insurance in last job, whether individual worked under formal contract in last job, blue-collar worker indicator in last job, white-collar worker indicator in last job. Clustered standard errors by day are considered when including experimental groups fixed effects in columns 3, 6 and 9. *** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.

Table 4: Heterogenous Impacts
Labor-Market Intermediation Program, Lima 2009-2010

	Month # 1		Month # 2		Month # 3	
dep. var: employment						
Panel A: Gender						
Intermediation	0.052	0.058	0.025	0.043	-0.011	0.001
	(0.047)	(0.043)	(0.046)	(0.042)	(0.046)	(0.046)
Intermediation*Men	0.019	0.007	0.052	0.022	0.022	-0.007
	(0.065)	(0.066)	(0.064)	(0.068)	(0.063)	(0.070)
Panel B: Work Experience						
Intermediation	-0.066	-0.073	0.052	0.072	-0.023	-0.016
	(0.076)	(0.087)	(0.075)	(0.078)	(0.075)	(0.075)
Intermediation*Workever	0.165**	0.165*	0.008	-0.020	0.035	0.016
	(0.084)	(0.095)	(0.083)	(0.089)	(0.082)	(0.078)
Panel C: Poor						
Middle	-0.005	-0.020	0.014	0.013	-0.020	-0.028
	(0.074)	(0.091)	(0.073)	(0.088)	(0.072)	(0.077)
High	0.029	-0.028	-0.019	-0.013	-0.107	-0.089
	(0.078)	(0.087)	(0.077)	(0.078)	(0.076)	(0.074)
Intermediation*Poor	0.054	0.053	0.061	0.064	-0.012	-0.019
	(0.040)	(0.040)	(0.039)	(0.041)	(0.039)	(0.039)
Intermediation*Middle	0.067	0.074	0.011	0.023	-0.004	0.017
	(0.077)	(0.083)	(0.076)	(0.080)	(0.076)	(0.074)
Intermediation*High	0.113	0.091	0.093	0.059	0.086	0.052
	(0.083)	(0.077)	(0.082)	(0.082)	(0.081)	(0.085)
p-value of F-test for equality of coeff.	0.819	0.915	0.750	0.914	0.546	0.691
N	1118	1118	1118	1118	1118	1118
covariates	no	yes	no	yes	no	yes
experimental groups FE	no	yes	no	yes	no	yes

Notes: Standard errrors in parenthesis. Estimates based on a parametric cross-sectional estimator. The treatment indicator takes the value 1 for those benefiting from labor-market intermediation, 0 otherwise. Socio-demographic covariates include age, gender, marital status, poverty index, whether individual has children, number of children, whether individual is migrant, number of years since migration, years of schooling.
Labor-market covariates include whether individual worked ever, an indicator for dicouraged worker, whether individual had access to a pension plan in last job, health insurance in last job, accident insurance in last job, whether individual worked under formal contract in last job, blue-collar worker indicator in last job, white-collar worker indicator in last job. Clustered standard errors by day are considered when including experimental groups fixed effects in columns 2,4 and 6.
*** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.

Table 5: Labor-market intermediation on job matching efficiency
Labor-Market Intermediation Program, Lima 2009-2010

	Month # 1		Month # 2		Month # 3	
dep. var: monthly earnings (soles)						
Overall Treatment	4	-10	28	11	34	16
	(28)	(27)	(26)	(24)	(26)	(24)
Type of Treatment						
non-digital treatemnt (D^{T1})	31	-6	36	0	42	13
	(34)	(35)	(31)	(32)	(32)	(33)
short-digital treatment (D^{T2})	-45	-44	-12	-4	5	-1
	(39)	(41)	(37)	(37)	(36)	(41)
enhance-digital treatment (D^{T3})	6	5	44	33	44	30
	(34)	(34)	(32)	(30)	(32)	(28)
dep. var: matching skills						
Overall Treatment	0.008	0.043	-0.014	0.014	-0.016	0.014
	(0.046)	(0.041)	(0.043)	(0.039)	(0.041)	(0.039)
Type of Treatment						
non-digital treatement (D^{T1})	0.046	-0.071	0.051	0.076	0.089	0.102*
	(0.055)	(0.051)	(0.058)	(0.054)	(0.062)	(0.056)
short-digital treatment (D^{T2})	0.003	0.068	0.022	0.098	-0.014	0.060
	(0.064)	(0.079)	(0.068)	(0.077)	(0.071)	(0.083)
enhance-digital treatment (D^{T3})	-0.026	-0.001	-0.031	0.000	-0.012	0.031
	(0.055)	(0.049)	(0.059)	(0.053)	(0.062)	(0.062)
N	570	570	650	650	682	682
Covariates	No	Yes	No	Yes	No	Yes
Experimental Groups FE	No	Yes	No	Yes	No	Yes

