Working Paper 2021-03b

Providing Information to Young People via SMS: Evidence from a Field Experiment

Jérémy Hervelin

Providing Information to Young People via SMS: Evidence from a Field Experiment*

Jérémy Hervelin
(CREST-ENSAE)

March 16, 2021

Abstract

Although SMS is constantly used to transmit information, little is known about the use of it by public institutions for publicizing their services. This paper presents a field experiment in France to analyze the effectiveness of SMS for providing information. The SMS directed young people, who are not in employment, education or training (NEET), to public assistance agencies seeking to enroll them. All the SMS were individualized and included specific information about the agencies. A subset of SMS was also written in a style based on how young people communicate. Results indicate that the SMS had no significant effect on enrollment whatever style was adopted. There is also no apparent heterogeneous effect according to individual, agency, or location characteristics. These findings show that sending SMS to this population is not an effective strategy for increasing public assistance agency uptake.

Keywords: NEET, Information provision, Public assistance, Field experiment
JEL codes: D04, D83, D64, J68

*I thank Pierre Cahuc, Philip Oreopoulos, Arne Uhlendorff, Philippe Zamora, and André Zylberberg for their guidance and constructive comments. I also thank all the participants at the DARES and CREST internal seminars for their helpful remarks. This project was possible thanks to the former Ministerial Delegation of *Missions Locales* (DMML) for their support during the pilot of the experiment, and the Ministry of the Army (DSNJ) and the Ministry of Labor (DARES) for data access and legal support. This project was conducted under the patronage of the *Sécurisation des parcours professionnels* Chair (chaire-securisation.fr), whose partners are the Ministry of Labor, Pôle emploi (public employment service), Unédic (public unemployment insurance), Alpha group (consultancy firms specialized in labor relations), Sciences Po, and CREST-ENSAE. The steering committee of the Chair, composed of representatives of these institutions, approved this experiment without imposing any constraint on the design proposed by the author. It was financed by the *Sécurisation des Parcours Professionnels* Chair and administratively supported by the Institut Louis Bachelier (ILB). Contact at jeremy.hervelin@ensae.fr.

1 Introduction

Many countries face hard times to identify and attract young people, in difficulty vis-à-vis the labor market, in public programs.[1] Every year in France, about 40,000 young people are identified as not in employment, education, or training (NEET) during the French national "army days". Military instructors are required to guide this population toward active programs supplied by partner public institutions. Among them, the *mission locale* is the main institution that helps young NEETs to deal with their problems (employment, housing, transport, etc.). As well as young people who approach them directly, the local agencies are required to contact all NEETs whose details they receive from military centers. However, data indicate that almost 50% of NEETs do not go to an agency and remain off track. This figure raises questions about how institutions communicate and suggests that they should consider other ways of communicating to enroll greater numbers.

Nowadays, most individuals communicate through SMS on a daily basis.[2] Whether they are sent to relatives to maintain relationships (Ling, 2010), by private firms to sell their goods (Rettie et al., 2005), or by medical centers to sustain individuals' efforts in combating substance abuse (Mason et al., 2015), SMS seem to be an effective channel of communication for transmitting salient information. Accordingly, might SMS be an appropriate solution for public assistance agencies to reach young NEETs?

SMS must be appropriately used to be effective, especially for young people. Some studies show that texts addressed to young people should be more carefully analyzed if they are to provide them with better advice about educational, health or life choices (Hudson et al., 2012; Graham, 2013; Ehrenreich et al., 2014). For instance, the US firm AT&T saw an increase in positive reactions from young people after broadcasting a series of TV commercials in which the protagonists spoke like young people's text messages (Jones and Schieffelin, 2009). Accordingly, if public assistance agencies were to adopt certain features of young people's communication style such as abbreviations, exclamation marks and emojis, would they be more effective in attracting young NEETs?

I address these two questions in this paper. I adopt the point of view of the public authorities and test new ways of delivering information to young NEETs.[3] More specifically, information was provided experimentally via texts directly sent to NEETs' phone numbers. Some youths were identified as NEET during the French national army days, which are compulsory for all French individuals under the age of 25. Those who were identified as NEET between January and May 2019 were randomly assigned to one of five different groups

[1]See for instance the OECD collection *Investing in Youth* at https://www.oecd-ilibrary.org/employment/investing-in-youth_24126357 in which each country reports such difficulty.

[2]I use the terms *SMS*, *texts*, *text messages*, or *text messaging* as synonyms throughout the whole paper.

[3]See Sunstein and Thaler (2003) and Chetty (2015) for more general discussions and theoretical justifications for these types of methods given the implicit assumptions of imperfect information and/or bounded rationality.

with equal probability. They received information on the nearest *mission locale* agency. The first group did not receive any texts and served as the control group. The second group assigned to an initial treatment received a typical text containing the name of the assistance agency, a sentence about what it broadly did, and its postal address. Three other groups were assigned to a second treatment and received stylized texts with additional specific information. In addition to the same basic information given to the first treatment group: the third group was told the exact distance in kilometers between them and agency locations; the fourth group was told the exact number of youths enrolled in the agency during the previous month; and the fifth group received all this information. Except for those in the control group, all participants received the same text twice, the second being a reminder of the first.

Texts received by the first treatment group are similar to typical texts sent by some institutions, with basic information (name and location of the agency) and no particular design for the text content. In contrast, the other texts were designed and constructed on the basis of an extensive literature in psychology and brain science in order to better match the way young people communicate. Jones and Schieffelin (2009) note that young people communicate through texting in a way that differs from the standard forms of speaking or writing, by playing with words, grammar, etc. Though structurally similar to typical texts for statistical comparisons, they include specific elements such as an intimate tone or punctuation marks associated with positive emotions when referring to oneself or undertaking actions after reading the texts. Riordan and Kreuz (2010) and Ling and Baron (2016) show that computer-based-communication (CMC) includes particular cues that differ from those used in face-to-face (F2F) communication. For instance, emoticons are an important part of texts because they allow individuals to mimic different facial expressions that cannot be easily displayed in CMC.

The information included in the texts was chosen for at least four reasons. First, the name and postal address of the agency clearly state the position of a public assistance agency which the person addressed may previously not have heard of or know little about after the army days. Second, the exact distance in kilometers may help the receivers to better estimate the time needed to get to the agency from where they are currently located. Third, past enrollment may give a better sense of the number of youths similar to those receiving the texts. This information can be used as a way of correcting certain prior beliefs about what similar young people may do. Fourth, other information related to the success rates of agencies, which might be of interest to this population, were difficult to transmit because of the time needed to ascertain them.

In total, 4,457 young people were included in the experiment and 3,540 of them received text messages between March and July 2019 throughout mainland France and French overseas territories. Based on administrative records, both linear regressions and duration analyses are performed. Analyses indicate that the texts have no overall effect, irrespective of the text style. Nor do they reveal any heterogeneity in relation to individual, agency, or location characteristics, especially after robustness checks were carried out. Regarding the effects of distance on NEET take-up, all texts seem to attenuate the small negative effect of distance, probably because of the provision of the exact postal address, which could allow individuals to better estimate the time needed to get there. However, texts do not change the effect of past enrollment on NEET take-up, even though this information is not easily available online and may alter beliefs about what other young NEETs may do.

There are several possible reasons for the non-significant effect of text messaging. First, information on distance and past enrollment may not be relevant for this population. Second, the laps of time between the army days and sending the texts may have been too long in practice - 50 days on average, although variations in transmission timing over a month do not reveal any differences -, especially as the military instructors may have first informed the young people about the existence of *mission locale* agencies during the army days. Third, alternative designs for text messages might have been more appropriate, rather than sending only two texts following the army days. It would have been possible, for example, to have sent several texts over time to support the receivers, with other elements in the message such as words of encouragement, more or fewer emoticons, two-way interaction, etc. Fourth, the psychological and external barriers encountered by young people may be too great for text messaging alone to motivate them. Given that NEETs may wrongly estimate their ability to improve their situation or may feel locked into it, greater interaction in communicating with them would be more effective. Indeed, caseworkers or third-parties engaged in matching youths to specific programs can adapt in real time to their expectations and the range of programs available.

The particular vulnerability of the NEET population with respect to the structural functioning of local labor markets and macroeconomic conditions makes public interventions necessary. Even though it is not clear whether young NEETs should go to public assistance agencies if they are seeking better positions on the labor market,[4] it is still worthwhile collecting more information on what they value and the barriers they face if a minimum amount of social cohesion is to be preserved. Such further research aims to design appropriate information campaigns to direct young NEETs towards the most suitable solutions.

This paper mostly relies on the literature the effect of texting as a communication medium for transmitting information. Meta-analyses and reviews from medical science suggest that low-cost automated text messaging, designed to sustain individual efforts, is effective in helping people to smoke less, fight against diabetes and lose excess weight. (Cole-Lewis and

[4]Reviews by Card et al. (2018) and Caliendo and Schmidl (2016) show that JSA programs have mostly no effect for young people in difficulty in European countries. On the other hand, micro-econometric studies by Crépon et al. (2005) and Behaghel et al. (2014) reveal positive effects of JSA on employment in France. However, Cahuc and Le Barbanchon (2010) and Crépon et al. (2013) show the existence of negative spillover effects leaving youth unemployment barely or completely unchanged.

Kershaw, 2010; Mason et al., 2015). Thomas et al. (2017) also propose that automated text messaging is effective in helping students to drink less alcohol during their tuition. Studies from the marketing literature also pinpoint mostly positive effects of SMS as an effective channel for firms to increase the demand for their goods and services. Based on surveys following large brand SMS campaigns carried out in 2001-2002 in the US with about 5,400 respondents, Rettie et al. (2005) indeed show that advertising physical goods is effective in increasing consumers' purchasing intention. Field experiments in the economics of education yield more mixed results. Castleman and Page (2015) detect a positive effect of about 10% on higher education enrollment from sending a series of texts to high school students during summer time, in order to counteract a potential drop in motivation. The effects were positive only for students who had no existing plans after high school. Fryer (2016) find no effect on grades from supportive texts for high school students in the US when they are provided with free cell phones and texts sent daily. Oreopoulos and Petronijevic (2019) and Oreopoulos et al. (2020) also find no effect from coaching text messages on academic performance for students at the University of Toronto, even for those at risk of dropping out. To my knowledge, the present paper is the first to test whether text messaging could be a viable way of informing young NEETs about the existence of public assistance agencies located nearby. In contrast to the results in the marketing literature and medical science, which find mostly positive effects, but similarly to those found by the few field experiments in the economics of education, I find no effect from texts as a communication medium for public agencies seeking to enroll more young NEETs. As discussed below, this population may be hampered by deep psychological or external barriers that cannot be overcome simply by sending text messages.

This paper also connects to the literature on program take-up through the provision of information. In the US, some studies find positive effects from information letters on disability insurance take-up (Armour, 2018), on the demand for tax credits (Bhargava and Manoli, 2015), on social security subscription (Finkelstein and Notowidigdo, 2019), on voting for political elections (Gerber et al., 2008), and on labor force participation from letters correcting misconceptions about social security earnings (Liebman and Luttmer, 2015). Barr and Turner (2018) find a positive effect on higher education enrollment from letters pointing out the benefits of training for displaced workers after the financial crisis. Bettinger et al. (2012) find positive effects on college enrollment of American high-school students by assisting them throughout the application process. In Canada, Oreopoulos and Dunn (2013) find that online information and video tutorials increase the willingness of high-school students to pursue higher education. In Germany, Berkes et al. (2019) find positive effects on improving graduate students' beliefs about the benefits of graduation returns by providing online information via an interactive survey. Altmann et al. (2018) find a positive effect on exit from unemployment from an information brochure pointing out the harm of being unemployed and suggesting strategies for a return to job-seeking, but only among long-term high-risk unemployed job-seekers. In France, Goldzahl et al. (2018) find no effect from information letters on breast-cancer screening uptake, which describe the risks of this form of cancer and suggest a free-of-charge service with a voucher. However, it is difficult to disentangle the effect of the information itself and the support arising from the way it is channeled in these studies, especially for those which involve several communication media or multiple information content over time. In the present study, I go one step further in stylizing text messages with elements taken from the literature in psychology and neuroscience about communication, allowing me to disentangle the effect of style from the information itself. The study brings novel results on, whether or not, providing information through stylized texts is relevant for boosting the probability of NEET uptake of public assistance agencies compared to more standard texts. It concludes that sending such texts does not increase the likelihood of NEET enrollment, and that distance and past enrollment rates are not relevant in appealing to young NEETs.

The rest of the paper is organized as follows. Section 2 presents the relevant French institutions and some characteristics of young NEETs. Section 3 describes the experimental design. Section 4 shows and discusses the results of the experiment. Section 5 presents the conclusions.

2 Background

This study concerns NEETs and information provision to encourage the uptake of public assistance agencies. I start by briefly presenting the army days, then I portray the NEETs identified, and finish with the presentation of the *missions locales*.

2.1 The French army day

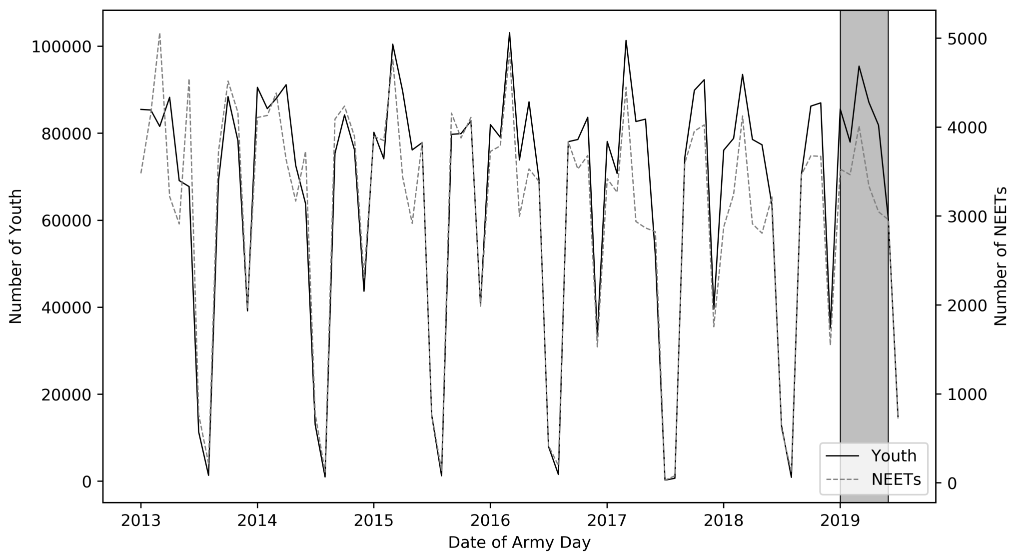
All French youth are required to remain in the education system until the age of 16. While at school, they start a citizenship pathway built on three compulsory stages. The first concerns classes related to national defense all along 9th grade and 11th grade. The second involves registering at the town hall at most three months after the sixteenth birthday. The third stage is the army day, called "*La Journée Défense et Citoyenneté*" (JDC).[5]

Young people attend the army day once after receiving an official invitation from the Ministry of the Army, generally between their registration at the town hall and their eighteenth birthday.[6] Army days have taken place every year at different military centers since 1998. About 40 to 50 young people attend a given army day at a specific military center. The army day agenda takes place between 8:30 am and 5 pm. At the beginning of the day, all participants have to fill in a form pertaining to their situation with respect to schooling

[5] More details at https://www.defense.gouv.fr/jdc/parcours-citoyennete.

