School-to-Work Transitions and Related Public Policies: Evidence from Field Experiments in France

Jérémy H. Hervelin

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JÉRÉMY HERVELIN

Composition du Jury :

Arne Uhlendorff Researcher CNRS, CREST	Président
Stijn Baert Associate Professor, Ghent University	Rapporteur
Yannick L'Horty Professor, Gustave Eiffel University	Rapporteur
Philip Oreopoulos Professor, University of Toronto	Examinateur
Pierre Cahuc Professor, Sciences Po	Directeur de thèse

La vie est belle le destin s'en écarte

Personne ne joue avec les mêmes cartes

Le berceau lève le voile, multiples sont les routes qu'il dévoile

Tant pis on n'est pas nés sous la même étoile

IAM, *Nés sous la même étoile*

L'école du micro d'argent, 1997

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Executive summary

Cette thèse se concentre sur les transitions de l'école à l'emploi et les politiques du marché du travail qui y sont liés, en particulier pour les jeunes en difficulté. Basée sur des expériences de terrain menées en France en 2018 et 2019, elle comprend un chapitre introductif et trois autres chapitres qui ajoutent de nouvelles preuves empiriques à la littérature économique.

Le chapitre introductif apporte une mise en contexte de la situation des jeunes individus vis-à-vis du marché de l'emploi. Il montre que le taux de chômage des jeunes est l'un des principaux problèmes dans la plupart des pays, en illustrant le cas de la France. Par ailleurs, cette situation est d'autant plus difficile pour les jeunes possédant peu de qualifications et peu de connexions avec les entreprises.

Ce chapitre décrit ensuite une série de politiques publiques mises en place depuis les années 1970 pour lutter contre le chômage des jeunes. D'un côté, les mesures consistent à maintenir les jeunes le plus longtemps dans le système éducatif et à accroître leur stock de connaissances. De l'autre côté, les mesures consistent à aider les jeunes sortis du système éducatif à trouver un emploi le plus rapidement possible, notamment grâce à des politiques dites actives. Ces politiques sont basées sur l'accompagnement à la recherche d'emploi et/ou l'accumulation de compétences via la formation professionnelle continue ou les emplois subventionnés. Malheureusement, peu d'évaluations quantitatives rigoureuses ont été menées et de nombreuses zones d'ombre restent encore à éclaircir.

Le deuxième chapitre apporte de nouveaux éléments sur la forte insertion professionnelle des apprentis. Les études empiriques montrent souvent que les apprentis ont un meilleur accès à l'emploi que les lycéens professionnels. Ce fait, ainsi que le succès largement médiatisé du système d'apprentissage allemand, motivent de nombreuses politiques publiques à essayer d'accroître les effectifs en apprentissage pour favoriser l'emploi des jeunes. Cependant, on ne sait que peu de choses sur les raisons pour lesquelles les apprentis peuvent être plus performants en début de carrière.

Ce chapitre montre ainsi que le succès de l'apprentissage ne repose pas, dans le contexte français, sur un meilleur accès à l'emploi de ceux qui ne restent pas dans leur entreprise de formation. Au contraire, la différence entre le taux d'emploi des apprentis et le taux d'emploi des lycéens est grandement expliqué par la plus forte rétention en entreprise de formation pour les apprentis. Ces résultats ont été obtenus grâce à une expérimentation de terrain – consistant à envoyer des candidatures fictives à de réelles offres d'emploi – et à l'exploration de données d'enquêtes au niveau national.

Pour approfondir cette question, nous proposons une modélisation théorique qui nous permet de reproduire les principaux faits stylisés d'un marché du travail, composé de jeunes lycéens professionnels et apprentis. Dans ce modèle, les lycéens et apprentis qui ne sont pas retenus dans leur entreprise de formation à la fin de leurs études sont en concurrence pour obtenir un emploi. L'estimation de ce modèle montre qu'augmenter la part des apprentis a un impact limité sur le chômage des jeunes si elle ne s'accompagne pas d'une amélioration du taux de rétention dans les entreprises de formation.

La conclusion - selon laquelle les apprentis n'obtiennent pas de meilleurs résultats que les étudiants lorsqu'ils cherchent un emploi en dehors de l'entreprise dans laquelle ils ont été formés - a des conséquences importantes pour la politique publique. Si le principal avantage de l'apprentissage est la création d'une meilleure adéquation entre les nouveaux arrivants sur le marché du travail et les emplois, les politiques devraient être davantage axées sur cette dimension et favoriser la collaboration entre les lycées et le service public de l'emploi.

Le troisième chapitre contribue à mieux comprendre les préférences des employeurs concernant des profils de jeunes décrocheurs scolaires. Pour aider les jeunes qui quittent l'école avant d'avoir obtenu leur diplôme, plusieurs politiques publiques ont été mises en place tout au long de ces dernières années. La tendance de la politique française indique d'ailleurs un glissement vers des politiques hybrides du marché du travail dans lesquelles les jeunes peuvent bénéficier d'un mélange de programmes actifs. Cette orientation politique récente fournit un environnement spécifique dans lequel nous pouvons tester empiriquement si les différents types de politiques actives donnent aux jeunes décrocheurs scolaires une seconde chance sur le marché du travail.

Ce chapitre montre ainsi que les décrocheurs qui sont restés inactifs pendant plus de deux ans ont beaucoup moins de chances d'être rappelés pour un emploi que les diplômés du secondaire. Les contrats aidés et la formation professionnelle continue augmentent les chances des décrocheurs, mais leurs chances restent encore faibles. Seule la combinaison de ces deux politiques, en tant que politique active hybride, permet aux jeunes décrocheurs de rattraper ceux qui n'ont pas abandonné l'école. Leurs chances de décrocher un entretien d'embauche sont alors quasiment équivalentes.

La combinaison de politiques actives, visant à accroître l'expérience professionnelle sur le terrain et l'accumulation de connaissances en formation semble réduire les signaux négatifs associés au décrochage scolaire et à la durée d'inactivité.

Le quatrième chapitre contribue à analyser une méthode originale pour diffuser de l'information auprès d'un public jeune qui ne participe à aucun programme d'aide public. Chaque mois en France, les journées défense et citoyenneté (JDC) permettent de détecter des jeunes en situation de retrait vis-à-vis de l'emploi ou de la formation. Les jeunes sont alors redirigés vers des structures d'aides spécifiques. Toutefois, peu d'éléments sont à notre disposition pour savoir comment cette redirection est effectuée, et si elle est efficace.

Ce chapitre présente une expérience de terrain visant à analyser l'efficacité de SMS envoyés pour diriger des jeunes ni en emploi, ni en formation (NEET), vers des structures publiques d'aide. Tous les SMS ont été individualisés et comprenaient des informations spécifiques sur ces structures. Les résultats indiquent que l'envoi d'informations spécifiques par SMS à ce public n'est pas une stratégie efficace pour améliorer leur participation. Plusieurs raisons peuvent expliquer cette absence d'impact comme la non-pertinence des informations transmises ou le manque d'incitations à aller participer à un programme d'aide.

La vulnérabilité particulière de cette population en retrait des radars publics - en ce qui concerne le fonctionnement structurel des marchés du travail et les conditions macroéconomiques - rend néanmoins les interventions publiques nécessaires. Même s'il n'est pas clair que les jeunes NEET doivent s'adresser aux organismes d'aide publique s'ils cherchent à obtenir de meilleures positions sur le marché du travail, il est toujours utile de recueillir davantage d'informations sur ce qu'ils apprécient et sur les obstacles auxquels ils sont confrontés si l'on veut préserver un minimum de cohésion sociale.

L'argument principal de cette thèse est donc de combler les écarts entre les écoles et les entreprises, afin qu'une proportion significative de jeunes puisse éviter une situation de non-emploi comme première expérience sur le marché du travail.

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Introduction

This thesis focuses on school-to-work transitions and related labor market policies designed to smooth these transitions, especially for young people in difficulty. Based on field experiments carried out in France in 2018 and 2019, it comprises three chapters that add new empirical evidence to the economic literature. The main argument of the thesis advocates closing gaps between schools and firms, so that a significant proportion of young people may avoid a non-employment situation as their first experience in the labor market.

To provide a clearer view of the argument, I first describe the French context in which young people search for jobs after leaving school. I then briefly summarize the basic empirical framework of causal inference upon which the experiments were built. In conclusion, I provide an extended summary for each of the three chapters.

1.1 French context

This section provides some statistics regarding the French labor market so as to outline the context in which young people try and find jobs after leaving school.

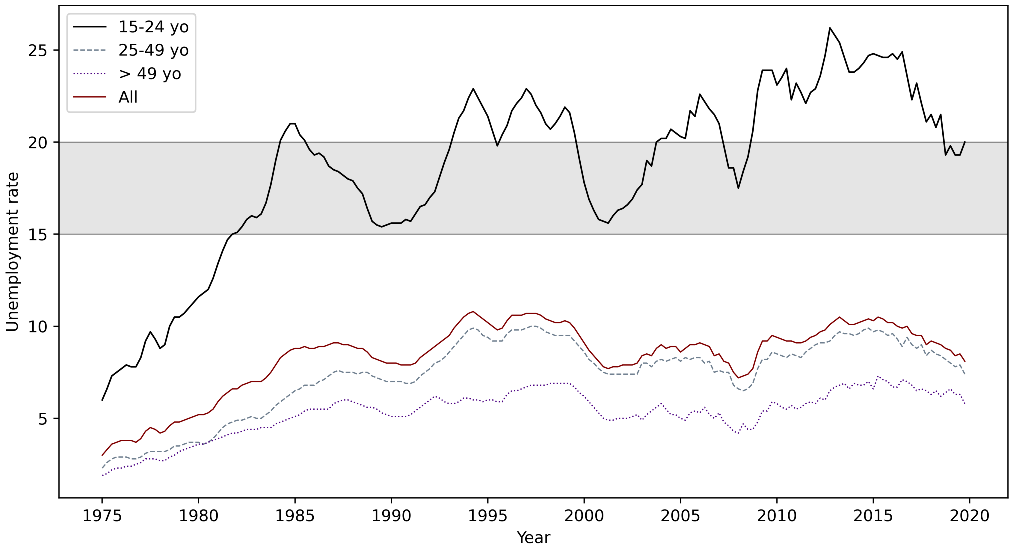
1.1.1 Youth unemployment rates

Over the last 40 years, youth unemployment is one the most striking feature of the French labor market. Figure 1.1 shows that the unemployment rate for 15-24 year-old is much higher than for the rest of the population and higher than the overall average. Whereas the mean unemployment rate in France rose from 3.5% in 1975 to 8.5% in 2019, the youth unemployment rate skyrocketed from 6.8% to 19.5%.

The youth unemployment rate is more sensitive to business cycles, but its response to these are asymmetric, increasing rapidly during economic downturns, while decreasing slowly during economic recoveries. In fact, the youth unemployment rate consistently remained above 15% after 1981, following the two oil crises, and rose to above 20% since 2009 following the global financial crisis. While an encouraging decline has appeared over the last two years, the covid-19 crisis will likely reverse this trend.

Currently, the structural youth unemployment rate in France seems to lie between 15% and 20%, which is excessively high given the standard threshold of 5% that economists and politicians view as representing full employment.

FIGURE 1.1: Evolution of the unemployment rates in France from 1975 to 2019



Source: Labor force survey, INSEE.

It is also higher than the average OECD unemployment rate (11.5%), and much higher than the youth unemployment rate in Japan (3%) or Germany (5%) (which exhibit interesting features for smoothing school-to-work transitions, as described in the first chapter).

The causes of youth unemployment are numerous and complex. They include weak macroeconomic performance, institutional rigidity in both the labor market and the product market (trade union agreements, minimum wage, etc.), lack of educational qualifications, and inadequate skills for job tasks. Because of these different factors, the aggregate youth unemployment rate masks varied situations for young people, depending on their educational level.

1.1.2 School-to-work transitions

Every year, more than 800,000 pupils aged about 6 enter elementary schools in France. They learn the basics in several subjects (French, mathematics, history, geography, etc.) up until 9th grade in middle school. At this stage, around 75% of pupils are age about 15 and 25% are aged 16 due to having repeating a year. The now must decide which education pathway they want to follow for their professional careers. They may also decide to leave the education system altogether, given that the legal age for doing so is 16.

Table 1 shows that 60,000 youth follow a 2-year vocational education program ("Certificat d'aptitude professionnelle": CAP), 180,000 a 3-year vocational education program ("Baccalauréat professionnel": Bac Pro), and 555,000 general or technical education program ("Baccalauréat général ou technologique": Bac GT). Therefore, most of them continue their studies after middle school. However on average, about 100,00 youths left school before the end of their curricula each year over the period 2014-2018.

TABLE 1.1
Youth in education programs and their evolution in the labor market

Grade	**Education pathway**																	
1st-5th	Elementary school																	
	820,000																	
6th-9th	Middle school																	
	820,000																	
	Vocational high-school												High School					
	2-year education program (CAP)						3-year education program (Bac Pro)						3-year general education program (Bac GT)					
10th	60,000						180,000						555,000					
11th	50,000						175,000						510,000					
12th	-						170,000						500,000					
Month	**Labor market situations for those who leave school (%)**																	
	E		U		I		E		U		I		E		U		I	
	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND
1	42	26	50	61	8	13	45	30	45	55	10	15	51	43	35	44	14	13
6	50	38	42	50	8	12	63	38	30	50	7	12	67	60	22	25	11	15
12	60	48	33	43	7	9	73	44	20	44	7	12	72	68	16	20	11	12
24	68	50	26	43	6	7	78	53	17	36	5	11	80	72	13	15	7	14
36	67	50	28	45	5	10	78	57	17	28	5	15	86	65	10	24	4	11

Note: This table reports descriptive statistics about the number of youth according to the education program. It also indicates the share of youth in different status on the labor market for those who decided to finish school at the end of their program. "E" stands for employment, "U" for unemployment, "I" for inactive, "D" for diploma (or graduated students), and "ND" for no diploma (or non graduated students).
Source: *Base Centrale Scolarité* (2014-2018) and *Génération* survey (2016), author's calculations.

Table 1 also shows the situation in the labor market for those who decided to stop school at the end of their program and did not go on to higher education. It is clear that the situation in the labor market is very different for the different populations. First, the more general the education program, the lower the subsequent non-employment rate, especially after three years. Second, the non-employment rate is lower within each education pathway for those who graduated from secondary compared to those who did not obtained a diploma. Third, the employment rate increases steadily for each population during the first year in the labor market but stabilizes over the next two years.

Three factors seem particularly important for smoothing the school-to-work transition and enhancing later positions in the labor market: having a diploma, connections with private firms, and support from family and relatives (Kramarz and Viarengo, 2015). Therefore, the population facing the greatest difficulty in the labor market are those with a low general education level, no diploma, and few links with potential employers.

A report from Eurofund (2012) estimated that the total cost of having young people not in employment, education or training (NEET) in France was about 22.1 billion euros in 2011, or $\approx$ 1.1% of its gross domestic product (GDP). But this cost is likely underestimated since it does not include external effects, such as legal costs. Moreover, the cost for the youth themselves is also high. Not only does experiencing non-employment after school reduce their chances of obtaining stable well-paid employment (Jarosch and Pilossoph, 2019), it also increases the probability of mental and physical illness (Kuhn et al., 2009).

It is not surprising therefore that successive governments have introduced public policies to remedy the situation, mostly by targeting the supply side of the labor market.

1.1.3 Labor market transition policies

A number of policies have been introduced to combat youth unemployment, especially since the beginning of the 1970s. These policies are mainly of two types: discouraging young people from dropping out of school on the one hand and actively helping young job seekers find a sustainable job on the other.

Among the policies designed to deter students from dropping out of school, the first is the increase in the number of obligatory years of schooling. While the legal obligation to remain at school up to the age of 16 has remained the same since 1959, the starting age was lowered from 6 to 3 years old in 2019. However, about 98% of 3 year-old pupils over the past decade were already attending school. The rationale behind increasing school duration is based on the finding provided by the economics of education that every additional year of schooling increases earnings and the probability of employment.

Second, social grants for students who would like to go on to higher education have been extended in recent years. The system involves a monthly financial allocation inversely proportional to the parents' income: the lower their income, the higher the allocation. Fack and Grenet (2015) show that results are encouraging in terms of enrollment and graduation rates. However, the academic performance of those who enrolled in universities as a result of the grand is still lower than that of those who would have enrolled anyway.

Third, vocational education has been introduced mostly for youths who are at risk of dropping out after middle school or those with relatively weak academic results. The associated programs are relatively weak academic results. The associated programs are relatively short (two or three years) and combine both professional experience through internships in firms and classroom training with teachers. In recent decades, much effort has been devoted to boosting training of this kind through apprenticeships. In this system, youths need to find a training firm so as to obtain their professional experience throughout the educational program, and to follow classroom training in an apprenticeship training center. The first chapter of the thesis describes in detail this type of training and its effect on employment.

Turning to public policies designed to actively help young job seekers find a sustainable job after leaving school, these can be grouped into three broad categories: 1/ job search assistance; 2/ vocational training; and 3/ subsidized jobs. *Pôle emploi* and the *missions locales* are the two main institutions that provide active policies for young job seekers.

Job search assistance (JSA) aims to reduce job search costs by finding matches between firms with vacant jobs and persons looking for employment. These two institutions help in drafting unemployed people's resumes, defining personalized search strategies and putting them in contact with potential employers. At *Pôle emploi*, the main program targeting young people is the *Accompagnement intensif des jeunes à la recherche d'emploi* (AIJ). The program involves a number of individual meetings with a dedicated caseworker over a six-month period for working on a professional project, which can be complemented with collective workshops for three months. As of

July 2016, 154,000 young people were registered in the program and their employment probability appears to have increased by about 28% (Blache and Greco, 2017). *Missions locales*, on the other hand, provide programs entirely devoted to NEETs aged 16 to 25 year-old. The third chapter of the thesis provides further information about this institution and its programs.

Labor market training constitutes the bulk of active policy for job seekers. Training aims to increase the set of skills individuals need for particular job tasks. The prevalent form of labor market training is classroom training (CT), whose duration varies according to the field and the type of training. It also includes periods of immersion and internships in private firms. The content of training is provided by training centers such as *Écoles de la deuxième chance* (E2C), *Établissements pour l'insertion dans l'emploi* (EPIDE), *Agence nationale pour la formation professionnelle des adultes* (AFPA), *Groupements d'établissements* (GRETA), etc. These training courses can lead to various forms of certification, ranging from a basic certificate of participation issued by the training center to a national diploma certified by the Ministry of Education or Ministry of Labor. *Pôle emploi* is the main provider of vocational training, with about 50% of registrations. The remaining proportion is accounted for by the French regions and other public administrations. About 320,000 young people were in vocational training in 2016. Recently, the French president Emmanuel Macron launched a large-scale program called *Plan d'investissement dans les compétences* (PIC), with the objective of training a million young people with no or low qualifications by the end of 2022.

Subsidized employment covers a wide range of measures. In the private sector, it generally takes the form of transfers to firms that hire members of particular groups, while in the public sector it consists mostly of direct creation of jobs. The goal of such on-the-job training (OJT) programs is to give employers an incentive (through subsidies) to directly provide training and professional experience to disadvantaged categories of workers. Many types of subsidized employment have been introduced in France since the 1970s. The successive schemes all have similar aims and follow the same principles, but differ in their eligibility conditions. Since 2012 and the creation of the *Emploi d'avenir*, a specific subsidized contract for 16 to 25 year-old, the arrangements vary in terms of employers' obligations to provide additional and general training to youth. More than 300,000 young people have benefited from this scheme. The second chapter of the thesis provides additional descriptive statistics on the youth population in subsidized jobs and in vocational training.

In addition to these programs, France introduced the *service civique* in 2012. This program involved matching young people with various associations with a view to carrying out tasks in areas recognized as a priority, such as health, education, and the environment. Anyone aged between 16 and 25 is eligible to enroll in this program. The missions generally last between 6 and 12 months, and provide a monthly minimum income of about €520. In 2017, 145,000 young people were enrolled in this program, though the impact on education and employment has not yet been assessed.

Very few of the other labor market programs have been rigorously assessed either. Fougère et al. (2000) conducted a first survey on the effects of French policies on youth employment before the 2000s. They summarize their results as follows: “Training programs directed at unemployed young persons have no effect on post-training wages or employment probabilities unless they have a large training content; On the other hand, payroll tax subsidies have significant effects on employment probabilities of low-wage workers, but their largest effects concern workers between 25 and 30”.

Kramarz and Viarengo (2015) summarize the main scientific studies assessing some of these programs during the 2000s and early 2010s. They emphasize that the impact on employment is mixed. It appears that job search assistance programs have little effect on employment for youth in difficulty. Although the participants have more meetings with caseworkers, there is little subsequent effect in terms of the labor market. Vocational training still has no or little short-term effect on employment. Subsidized job schemes yield mixed results. While subsidized jobs in the market sector seem to boost later employment for youth, in the non-market sector they have no or even a negative effect on employment. However, the mechanisms leading to these results have received less attention in the French academic literature.

Consequently we know little or nothing about why these policies failed or succeeded. For instance, little is known about employers’ preferences for the different types of programs aimed at increasing young people’s productivity. Similarly, very little is known about the type of information and the appropriate communication media that might be effective in increasing the enrollment rate in these programs. This thesis therefore resorts to a well-structured empirical framework to provide new evidence in this regard.

1.2 Empirical framework

The thesis presents evidence established through the now well-known framework of causal inference popularized by Rubin (1974). I briefly describe the main features of this framework, drawing extensively on Angrist and Pischke (2009) and Athey and Imbens (2017b).

1.2.1 Selection problem

As stated above, few rigorous quantitative assessments of the French labor market programs have been made. The main reason is the difficulty of convincingly distinguishing the effect of the program *per se* from other potentially confounding factors. To establish this distinction, one must be able to determine what would have happened if the youths had not entered the program. Selection of individuals for these programs is generally based on several criteria. It is therefore important to have access to good databases so as to control for all the elements that may influence professional trajectories. Unfortunately, this is rarely the case.

To describe this problem more precisely, we can use the potential outcome framework first proposed by Rubin (1974) and thereafter further developed by other researchers. Let us denote by $D_i = \{0, 1\}$ a binary variable indicating whether or not individual i entered into a program. The outcome of interest, employment status for instance, is denoted by Y_i. The interesting question is therefore to establish the extent to which the decision to participate in the program affects Y_i. We can then imagine two states: one where the individual participated in the program; and the other where the individual did not. Hence, for any individual i, there are two potential employment variables:

$$\text{Potential outcome:} \quad Y_i = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases} = Y_{0i} + (Y_{1i} - Y_{0i})\, D_i \tag{1.1}$$

In other words, Y_{1i} is the employment status of individual i if he joined the program, while Y_{0i} is his employment status if he did not. The measure of interest is then the difference Y_{1i} - Y_{0i}, which measures the causal impact of the program on employment. However, it is not possible to estimate this difference at the individual level because no one can be in the program and not be in the program at the same time.

One must look at the employment status of a group of individuals who attended the program, compared with the employment status of a group that did not. A simple comparison would involve comparing the average employment rates of the two groups, $E[Y_i|D_i = 1] - E[Y_i|D_i = 0]$, and looking at the difference due to the program.

However, a simple mathematical manipulation shows a bias in the estimation such that:

$$\begin{aligned} \underbrace{E[Y_i|D_i = 1] - E[Y_i|D_i = 0]}_{\text{Observed difference in average employment}} &= \underbrace{E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]}_{\text{Average treatment effect on the treated}} + \\ &\quad \underbrace{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]}_{\text{Selection bias}} \end{aligned} \tag{1.2}$$

Indeed, because individuals self select with regard to joining the program, it is highly probable that the two groups are not comparable. For instance, youths who entered to the program may be on average more motivated than those who did not, so the difference in average employment would not only be due to the program itself but to the motivation level. This problem is known as “selection bias”. Although there are several statistical techniques to overcome this bias, random assignment to the program is the best solution.

1.2.2 Random assignment

Assigning individuals randomly to a program makes the criteria for participating in the program independent of any other factors. Formally, we obtain the following identity:

$$E[Y_{0i}|D_i = 1] = E[Y_{0i}|D_i = 0] \tag{1.3}$$

By substituting equality (1.3) in equation (1.2), it becomes clear that the selection bias disappears. However, there must be a sufficient number of individuals for this equality to be verified. Indeed, the law of large numbers stipulates that the observed average of a sample gets closer to the true population average when the sample size increases. Having lots of individuals in both groups then ensures that the means of different characteristics are similar in both groups. Therefore, if the employment rates are not the same in the two groups, this is due solely to the effect of the program.

Experiments in this thesis only used simple randomization to allocate individuals to treatments, i.e. individuals were assigned to one among n groups with probability $1/n$. Cluster, stratified, and pairwise randomization are different randomization processes that were not used, although they could provide useful insights for future experiments.

1.2.3 Regression analysis

Linear regression is a useful tool for measuring causal impact in case of simple random assignment. One can link the outcome variable Y_i to the treatment variable D_i through a linear relationship (of type $ax + b$) as follows:

$$Y_i = \alpha + \rho D_i + \eta_i \tag{1.4}$$

Each term of the regression can be related to a quantity of interest. More precisely, α measures the average employment rate of the group of individuals who did not participate in the program. ρ measures the effect of the program, i.e. the differential in employment rates between the two groups, which is supposed constant here. η_i is a random term that averages to zero under certain hypotheses.

Evaluating the conditional expectation of equation 1.4 shows:

$$\begin{aligned}
&E[Y_i|D_i = 1] = \alpha + \rho + E[\eta_i|D_i = 1] \\
&E[Y_i|D_i = 0] = \alpha + E[\eta_i|D_i = 0] \\
&\implies E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = \rho = \text{Average treatment effect on the treated}
\end{aligned}$$

The above equality holds because random assignment implies that participation in the program is independent of any other factor such that $E[\eta_i|D_i = 1] = E[\eta_i|D_i = 0]$. Nonetheless, it is possible to include other individual and program characteristics in equation (1.4) in order to improve the precision of the estimation. Such inclusion will not change the estimation of the effect of the program on employment, but it will give us a more precise window in which the estimation lies and allow us to carry out more precise statistical significance tests. Obviously, one needs an appropriate database providing information on both Y and D for each individual i, so it is possible to use the ordinary least squares (OLS) estimator to have precise measures for both α and especially ρ.

More advanced considerations, such as a dynamic treatment effect or the existence of spillover effects on those not treated, are not addressed in the thesis. But they are important elements that should be considered for future research, even though they complicate both the type of experiment needed and the statistical analyses. They also require additional data that could not be obtained for the thesis, either because it does not exist or because of the legal complexity involved in merging different administrative databases.

1.3 Summaries and contributions

The thesis is composed of three independent chapters that bring contributions to the literature associated to school-to-work transitions and related labor market policies.

1.3.1 Chapter 1 - Apprenticeship and youth unemployment

Empirical studies often document that apprentices have better access to employment than other vocational students after leaving school (Wolter and Ryan, 2011). These facts, together with the widely publicized success of the German apprenticeship system, motivate many public policies aiming at boosting apprenticeship to foster youth employment (Kuczerat, 2017).

However, little is known about the reasons why apprentices may perform better at the start of their career. Apprenticeship is generally more developed in occupations and areas whose labor market is tight, making it difficult to disentangle the effects of potential specific skills of apprentices from the demand of firms for these occupations. Potential selection of individuals with specific abilities into apprenticeship implies that estimating the impact of apprenticeship on access to jobs is difficult. Furthermore, the higher employment rate of apprentices may be the consequence of retention in their training firm, without providing any advantage in access to jobs in other firms. Thus, to know whether and how apprenticeship really fosters the integration of youths into employment, it is important to answer the following question: How do employers compare identical graduates of the same diploma acquired either after apprenticeship or after vocational education in school?

To answer this question, we measured the chances of getting a callback from employers for unemployed youth who were formerly either apprentices or vocational students. The method involves sending résumés of unemployed young applicants to actual job offers, whereby the applicants are similar in all ways except for the pathway through which they got their secondary school diploma. This strategy ensures that résumés can vary in one dimension only, which serves to identify the effects of different education pathways on the probability of callback, and consequently the preferences of employers for these pathways.

We sent 3,110 applications from January to July 2018 to job offers posted in France for cook and bricklayer positions. At the aggregate level, we detect no difference in the callback probability of apprentices and vocational students. This result holds true for both occupations. It also holds true for small and large firms and for temporary and permanent jobs. The only small difference, to the advantage of apprentices, arises in commuting zones where the unemployment rate is high. This is consistent with a situation in which employers have a slight preference for apprentices, which has an impact on callback probabilities only if employers can choose among a large pool of applicants.

Relying on the Génération survey, which provides a large representative sample of students leaving education, we generate descriptive statistics showing that the findings of our correspondence study are consistent with the overall school-to-work transitions of apprentices and vocational students in France. This data also indicate that, on average, the unemployment rate of apprentices is 10 to 15 percentage points lower than that of their counterparts right after graduation. This gap corresponds to the difference between the share of apprentices who remain in their training firm and the share of vocational students who remain in the firm where they were interns before leaving school. In addition, data from the Génération survey that, conditional on observable characteristics, apprentices do not perform better in getting jobs than vocational students once they are non-employed, whether unemployed or inactive.

To explore this issue further, we build and estimate a search and matching model which allows us to reproduce the main stylized facts of a youth labor market with vocational students and apprentices. In this model, students and apprentices not retained in their training firm at the completion of their apprenticeship compete to get jobs. The estimation of this model shows that expanding the share of apprentices has limited impact on youth unemployment if this is not accompanied by an improvement in the retention rate of apprentices in training firms.

The conclusion that apprentices do not perform significantly better than vocational students when they look for jobs outside the firm in which they trained has important consequences for public policy. If the main advantage of apprenticeship is the creation of better matches between labor market entrants and jobs, policies should be more focused on this dimension and favor collaboration between schools and public employment services.

This collaboration, which is almost non-existent in many OECD countries, is well developed in Japan and in Germany, which share important common attributes in this respect (Ryan, 2001) and are very successful at integrating youths into employment. In Japan, where apprenticeship is very rare, high schools provide career support for their students (OECD, 2017). Counseling and job search training are often part of senior high school curricula from the first year. In the second year of high school, many schools have specific career preparation classes for students who do not intend to pursue higher education. In the third year of high school, aspiring labor market entrants undergo a regulated job placement process at school in which the teachers responsible for career guidance match students to the available positions based on vacancy lists provided by public employment agencies. The application process follows a strict schedule to promote equal opportunities among graduates and to ensure that students focus on completing their studies. Students are not allowed to seek work independently, and employers are expected to cooperate with public employment agencies when hiring future graduates. The job placement of high school graduates is remarkably effective, averaging about 90%, and there is little evidence that it comes at the cost of lower job stability. In Germany, the Federal Employment Office recommends secondary school applicants to sponsoring employers. As in Japan, there are important interactions between schools and public employment agencies. The effectiveness of this strategy is also stressed by Noelke and Horn (2014) who argues that economic liberalization in post-socialist countries like Hungary has made the transition from vocational education to work more difficult by breaking linkages from schools to employers that performed a critical matching function.

Our findings suggest that the German-Japanese strategy targets an important cause of youth unemployment:

the difficulty for job market entrants in finding jobs to which they are suited. Hence, improving the job placement of school leavers through the active involvement of public employment services in schools may be an important lever to boost youth employment.

1.3.2 Chapter 2 - Labor market policies for young dropouts

To help Youths who leave school before graduation, several public policies were put in place all along the past years. Meta-analyses indicate that vocational training moderately increase youth employability, such as subsidized jobs in the market sector. However, subsidized jobs in the non market sector exhibit zero or negative effect (Caliendo and Schmidl, 2016a). However, little is known about employers preferences for these different policies. The trend in French policy indicates a shift toward hybrid labor market policies in which youth can benefit from a mixed of active programs. This recent policy orientation provides a specific environment in which we can test empirically whether different types of active policy give high-school dropouts a second chance on the labor market.

Our article contributes to the understanding of youth transition in the labor market by focusing on potential recruiters' preferences with regard to educational and professional items in low-skilled profiles. In particular, we test whether hybrid programs yield a better outcome for youths than training programs or subsidized contracts alone, by comparing their relative importance for employers. We are able to rule out potential selection bias in the labor market resulting from skills, knowledge, network or social conditions by carrying an audit correspondence study. From January to July 2018, we sequentially sent more than 10,000 job offer applications randomly throughout mainland France. We designed resumes for 18/19-year-old virtual job seekers, identical in all respects except for graduation and their labor market pathway in the two years preceding the application. We target firms that hire cooks and bricklayers at the vocational education level, which are two jobs for which youth have similar school-to-work transitions than the average youth at this level of education.

We constituted five typical groups of youth after they end middle school. On the one hand, some of them continued their education to obtain a CAP diploma, either in vocational school or in apprenticeship. This group serves as the control group, since it corresponds to the natural path in the education system. We call this first group "Graduates". We apply different treatments for school dropouts than for other youths. During first year after dropping out, they had two one-month temporary contracts, with no link to the occupations targeted in the audit correspondence study, and ten months of non-employment. This year of inactivity acts as a signal of dropping out when employers look at the applications. The second year after dropping out is differentiated among dropouts. Some youths once again experienced two one-month temporary contracts without any link with the targeted occupations (we call this group "Inactives"), while other underwent seven-month vocational training leading to a CAP diploma ("Trainees"), or a one-year subsidized contract which could be combined with certified training leading to a CAP diploma ("Trained Workers") or not ("Workers").