Notes: Standard errrors in parenthesis. Estimates based on a parametric cross-sectional estimator conditional on working status. The treatment indicator takes the value 1 for those benefiting from labor-market intermediation, 0 otherwise. Socio-demographic covariates include age, gender, marital status, poverty index, whether individual has children, number of children, whether individual is migrant, number of years since migration, years of schooling. Labor-market covariates include whether individual worked ever, an indicator for dicouraged worker, whether individual had access to pension plan in last job, health insurance in last job, accident insurance in last job, whether individual worked under formal contract in last job, blue-collar worker indicator in last job, white-collar worker indicator in last job. Clustered standard errors by day are considered when including experimental group fixed effects in columns 2,4 and 6.
*** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.

Table 6: Impact of Labor-market intermediation on other intermediate outcomes
Labor-Market Intermediation Program, Lima 2009-2010

	Internet-based job search		Traditional search channels	
Overall Treatment	0.053*	0.062*	-0.012	0.013
	(0.031)	(0.032)	(0.056)	(0.060)
Type of Treatment				
non-digital treatment (D^{T1})	0.036	0.049	-0.008	0.028
	(0.038)	(0.038)	(0.066)	(0.065)
short-digital treatment (D^{T2})	0.056	0.056	-0.022	0.051
	(0.045)	(0.046)	(0.084)	(0.094)
enhance-digital treatment (D^{T3})	0.069*	0.079*	-0.011	-0.029
	(0.039)	(0.042)	(0.070)	(0.082)
N	1140	1140	372	372
Covariates	No	Yes	No	Yes
Experimental Groups FE	No	Yes	No	Yes

Notes: Standard errrors in parenthesis. Estimates based on a parametric cross-sectional estimator. Internet-based search is estimated over the full sample, while traditional search methods is estimated over the sample of unemployed three months after the start of treatment. The treatment indicator takes the value 1 for those for those benefiting from labor-market intermediation, 0 otherwise. Socio-demographic covariates include age, gender, marital status, poverty index, whether individual has children, number of children, whether individual is migrant, number of years since migration, years of schooling. Labor-market covariates include whether individual worked ever, an indicator for dicouraged worker, whether individual had access to pension plan in last job, health insurance in last job, accident insurance in last job, whether individual worked under formal contract in last job, blue-collar worker indicator in last job, white-collar worker indicator in last job. Clustered standard errors by day are considered in columns 2 and 4.
*** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.

Table Appendix A1: Labor market intermediation on employment outcome, unrestricted difference-in-differences
Labor-Market Intermediation Program, Lima 2009-2010

	Month # 1	Month # 2	Month # 3
Dep variable: employment			
Overall Treatment	0.055**	0.047*	-0.010
	(0.027)	(0.028)	(0.033)
Type of Treatment			
non-digital treatment (D^{T1})	0.024	0.03	-0.044
	(0.035)	(0.037)	(0.045)
short-digital treatment (D^{T2})	0.073*	0.049	0.022
	(0.042)	(0.043)	(0.044)
enhance-digital treatment (D^{T3})	0.078**	0.066*	0.005
	(0.034)	(0.038)	(0.036)
N	1118	1118	118
Covariates	Yes	Yes	Yes
Experimental Groups FE	Yes	Yes	Yes

Notes: Clustered standard errrors in parenthesis. The unrestricted difference-in-differences model follows from Lalonde (1986). The right-hand side variables include the same set as reported in table 3 plus the baseline work status.

*** statistically significant at 1%, ** statistically significant at 5%, *statistically significant at 10%.