[6] There are some exemptions and possibilities for rescheduling the army day under certain specific conditions. Youth are allowed to attend an army day up until the age of 25.

Figure 1: Evolution of the number of youths and NEETs attending army days per month



Source: SAGA 2013-2019 database, 5,154,495 observations, author calculations.

or the labor market. They take a 30-minute test before lunch to assess their proficiency in French. During the rest of the day, military instructors aim to raise the participants awareness of national security and of other social issues such as drug abuse, road safety, racism, etc. They may also inform participants about public institutions that offer active programs of possible interest to them. At the end of the day, participants receive a certificate of army day attendance. This is required when taking any diploma or competitive exam under the control of the public authority.[7]

Every year about 800,000 young people participate in army days. According to a report from the French general accounting office, 96% of all French-born individuals do their army day before they turn 25 (Courdescomptes, 2016). Figure 1 shows the numbers attending the army days per month from January 2013 to July 2019. A cyclical pattern repeats itself every year with regard to the number attending army days. The majority of French young people do their army day between January and May or between September and November. Summer time and December are generally reserved for individuals who were unable to attend their army day following the first notification. A notable feature from the data is the persistence of the number of NEETs attending the army day. Every month, about 5% of all participants are NEET.

[7]Recently, young people only need to bring an official document stating their position with respect to the army day without the need to attend it. The certificate is not needed after the age of 25.

Table 1: Descriptive statistics of youth and NEETs during army days

Characteristics	% of all youth (1)	% of all NEETs (2)
Sex (*Male*)	51.11	61.15
Age		
16-17 yo	95.55	75.24
18-21 yo	3.85	21.14
22-25 yo	0.60	3.62
School		
Lower-Secondary	83.95	99.77
Vocational Upper-Secondary	10.58	0.21
General Upper-Secondary	5.05	0.02
Post-Secondary	0.42	0.00
Literacy		
Level A	88.44	64.72
Level B	2.99	13.23
Level C	1.87	5.62
Level D	2.66	8.56
Level E	3.27	7.04
Guidance		
Toward any partner public institution	11.79	63.49
Toward missions locales	2.19	32.46
Total number of observations	5,154,495	237,110

Note: This table reports descriptive statistics about some characteristics of youth and NEETs during army days. "Age" is age at the army day. The category "School" for NEETs corresponds to the level at which youth drop out of the school system. *Level A* for "Literacy" corresponds to "normal literacy", while *Level E* corresponds to "illiteracy" and Levels *B* to *D* ranges for decreasing medium levels. Partner public institutions of army days include *Établissements pour l'insertion dans l'emploi* (EPIDE), *Service militaire adapté* (SMA), *Centres d'informations et d'orientation* (CIO), *Savoirs pour réussir* (SPR) and the *missions locales* (ML).
Source: SAGA 2013-2019 database, author calculations.

2.2 Characteristics of army day participants

Information filled by youth at the beginning of the army day are recorded by military men in an information system called *Système d'aide à la gestion des administrés* (SAGA). This database is primarily used as an up-to-date census of French people who could be called-up in wartime. It contains basic information on young people including their name, gender, date of birth, birthplace, residential address, phone number, proficiency in French based on the 30-minute test, the educational level, and a set of dummies for NEET and guidance towards partner public institutions.

Table 1 shows aggregated values of some characteristics averaged over the period January

2013-July 2019. Information on all youths who attended the army day are shown in column (1), while column (2) restricts the sample to NEETs. It appears that NEETs are more often males, do their army day more often when older, more often have an educational level equivalent to middle school, are less proficient in French, and are more inclined to agree to be guided toward a partner institution which supplies mostly active labor market programs.[8]

2.3 *Missions locales*

Missions locales (ML) are a French institution dedicated to dealing with 16 to 25-years old who potentially face problems in relation to employment, health, housing, transport, psychology, etc. ML were created in 1982, extended over the following decades, and are now part of the French public employment service.

There are about 440 agencies spread over the whole territory, accounting for about 6,500 reception sites and 13,000 caseworkers with connections with various local actors. On average, 485,000 youths registered annually for the first time over the last decade, nearly 60% of them between the ages of 18 and 22. The *mission locale* agencies generally arrange individual meetings, with more than 4,000,000 such meetings each year over the last decade (Seijo-Lopez et al., 2018). These meetings may simply reflect an occasional need of information from the youths or be carried out in the framework of a specific job search assistance program.

The institution has adopted a national strategy since 2014, based on a "work first" principle to help youths to overcome their problem through employment. In line with this strategy, the institution created a new job search counseling program *Garantie jeunes* consisting of collective workshops to find a job, individual meetings thereafter to support the efforts made, and a monthly monetary allocation (≈ €500 maximum) for a year. The implementation of the program had a positive effect on permanent employment of about +50% one year later, and +30% after two years (Guillerm and Hilary, 2019). However, this program accepts candidates with specific characteristics, and those who do not meet the criteria only have meetings with caseworkers specialized in the area where they have a problem.

2.4 Military guidance towards the *mission locale* agencies

Despite the encouraging placements in the labor market, the overall level of enrollment in the *mission locale* agencies is tending to diminish, falling from 534,000 in 2013 to 400,000 in 2017. To reverse this trend at the local level, each agency is free to publicize its service through an appropriate medium. Agencies may variously put up posters on walls, communicate through

[8] Eckstein and Wolpin (1999) showed that young dropouts have different characteristics than their graduate counterparts and face more adverse consequences on the labor market. More recent empirical studies confirm their lower likelihood of being invited for job interviews, or being in employment and their lower earnings (Oreopoulos, 2007; Campolieti et al., 2010; Hervelin et al., 2020). They also report lower levels of well-being and more health problems such as depression and substance abuse (Basta et al., 2019; Klug et al., 2019).

social media, participate in school or business meetings, and so on. However, there is no record or follow-up about the effects of such attempts.

At the national level, the main call for NEETs to join is made by military instructors during the army days. Instructors are obliged to meet young people identified as NEET and invite them with an individual meeting during the day's break or lunch period. The instructors first check that youths are NEET and the present them with a set of alternatives, including the *missions locale*. If NEETs are motivated by this proposal, the instructors encourage them to join the program. In parallel, they send names and details of the NEETs to the nearest agencies, which are then supposed to contact the youths. Table 1 shows that about one-third of the NEETs agree to be guided to a *mission locale* agency. Nevertheless, the instructors are not able to determine whether the NEETs actually go to the agencies afterwards, or whether the agencies make contact with them.

It is only possible to establish this by merging SAGA together with the information of the *missions locale* IMILO on individual personal records. Table A.1.1 in Appendix A.1 shows that the effect of military guidance becomes positives when controlling for individual characteristics and time. It increases the baseline probability of going to an agency (50%) by about 20% (8.2 pp), and it shortens the average duration of going there (500 days) by about 2.5 months (-78 days). This effect is mostly explained by selection effects, because the NEETs have the final word on being recorded as guided toward an agency. One important missing variable is the date when youths became NEET, because their decision to be guided toward an agency could be largely influenced by NEET duration.[9] From these results, it follows that the remaining share of young NEETs who do not go to a *missions locale* agency is still large. These considerations were taken into account in the field experiment presented in the next section.

3 Field Experiment

The experiment aims to analyze the probability of going to a public assistance agency following the receipt of a text containing specific information. I start by presenting the different treatment groups, then describe the structure of the texts and conclude with the protocol.

3.1 Treatment groups

The experiment involved sending two texts to youths identified as NEET during army days. The texts include information about *missions locale*, the main actors dealing with youth in France. The texts automatically guide NEETs to this public institution by providing information on the agency located nearest to them. The information provided to NEETs

[9] The content of individual meetings are not recorded and informal discussions with representatives of the army day indicate that instructors emphasize different elements when talking with the youths.

Table 2: Control and treatment groups

Group	Name
Control	No text
Treatment 1	Neutral text
HELLO {FIRSTNAME}, THE {ML NAME} ADVISES YOUTHS ON THEIR PROJECTS. MORE INFORMATION AT {ML ADDRESS}. THE 1ST MEETING DOES NOT REQUIRE AN APPOINTMENT.	
Treatment 2a	Stylized text + distance
HEY {FIRSTNAME}, THE {ML NAME} ADVISES YOUTHS ON THEIR PROJECTS. THIS ONE IS LOCATED ONLY {ML DISTANCE} KM FROM WHERE YOU ARE. MORE INFORMATION AT {ML ADDRESS}. THE 1ST MEETING DOES NOT REQUIRE AN APPOINTMENT! :)	
Treatment 2b	Stylized text + enrollment
HEY {FIRSTNAME}, THE {ML NAME} ADVISES YOUTHS ON THEIR PROJECTS. {ML #ENROLLMENT} YOUNG PEOPLE LIKE YOU WERE ENROLLED LAST MONTH. MORE INFORMATION AT {ML ADDRESS}. THE 1ST MEETING DOES NOT REQUIRE AN APPOINTMENT! :)	
Treatment 2c	Stylized text + distance & enrollment
HEY {FIRSTNAME}, THE {ML NAME} ADVISES YOUTHS ON THEIR PROJECTS. {ML #ENROLLMENT} YOUNG PEOPLE LIKE YOU WERE ENROLLED LAST MONTH. MOREOVER, THIS ONE IS LOCATED ONLY {ML DISTANCE} KM FROM WHERE YOU ARE. MORE INFORMATION AT {ML ADDRESS}. THE 1ST MEETING DOES NOT REQUIRE AN APPOINTMENT! :)	

Note: This table reports the different groups in which youth were allocated during the experiment and the content of the text they received. Elements in curly brackets are variables that changed according to individual name and location.

differs according to different treatment texts in order to analyze the effect of this information on the decision to go to the *missions locale*.

NEETs were randomly allocated to one of five groups with equal probability after their army days. One fifth of the NEETs did not receive a text and thus constituted the control group. Another fifth made up the first group treated and received a neutral text giving the name and the postal address of the nearest agency. The remaining three fifths were allocated to a second treatment group that differed in terms of the design of texts and sub-divided according to an additional specific piece of information. All the second treatment groups received the same basic information as the first. The first sub-treatment group "2a" was in addition given the distance in kilometers between the individual and the agency. The second sub-treatment group "2b" was in addition given the number of youths who went to this agency the month before the army day. The third sub-treatment group "2c" combines information

Table 3: Structure of the text messages

Structure	Elements
HELLO/HEY {FIRSTNAME}	Upper-case
	First-name
< CORE OF THE TEXT + SPECIFIC INFORMATION >	Personal tone
	Exclamation mark
THE 1ST MEETING DOES NOT REQUIRE AN APPOINTMENT! :)	Smiling emoticon

Note: This table reports the main structure of the texts sent to treatment groups and their related elements.

provided in "2a" and "2b". These two types of information are potentially important, because knowing the exact distance to an agency can help to better evaluate the time needed to get there, while the number of previous enrollments can help the individual better evaluate the number of other young people who are in the same situation as its own.

Full texts related to each group are shown in Table 2[10]. All texts are sent twice. Second texts are similar to the first except they include an additional question asking if the youth went to a *mission locale*. In line with the first texts, they are sent as a reminder because some individuals, especially young people, may be time-inconsistent and thus procrastinate doing some tasks (O'Donoghue and Rabin, 1999, 2001) or fail to predict their future behavior (Ericson, 2011; Acland and Levy, 2015).[11]

3.2 Structure of the texts

Table 3 shows the main elements used to create the treatment texts. While neutral texts look more formal and are quite similar to usual texts sent by some *missions locale* to their youths, the other texts adopt a much informal tone and mimic what might be said in a face-to-face conversation. This approach was motivated by the related literature in psychology and brain sciences.[12] Though upper-cases and the use of first names are two elements used in all texts, the other elements are limited to the stylized texts.

Upper-case It is commonly acknowledged, after influential articles of Miles Tinker (1966) that the speed of reading texts is faster when they are written in lower-case rather than mixed- or upper-case. However the shape of letters and reading words instead of separate

[10] Table A.2.1 in Appendix A.2 shows the text contents in the original version and Figure A.2.1 shows how they are displayed on a smartphone screen.

[11] Reminders seem to be effective to alleviate this problem (Altmann et al., 2017; Calzolari and Nardotto, 2016). The effect of reminders seem even larger when they are not expected by individuals (Ericson, 2017). This reason led the experiment to include a second text one week after the first, without any previous notification being sent.

[12] Different texts were presented to a group of caseworkers and youths enrolled in a *mission locale* agency in the Paris area and were discussed until all agreed on the design and the content of information.

letters influences the speed of reading (Perea and Rosa, 2002). In this regard, when the point size is fixed as in phone texts, upper-case texts appear to be more legible than lower- or mixed-case texts (Arditi and Cho, 2007).

First-name Many studies that require reflection on internal processes, such as theory of mind, emotion, or perspective taking, find that subjects use similar active brain regions (Wicker et al., 2003). Individuals' MRI show a more active brain response in these zones when individuals hear their own names (Carmody and Lewis, 2006).[13] The same parts of the brain are activated when subjects engage in a theory-of-mind task in relation to reading sentences (Mitchell et al., 2002).