By analyzing the differences in callback rates with respect to non-dropouts, we find a clear ranking of profiles by employers. School dropouts have a significantly smaller likelihood of being called back for a job vacancy. We find that the probability of callback decreases by 67% on average for an "Inactive" dropout compared to a "Graduated" non-dropout. It appears that seven months vocational training leading to a certificate, or a one-year subsidized contract, reduces the negative sign of dropping out with the same order of magnitude by three, but the probability of callback of "Trainee" and "Worker" dropouts still remains lower than for "Graduates", by $\approx$ 25%. More interestingly, work experience gained through a one-year subsidized contract and certified by a state diploma after complementary vocational training improves the dropout likelihood almost to the same level as those who graduated. The probability of being called back for a job for "Trained Workers" is only 8% less than that of "Graduates" and it is entirely driven by the cook occupations.

The ranking of profiles is quite similar when looking across heterogeneous dimensions, only the discrepancies between non-dropout and dropout applicants is varying depending on firm characteristics (market/non-market, number of workers), labor contract characteristics (temporary/permanent, required experience), job occupation (cook/bricklayer), and external environment (local unemployment rate, distance the job location). We also sent more than 10,000 speculative applications randomly to firms that did not post job offers online from October to December 2018. The results support the conclusion drawn from the initial testing. If students drop out of school before graduation, their applications receive less consideration, which is quite pronounced if they have been inactive for two years, although this reduction seems alleviated through labor market policies.

Even if our experiment was not designed to illustrate properly the potential underlying mechanisms, we manipulate our different treatment groups to provide some information and think of two potential mechanisms that may explain what drives the negative sign of our dropout treatment profiles. The first mechanism concerns the negative signal that dropping out of the school system entails for youths. Their doing so may suggest to employers that these youths are incapable of fitting into a proper formal system. It could also indicate that they have not acquired the skills needed to do the job and will not produce positive results for the firm (Piopunik et al., 2020). The second mechanism, which has received much attention in the literature, could be the duration of unemployment dependence. Various studies have analyzed the effect of unemployment duration on the probability of callback and show that the longer the duration in unemployment, the lower the probability of getting a job (Kroft et al., 2013a). This is because this duration entails information about the incapacity of finding jobs while there are offers posted online. We find some evidence in favor of these two mechanisms.

Our experiment is as internally valid as possible, but some questions about its external validity remain. In reality, the productivity of a worker is not known by the employer and observables in a resume cannot provide full information (Neumark, 2012). This audit study only measures the interviewing stage of the hiring process and employers may have specific expectations during the hiring stage, changing the hierarchy of profiles. Nevertheless, our results suggest that employers, who are not indifferent between graduates and dropouts when they select applications, contribute to the polarization among these two populations. Our experiment thus points to the value of preventing dropping out of school or acting as early as possible after dropping out of school, in order to give dropouts the skills documented by a national certificate, since doing so boosts their chances of being called back by employers.

1.3.3 Chapter 3 - Providing information to young NEETs

Every month in France, military instructors are required to guide young people identified as NEET toward active programs supplied by partner public institutions, especially to the *mission locale*. 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 so as to enroll greater numbers.

Texts seem to be an effective channel of communication for transmitting salient information, as everyone communicate via texts to maintain relationships, private firms used them to send notifications for purchasing their goods, and medical centers for sustaining individuals' efforts in fighting against substance abuse. Nonetheless 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 (Ehrenreich et al., 2014). In this case, might SMS be an appropriate solution for public assistance agencies to reach young NEETs? And 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?

To answer these two questions, information about *mission locale* agencies was provided experimentally via text messaging directly sent to NEET phone numbers, identified during the army days that took place between January and May 2019. Youth were then randomly assigned to one of five different groups with equal probability. They received information on the nearest *mission locale* agency. The first group did not receive any text 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. 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. Some studies 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 (Ling and Baron, 2016).

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 duration analyses and linear regression analyses indicate that the texts had no overall effect. Nor did 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 seemed 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 did 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 be not relevant for this population. Second, the time delay 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 because 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, 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.

Apprenticeship and Youth Unemployment

Abstract In France, two years after school completion and getting the same diploma, the employment rate of apprentices is about 15 percentage points higher than that of vocational students. Despite this difference, this paper shows that there is almost no difference between the probability of getting a callback from employers for unemployed youth formerly either apprentices or vocational students. This result indicates that the higher employment rate of apprentices does not rely, in the French context, on better job access of those who do not remain in their training firms. The estimation of a job search and matching model shows that the expansion of apprenticeship has very limited effects on youth unemployment if this is not accompanied by an increase in the retention of apprentices in their training firm.

Based on: *Apprenticeship and Youth Unemployment*, IZA DP No. 13154
Joint with: Pierre Cahuc (SciencesPo, IZA, CEPR)
Keywords: Apprenticeship, School-to-work transitions, Field experiment
JEL codes: J24, M53, M51

2.1 Introduction

Empirical studies often document that apprentices have better access to employment than other vocational students after leaving school.[1] These facts, together with the widely publicized success of the German apprenticeship system, motivate many public policies aiming at boosting apprenticeship to foster youth employment (Kuczerat, 2017).

However, little is known about the reasons why apprentices may perform better at the start of their career. Apprenticeship is generally more developed in occupations and areas whose labor market is tight, making it difficult to disentangle the effects of potential specific skills of apprentices from the demand of firms for these occupations. Potential selection of individuals with specific abilities into apprenticeship implies that estimating the impact of apprenticeship on access to jobs is difficult. Furthermore, the higher employment rate of apprentices may be the consequence of retention in their training firm, without providing any advantage in access to jobs in other firms. Thus, to know whether and how the expansion of apprenticeship really fosters the integration of youths into employment, it is important to answer the following question: How do employers compare graduates of the same diploma acquired either after apprenticeship or after vocational education in school?

This is exactly the question addressed in this paper. To answer this question, we measure the chances of getting a callback from employers for unemployed youth who were formerly either apprentices or vocational students. The method involves sending résumés, to actual job offers, of unemployed young applicants who are similar except for the pathway through which they got their secondary school diploma.[2] This strategy serves to identify the preferences of employers for unemployed youth coming from these pathways. Obviously, entry into apprenticeship results from a selection which implies that the characteristics of apprentices may differ from those of young people in vocational high schools, regardless of the impact of apprenticeship. In addition, former apprentices who are unemployed might differ from those remaining in their training firm because employers try to keep the best apprentices and the best apprentices sometimes prefer to look for better opportunities. Our purpose is not to analyze these selections but to study the unemployment impact of expansion in apprenticeship accounting for the actual hiring behavior of employers towards former apprentices and former vocational students.[3] This issue is of first importance insofar as a large share of apprentices do not remain in their training not only in France, but also in other countries.[4]

We sent 3,110 applications from January to July 2018 to job offers posted in France for cook and bricklayer positions. The choice of these occupations is motivated by several reasons. First, these occupations attract a sig-

[1]See for instance Fersterer et al. (2008) for Austria, Corseuil et al. (2019) for Brazil, Bonnal et al. (2002) for France, Winkelmann (1996) for Germany, Noelke and Horn (2014) for Hungary, Picchio and Staffolani (2019) for Italy, Mcintosh (2004) for the UK. Wolter and Ryan (2011) (p. 553) conclude their survey of the empirical evidence as follows: "The well-documented benefits of apprenticeship for the transition from school to work—once selection into different training options is taken into account—are followed by economic returns in early adulthood that in some countries are similarly favorable but that in others involve smaller pay gains and more unstable employment."

[2]Apprentices and vocational students get the same diploma, but on average, apprentices typically work three days per week during two years in their training firm while the internships of vocational students last from zero ($\approx$ 16% of students) to four months, generally in different firms.

[3]The impact of potential changes in the selection of apprentices when their share increases is discussed in section 2.6.4.

[4]According to available empirical evidence, this share is around to 35% in the UK (CEBR, 2015), 45% in Germany (Brébion, 2017), 30% in Estonia (EuropeanCommission, 2013).

nificant share of low skill youth, who complete their education at the secondary school level. Second, the shares of apprentices and vocational students are important in both occupations. Third, these occupations belong to different industries, which is relevant for assessing external validity. Fourth, the school-to-work transitions of vocational students and apprentices who intend to work in the hotel and restaurant and construction sectors are similar to those of all students and apprentices.

At the aggregate level, we detect no difference in the callback probability of apprentices and vocational students. This result holds true for both occupations. It also holds true for small and large firms and for temporary and permanent jobs. The only small difference, to the advantage of apprentices, arises in commuting zones where the unemployment rate is high. This is consistent with a situation in which employers have a slight preference for apprentices which has an impact on callback probabilities only if employers can choose among a large pool of applicants.

Relying on the *Génération* survey, which provides a large representative sample of students leaving education, we generate descriptive statistics showing that the findings of our correspondence study are consistent with the overall school-to-work transitions of apprentices and vocational students in France. On average, the unemployment rate of apprentices is 10 to 15 percentage points lower than that of their counterparts right after graduation. This figure corresponds to the difference between the share of apprentices who remain in their training firm and the share of vocational students who remain in the firm where they were interns before leaving school. Data from the *Génération* survey also show that, conditional on observable characteristics, apprentices do not perform better in getting jobs than vocational students once they are non-employed, whether unemployed or inactive.

This suggests that expanding the share of apprentices might have very limited impact on youth unemployment if this is not accompanied by high retention rates of apprentices in their training firm. However, expanding apprenticeship has several consequences which need to be taken into account to evaluate its impact on youth unemployment. This expansion may crowd out vocational students facing more competition from more numerous apprentices. It may increase competition among apprentices. It may reduce the average quality of apprentices. These effects may contribute to dampen the effectiveness of apprenticeship to improving labor market performance. On the other hand, if apprentices are more productive, increasing their share may foster job creation. To evaluate these mechanisms, we build and estimate a job search and matching model which models the choice between apprentices and vocational students in the hiring process. This model allows us to reproduce the main stylized facts of a youth labor market with vocational students and apprentices. The estimation of this model, using data from the *Génération* survey, indicates that apprentices not retained in their training firm are only slightly more productive than students. The model also predicts, in line with the results of the correspondence study, that the exit rates from unemployment of students and apprentices are very close at the average unemployment rate, but that apprentices are more often called back for interview and then more often recruited than students when the unemployment rate is higher. Counterfactual exercises show that expanding the share of apprentices has limited impact on youth unemployment if this is not accompanied by an improvement in the retention rate of apprentices in training firms. It is worth noting that these are conservative results when it comes to the effectiveness of apprenticeship expansion in decreasing youth unemployment insofar as it is likely that apprenticeship attracts students more motivated by professional careers. Hence, the expansion of apprenticeship may attract less motivated students, leading to a decrease in its effectiveness.

These results have important consequences for policy. If the main advantage of apprenticeship is the creation of better matches between labor market entrants and jobs, policies should be more focused on this dimension. The collaboration between schools and public employment services can be a powerful lever, as discussed in our concluding comments which highlight the apparently very successful German and Japanese experiences in this domain.

Our paper is related to several strands of the literature. Many contributions analyze the labor market performance of apprentices and vocational students (see the surveys of Wolter and Ryan (2011) and Riphahn and Zibrowius (2016)). As far as we are aware, only a few studies aim at identifying the causal impact of apprenticeship on job access or remuneration. Those which do so find higher returns to apprenticeship in terms of remuneration or access to stable jobs (see Fersterer et al. (2008) in Austria, Bonnal et al. (2002) for France, Plug and Groot (1998) for the Netherlands, Albanese et al. (2019) for Italy). The contributions focused on labor market transitions after apprenticeship generally stress the importance of retention of apprentices in their training firms (Riphahn and Zibrowius (2016), Albanese et al. (2019)). In particular, Von Wachter and Bender (2006) find that wage losses of German apprentices who do not remain in their training firm are initially 15 percent, and then drop to zero within five years. This indicates that retention in training firms does play a key role in the success of apprentices at the outset of their careers. Although our analysis is focused on a different country, our results are consistent with the findings of Von Wachter and Bender (2006). These results are also consistent with previous studies which find that apprentices not hired by their training firm do not have better positions than vocational students in France (Bonnal et al. (2002), Léné and Cart (2018)). Our approach allows us to conclude that this situation does not stem from lower job search activity by non-retained apprentices, but from the recruitment behavior of firms.

Our analysis contributes to the literature based on correspondence studies devoted to the effect of work experience and education on the likelihood of being invited to an interview. This approach is useful to evaluate the impact of different education or training pathways on school-to-work or training-to-work transitions, leaving aside the analysis of their long run impact.[5] From this perspective, Nunley et al. (2016) find that the internship experience significantly increases the interview rate of college graduates in the US. Gaulke et al. (2019) find that post-baccalaureate business certificates do not improve chances of receiving a callback in the US. Cahuc et al. (2019a) show that, compared to those who have stayed unemployed since leaving school in France, the callback rate of high school dropouts unemployed four year after leaving school is not raised for those with employment experience, whether it

[5]The analysis of the long run impact, which is beyond the scope of this paper, can be useful in identifying the signaling and human capital accumulation components of the returns to education and training as shown by Farber and Gibbons (1996), Altonji and Pierret (2001), Aryal et al. (2019) among others.

is subsidized or non-subsidized, if there is no training accompanied by skill certification. The contribution of Hervelin et al. (2020a), also focused on high school dropouts in France, finds that only dropouts with both job related experience and training leading to a qualification manage to catch up with their non-dropout peers. Our paper contributes to this strand of the literature by examining the callback rates of graduates low-skilled in a context where the same diploma can be obtained either through apprenticeship or the vocational school pathway.

Finally, our paper is related to the literature which analyzes the link between callback to interviews and hiring decisions. Jarosch and Pilossoph (2018a) show that differences in callbacks of unemployed workers depending on their unemployment spell can have limited consequences for hiring decisions. Cahuc et al. (2019c) set out a model showing that the difference in callback rates between two groups of workers at the stage of invitation to interviews can be a poor predictor of eventual hiring differences. We complement this approach by providing and estimating a search and matching model which allows us to infer eventual hiring decisions from the callback to interviews of apprentices and vocational students. This approach eventually helps to relate the results of the correspondence study to the hiring decisions of firms, and to show that the higher employment rate of apprentices after leaving school is almost entirely due to the retention rate in the firms where they were trained.

The paper is organized as follows. Section 2.2 presents the school system and the features of vocational students and apprentices in France. Section 2.3 describes the experimental design. Section 2.4 presents the main findings of the correspondence study. Section 2.5 discusses the external validity and the interpretation of these findings by examining the school-to-work and the labor market transitions of all vocational secondary school graduates from the *Génération* survey. Section 2.6 presents the conceptual framework which enables us to empirically explore the consequences on youth unemployment of expanding the share of apprentices. Section 2.7 provides concluding comments about the policy implications of our results.

2.2 Background

Since our analysis is focused on youth who completed their vocational education at the upper secondary level, we start by presenting the main features of the upper secondary vocational education system before describing the characteristics of apprentices and vocational students.

2.2.1 The vocational education system

In France, at the end of lower secondary education (ninth grade), students have the choice between two education paths. First, they can choose three-year general education programs to prepare for the high school diploma (*baccalauréat*). About 62% of students choose this path.[6] Second, about 33% choose vocational programs for two or three years either in vocational schools (*Lycée professionnel*, 28%) or in apprenticeship centers (*Centre de forma-*

[6] See Testas et al. (2018) for data about the paths of students at the end of lower secondary education.

tion des apprentis, CFA, 5%). The two-year vocational programs, which are chosen by 11% of students, lead to a diploma called *certificat d'aptitude professionnelle* (CAP), with different specializations. The three-year programs, chosen by 22% of students, lead to the *professional baccalauréat*. Our study is focused on young people from the two-year vocational programs because the share of apprentices, which represents about half of these young people, is large relative to the three-year programs, in which there is a tiny fraction of apprentices.[7]

During their ninth grade, students have to list the different specializations for the CAP they want to apply for. These lists are addressed to their school. The schools then send some students files to the targeted vocational schools. While there can be some selection into some specializations due to budgetary constraints or behavioral standards, registration into a vocational school is otherwise automatic. However, students seeking to become apprentices need to find a firm willing to hire them for two years. If the young person is hired, the two parties settle a contract which stipulates the task contents of the occupation, the wage as a percentage of the floor wage in the sector, and the content of the training provided by the employer. Apprentices are registered with an apprenticeship center (known under the acronym CFA, for *Centre de Formation des Apprentis*) which provides general and vocational education. In most cases, apprentices spend between half and two-thirds of their time in the firm each month, and the remainder in the apprenticeship center.

Vocational students who are not apprentices study in vocational high schools. About one third study in the classroom exclusively, while the other two thirds combine education in their vocational schools with internships in training firms. According to French labor law, training firms do not have the obligation to pay students if the total number of weeks of internship during a year does not exceed eight weeks. Accordingly, the duration of internships for vocational students is usually no longer than eight weeks. The only obligation training firms face is the commitment to an internship agreement, which describes the task contents and working conditions. This internship agreement has to be signed by the training firm, the student and the vocational school. Since the *circulaire numéro 2015-035 du 26 février 2015* and the *circulaire numéro 2016-055 du 29 mars 2016*, teachers in each specific training program have to create an internship center to reinforce equity among students and to help them find a training firm. Teachers also have to conduct a preparation week before the first period of internship. During this week, students participate in workshops and talks to prepare for their internship.

Whatever the chosen path, students and apprentices have to pass the *same* national exam at the end of the two-year program. Depending on the courses, exams can be written, oral, or both. Some bonus points can be awarded during the two-year program through a system of continuous evaluation, depending on the specialization. The CAP diploma is obtained if the average grade is at least 10/20. The CAP certifies the skills that any worker in the specified occupation must master to be employable.

Table 2.1 displays the main features of the two-year education programs of vocational students and apprentices. On average, apprentices spend half as much time in the classroom as vocational students. Conversely, apprentices

[7] Vocational education and apprenticeship can also take place at higher education levels.

TABLE 2.1
Training contents in vocational school and apprenticeship center

		Vocational school		Apprenticeship center	
	Academics				
Courses	Description	1^{st}-year	2^{nd}-year	1^{st}-year	2^{nd}-year
French	Oral (listen, react, express), written (read, analyze, write)				
History	French workforce and republics, world discoveries, world wars	3h30 - 4h	3h30 - 4h	-	-
Geography	Globalization, inequality, agriculture, technological risks				
Morality, Civic education	Rights and duties, citizenship, discrimination, medias	30min	30min	-	-
Art, Culture	Product design, communication design, space design	2h	2h	-	-
Health, Environment	Manage one's health, budget, working and leisure time	1h	1h30	-	-
Foreign language	Objective: A2 level in 1 among 6 languages	2h	2h30	-	-
Sport	3 disciplines among the academic and national lists	2h30	2h30	-	-
Mathematics	Calculus, graphics, proportionality, equations, statistics	3h30 - 4h	3h30	-	-
Sciences	Matter, pH, kinematic, waves, electricity			-	-
Technical, Professional	Lessons, practical work and workshops defined by schools	17h - 18h	17h - 18h	-	-
Total (weekly)		32h - 34h	32h - 34h	-	-
Total (yearly)		**896h - 1,140h**	**812h - 1,026h**	**438h**	**439h**
	Professional				
Type		Internships		Apprenticeship	
Legal document		Internship agreement		Contract of apprenticeship	
Duration		From 12 to 16 weeks		22 months	
Working time		Set by the training firm		35 hours per week	
Salary		None if total duration $\leq$ 8 weeks		€515.15 per month	

Note: This table reports information about the vocational education system in France depending on whether the CAP diploma is obtained in vocational school or in apprenticeship. The information comes from the following sources: *Bulletin officiel spécial numéro 6 du 25 juin 2015*, *Bulletin officiel spécial numéro 8 du 25 février 2010*, *Bulletin officiel spécial numéro 2 du 19 février 2009*, Bull*etin officiel numéro 42 du 12 novembre 2009*, *Circulaire numéro 2015-035 du 26 février 2015*, *Circulaire numéro 2016-055 du 29 mars 2016* for vocational students and *Ari@ne 2015* for apprentices. As indicated in the text, each apprenticeship center can decide the amount of time allocated to each course under the constraint that there is a minimum of 400 hours of lessons per year. There is no available information on the time schedule in apprenticeship centers.

work 35 hours per week in training firms, during 22 months for a monthly wage of about €515. Academic courses are given by apprenticeship centers at their discretion. The only obligation apprenticeship centers face is to ensure a minimum of 400 hours of lessons per year of training. Apprenticeship centers can decide the amount of time allocated to each course.

Overall, vocational students spend between thirty-two and thirty-four hours per week in the classroom. The number of hours of academic lessons is split evenly between general and vocational education. The exact total number of hours of academic lessons depends on the specialization of students. The higher the total duration of internships, the lower the number of hours of academic education. While the content of general education is common to all specializations, the content of vocational lessons is specialization specific,[8] as is the number of weeks for internships. The manner in which the number of weeks for internships needs to be completed is decided by each vocational school.

2.2.2 Characteristics of apprentices and vocational students

Table 2.2 reports the main characteristics of students and apprentices who obtained their CAP in 2000s. We rely on the national surveys *Enquête Génération* run in 2004, 2010, 2013 and 2016,[9], which asks questions to a representative sample of around 25,000 youngsters who completed school at the end of a specific academic year.[10] About half of youngsters who obtain their CAP are apprentices. Apprentices are more often males and come from a more favorable environment compared with vocational students: their parents are less often immigrants, are more educated and are more often employed. Moreover, data from the Ministry of education[11] show that apprentices are more skilled in French and mathematics than vocational students. They also have a better subjective self-judgment of their abilities in the social sphere (participation in activities, creation of social relations...). Although apprentices are overall in more favorable situations than vocational students, Table 2.2 indicates that their graduation rates are almost identical.

Table 2.2 reports that almost half of vocational students declare that they would have preferred apprenticeship. 66% of those who would have preferred apprenticeship either did not find any apprenticeship center (CFA), or employer, or found neither. In addition, about 20% of vocational students did not do an internship during their training in a vocational school. For the others, about half of them had to do at least three internships to meet the legal duration of internships during the vocational program. We are not able to see from the data whether these different internships had been done within the same training firm or not. Around 66% of vocational students declared

[8]See Tables 2.13 and 2.18 in Appendix 2.8.4 for details regarding the targeted cook and bricklayer occupations respectively in the field experiment.

[9]https://www.cereq.fr/enquetes-et-donnees/insertion-professionnelle-generation.

[10]All young people who went back to school for a specific training within a year after the one they were supposed to finish are excluded from the survey. We also exclude youngsters who obtained another diploma before their CAP, irrespective of the field of training. Overall, the selected sample is purged of any potential school dropouts or multi-graduated youths, who both constitute specific sub-samples. Finally, we are able to observe at least 10,000 youths followed during 34 months after they ended school whether in 2001, 2007, 2010, or 2013 within the *Génération* surveys 2004, 2010, 2013 and 2016 respectively.

[11]See Testas et al. (2018).

TABLE 2.2
Statistical portrait of students and apprentices

Component	Information	Students	Apprentices
		57.55%	42.45%
Individual	Sex (male)	54.62%	72.17%
	Age	20 y.o.	20 y.o.
	Handicap	1.79%	2.36%
	Driving license	33.49%	55.40%
Family	District area		
	Downtown	33.71%	26.25%
	Suburb	31.61%	32.98%
	Small city	10.93%	11.54%
	Village	23.75%	29.22%
	Siblings	92.72%	90.32%
	French language	92.62%	96.07%
	Birthplace of father		
	France	74.32%	84.17%
	European countries	4.53%	5.10%
	Arabic countries	15.39%	8.36%
	African countries	4.31%	1.49%
	Rest of the world	1.44%	0.88%
	Birthplace of mother		
	France	76.85%	87.09%
	European countries	4.72%	4.18%
	Arabic countries	13.12%	6.49%
	African countries	4.16%	1.57%
	Rest of the world	1.15%	0.67%
	School level of father		
	No diploma	45.53%	33.46%
	Cap/Bep	40.43%	47.31%
	Bac	8.94%	12.63%
	Bac+	5.09%	6.60%
	School level of mother		
	No diploma	43.77%	34.69%
	Cap/Bep	38.32%	39.00%
	Bac	13.41%	17.97%
	Bac+	4.49%	8.34%
	Father works	80.46%	86.28%
	Mother works	61.65%	72.46%
Education	Repeat year before 6th grade	37.87%	38.48%
	Normal middle school program	59.24%	59.75%
	Would have preferred apprenticeship	47.03%	-
	Reason of non-apprenticeship		
	No CFA	4.80%	-
	No employer	31.50%	-
	Neither CFA, nor employer	29.60%	-
	Other	34.09%	-
	Internships / Apprenticeship Tutor	83.83%	87.96%
	Number of internships		
	1	24.55%	-
	2	28.91%	-
	3 or more	46.54%	-
	Contact with the (last) training firm		
	Self	41.90%	46.40%
	Family and friends	27.58%	35.17%
	School / Apprenticeship center	21.46%	10.62%
	Other Public Structure	0.16%	5.73%
	Other	8.89%	2.07%
	Graduated	93.02%	91.47%

Note: This table reports descriptive statistics for both apprentices and vocational students. Shares of students who made interships and the mode of contact with the last training firm are computed from the *Génération 2010* survey only, while the respective shares for apprentices are computed from the *Génération 2001* survey, because of variation in the specific questions. The share of graduated students and apprentices are computed with both the *Génération 2010-2013* surveys because of changes in the content of the level V diploma in 2009 in France.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ ($N = 10,947$ individuals)

that their last training firm was found thanks to their private network (self, family or friends), and 22% thanks to a public network (teacher or a school service). On the contrary, these proportions rose to 81% and declined to 15% respectively for apprentices.

All in all, it seems that apprentices are more employable than vocational students: they get the same diploma, but they come from more favorable backgrounds, they were better students in lower secondary schools, they have better subjective self-judgments of their social abilities and their acquired more work experience. The next section presents an experimental design which allows us to analyze how employers compare former apprentices and vocational students with identical characteristics usually reported in resumes.

2.3 Experimental design

The experiment aims at comparing the probability of callback to job applications of otherwise identical apprentices and vocational students. We start by presenting the applicants before describing the applications.

2.3.1 The applicants

The applicants, who are all unemployed at the time of their response to job offers, are identical in all points, with the exception of their education path while they were in upper-secondary vocational education. The characteristics of the fictitious applicants were chosen so as to match those of real apprentices and vocational students when they leave school.

Applicants are young males aged 18 at the date of graduation. We focus on males because it is much less common for women to be apprentices, especially in construction, where almost all apprentices are males. Their names have been chosen among those most commonly encountered in the French population. According to the *Fichier des prénoms* (INSEE), the two first names used in the experiment, Alexis and Théo, were respectively ranked 13 and 9 in the most given first names in 1999.[12] And according to the *Fichier patronymique* (INSEE), the surnames, Dubois and Petit, were respectively ranked 7 and 6.[13]

Given financial and organizational constraints, two occupations were selected. The choice of occupations relies on the following criteria: belonging to different industries, existence of an official state certification for the diploma that is normally a prerequisite to be hired, having sufficient shares of former upper-secondary vocational students and apprentices, having a sufficiently large number of job offers, being present in both market and non-market sectors to enlarge the potential number of job offers, having school-to-work transitions similar to those of the overall apprentices and vocational students displayed in the previous section.[14] This led us to select cook (ROME G1602) and bricklayer (ROME F1703) occupations. The features of the young people belonging to these two occupations

[12]The first names have been chosen randomly among the top 20.

[13]The same has been done for surnames.

[14]We used various sources, including the Labor Force Survey (*Enquête emploi, INSEE)* and the *Répertoire National des Certifications Profesionelles* (RNCP), to verify the existence of national diploma, the *Pôle emploi* database to evaluate the number of job offers.

and of their school-to-work transitions are documented in Tables 2.14 and 2.19 for cooks and bricklayers in Appendix 2.8.4. Although there are more males and the share of apprentices is much larger in construction (69.7% versus 49.5% for all occupations and 50.7% for food services), CAP graduates from construction and food services share important common features with all apprentices and vocational students, for our purpose. For both occupations, the employment rate of apprentices is higher than that of vocational students from the date of school completion. Moreover, the employment rate difference between apprentices and vocational students vanishes when individual characteristics and retention in the training firms are taken into account.

The profiles of applicants were then designed for these two occupations. They obtained the *CAP cuisine* for cook and the *CAP maçon* for bricklayer occupations in June 2017. Since then, they have been unemployed without any work experience from the date of graduation to the dates of job applications, which are sent from 22 January 2018 to 23 July 2018. They have a mix of soft skills (the ones expected in a firm) and hard skills (the ones expected in the occupation).[15]

2.3.2 The applications

All applications included a résumé and a cover letter. They were accompanied by a short email message. Two templates have been created to ensure that callbacks do not depend on employers' preferences for a given presentation.[16] The templates have been inspired by different samples taken from the *Pôle emploi CVthèque*,[17] a youth center sample, and Google searches. The cover letters contained five paragraphs each. Sentences were written in a similar way so there was no apparent literacy difference among the two templates.[18]

Since applications were sent to job offers in all French *départements*, applicants' addresses were chosen to be in the center of whatever city serves as the administrative capital (préfecture) of the department in which the job was posted, in order to ensure that candidates live sufficiently close to their potential future job.[19] Since the diploma is national, there is no information about the school, which is common in résumés for this type of application. The address of training firms where students and apprentices worked during their studies is not provided, to avoid detection of fictitious applications. These training firms are large well known firms (Flunch, Hyppopotamus for cooks and Bouygues Construction and Lafarge for construction) for which it is unusual to mention the address of the establishment in which one has been employed.

Job offers for both occupations were identified using mainly the website of *Pôle emploi*, the French public employment agency.[20] Applications were sent only when it was possible to contact the recruiter directly by email,

[15]These skills have been taken from the *fiches métiers Pôle emploi*. Occupation related hobbies are cuisine, pastry, international cuisine for cook and DIY, for bricklayer. Other hobbies are: cinema, sport, handball, music. More details here for cooks and here for bricklayers.

[16]See Appendix 2.8.1 for examples of résumés and cover letters.

[17]This public databank is available to help recruiters in selecting different available profiles. More details at https://www.pole-emploi.fr/employeur/consultez-librement-des-cv-de-candidats.

[18]We check that the callback rates are not correlated with the layout types to avoid the potential issues of "template bias", addressed in Lahey and Beasley (2009).

[19]Addresses have been collected and verified via *Google maps*.

[20]A few private job search websites, such as *Le Bon Coin* or *Indeed* were also used when the number of offers available on the *Pôle emploi*

hence job offers issued by temporary work agencies or other intermediaries were not considered. Moreover, the same recruiter could never be contacted more than once, even if he posted different job positions in different areas of France throughout the entire experiment period. The same goes for offers providing only a *Pôle emploi* counselor email address. If a job vacancy met these criteria, one (and only one) application was sent from one of the two fictitious candidates. The name of the applicant, the applicant profile (apprentice or student), and the layout type were all selected at random.

Replies from recruiters were collected up to the last recorded phone call and email message on 10 October 2018. When recruiters provided a positive answer to an application by inviting the applicant to an interview or requesting additional information about the application, an email was sent in order to thank the recruiter and inform him that the applicant had signed an open-ended contract with a different employer.

In total, 3,110 applications were sent from 22 January 2018 to 13 July 2018. As shown in Table 2.3, there are 2542 applications from cooks and 568 from bricklayers. The relatively low number of applications for positions as bricklayers stems from the large share of job ads posted by temporary work agencies in the construction industry. Since our fictitious candidates could not apply to these job offers without a high probability of being detected, the number of applications for this occupation was limited.[21] Table 2.11 in Appendix 2.8.2 provides randomization tests. Due to the randomized design of the field experiment, this table confirms that the covariates characterizing the job vacancies are balanced between apprentices and vocational students.

2.4 Results

We start by presenting the callback rates to all applications before analyzing whether the results obtained at the aggregate level depend on the type of applications (temporary versus permanent jobs; job ads posted by large versus small firms) and on the local unemployment rate.

2.4.1 Callbacks to all applications

A reply from a recruiter who stated that he did not select the application for the job vacancy is classified as a negative callback, like the absence of callback. Any other reply is considered as positive callback, but we distinguish two grade of positivity. “Positive callbacks” show some interest in the application, ranging from the vague request “please call me back” to more precise inquiries about the training or experience of the applicant, or his means of transportation if the worksite is located more than a few kilometers away from where he (supposedly) lives. We regard these requests as positive because they are likely motivated by genuine interest in the application on the part

platform was too low on a given day.

[21] The sample size has been chosen to detect a difference of 0.05 at 5% significance level and power of 80% between the baseline callback rate of vocational students and that of apprentices. It appeared quickly that the baseline callback rate was around 25% for both occupations. In this context, the minimum sample size is equal to 1,251 per group, which is reached for the whole sample and also for cooks as shown by Table 2.3. This target was clearly unreachable for bricklayers, given the availability of job offers to which it was possible to apply.

TABLE 2.3
Callback rates descriptive statistics by profile

	Students	Apprentices	Difference (2)−(1)	p-value
	(1)	(2)	(3)	(4)
All				
# Observations	1,541	1,569		
Positive callback	.2745	.2830	.0085	.5979
	(.0114)	(.0114)	(.0161)	
Proposition	.2284	.2390	.0106	.4858
	(.0107)	(.0108)	(.0152)	
Cook				
# Observations	1,278	1,264		
Positive callback	.2793	.2975	.0181	.3133
	(.0126)	(.0129)	(.0180)	
Proposition	.2316	.2532	.0216	.2050
	(.0118)	(.0122)	(.0170)	
Bricklayer				
# Observations	263	305		
Positive callback	.2510	.2230	-.0280	.4341
	(.0268)	(.0239)	(.0358)	
Proposition	.2129	.1803	-.0326	.3294
	(.0253)	(.0221)	(.0334)	

Note: This table reports the number of observations per profile and the mean value of the primary dependent variables. A positive callback is equal to one if the fictitious candidate received a demand for complementary information, sometimes with a suggestion for interview or hiring. Proposition corresponds to callbacks which straightforwardly propose an interview or hiring. Standard error of the mean is reported in parentheses below the mean. Column (3) reports the difference between column (2) and column (1) and column (4) displays the p-value for the test $H_0 : \{\Delta$ = callback[apprentices] - callback[students] $= 0\}$ vs $H_1 : \{\Delta \neq 0\}$.

of the recruiter, and indeed some replies we classify as positive may not only request information, but may suggest an interview or even a hire. "Propositions" are more positive in that they straightforwardly propose an interview or a hire.

Then, we consider two categories of positive callbacks. First, "positive callbacks", which include propositions for interview, for hiring or a demand for complement information. Requirements for complementary information could be quite vague, asking "Please, call me back". They could also ask more precise information about the training or the experience of candidates, their means of locomotion when the job was located quite far from the address of the candidate. We interpret these types of callbacks as positive insofar as it is likely that they are motivated by the potential interest of the recruiter for the candidate. Second, we consider the category entitled "proposition" for callbacks which propose an interview or hiring.

The mean callback rates by category of callback and by profile of applicant are displayed in Table 2.3. Callback

TABLE 2.4
Effects of apprenticeship on callback probability

	All applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Dep var: Positive callback					
Apprenticeship	0.00849	0.00766	0.00903	0.0172	-0.0309
	(0.0170)	(0.0168)	(0.0172)	(0.0196)	(0.0444)
Student mean	0.2745***	0.2745***	0.2745***	0.2793***	0.2510***
	(0.0114)	(0.0114)	(0.0114)	(0.0126)	(0.0268)
Observations	3,110	3,110	3,110	2,542	568
R-squared	0.000	0.003	0.043	0.050	0.197
Dep var: Proposition					
Apprenticeship	0.0106	0.00993	0.0119	0.0223	-0.0330
	(0.0146)	(0.0145)	(0.0147)	(0.0169)	(0.0411)
Student mean	0.2284***	0.2284***	0.2284***	0.2316***	0.2129***
	(0.0107)	(0.0107)	(0.0107)	(0.0118)	(0.0253)
Observations	3,110	3,110	3,110	2,542	568
R-squared	0.000	0.003	0.043	0.050	0.184
Month FE	No	Yes	Yes	Yes	Yes
Department FE	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

rates are relatively high, about 28% for “positive callbacks” and 23% for “propositions”, despite the relatively low level of education of applicants. Actually, like in all occupations where apprenticeship is well developed, the market of cooks and bricklayers is quite tight, which provides good employment opportunities to applicants. Indeed, apprenticeship, which is partly funded by employers, is more developed in sectors where employers face hiring difficulties.

It is clear from Table 2.3 that there are no statistically significant callback rate differences between apprentices and students. There is a tiny non-statistically significant positive difference in favor of apprentices taken as a whole and for cooks, of about 1 percentage point. Compared with the baseline callback rate, which is above 25% for “positive callbacks”, this difference would be economically negligible if it were statistically significant.[22]

To analyze the data more extensively, we estimate the following linear probability model:

$$y_{ij} = \alpha + \beta \mathbb{1}_{i=apprentice} + x_j'\gamma + \varepsilon_{ij}$$

[22] Detection of such small difference is beyond the reach of this paper. Two-sample proportion tests imply that the sample size of each group must be equal to more that 29,800 to detect a difference of 0.01 at 5% significance level and power of 80% between the baseline callback rate of vocational students equal to 25% and that of apprentices.

where y_{ij} is an indicator variable equal to one if applicant i gets called back for job j. $\mathbb{1}_{i=apprentice}$ is an indicator variable equal to one if applicant i is an apprentice. β measures the callback rate difference between apprentices and vocational students. x_j is a vector of department and month fixed effects. ε_{ij} is a residual term.

The OLS estimates of β are reported in Table 2.4. The three first columns report the estimates for occupations pooled together, for different specifications including department and month fixed effects, and for the two categories of callbacks: "positive callbacks" and "propositions". The results, which are very stable across specifications and callback categories, confirm the absence of statistically signficant callback rates differences between apprentices and vocational students. Columns (4) displays the results for cooks and column (5) for bricklayers. Once again, the estimates of the β parameter are not statistically different from zero.[23]

2.4.2 Callbacks from large and small firms

Employers in small and large firms might have different preferences for apprentices versus vocational students, implying that the similarity of callback rates for apprentices and vocational students observed at the aggregate level could be the consequence of composition effects, stemming from relatively high callback rates for apprentices in small firms and relative low callback rates for apprentices in large firms. Indeed, apprentices might be more valuable in small firms, which need workers who are immediately productive and have less possibility to provide complementary on-the-job training. It is also likely that vocational students, whose education is more classroom-oriented than that of apprentices, have more transferable skills, which could be more valuable for large firms which can offer more varieties of jobs.

Table 2.5 shows that there is no difference in the callback rates of apprentices and vocational students between large and small firms. Therefore, the absence of difference between callback rates of apprentices and vocational students observed at the aggregate level is not the consequence of composition effects in the population of firms stemming from different behaviors of small and large firms.[24]

2.4.3 Callbacks for temporary and permanent jobs

It is possible that temporary jobs, which need employees immediately operational, are more suited for apprentices than for vocational students, whose abilities are less operational inasmuch they have much less work experience. On the other hand, permanent jobs, often associated with career perspectives within the firm, could be more suited for vocational students, whose spectrum of competencies might be wider than that of apprentices. Hence, one could expect that employers favor apprentices relative to vocational students for temporary jobs and make the opposite choice for permanent jobs.

[23]To address concerns about non-linear effects, we report the results of Table 2.4 replacing the linear probability model with a Probit model in Appendix 2.8.3. The Probit results in Table 2.12 show that the estimated marginal effects are very similar to the OLS results. This similarity holds for all the results in the paper.

[24]Similar results are displayed in Tables 2.15 and 2.20 for cooks and bricklayers respectively.

TABLE 2.5
Effects of apprenticeship on callback probability given different firm sizes

	Small Firms			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0316	0.0252	0.0294	0.00396	0.00223	-0.00428
	(0.0293)	(0.0307)	(0.0328)	(0.0212)	(0.0211)	(0.0223)
Student mean	0.2984***	0.2984***	0.2984***	0.2652***	0.2652***	0.2652***
	(0.0204)	(0.0204)	(0.0204)	(0.0156)	(0.0156)	(0.0156)
Observations	1,015	1,015	1,015	1,617	1,617	1,617
R-squared	0.001	0.009	0.116	0.000	0.003	0.071
Dep var: Proposition						
Apprenticeship	0.0201	0.0139	0.0183	0.00534	0.00484	-0.000404
	(0.0268)	(0.0276)	(0.0306)	(0.0195)	(0.0197)	(0.0205)
Student mean	0.2549***	0.2549***	0.2549***	0.2243***	0.2243***	0.2243***
	(0.0194)	(0.0194)	(0.0194)	(0.0147)	(0.0147)	(0.0147)
Observations	1,015	1,015	1,015	1,617	1,617	1,617
R-squared	0.001	0.009	0.122	0.000	0.003	0.059
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Small firms have less than 10 employees and large firms have at least 10 employees. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

Table 2.6 reports the callback rates for temporary and permanent jobs. The similarity of callback rates for apprentices and vocational students observed at the aggregate level is also observed for temporary jobs and permanent jobs.[25]

2.4.4 Callbacks in different labor market conditions

On tight labor markets, employers face hiring difficulties which imply that they tend not to be choosy when they select their workers. Since the callback rates of our applicants are quite high, about 25%, we can consider that our experiment concerns relatively tight labor markets. This may imply that we do not observe callback rate differences between apprentices and vocational students because employers have little choice. But it might be that callback rate differences show up on less tight labor markets.

To deal with this issue, we analyze how the callback rate difference between apprentices and vocational students varies according to the local unemployment rate. We estimate the difference in callback rate between apprentices and vocational students for each tercile of the unemployment rate at the commuting zone level.[26] The youth un-

[25] Similar results are displayed in Tables 2.16 and 2.21 for cooks and bricklayers respectively.
[26] We use the "zones d'emploi" from "INSEE". There are 304 "zones d'emploi" in metropolitan France.

TABLE 2.6
Effects of apprenticeship on callback probability given different contracts

	Temporary Jobs			Permanent Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0237	0.0227	0.0259	-0.0117	-0.0131	-0.00694
	(0.0198)	(0.0194)	(0.0198)	(0.0255)	(0.0259)	(0.0274)
Student mean	0.2871***	0.2871***	0.2871***	0.2564***	0.2564***	0.2464***
	(0.0150)	(0.0150)	(0.0150)	(0.0175)	(0.0175)	(0.0175)
Observations	1,820	1,820	1,820	1,286	1,286	1,286
R-squared	0.001	0.006	0.065	0.000	0.004	0.083
Dep var: Proposition						
Apprenticeship	0.0208	0.0205	0.0238	-0.00363	-0.00544	0.00293
	(0.0174)	(0.0175)	(0.0181)	(0.0245)	(0.0246)	(0.0261)
Student mean	0.2336***	0.2336***	0.2336***	0.2212***	0.2212***	0.2212***
	(0.0140)	(0.0140)	(0.0140)	(0.0166)	(0.0166)	(0.0166)
Observations	1,820	1,820	1,820	1,286	1,286	1,286
R-squared	0.001	0.004	0.061	0.000	0.004	0.091
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Temporary jobs comprise all offers for a seasonal contract or a determined duration contract. Permanent jobs are the complement. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

employment rate varies from 9.6% in the bottom tercile to 39.7% in the top tercile. The callback rate of students goes from 36.0% in the top tercile of unemployment rate to 22.6% in the bottom tercile. Table 2.7 shows that the callback rate of apprentices is not different from that of students, except in the top tercile of local unemployment rate. It is about 5 percentage points higher for positive callbacks and 4 percentage points higher (and significant at 10% confidence level only) for callbacks with a proposition for interview or hiring. This result holds when firms and job characteristics are controlled for. This indicates that apprentices have a comparative advantage which arises only when the local unemployment rate is very high, so that employers can be choosy because they have access to abundant job offers.[27]

[27]Similar results are displayed in Table 2.17 for cooks but not for bricklayers in 2.22, probably due to the low number of available observations.

TABLE 2.7
Effects of apprenticeship on callback probability given different labor markets

	All	T1 (7.2%)	T2 (8.5%)	T3 (10.8%)
	(1)	(2)	(3)	(4)
Youth unemployment rate	0.2500	0.0964	0.2050	0.3973
Dep var: Positive callback				
Apprenticeship	0.0184	-0.00668	-0.00178	0.0545**
	(0.0201)	(0.0423)	(0.0346)	(0.0270)
Student mean	0.2966***	0.3600***	0.3013***	0.2259***
	(0.0136)	(0.0248)	(0.0231)	(0.0220)
Observations	2,281	763	759	759
R-squared	0.079	0.103	0.091	0.091
Dep var: Proposition				
Apprenticeship	0.0152	-0.0133	0.0188	0.0399*
	(0.0169)	(0.0379)	(0.0283)	(0.0226)
Student mean	0.2524***	0.3147***	0.2456***	0.1956***
	(0.0129)	(0.0240)	(0.0217)	(0.0209)
Observations	2,281	763	759	759
R-squared	0.069	0.085	0.090	0.091
Month & Department FE	Yes	Yes	Yes	Yes
Firm & Job Characteristics	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. TX corresponds to the Xth tercile of the unemployment rate at the commuting zone level. Youth unemployment rates are computed from the French labor force survey, for youth aged 16 to 25, with secondary school vocational diploma, over 2014-2018 to get a sufficient number of observations at the commuting zone level. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

2.5 External validity and interpretation

Our correspondence study indicates that the callback rates of apprentices and students who apply for jobs as cooks and bricklayers are identical at the aggregate level. A small difference arises only when the local unemployment rate is high, suggesting that the employers have a slight preference for hiring apprentices. To interpret our results and explore whether the absence of comparative advantage for apprentices at the aggregate level may apply to other professions, we analyze the school-to-work and labor market transitions of vocational secondary school graduates using the *Génération* survey.[28]

Figure 2.1 displays the evolution of the employment rates of apprentices and vocational students who graduated in June-July of the year they left school.[29] The employment rates are displayed from October (month one) to

[28]The external validity of our findings outside the French context is discussed in the conclusion of the paper.

[29]Figures 2.8 and 2.9 in Appendix 2.8.4 and 2.8.4 display similar graphs for youths in the food sector and construction sector respectively with a similar interpretation.

September three years later. Apprentices perform much better: their employment rate is about 15 percentage points higher than that of vocational students over the whole period. The time profiles of employment rates are similar: they increase steadily during the first year and are approximately stable the two following years. The employment rate difference between apprentices and vocational students is approximately stable over the three years after graduation. The difference originates mostly from the start of the period, i.e. just after graduation. It reflects the difference between the share of apprentices who remain in their training firm and the share of vocational students who remain in the firm where they were interns before leaving school. 33.6% of apprentices have been hired by their training firm while 8.5% of vocational students have been hired after graduation in a firm where they were interns. Figure 2.1 shows that the profile of unemployment rates follows the same pattern. The unemployment rate of apprentices is lower than that of students just after graduation and the difference remains stable over three years.

Table 2.8, column 2, shows that the employment rate difference between apprentices and vocational students drops by half when observable characteristics, including gender, family background, industry and past school performance are accounted for. This is the consequence of the selection of the most advantaged students into apprenticeship described in section 2.2.2. Column 3 shows that the employment rate difference between apprentices and vocational students is no longer significantly different from zero over the three-year post-school period when observable characteristics *and* the retention rate in the training firms are accounted for. The three last columns of Table 2.8 show that the employment rate difference three years after leaving school vanishes when the observable characteristics and retention rates are taken into account. A similar pattern arises for the unemployment rates. The unemployment rate difference drops when the individual characteristics and the retention rates are accounted for.

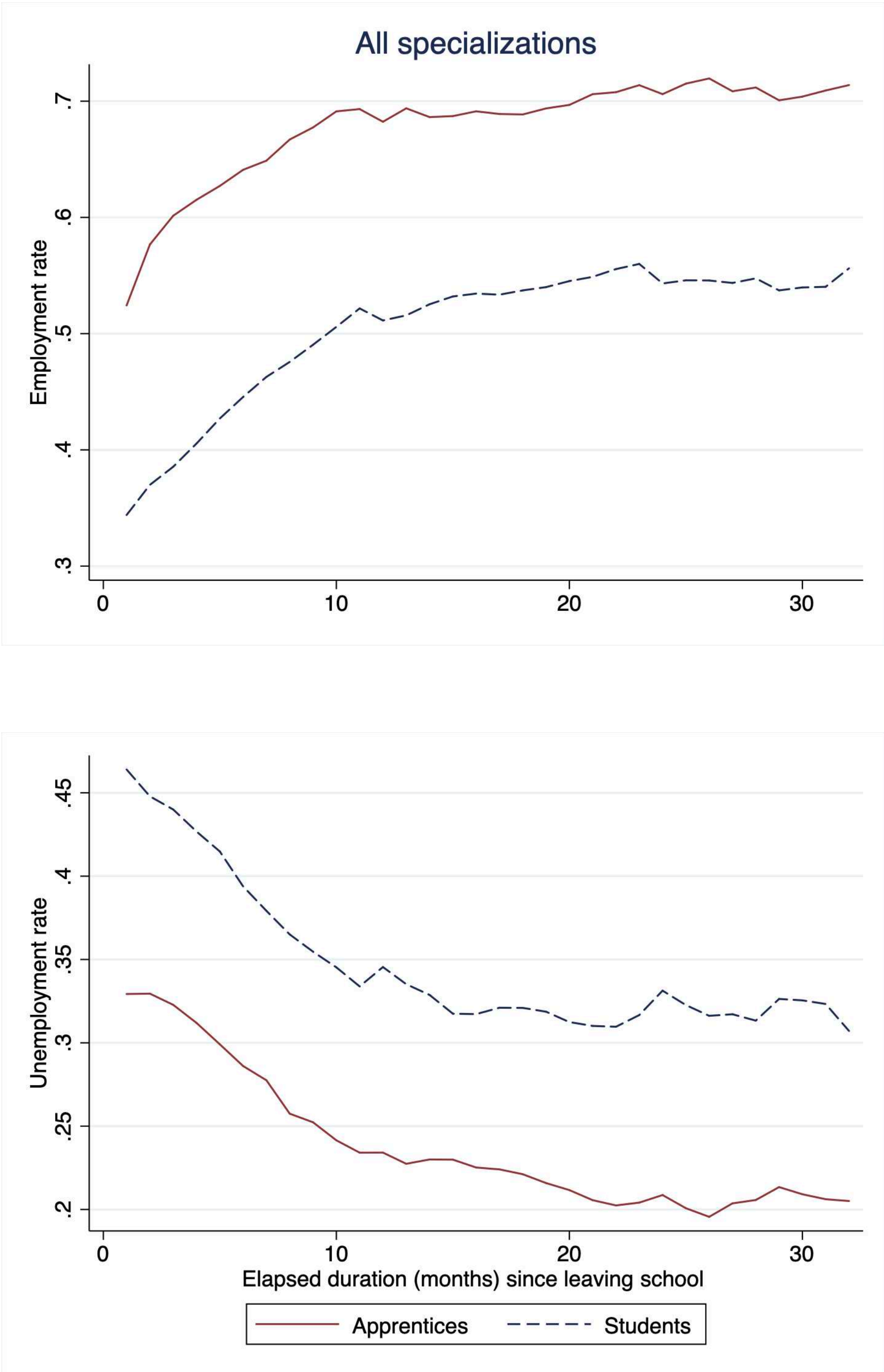
These facts are consistent with the findings of our correspondence study: the higher employment rate of apprentices after leaving school arises from their high retention rate in training firms compared with that of vocational students. Indeed, once they have been unemployed, apprentices do not get jobs at higher rate than vocational students. Table 2.9, which reports the estimation of proportional hazard models shows that the unemployment to employment and the non-employment to employment transitions of apprentices and vocational students are not statistically different once observable individual characteristics are controlled for.

We have also explored whether differences in unemployment rates or in exit rates from unemployment between apprentices and vocational students arise when the local unemployment rate is high, insofar as our correspondence study shows that the apprentices are more often called back than vocational students when the local unemployment rate is higher. We do not find any statistically significant difference between apprentices and vocational students for these outcomes.[30] This may be due to the insufficient number of observations.

All in all, this section shows that the results of our correspondence study, according to which there is almost no difference between the probability of getting a callback from employers for unemployed young cooks and bricklayers,

[30] This result, not shown in the paper to save space, is available on request.

FIGURE 2.1: Evolution of the share of students and apprentices in employment or unemployment after leaving school



Note: Students got their CAP diploma in June-July. Month zero stands for September.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ.

TABLE 2.8
OLS Regressions

Situations	All Years			3 Years After		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Employment						
Apprenticeship	0.145***	0.0789***	0.0336	0.118***	0.0459	0.0211
	(0.0224)	(0.0240)	(0.0238)	(0.0279)	(0.0303)	(0.0307)
Male		0.0908***	0.0756***		0.0635*	0.0552*
		(0.0261)	(0.0249)		(0.0330)	(0.0323)
Driving license		0.0931***	0.101***		0.121***	0.125***
		(0.0230)	(0.0216)		(0.0291)	(0.0288)
Graduated		0.0852**	0.0676*		0.0803	0.0709
		(0.0419)	(0.0391)		(0.0532)	(0.0521)
Firm retention			0.259***			0.142***
			(0.0236)			(0.0338)
Constant	0.551***	0.549***	0.572***	0.602***	0.621***	0.632***
	(0.0159)	(0.0241)	(0.0231)	(0.0203)	(0.0197)	(0.0196)
Observations	42,318	42,318	42,318	8,771	8,771	8,771
R-squared	0.022	0.172	0.204	0.016	0.214	0.224
Dep var: Unemployment						
Apprenticeship	-0.0888***	-0.0574***	-0.0210	-0.0776***	-0.0413	-0.0246
	(0.0206)	(0.0218)	(0.0217)	(0.0250)	(0.0274)	(0.0276)
Male		-0.0424*	-0.0303		-0.0190	-0.0134
		(0.0244)	(0.0237)		(0.0302)	(0.0300)
Driving license		-0.0813***	-0.0877***		-0.111***	-0.114***
		(0.0211)	(0.0203)		(0.0264)	(0.0263)
Graduated		-0.0728*	-0.0586		-0.0385	-0.0321
		(0.0397)	(0.0380)		(0.0516)	(0.0509)
Firm retention			-0.208***			-0.0959***
			(0.0208)			(0.0284)
Constant	0.328***	0.338***	0.319***	0.281***	0.283***	0.275***
	(0.0148)	(0.0248)	(0.0240)	(0.0184)	(0.0184)	(0.0182)
Observations	42,318	42,318	42,318	8,771	8,771	8,771
R-squared	0.010	0.147	0.171	0.008	0.183	0.189
Control Variables	No	Yes	Yes	No	Yes	Yes

Note: This table reports OLS estimates, where the dependent variable is a dummy variable equal to one if the individual is in employment, zero otherwise. “Apprenticeship” is a dummy variable equal to one if the individual has followed his vocational education as an apprentice. Columns (1) to (3) include all available years after leaving school, while columns (4) to (6) yield results three years after leaving school. We control for additional covariates in columns (2), (3), (5), and (6). Unreported control variables include demeaned dummies for the age at school end, being disabled, school level of father, school level of mother, father in employment, mother in employment, birthplace of father, birthplace of mother, department of residency, region of the training establishment, speciality of training, date. Firm retention is a demeaned dummy variable equal to one if the individual has been retained by his training firm after ending school. Robust standard errors are clustered at the individual level and presented in parentheses below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ

TABLE 2.9
Cox Regressions

Transitions	Non-Employment $\rightarrow$ Employment		Unemployment $\rightarrow$ Employment	
	(1)	(2)	(3)	(4)
Apprenticeship	1.3065***	1.0345	1.3375***	0.9344
	(0.1104)	(0.1316)	(0.1362)	(0.1653)
Male		1.1615		1.1036
		(0.1525)		(0.2044)
Driving license		1.5218***		2.0566***
		(0.1999)		(0.3811)
Graduated		1.8919***		2.3843**
		(0.4653)		(0.8244)
Observations	7,593	7,593	5,795	5,795
Control Variables	No	Yes	No	Yes

Note: This table reports probability ratio estimates from a proportional hazards model estimated with Cox regressions, where the dependent variable is a dummy variable equal to one if the individual has undergone a transition from a non-employment situation to an employment situation. "Apprenticeship" is a dummy variable equal to one if the individual has followed his vocational education as an apprentice. Columns (1) to (2) consider any situations of non-employment from employment situations. While columns (3) to (4) yield estimates from unemployment to employment situations. We control for additional covariates in columns (2) and (4). All of the control variables are fixed over time. Unreported control variables include dummies for the age at school leaving, being disabled, school level of father, school level of mother, father in employment, mother in employment, birthplace of father, birthplace of mother, department of residency, region of the training establishment, speciality of training. Robust standard errors are clustered at the individual level and presented in parentheses below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ

formerly either apprentice or vocational student, is consistent with the school-to-work and labor market transitions of overall low skilled youth. The next section builds and estimates a model to evaluate the impact of apprenticeship expansion on youth unemployment in this context.

2.6 The model

This section sets out and estimates a search and matching model which allows us to reproduce the main stylized facts of the French youth labor market of vocational students and apprentices who have just graduated. Then, the model is used to simulate the impact of the expansion of apprenticeship on the youth unemployment rate.

2.6.1 Conceptual framework

We consider a population of N young individuals who complete their initial education. There are N_a apprentices and N_s students (i.e. individuals who studied without being apprentices):

$$N = N_a + N_s \tag{2.1}$$

This is a static, one period model. Insofar as we focus on school-to-work transitions and the data displayed above show that the employment rate difference between apprentices and students remains almost constant over the three year period that we analyze, there is no obvious gain to considering a dynamic multi-period model.

Individuals are risk neutral and derive utility from consumption only. The timing of events is as follows. 1/ the share ρ of apprentices remain in their training firm and the complementary share look for jobs; 2/ firms create job vacancies; 3/ students and apprentices looking for jobs send applications to job vacancies; 4/ employers select the workers they want to hire: 5/ wages are bargained over and production takes place.

We start by assuming that there is an exogenous share ρ of apprentices who remain in the firm where they were apprentice. This assumptions is relaxed below. Accordingly, we now focus on youth looking for jobs. The productivity of an individual starting a job after education completion is denoted by y. This productivity is drawn in different distributions for apprentices and students. The draw is made at the instant of the match between the youth and the job. This means that the productivity is job specific. The cumulative distribution of y is denoted by G_s for students and by G_a for apprentices who apply to firms in which they did not train.

A job with productivity y yields profits

$$J(y) = y - w(y) \tag{2.2}$$

where $w(y)$ stands for the wage whose value is determined by bargaining. The bargaining implies that workers get the share β of job surplus. In case of agreement, workers get utility $w(y)$ and firms profits $y - w(y)$. In case of disagreement, worker get the unemployment income z and firms get zero profits. Therefore, the surplus of a job with productivity y is equal to $y - z$.

Labor costs have a lower bound induced by the minimum wage $w_{\min}$, which is larger than z the income of unemployed individuals. Therefore, wages are set by bargaining subject to the minimum wage constraint:

$$w(y) = \begin{cases} z + \beta(y - z) & \text{if } y \geq \bar{y} \\ w_{\min} & \text{if } w_{\min} \leq y < \bar{y} \end{cases} \tag{2.3}$$

where $\bar{y} = \left[w_{\min} - (1-\beta)z\right]/\beta$. This equation indicates that the wage is equal to $z + \beta(y - z)$ if the productivity is larger than $\bar{y}$ and to the minimum wage if it belongs to the interval $[w_{min}, \bar{y}]$. The job is not filled is the productivity is smaller than $w_{\min}$, which corresponds to the reservation productivity.

Students and apprentices who did not remain in their training firm look for jobs. To do so, they send applications to job offers. It is assumed that matches between job openings and applications are determined by an urn-ball matching process[31] where job openings are assimilated to urns, and job applications to balls tossed at the urns by job seekers. In this framework, a match occurs when a ball goes into an urn. As job seekers simultaneously apply for jobs not knowing where other job seekers are sending their applications, some vacancies get no application, while others may get one or more applications. For the sake of simplicity, it is assumed that each applicant sends one application.

[31] Hall (1979), Pissarides (1979), Blanchard and Diamond (1994).

Hiring decisions

Firms observe the total number of applicants, $n = n_a + n_s$ at zero costs, but face screening costs, denoted by c, to screen each application. The screening costs are different across firms. Firms discover the productivity of the applicant after the hiring interview. If the productivity is above its reservation level $w_{\min}$, the applicant is hired. If the productivity is below the reservation productivity, the firm does not keep the applicant and makes zero profits during the period. [32] Therefore, the expected profit from calling back an apprentice and a student is, respectively:

$$\begin{aligned}\pi_a &= \int_{w_{\min}}^{y_{\sup}} J(y)\text{d}G_a(y) \\ \pi_s &= \int_{w_{\min}}^{y_{\sup}} J(y)\text{d}G_s(y)\end{aligned}$$

In this context, the expected profit of firms with one applicant and screening costs c is

$$\pi(1, c) = p(a)\pi_a + [1 - p(a)]\,\pi_s - c \tag{2.4}$$

where

$$p(a) = \frac{\alpha(1-\rho)}{\alpha(1-\rho) + 1 - \alpha}$$

denotes the probability to draw a apprentice, $\alpha = N_a/N$ is the share of apprentices in the youth population and ρ the retention rate of apprentices in their training firm.

A firm with two applicants which draws an apprentice first decides to stop screening résumés because firms prefer to hire apprentices. If the first résumé belongs to a student, the firm continue screening if the expected profit from calling back the student, equal to π_s, is smaller than $\pi(1)$, the expected profit from screening the last résumé. Therefore, the expected profit of a firm with two applicants is equal to

$$\pi(2, c) = p(a)\pi_a + [1 - p(a)] \max\{\pi(1, c), \pi_s\} - c.$$

Using the same reasoning, the expected profit of a firm with $n > 1$ applicants can be computed recursively:

$$\pi(n, c) = p(a)\pi_a + [1 - p(a)] \max\{\pi(n-1, c), \pi_s\} - c$$

A firm with $n > 0$ applications which has screened $x < n$ applications of students continues screening applications if $\pi(n - x, c) > \pi_s$ and stops if $\pi(n - x, c) \leq \pi_s$. Thus, a firm with n applications screens at most $m(n, c) \in \mathbb{N}$

[32] It is assumed that firms can interview one applicant only. Assuming that employers can interview several applicants complicates the analysis without allowing us to better estimate the substitutability between apprentices and students at the hiring stage insofar as there are no available data which disentangle the callback stage and the hiring stage of the hiring process.

applications, where

$$m(n,c) = \{\text{floor of } \zeta | \pi(n-\zeta, c) = \pi_s\} \tag{2.5}$$

Equation (2.5) determines a unique value of $m(n,c)$, the maximum number of screened applications for firms with n applications and screening costs c, because $\pi(n,c)$ is an increasing function of the number of applicants.

Since firms get an apprentice with probability $p(a)$ each time they draw an application, a firm with n applicants and screening costs c calls back an apprentice with probability

$$p(a|n,c) = \begin{cases} p(a) \sum_{i=0}^{m(n,c)-1} [1-p(a)]^i & \text{if } n > 0 \\ 0 & \text{if } n = 0 \end{cases}$$

and a student with the complementary probability

$$p(s|n,c) = \begin{cases} 1 - p(a|n,c) & \text{if } n > 0 \\ 0 & \text{if } n = 0 \end{cases}$$

For each firm, the total screening costs of applications is equal to c times the number of screened applications. Therefore, the expected total screening costs of firms with $n > 0$ applications are equal to the screening costs c times the expected number of screened applications:

$$C(n,c) = c \sum_{i=0}^{m(n,c)} [1-p(a)]^i$$

Once the probability to hire an apprentice and a student and the total screening costs are determined, one can compute the expected profit of firms with n applicants and inspection costs c:

$$\Pi(n,c) = \begin{cases} p(a|n,c)\pi_a + [1-p(a|n,c)]\,\pi_s - C(n,c) & \text{if } n > 0 \\ 0 & \text{if } n = 0 \end{cases}$$

The value of job vacancies

Since the matching between job applications and job openings is determined by the urn-ball model where each job seeker sends one application, the probability that a vacant job gets n_a applications from apprentices is defined by the binomial probability function with parameters $(1-\rho)N_a$ (the number of trials) and $1/v$ (the probability of success of each trial), denoted by $b(n_a, (1-\rho)N_a, 1/v)$. Similarly, the probability to receive n_s applications from students is defined by the binomial probability function $b(n_s, N_s, 1/v)$. Once applications have been received, firms draw the inspection costs in the distribution whose cumulative distribution function is denoted by F assumed to be continuous on the interval $[c_{\min}, c_{\max}]$, where is strictly positive and finite. Therefore, the value of a vacant job is

$$V = -h + \sum_{n_a=0}^{(1-\rho)N_a} b(n_a,(1-\rho)N_a,1/v) \sum_{n_s=0}^{N_s} b(n_s,N_s,1/v) \int_{c_{\min}}^{c_{\max}} \Pi(n_a+n_s,c)\mathsf{d}F(c) \tag{2.6}$$

where h stands for the costs of job vacancy.

Job creation

Free entry implies that firms create jobs until the value of vacant jobs is equal to zero: $V = 0$. From equation (2.6) the free entry condition implies that:

$$h = \sum_{n_a=0}^{(1-\rho)N_a} b(n_a,(1-\rho)N_a,1/v) \sum_{n_s=0}^{N_s} b(n_s,N_s,1/v) \int_{c_{\min}}^{c_{\max}} \Pi(n_a+n_s,c)\mathsf{d}F(c) \tag{2.7}$$

Labor market equilibrium

The equilibrium value of the number of vacant jobs is determined by equation (2.7). This value is unique (assuming its existence), since the binomial probability function necessarily decreases with the number of vacant jobs.

Once v has been determined, one can compute the number of jobs won by apprentices who have not been retained in their firm and the number of jobs won by students.

Firms which choose among their applicants draw an application of apprentice if there is at least one apprentice among their applicants. Therefore, the number of jobs won by apprentices who have not been retained in their firm and the number of jobs won by students are:

$$\begin{aligned} L_a &= v \sum_{n_a=0}^{(1-\rho)N_a} \sum_{n_s=0}^{N_s} b(n_a,(1-\rho)N_a,1/v) b(n_s,N_s,1/v) \int_{c_{\min}}^{c_{\max}} p(a|n_a+n_s,c)\mathsf{d}F(c)\left[1-G_a(w_{\min})\right] \\ L_s &= v \sum_{n_a=0}^{(1-\rho)N_a} \sum_{n_s=0}^{N_s} b(n_a,(1-\rho)N_a,1/v) b(n_s,N_s,1/v) \int_{c_{\min}}^{c_{\max}} p(s|n_a+n_s,c)\mathsf{d}F(c)\left[1-G_s(w_{\min})\right] \end{aligned}$$

From these two equations we can determine the hiring probability of apprentices and students, equal to $L_a/(1-\rho)N_a$ and L_s/N_s respectively. Then, the unemployment rates of apprentices and students follow

$$u_a = 1-\rho-\frac{L_a}{\alpha N} \tag{2.8}$$

$$u_s = 1-\frac{L_s}{(1-\alpha)N} \tag{2.9}$$

which yield the youth unemployment rate:

$$u = \frac{N-\rho\alpha N - L_a - L_s}{N} = \alpha u_a + (1-\alpha)u_s \tag{2.10}$$

and the unemployment rate of individuals who are looking for a job, i.e. those who do not remain in their training firm:

$$\tilde{u} = \frac{N - \rho\alpha N - L_a - L_s}{N - \rho\alpha N} = 1 - \frac{L_a + L_s}{(1 - \rho\alpha)N}$$

The callback probabilities are computed in Appendix 2.8.5.