Personal tone With few exceptions, the tone of a conversation is led by a reciprocity principle between people in the same environment (Jobert, 2010). Though a public text should be aimed at numerous readers, it can be expressed as a private text addressed to a specific person. Such a strategy justifies the use of the informal "*tu*" rather than the formal "*vous*". This introduces an informal, friendly and appropriate tone for some readers, and implies a simple and direct action to comment or to follow. It can be also translated into a comprehension of social and cultural position (Pires, 2004). Moreover, it seems that "*tu*" is used in the same way as "*vous*" in computer mediated communications (Williams and van Compernolle, 2009).[14] Other parts of the texts like "FROM WHERE YOU ARE" or "YOUNG PEOPLE LIKE YOU" are added to involve the reader more deeply. Mahatanankoon and O'Sullivan (2008) show that information technology adoption is related to non-cognitive abilities and that individuals with more external locus of control tend to favor less texting. Inclusion of elements such as an informal tone are intended to reverse this feeling.

Exclamation mark Individual intuitions suggest that the use of a period at the end of phone text is a negative signal.[15]. Empirical investigations tend to confirm this intuition (Ling and Baron, 2016), especially for young students (Gunraj et al., 2016). Though there is no scientific output on the use of exclamation point I am aware of, a search for "exclamation mark in text message" on Google indicates that exclamation marks are used to add emphasis or express strong emotion such as excitement. Here, an exclamation mark is put at the very end to give a feeling of dynamism when NEETs read the texts.

Smiling emoticon The basic functions of nonverbal cues in face-to-face communications are providing information, regulating social interaction, and expressing intimacy that may intensify or tone down the emotional expression (Lee and Wagner, 2002). In computer mediated

[13] *"Remember that a person's name is, to that person, the sweetest and most important sound in any language."*, Dale Carnegie, How to Win Friends and Influence People, 1936.

[14] Note that in French, there are two forms of "*you*" when interacting with another person: "*tu*" and "*vous*". The latter is a more polite way of speaking and more often used when the two people do not know each other.

[15] *"The period was always the humblest of punctuation marks. Recently, however, it's started getting angry. I've noticed it in my text messages and online chats, where people use the period not simply to conclude a sentence, but to announce 'I am not happy about the sentence I just concluded.'"* Ben Crair, sentence in *New Republic* article, 2013, quoted in Gunraj et al. (2016).

communication, there is an inherent lack of visual cues, which means that not all information is fully transferred and may be misinterpreted (McKenna and Bargh, 2016). Therefore emoticons can be used for the expression of emotion and/or for strengthening the verbal part of the message. In particular, Derks et al. (2008) report that teenagers perceive a message as more positive when it has a smiley in it.

3.3 Protocol and data collection

The experiment include youths who did their army day between 1st January 2019 and 31st May 2019, as shown by the gray area in Figure 1. There were two particular conditions to be satisfied in making the selection:

1. The youth was NEET and had never attended a *mission locale* agency.
2. A cell phone number was provided in order to deliver the texts properly;[16]

I used two administrative databases to carry out the experiment: SAGA and IMILO. Both databases are updated monthly with a one-month lag, i.e. the SAGA database of February 2019 included all youths who did their army day up to January 31st. The same applies for IMILO. After obtaining a copy of the two databases, I cleaned the information related to personal records (last name + first name + gender + date of birth + place of birth). Once the two databases were cleaned, I extracted the sample by merging them on names, using the Jaro-Wrinkler distance algorithm (Christen, 2006) and exact matching on gender, date of birth and place of birth. The output file listed NEETs who had never registered with a *mission locale* agency.

The next task was to assign a particular *mission locale* agency to each youth. *mission locale* agencies only accept youths who live in the same geographical area, generally at commuting zone level or at department level if there is no small local agency. Otherwise, they redirect them to the appropriate agency. Since postal address of both youth and *mission locale* agencies were available in the data, I assigned the agency located nearest to each individual, based on the geodesic distance algorithm (Karney, 2013) provided it was in the same administrative department.

I ended up with a file containing an anonymous ID - linked with official IDs to recover all the required information once the experiment was complete -, the first name of the NEET, the name of the assigned *mission locale* agency, the postal address of the agency, the distance in kilometers, and the number of youths enrolled in this agency during the month prior the army day of the NEET. The youths were then randomly allocated to one of the five groups with equal probability through a *Python* program. Those who were assigned to a treatment

[16] It appears that about 65% to 75% provided a (valid) phone number. This sample is similar to the whole sample based on the available characteristics provided in SAGA.

group received the first text on the following Wednesday morning around 10 am.[17] The second texts were sent seven days later at the same time.[18] The two texts were individualized with the information in the final file. The duration between the first text and the army day was somewhat random according to when the Ministry of the Army delivered its database.

In total, 4,457 youths were in the experiment and 3,540 texts were sent two times from 6 March 2019 to 17 July 2019. Figure A.4 in Appendix A.4 shows the minimum effect I am able to detect given the different sample sizes. It is clear that the experiment allows me to detect a minimum effect of about ±4.5 pp at the 5% significance level and about ±3.7 pp at the 10% significance level, considering a power of 80% when pooling all the groups who received the SMS compared to the one who did not.[19].

To conclude this section, Table A.3.1 in Appendix A.3 provides randomization tests with differences in variable means. It appears that with very few exceptions the randomization was successful. To ensure that the few statistically significant variables had zero impact on the treatment assignment, I ran linear regressions of the treatment variables on the same set of individual characteristics. Fisher tests show that every variable has a non-significant impact on explaining treatment assignment. To complete the experiment, I merged the list of NEETs participating in the experiment with the latest available version of IMILO (June 2020), giving me an average one-year window to analyze whether or not the texts were effective in increasing *mission locale* take-up.

4 Results

I start by presenting the intention-to-treat effects obtained on average and across several dimensions. I also look at the effects of distance and previous enrollment on NEETs' agency take-up. Then, I turn to the probability of going to a *mission locale* agency over time.

4.1 Regression analyses

To analyze the overall effect of the texts and not only at a particular date, I estimate the following linear probability model with Ordinary Least Squares (OLS) estimators:

$$y_{ij} = \alpha + \beta_k T_{i=k} + X'\gamma + \varepsilon_{ij}$$

[17]Twilio was the platform through which texts were sent. More information at twilio.org. The text sender's name was restricted to eight characters and set to "INFOS ML" for "Informations Missions Locales".

[18]This schedule was chosen because Wednesday is a day when students have a whole free afternoon and generally take decisions at this time. Given that NEETs might still behave like students according to some informal discussions with *mission locale* caseworkers, it was hoped to maximize the effect of the texts.

[19]The expected sample size was about 10,000 youths so as to detect a minimum effect of ±0.025/0.030 with a baseline *mission locale* take-up rate of about 25% one month after army day, at a 5% significance level and a power of 80%. This sample size was first targeted by sending texts to NEETS who did their army days between 1 January 2019 to 31 December 2019 but a technical incident in June 2019 at the Ministry of the Army and a change their information system in September 2019 changed the initial plan.

Table 4: Intention-to-treat effects

OLS Estimates	Entry to ML (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Neutral text	-0.0003	-0.0000	0.0016	0.0020	0.0026	0.0020
	(0.0165)	(0.0168)	(0.0171)	(0.0174)	(0.0180)	(0.0181)
Distance text	-0.0118	-0.0123	-0.0119	-0.0122	-0.0128	-0.0128
	(0.0110)	(0.0111)	(0.0139)	(0.0140)	(0.0150)	(0.0152)
Enrollment text	-0.0116	-0.0118	-0.0070	-0.0068	-0.0056	-0.0054
	(0.0200)	(0.0200)	(0.0195)	(0.0194)	(0.0199)	(0.0200)
Distance + Enrollment text	-0.0155	-0.0162	-0.0201	-0.0200	-0.0215	-0.0217
	(0.0132)	(0.0131)	(0.0147)	(0.0152)	(0.0153)	(0.0158)
Constant ($\approx$ No text mean)	0.1864***	0.1866***	0.1860***	0.1858***	0.1859***	0.1861***
	(0.0147)	(0.0146)	(0.0159)	(0.0160)	(0.0166)	(0.0130)
N	4,103	4,103	4,103	4,103	4,103	4,103
R-squared	.0003	.0007	.0223	.0242	.0281	.0299
$\beta_{\text{Neutral}} = \beta_{\text{Stylized}}$	.1599	.1314	.1099	.1107	.0957	.1020
Information displayed	No	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Agency characteristics	No	No	No	Yes	Yes	Yes
Location characteristics	No	No	No	No	Yes	Yes
Month fixed effects	No	No	No	No	No	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* after its army day, zero otherwise. "X text" are dummy variables equal to one if the individual received a specific treatment text, zero otherwise. Displayed information corresponds to variables that might have been displayed in the different treatment texts as the distance in km to the agency and the number of youths enrolled in the agency on the month before the army day. Individuals characteristics include demeaned dummies for gender, birthplace, age at the army day, literacy level, region of residency. Agency characteristics include demeaned dummies for the number of agencies, number of committee rooms, number of points of contacts, number of firms in portfolio, number of caseworkers, mean age of caseworkers, share of male caseworkers, average number of caseload per caseworker. Location characteristics include demeaned dummies for disadvantaged area, type of city, local unemployment rate, number of services, number of stores, number of schools, number of transport modes, and number of leisure facilities. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses. Finally, the same regressions are re-ran with merged "Distance" & "Enrollment" & "Distance + Enrollment" texts into one "Stylized text" variable, equal to one if at least one the three others is equal to one, to perform a Student test for equality between "Neutral text" and "Stylized text". The p-value of this test is shown in the line $\beta_{\text{Neutral}} = \beta_{\text{Stylized}}$. *** significant at 1 percent.

where y_{ij} is a dummy variable equal to one if youth i went to the *mission locale* agency j, zero otherwise. $T_{i=k}$ is a dummy variable equal to one if youth i received texts with information $k \in \{\text{Neutral, Distance, Enrollment, Distance + Enrollment}\}$ as depicted in Section 3.1. X is a vector of control variables including information displayed in the text (the distance in kilometers to the agency j and/or the number of youths who registered at the agency j during the month prior the army day), individual characteristics, agency characteristics, location characteristics, and month fixed effects. These control variables are introduced as demeaned dummies. ε_{ij} is a residual term, orthogonal to treatment variables through randomization. Turning to parameters, β_k is of interest and measures the intention-to-treat (ITT) effects, i.e. the differential in probabilities of going to a *mission locale* agency in comparison to the control group (which receive no text at all) with each group receiving a treatment text k.

The OLS estimates of β are reported in Table 4. Column (1) reports the estimates without control variables as a baseline estimation, while columns (2) to (6) introduce all the covariates progressively. The results, which are very stable across specifications, confirm the absence of statistically significant effects of treatment texts on the probability of going to a *mission locale* agency.[20] Neutral texts induce a quasi-positive zero effect, while enrollment texts induce a quasi-negative zero effect. Distance texts and distance + enrollment texts induce a negative effect of about -1.3 pp and -2.2 pp respectively, i.e. a negative effect of about -6.9% and -11.7% given the baseline take-up of the control group (18.6%). Neither of results are statistically different from zero.[21] In addition, I re-run the same regressions by merging the different second sub-treatment groups into one group called "Stylized text" and carry out a Student test to analyze whether stylized texts have a different effect from neutral texts. P-values reported in Table 4 show the two types of treatments do not differ from each other.

The probability of going to a *mission locale* agency might differ on different dimensions. In order to analyze potential heterogeneous effects, I provide estimates of β by splitting my sample according to the characteristics included as control variables in the above equation. Tables A.8.1, A.8.2, and A.8.3 in Appendix A.8 show estimates according to individual, agency and location characteristics respectively. Individual characteristics thus include gender, age at the army day, literacy level, and being guided to a *mission locale* by military instructors. Agency characteristics include the number of offices related to the agency, the number of committee rooms, points of contacts, and partnership firms. It also shows estimates according to caseworkers working for the agency, such as their number, the share of males, their age, and the average number of caseloads per caseworker. Location characteristics include the disadvantaged nature of the area[22], the type of city, the unemployment rate, and the number services, schools, forms of transports, and leisure facilities.[23]

Standard inferences from OLS regressions are shown in panels A of the three tables and indicate that some stylized texts have a significant effect on the uptake probability across some characteristics. For instance, it seems that stylized texts providing information on past enrollment increase the uptake probability by 34% (6.2 pp) when the individuals lives in a disadvantaged area. However, each table also contains robustness checks with boostrap p-values in panels B, and randomization inference p-values in panels C, each obtained after 1,000 random replications. It is clear that estimates of treatment texts which were significant are not robust to these two procedures and become non-significant or very few become nearly significant at the 10% confidence level. More replications and use of alternative statistics for

[20] To address concerns about non-linear effects, I report the estimate of β with a Probit model. Table A.7.1 in Appendix A.7 shows that the estimated marginal effects are very similar to the OLS results. This similarity holds for all the results in the paper using OLS estimations.

[21] I am not able to determine whether or not youth actually opened their text messages but according to the 2018 annual barometer of the *marketing mobile association France*, about 95% of commercial texts were opened. According to Esendex, 100% of those aged 18-24 opened their texts in 2018 when a name was provided. Overall, the average treatment effects on the treated (ATT) should be similar to the ITT.

[22] Disadvantaged areas refer more specifically to the French *quartiers prioritaires de la ville*, which refer to areas within cities that need more political and economic support.

[23] Youth characteristics were taken from SAGA, agency characteristics from IMILO, and location characteristics from the French statistical institute's open data. When the covariate is originally a continuous variable, it is transformed into a dummy variable equal to one if its original value is higher than the median value, zero otherwise. Results are similar when the chosen threshold is the mean value (results are available upon request).

Table 5: Effects of distance and enrollment on take-up

OLS Estimates	Control	Neutral	Stylized		
			Distance	Enrollment	Dist. + Enroll.
	(1)	(2)	(3)	(4)	(5)
log(distance)	-0.0168**	-0.0039	-0.0008	-0.0014	0.0018
	(0.0084)	(0.0133)	(0.0081)	(0.0058)	(0.0086)
log(enrollment)	0.0293	-0.0194	0.0189	0.0065	0.0356
	(0.0284)	(0.0214)	(0.0216)	(0.0078)	(0.0250)
N	837	833	802	841	790
R-squared	0.0414	0.0476	0.0411	0.0468	0.0495
Month fixed effects	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* agency after its army day, zero otherwise. Distance between the youth location and agency location is in log-km. Enrollment is the logarithm of the number of youths enrolled in the agency in the month before the army day. Month fixed effects are accounted for the timing at which the texts were sent. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses. ** significant at 5 percent.

the randomization inference procedure deliver non-significant effects of the treatment text.[24]

As complementary elements, Table 5 shows the specific effects of distance and previous enrollment rates on the current take-up probability for each group of the experiment. Firstly, it appears that distance has a negative effect on take-up for the control group. When the distance between a youth and an agency increases by 1%, the take-up probability decreases by 1.7 pp on average. However, this negative effect disappears when youths received a text with information on the agency. This effect might be the result of better knowledge about the agency's exact location, which allow the receiver to better assess the time needed to get there, instead of approximation without this information. Secondly, the number of previous enrollments in the agency has no impact on the take-up probability for the control group and this impact remains null for treated groups.