2.6.2 Estimation and calibration

To bring the model to the data and to consider a population similar to that of our correspondence study, we rely on the *Generation* surveys conducted in 2013 and 2016 that we harmonized and pooled together. In line with our correspondence study, the analysis is restricted to young males who enrolled in a CAP-equivalent program after middle school and work in construction, restaurant and hotel and related sectors to get a sufficient number of observations (see Appendix 2.8.6).

One needs to determine the value of seven parameters, plus the shapes of the productivity distributions of apprentices and students. The seven parameters are: 1/ the share of apprentices, α, set to 0.5 to match the observed share in our population; 2/ the retention rate of apprentices in their training firms, ρ, set to 0.25 to match the difference between the retention rate of apprentices and the share of vocational students employed in firms in which they were interns when they studied; 3/ the income of unemployed workers, z, the value of which is set to €904;[33] 4/ the bargaining power parameter, β, set to 0.5 in the benchmark version (Appendix 2.8.7 shows that our conclusions remain qualitatively unchanged for different values of β) ; 5/ the cost of creation of vacant jobs, h. 6/ The upper and the lower bound the distribution of screening costs assumed to be uniform on the interval $[c_{min}, c_{max}]$. We set c_{max} =€5 and jointly determine the values of h and c_{min} to match the unemployment rates of apprentices and students, once their productivity distributions have been estimated.

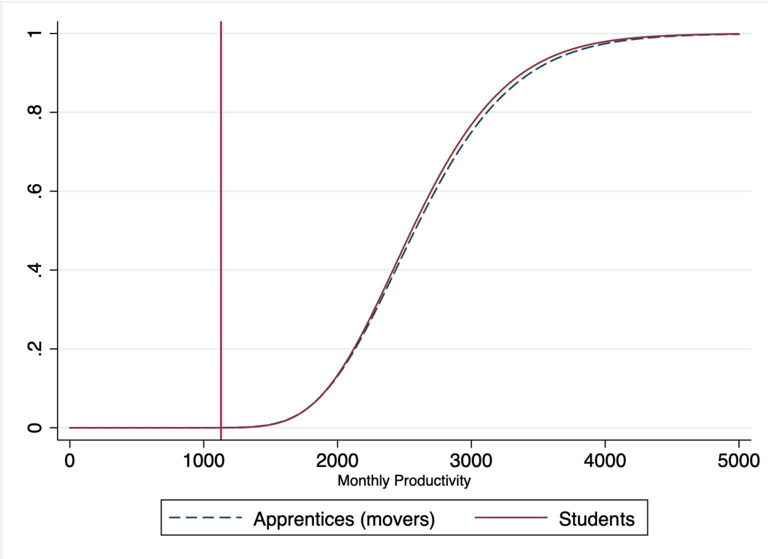
The productivity distributions of apprentices and vocational students, $G^j(y),\ j = a, s$, are estimated assuming that wages are determined by the wage bargaining solution described in equation (2.3). This implies the following relation between wage and productivity:

$$y = \frac{w(y) - z(1-\beta)}{\beta} \text{ if } w(y) > w_{min} \quad \text{and} \quad y \leq \frac{w(y) - z(1-\beta)}{\beta} \text{ otherwise} \tag{2.11}$$

We start by estimating the wage distributions of apprentices not retained in their training firm and of vocational students, conditional on experience, region of residence, family situation and work environment, from which we retrieve the productivity distributions. These productivity distributions are displayed on Figure 2.2 (see Appendix 2.8.6 for details about the estimation of these distributions). The two distributions are very close, which is consistent with the absence of statistically significant difference between the exit rate from unemployment of apprentices and

[33] This corresponds to the mean value of unemployment benefits for a male unemployed worker aged below 25 years receiving unemployment benefits in 2016. More details here.

FIGURE 2.2: Cumulative distributions of productivity of students and apprentices not retained in their training firm



Source: pooled *Génération 2010-2013* surveys, CEREQ.

students. Nevertheless, these distributions imply that employers prefer to invite apprentices for interview if selecting applicants is not costly, because the average productivity (conditional on being larger than the reservation productivity) of apprentices is slightly larger than that of students, as shown in Table 2.10, although the difference is not statistically significant (p-value$= 0.81$). The effects of this preference for apprentices on the callback and hiring probabilities of apprentices and students depend on the number of applicants received by each firm. If this number is small, which is the case when the unemployment rate is low, the preference for interviewing apprentices first has almost no impact on the hiring probability difference between students and apprentices, to the extent that firms have small pools of applicants. However, if the number of applicants is large, the preference for interviewing apprentices first may induce significant callback and hiring rates differences.

The values of parameters are summarized in Table 2.10. All in all, the model reproduces an unemployment rate difference between apprentices and students that is compatible with their empirical wage distributions. The callback rate difference between apprentices and students predicted by the model, which is equal to 2.6 percentage points (as displayed in Figure 2.3b), is in line with the 95% interval confidence of our correspondence study, as shown in Table 2.4. The model is also able to reproduce the finding of our correspondence study that the callback rate difference between apprentices and students increases with the local unemployment rate. This is shown on Figure 2.3 which displays the effects of changes in h, the costs of job creation. Increases in job creation costs, which decrease job creation, raise unemployment for apprentices and students. This is accompanied by a rise in the apprentice/student callback rate difference consistent with the results of our correspondence study. As reported in Table 2.7, which displays the results of the correspondence study, the callback rate for interview difference between

TABLE 2.10
Calibration of Exogenous Parameters

Description	Parameter	Value
Initial unemployment rate of apprentices	u_a	0.1972
Initial unemployment rate of students	u_s	0.2894
Share of apprentices	α	0.5
Share of the job surplus going to workers	β	0.5
Share of apprentices retained in their training firm	ρ	0.25
Level of unemployment benefits	z	€904
Level of net minimum wage	w_{min}	€1,129.30
Average productivity of apprentices	$\mathbb{E}[y\vert G_a]$	€2,643.20 (SE=36.22)
Average productivity of students	$\mathbb{E}[y\vert G_s]$	€2,627.24 (SE=44.52)
Cost of job creation	h	€433.48
Share of firms drawing applications at random	η	0.90

Note: This table reports the values associated with the exogenous parameters of the model. α, ρ, u_a and u_s are estimated from the pooled *Génération 2010-2013* surveys. w_{min} and z come from official sources of Insee and Pôle emploi respectively. h and η are jointly determined to match the equilibrium values of the unemployment rates of apprentices and students with their empirical values. Productivity is the monthly amount of production in euros estimated from the method described in Appendix 2.8.6. In this table, apprentices accounted for are those not retained in their training firm.

apprentices and students belong to the 95 percent confidence interval $[0.0, 0.8]$ when the unemployment rate is very high, about 40%, meaning that the callback difference *slightly* increases with the unemployment rate. The model reproduces well the fact that the apprentice/student callback rate difference varies little with the unemployment rate. According to Figure 2.3, this difference reaches 3.5 pp when the unemployment rate amounts to 40%, which is consistent with the results reported in Table 2.7.

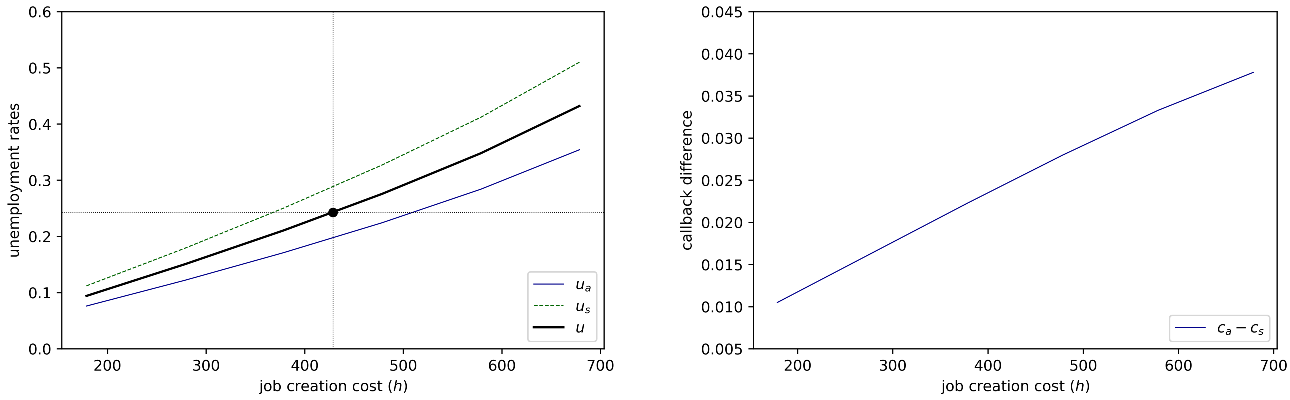
2.6.3 Counterfactual exercises

The model can be used to analyze the consequences of expansions of apprenticeship on labor market outcomes. We start by analyzing the effects of the expansion of the share of apprentices α by 10 percentage points from its benchmark value equal to 50%, assuming that the retention rate of apprentices in their training firm and the productivity distribution of apprentices and students remain constant when the share of apprentices changes. These assumptions are relaxed and discussed below.

Figure 2.4d shows that the expansion of the share of apprentices α reduces the number of job vacancies because there are less youth looking for jobs. The number of job vacancies decreases because the increase in expected profits associated with the increase in the share of apprentices, whose productivity is slightly higher than that of students, does not compensate the drop in the number of applicants, due to the increased number of apprentices remaining in their training firms.

The expansion of apprenticeship increases the unemployment rate of vocational students (Figure 2.4b), because they face a more intense competition from apprentices. The unemployment rate of apprentices also slightly

FIGURE 2.3: Relation between cost of job creation, unemployment rates and callback difference between apprentices and students



(A) Unemployment Rates

(B) Callback Difference

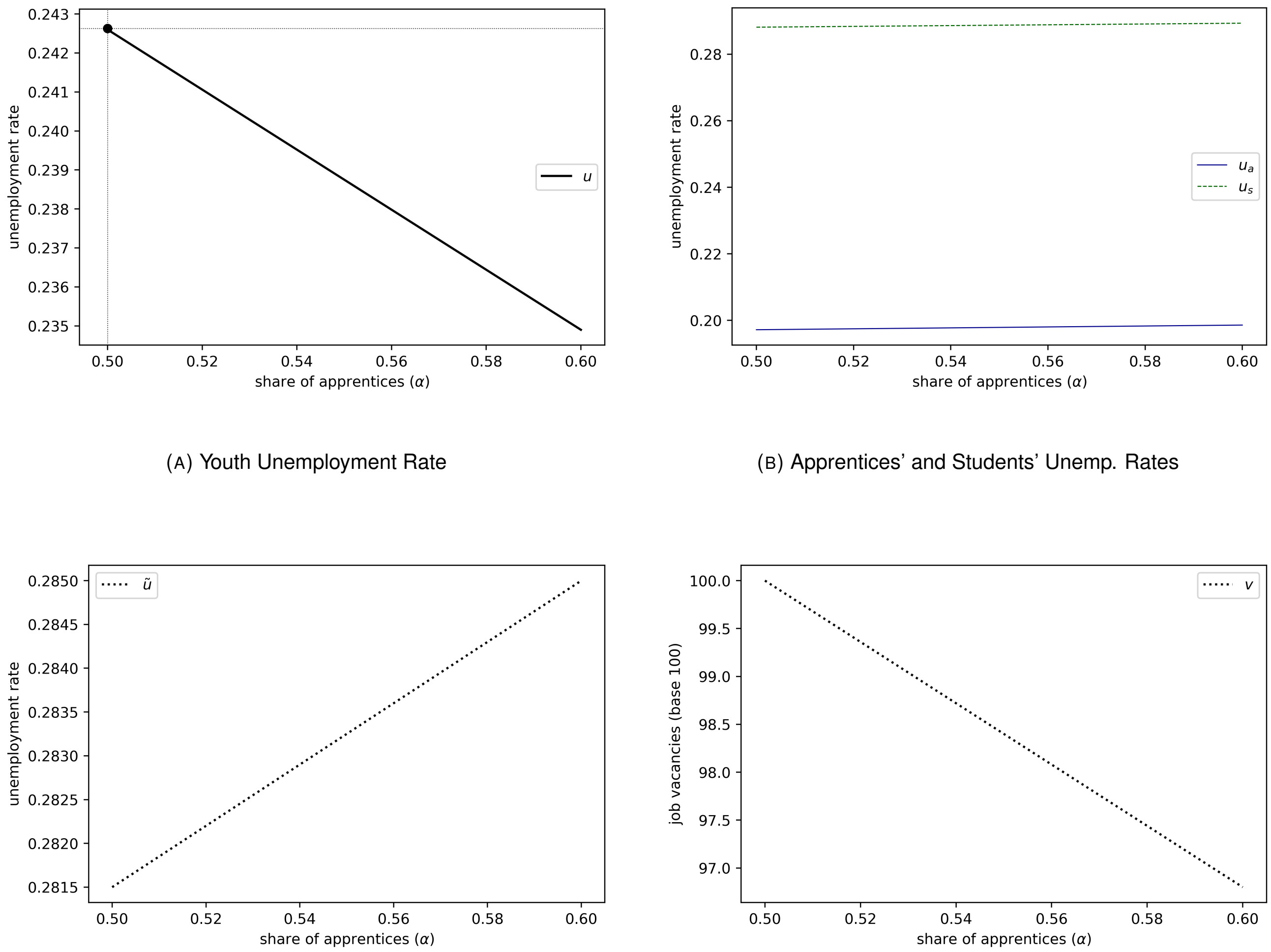
increases because they compete more often with other apprentices rather than with students. Let us remark that the increase in the unemployment rate of apprentices not retained in their training firm *and* in the unemployment rate of students is compatible with a decrease in the unemployment rate of the population composed of apprentices not retained in their training firm and of students (i.e. the population of job seekers) as shown on Figure 2.4c, because raising the share of apprentices increases the share of individuals whose unemployment rate is lower.

Figure 2.4a shows that the youth unemployment rate drops from 24.3% to 23.6% when α, the share of apprentices, increases by 10 percentage points. If the unemployment rates of apprentices and student remained constant, the unemployment rate would decrease by 0.9 percentage points.[34] The model shows that the unemployment rate drops by 0.7 percentage points when the unemployment rates of apprentices and students adjust. This is a very small drop suggesting that increasing the share of apprentices has a very limited impact on youth unemployment. The small size of the drop is mainly the consequence of the relatively low retention rate of apprentices in their training firm, which is only 25 percentage points higher than that of vocational students, and of the absence of positive effects of apprenticeship on the likelihood to find jobs for apprentices not retained in their training firm. It is also due, to a lesser extent, to the increase in the unemployment rate of vocational students and of apprentices, as explained above.

Figure 2.5 displays the effects of larger changes in the share of apprentices, which goes from zero to one. The expansion of apprenticeship always raises the unemployment rates of students and apprentices for the reasons just explained. It is striking that very large changes in the share of apprentices induce limited changes in youth unemployment, which goes from 28.2% to 20.6% when the share of apprentices goes from zero to one. This drop is

[34] According to equation (2.10), the unemployment rate varies by $(u_a - u_s)\mathrm{d}\alpha$ when the share of apprentices changes by $\mathrm{d}\alpha$. Using the figures reported in Table 2.10, we determine that the unemployment rate decreases by 0.9 percentage points if α increases by 10 percentage points.

FIGURE 2.4: Evolution of indicators when the Share of Apprentices is increasing



(A) Youth Unemployment Rate

(B) Apprentices' and Students' Unemp. Rates

(C) Youth Job Seeker Unemp. Rate

(D) Labor Market Tightness

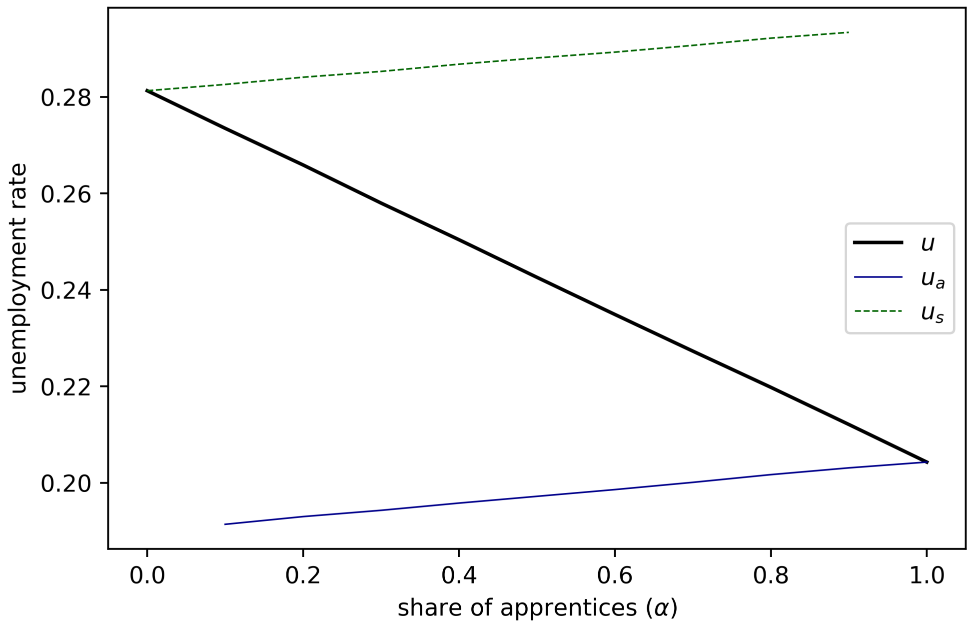
entirely due to the increase in the retention rate of youth in training firms associated with apprenticeship. Contrary to what might be expected, the expansion of apprenticeship does not sufficiently boost job creation to amplify the effects of the increase in the retention rate in training firms. Actually, the opposite occurs: the overall effects of the expansion of apprenticeship on the drop in youth unemployment is smaller than that induced by the increase in the retention of youth in their training firm. The ultimate reason for this result is that the productivity of apprentices outside their training firm is very close to that of vocational students according to our estimation.

2.6.4 Scope of results

The impact of apprenticeship expansion on the youth unemployment rate is estimated to be small by our model. We now discuss to what extent this result may hinge on specific assumptions.

First, it is assumed that there are no selection effects associated with changes in the share of apprentices insofar

FIGURE 2.5: Share of Apprentices and Youth Unemployment Rates



as counterfactual exercises assume that the retention rate of apprentices in their training firm and the productivity distribution of apprentices and students remain constant when the share of apprentices changes. However, as shown in section 2.2.2, young people who choose apprenticeship are generally more employable than those who choose the vocational school path. Therefore, it is likely that increasing the share of apprentices attracts less employable youth facing more difficulties in finding jobs when unemployed. This implies that not accounting for selection effects leads to overestimate the positive impact of apprenticeship expansion on youth employment.

Second, the retention rate in training firms has been assumed to be exogenous. It is likely that the selection of youth less motivated by apprenticeship when apprenticeship is expanded reduces the retention rate, thus reinforcing our result according to which apprenticeship expansion has a small negative impact on youth unemployment. On the other hand, the expansion of apprenticeship worsens the employment opportunities of apprentices leaving their training firms, because the unemployment rate of apprentices increases when the share of apprentices rises, as shown above.

This can be seen by making the retention rate endogenous. To do so, let us assume, in line with discrete choice models, that the utility obtained from remaining in the training firm depends on an individual specific additive preference parameter, denoted by $e \in \mathbb{R}$. Hence, the utility of remaining in the training firm is equal to the income plus e, while the utility of working elsewhere is equal to the income.

The timing of decisions is as follow. 1/ Apprentices decide either to stay or to leave their training firm at the end of their apprenticeship. If they leave, they look for another job; 2/ If they decide to remain in their training firm, they draw their productivity y in the distribution with cumulative distribution function G_0; 3/ If the productivity is above the reservation productivity, they bargain their wage, otherwise, they are unemployed.

The optimal decisions are found by backward induction. In step 3/ apprentices remain in the firm if their productivity y is larger than the minimum wage $w_{\min}$, in which case their wage is determined as for the other apprentices, i.e. by equation (2.3). In step 1/ apprentices decide to remain in the firm if their expected utility from doing so is larger than that obtained from looking for a job elsewhere.

An apprentice i who decides to remain in his training firm gets the expected utility

$$\mathbb{E}[U \,|\, \text{remaining in training firm}] = \int_{w_{\min}}^{y_{\sup}} w(y)\mathrm{d}G_0(y) + G_0(w_{\min})z + e$$

An apprentice who decides to leave his training firm gets the expected utility

$$\mathbb{E}[U \,|\, \text{leaving training firm}] = \frac{1-\tilde{u}_a}{1-G_a(w_{\min})} \int_{w_{\min}}^{y_{\sup}} w(y)\mathrm{d}G_a(y) + \tilde{u}_a z$$

where $\tilde{u}_a$ is the unemployment rate of apprentices who leave their training firm. In this framework, an apprentice decides to remain in his training firm if and only if

$$e \geq \bar{e} = \frac{1-\tilde{u}_a}{1-G_a(w_{\min})} \int_{w_{\min}}^{y_{\sup}} w(y)\mathrm{d}G_a(y) + \left[\tilde{u}_a - G_0(w_{\min})\right] z - \int_{w_{\min}}^{y_{\sup}} w(y)\mathrm{d}G_0(y) \tag{2.12}$$

This equation implies that the threshold value $\bar{e}$ of the preference parameter below which the apprentices leave the firm decreases with the unemployment rate of apprentices, meaning that apprentices are more induced to remain in their training firm when their unemployment rate is higher. Denoting by Φ the cumulative distribution function of e, the retention rate is equal to

$$\rho = 1 - \Phi(\bar{e})$$

From this definition, one can compute the impact of changes in α, the share of apprentices on the retention rate. Insofar as equation (2.12) shows that changes in the share of apprentices induce changes in $\bar{e}$ only through their effects on $\tilde{u}_a$, the unemployment rate of apprentices who leave their training firm, the impact of α on ρ is given by

$$\frac{\partial \rho}{\partial \alpha} = \underbrace{-\Phi'(\bar{e})}_{<0} \underbrace{\frac{\partial \bar{e}}{\partial \tilde{u}_a}}_{<0} \underbrace{\frac{\partial \tilde{u}_a}{\partial \alpha}}_{>0} > 0.$$

This term is positive because increasing the share of apprentices increases $\tilde{u}_a$, the unemployment rate of apprentices leaving their training firms. The increase in the unemployment rate induces apprentices to remain in their training firm because the probability of finding a job on the labor market is reduced, which corresponds to the term $\partial\bar{e}/\partial\tilde{u}_a$. Hence, this mechanism implies that expanding the share of apprentices should increase the retention rate. However, it is likely that the size of this effect is very limited because the unemployment rate of apprentices reacts very little to changes in the share of apprentices, as shown by Figure 2.5.

All in all, the sign of the impact of changes in the share of apprentices on their retention rate in their training firms is ambiguous in theory. It depends on the relative importance of the selection effects, which yield a negative relation between the share of apprentices and the retention rate, and of the impact of the unemployment rate response, which yields a relation of opposite sign. However, the empirical contribution of Brébion (2020) finds that policies which increased the share of apprentices in France reduced the retention rate of apprentices, suggesting that the selection effects dominate the unemployment effect. This conclusion suggests that our benchmark evaluation, which does not account for the reaction of the retention rate, overestimates the positive impact of apprenticeship on employment. This reinforces our conclusion according to which expanding apprenticeship should be accompanied by policies that increase the retention rate to effectively foster youth employment.

2.7 Conclusion

This paper shows that apprentices do not perform significantly better than vocational students when they look for jobs outside the firm in which they were trained. Obviously, this result has been obtained in the French context and it is possible that apprentices are selected and trained differently in firms in other contexts. Dustmann and Schönberg (2012) argue that the well-structured regulatory framework and monitoring institutions that exist in Germany entail that apprenticeship training schemes are more successful in countries like Germany rather than in Anglo-Saxon countries like the United Kingdom, because more firms are able to commit to training provision. Ryan (2000) stresses that the involvement of trade unions and employers' associations, which is different in these two types of country, may also play a role. Hence, specific institutional features might explain the absence of comparative advantage for apprentices in France (Cahuc et al., 2014).

Nevertheless, economic theory shows that employers have limited incentives to transmit to apprentices knowledge of value outside the training firm (Becker, 1964, Acemoglu and Pischke, 1998, Malcomson et al., 2003, Garicano and Rayo, 2017, Fudenberg and Rayo, 2019). When apprentices obtain the same diploma as vocational students and can leave their training firm after graduation, employers may have limited incentives to transmit more knowledge to their apprentices than that acquired by vocational students in the classroom. Otherwise, apprentices could easily benefit from a competitive advantage that would allow them to bargain wage increases after graduation. Hence, economic theory suggests that the absence of significant competitive advantage of apprentices with respect to vocational students observed in the French context might be true in other contexts.

The conclusion that apprentices do not necessarily perform significantly better than vocational students when they look for jobs outside the firm in which they trained has important consequences for public policy. If the main advantage of apprenticeship is the creation of better matches between labor market entrants and jobs, policies should be more focused on this dimension and favor collaboration between schools and public employment services. This collaboration, which is almost non-existent in many OECD countries, is well developed in Japan and in Germany, which share important common attributes in this respect (Ryan (2001), p. 59) and which are very successful at integrating youths into employment. In Japan, where apprenticeship is very rare, high schools provide career support for their students.[35] Counselling and job search training are often part of senior high school curricula from the first year. In the second year of high school, many schools have specific career preparation classes for students who do not intend to pursue higher education. In the third year of high school, aspiring labor market entrants undergo a regulated job placement process at school in which the teachers responsible for career guidance match students to the available positions based on vacancy lists provided by public employment agencies. The application process follows a strict schedule to promote equal opportunities among graduates and to ensure that students focus on completing their studies. Students are not allowed to seek work independently, and employers are expected to cooperate with public employment agencies when hiring future graduates. The job placement of high school graduates is remarkably effective, about 90%, and there is little evidence that it comes at the cost of lower job stability. In Germany, the Federal Employment Office recommends secondary school applicants to sponsoring employers. As in Japan, there are important interactions between schools and public employment agencies. The effectiveness of this strategy is also stressed by Noelke and Horn (2014) who argue that economic liberalization in post-socialist countries like Hungary has made the transition from vocational education to work more difficult by breaking linkages from schools to employers that performed a critical matching function.

Our findings suggest that the German-Japanese strategy targets an important cause of youth unemployment: the difficulty for job market entrants in finding jobs to which they are suited. Hence, improving the job placement of school leavers thanks to the involvement of public employment services in schools may be an important lever to boost youth employment.

[35] See OECD (2017), pp. 134 ss.

2.8 Appendix

2.8.1 Examples of documents for applications

Application email messages (by layout)

For type 1 applications, the email message was the following:

Object: Application job offer n°XXX

Attached files: Curriculum_Vitae.pdf, Lettre_Motivation.pdf

Dear Madam, Sir,

With reference to your advertisement XXX for the position of YYY, I wish to submit my application. Please find enclosed my cover letter and my resume. May I assure you, Madam, Sir, of my sincere gratitude.

First name, Last name

Phone number

For type 2 applications, the email message was the following:

Object: Application (job ads XXX)

Attached files: CV.pdf, LM.pdf

Dear Madam, Sir,

I am pleased to submit my application for the position of YYY following your advertisement XXX published on the website Pôle Emploi.

I am sending you in the attachment my resume and my cover letter.

May I assure you, Madam, Sir, that I remain faithfully yours.

First name, Last name

Phone number

<u>Application reply email messages</u> (by candidate)

For Alexis Dubois application reply, the email message was the following:

Greetings,

Thank you for your consideration of my application. However, I am unable to respond favourably. Indeed, I have accepted another offer.

With kind regards,
Alexis Dubois

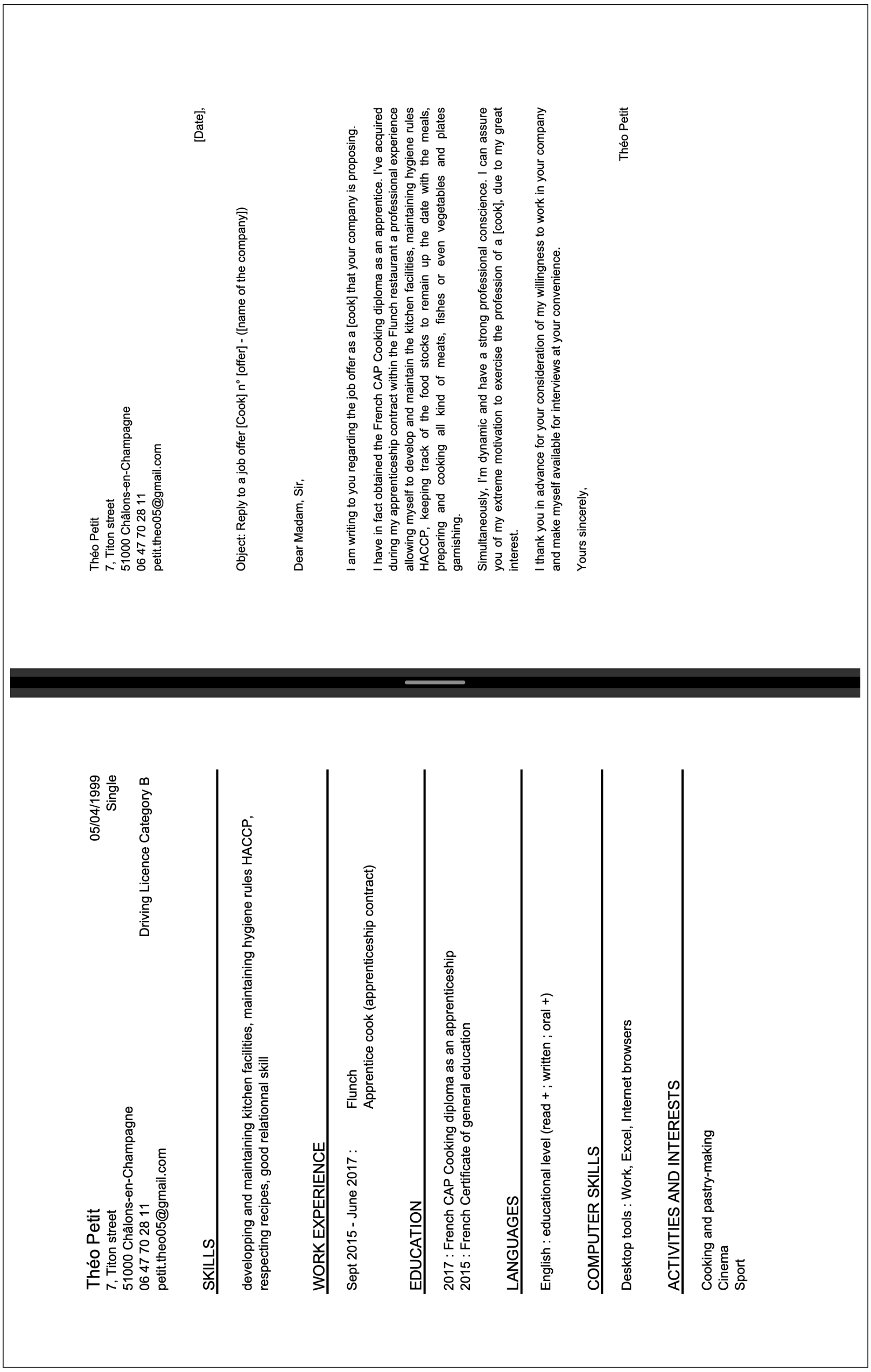
For Théo Petit application reply, the email message was the following:

Good morning,

I thank you for your answer regarding my application. Nevertheless, I have just accepted another offer.

Sincerely,
Théo Petit

FIGURE 2.6: Example of CV and Cover Letter (Cook Apprentices - layout 1)



Théo Petit
7, Titon street
51000 Châlons-en-Champagne
06 47 70 28 11
petit.theo05@gmail.com

05/04/1999
Single
Driving Licence Category B

SKILLS

developping and maintaining kitchen facilities, maintaining hygiene rules HACCP, respecting recipes, good relationnal skill

WORK EXPERIENCE

Sept 2015 - June 2017 : Flunch
Apprentice cook (apprenticeship contract)

EDUCATION

2017 : French CAP Cooking diploma as an apprenticeship
2015 : French Certificate of general education

LANGUAGES

English : educational level (read + ; written ; oral +)

COMPUTER SKILLS

Desktop tools : Work, Excel, Internet browsers

ACTIVITIES AND INTERESTS

Cooking and pastry-making
Cinema
Sport

Théo Petit
7, Titon street
51000 Châlons-en-Champagne
06 47 70 28 11
petit.theo05@gmail.com

[Date],

Object: Reply to a job offer [Cook] n° [offer] - ([name of the company])

Dear Madam, Sir,

I am writing to you regarding the job offer as a [cook] that your company is proposing.

I have in fact obtained the French CAP Cooking diploma as an apprentice. I've acquired during my apprenticeship contract within the Flunch restaurant a professional experience allowing myself to develop and maintain the kitchen facilities, maintaining hygiene rules HACCP, keeping track of the food stocks to remain up the date with the meals, preparing and cooking all kind of meats, fishes or even vegetables and plates garnishing.

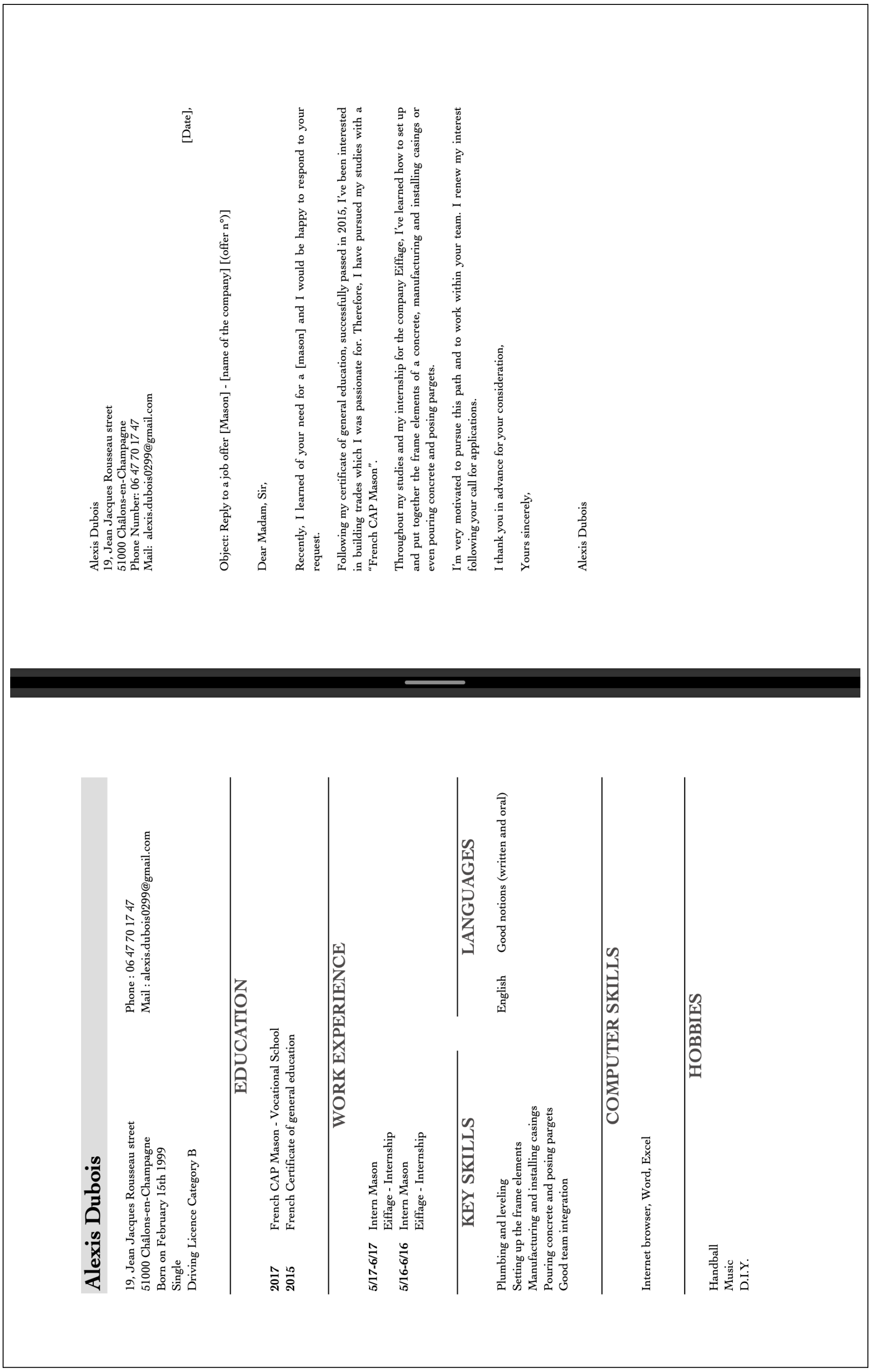
Simultaneously, I'm dynamic and have a strong professional conscience. I can assure you of my extreme motivation to exercise the profession of a [cook], due to my great interest.

I thank you in advance for your consideration of my willingness to work in your company and make myself available for interviews at your convenience.

Yours sincerely,

Théo Petit

FIGURE 2.7: Example of CV and Cover Letter (Cook Students - layout 2)



Alexis Dubois

19, Jean Jacques Rousseau street
51000 Châlons-en-Champagne
Born on February 15th 1999
Single
Driving Licence Category B

Phone : 06 47 70 17 47
Mail : alexis.dubois0299@gmail.com

EDUCATION

2017 French CAP Mason - Vocational School
2015 French Certificate of general education

WORK EXPERIENCE

5/17-6/17 Intern Mason
Eiffage - Internship
5/16-6/16 Intern Mason
Eiffage - Internship

KEY SKILLS

Plumbing and leveling
Setting up the frame elements
Manufacturing and installing casings
Pouring concrete and posing pargets
Good team integration

LANGUAGES

English Good notions (written and oral)

COMPUTER SKILLS

Internet browser, Word, Excel

HOBBIES

Handball
Music
D.I.Y.

Alexis Dubois
19, Jean Jacques Rousseau street
51000 Châlons-en-Champagne
Phone Number: 06 47 70 17 47
Mail: alexis.dubois0299@gmail.com

[Date],

Object: Reply to a job offer [Mason] - [name of the company] [(offer n°)]

Dear Madam, Sir,

Recently, I learned of your need for a [mason] and I would be happy to respond to your request.

Following my certificate of general education, successfully passed in 2015, I've been interested in building trades which I was passionate for. Therefore, I have pursued my studies with a "French CAP Mason".

Throughout my studies and my internship for the company Eiffage, I've learned how to set up and put together the frame elements of a concrete, manufacturing and installing casings or even pouring concrete and posing pargets.

I'm very motivated to pursue this path and to work within your team. I renew my interest following your call for applications.

I thank you in advance for your consideration,

Yours sincerely,

Alexis Dubois

2.8.2 Balancing table

TABLE 2.11
Randomization tests

	Students	Apprentices	
	(1)	(2)	(3)
	Sample mean	Sample mean	p-value (2)-(1)
For-profit	.9489	.9505	.8407
Not-for-profit	.0510	.0494	.8407
Primary sector	.0006	.0006	.9940
Secondary sector	.0006	.0000	.3148
Tertiary sector	.8477	.8320	.2422
Construction sector	.1509	.1673	.2212
Small firm (vs large firm)	.6146	.6141	.9781
Permanent contract (vs temporary)	.4051	.4227	.3213
Full-time job	.9395	.9342	.5406
Part-time job	.0604	.0657	.4060
No diploma required	.0468	.0602	.2239
Cap required	.9261	.9084	.1872
Bac required	.0269	.0313	.5949
Male recruiter (vs female recruiter)	.6229	.6120	.5398

Note: This Table reports means across subsamples of the experimental sample and presents randomization tests based on comparing the means across subsamples. Column (3) displays the p-value for the test $H_0 : \{\Delta$ = mean_callback[apprentices] - mean_callback[students] = 0$\}$ vs $H_1 : \{\Delta \neq 0\}$.

2.8.3 Probit model

TABLE 2.12
Marginal Effects of Apprenticeship on the Probability of Callback

	All applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Dep var: Positive callback					
Apprenticeship	0.00849	0.00809	0.0102	0.0195	-0.0367
	(0.0170)	(0.0167)	(0.0172)	(0.0198)	(0.0536)
Dep var: Proposition					
Apprenticeship	0.0106	0.0102	0.0123	0.0242	-0.0501
	(0.0146)	(0.0144)	(0.0145)	(0.0168)	(0.0537)
Observations	3,110	3,105	3,105	2,531	447
Month FE	No	Yes	Yes	Yes	Yes
Department FE	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Reported estimates are marginal effects from a Probit model. Robust standard errors are clustered at the department level and reported below the coefficients.

2.8.4 Replicates of the tables by selected occupation

Cook

TABLE 2.13
Description of the cook occupation

Occupation	**Cook**				
Diploma	CAP Cuisine				
Definition	The owner of the diploma can work in any kind of cuisine under the authority of a chef				
Uniting	**Activities**	**Skills**	**Exams**		
			Modality	**Tests**	**Coeff.**
Organization of the production in the cuisine	Participating in supply operations	Accept, control, and store the supplies	Continuous evaluation	4 case studies as written exams + 1 interview in the 2nd year	4
	Contributing to organize food preparation	Collect all the information for the recipe			
Preparation and delivery of the cuisine production	Organizing the kitchen quarters	Prepare, organize and manage the kitchen quarters all along the recipe	Continuous evaluation	1 real situation in the training center + 1 interview in the training firm	14
	Applying basic food skills	Master food techniques to realize the production			
	Engaging in food production	Analyze, control the quality of the food production and send it			
	Communicating in a professional environment	Respect the usage of the profession			
Health, environment			Continuous evaluation	1 written exam + 1 practical exam	1
French, History, Geography, and Moral			Continuous evaluation	1 written exam in French + 1 oral exam in History, Geography, and Moral	3
Mathematics, Physics, and Chemistry			Continuous evaluation	1 written exam in Maths + 2 practical exams in Physics & Chemistry	2
Sport			Continuous evaluation	3 evaluations	1
Foreign language			Continuous evaluation	1 written exam + 1 oral exam + 1 restitution exam	1

Source: *Arrêté du 17 mars 2016 portant création de la spécialité cuisine du certificat d'aptitude professionnelle et fixant ses modalités de délivrance.*

TABLE 2.14
Statistical portrait of students and apprentices in food services

Component	Information	Students	Apprentices
		31.43%	**68.57%**
Individual	Sex (male)	43.52%	54.47%
	Age	18.5 y.o.	20 y.o.
	Handicap	7.17%	9.82%
	Driving license	16.23%	30.96%
Family	District area		
	Downtown	32.52%	28.22%
	Suburb	31.99%	36.19%
	Small city	9.70%	13.77%
	Village	25.79%	21.82%
	Siblings	89.89%	95.17%
	French language	89.93%	96.41%
	Birthplace of father		
	France	76.43%	85.32%
	European countries	5.59%	3.94%
	Arabic countries	8.54%	8.72%
	African countries	4.40%	0.73%
	Rest of the world	5.05%	1.29%
	Birthplace of mother		
	France	78.35%	89.23%
	Europe	6.42%	2.02%
	Arabic countries	6.59%	7.93%
	African countries	4.33%	0.82%
	Rest of the world	4.31%	0.00%
	School level of father		
	No diploma	28.96%	43.76%
	Cap/Bep	54.79%	36.23%
	Bac	10.46%	14.76%
	Bac+	5.78%	5.24%
	School level of mother		
	No diploma	45.17%	33.18%
	Cap/Bep	37.95%	45.30%
	Bac	13.83%	15.21%
	Bac+	3.04%	6.30%
	Father works	85.75%	82.64%
	Mother works	63.91%	72.02%
Education	Repeater year before 6th grade	51.46%	46.90%
	Normal middle school program	34.24%	67.01%
	Would have preferred apprenticeship	52.84%	-
	Reason of non-apprenticeship		
	No CFA	0.00%	-
	No employer	28.16%	-
	Neither CFA, nor employer	32.70%	-
	Other	39.14%	-
	Internships / Apprenticeship Tutor	72.50%	-
	Number of internships		
	1	12.57%	-
	2	34.73%	-
	3 or more	52.70%	-
	Contact with the (last) training firm		
	Self	29.29%	-
	Family and friends	13.28%	-
	School / Apprenticeship center	46.90%	-
	Other Public Structure	0.95%	-
	Other	9.59%	-
	Graduated	93.66%	85.85%

Note: This table reports descriptive statistics for both apprentices and vocational students in the food services. Shares of students who made interships and the mode of contact with the last training firm are computed from the *Génération 2010* survey only because of the specific questions. The share of graduated students and apprentices are computed with both the *Génération 2010-2013* surveys because of changes in the content of the level V diploma in 2009 in France.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ ($N = 445$ individuals)

TABLE 2.15
Effects of apprenticeship on the probability of getting a callback given the size of firms for cook

	Small Firms			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0322	0.0258	0.0257	0.0220	0.0208	0.0155
	(0.0314)	(0.0328)	(0.0352)	(0.0247)	(0.0245)	(0.0258)
Student mean	0.3141***	0.3141***	0.3141***	0.2644***	0.2644***	0.2644***
	(0.0223)	(0.0223)	(0.0223)	(0.0174)	(0.0174)	(0.0174)
Observations	872	872	872	1,268	1,268	1,268
R-squared	0.001	0.013	0.139	0.001	0.003	0.078
Dep var: Proposition						
Apprenticeship	0.0191	0.0126	0.0119	0.0272	0.0263	0.0235
	(0.0285)	(0.0291)	(0.0329)	(0.0225)	(0.0224)	(0.0231)
Student mean	0.2679***	0.2679***	0.2679***	0.2208***	0.2208***	0.2208***
	(0.0213)	(0.0213)	(0.0213)	(0.0164)	(0.0164)	(0.0164)
Observations	872	872	872	1,268	1,268	1,268
R-squared	0.000	0.014	0.147	0.001	0.002	0.062
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Small firms have less than 10 employees and large firms have at least 10 employees. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 2.16

Effects of apprenticeship on the probability of getting a callback for temporary and permanent jobs for cook

	Temporary Jobs			Permanent Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0218	0.0190	0.0190	0.0128	0.0130	0.0176
	(0.0226)	(0.0222)	(0.0231)	(0.0281)	(0.0284)	(0.0294)
Student mean	0.2949***	0.2949***	0.2949***	0.2542***	0.2542***	0.2542***
	(0.0162)	(0.0162)	(0.0162)	(0.0199)	(0.0199)	(0.0199)
Observations	1,558	1,558	1,558	982	982	982
R-squared	0.001	0.007	0.076	0.000	0.004	0.117
Dep var: Proposition						
Apprenticeship	0.0193	0.0170	0.0199	0.0244	0.0245	0.0313
	(0.0204)	(0.0203)	(0.0214)	(0.0267)	(0.0266)	(0.0275)
Student mean	0.2409***	0.2409***	0.2409***	0.2167***	0.2167***	0.2167***
	(0.0152)	(0.0152)	(0.0152)	(0.0188)	(0.0188)	(0.0188)
Observations	1,558	1,558	1,558	982	982	982
R-squared	0.000	0.006	0.081	0.001	0.004	0.122
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

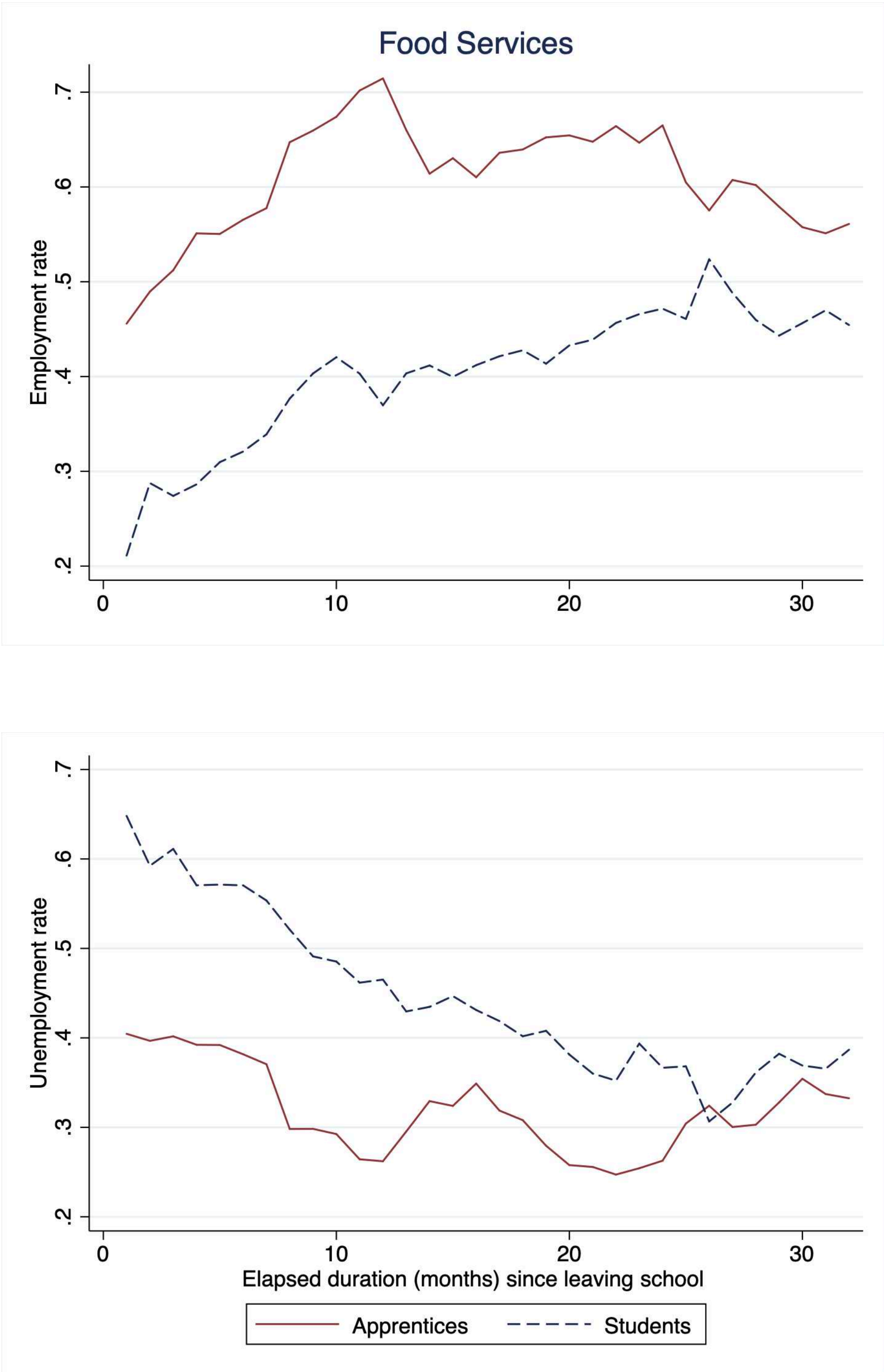
Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Temporary jobs comprise all offers for a seasonal contract or a determined duration contract. Permanent jobs are the complement. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 2.17
Effects of apprenticeship on callback probability given different unemployment rates at the commuting zone level for cook

	All	T1 (7.2%)	T2 (8.5%)	T3 (10.8%)
	(1)	(2)	(3)	(4)
Dep var: Positive callback				
Apprenticeship	0.0293	0.0411	-0.0119	0.0508*
	(0.0217)	(0.0472)	(0.0406)	(0.0270)
Student mean	0.3029***	0.3576***	0.3127***	0.2386***
	(0.0151)	(0.0276)	(0.0258)	(0.0244)
Observations	1,869	621	616	632
R-squared	0.083	0.105	0.104	0.097
Dep var: Proposition				
Apprenticeship	0.0259	0.0200	0.0179	0.0339
	(0.0185)	(0.0410)	(0.0361)	(0.0220)
Student mean	0.2567***	0.3113***	0.2508***	0.2092***
	(0.0143)	(0.0267)	(0.0242)	(0.0233)
Observations	1,869	621	616	632
R-squared	0.078	0.087	0.103	0.099
Month & Department FE	Yes	Yes	Yes	Yes
Firm & Job Characteristics FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. TX corresponds to the Xth tercile of the unemployment rate at the commuting zone level. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

FIGURE 2.8: Evolution of the share of students and apprentices in employment or unemployment after leaving school in food services.



Note: Students got their CAP diploma in June-July 2010. Month zero stands for September 2010.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ.

Bricklayer

TABLE 2.18
Description of the bricklayer occupation

Occupation	**Bricklayer**				
Diploma	CAP Maçon				
Definition	The owner of the diploma can work in any kind of building firm with structural work tasks				
Uniting	**Activities**	**Skills**	**Exams**		
			Modality	**Tests**	**Coeff.**
Analysis of a professional situation	Preparing its materials on the construction site Explaining the realizations to colleagues or supervisors	Mastering rules in a building site Speak and listen in a professional context	Continuous evaluation	2 oral examinations in the training center	4
Normal working tasks	Reading and applying instructions for normal working tasks	Lay composite materials for construction	Continuous evaluation + practical exam	1 practical session in the training center + 1 practical session in the training firm	8
Additional working tasks	Reading and applying instructions for additional working tasks	Lay composite materials for construction	Continuous evaluation	1 practical session in the training center + 1 practical session in the training firm	4
French language			Written exam	text comprehension and short essay	3
Mathematics, Physics, and Chemistry			Written exam	Several exercises	2
Social and Working Life			Written exam	Real life questions	1
Sport			Continuous evaluation	3 evaluations	1

Source: *Arrêté du 17 août 2004 modifiant l'arêté du 21 août 2002 modifié, portant création du certificat d'aptitude professionnelle maçon.*

TABLE 2.19
Statistical portrait of students and apprentices in Construction

Component	Information	Students	Apprentices
		22.35%	**77.65%**
Individual	Sex (male)	90.53%	99.95%
	Age	19 y.o.	21 y.o.
	Handicap	7.98%	6.70%
	Driving license	37.86%	49.16%
Family	District area		
	Downtown	30.84%	22.32%
	Suburb	27.59%	32.58%
	Small city	13.41%	15.98%
	Village	28.16%	29.12%
	Siblings	86.70%	84.32%
	French language	89.01%	95.07%
	Birthplace of father		
	France	83.95%	88.67%
	European countries	6.00%	3.11%
	Arabic countries	6.13%	7.73%
	African countries	2.96%	0.32%
	Rest of the world	0.96%	0.18%
	Birthplace of mother		
	France	85.33%	88.92%
	Europe	4.72%	3.52%
	Arabic countries	7.23%	6.95%
	African countries	1.78%	0.42%
	Rest of the world	0.95%	0.18%
	School level of father		
	No diploma	44.29%	29.49%
	Cap/Bep	43.94%	48.08%
	Bac	4.20%	12.90%
	Bac+	7.57%	9.53%
	School level of mother		
	No diploma	31.70%	36.13%
	Cap/Bep	29.20%	42.43%
	Bac	34.03%	16.29%
	Bac+	5.07%	5.15%
	Father works	82.86%	88.14%
	Mother works	70.13%	72.25%
Education	Repeater year before 6th grade	50.03%	44.34%
	Normal middle school program	52.60%	62.67%
	Would have preferred apprenticeship	60.46%	-
	Reason of non-apprenticeship		
	No CFA	3.51%	-
	No employer	20.79%	-
	Neither CFA, nor employer	22.92%	-
	Other	52.78%	-
	Internships / Apprenticeship Tutor	75.05%	-
	Number of internships		
	1	15.46%	-
	2	33.41%	-
	3 or more	51.13%	-
	Contact with the (last) training firm		
	Self	35.64%	-
	Family and friends	45.40%	-
	School / Apprenticeship center	7.70%	-
	Other Public Structure	0.62%	-
	Other	10.64%	-
	Graduated	71.90%	93.27%

Note: This table reports descriptive statistics for both apprentices and vocational students in the construction sector. Shares of students who did interships and the mode of contact with the last training firm are computed from the *Génération 2010* survey only because of the specific questions. The share of graduated students and apprentices are computed with both the *Génération 2010-2013* surveys because of changes in the content of the level V diploma in 2009 in France.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ ($N = 418$ individuals)

TABLE 2.20
Effects of apprenticeship on the probability of getting a callback given the size of firms for bricklayer

	Small Firms			Large Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0159	0.0314	0.0839	-0.0567	-0.0609	-0.0805
	(0.0673)	(0.0693)	(0.143)	(0.0497)	(0.0501)	(0.0727)
Student mean	0.2029***	0.2029***	0.2029***	0.2739***	0.2739***	0.2739***
	(0.0488)	(0.0488)	(0.0488)	(0.0357)	(0.0357)	(0.0357)
Observations	133	133	133	332	332	332
R-squared	0.000	0.030	0.581	0.004	0.017	0.294
Dep var: Proposition						
Apprenticeship	0.0136	0.0268	0.0894	-0.0649	-0.0665	-0.0727
	(0.0642)	(0.0633)	(0.141)	(0.0437)	(0.0442)	(0.0631)
Student mean	0.1739***	0.1739***	0.1739***	0.2420***	0.2420***	0.2420***
	(0.0460)	(0.0460)	(0.0460)	(0.0341)	(0.0341)	(0.0341)
Observations	133	133	133	332	332	332
R-squared	0.000	0.034	0.563	0.006	0.023	0.283
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Small firms have at most 10 employees and large firms have more than 10 employees. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 2.21
Effects of apprenticeship on the probability of getting a callback for temporary and permanent jobs for bricklayer

	Temporary Jobs			Permanent Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Positive callback						
Apprenticeship	0.0286	0.0328	0.0377	-0.0856	-0.0879	-0.0835
	(0.0632)	(0.0623)	(0.0953)	(0.0525)	(0.0529)	(0.0861)
Student mean	0.2424***	0.2424***	0.2424***	0.2598***	0.2598***	0.2598***
	(0.0431)	(0.0431)	(0.0431)	(0.0391)	(0.0391)	(0.0391)
Observations	206	206	206	259	259	259
R-squared	0.001	0.026	0.478	0.011	0.037	0.328
Dep var: Proposition						
Apprenticeship	0.00359	0.00692	0.0223	-0.0771	-0.0791	-0.0827
	(0.0547)	(0.0545)	(0.0835)	(0.0490)	(0.0499)	(0.0817)
Student mean	0.2020***	0.2020***	0.2020***	0.2362***	0.2362***	0.2362***
	(0.0406)	(0.0406)	(0.0406)	(0.0378)	(0.0378)	(0.0378)
Observations	206	206	206	259	259	259
R-squared	0.000	0.032	0.475	0.009	0.035	0.345
Month FE	No	Yes	Yes	No	Yes	Yes
Department FE	No	No	Yes	No	No	Yes

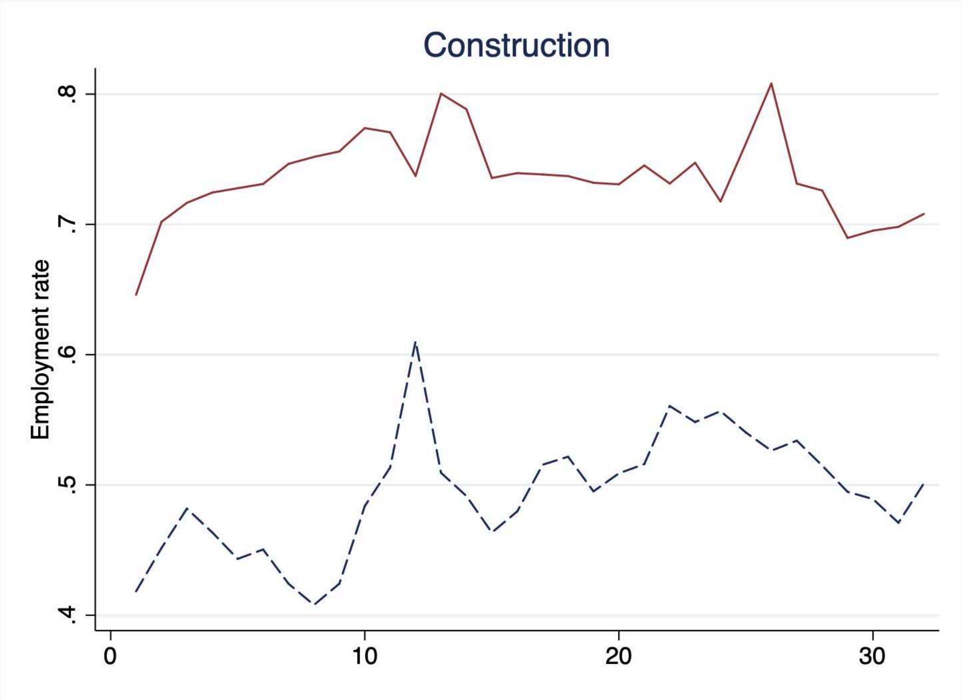
Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. Temporary jobs comprise all offers for a seasonal contract or a determined duration contract. Permanent jobs are the complement. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

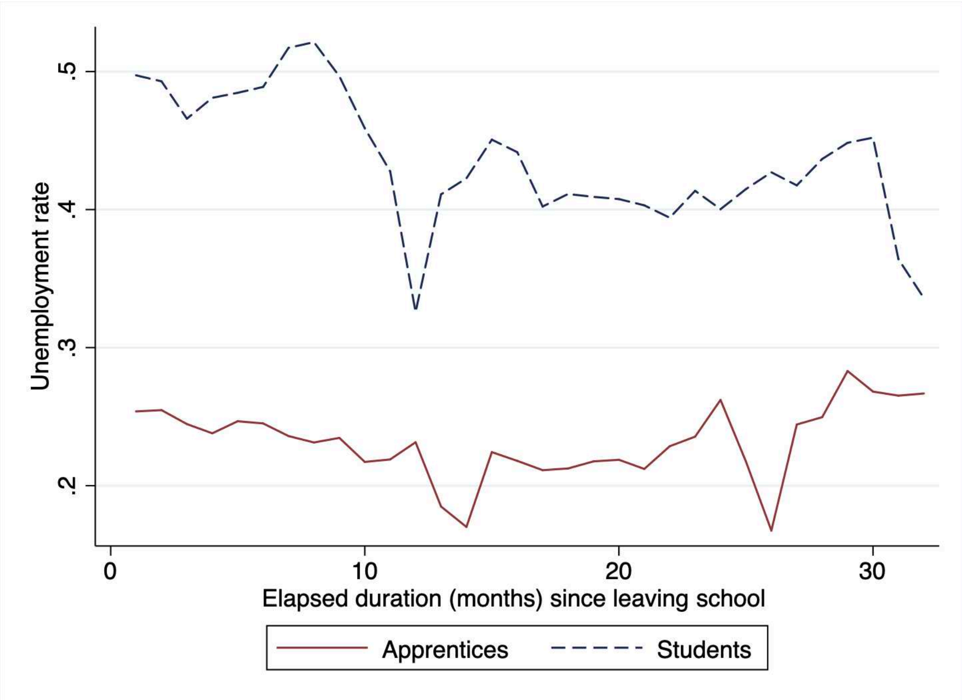
TABLE 2.22
Effects of apprenticeship on callback probability given different unemployment rates at the commuting zone level for bricklayer

	All	T1	T2	T3
	(1)	(2)	(3)	(4)
Dep var: Positive callback				
Apprenticeship	-0.0578	-0.308***	0.0501	0.0392
	(0.0561)	(0.0988)	(0.114)	(0.106)
Student mean	0.2673***	0.3699***	0.2500***	0.1579***
	(0.0312)	(0.0569)	(0.0514)	(0.0487)
Observations	412	142	143	127
R-squared	0.291	0.419	0.339	0.302
Dep var: Proposition				
Apprenticeship	-0.0564	-0.275**	0.0384	0.0203
	(0.0515)	(0.107)	(0.111)	(0.0874)
Student mean	0.2327***	0.3288***	0.2222***	0.1228***
	(0.0298)	(0.0554)	(0.0493)	(0.0439)
Observations	412	142	143	127
R-squared	0.260	0.382	0.326	0.254
Month & Department FE	Yes	Yes	Yes	Yes
Firm & Job Characteristics FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback or a proposition. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a suggestion for interview or hiring. Proposition corresponds to callbacks with interview or hiring proposition. Apprenticeship is a dummy variable equal to one if the application was from an apprentice. TX corresponds to the Xth tercile of the unemployment rate at the commuting zone level. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

FIGURE 2.9: Evolution of the share of students and apprentices in employment or unemployment after leaving school in construction.





Note: Students got their CAP diploma in June-July 2010. Month zero stands for September 2010.
Source: pooled *Génération 2001-2007-2010-2013* surveys, CEREQ.

2.8.5 Callback probabilities

This appendix presents the computation of the callback probability of apprentices and students.

Callback probability of apprentices

Let us consider an apprentice who applies to a job with $n_a + n_s > 1$ applicants. The firm draws a maximum number of applications equal to $m(n_a + n_s, c)$ defined equation (2.7).