4.2 Duration analyses

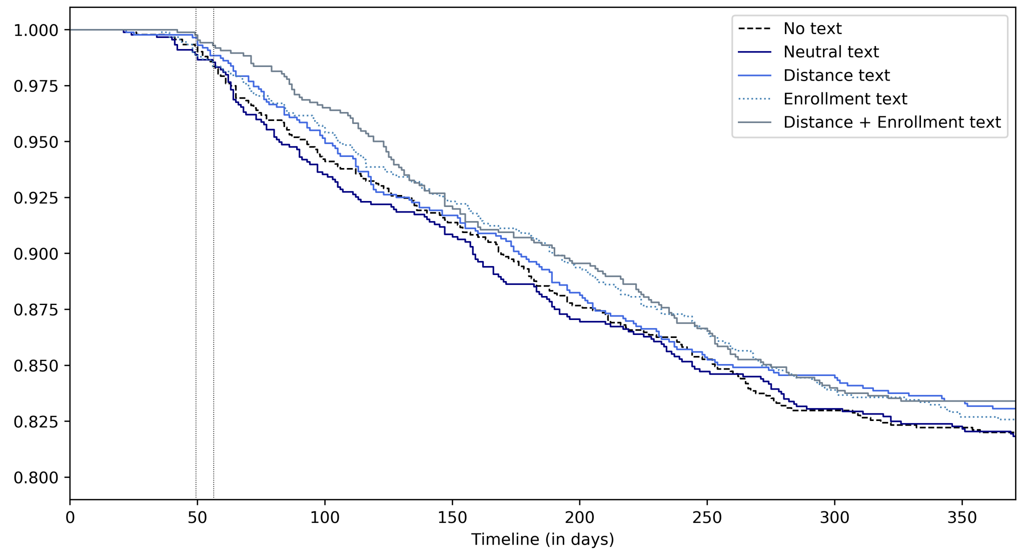
I push the analysis further by looking at the evolution of the *mission locale* take-up rate over time with respect to the type of group NEETs were allocated to.[25] Figure 2 shows the survival curve associated with each group obtained after a Kaplan-Meier estimation of the respective survival rate, assuming random censoring.[26] Here, the "event of death" is to go to an agency at some date, making survivors those who are not yet registered at an agency.

[24]It should be noted that the experiment was not designed to test heterogeneous effects in the first place.

[25]Potential dynamic selection can appear over time such that the different groups are not comparable anymore. Duration models are rather used to test the robustness of the linear model in this section.

[26]The survival rate is the probability that an event of interest has not occurred at time t, or survive after time t. Its mathematical formulation is $S(t) = Pr(T > t) = 1 - F(T)$, where t is the number of days elapsed since the day of start, T is the number of days before the event occurs, and $F(T)$ the probability distribution function of random variable T. Random censoring is when each individual has a censoring time that is statistically independent of their failure time.

Figure 2: Survival rates in non-ML situation



Note: Date 0 corresponds to the date of the army day. The two vertical dotted lines show the mean dates at which the first and second SMS were sent respectively. "Non-ML" situation refers to a situation where youths are not registered at a *mission locale* yet (N = 4,457).

Date 0 is the date of army day. The data allows me to follow youths for about one year. It appears that none of them went to a public agency during the first three weeks following their army days.[27] The survival rates then steadily decrease over 300 days and stabilize at 82.5% thereafter. This figure means that after 300 days from the army day, 27.5% of the NEETs had gone to a *mission locale* agency. In other words, the probability of a NEET going to a *mission locale* agency after 300 days is 27.5%. There is no clear evidence that the probability of going to a public agency changes in a different manner over time from one group to another.

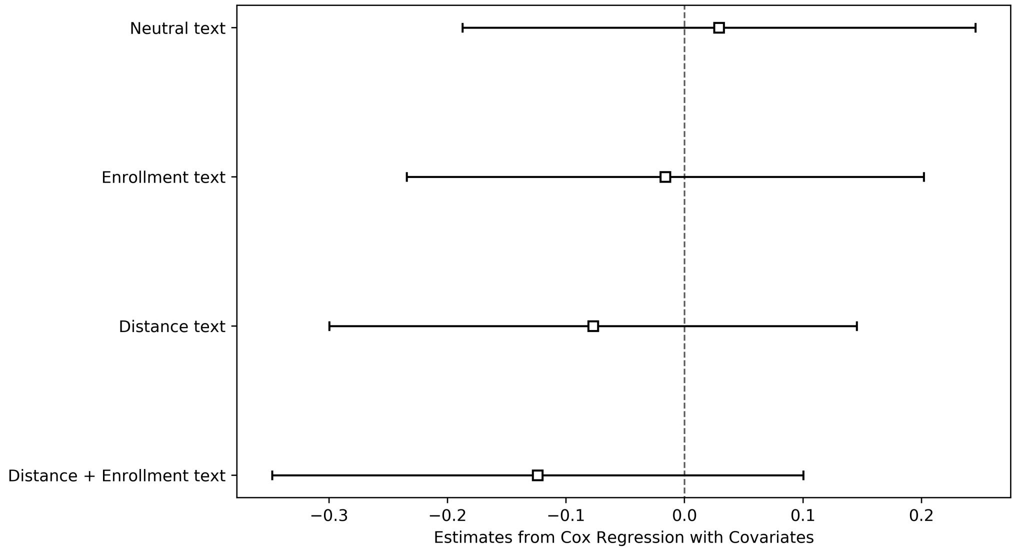
Confidence intervals are not display for aesthetic reasons but Table A.5.1 in Appendix 4.2 provides p-values associated to log rank tests of equality between all survival curves. It is clear that I am not able to reject the null hypothesis of equality, meaning that no treatment text shortens the duration at which NEETs take up the *mission locale* agency proposition. Figure A.5.1 in Appendix 4.2 shows the survival curves by month of the army day since the timing at which the texts were sent differs, but there is no difference with the general pattern.

I then turn to a proportional hazard model to estimate the effect of the different texts on the probability of going to a public agency at a particular date after the army day, controlling for time and individual characteristics.[28] The proportional hazard model is estimated with

[27]In fact, about 300 individuals were removed from the experiment ex-post because they went to a *mission locale* agency between the date of their army day and the date of the first text they received.

[28]The proportional hazard model assumes that the hazard ratio should be constant throughout the study period. The hazard ratio is the ratio of the hazard rate of a particular group over the hazard rate of the

Figure 3: Estimates of treatment effects on the hazard ratios



Note: Estimates of treatment effects on the hazard ratios are obtained with a proportional hazard model estimated by Cox regression with covariates (N = 4,457). Results are shown in Table A.6.1.

a Cox regression and results are shown in Table A.6.1 in Appendix A.6. The effect of the treatment groups are separately shown in Figure 3 for easier representation.[29] The effect of the neutral texts is slightly positive, while the effect of the stylized texts are slightly negative. However, it is clear that none of the texts has an effect significantly different from zero on the probability of going to a public agency at a particular date compared to the control group. As stated above, potential dynamic selection can appear over time and the results must be seen as robustness checks of linear regression models, especially as the Cox estimates are in line with the OLS estimates.

4.3 Interpretation

Overall, the treatment texts have a non-significant effect on the probability of going to a *mission locale* agency, whether they are written in the simplest way or stylized according to how youths communicate. They also have a non-significant effect in relation to various characteristics, whether at the individual, agency or location level. Apart from the minimum effect the experiment is able to detect, there may be several reasons for the absence of significant

reference group. The hazard rate is defined as the probability that an event occurs at a particular date, given the number of days already elapsed. Its basic mathematical notation is $\theta(t;x) = \lim_{dt\to 0} \frac{Pr(T|T\in[t;t+dt[,x)}{dt}$, where t is the number of elapsed days since the date 0, T is the date at which the event occurs, dt is the variation of time, and x is a set of characteristics. This model also assumes that the characteristics are fixed over time, which is the case here given the variables included in x.

[29] The impact of all covariates are represented graphically in Figure A.6.1 in Appendix A.6.

results.

First, information on distance and past enrollment may be not relevant for this population. Figures A.9.1 and A.9.2 in Appendix A.9 show densities of both guided and non-guided youths after the army days in relation to the distance to and previous enrollment in a *mission locale* agency. For both these, it seems that the share of NEETs is the same throughout the two distributions, irrespective of whether or not guidance is given by military instructors. It is thus an implicit way of saying that military actions do not rely on these two pieces of information, at least in a distinctive way. Instead, military instructors could emphasize other elements to increase uptake probability, such as the importance of not remaining NEET. Otherwise the chances of entering the labor market afterwards are reduced.

Second, the time delay between the army days and the texts may have been too long in practice. On average, texts were sent 50 days after an army day because of the time constraint in obtaining the data. This time window may have been too wide for a text to be effective, whereas a smaller windows might have been preferable, since military instructors had first inform the youths about the existence of a *mission locale* agency. Thus, providing a text sooner after the army day might have been more effective, although when looking at daily variations between the army days and the texts does not yield significant effect.

Third, the design of the texts may be unsatisfactory and alternative designs might be more appropriate. One can imagine sending several texts at time intervals. These texts could be a combination of both salient information and coaching messages to engage the recipients to take action. They could also include other aspects of how youths communicate through texts and integrate the possibility of two-way interaction. Interactions could be managed by a robot trained to interact with youth, based on "chatbots" in firms' websites.

Fourth, the psychological constraints may be too strong for a text to be effective. Human decision behavior is complex, flexible, and context dependent. Although texts were individualized, each NEET may face a unique problem that prevents changing his behavior. Though selected, positive effects of military guidance may mean that face-to-face communication is more effective at triggering a change in the behavior of some youths. Combined with the aura of the uniform, they may be more sensitive to the so-called "messenger effect" (Wilson and Sherrell, 1993), and individual meetings seem appropriate to update in real time the set of information needed to adjust incentives (Dolan et al., 2012).

One may argue that young people's expectations are misaligned with reality. Some may overestimate their propensity to exit from a NEET situation and find a sustainable alternative by themselves.[30] Young NEET may try to use their private and informal networks to gain

[30] Spinnewijn (2015) shows that 80% of US job seekers underestimated their unemployment duration. Mueller et al. (2018) show that about 10% of the incidence of long-term unemployment can be attributable to optimistic bias in the job finding rate. Algan et al. (2016) demonstrate that youths who received assistance from the *missions locales* to create their own firm had unrealistic projects given their skills and the current state of local labor markets.

access to the labor market, if it appears to them to be an effective strategy to get stable employment and higher wages (Kramarz and Skans, 2014; Dustmann et al., 2016). However, the formation of private job information network is likely endogenous (Ioannides and Loury, 2004) and it is likely that NEETs are locaed in the bottom tier of their network rather than the top tier (or at its periphery rather than its core), making them more likely to end up in lower payoff situations (Herskovic and Ramos, 2020). Conversely, young NEETs may underestimate their own abilities and present external locus of control and/or display serious lack of confidence in themselves (Mendolia and Walker, 2015; Mawn et al., 2017). In turns, this induces NEETs to reduce their search effort for employment (Kanfer et al., 2001; Caliendo et al., 2014) and probably other alternatives, especially during a period of mass unemployment (Krueger and Mueller, 2011). As NEETs may be located beyond the reach of public authorities, they may even feel abandoned and locked into their NEET situation. Thus, informing young NEETs through simple SMS has little chance of triggering the hoped-for behavior.

In line with the above statements and associated to the difficulty of implementing more face-to-face communications with NEETs when outside the reach of the authorities, text messages with information can not be effective if the barriers that impel youths to enroll are also structural, such as the absence of transport, lack of monetary resources, residence in an economically depressed area, etc. Even though it is not clear whether or not young people should attend job search assistance programs, dealing with public assistance agencies may still be a more valuable option for society than letting some of them remain NEET. Drawing on behavioral models, such as the Theoretical domains framework (TDF) (Atkins et al., 2017) or the Capability-Motivation-Opportunity behavior (COM-b) model (Michie et al., 2011), may be of help for enhancing understanding of the constraints young people face when choosing among a set of alternatives.

5 Conclusion

A non-negligible share of young NEETs are not in contact with the public employment service. Although it is not clear whether attending public assistance agencies helps this population to improve access on the labor market overall, there are other gains in helping this population to extract themselves from loneliness, health problems, and trust issues. This paper contributes to the understanding of some determinants that may help them to value differently the public assistance agency option. I provided information on location, distance in kilometers, and past enrollment of such agencies to NEETs located nearby. This information was provided experimentally through text messaging to randomly allocated NEETs. Moreover, some of the texts were stylized in accordance with the psychology and brain science literature. Results indicate no effect of texts on agency uptake probability overall or across several dimensions.

Texts do little to change the effect of this information on agency uptake. While information on distance and past enrollment rate do not seem relevant, information on other elements such as youth employment rates or monetary benefits could be of greater interest.

Lastly, further research to learn more about NEET characteristics and what NEETs value is essential in order to better understand the motives of this population and offer them more appropriate solutions.

References

Acland, Dan and Matthew R. Levy, "Naiveté, Projection Bias, and Habit Formation in Gym Attendance," *Management Science*, January 2015, *61* (1), 146–160.

Algan, Yann, Bruno Crépon, Esther Duflo, and Hélise Huilery, "Groupement de créateurs," Technical Report, CREST/J-PAL(EEP)/SCIENCES-PO September 2016.

Altmann, Steffen, Armin Falk, Simon Jäger, and Florian Zimmermann, "Learning about job search: A field experiment with job seekers in Germany," *Journal of Public Economics*, August 2018, *164*, 33–49.

__ , Christian Traxler, and Philipp Weinschenk, "Deadlines and Cognitive Limitations," *IZA Discussion Papers*, November 2017, *11129.*

Arditi, Aries and Jiana Cho, "Letter case and text legibility in normal and low vision.," *Vision Research*, August 2007, *47* (19), 2499–2505.