For this apprentice, the probability to be called back in the first draw is equal to

$$p_0 = \frac{1}{n_a + n_s}$$

The probability to be called back in the second draw is equal to the probability that an apprentice has not been called back in the first draw, equal to

$$1 - \frac{n_a}{n_a + n_s} = \frac{n_s}{n_a + n_s}$$

times the probability to be called back in the second draw, which yields (remark that there are necessarily $n_s - 1$ students in the second draw otherwise an apprentice has been drawn in the first draw implying that the employer stops screening applications):

$$\left(1 - \frac{n_a}{n_a + n_s}\right) \frac{1}{n_a + (n_s - 1)} = \frac{n_s}{n_a + n_s} \frac{1}{n_a + (n_s - 1)}$$

Thus, if $m = 2$, the probability to be called back is equal to the probability to be called back in the first draw plus the probability to be called back in the second raw, or

$$\frac{1}{n_a + n_s} + \left(1 - \frac{n_a}{n_a + n_s}\right) \frac{1}{n_a + (n_s - 1)} = \frac{1}{n_a + n_s} + \frac{n_s}{n_a + n_s} \frac{1}{n_a + (n_s - 1)}$$

Following the same reasoning, one can compute the probability to be called back for any value of (n_a, n_s) by a firm that screens at most $m(n_a + n_s, c)$ applicants:

$$\psi_a\left(n_a, n_s, c\right) = \frac{1}{n_a + n_s} + \mathbf{1}\left[m\left(n_a, n_s, c\right) > 1\right] \sum_{j=1}^{m(n_a+n_s,c)-1} \prod_{i=0}^{j-1} \frac{n_s - i}{n_a + (n_s - i)} \frac{1}{n_a + n_s - j}$$

Therefore, the callback probability of an apprentice, who competes with $(1-\rho)N_a - 1$ other apprentices on all vacancies, is equal to

$$\sum_{n_a=0}^{(1-\rho)N_a-1} \sum_{n_s=0}^{N_s} b(n_a, (1-\rho)N_a - 1, 1/v) b(n_s, N_s, 1/v) \int_{c_{\min}}^{c_{\max}} \psi_a\left(n_a + 1, n_s, c\right) \mathrm{d}F(c)$$

Callback probability of students

Now, let us compute the probability that a student is called back on a job with (n_a, n_s) applicants, which screens at most $m(n_a + n_s, c)$ applications. The probability that each apprentice is called back is equal to $\psi_a(n_a, n_s)$, implying that the probability that an apprentice is called back is equal to

$$n_a \psi_a (n_a, n_s, c)$$

Therefore, the probability that a student is called back is equal to $1 - n_a c_a (n_a, n_s)$ and the probability of being called back for a given student is

$$\psi_s (n_a, n_s, c) = \frac{1 - n_a \psi_a (n_a, n_s, c)}{n_s}$$

Eventually, the callback probability of a vocational student who competes with $(1-\rho)N_a$ apprentices and $N_s - 1$ other students on all vacancies, is equal to

$$\sum_{n_a=0}^{(1-\rho)N_a} \sum_{n_s=0}^{N_s-1} b(n_a, (1-\rho)N_a, 1/v) b(n_s, N_s - 1, 1/v) \int_{c_{\min}}^{c_{\max}} \psi_s (n_a, n_s + 1, c) \, \mathrm{d}F(c)$$

2.8.6 Wage and productivity of apprentices and students

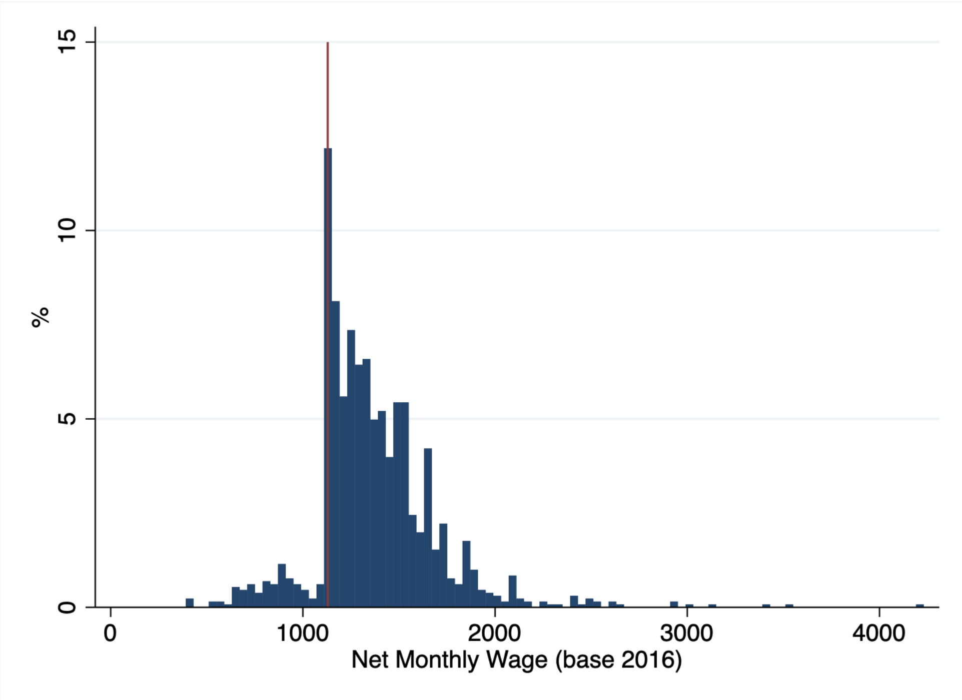
This appendix presents the estimation of the distributions of productivity of apprentices and vocational students, conditional on experience, region of residence, family situation and work environment. As explained in the main text, the productivity distributions of apprentices and vocational students, $G^j(y),\ j = a, s$, are estimated assuming that wages are determined by the wage bargaining solution, so that we start by estimating the wage distributions to retrieve the productivity distributions relying on equation (2.11).

In line with our correspondence study, the analysis is restricted to young males who enrolled in a CAP-equivalent program after middle school and are working in the construction industry, hotel and restaurants, and related sectors such as transport and retail in order to get a sufficient number of observations. The analysis is focused on the monthly wage of full-time workers to avoid important measurement errors. To compare entry wages conditional on individual characteristics, we run standard Mincer-like earnings regressions, where the log-wage is the dependent variable and explanatory variables include the number of months of labor market experience after leaving school, dummies for gender, the type of labor market contract and fixed effects for the department of residency, the sector of activity and years.

Figure 2.10 displays the histogram of wages. To account for the presence of the minimum wage, the wage distribution is left-truncated at the minimum wage level and log-wages are estimated with the maximum likelihood method. Another strategy could be to assume that wages are contaminated by measurement errors. However, the main source of measurement errors below the minimum wage is likely due to the fact that there are several subsidized jobs the status of which allows the employers to circumvent the minimum wage regulation, especially in the case of young workers. Insofar as the status of these jobs is not well reported in the *Génération* survey, there are some observations below the minimum wage. We hence discard these observations and truncate the wage distribution at the minimum wage to infer the productivity distributions from the wage distributions.

In order to estimate the wage distributions of ex-apprentice and ex-vocational student workers conditional on characteristics, we compute the residuals from the regression of log monthly starting wages for all workers. Once we have computed the residuals from the regression of log wages, we define the wage level of an apprentice worker as the mean wage of the whole sample times the exponential of his residual and the wage level of a student worker as the mean wage of the whole sample times the exponential of his residual. Then we compute the productivity y of each individual from equation (2.11). We assume that productivity is log-normally distributed, i.e. the distribution of y is $\log - \mathcal{N}(\mu_j, \sigma_j),\ j = a, s$. The estimation of the productivity distribution of apprentice workers yields $\mu_a = 7.8555488$, $\sigma_a = 0.2257112$; and that of students $\mu_s = 7.8457506$, $\sigma_s = 0.21937228$. The productivity distributions of apprentices and students are displayed on Figure 2.2.

FIGURE 2.10: Histogram of the Net Monthly Wages earned by Apprentices and Students.



Source: pooled *Génération 2010-2013* surveys, CEREQ.

2.8.7 Robustness of the model

TABLE 2.23
Robustness of the model simulations according to different values of β

Model	Estimates				
	(1)	(2)	(3)	(4)	(5)
β	0.3	0.4	0.5	0.6	0.7
μ_a	8.379575	8.0458825	7.8503906	7.7237941	7.6198244
σ_a	.21000747	.22228958	.22613206	.2215229	.22051209
μ_s	8.3548678	8.0349114	7.8407658	7.7126926	7.6159226
σ_s	.20924469	.21272207	.2181748	.2150759	.20936935
Benchmark ($\alpha = 0.5$)					
c	[€5.5, €8.0]	[€3.0, €5.5]	[€2.5, €5.0]	[€2.0, €4.5]	[€1.0, €3.5]
h	€1221.91	€681.58	€428.62	€277.66	€173.92
u_a	.1972	.1972	.1972	.1972	.1972
u_s	.2881	.2881	.2881	.2879	.2869
u	.2426	.2426	.2426	.2426	.2421
$\tilde{u}$	.2815	.2781	.2815	.2814	.2809
v	100	100	100	100	100
Counterfactual ($\alpha = 0.6$)					
u_a	.1992	.1992	.1986	.1992	.1991
u_s	.2902	.2902	.2893	.2900	.2809
u	.2356	.2356	.2349	.2355	.2351
$\tilde{u}$	.2858	.2858	.2799	.2857	.2852
v	96.8	96.8	96.8	96.8	96.1

Note: This table reports the indicators simulated by the model with different values of β both in the benchmark and one counterfactual situation. The estimates discussed in the core paper are presented in column (3) with $\beta = 0.5$.

Labor market policies for young dropouts

Abstract School dropouts often face persistent difficulties accessing the labor market, which policies fail to address. Our article contributes to the understanding of these difficulties by focusing on employers' preferences regarding dropout applicants. In 2018, we sequentially sent more than 10,000 applications to job offers and 10,000 speculative applications in France. By analyzing the differences in callback rates with respect to non-dropouts with a vocational upper-secondary diploma, we find that school dropouts who have remained inactive over two years have a significantly smaller chance (two-thirds on average) of being called back. Job related experience or training leading to a certificate boosts dropouts' chances, reducing by more than half the difference in callback probability, but their chances remain lower than that of non-dropout high school graduates. Only dropouts with both job related experience and training leading to a certificate manage to catch up with their non-dropout peers. We confirm our results through a battery of robustness checks.

Based on: *Is There a Second Chance for High-School Dropouts? Evidence from a Large Correspondence Study*, CSPP WP 2020-05

Joint with: Cécile Ballini (DARES) and Mathilde Gaini (DREES)

Keywords: School dropouts, Active labor market policies, Field experiment

JEL codes: J08, J24, M51

3.1 Introduction

Youths who leave school before graduation without any diploma suffer adverse consequences in the labor market. They face lower wages and lower probability of employment than their non-dropout counterparts (Oreopoulos, 2007, Campolieti et al., 2010a). This difficult situation has become a major concern for most OECD countries, because school dropouts are more likely to be found among young people who are not in employment, education or training (NEET) later on (OECD, 2019). Accordingly, France decided to boost opportunities for NEET through active labor market policies, in particular through the two pillars of vocational training and subsidized contracts. In fact, the number of youth trainees aged 16-25 rose from about 250,000 in 2009 at the beginning of the crisis in France to 320,000 in 2016. These figures correspond to 14% and 19% respectively of same-age unemployed youth (Guillon, 2019). Between 2012 and 2017, France also set up a specific subsidized contract for NEET youths, called ”Emploi d'avenir”, in which firms were required to provide additional specific training, either internally or externally in a training center. More than 300,000 youths benefited from the scheme. In the most favorable cases, the additional training could lead to a certificate. The trend in French policy indicates a shift toward hybrid labor market policies in which youth can benefit from both training and professional experience. This recent policy orientation provides a specific environment in which we can test empirically whether different types of active policy give high-school dropouts a second chance on the labor market.

Our article contributes to the understanding of youth transition in the labor market by focusing on potential recruiters' preferences with regard to educational and professional items in low-skilled profiles. In particular, we test whether hybrid programs yield a better outcome for youths than training programs or subsidized contracts alone, by comparing their relative importance for employers. We are able to rule out potential selection bias in the labor market resulting from skills, knowledge, network or social conditions by carrying an audit correspondence study. In the course of 2018, we sequentially sent more than 10,000 job offer applications and more than 10,000 speculative job applications randomly throughout mainland France. Targeting firms that hire cooks and bricklayers, we designed resumes for 18/19-year-old virtual job seekers, identical in all respects except for graduation and their labor market pathway in the two years preceding the application. Given the youth population targeted by recent active labor market policies in France, we consider youths who have completed vocational upper-secondary education as the reference group and we compare them with four typical profiles of dropouts: dropouts who remained inactive for two years after leaving school; dropouts who attended seven-months vocational training leading to a certificate; dropouts with a one-year professional experience through a subsidized contract (private or public sector); and dropouts with one year's professional experience through the same subsidized contract who also took complementary classroom training and obtained a certificate.

By analyzing the difference in callback rates with respect to non-dropouts, we find that school dropouts have a significantly smaller likelihood of being called back for a job vacancy. We find that the probability of callback decreases by 67% on average for an inactive dropout compared to a non-dropout. This discrepancy then ranges from 5% to 90% depending on dropouts' labor market experience, the firm concerned and the job profile. Training or professional experience boosts dropouts' chances of callback by a factor of three. Although their chances are better than those of inactive dropouts, dropouts who have attended vocational training still have 25% lower than the callback rate of their non-dropout peers. The callback rate is the same for dropouts who gained job-related experience through a one-year subsidized contract. Only dropouts with both professional experience and a certificate obtained through complementary classroom training almost manage to catch up their non-dropout peers.

Our findings suggest that even though school-dropouts may get a second chance on the labor market, their job prospects are on average lower than they were while at school. In order to confirm the ranking of profiles, we performed a battery of robustness checks such as changing the specification, looking for heterogeneous effects, controlling for additional information (distance in kilometers to the job location, the local unemployment rate), and sending applications spontaneously to firms.

Our results highlight the importance recruiters give to certificates in France. These results are consistent with what is reported in Section 3.2.2 showing that when youths leave school before graduation they find it difficult to enter the labor market. This finding is also consistent with a recent non-experimental study carried out in France, showing that acquiring a diploma is a major determinant for easier access to paid and stable employment (Marchal, 2018). Our results also underline the advantage of professional experience for recent dropouts. Cahuc et al. (2019b) carried out an experimental audit study with 24-year-old school dropouts. The applicants concerned were youngsters who had entered paid employment, whether or not through subsidized contracts, assorted with certified skills or not. In the control group, applicants remained mainly inactive. The authors show that only those dropouts who attended certifying training while working under (subsidized) contracts have significantly higher callback rates. In contrast to their results, we find that dropouts with work experience only also perform better than inactive dropouts.

The results may be of value for active labor market policies (ALPM) targeting youths. In France, micro-econometric studies find no, or low, short-term effect of vocational training for job-seekers (Caliendo and Schmidl, 2016a). The same applies to subsidized contracts in the non-market sector, but subsidized contracts in the market sector exhibit some positive effects (Benoteau, 2015). Meta-analyses reveal the same pattern for subsidized contracts in the United States, Germany and the Nordic countries, but in these countries vocational training produces positive long-run effects for job-seekers (Crépon and van den Berg, 2016, Card et al., 2018a, Vooren et al., 2019). We complement these findings by focusing on dropouts and on recruiters' preferences, while ruling out other determinants of youth insertion into the labor market, and looking at the relative importance of each program.

Many reasons can be put forward to explain difficult school-to-work transitions through ALPMs. One such reason is that active policies may be poorly designed, in relation to the specific characteristics of young dropouts who are eager to enter the labor market and do not see the benefits of education (Eckstein and Wolpin, 1999b, Oreopoulos, 2007). In the current French context, our paper argues for active labor market policies that combine *both* on-the-job training <u>and</u> certifying classroom training, so that youths who do not fit into the education system are better able to signal their competences in the labor market. Additional information on the costs and benefits of such policies are nonetheless necessary for governments trying to combat large-scale youth unemployment while subject to budgetary constraints. The limitations of our study and potential drawbacks of extending current active labor market policies to young school dropouts are discussed in Section 3.6.2. Complementary work on possibly less costly and easier-to-implement programs that prevent youths from dropping out of the school system should be given full considerations as well (Björklund and Salvanes, 2011).

The paper is organized as follows. Section 3.2 presents the French employment public policies and the situation of dropouts in the French labor market, in order to legitimate our experimental setting. Section 3.3 describes the experimental design. Section 3.4 presents the main findings. Section 3.5 presents robustness checks that confirm our main results. Section 3.6 discusses the potential mechanisms and the external validity of our experiment. Section 3.7 concludes.

3.2 Background

Since our study concerns youths who left education after middle school at the age of 16 instead of pursuing vocational education at the upper secondary level, we start by presenting briefly the main features of existing active labor market policies for youths, and then describe the characteristics and situations of dropouts.

3.2.1 The French employment policies

In France, the *certificat d'aptitude professionnelle* (CAP), corresponding to the two-year vocational diploma of upper secondary level (11th grade), can be obtained through two different paths, either in a vocational school program or in apprenticeship. Each year, there are about 120,000 youths ($\approx$ 15% of the cohort) who enroll in this program after middle school (9th grade). However, there are also about 100,000 youths who drop out of the school system without any diploma.[1] It has been shown by Cayouette-Remblière and de Saint Pol (2013) that youths face various obstacles before graduating and find it difficult to remain in the education system until the end of 11th grade. Instead, they may prefer to leave when the compulsory age threshold has been met and try their chances in the labor market.

Because the insertion of dropouts into the labor market is difficult (as discussed in Section 3.2.2), successive governments have decided to promote active labor market policies, especially with regard to vocational training and subsidized contracts. Vocational training may be provided by any private or public training center and the main silent providers are *Pôle emploi* and the French *Régions*. This training can be carried out variously through classroom training, on-the-job training, or in most cases a mixture of the two (Guillon, 2019). Table 3.10 in Appendix 3.8.1 presents descriptive statistics on the training undertaken by youths registered at *Pôle emploi*. It appears that

[1] Go to https://www.education.gouv.fr/bcp/mainFrame.jsp?p=1 for more open data.

around 80% to 95% of youths under 18 have a school level lower than or equivalent to 11th grade (CAP) and enter in a program at the age of 16.5. Vocational training lasts on average five to six months and leads mostly to a CAP level, although only a few training schemes actually deliver a CAP diploma. Interestingly, half to two-thirds of the youths have experiences time spent with a firm.

In parallel, the *Emploi d'Avenir* (EAv), operating between 2012 and 2018, was a program aimed at reducing the labor cost for firms when hiring unskilled youths aged between 16 and 25. Between 35% to 75% of the gross minimum wage was paid by the state and the duration of the contract could be up to three years. EAv provided the main subsidized contracts for youths, and one innovation compared to other subsidized contracts was that employers were obliged to offer training. In total, more than 360,000 contracts were signed during this period.[2] Table 3.11 in Appendix 3.8.1 presents statistics related to youths in EAv. It appears that about three-quarters of contracts were one year temporary contracts, of which very few were renewed, and they were mainly with small and medium-sized firms. Finally, only a third of contracts seemingly led to a certified training, and in these cases more than 80% of training programs were carried out in centers external to the firm. However, a national survey shows that only a small proportion of youths were in fact enrolled in a certified training (Mourlot, 2018).

3.2.2 Profile of school dropouts

We use a sample of the TRAJAM[3] database to follow youths who have been flagged as dropouts and avoid certain composition effects among the different labor market status discussed above. In particular, we use the one-day military census *Journée Défense et Citoyenneté* (JDC) as a starting point that French youths are required to participate in the age of 25.[4] During JDC day, they have to declare whether or not they are NEETs. The large majority of youths do this aged 17, so we consider these young NEETS as school dropouts.

Table 3.12 in Appendix 3.8.1 displays some of the available characteristics of youths and dropouts during the JDC. It appears that dropouts are predominantly male and have a school level lower than or equivalent to 9th grade. Moreover, their literacy level, which is determined by a 30-minute French test during the JDC, is far lower than for non-dropouts, even though more than 70% of dropouts have the normal literacy level expected. It has also been shown by Bouhia et al. (2011) that dropouts are those who have had the greatest difficulties at school are more likely to come from disadvantageous socio-economic backgrounds. This is reflected in their subsequent situations. While the majority of youths stay on in school after the JDC, about 13% have at least one period of open unemployment (i.e. being officially registered at *Pôle emploi*) during the following thirty months, against more than 47% of school

[2] Go to http://poem.travail-emploi.gouv.fr/ for more trends.

[3] *TRAjectoires des Jeunes Appariés aux Mesures actives du marché du travail.*

[4] The TRAJAM scale is 1:12 and it is representative of all French youths (16-25) who have been in paid employment, unemployment, or in active programs, at least once since 2010 in France. It is worth noting that this database is still in a preliminary version with little information available that need to be consolidated. We were thus able to obtain information at the date of the JDC only on gender, date of birth, place of birth, place of residence, school level, and an indicator of literacy level. The latest records in the database were in December 2015, so we select only dropouts who were flagged between January and June 2013. This time window allows us to track the youths, especially the dropouts, for about 30 months.

TABLE 3.1
Correlations between Labor Market Experiences and Being a Dropout

OLS Estimates	Employment		Unemployment		Active Program	
	(1)	(2)	(3)	(4)	(5)	(6)
Dropout	-0.0394***	-0.0285**	0.0835***	0.0803***	0.0027**	0.0024*
	(0.0133)	(0.0134)	(0.0081)	(0.0080)	(0.0013)	(0.0014)
Constant	0.2340***	0.2338***	0.0221***	0.0222***	0.0016***	0.0016***
	(0.0023)	(0.0023)	(0.0007)	(0.0006)	(0.0001)	(0.0001)
Observations	487,041	487,041	487,041	487,041	487,041	487,041
R-squared	0.0002	0.0657	0.0078	0.0341	0.0001	0.0048
Control Variables	No	Yes	No	Yes	No	Yes

Note: This table reports OLS estimates, where the dependent variable is the number of days a school dropouts has experienced in employment from whatever date he started up to December 31 2015, for columns (1) and (2); in open unemployment for columns (3) and (4); or in an active program (vocational training or subsidized job) for columns (5) and (6). "Dropout" is a dummy variable equal to one if the individual has been recognized as a school dropout by legal authorities at the date of the army day (JDC). Unreported control variables in columns (2), (4), and (6) include demeaned dummies for sex, year of birth, department of birth, school level, literacy level, department of residency, and elapsed months since the JDC. Robust standard errors are clustered at the individual level and reported below coefficients in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.
Source: sample from TRAJAM (2015), authors' calculations.

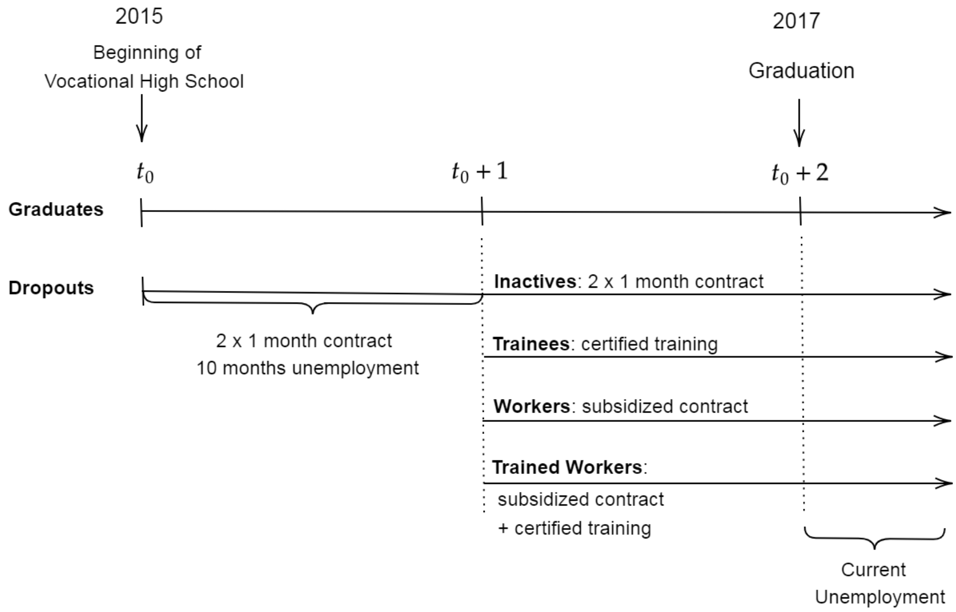
dropouts. Moreover, more than 9% of non-dropouts have had at least one period of paid employment, as opposed to only 3.5% of dropouts. Dropouts are also more likely to enroll in vocational training or a subsidized job program thereafter.

Estimates from a simple linear probability model controlling for individual characteristics that are fixed over time leads to correlations between dropout status and labor market status. Table 3.1 presents the correlations, obtained with ordinary least squares (OLS) estimations, between being a dropout and being in employment, in unemployment, and in an active program. It is clear that dropouts have a lower probability to be in paid employment than non-dropouts. Similarly, they have a higher probability of being in open unemployment or being in an active program. These results are in line with findings in the French literature on the difficulty of access to employment for dropouts (Goux and Maurin, 1994), even for those who benefited from labor market programs (Brodaty et al., 2000). Accordingly, in order to better assess the difficulties of school dropouts in accessing paid employment, it is important to get information about employers' preferences. The correspondence study presented in the next section has been designed to provide such information.

3.3 Field experiment

The experiment aims to compare the probability of callback following job applications of otherwise identical young graduates and school dropouts with different pathways in the labor market. We start by presenting the profiles of applicants and then describe the process of application and the collection of data.

FIGURE 3.1: Diagram of Treatment Profiles



3.3.1 Treatment groups

The applicants are recently unemployed young adults. They all finished lower-secondary school in June 2015, but they faced different situations over the next two years, as depicted in Figure 3.1. On the one hand, some of them continued their education to obtain a CAP diploma, either in vocational school or in apprenticeship. This group serves as the control group, since it corresponds to the natural path in the education system. We call this first group "Graduates". We apply different treatments for school dropouts than for other youths. During first year after dropping out, they had two one-month temporary contracts, with no link to the occupations targeted in the audit correspondence study, and ten months of non-employment. This year of inactivity acts as a signal of dropping out when employers look at the applications.[5] The second year after dropping out is differentiated among dropouts. Some youths once again experienced two one-month temporary contracts without any link with the targeted occupations (we call this group "Inactives"), while other underwent seven-month vocational training leading to a CAP diploma ("Trainees"), or a one-year EAv contract which could be combined with certified training leading to a CAP diploma ("Trained Workers") or not ("Workers"). These three different types of experience were linked with the targeted occupations. We stop the last line of resumes in June 2017 to make sure all the applications shared the same final duration of unemployment before applying to job vacancies.

[5] Even though this is not the conventional definition, we refer to inactivity from the employer's viewpoint of both temporary employment within another occupation and of non-employment.

3.3.2 The occupations

In view of the financial and organizational constraints, two occupations were selected. The choice of occupations is based on the following criteria: belonging to different industries, the existence of an official state certification for the diploma usually required for being hired, a sufficient proportion of former graduate upper-secondary vocational students and apprentices, a sufficient proportion of school dropouts, a relatively small age difference between graduates and dropouts at the hiring age, a sufficiently large number of job offers, being present in both market and non-market sectors so to increase the potential number of job offers, and enough employees under subsidized contracts.[6] These criteria led us to select the occupations of cook (ROME G1602) and bricklayer (ROME F1703). The vocational training characteristics leading to these two occupations through the acquisition of skills and subsidized contracts operating in these occupations are shown in Appendix 3.8.1. For our purposes, youths in construction and food services have important features in common with all youths in similar programs, and more generally with all youths at the CAP level.[7] For both occupations, the profiles are then in line with real applicants that employers encounter, even though "Trained Workers" are less usual.

3.3.3 The applicants

The profiles of applicants were then designed for these two occupations so that they have a mix of soft skills (the ones expected in a firm) and hard skills (the ones expected in the occupation).[8] Applicants are young males aged 18 at the beginning of applications and 19 at the end. We focus on men because the majority of cooks and bricklayers are male. Their names were chosen among those most commonly found in the French population. According to the *Fichiers des prénoms* (INSEE), the two first names used in the experiment, Théo and Alexis, were respectively the 9th and 13th most popular first names in 1999.[9] The surnames, Petit and Dubois, were respectively ranked 6 and 7, according to the *Fichier patronymique* (INSEE).[10] Thus our applicants, *Alexis Dubois* and *Théo Petit*, have names that are too general for them to be identified on the Internet. All in all, we chose these characteristics to avoid spurious correlations with our different labor market experiences profiles, so that there is no gender, age or ethnicity discrimination. Except for "Inactive" dropouts who have never worked as a cook or bricklayer, there is no signaling of difference in skills.

Applicants' addresses were chosen to be in the center of whatever city is the administrative capital (*préfecture*) of the department in which the job was posted, in order to ensure that candidates live sufficiently close to their potential future job and to avoid geographic discrimination.[11] Since the diploma is national, there is no information about the

[6] We used various sources, including the French Labor Force Survey (*Enquête emploi*, INSEE), the *Répertoire National des Certifications Professionelles* (RNCP) to verify the existence of national diploma, the *Pôle emploi* database to assess the number of job offers.

[7] See Cahuc and Hervelin (2020) for details.

[8] These skills were taken from the *fiches métiers Pôle emploi*. Occupation-related hobbies are cooking, pastry, international cuisine for cook, and DIY for bricklayer. Other hobbies are cinema, sport, handball, music. More details here for cooks and here for bricklayers.

[9] The first-names were chosen randomly among the top 20.

[10] The same method was done for surnames.

[11] Addresses were collected and verified through *Google Street View*.

school or about the specific training center, as usual in resumes for this type of application. The address of training firms where graduates and dropouts worked during their professional experience is not provided, in order to avoid detection of fictitious applications. These training firms are large well-known firms (*Flunch* and *Hyppopotamus* for food services and *Bouygues Construction* and *Lafarge* for construction)[12] for which the address of the establishment where one has been employed is not usually mentioned.

Moreover, we did not emphasize their dropping out after middle school, as advised by caseworkers helping this population. We mentioned only in their cover letters that "Workers" and "Trained Workers" did their professional experience through a subsidized contract. Finally, we pre-submitted our fictitious applications in cool and bricklayer positions to real actors - such as workers and caseworkers - to ensure credibility.

3.3.4 The applications

All applications included a resume and a cover letter. They were accompanied by a short email message. We sent two applications to each job vacancy in order to increase statistical power. Accordingly, two templates were created first to avoid detection by the firm, and second to ensure that callbacks did not depend on employers' preferences for a given presentation.[13] The templates were based on different samples taken from the *Pôle emploi CVthèque*,[14] a youth center sample, and Google searches. The cover letters each contained five paragraphs. The letters were written in a similar way to avoid any apparent differences in literacy between the two templates.[15]

Job offers for both occupations were mainly identified using the *Pôle emploi* website.[16] Applications were sent only when it was possible to contact the recruiter directly by email. Therefore job offers issued by temporary work agencies or other intermediaries were not considered. Moreover, the same recruiter could never be contacted more than once, even if he posted different job positions in different French areas throughout the entire experiment period.[17] The same applied for offers providing only a *Pôle emploi* counselor email address. If a job vacancy met these criteria, one (and only one) pair of applications was sent. The name of the applicant, the applicant profile, and the layout type were all selected at random. To further avoid detection by the firm, one profile among {"Workers", "Trained Workers"} on the one hand and one profile among {"Graduates", "Trainees", "Inactives"} on the other were drawn randomly. Thus a given recruiting firm cannot receive two applications sharing the same name, layout or profile.

[12]We made sure by looking at their website that these firms were present in all the French departments and that they were used to hiring people, whether apprentices, vocational students, trainees or temporary workers.

[13]See appendix 3.8.2 for examples of resumes and cover letters.

[14]This public databank is available to help recruiters in selecting different available profiles. More details at https://www.pole-emploi.fr/employeur/consultez-librement-des-cv-de-candidats.

[15]We checked that the different profiles were not correlated with the layout types so as to avoid the potential issue of template bias, addressed in Lahey and Beasley (2009).

[16]A few private job search websites, such as *Le Bon Coin* or *Indeed* were also used when the number of offers available on the *Pôle emploi* platform was too low on a given day.

[17]We also used the spontaneous applications channel to improve the validity of our results, such as discussed in Section 3.5.2 with more than 10,000 applications.

3.3.5 Data collection

In total, 10,938 applications were sent from 22 January 2018 to 13 July 2018[18]. This sample size largely satisfied our power calculations. The overall sample size was chosen to detect a minimum effect of $\pm$0.025 between the baseline callback rate of "Graduates" and that of "Dropouts", at a 5% significance level and power of 80%, using the formula in Djimeu and Houndolo (2016).[19] We then made sure that the job offer characteristics were not correlated with the different profiles. Table 3.2 provides such randomization tests with differences in means. It appears that with very few exceptions the randomization was successful, thus making our subsequent treatment estimates unbiased.

Replies from recruiters were collected up to the last recorded phone call and email message on 10 October 2018. A reply from a recruiter who stated that he did not select the application for the job vacancy is classified as a negative callback, along with the absence of callback. Any other reply is considered as a positive callback. Then, we consider two categories of positive callbacks. First, "positive callbacks", which include interview or hiring propositions and requests for further information. Requests for further information could be quite vague, such as "*Please, call me back*". They could also ask for more precise information about the candidates' training or experience, their means of transport when the job was located some way from the candidates' address, and so on. We interpret these types of callback as positive, since it is likely that they are motivated by the recruiter's potential interest in the candidate. Second, we use the category "propositions" for callbacks which offer an interview or hiring. When recruiters provided a positive answer to an application and invited the applicant to an interview or requested additional information about the application, an email was sent to thank them and inform them that the applicant had signed a labor contract with another employer.

[18]The number of applications per profile differs because of different sub-items within each profile in order to avoid firm detection and to increase internal validity. Moreover, we were able to collect some firm and job characteristics posted on 5,150 job offers thus allowing us to fully use 10,300 applications.

[19]The formula is based on the Normal distribution assumption of the error term which leads to: $n = \left\{ \frac{P}{T\delta^2} \frac{1-P}{1-T} (t_1 + t_2)^2 \right\}$, where n is the sample size, $\delta \in [0.02, 0.05]$ is the minimum detectable effect, $t_1 = 1.96$ is the t-value for a 5% significance level, $t_2 = 0.84$ is the t-value for a power of 80%, $P \in [0.07, 0.10]$ is the proportion of the study population that would get a callback in the absence of treatment (based on previous experiments), and $T = 0.5$ is the proportion of individuals randomly assigned to the treatment group.

TABLE 3.2
Randomization Tests

	Graduates	Dropouts							
		Inactives		Trainees		Workers		Trained Workers	
	(1) Sample mean	(2) Sample mean	(3) p-value (2)-(1)	(4) Sample mean	(5) p-value (4)-(1)	(6) Sample mean	(7) p-value (6)-(1)	(8) Sample mean	(9) p-value (8)-(1)
Number of observations	3,110	799		1,560		3,673		1,796	
Cook (vs bricklayer)	.8173	.7997	.2541	.7967	.0908	.8042	.1699	.8184	.9219
For-profit (vs not-for-profit)	.9497	.9495	.9831	.9400	.1714	.9474	.6742	.9459	.5702
Primary sector	.0006	.0013	.5800	.0020	.2066	.0017	.2353	.0000	.2871
Secondary sector	.0003	.0000	.6122	.0013	.2214	.0008	.4015	.0000	.4466
Tertiary sector	.8398	.9213	.2189	.8160	.0450	.8242	.0956	.8426	.7951
Construction sector	.1591	.1773	.2253	.1806	.0695	.1731	.1320	.1573	.8658
Small firm (vs large firm)	.6143	.6181	.8578	.6044	.5500	.6068	.5609	.6230	.5823
Permanent contract (vs temporary)	.4140	.4040	.6082	.4006	.3807	.4157	.8861	.3944	.1783
Full-time job (vs part-time job)	.9368	.9446	.4156	.9420	.4851	.9386	.7665	.9412	.5375
$<$ 1-year required experience	.3541	.3906	.0568	.3526	.9202	.3661	.3073	.3444	.4984
$=$ 1-year required experience	.2228	.1871	.0295	.1990	.0648	.2064	.1033	.2198	.8108
$>$ 1-year required experience	.4230	.4222	.9671	.4482	.1035	.4274	.7192	.4356	.3931
Male recruiter (vs female)	.6174	.6259	.6638	.6358	.2297	.6196	.8528	.6327	.2974

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.

3.4 Results

Table 3.3 presents our two main outcome variables by occupation for the different profiles. It emerges that positive callback rates are about 27% for "Graduates" and 23% when restricting to interview propositions. There are statistically significant callback rate differences between "Graduates" and all "Dropouts", whose callback rates are lower.

3.4.1 The lower callback rates of school dropouts

To analyze more extensively the callback rate differences, we estimate the following linear probability model with Ordinary Least Squares (OLS) estimators:

$$y_{ij} = \alpha + \beta_k T_{i=k} + x_j' \gamma + \varepsilon_{ij} \tag{3.1}$$

where y_{ij} is a dummy variable equal to one if applicant i gets called back for job j. $T_{i=k}$ is a dummy variable equal to one if applicant i is a school dropout of a particular profile $k \in \{$Inactive, Trainee, Worker, Trained Worker$\}$ as depicted in Section 3.3.1. x_j is a vector of control variables with department and month fixed effects, and job characteristics. These control variables are introduced as demeaned dummies. ε_{ij} is a residual term, orthogonal to treatment regressors thanks to randomization. Turning to parameters, β_k is of interest and measures the callback rates differences with "Graduate" for each profile k.

The OLS estimates of equation (3.1) are reported in Table 3.4.[20] The three first columns report the estimates for occupations pooled together, for different specifications including department and month fixed effects in column (2), and job characteristics in column (3), for "positive callbacks".[21] It is clear that depending on what type of labor market experience a dropout had, the probability of callback differs. The results, which are very stable across specifications, confirm the presence of statistically different callback rates between "Graduates" and "Inactive" dropouts of about -18 percentage points. Given the average callback rate in column (1) ($\approx 28\%$), dropping out of school before graduation and remaining NEET reduces the probability of having a positive callback by 67%. Column (4) displays the results for cooks and column (5) for bricklayers. Once again, the estimates of the $\beta_{k=Inactive}$ parameter are statistically different from zero and are of the same order of magnitude. However, this negative sign associated with inactivity can be reduced by active labor market policies, at least partially. Accordingly, it appears that seven months vocational training leading to a certificate, or a one-year subsidized contract, reduces the negative sign of dropping out with the same order of magnitude, i.e. by three, going -18 pp to -6 pp comparing with "Graduates". In other words, the probability of callback of "Trainee" and "Worker" dropouts still remains lower than for "Graduates",

[20] To address concerns about non-linear effects, we report the results of Table 3.13 replacing the OLS (linear probability) model with a Probit model in Appendix 3.8.3. The Probit results show that the estimated marginal effects are very similar to the OLS results. This similarity holds for all results in the paper.

[21] The results also hold when considering the more restrictive definition of callback "propositions" as presented in Table 3.14 in Appendix 3.8.3.

TABLE 3.3
Callback Rates Descriptive Statistics by Profile

	Graduates	Dropouts									
		All		Inactives		Trainees		Workers		Trained Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
All											
# Observations	3,110	7,828		799		1,560		3,673		1,796	
Positive Callback	.2787	.2124	-.0663***	.1001	-.1786***	.2185	-.060***	.2104	-.0683***	.2611	-.0176
	(.008)	(.004)	(.008)	(.010)	(.016)	(.010)	(.013)	(.005)	(.010)	(.010)	(.013)
Proposition	.2337	.1748	-.0588***	.0763	-.1574***	.1769	-.0568***	.1747	-.0589***	.2171	-.0166
	(.007)	(.004)	(.008)	(.009)	(.015)	(.009)	(.012)	(.006)	(.009)	(.009)	(.012)
Cook											
# Observations	2,542	6,306		639		1,243		2,954		1,470	
Positive Callback	.2883	.2201	-.0682***	.1048	-.1835***	.2276	-.0606***	.2183	-.070***	.2673	-.0210
	(.008)	(.005)	(.010)	(.012)	(.018)	(.011)	(.015)	(.007)	(.011)	(.011)	(.014)
Proposition	.2423	.1817	-.0605***	.0782	-.1640***	.1818	-.0605***	.1831	-.059***	.2238	-.0185
	(.008)	(.004)	(.009)	(.010)	(.017)	(.010)	(.014)	(.007)	(.011)	(.010)	(.013)
Bricklayer											
# Observations	568	1,522		160		317		719		326	
Positive Callback	.2359	.1806	-.0552***	.0812	-.1546***	.1829	-.0529*	.1780	-.0578**	.2331	-.0027
	(.017)	(.009)	(.019)	(.021)	(.035)	(.021)	(.028)	(.014)	(.022)	(.023)	(.029)
Proposition	.1954	.1465	-.0489***	.0687	-.1266***	.1577	-.0376	.1404	-.0549***	.1871	-.0083
	(.016)	(.009)	(.017)	(.020)	(.033)	(.020)	(.027)	(.012)	(.020)	(.021)	(.027)

Note: This table reports the number of observations per profile and the mean value of the primary dependent variables. A positive callback is equal to one if the fictitious candidate received a demand for complement information or a proposition for interview or hiring. Proposition corresponds to callbacks which propose an interview or hiring. Standard error of the mean is reported in parentheses below the mean. Columns (1), (2), (4), (6), (8), and (10), report the mean callback rate for each profile. While columns (3), (5), (7), (9), and (11), report the mean difference with column (1). * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent, for p-values associated with the test $H_0 : \{\Delta$ = callback[graduates] - callback[dropouts] = $0\}$ vs $H_1 : \{\Delta \neq 0\}$.

TABLE 3.4
Effects of Labor Market Experiences on Callbacks

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Inactive	-0.1854***	-0.1874***	-0.1861***	-0.1955***	-0.1576***
	(0.0137)	(0.0137)	(0.0137)	(0.0155)	(0.0297)
Trainee	-0.0661***	-0.0684***	-0.0648***	-0.0696***	-0.0423
	(0.0136)	(0.0135)	(0.0134)	(0.0151)	(0.0293)
Worker	-0.0748***	-0.0767***	-0.0754***	-0.0786***	-0.0605***
	(0.0095)	(0.0095)	(0.0094)	(0.0106)	(0.0211)
Trained Worker	-0.0215*	-0.0208*	-0.0197*	-0.0260**	0.0045
	(0.0120)	(0.0118)	(0.0117)	(0.0131)	(0.0265)
Graduate mean	0.2847***	0.2847***	0.2847***	0.2944***	0.2410***
	(0.0084)	(0.0084)	(0.0084)	(0.0093)	(0.0187)
Observations	10,300	10,300	10,300	8,348	1,952
R-squared	0.0136	0.0433	0.0576	0.0594	0.1210
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, years of professional experiences, and gender of the recruiter. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

by $\approx$ 25%. More interestingly, work experience gained through a one-year subsidized contract and certified by a state diploma after complementary vocational training improves the dropout likelihood almost to the same level as those who graduated. The probability of being called back for a job for "Trained Workers" is only 8% less than that of "Graduates". This difference is noteworthy and entirely driven by cooks, as there is a statistically non-significant difference with "Graduates" in the case of bricklayers. Compared with the baseline callback rate, this difference would be economically negligible if it were statistically significant.[22]

3.4.2 Training and experience as partial compensations only

While Table 3.4 presented the effects of labor market experiences on all callback rates, here we take advantage of the fact that each firm received two random applications per job vacancy in our setting. We look at firms which responded to only one profile, thus looking at within-posting variation. Among the 5,469 firms who received two applications, 20% of them responded to only one profile.[23] Although firms could have received more than our two applications for their job vacancies, Table 3.5 gives a second view on the ranking of profiles by recruiters.

Table 3.5 presents the same specifications as in Table 3.4. We additionally control for the pair of resumes sent to a specific job offer.[24] The difference in the probability of being called back among dropout profiles and graduates

[22] This result is also valid when one looks at the survival rate of an application as depicted in Figure 3.6 in Appendix 3.8.3. "Graduate" and "Trained Worker" applications received more callbacks sooner and for a longer period of time than of "Inactive", "Trainee" and "Worker" applications.

[23] 67% of firms did not respond to any profile, while 13% responded to both.

[24] Recall that one feature of our correspondence study was to send one profile among the pool {"Workers", "Trained Workers"} on the one hand and one profile among {"Graduates", "Trainees", "Inactives"} on the other, randomly in first or second position, to avoid firm detection. As

TABLE 3.5
Effects of Labor Market Experiences using Within-Posting Variation

Positive Callbacks	All Applicants (1)	(2)	(3)	Cook (4)	Bricklayer (5)
Inactive	-0.9054***	-0.9052***	-0.9052***	-0.9355***	-0.7444***
	(0.0756)	(0.0775)	(0.0776)	(0.0855)	(0.2422)
Trainee	-0.2864***	-0.2862***	-0.2862***	-0.3214***	-0.1028
	(0.0708)	(0.0725)	(0.0726)	(0.0806)	(0.2179)
Worker	-0.2927***	-0.2925***	-0.2925***	-0.3142***	-0.1802
	(0.0435)	(0.0446)	(0.0447)	(0.0491)	(0.1391)
Trained Worker	-0.1774***	-0.1772***	-0.1772***	-0.1941***	-0.0713
	(0.0599)	(0.0614)	(0.0615)	(0.0679)	(0.1928)
Graduate mean	0.7293***	0.7293***	0.7293***	0.7417***	0.6727***
	(0.0295)	(0.0302)	(0.0302)	(0.0335)	(0.0922)
Observations	2,140	2,140	2,140	1,776	364
R-squared	0.0997	0.0999	0.0999	0.1081	0.0752
Resume Couple	Yes	Yes	Yes	Yes	Yes
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The variation in profile treatment within job posting in each round provides the opportunity to examine within-posting variation in callback rates by profile treatment. The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. “Resume Couple” are demeaned dummy variables controlling for the pair of resumes sent to one job offer and the order of each resume (whether first or second). Department and month fixed effects are demeaned dummies. Job characteristics include dummies for th e type of contract, working time, gender of the recruiter, and years of professional experience. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. *** significant at 1 percent.

remains qualitatively similar to that for between-posting variation. However the gap between the probability of being called back for a job offer for “Graduates” and every type of “Dropouts” has increased. Indeed, the baseline callback rate for “Graduates” is now about 73% and the absolute decline for “Trained Worker” dropouts is -18 pp. It represents a decrease in the probability of about -25%, which is higher than the 8% percent difference overall as presented in Section 3.4.1. When applying the same reasoning to other profiles, we find higher drops in the probability of callback than overall, whether applications are pooled or split by occupation. When we consider only “proposition” callbacks as shown in Table 3.15 in Appendix 3.8.3, the magnitudes of callback differences remain quite similar. This result implies that when it comes to selecting candidates within a given pool of applicants, firms tend to be less favorable towards school dropouts.

3.4.3 The effects of firm characteristics

So far, we have found that only dropouts who had performed in the targeted occupations through a subsidized contract associated with certified training could match freshly graduated students or apprentices for different job offers on average. Yet the differences in callback rates between “Graduates” and all kinds of “Dropouts” could be heterogeneous depending on firm characteristics. For instance, it could be that firms which seek profits need more

a consequence, all the profiles are not paired with one another. We then control for this feature in Table 3.5 by adding dummy variables for each pair sent.

TABLE 3.6
Probability of Callbacks given Firm Characteristics

Positive Callbacks	Firm Type		Firm Size	
	For-Profit	Not For-Profit	Small	Large
	(1)	(2)	(3)	(4)
Inactive	-0.1787***	-0.3129***	-0.1631***	-0.2303***
	(0.0147)	(0.0467)	(0.0189)	(0.0241)
Trainee	-0.0697***	-0.0926*	-0.0682***	-0.0744***
	(0.0143)	(0.0532)	(0.0184)	(0.0244)
Worker	-0.0683***	-0.1780***	-0.0580***	-0.1122***
	(0.0100)	(0.0367)	(0.0131)	(0.0167)
Trained Worker	-0.0243**	0.0113	-0.0104	-0.0220
	(0.0123)	(0.0501)	(0.0157)	(0.0218)
Graduate mean	0.2814***	0.3450***	0.2714***	0.3191***
	(0.0088)	(0.0337)	(0.0113)	(0.0151)
Observations	9,206	732	5,392	3,396
R-squared	0.0439	0.2630	0.0547	0.0852
Department & Month FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. For-profit firms are firms which sell products or services for profits. Small firms are firms with at most 10 employees. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

readily skilled workers and discriminate more against dropouts with skills obtained in the classroom than not-for-profit firms. It could also be that case that small firms have less opportunity to provide on-the-job training than large firms because of tighter financial constraints, thus favoring applicants with professional experience. Or it could be that large firms have centralized a human resources platform and receive more applications, thus favoring applicants with more theoretical skills signaling competences other than just the one needed for the job tasks. In addition, not for-profit firms, like large firms, might favor applicants who have a certificate, signaling more transferable skills than applicants who only possess professional experience in the occupation.

Table 3.6 first presents the callback rate differences between profiles for for-profit and not for-profit firms in columns (1) and (2) respectively. Even though, most of our sample is constituted by for-profit firms which drive the overall results, it appears that not-for-profit firms issue fewer callbacks to applicants without any diploma. The probability of positive callback then decreases by almost 90% for "Inactive" dropouts and by around 50% for "Workers". On the other hand, dropouts who signal a CAP diploma after dropping out of school have lower callback rates than "Graduates" but they have better chances than the other dropouts, especially those who combined vocational training with work experience. To some extent this pattern is the same when decomposing firms by size into small firms versus large firms in columns (3) and (4) respectively.[25] Large firms seem to consider applicants without skills certified by any diploma to a lesser extent than applicants who do. Tables 3.16 and 3.17 in Appendix 3.8.3 indicate

[25]Because of noise in our firm size variable obtained from job ads, we define small firms as small when they have fewer than 10 employees and large firms otherwise.

TABLE 3.7
Probability of Callbacks given Contract Characteristics

Positive Callbacks	Type of Contract: Temporary (1)	Type of Contract: Permanent (2)	Required Experience: $\leq$ 1y (3)	Required Experience: $>$ 1y (4)
Inactive	-0.1990***	-0.1701***	-0.2393***	-0.1222***
	(0.0185)	(0.0199)	(0.0195)	(0.0191)
Trainee	-0.0707***	-0.0699***	-0.0798***	-0.0483***
	(0.0181)	(0.0203)	(0.0193)	(0.0180)
Worker	-0.0858***	-0.0647***	-0.0949***	-0.0504***
	(0.0126)	(0.0143)	(0.0132)	(0.0133)
Trained Worker	-0.0222	-0.0210	-0.0183	-0.0246
	(0.0155)	(0.0180)	(0.0165)	(0.0163)
Graduate mean	0.3045***	0.2570***	0.3420***	0.2062***
	(0.0111)	(0.0126)	(0.0115)	(0.0115)
Observations	6,060	4,240	5,856	4,444
R-squared	0.0585	0.0560	0.0571	0.0490
Department & Month FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. "1y" stands for one year's experience in the occupation. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. *** significant at 1 percent.

similar results for cooks and not that much for bricklayer positions, probably because of too few observations.

3.4.4 The effects of contract characteristics

Callback rate differences among profiles could also be heterogeneous given contract characteristics. Firms that recruit under seasonal or temporary contracts might need operational workers and favor applicants with more practical job-related skills compared to applicants who stayed inactive or had vocational training only. Accordingly, firms which offer a permanent contract could be more willing to create a long-term match with their employee when more theoretical skills would be valued more than practical skills if the task contents of the job change. Another important feature for filling the vacancy is the amount of professional experience required by firms. Firms which request previous professional experience in the occupation could be more reluctant to call back applicants whose maximum experience is two years for "Graduates", one year for "Workers" and "Trained Workers", few weeks for "Trainees", and none for "Inactive" dropouts.

Table 3.7 reports the callback rates for temporary contracts in column (1) and permanent contracts in column(2), and for jobs with at most one year experience in the occupation in column (3) and more than one year of experience in column (4). With regard to the type of contract, there is no major difference in callback profiles between temporary and permanent contracts, and overall results. Turning to the required experience asked for by the firm in the occupation, the first apparent and expected element is the lowering of baseline callback for "Graduates" when experience required increases, falling from 34% when less than one year or equal of experience is required to 21% when more than one year is required. In our setting, "Trainee" applicants have a maximum of two-months on-the-job training during their vocational training, whereas both "Worker" and "trained Worker" applicants have a year's professional experience. Yet estimates point to a difference in callback rates similar to overall results when compared to the baseline callback rate of "Graduates". This can be viewed as proof that signaling a diploma matters more when it is associated with longer period in firms than with brief periods only. Tables 3.18 and 3.19 in Appendix 3.8.3 show similar results for both cook and bricklayer positions.

All in all, whatever the occupation, the specification and the sub-sample, our results point to a clear ranking of youth profiles by employers:

$$\underbrace{\text{Inactives} \prec \text{Workers} \approx \text{Trainees} \prec \text{Trained Workers}}_{Dropouts} \preceq \text{Graduates}$$

3.5 Robustness checks

We confirm the results obtained in the audit correspondence study through a battery of robustness checks, in particular by adding external information to our database and exploring a second channel of application.

3.5.1 Additional information

We first test our results by adding external information to our database, especially two new variables, namely the distance to the job location and the unemployment rate in the firm's commuting zone.[26]

For each job vacancy that received an application, we recorded the location of the job. Since, as stated in 2.3.1, each applicant lives in the city that is the administrative center of the department where the job vacancy was posted. We were able to determine the distance in kilometers between the applicant's place of residence and the job location. In our sample, the distance to a job location ranges from 0.04 km to 299.25 km. The mean distance is 31.5 km. We also consider the quarterly unemployment rate in the commuting zone in which firms operate. Since the official unemployment rate by commuting zone is available quarterly, and since our experiment ran from January to July 2018, we link either the first-quarter or second-quarter unemployment rate to each profile-commuting zone pair, depending on the time of application. In our sample, the unemployment rate ranges from 4.4% to 16.8%. The mean unemployment rate is 8.9%. Following Athey and Imbens (2017a), we demeaned our two continuous variables and fully interacted them with our profile variables to ensure unbiased estimates.

First, Table 3.8 shows that the signs of "Job Distance" and "Unemployment Rate" are as expected. The greater

[26] A commuting zone is a geographic area determined by the French national statistic institute (INSEE), inside which most of the active agents live and work. We were able to collect information on these two variables for about 90% of our sample, because of reported errors in firm locations.

TABLE 3.8
Probability of Callbacks with Interacted Additional Information

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Job Distance (km)	-0.0475	-0.0458	-0.0653**	-0.0799**	0.0066
	(0.0292)	(0.0292)	(0.0290)	(0.0315)	(0.0740)
Unemployment Rate (%)	-0.0191***	-0.0191***	-0.0175***	-0.0191***	-0.0101
	(0.0044)	(0.0044)	(0.0044)	(0.0050)	(0.0093)
Inactive	-0.1978***	-0.1988***	-0.1988***	-0.2110***	-0.1509***
	(0.0153)	(0.0153)	(0.0152)	(0.0171)	(0.0356)
Inactive × Job Dist.	0.0720	0.0715	0.0548	0.0522	0.0850
	(0.0610)	(0.0612)	(0.0601)	(0.0644)	(0.1735)
Inactive × Unemp. Rate	0.0140*	0.0139*	0.0152**	0.0153*	0.0151
	(0.0077)	(0.0077)	(0.0077)	(0.0087)	(0.0151)
Trainee	-0.0763***	-0.0773***	-0.0742***	-0.0791***	-0.0527
	(0.0151)	(0.0151)	(0.0149)	(0.0167)	(0.0332)
Trainee × Job Dist.	0.0885	0.0863	0.0706	0.0949	-0.0664
	(0.0554)	(0.0553)	(0.0548)	(0.0596)	(0.1396)
Trainee × Unemp. Rate	-0.0012	-0.0011	0.0008	0.0004	0.0038
	(0.0074)	(0.0074)	(0.0074)	(0.0082)	(0.0167)
Worker	-0.0823***	-0.0828***	-0.0819***	-0.0858***	-0.0603***
	(0.0105)	(0.0105)	(0.0104)	(0.0117)	(0.0231)
Worker × Job Dist.	0.0639**	0.0627**	0.0566*	0.0737**	-0.0369
	(0.0308)	(0.0307)	(0.0306)	(0.0334)	(0.0770)
Worker × Unemp. Rate	0.0043	0.0043	0.0048	0.0016	0.0194*
	(0.0049)	(0.0049)	(0.0048)	(0.0055)	(0.0101)
Trained Worker	-0.0253*	-0.0259**	-0.0253*	-0.0321**	0.0048
	(0.0131)	(0.0131)	(0.0129)	(0.0144)	(0.0303)
Trained Worker × Job Dist.	0.0270	0.0261	0.0234	0.0230	0.0220
	(0.0424)	(0.0423)	(0.0416)	(0.0453)	(0.1048)
Trained Worker × Unemp. Rate	-0.0016	-0.0017	-0.0008	0.0040	-0.0224
	(0.0065)	(0.0065)	(0.0065)	(0.0073)	(0.0145)
Constant (≈ Graduate mean)	0.3025***	0.3030***	0.3021***	0.3130***	0.2444***
	(0.0092)	(0.0092)	(0.0091)	(0.0109)	(0.0216)
Observations	8,600	8,600	8,600	7,024	1,576
R-squared	0.0222	0.0246	0.0453	0.0472	0.0470
Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. "Job Distance" is a demeaned continuous variable in kilometers. "Unemployment Rate" is a demeaned continuous variable of the ratio of individuals seeking for jobs over the labor force by commuting zone. Department and month fixed effects are demeaned dummies. Job characteristics include demeaned dummies for the type of contract, working time, gender of the recruiter, and years of professional experiences. All columns report OLS linear probability model estimates. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

the distance to the job location, the lower the likelihood of being called back. Similarly, the higher the unemployment rate at the local level, the lower the likelihood of being called back. Second, even with the introduction of these two external variables and of interactions with our profile dummies, both the ranking of profiles and the drop in the probability of callback in terms of percentage are respected. Third, except marginally for dropouts with one-year work experience, the location of the job does not matter for the different types of dropouts. Fourth, estimates indicate that, compared to "Graduate" applicants, "Inactive" school dropouts get a lower negative signal when the job is located in a city where the unemployment rate is higher.

3.5.2 Speculative applications

It appears that a high proportion of job vacancies was managed by temporary work agencies during the experiment, especially for bricklayer positions.[27] One feature of our occupations makes it also likely that workers are aware of a small but non-negligible number of job vacancies through network information or a word of mouth. Accordingly, we considered spontaneous applications as a second channel of application, that is to say, we send the profiles of applications to firms operating in these two occupations without answering to any job ads.

We obtained a list of firms operating in these two occupation areas from the Internet.[28] We then refined the list to ensure that some firms did not receive a previous candidate from our initial testing. We also delete plants belonging to the same firm. At the same time, we used the same resumes and cover letters. We simply changed some brief sentences in the cover letter and the email to better match a spontaneous application. We also randomized the profile, the template, and the name of fictitious applicant be sent to a firm.L We additionally picked a random date and time of sending.[29] Here each firm received one, and only one, application.

We ended up sending 10,963 spontaneous applications to firms in October 2018 for bricklayers and in November and December 2018 for cooks. Our fictitious applicants were therefore in direct competition with real freshly graduated students or apprentices for applications in the last quarter of 2018. Our resumes were then updated by one year to match the end of the new academic year and to avoid too strong a negative signal associated with the duration of unemployment.

Results are shown in Table 3.9. We consider the same outcome variable and specifications as in section 2.4. Although applying spontaneously for certain jobs seem to be less successful than applying to a job offer, indicated by lower callback rates, the hierarchy of profiles remains identical. The negative signal associated with weaker profiles is also slightly less strong than in the original study. Here, the loss of attractiveness when applying spontaneously to a firm is about 43% for "Inactive" dropouts, and between 17% and 25% for "Trainees" and "Workers" respectively.

[27] For a given week checked in July 2018, more than 60% of job vacancies were managed by temporary work agencies on the online *Pôle emploi* platform.

[28] We extracted various information such as the national id of the firm, the zip code, the phone number and email address from *Qualibat* and *La Bonne Boite* websites.

[29] The date was randomly drawn from Monday to Friday and the time was randomly drawn from 8 am to 9 pm, as in the initial correspondence study.

TABLE 3.9
Probability of Callbacks with Speculative Job Applications

Positive Callbacks	All applicants		Cook	Bricklayer
	(1)	(2)	(3)	(4)
Inactive	-0.0332***	-0.0316***	-0.0354***	-0.0254*
	(0.0075)	(0.0075)	(0.0088)	(0.0145)
Trainee	-0.0138**	-0.0140**	-0.0135	-0.0128
	(0.0069)	(0.0069)	(0.0082)	(0.0131)
Worker	-0.0206***	-0.0200***	-0.0170**	-0.0283**
	(0.0068)	(0.0068)	(0.0082)	(0.0124)
Trained Worker	-0.0052	-0.0048	-0.0076	0.0032
	(0.0087)	(0.0086)	(0.0102)	(0.0164)
Graduate mean	0.0780***	0.0780***	0.0779***	0.0783***
	(0.0051)	(0.0051)	(0.0060)	(0.0096)
Observations	10,963	10,963	7,812	3,151
R-squared	0.0019	0.0201	0.0260	0.0449
Department & Day FE	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. Department and day fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the department level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

There is also a small statistically non-significant difference between “Graduates” and “Trained Workers”. These results thus support the conclusion drawn from the initial testing. If students drop out of school before graduation, their applications receive less consideration, which is quite pronounced if they have been inactive for two years, although this problem could be alleviated through active labor market policies.

3.6 Open discussion

Before concluding, we present some of the potential mechanisms accounting for the lower probability of callback for dropout applicants and open a discussion on the limits and external validity of our experiment (Banerjee et al., 2017).

3.6.1 Potential mechanisms

We think of two potential mechanisms that may explain what drives the negative sign of our dropout treatment profiles.[30] The first mechanism concerns the negative signal that dropping out of the school system entails for youths. Their doing so may suggest to employers that these youths are incapable of fitting into a proper formal

[30] Even if our experiment had not been designed to illustrate properly the potential underlying mechanisms, we manipulate our different treatment groups to provide some information. However, we do not provide explanations for the likeliness of “Trainee” and “Worker” estimates as we are not able to say whether it comes from the skill content similarities, or from the design of our profiles. Additional questions related to firm retention after a subsidized contract are also left apart from this discussion as it is not our primary interest here, but they are analyzed in ongoing research.

system. It could also indicate that they have not acquired the skills needed to do the job and will not produce positive results for the firm (Piopunik et al., 2020). Private actors may use the failure to finish school to filter applicants for job positions before the hiring stage. This might explain why signaling the necessary skills for the jobs after a vocational training program or a subsidized job program reduces the negative sign associated with dropping out of school. But this is not sufficient to completely offset the shortfall. Accordingly, the combination of a nationally recognized certificate and professional experience seems a necessary condition to boost further the chances of dropouts who only had previous experience in the occupations, as in Cahuc et al. (2019b), or only classroom training. Indeed, Table 3.20 in Appendix 3.8.4 shows that dropout workers with a skill certificate from their employers perform no better than dropout workers without any certificate, but they are given less consideration by recruiters than dropout workers who signal their skills through a public national certificate.[31]

The other mechanism, which has received much attention in the literature, could be the duration of unemployment dependence. Various studies have analyzed the effect of unemployment duration on the probability of callback. For the US, Kroft et al. (2013b) find a clear decline in the probability of callback for individuals during the first eight months of unemployment, whereas after that period callback rates remain stable at a low level of about 4%. However, Farber et al. (2016) and Nunley et al. (2017) find no such pattern. Farber et al. (2019) suggest that there is adverse unemployment duration effect on callback only after one year of unemployment. They also take into account different age profiles and find an inverted U-shaped curve between age and callback rates, with a lower probability of callbacks for younger as opposed to older applicants. But they do not find any cross-effect of age and unemployment duration on callbacks. For young people in Sweden, Eriksson and Rooth (2014) find that only contemporary unemployment leads to a reduction in the probability of callback for low and medium skilled workers, but not because of previous unemployment. They find also no effect for high skilled workers. They find that the negative effect occurs only after nine months of unemployment. In Switzerland, Oberholzer-Gee (2008) finds adverse effect after thirty months. For France, as shown in Table 3.21 in Appendix 3.8.4, we find that longer unemployment leads to lower callback rates for low-skilled youths. Though the magnitude of the effect cannot be fully discussed, it seems relatively small in our case probably because of the young age of applicants. One way to (partially) alleviate this negative dependence, if any, would be participation in an active labor market program, thereby raising the attractiveness of participants to that of those with a non-inactive profile.[32]

3.6.2 External validity

Our experiment is as internally valid as possible, but some questions about its external validity remain. In reality, the productivity of a worker is not known by the employer and observables in a resume cannot provide full information

[31] We put this proposition into perspective, since we do not bring any specific information about the previous employers of the youths, or a copy of the private certificate. More research is needed in this direction.

[32] Future research should focus on disentangling human capital from signaling effect for explaining why such policies are better perceived by employers. Whereas here, we only discuss why school dropouts have a lower probability of callbacks than non-dropouts.

(Heckman, 1998). This audit study only measures the interviewing stage of the hiring process and employers may have specific expectations during the hiring stage, changing the hierarchy of profiles. External validity is also constrained by each decision in the design, such as the occupations targeted and the timing of applications (Lahey and Beasley, 2009, 2016). Ultimately, this audit study sheds light on potential differences between school graduates and dropouts, not real differences (Fougère et al., 2011), which could be higher, mainly because of greater differences in the composition of the pool of applicants and/or differences in employers' expectations given their prior experience with youths (Neumark, 2012). Moreover, our analysis focuses only on the very short term effect of some active labor market policies and ignores any longer run effect or impact on wages.

Additionally, we test only long-term vocational training with certification and leave aside shorter vocational training or vocational training which can lead to no or a lower level of certification. The recent rise in such training, whether provided by public or private operators, should be interesting to analyze - for example, as massive open online courses (MOOC) which enable anyone to obtain private certification for different occupations at almost any level of qualification. Deming et al. (2016) show that, depending where the certification has been obtained, this is a component that employers look at, at least in the US for students with bachelor qualifications. Similarly, Osikominu (2013) indicated that longer term vocational training performs better than shorter training in helping job seekers to find stable and better paid positions on the labor market, but that shorter training is cost-effective in the short run. Accordingly, we sent our applications in occupations where the market is tight. In less tight occupations, dropout applicants may suffer adversely as a result of not having the required skills or having too little professional experience because of their young age, and longer vocational training would be preferred. Concerns about general equilibrium effects should also be kept in mind, as active policies could possibly change the composition of the job queue instead of reducing youth unemployment, especially when labor demand is low (Crépon et al., 2013a).

Nevertheless, our results suggest that employers, who are not indifferent between graduates and dropouts when they select applications, contribute to the polarization among these two populations. Though there may be several mechanisms operating behind a match between a worker and a job (Petrongolo and Pissarides, 2001), it particularly concerns the ranking of applicants made by firms. It has been demonstrated that firms may prefer candidates with less time spent non-employed, which is mostly the case for non-dropouts. Because setting up interviews is costly, if an unemployed worker has not previously had a job, it signals to potential employers that such worker is not productive enough, thus leading to unemployment duration signaling low ability (Blanchard and Diamond, 1994, Jarosch and Pilossoph, 2018b). Wolthoff (2018) even shows that when there is a positive aggregate productivity shock, firms may use a high recruiting intensity strategy, i.e. they select more applicants than needed for a job, leading to low differences at the callback stage, but still high differences at the hiring stage. Moreover, if there is a sufficient pool of applicants for vacancies, then long-term unemployed (or dropouts in our case) face even higher risks from remaining in non-employment situations. In turn, this induces applicants to apply for jobs with lower wages and less favorable contracts (Le Barbanchon et al., 2017), thereby accentuating a dual labor market. Our experiment thus points to the value of preventing dropping out of school or acting as early as possible after dropping out of school, in order to give dropouts the skills documented by a national certificate, since doing so boosts their chances of being called back by employers.