Armour, Philip, "The Role of Information in Disability Insurance Application: An Analysis of the Social Security Statement Phase-In," *American Economic Journal: Economic Policy*, August 2018, *10* (3), 1–41.

Atkins, Lou, Jill Francis, Rafat Islam, Denise O'Connor, Andrea Patey, Noah Ivers, Robbie Foy, Eilidh M. Duncan, Heather Colquhoun, Jeremy M. Grimshaw, Rebecca Lawton, and Susan Michie, "A guide to using the Theoretical Domains Framework of behaviour change to investigate implementation problems," *Implementation Science*, June 2017, *12* (1), 77.

Barr, Andrew and Sarah Turner, "A Letter and Encouragement: Does Information Increase Postsecondary Enrollment of UI Recipients?," *American Economic Journal: Economic Policy*, August 2018, *10* (3), 42–68.

Basta, Maria, Stamatis Karakonstantis, Katerina Koutra, Vassilis Dafermos, Antonis Papargiris, Maria Drakaki, Stelios Tzagkarakis, Alexandros Vgontzas, Panagiotis Simos, and Nikos Papadakis, "NEET status among young Greeks: Association with mental health and substance use," *Journal of Affective Disorders*, June 2019, *253*, 210–217.

Behaghel, Luc, Bruno Crépon, and Marc Gurgand, "Private and Public Provision of Counseling to Job Seekers: Evidence from a Large Controlled Experiment," *American Economic Journal: Applied Economics*, October 2014, *6* (4), 142–174.

Berkes, Jan, Frauke Peter, C Katharina Spiess, and Felix Weinhardt, "Information Provision and Postgraduate Studies," *IZA Discussion Paper Series*, 2019, *No. 12735*, 40.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu, "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block Fafsa Experiment*," *The Quarterly Journal of Economics*, August 2012, *127* (3), 1205–1242.

Bhargava, Saurabh and Dayanand Manoli, “Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment,” *American Economic Review*, November 2015, *105* (11), 3489–3529.

Cahuc, Pierre and Thomas Le Barbanchon, “Labor market policy evaluation in equilibrium: Some lessons of the job search and matching model,” *Labour Economics*, January 2010, *17* (1), 196–205.

Caliendo, Marco and Ricarda Schmidl, “Youth Unemployment and Active Labor Market Policies in Europe,” *IZA Journal of Labor Policy*, 2016, *5* (1), 30.

—, Deborah A. Cobb-Clark, and Arne Uhlendorff, “Locus of Control and Job Search Strategies,” *The Review of Economics and Statistics*, June 2014, *97* (1), 88–103. Publisher: MIT Press.

Calzolari, Giacomo and Mattia Nardotto, “Effective Reminders,” *Management Science*, June 2016, *63* (9), 2915–2932.

Campolieti, Michele, Tony Fang, and Morley Gunderson, “Labour Market Outcomes and Skill Acquisition of High-School Dropouts,” *Journal of Labor Research*, March 2010, *31* (1), 39–52.

Card, David, Jochen Kluve, and Andrea Weber, “What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations,” *Journal of the European Economic Association*, June 2018, *16* (3), 894–931.

Carmody, Dennis P. and Michael Lewis, “Brain activation when hearing one’s own and others’ names,” *Brain Research*, October 2006, *1116* (1), 153–158.

Castleman, Benjamin L. and Lindsay C. Page, “Summer nudging: Can personalized text messages and peer mentor outreach increase college going among low-income high school graduates?,” *Journal of Economic Behavior & Organization*, July 2015, *115*, 144–160.

Chetty, Raj, “Behavioral Economics and Public Policy: A Pragmatic Perspective,” *American Economic Review*, May 2015, *105* (5), 1–33.

Christen, Peter, “A Comparison of Personal Name Matching: Techniques and Practical Issues,” *in ‘The Second International Workshop on Mining Complex Data*, December 2006.

Cole-Lewis, Heather and Trace Kershaw, “Text Messaging as a Tool for Behavior Change in Disease Prevention and Management,” *Epidemiologic reviews*, April 2010, *32* (1), 56–69.

Courdescomptes, “La Journée Défense et Citoyenneté,” Technical Report, Cour des comptes January 2016. Communication à la Commission des finances du Sénat.

Crépon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora, “Do Labor Market Policies have Displacement Effects? Evidence from a Clustered Randomized Experiment,” *The Quarterly Journal of Economics*, May 2013, *128* (2), 531–580.

—, Muriel Dejemeppe, and Marc Gurgand, “Counseling the Unemployed: Does It Lower Unemployment Duration and Recurrence?,” *IZA Discussion Paper Series*, 2005, *No. 1796*, 39.

Derks, Daantje, Arjan E. R. Bos, and Jasper von Grumbkow, “Emoticons and Online Message Interpretation,” *Social Science Computer Review*, August 2008, *26* (3), 379–388.

Dolan, P., M. Hallsworth, D. Halpern, D. King, R. Metcalfe, and I. Vlaev, “Influencing behaviour: The mindspace way,” *Journal of Economic Psychology*, February 2012, *33* (1), 264–277.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker, "Referral-based Job Search Networks," *The Review of Economic Studies*, April 2016, *83* (2), 514–546. Publisher: Oxford Academic.

Eckstein, Zvi and Kenneth I. Wolpin, "Why Youths Drop Out of High School: The Impact of Preferences, Opportunities, and Abilities," *Econometrica*, 1999, *67* (6), 1295–1339.

Ehrenreich, Samuel E., Marion K. Underwood, and Robert A. Ackerman, "Adolescents' Text Message Communication and Growth in Antisocial Behavior across the First Year of High School," *Journal of abnormal child psychology*, February 2014, *42* (2), 251–264.

Ericson, Keith M. Marzilli, "Forgetting We Forget: Overconfidence and Memory," *Journal of the European Economic Association*, 2011, *9* (1), 43–60.

Ericson, Keith Marzilli, "On the Interaction of Memory and Procrastination: Implications for Reminders, Deadlines, and Empirical Estimation," *Journal of the European Economic Association*, July 2017, *15* (3), 692–719.

Finkelstein, Amy and Matthew J. Notowidigdo, "Take-Up and Targeting: Experimental Evidence from SNAP," *The Quarterly Journal of Economics*, August 2019, *134* (3), 1505–1556. Publisher: Oxford Academic.

Fryer, Roland G., "Information, non-financial incentives, and student achievement: Evidence from a text messaging experiment," *Journal of Public Economics*, December 2016, *144*, 109–121.

Gerber, Alan S., Donald P. Green, and Christopher W. Larimer, "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment," *American Political Science Review*, February 2008, *102* (1), 33–48.

Goldzahl, Léontine, Guillaume Hollard, and Florence Jusot, "Increasing breast-cancer screening uptake: A randomized controlled experiment," *Journal of Health Economics*, March 2018, *58*, 228–252.

Graham, Jacqueline B, "Impacts of Text Messaging on Adolescents' Communication Skills: School Social Workers' Perceptions," *Master of Social Work Clinical Research Papers*, 2013, *5-2013*, 63.

Guillerm, Marine and Solène Hilary, "La Garantie jeunes : quels jeunes et quel bilan après cinq ans ?," *Dares Analyses*, 2019, *N°018.*

Gunraj, Danielle N., April M. Drumm-Hewitt, Erica M. Dashow, Sri Siddhi N. Upadhyay, and Celia M. Klin, "Texting insincerely: The role of the period in text messaging," *Computers in Human Behavior*, February 2016, *55*, 1067–1075.

Herskovic, Bernard and João Ramos, "Acquiring Information through Peers," *American Economic Review*, July 2020, *110* (7), 2128–2152.

Hervelin, Jérémy, Cécile Ballini, and Mathilde Gaini, "Is There a Second Chance for High-School Dropouts? Evidence from a Large-Scale Correspondence Study," *Chaire Sécurisation des Parcours Professionnels Working Paper*, 2020, *2020-05.*

Hudson, Heather K., Kadi R. Bliss, and Joyce V. Fetro, "Effects of Text Messaging on College Students' Perceptions of Personal Health," *Health Educator*, 2012, *44* (1), 28–35.

Ioannides, Yannis M and Linda Datcher Loury, "Job Information Networks, Neighborhood Effects, and Inequality," *Journal of Economic Literature*, November 2004, *42* (4), 1056–1093.

Jobert, Manuel, "L'impolitesse linguistique : vers un nouveau paradigme de recherche ?," *Lexis. Journal in English Lexicology*, September 2010, *HS 2.*

Jones, Graham M. and Bambi B. Schieffelin, "Talking Text and Talking Back: "My BFF Jill" from Boob Tube to YouTube," *Journal of Computer-Mediated Communication*, 2009, *14* (4), 1050–1079.

Kanfer, Ruth, Connie Wanberg, and Tracy Kantrowitz, "Job search and employment: A personality-motivational analysis and meta-analytic review. Journal of Applied Psychology, 86, 837-855," *The Journal of applied psychology*, November 2001, *86*, 837–55.

Karney, Charles F. F., "Algorithms for geodesics," *Journal of Geodesy*, January 2013, *87* (1), 43–55. arXiv: 1109.4448.

Klug, Katharina, Sonja Drobnič, and Hilke Brockmann, "Trajectories of insecurity: Young adults' employment entry, health and well-being," *Journal of Vocational Behavior*, December 2019, *115.*

Kramarz, Francis and Oskar Nordström Skans, "When Strong Ties are Strong: Networks and Youth Labour Market Entry," *The Review of Economic Studies*, July 2014, *81* (3), 1164–1200.

Krueger, Alan B. and Andreas Mueller, "Job Search, Emotional Well-Being, and Job Finding in a Period of Mass Unemployment: Evidence from High-Frequency Longitudinal Data," *Brookings*, March 2011.

Lee, Victoria and Hugh Wagner, "The Effect of Social Presence on the Facial and Verbal Expression of Emotion and the Interrelationships Among Emotion Components," *Journal of Nonverbal Behavior*, March 2002, *26* (1), 3–25.

Liebman, Jeffrey B. and Erzo F. P. Luttmer, "Would People Behave Differently If They Better Understood Social Security? Evidence from a Field Experiment," *American Economic Journal: Economic Policy*, February 2015, *7* (1), 275–299.

Ling, Rich, "Texting as a life phase medium," *Journal of Computer-Mediated Communication*, 2010, *15* (2), 277–292.

_ and Naomi S. Baron, "Text Messaging and IM: Linguistic Comparison of American College Data," *Journal of Language and Social Psychology*, July 2016.

Mahatanankoon, Pruthikrai and Patrick O'Sullivan, "Attitude Toward Mobile Text Messaging: An Expectancy-Based Perspective," *Journal of Computer-Mediated Communication*, 2008, *13* (4), 973–992.

Mason, Michael, Bolanle Ola, Nikola Zaharakis, and Jing Zhang, "Text Messaging Interventions for Adolescent and Young Adult Substance Use: a Meta-Analysis," *Prevention Science*, February 2015, *16* (2), 181–188.

Mawn, Lauren, Emily J. Oliver, Nasima Akhter, Clare L. Bambra, Carole Torgerson, Chris Bridle, and Helen J. Stain, "Are we failing young people not in employment, education or training (NEETs)? A systematic review and meta-analysis of re-engagement interventions," *Systematic Reviews*, January 2017, *6.*

McKenna, Katelyn Y. A. and John A. Bargh, "Plan 9 From Cyberspace: The Implications of the Internet for Personality and Social Psychology:," *Personality and Social Psychology Review*, December 2016. Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

Mendolia, Silvia and Ian Walker, "Youth unemployment and personality traits," *IZA Journal of Labor Economics*, October 2015, *4* (1), 19.

Michie, Susan, Maartje M. van Stralen, and Robert West, "The behaviour change wheel: A new method for characterising and designing behaviour change interventions," *Implementation Science*, April 2011, *6* (1), 42.

Mitchell, Jason P., Todd F. Heatherton, and C. Neil Macrae, "Distinct neural systems subserve person and object knowledge," *Proceedings of the National Academy of Sciences of the United States of America*, November 2002, *99* (23), 15238–15243.

Mueller, Andreas, Johannes Spinnewijn, and Giorgio Topa, "Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias," *NBER Working Paper Series*, November 2018, *w25294.*

O'Donoghue, Ted and Matthew Rabin, "Doing It Now or Later," *American Economic Review*, March 1999, *89* (1), 103–124.

— and — , "Choice and Procrastination," *The Quarterly Journal of Economics*, 2001, *116* (1), 121–160.

Oreopoulos, Philip, "Do dropouts drop out too soon? Wealth, health and happiness from compulsory schooling," *Journal of Public Economics*, December 2007, *91* (11), 2213–2229.

— and Ryan Dunn, "Information and College Access: Evidence from a Randomized Field Experiment," *The Scandinavian Journal of Economics*, 2013, *115* (1), 3–26.

— and Uros Petronijevic, "The Remarkable Unresponsiveness of College Students to Nudging And What We Can Learn from It," *IZA Discussion Paper Series*, July 2019, *No. 12460.*

— , — , Christine Logel, and Graham Beattie, "Improving non-academic student outcomes using online and text-message coaching," *Journal of Economic Behavior & Organization*, March 2020, *171*, 342–360.

Perea, Manuel and Eva Rosa, "The effects of associative and semantic priming in the lexical decision task," *Psychological Research*, August 2002, *66* (3), 180–194.

Pires, Mat, "Usages et stratégies de tutoiement dans l'écrit public," *Langage et societe*, 2004, *n° 108* (2), 27–56. Publisher: Éditions de la Maison des sciences de l'homme.

Rettie, Ruth, Ursula Grandcolas, and Bethan Deakins, "Text message advertising: Response rates and branding effects," *Journal of Targeting, Measurement and Analysis for Marketing*, July 2005, *13* (4), 304–312.

Riordan, Monica A. and Roger J. Kreuz, "Cues in computer-mediated communication: A corpus analysis," *Computers in Human Behavior*, November 2010, *26* (6), 1806–1817.

Seijo-Lopez, Jean-Marc, Clément Vincent Bosc and Cohen, and Solène Hilary, "Bilan d'activité des missions locales 2017," Technical Report, Délégé Ministériel aux Missions Locales 2018.

Spinnewijn, Johannes, "Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs," *Journal of the European Economic Association*, 2015, *13* (1), 130–167.

Sunstein, Cass and Richard Thaler, "Libertarian Paternalism," *American Economic Association: Papers & Proceedings*, 2003, *93* (2), 5.

Thomas, Kristin, Marcus Bendtsen, Catharina Linderoth, Nadine Karlsson, Preben Bendtsen, and Ulrika Müssener, "Short message service (SMS)-based intervention targeting alcohol consumption among university students: study protocol of a randomized controlled trial," *Trials*, April 2017, *18* (1), 156.

Tinker, Miles A., "Experimental Studies on the Legibility of Print: An Annotated Bibliography," *Reading Research Quarterly*, 1966, *1* (4), 67–118.

Wicker, Bruno, Christian Keysers, Jane Plailly, Jean-Pierre Royet, Vittorio Gallese, and Giacomo Rizzolatti, "Both of Us Disgusted in My Insula: The Common Neural Basis of Seeing and Feeling Disgust," *Neuron*, October 2003, *40* (3), 655–664.

Williams, Lawrence and Rémi A. van Compernolle, "On versus tu and vous: Pronouns with indefinite reference in synchronous electronic French discourse," *Language Sciences*, July 2009, *31* (4), 409–427.

Wilson, Elizabeth J. and Daniel L. Sherrell, "Source Effects in Communication and Persuasion Research: A Meta-Analysis of Effect Size," *Journal of the Academy of Marketing Science*, March 1993, *21* (2), 101–112.

A Appendix

A.1 Military guidance

Table A.1.1: Effects of military guidance on *mission locale* uptake

OLS Estimates	Entry to ML (0/1)			Time delay (in days)		
	(1)	(2)	(3)	(4)	(5)	(6)
Guided	-0.0826***	0.0196**	0.0827***	-39.0245***	-180.2866***	-78.3699***
	(0.0039)	(0.0078)	(0.0107)	(5.8361)	(33.4892)	(21.6401)
Male		0.0132***	0.0132***		-22.5268***	-19.7562***
		(0.0033)	(0.0033)		(5.1857)	(4.9097)
Under 18		0.0329***	0.0409***		-72.5877***	-48.7616***
		(0.0038)	(0.0034)		(7.0893)	(5.0210)
No diploma		-0.0721**	-0.0522*		130.8770***	114.9493***
		(0.0284)	(0.0273)		(38.8556)	(40.2545)
Normal literacy		0.0555***	0.1060***		-140.2672***	-61.2704***
		(0.0086)	(0.0105)		(31.3574)	(20.6465)
Constant	0.4842***	0.4490***	0.4272***	496.4775***	582.8007***	496.6834***
	(0.0148)	(0.0132)	(0.0037)	(24.0999)	(29.5355)	(7.7115)
N	110,121	110,121	110,121	50,186	50,186	50,186
R-squared	.0062	.1063	.1578	.0013	.0177	.1535
Control variables	No	Yes	Yes	No	Yes	Yes
Month×Year fixed effects	No	No	Yes	No	No	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* after its army day, zero otherwise, for columns (1) to (3); and a continuous variable indicating the time to go in a *mission locale* in month if he actually went to a *mission locale* for columns (4) to (6). "Guided" is a dummy variable equal to one if the individual has been openly guided toward a *mission locale* during its JDC, zero otherwise. Individuals characteristics include demeaned dummies for gender, birthplace, age at the army day, school level, literacy level, department of residency. Robust standard errors are reported below coefficients in parentheses. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent. Source: merged SAGA (2013-2019) and IMILO (2020).

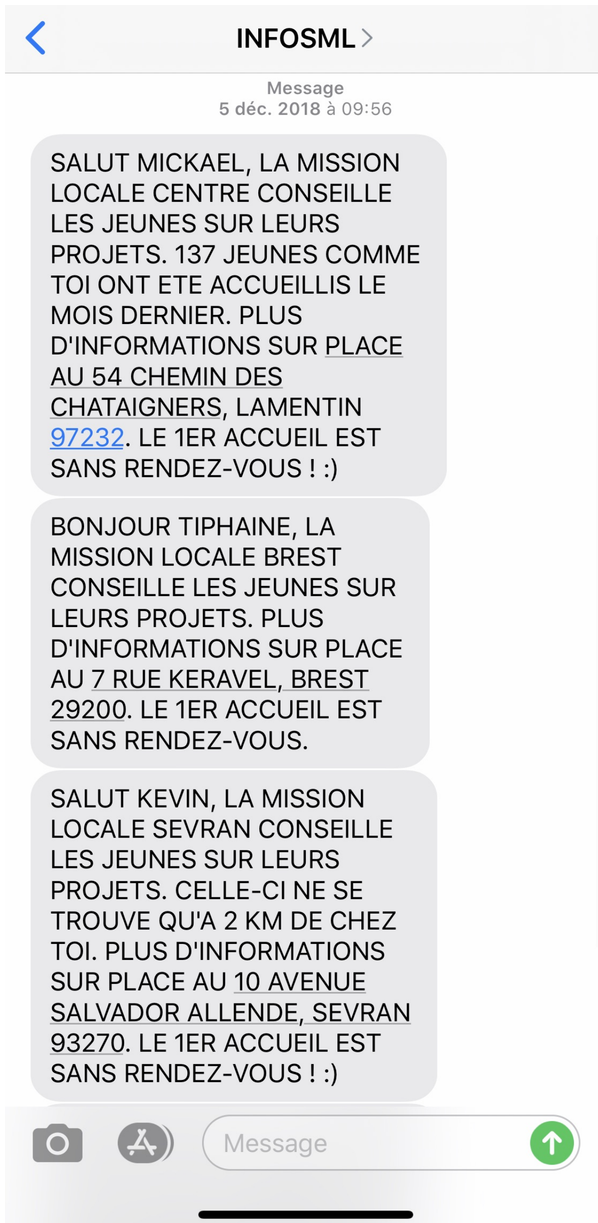
A.2 Original version of the texts

Table A.2.1: Control and treatment groups

Group	Name
Control	No text
Treatment 1	Neutral text
BONJOUR {PRÉNOM}, LA MISSION LOCALE {NOM ML} AIDE LES JEUNES À TRAVAILLER SUR LEUR PROJET. PLUS D'INFORMATIONS SUR PLACE AU {ADRESSE ML}. LE 1ER ACCUEIL EST SANS RENDEZ-VOUS.	
Treatment 2a	Distance text
SALUT {PRÉNOM}, LA MISSION LOCALE {NOM ML} AIDE LES JEUNES À TRAVAILLER SUR LEUR PROJET. CELLE-CI NE SE TROUVE QU'À {DISTANCE KM ML} KM DE CHEZ TOI. PLUS D'INFORMATIONS SUR PLACE AU {ADRESSE ML}. LE 1ER ACCUEIL EST SANS RENDEZ-VOUS ! :)	
Treatment 2b	Enrollment text
SALUT {PRÉNOM}, LA MISSION LOCALE {NOM ML} AIDE LES JEUNES À TRAVAILLER SUR LEUR PROJET. {NB JEUNES AIDÉS ML} JEUNES COMME TOI ONT ÉTÉ ACCUEILLIS LE MOIS DERNIER. PLUS D'INFORMATIONS SUR PLACE AU {ADRESSE ML}. LE 1ER ACCUEIL EST SANS RENDEZ-VOUS ! :)	
Treatment 2c	Distance + Enrollment text
SALUT {PRÉNOM}, LA MISSION LOCALE {NOM ML} AIDE LES JEUNES À TRAVAILLER SUR LEUR PROJET. {NB JEUNES AIDÉS ML} JEUNES COMME TOI ONT ÉTÉ ACCUEILLIS LE MOIS DERNIER. EN PLUS, CELLE-CI NE SE TROUVE QU'À {DISTANCE KM ML} KM DE CHEZ TOI. PLUS D'INFORMATIONS SUR PLACE AU {ADRESSE ML}. LE 1ER ACCUEIL EST SANS RENDEZ-VOUS ! :)	

Note: This table reports the different treatment groups in which youth was allocated during the experiment and the original content of the text they received. Elements in braces are variables that changed according to individual name and residency.

Figure A.2.1: Real examples of texts displayed on an *iPhone* screen



Note: The texts are shown in a screenshot taken during the pilot experiment in December 2018.

A.3 Randomization tests

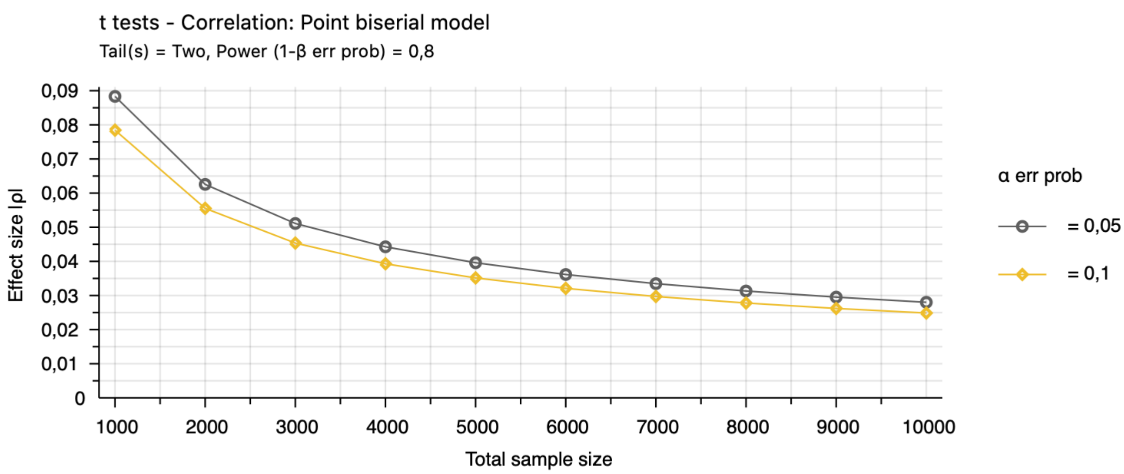
Table A.3.1: Randomization Tests

Characteristics	Control	Treatments							
		Neutral		Distance		Enrollment		Dist. + Enroll.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample mean	Sample mean	p-value (2)-(1)	Sample mean	p-value (4)-(1)	Sample mean	p-value (6)-(1)	Sample mean	p-value (8)-(1)
Male	.6242	.6024	.3338	.6004	.2981	.6051	.3969	.6141	.6574
Adult	.4336	.4440	.6530	.4220	.6162	.4440	.6521	.4222	.6248
Literacy	.6221	.6099	.5904	.6218	.9901	.6105	.6063	.6300	.7280
Guided	.3565	.3685	.5903	.3591	.9073	.3693	.5671	.3485	.7195
Distance to ml	.5000	.4504	.0322	.4949	.8293	.4578	.0681	.4972	.9039
Enrollment in ml	.6574	.6649	.7332	.6543	.8904	.9474	.6742	.6504	.7545
First Quarter	.6049	.6325	.2201	.6184	.5550	.6201	.5018	.6163	.6183
DOM Region	.0675	.0679	.9701	.0685	.9317	.0758	.4854	.0806	.2850
IDF Region	.1424	.1293	.4102	.1582	.3436	.1580	.3467	.1328	.5536
NE Region	.2313	.2166	.4480	.2110	.2975	.1868	.0179	.2429	.5601
NW Region	.1799	.1929	.4711	.1998	.2785	.1985	.3038	.1998	.2799
SE Region	.2527	.2608	.6893	.2559	.8748	.2551	.9054	.2452	.7121
SW Region	.1263	.1325	.6902	.1066	.1900	.1259	.9790	.0988	.0635
F-stat, p-value		0.7687	.6835	0.5214	.9022	1.0567	.3934	0.5538	.8798
Observations	917	897		868		913		862	

Note: This table reports means across sub-samples of the experimental sample and presents simple randomization tests based on comparing the means across the sub-samples. It also reports the F-stat corresponding to a joint test of null hypothesis for all coefficients estimated after OLS regressions of individual characteristics on treatment group, with p-values based on robust standard errors of the coefficients.

A.4 Power of the experiment

Figure A.4.1: Minimum detectable effect of the experiment



Note: The experiment include 4,457 observations which allow to detect a minimum detectable effect of ≈ 4.5 pp at 5% and ≈ 3.7 pp at 10% significance, with a power of 80%, when all treatment groups are pooled together.

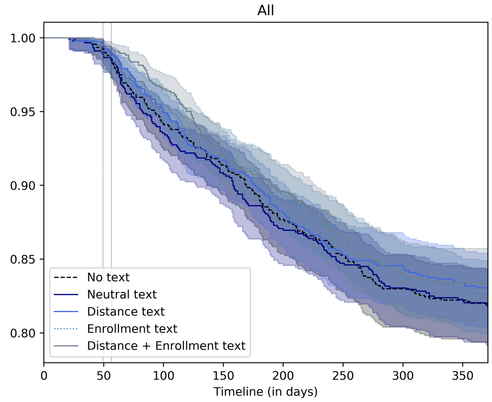
A.5 P-values and monthly survival curves

Table A.5.1: P-values for log rank tests

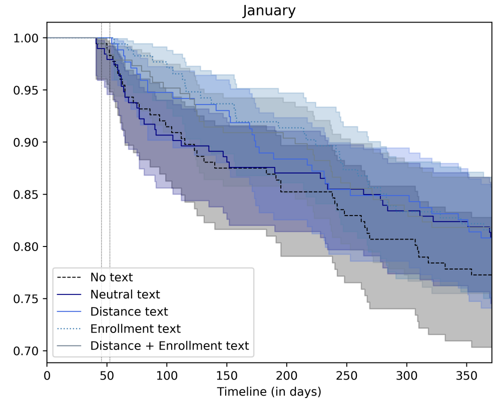
Type of text	No	Neutral	Distance	Enrollment	Dist. + Enroll.
	(1)	(2)	(3)	(4)	(5)
No	-	.8537	.5578	.6910	.3963
Neutral	.8537	-	.4399	.5645	.3037
Distance	.5578	.4399	-	.8442	.7870
Enrollment	.6910	.5645	.8442	-	.6462
Dist. + Enroll.	.3963	.3037	.7870	.6462	-

Note: This table reports the p-values associated to the log rank tests associated to the estimated survival functions in Section 4.2.

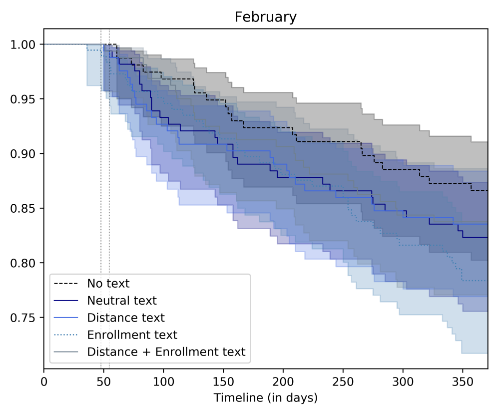
Figure A.5.1: Monthly survival curves



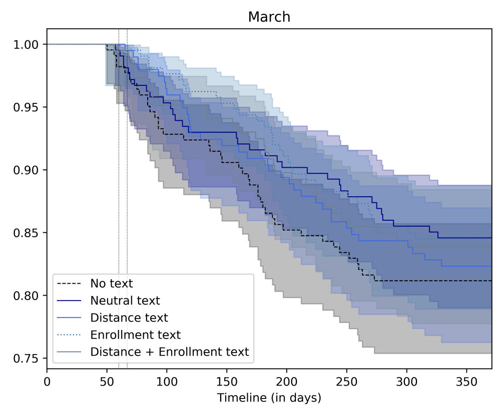
(a) Survival rates



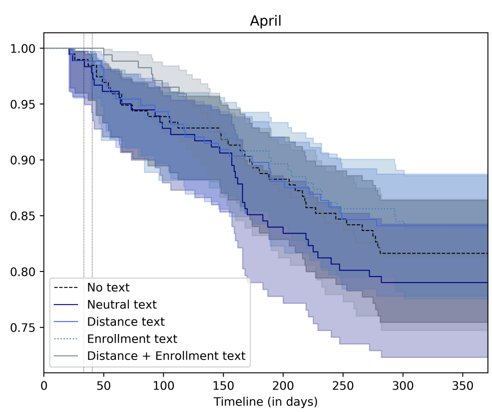
(b) Survival rates in January



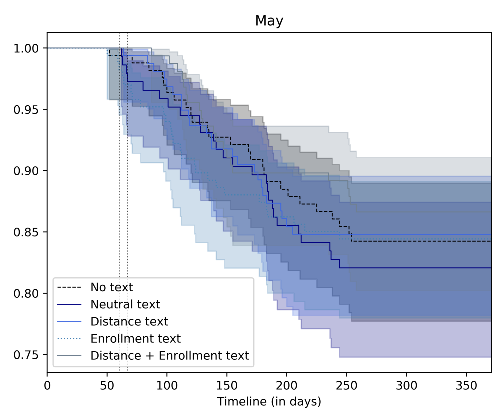
(c) Survival rates in February



(d) Survival rates in March



(e) Survival rates in April



(f) Survival rates in May

Note: Months are defined according to the month of the army day.

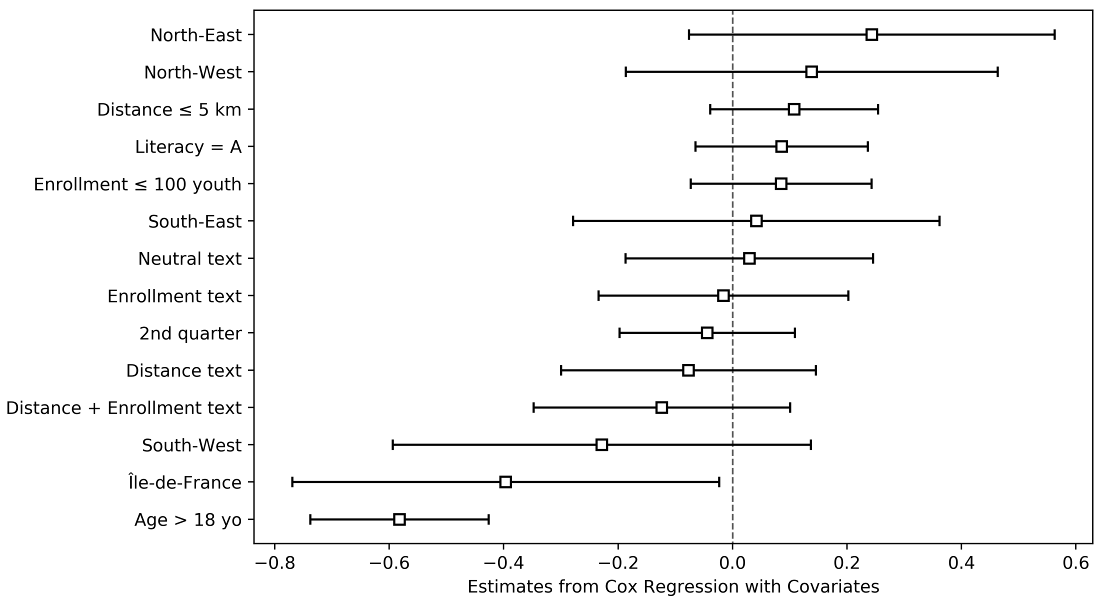
A.6 Proportional hazard model outputs

Table A.6.1: Effects of treatment and covariates on hazard rates

PHM Estimates	coef	exp(coef)	se(coef)	z	p	-log2(p)	lower 0.95	upper 0.95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neutral text	0.03	1.03	0.11	0.26	0.79	0.34	-0.19	0.25
Distance text	-0.08	0.93	0.11	-0.68	0.50	1.01	-0.30	0.15
Enrollment text	-0.02	0.98	0.11	-0.15	0.88	0.18	-0.23	0.20
Distance + Enrollment text	-0.12	0.88	0.11	-1.08	0.28	1.84	-0.35	0.10
Distance $\leq$ 5 km	0.11	1.11	0.07	1.44	0.15	2.73	-0.04	0.25
Enrollment $\leq$ 100 youth	0.08	1.09	0.08	1.05	0.29	1.77	-0.07	0.24
Age > 18 yo	-0.58	0.56	0.08	-7.33	¡0.005	41.99	-0.74	-0.43
Literacy = A	0.09	1.09	0.08	1.11	0.27	1.91	-0.07	0.24
2nd quarter	-0.04	0.96	0.08	-0.57	0.57	0.81	-0.20	0.11
Ile-de-France	-0.40	0.67	0.19	-2.08	0.04	4.75	-0.77	-0.02
North-East	0.24	1.28	0.16	1.49	0.14	2.88	-0.08	0.56
North-West	0.14	1.15	0.17	0.83	0.40	1.31	-0.19	0.46
South-East	0.04	1.04	0.16	0.25	0.80	0.32	-0.28	0.36
South-West	-0.23	0.80	0.19	-1.23	0.22	2.18	-0.59	0.14
Number of subjects								4,457
Number of events								778
Log-likelihood								-6415.30
Concordance								0.60
Log-likelihood ratio test								98.98
-log2(p)								46.94

Note: This table reports proportional hazard model estimates with a Cox regression, where the dependent variable is the hazard rate of going to a *mission locale* one specific day after the army day, given the number of elapsed days between the two events.

Figure A.6.1: Estimates of treatment and covariate effects on the hazard ratios



Note: Estimates of covariates on the hazard ratios are obtained with a proportional hazard model estimated by Cox regression shown in Table A.6.1.

A.7 Non-linear model estimates

Table A.7.1: Intention-to-treat effects

Probit Estimates	Entry to ML (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Neutral text	-0.0003	-0.0000	0.0023	0.0032	0.0037	0.0029
	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)
Distance text	-0.0117	-0.0122	-0.0111	-0.0112	-0.0122	-0.0123
	(0.011)	(0.011)	(0.014)	(0.014)	(0.015)	(0.015)
Enrollment text	-0.0115	-0.0115	-0.0070	-0.0062	-0.0056	-0.0053
	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)
Distance + Enrollment text	-0.0155	-0.0160	-0.0202	-0.0198	-0.0210	-0.0214
	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)
N	4,103	4,103	4,103	4,103	4,103	4,103
Pseudo R-squared	.0003	.0009	.0249	.0270	.0312	.0331
Information displayed	No	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Agency characteristics	No	No	No	Yes	Yes	Yes
Location characteristics	No	No	No	No	Yes	Yes
Month fixed effects	No	No	No	No	No	Yes

Note: This table reports marginal effects from Probit estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* after its army day, zero otherwise. "X text" are dummy variables equal to one if the individual received a specific treatment text, zero otherwise. Displayed information corresponds to variables that might have been displayed in the different treatment texts as the distance in km to the *mission locale* and the number of youths enrolled in the *mission locale* on the month before the army day. Individuals characteristics include demeaned dummies for gender, birthplace, age at the army day, literacy level, region of residency. Agency characteristics include demeaned dummies for the number of agencies, number of committee rooms, number of points of contacts, number of firms in portfolio, number of caseworkers, mean age of caseworkers, share of male caseworkers, average number of caseload per caseworker. Location characteristics include demeaned dummies for disadvantaged area, local unemployment rate, number of services, number of stores, number of schools, number of public transports, number of leisure facilities, number of tourism agencies. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses. *** significant at 1 percent.

A.8 Heterogeneous intention-to-treat effects

Table A.8.1: Intention-to-treat effects across individual characteristics

	Gender		Age		Literacy		Guided	
OLS Estimates	Female	Male	< 18 yo	≥ 18 yo	Bad	Good	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Standard inference								
Neutral text	-0.0074	0.0043	0.0103	-0.0174	0.0292	-0.0177	-0.0172	0.0303
	(0.0353)	(0.0176)	(0.0194)	(0.0234)	(0.0302)	(0.0136)	(0.0156)	(0.0242)
Distance text	0.0294	-0.0398	-0.0201	-0.0038	-0.0163	-0.0104	-0.0140	-0.0098
	(0.0343)	(0.0243)	(0.0148)	(0.0207)	(0.0253)	(0.0192)	(0.0177)	(0.0211)
Enrollment text	-0.0063	-0.0152	0.0013	-0.0248	-0.0022	-0.0167	-0.0182	0.0004
	(0.0249)	(0.0337)	(0.0254)	(0.0218)	(0.0211)	(0.0297)	(0.0284)	(0.0144)
Dist. + Enroll. text	-0.0185	-0.0155	-0.0131	-0.0247	-0.0513*	0.0040	0.0001	-0.0473*
	(0.0425)	(0.0337)	(0.0157)	(0.0151)	(0.0299)	(0.0125)	(0.0096)	(0.0288)
Constant ($\approx$ No text mean)	0.1634***	0.2019***	0.2203***	0.1395***	0.1761***	0.1926***	0.1933***	0.1743***
	(0.0256)	(0.0195)	(0.0117)	(0.0148)	(0.0200)	(0.0134)	(0.0128)	(0.0158)
Panel B: Bootstrap p-values								
Neutral text	0.8253	0.8521	0.7168	0.5127	0.3605	0.4606	0.4523	0.3280
Distance text	0.3206	0.0989*	0.4329	0.8725	0.5555	0.6739	0.5672	0.7484
Enrollment text	0.8691	0.5119	0.9608	0.3247	0.9096	0.4636	0.3937	0.9504
Dist. + Enroll. text	0.5134	0.5505	0.5909	0.3725	0.0627*	0.8400	0.9486	0.1340
Panel C: Randomization inference p-values								
Neutral text	0.8260	0.8330	0.7190	0.4960	0.3950	0.4420	0.5250	0.3700
Distance text	0.2940	0.0990*	0.4520	0.9170	0.5980	0.6600	0.5670	0.7510
Enrollment text	0.8720	0.5290	0.9840	0.3670	0.9940	0.4580	0.4120	0.9620
Dist. + Enroll. text	0.5340	0.5520	0.6160	0.3570	0.0940*	0.8800	0.9960	0.1170
N	1621	2482	2411	1692	1533	2570	2638	1465
R-squared	.0053	.0039	.0046	.0051	.0065	.0046	.0045	.0056
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* agency after its army day, zero otherwise. "X text" are dummy variables equal to one if the individual received a specific treatment text, zero otherwise. Control variables include variables that might have been displayed in the different treatment texts as the distance in km to the agency and the number of youths enrolled in the agency on the month before the army day. Control variables also include month fixed effects. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses in Panel A. Panel B reports p-values associated to the coefficients for a student test against the null hypothesis using a bootstrap procedure with 1,000 repetitions. Panel C reports Fisher exact p-values associated to the coefficients against the sharp null hypothesis using a randomization inference procedure with 1,000 random treatment assignments. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

Table A.8.2: Intention-to-treat effects across agency characteristics

OLS Estimates	Agencies								Caseworkers							
	Offices		Committee rooms		Points of contact		Firms		Number		Share of male		Age		Caseloads	
	≤	>	≤	>	≤	>	≤	>	≤	>	≤	>	≤	>	≤	>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Standard inference																
Neutral text	-0.0051	0.0034	0.0113	-0.0154	-0.0010	0.0027	0.0185	-0.0188	-0.0060	0.0036	0.0196	-0.0234	-0.0209	0.0219	-0.0184	0.0185
	(0.0185)	(0.0377)	(0.0226)	(0.0271)	(0.0146)	(0.0267)	(0.0316)	(0.0223)	(0.0146)	(0.0353)	(0.0232)	(0.0249)	(0.0249)	(0.0325)	(0.0413)	(0.0177)
Distance text	-0.0118	-0.0122	-0.0379	0.0164	0.0163	-0.0381***	-0.0067	-0.0182	-0.0001	-0.0282*	-0.0043	-0.0207	-0.0061	-0.0183	-0.0071	-0.0172
	(0.0185)	(0.0267)	(0.0256)	(0.0104)	(0.0139)	(0.0097)	(0.0294)	(0.0140)	(0.0149)	(0.0148)	(0.0339)	(0.0293)	(0.0150)	(0.0251)	(0.0212)	(0.0131)
Enrollment text	-0.0406***	0.0244	-0.0293	0.0091	-0.0113	-0.0095	-0.0273	0.0029	-0.0461**	0.0243	-0.0029	-0.0207	-0.0135	-0.0112	-0.0375	0.0120
	(0.0149)	(0.0301)	(0.0290)	(0.0241)	(0.0089)	(0.0339)	(0.0266)	(0.0197)	(0.0196)	(0.0257)	(0.0292)	(0.0191)	(0.0227)	(0.0291)	(0.0351)	(0.0191)
Dist. + Enroll. text	-0.0205	-0.0124	-0.0359**	0.0034	0.0205*	-0.0511***	-0.0074	-0.0279	-0.0160	-0.0183	-0.0121	-0.0231	-0.0366**	0.0004	-0.0136	-0.0213
	(0.0140)	(0.0319)	(0.0154)	(0.0180)	(0.0124)	(0.0164)	(0.0240)	(0.0256)	(0.0215)	(0.0305)	(0.0110)	(0.0232)	(0.0186)	(0.0113)	(0.0286)	(0.0231)
Constant (≈ No text mean)	0.1915***	0.1808***	0.1886***	0.1845***	0.1657***	0.2061***	0.1776***	0.1965***	0.1911***	0.1831***	0.1845***	0.1896***	0.1930***	0.1812***	0.2080***	0.1659***
	(0.0108)	(0.0223)	(0.0156)	(0.0126)	(0.0085)	(0.0157)	(0.0193)	(0.0112)	(0.0110)	(0.0175)	(0.0160)	(0.0131)	(0.0125)	(0.0181)	(0.0231)	(0.0089)
Panel B: Bootstrap p-values																
Neutral text	0.8494	0.8872	0.6547	0.5948	0.9654	0.9101	0.4796	0.4957	0.8216	0.8872	0.4573	0.3489	0.4080	0.4056	0.5589	0.4810
Distance text	0.6522	0.6716	0.1504	0.5461	0.5761	0.1733	0.7815	0.4977	0.9645	0.3356	0.8804	0.4218	0.8283	0.4639	0.8619	0.5168
Enrollment text	0.0850*	0.3697	0.2480	0.7548	0.6074	0.7298	0.2727	0.9177	0.0595*	0.3736	0.9240	0.3783	0.6014	0.6860	0.1769	0.6615
Dist. + Enroll. text	0.4171	0.6564	0.1668	0.9139	0.4572	0.0561*	0.7914	0.3115	0.5569	0.5503	0.6361	0.3859	0.1936	0.9800	0.6945	0.4123
Panel C: Randomization inference p-values																
Neutral text	0.8610	0.8860	0.6690	0.6280	0.9530	0.9530	0.4900	0.4590	0.8120	0.9150	0.4570	0.3700	0.4040	0.4030	0.5560	0.4440
Distance text	0.6420	0.6900	0.1480	0.5420	0.5430	0.1430	0.8230	0.5120	0.9390	0.3060	0.8540	0.4730	0.8970	0.4930	0.7620	0.4590
Enrollment text	0.1090	0.4090	0.2680	0.7950	0.6720	0.6730	0.3010	0.9410	0.0730*	0.3740	0.8760	0.4820	0.5820	0.6430	0.1800	0.6750
Dist. + Enroll. text	0.4150	0.7570	0.1450	0.8950	0.4330	0.0660*	0.7700	0.3790	0.5360	0.5850	0.6210	0.4410	0.1780	0.9620	0.6780	0.3900
N	2,311	1,792	2,148	1,955	2,068	2,035	2,073	2,030	2,134	1,969	2,100	2,003	2,087	2,016	2,056	2,047
R-squared	.0048	.0042	.0065	.0015	.0062	.0080	.0048	.0050	0.0030	.0063	.0031	.0042	.0048	.0044	.0021	.0085
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* after its army day, zero otherwise. "X text" are dummy variables equal to one if the individual received a specific treatment text, zero otherwise. The heterogeneous dimensions across agencies are dummies set below or above the median number of the dimension. Control variables include variables that might have been displayed in the different treatment texts as the distance in km to the agency and the number of youths enrolled in the agency on the month before the army day. Control variables also include month fixed effects. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses in Panel A. Panel B reports p-values associated to the coefficients for a student test against the null hypothesis using a bootstrap procedure with 1,000 repetitions. Panel C reports Fisher exact p-values associated to the coefficients against the sharp null hypothesis using a randomization inference procedure with 1,000 random treatment assignments. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

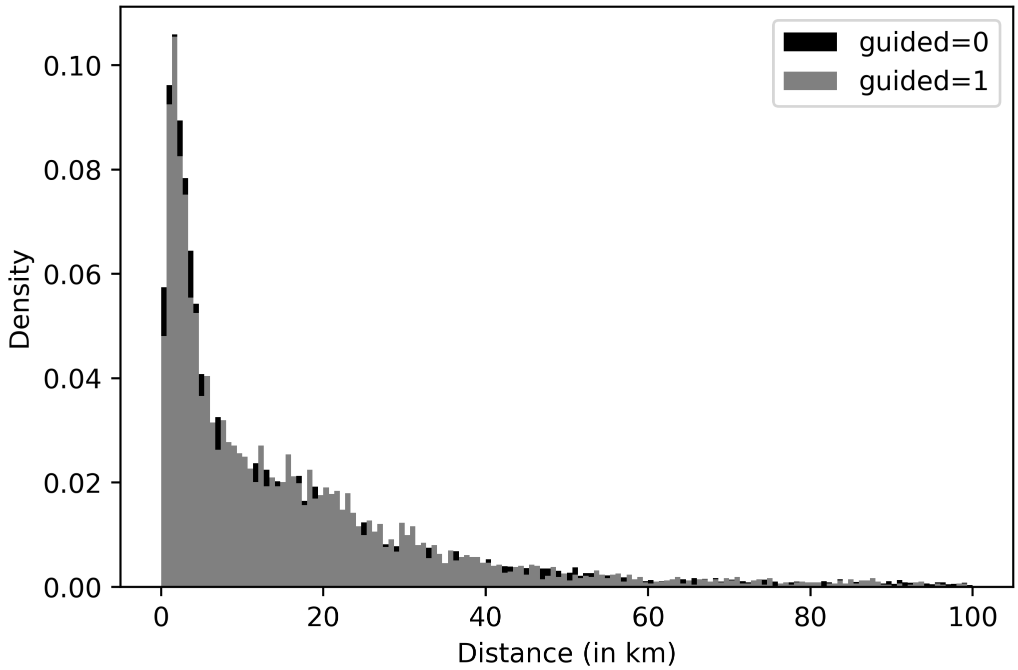
Table A.8.3: Intention-to-treat effects across location characteristics

OLS Estimates	Disadvantaged area		Type of city		Unemployment rate		Services		Stores		Schools		Transport modes		Leisure facilities	
	No	Yes	Rural	Urban	≤	>	≤	>	≤	>	≤	>	≤	>	≤	>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Standard inference																
Neutral text	-0.0056	0.0291	-0.0127	0.0015	0.0123	-0.0186	-0.0100	0.0082	-0.0136	0.0128	-0.0082	0.0061	-0.0148	0.0142	-0.0288	0.0279*
	(0.0188)	(0.0311)	(0.0235)	(0.0184)	(0.0231)	(0.0231)	(0.0275)	(0.0107)	(0.0247)	(0.0101)	(0.0318)	(0.0131)	(0.0207)	(0.0212)	(0.0269)	(0.0162)
Distance text	-0.0147	0.0051	0.0742*	-0.0288**	-0.0108	-0.0151	0.0028	-0.0277**	0.0050	-0.0305	-0.0000	-0.0249	-0.0114	-0.0132	-0.0070	-0.0186
	(0.0205)	(0.0402)	(0.0433)	(0.0128)	(0.0172)	(0.0147)	(0.0226)	(0.0136)	(0.0263)	(0.0187)	(0.0262)	(0.0176)	(0.0177)	(0.0108)	(0.0332)	(0.0185)
Enrollment text	-0.0277	0.0622*	0.0008	-0.0130	-0.0142	-0.0122	-0.0284	0.0061	-0.0267	0.0038	-0.0258	0.0036	-0.0465**	0.0283	-0.0365	0.0142
	(0.0296)	(0.0323)	(0.0250)	(0.0206)	(0.0211)	(0.0350)	(0.0248)	(0.0241)	(0.0242)	(0.0241)	(0.0288)	(0.0259)	(0.0214)	(0.0208)	(0.0258)	(0.0137)
Dist. + Enroll. text	-0.0173	-0.0089	0.0122	-0.0226	-0.0142	-0.0243	0.0025	-0.0368***	0.0015	-0.0351***	0.0027	-0.0370**	-0.0062	-0.0311	-0.0113	-0.0225***
	(0.0176)	(0.0149)	(0.0179)	(0.0157)	(0.0169)	(0.0273)	(0.0208)	(0.0116)	(0.0197)	(0.0092)	(0.0171)	(0.0173)	(0.0084)	(0.0262)	(0.0289)	(0.0076)
Constant (≈ No text mean)	0.1868***	0.1833***	0.1805***	0.1879***	0.1675***	0.2110***	0.1883***	0.1860***	0.1913***	0.1830***	0.1865***	0.1879***	0.2006***	0.1722***	0.1977***	0.1768***
	(0.0167)	(0.0190)	(0.0149)	(0.0126)	(0.0100)	(0.0177)	(0.0179)	(0.0086)	(0.0177)	(0.0090)	(0.0198)	(0.0113)	(0.0115)	(0.0133)	(0.0215)	(0.0071)
Panel B: Bootstrap p-values																
Neutral text	0.8131	0.5246	0.7635	0.9455	0.6099	0.5927	0.6800	0.7733	0.6159	0.6166	0.7634	0.8320	0.5553	0.6329	0.2408	0.2888
Distance text	0.5297	0.9116	0.1697	0.1519	0.6582	0.6655	0.9222	0.3108	0.8459	0.2351	0.9933	0.3515	0.6609	0.6296	0.7888	0.4645
Enrollment text	0.1828	0.1724	0.9965	0.5062	0.5697	0.7145	0.2707	0.8281	0.3120	0.8537	0.3213	0.8817	0.0639*	0.3351	0.1480	0.5994
Dist. + Enroll. text	0.4114	0.8567	0.8124	0.2834	0.5917	0.4191	0.9374	0.1503	0.9590	0.1722	0.9524	0.1574	0.8056	0.2500	0.6809	0.4118
Panel C: Randomization inference p-values																
Neutral text	0.8100	0.5390	0.7050	0.9480	0.6240	0.5010	0.7110	0.7130	0.5960	0.6180	0.8040	0.8040	0.5600	0.6220	0.3030	0.3080
Distance text	0.5080	0.9240	0.1660	0.1500	0.6350	0.6310	0.8780	0.2970	0.8390	0.2560	0.9740	0.3280	0.6900	0.6260	0.8490	0.4490
Enrollment text	0.1500	0.1680	0.7660	0.5230	0.5280	0.6910	0.2930	0.8830	0.3120	0.9820	0.3330	0.9240	0.0650*	0.3520	0.1920	0.6680
Dist. + Enroll. text	0.4020	0.9220	0.8430	0.2810	0.5120	0.4130	0.9120	0.1570	0.9160	0.1700	0.8250	0.1730	0.8540	0.2230	0.6880	0.3820
N	3326	777	684	3419	2167	1936	2065	2038	2071	2032	2092	2011	2207	1896	2084	2019
R-squared	.0036	.0177	.0102	.0037	.0035	.0033	.0036	.0052	.0039	.0059	.0037	.0057	.0047	.0058	.0038	.0062
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual went to a *mission locale* after its army day, zero otherwise. "X text" are dummy variables equal to one if the individual received a specific treatment text, zero otherwise. The heterogeneous dimensions across locations are dummies set below or above the median number of the dimension. Control variables include variables that might have been displayed in the different treatment texts as the distance in km to the agency and the number of youths enrolled in the agency on the month before the army day. Control variables also include month fixed effects. Robust standard errors are clustered at the month of the army day level and reported below coefficients in parentheses in Panel A. Panel B reports p-values associated to the coefficients for a student test against the null hypothesis using a bootstrap procedure with 1,000 repetitions. Panel C reports Fisher exact p-values associated to the coefficients against the sharp null hypothesis using a randomization inference procedure with 1,000 random treatment assignments. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

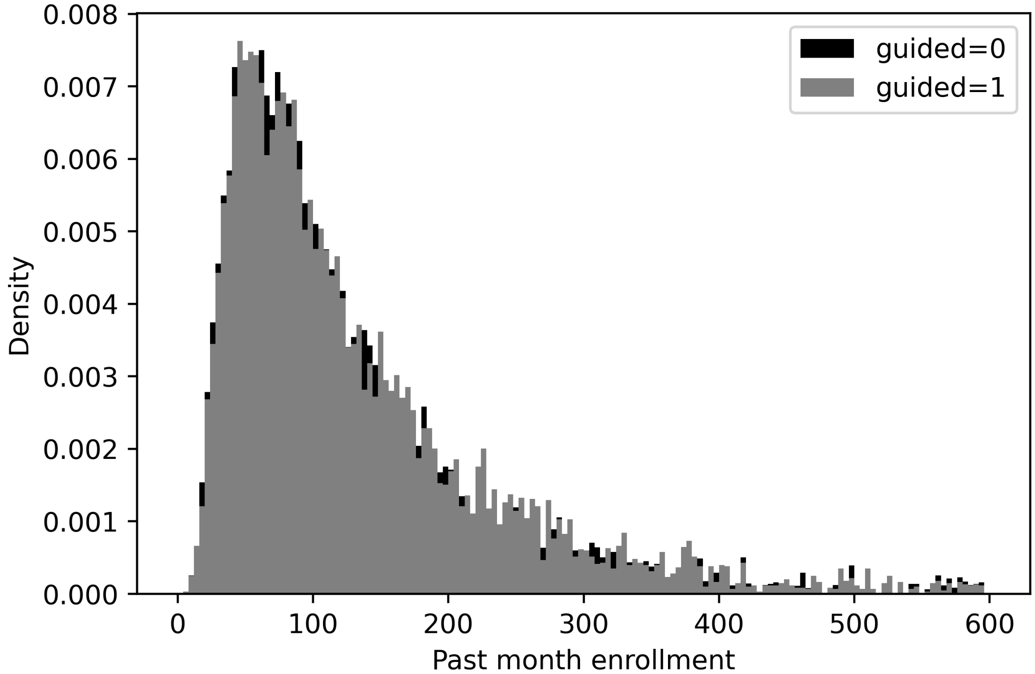
A.9 Histograms of distance and enrollment for compliers

Figure A.9.1: Density of youth enrolled in missions locales according to distance



Note: The distance is calculated in kilometers between youth's address and the mission locale address he enrolled in after the army day.
Source: merged SAGA (2013-2019) and IMILO (2020), author calculations.

Figure A.9.2: Density of youth enrolled in missions locales according to previous enrollment



Note: Past month enrollment corresponds to the number of youths enrolled in the mission locale one month before the army day.
Source: merged SAGA (2013-2019) and IMILO (2020), author calculations.