3.7 Conclusion

School dropouts often face persistent difficulties entering the labor market, which public policies fail to address. Our article contributes to the understanding of those difficulties by focusing on employers' for different items in youth applications. We were able to rule out potential selection bias by performing a correspondence study. During 2018, we sequentially sent more than 10,000 applications to job offers and 10,000 speculative applications, throughout metropolitan France. We find that the probability of being called back for a job decreases by 67% on average for a school dropout who has been inactive for two years compared to a non-dropout school leaver. The callback rate increases if dropouts enter an active labor market program within two years, such as attending certifying vocational training or obtaining a one-year subsidized contract, but it is still about 20% lower than that of non-dropout school graduates. Only dropouts who have acquired relevant experience from a one-year subsidized contract and have their skills certified with a state diploma have the same callback rate as their non-dropouts peers. Various sensitivity analyses and robustness checks confirm our results.

Lastly, our results highlight the importance that employers give to diplomas and experience in France. The French government recently mandated under the Youth Guarantee that anyone who drops out from school should receive training within the four months. This new policy should provide further opportunities to confirm our results in the coming years.

3.8 Appendix

3.8.1 Related descriptive statistics

TABLE 3.10
Descriptive Statistics about Vocational Training

	All	Under 18 (2.39%)		
		All	Cook	Bricklayer
	(1)	(2)	(3)	(4)
Sex (male)	49.28%	56.36%	55.80%	53.39%
School level				
BAC+	27.11%	3.15%	1.70%	1.44%
BAC	22.09%	18.99%	22.34%	18.73%
CAP	32.83%	44.46%	41.28%	45.82%
DNB	17.97%	33.40%	34.68%	34.01%
Mean age (at entry)	34 yo	16.5 yo	16.5 yo	16.5 yo
Training duration (in months)	5	6	5	5.5
Training intensity (in hours)	687	826	797	859
Training level				
BAC+	19.17%	23.77%	1.97%	1.27%
BAC	16.74%	17.96%	8.06%	5.08%
CAP	40.88%	36.07%	63.08%	63.96%
DNB	23.21%	22.21%	26.88%	29.70%
Certified training	9.38%	9.24%	8.07%	11.85%
Diploma	43.20%	45.26%	49.93%	34.70%
Title	15.96%	15.72%	12.24%	29.96%
Periods in firm	56.86%	57.07%	69.26%	73.28%

Note: Vocational training are training financed by the French employment public service (*Pôle emploi*).
Source: FHA (2015-T4), 3,246,881 obs, authors' calculations.

TABLE 3.11
Descriptive Statistics about Subsidized Jobs

	All	Under 18 (1.18%)		
		All	Cook	Bricklayer
	(1)	(2)	(3)	(4)
Sex (male)	50.05%	63.34%	76.03%	100.0%
School level				
BAC+	4.43%	0.00%	0.00%	0.00%
BAC	20.09%	2.52%	0.00%	0.00%
CAP	51.37%	40.23%	60.33%	36.96%
DNB	24.11%	57.27%	39.67%	63.04%
Mean age (at entry)	21.5 yo	16.5 yo	16.5 yo	16.5 yo
Temporary contract	77.01%	67.79%	33.06%	63.04%
Contract duration				
$\leq$ 1 year	68.33%	72.43%	78.51%	80.43%
$\leq$ 3 years	31.67%	27.57%	21.49%	19.57%
# of renewals				
1	15.60%	2.11%	0.82%	2.13%
2	4.77%	0.00%	0.00%	0.00%
3	0.20%	0.00%	0.00%	0.00%
# of ruptures	24.56%	29.91%	42.15%	23.91%
By employee	45.11%	50.24%	50.98%	45.45%
Firm size				
Small	32.39%	48.37%	68.32%	69.23%
Medium	52.26%	45.92%	28.71%	28.21%
Large	15.35%	5.71%	2.97%	2.56%
W/ certified training	30.92%	32.85%	29.75%	36.96%
In center	72.30%	78.12%	83.33%	88.24%

Note: Subsidized jobs are *Emploi d'Avenir* (EAv).
Source: NOÉ (2012-2015), 234,643 obs, authors' calculations.

TABLE 3.12
Profile of School Dropouts under 18

	All		Dropouts	
	(1)	(2)	(3)	(4)
Frequencies	19,186	100%	510	2.66%
Sex (male)	9,714	50.63%	321	62.94%
School level				
BAC+	7	0.04%	0	0.00%
BAC	264	1.38%	0	0.00%
CAP	1,284	6.69%	2	0.39%
DNB	17,635	91.90%	508	99.61%
Literacy				
A	17,450	90.95%	372	72.94%
B	310	1.62%	43	8.43%
C	317	1.65%	29	5.69%
D	359	1.87%	27	5.29%
E	625	3.26%	37	7.25%
Missing	125	0.65%	2	0.39%
Labor market experience (within the next 30 months)				
Unemployment	2,536	13.22%	242	47.45%
Vocational training	136	0.71%	11	2.16%
Subsidized job	143	0.75%	9	1.76%
Employment	1,843	9.60%	18	3.53%

Note: The selected sample corresponds to French youths, under 18 ($\approx 85\%$ of the total sample), who had their army day (JDC) between January and June 2013. A dropout is a youth not registered in school at the moment of the JDC. Literacy levels are reported after a French test during the JDC where A stands for "Normal reader" to E for "Illiterate". The bottom part "Situation" indicates that $x\%$ of youths have experienced at least one situation among the four situations presented within the next two years and a half after their JDC (e.g. 47.45% of dropouts have experienced at least one situation of open unemployment within the next 2.5 years after their JDC).
Source: sample from TRAJAM (2013-2015), authors' calculations.

3.8.2 Examples of documents for applications

Application email messages (by layout)

For type 1 applications, the email message was the following:

Object: Application job offer n°XXX

Attached files: Curriculum_Vitae.pdf, Lettre_Motivation.pdf

Dear Madam, Sir,

With reference to your advertisement XXX for the position of YYY, I wish to submit my application.
Please find enclosed my cover letter and my resume.
May I assure you, Madam, Sir, of my sincere gratitude.

First name, Last name
Phone number

For type 2 applications, the email message was the following:

Object: Application (job ads XXX)

Attached files: CV.pdf, LM.pdf

Dear Madam, Sir,

I am pleased to submit my application for the position of YYY following your advertisement XXX published on the website Pôle emploi.
I am sending you in the attachment my resume and my cover letter.
May I assure you, Madam, Sir, that I remain faithfully yours.

First name, Last name
Phone number

Application reply email messages (by candidate)

For Alexis Dubois application reply, the email message was the following:

Greetings,

Thank you for your consideration of my application. However, I am unable to respond favorably. Indeed, I have accepted another offer.

With kind regards,
Alexis Dubois

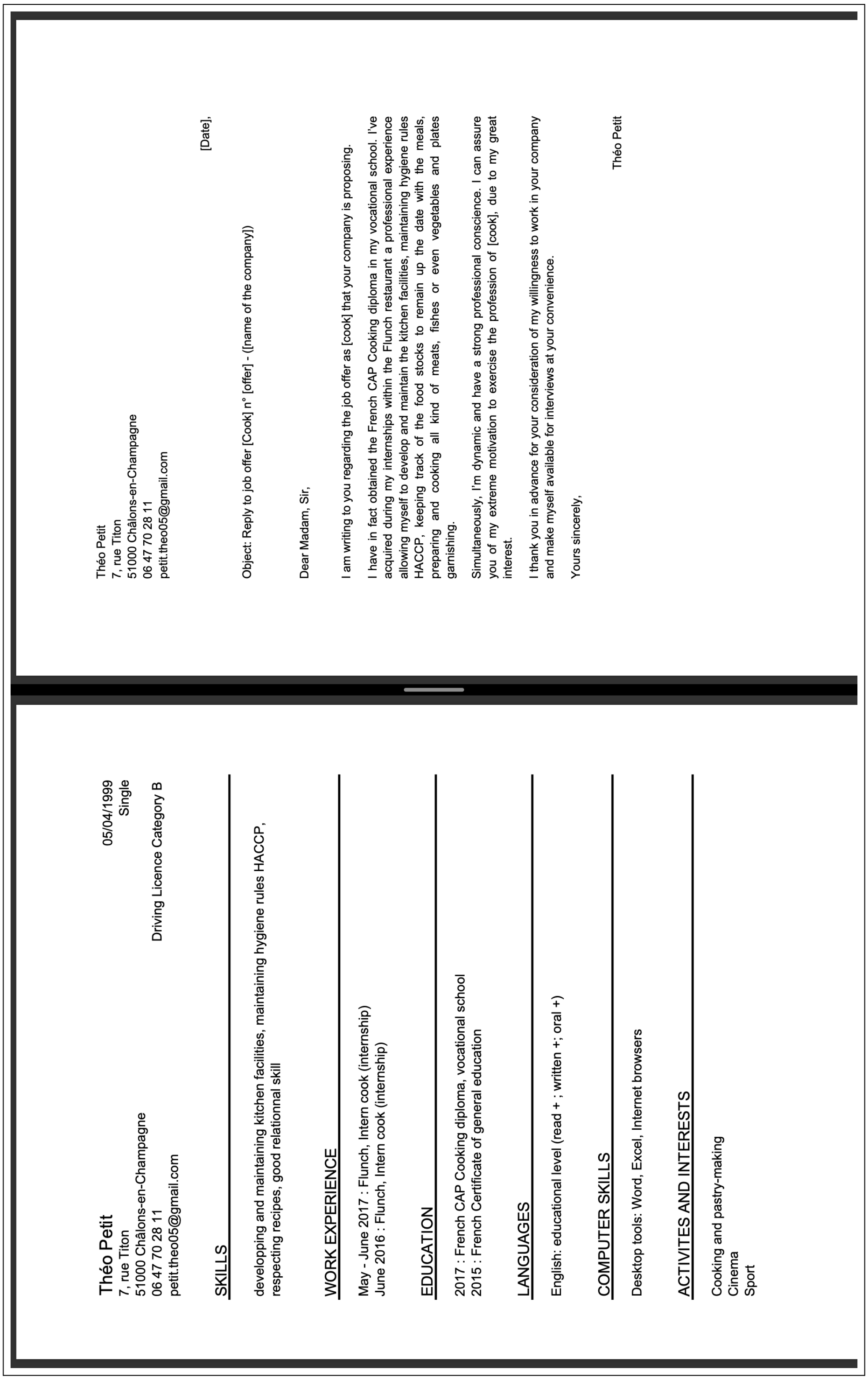
For Théo Petit application reply, the email message was the following:

Good morning,

I thank you for your answer regarding my application. Nevertheless, I have just accepted another offer.

Sincerely,
Théo Petit

FIGURE 3.2: Example of CV and Cover Letter (Cook Student - layout 1)



Théo Petit
7, rue Titon
51000 Châlons-en-Champagne
06 47 70 28 11
petit.theo05@gmail.com

05/04/1999
Single
Driving Licence Category B

SKILLS

developping and maintaining kitchen facilities, maintaining hygiene rules HACCP, respecting recipes, good relationnal skill

WORK EXPERIENCE

May - June 2017 : Flunch, Intern cook (internship)
June 2016 : Flunch, Intern cook (internship)

EDUCATION

2017 : French CAP Cooking diploma, vocational school
2015 : French Certificate of general education

LANGUAGES

English: educational level (read + ; written +; oral +)

COMPUTER SKILLS

Desktop tools: Word, Excel, Internet browsers

ACTIVITES AND INTERESTS

Cooking and pastry-making
Cinema
Sport

Théo Petit
7, rue Titon
51000 Châlons-en-Champagne
06 47 70 28 11
petit.theo05@gmail.com

[Date],

Object: Reply to job offer [Cook] n° [offer] - ([name of the company])

Dear Madam, Sir,

I am writing to you regarding the job offer as [cook] that your company is proposing.

I have in fact obtained the French CAP Cooking diploma in my vocational school. I've acquired during my internships within the Flunch restaurant a professional experience allowing myself to develop and maintain the kitchen facilities, maintaining hygiene rules HACCP, keeping track of the food stocks to remain up the date with the meals, preparing and cooking all kind of meats, fishes or even vegetables and plates garnishing.

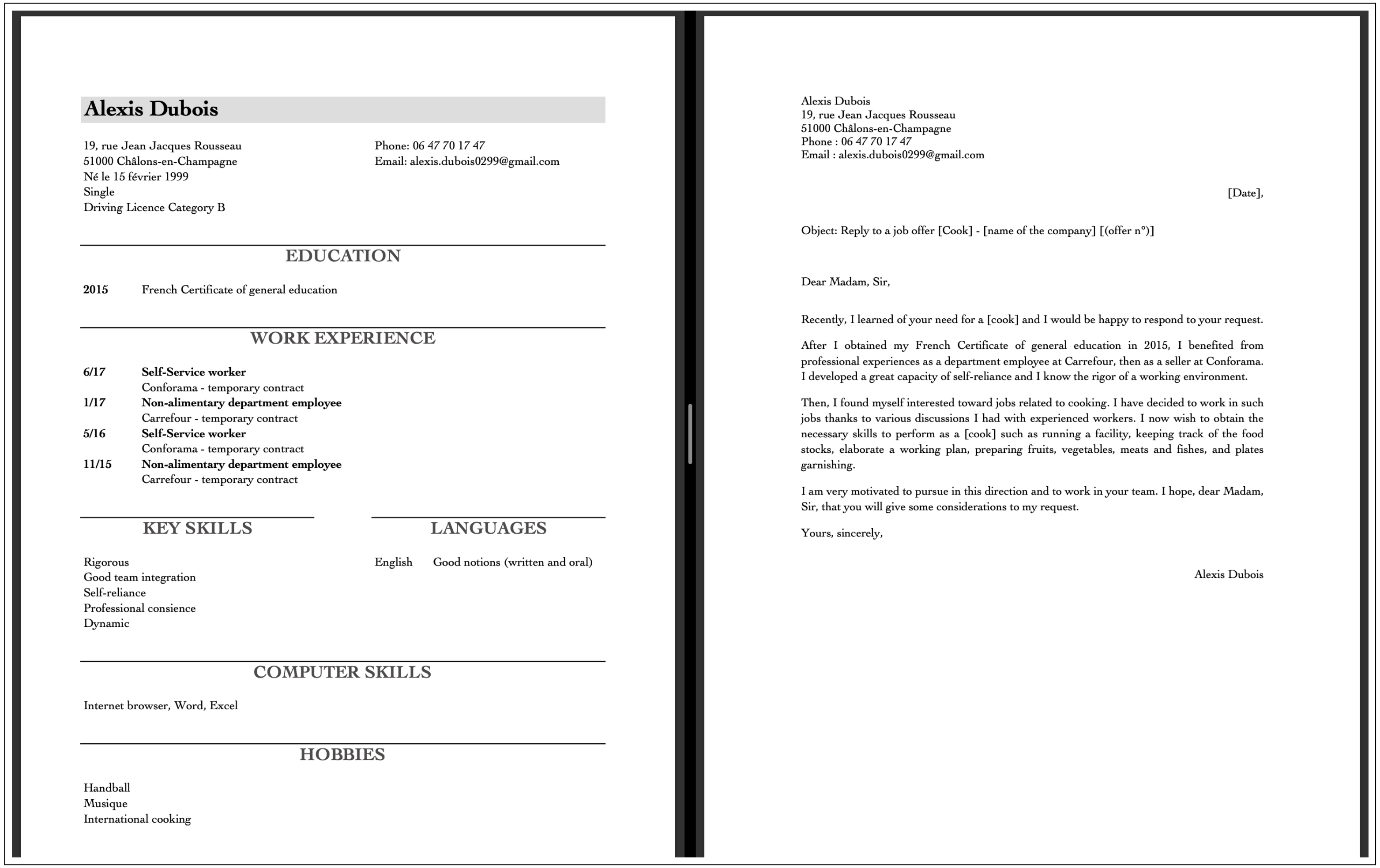
Simultaneously, I'm dynamic and have a strong professional conscience. I can assure you of my extreme motivation to exercise the profession of [cook], due to my great interest.

I thank you in advance for your consideration of my willingness to work in your company and make myself available for interviews at your convenience.

Yours sincerely,

Théo Petit

FIGURE 3.3: Example of CV and Cover Letter (Cook Inactive - layout 2)



Alexis Dubois

19, rue Jean Jacques Rousseau
51000 Châlons-en-Champagne
Né le 15 février 1999
Single
Driving Licence Category B

Phone: 06 47 70 17 47
Email: alexis.dubois0299@gmail.com

EDUCATION

2015 French Certificate of general education

WORK EXPERIENCE

6/17 **Self-Service worker**
Conforama - temporary contract
1/17 **Non-alimentary department employee**
Carrefour - temporary contract
5/16 **Self-Service worker**
Conforama - temporary contract
11/15 **Non-alimentary department employee**
Carrefour - temporary contract

KEY SKILLS

Rigorous
Good team integration
Self-reliance
Professional consience
Dynamic

LANGUAGES

English Good notions (written and oral)

COMPUTER SKILLS

Internet browser, Word, Excel

HOBBIES

Handball
Musique
International cooking

Alexis Dubois
19, rue Jean Jacques Rousseau
51000 Châlons-en-Champagne
Phone : 06 47 70 17 47
Email : alexis.dubois0299@gmail.com

[Date],

Object: Reply to a job offer [Cook] - [name of the company] [(offer n°)]

Dear Madam, Sir,

Recently, I learned of your need for a [cook] and I would be happy to respond to your request.

After I obtained my French Certificate of general education in 2015, I benefited from professional experiences as a department employee at Carrefour, then as a seller at Conforama. I developed a great capacity of self-reliance and I know the rigor of a working environment.

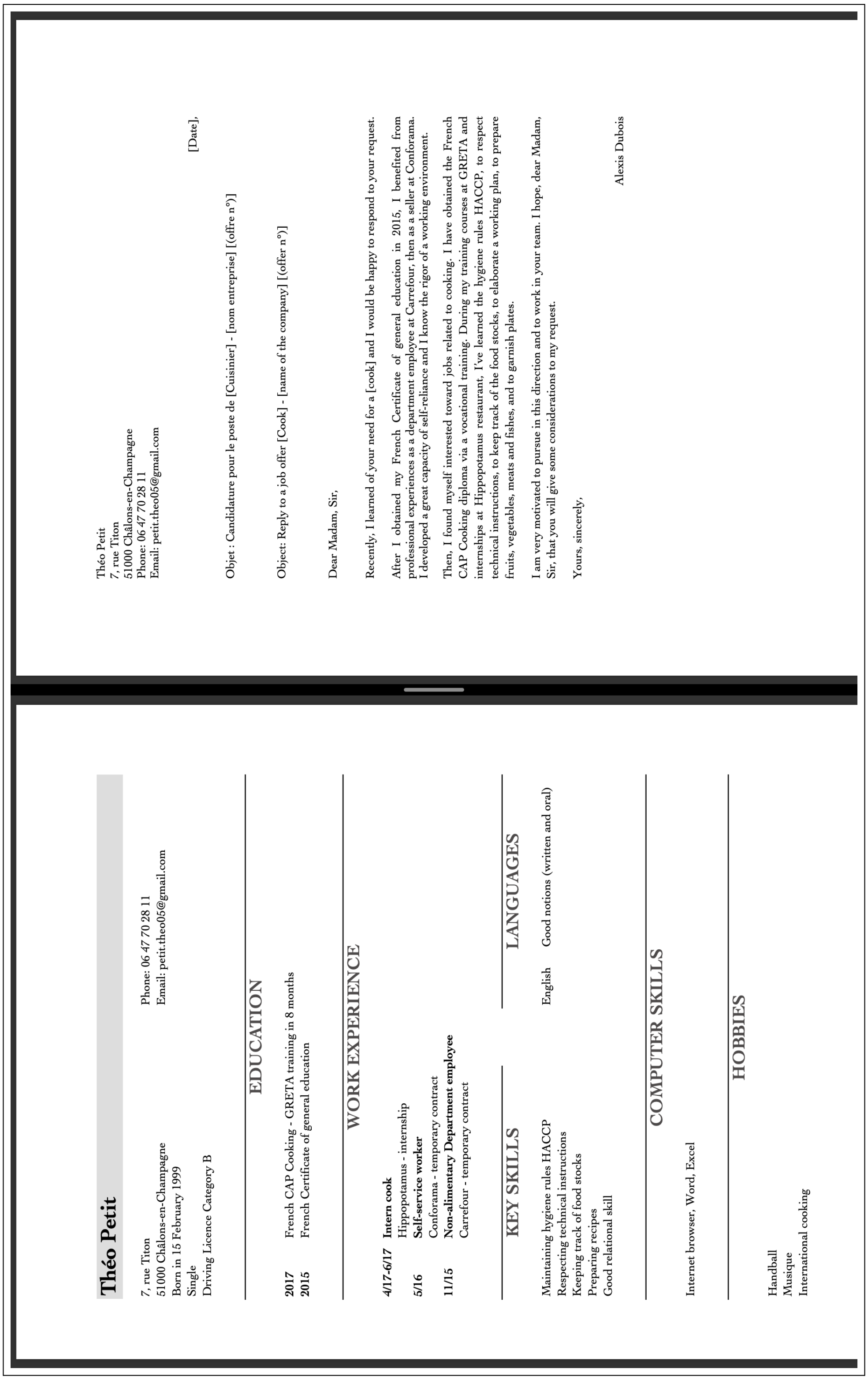
Then, I found myself interested toward jobs related to cooking. I have decided to work in such jobs thanks to various discussions I had with experienced workers. I now wish to obtain the necessary skills to perform as a [cook] such as running a facility, keeping track of the food stocks, elaborate a working plan, preparing fruits, vegetables, meats and fishes, and plates garnishing.

I am very motivated to pursue in this direction and to work in your team. I hope, dear Madam, Sir, that you will give some considerations to my request.

Yours, sincerely,

Alexis Dubois

FIGURE 3.4: Example of CV and Cover Letter (Cook Trainee - layout 2)



Théo Petit

7, rue Titon
51000 Châlons-en-Champagne
Born in 15 February 1999
Single
Driving Licence Category B

Phone: 06 47 70 28 11
Email: petit.theo05@gmail.com

EDUCATION

2017 French CAP Cooking - GRETA training in 8 months
2015 French Certificate of general education

WORK EXPERIENCE

4/17-6/17 **Intern cook**
Hippopotamus - internship
5/16 **Self-service worker**
Conforama - temporary contract
11/15 **Non-alimentary Department employee**
Carrefour - temporary contract

KEY SKILLS

Maintaining hygiene rules HACCP
Respecting technical instructions
Keeping track of food stocks
Preparing recipes
Good relational skill

LANGUAGES

English Good notions (written and oral)

COMPUTER SKILLS

Internet browser, Word, Excel

HOBBIES

Handball
Musique
International cooking

Théo Petit
7, rue Titon
51000 Châlons-en-Champagne
Phone: 06 47 70 28 11
Email: petit.theo05@gmail.com

[Date],

Objet : Candidature pour le poste de [Cuisinier] - [nom entreprise] [(offre n°)]

Object: Reply to a job offer [Cook] - [name of the company] [(offer n°)]

Dear Madam, Sir,

Recently, I learned of your need for a [cook] and I would be happy to respond to your request.

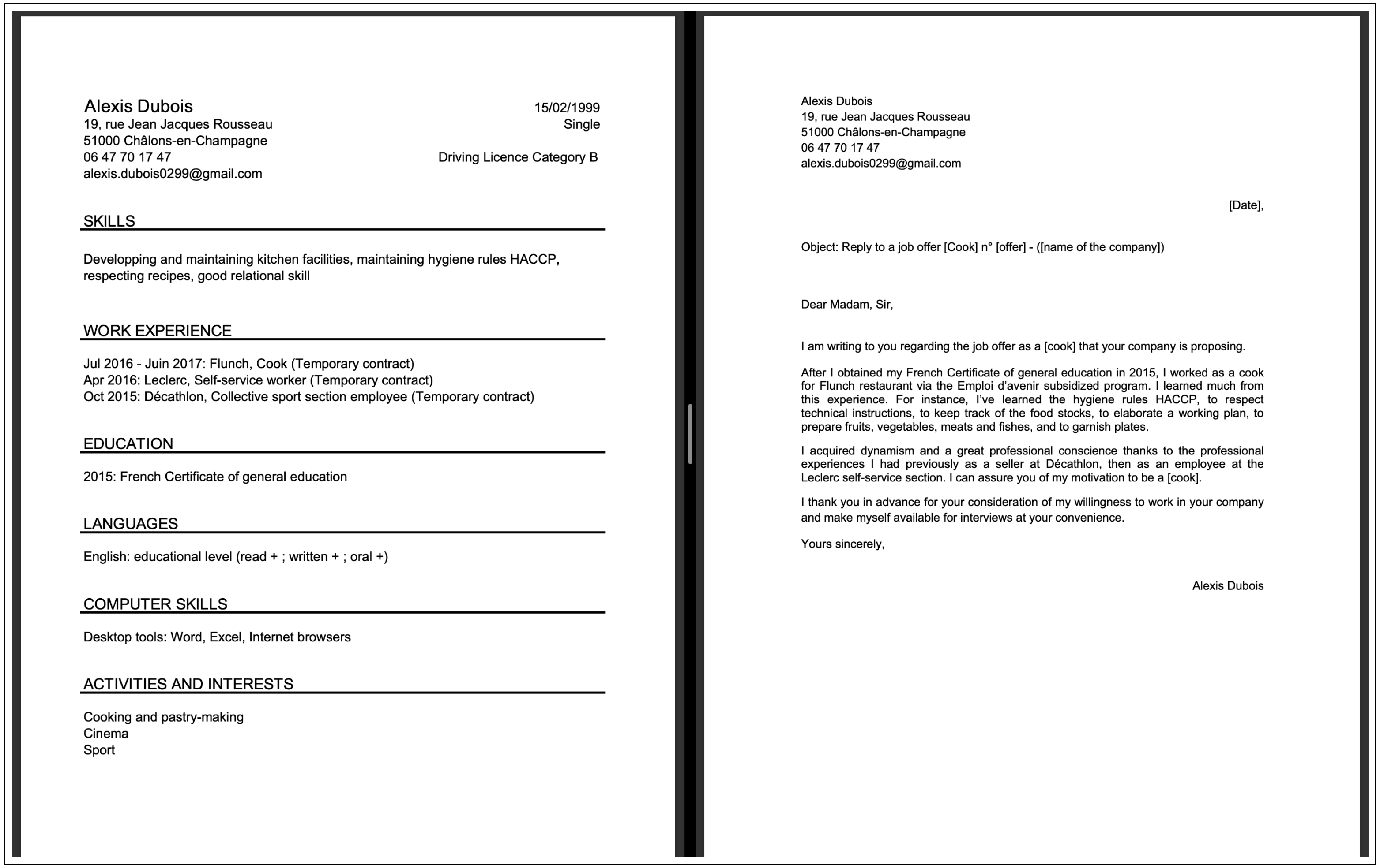
After I obtained my French Certificate of general education in 2015, I benefited from professional experiences as a department employee at Carrefour, then as a seller at Conforama. I developed a great capacity of self-reliance and I know the rigor of a working environment.

Then, I found myself interested toward jobs related to cooking. I have obtained the French CAP Cooking diploma via a vocational training. During my training courses at GRETA and internships at Hippopotamus restaurant, I've learned the hygiene rules HACCP, to respect technical instructions, to keep track of the food stocks, to elaborate a working plan, to prepare fruits, vegetables, meats and fishes, and to garnish plates.

I am very motivated to pursue in this direction and to work in your team. I hope, dear Madam, Sir, that you will give some considerations to my request.

Yours, sincerely,

Alexis Dubois



Alexis Dubois
19, rue Jean Jacques Rousseau
51000 Châlons-en-Champagne
06 47 70 17 47
alexis.dubois0299@gmail.com

15/02/1999
Single

Driving Licence Category B

SKILLS

Developping and maintaining kitchen facilities, maintaining hygiene rules HACCP, respecting recipes, good relational skill

WORK EXPERIENCE

Jul 2016 - Juin 2017: Flunch, Cook (Temporary contract)
Apr 2016: Leclerc, Self-service worker (Temporary contract)
Oct 2015: Décathlon, Collective sport section employee (Temporary contract)

EDUCATION

2015: French Certificate of general education

LANGUAGES

English: educational level (read + ; written + ; oral +)

COMPUTER SKILLS

Desktop tools: Word, Excel, Internet browsers

ACTIVITIES AND INTERESTS

Cooking and pastry-making
Cinema
Sport

Alexis Dubois
19, rue Jean Jacques Rousseau
51000 Châlons-en-Champagne
06 47 70 17 47
alexis.dubois0299@gmail.com

[Date],

Object: Reply to a job offer [Cook] n° [offer] - ([name of the company])

Dear Madam, Sir,

I am writing to you regarding the job offer as a [cook] that your company is proposing.

After I obtained my French Certificate of general education in 2015, I worked as a cook for Flunch restaurant via the Emploi d'avenir subsidized program. I learned much from this experience. For instance, I've learned the hygiene rules HACCP, to respect technical instructions, to keep track of the food stocks, to elaborate a working plan, to prepare fruits, vegetables, meats and fishes, and to garnish plates.

I acquired dynamism and a great professional conscience thanks to the professional experiences I had previously as a seller at Décathlon, then as an employee at the Leclerc self-service section. I can assure you of my motivation to be a [cook].

I thank you in advance for your consideration of my willingness to work in your company and make myself available for interviews at your convenience.

Yours sincerely,

Alexis Dubois

FIGURE 3.5: Example of CV and Cover Letter (Cook Worker - layout 1)

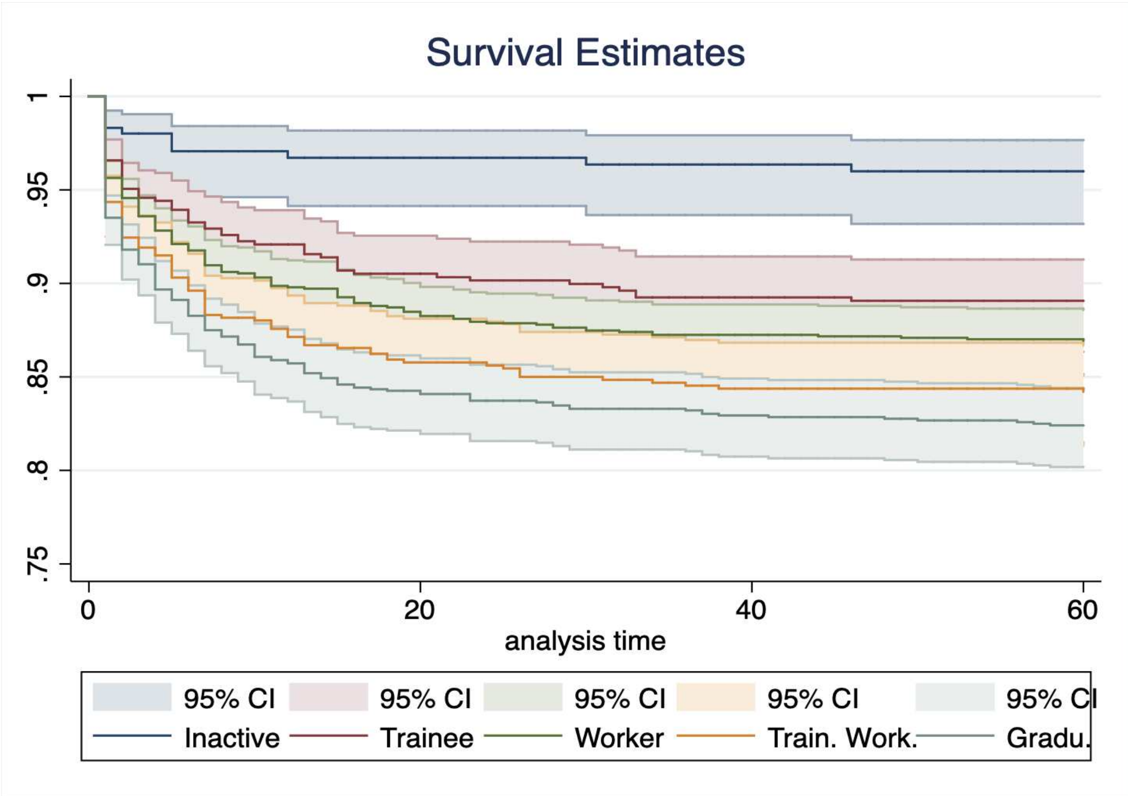
3.8.3 Additional robustness checks

TABLE 3.13
Probit Estimates of Labor Market Experiences on Callbacks

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Inactive	-0.1752***	-0.1770***	-0.1759***	-0.1860***	-0.1487***
	(0.0120)	(0.0114)	(0.0112)	(0.0124)	(0.0215)
Trainee	-0.0677***	-0.0729***	-0.0694***	-0.0753***	-0.0318
	(0.0131)	(0.0129)	(0.0129)	(0.0144)	(0.0302)
Worker	-0.0760***	-0.0804***	-0.0788***	-0.0837***	-0.0532**
	(0.0094)	(0.0094)	(0.0094)	(0.0106)	(0.0211)
Trained Worker	-0.0223*	-0.0239**	-0.0233**	-0.0305**	0.0012
	(0.0116)	(0.0115)	(0.0115)	(0.0128)	(0.0267)
Observations	8,600	8,600	8,600	7,022	1,499
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, gender of the recruiter, and years of professional experiences. All columns report marginal effects from a Probit model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

FIGURE 3.6: Survival Rate of Applications



Note: The event relevant to non-survival is being called back for more information or a job interview or hiring. The timeline is in days. Most of the calls for a vacancy happen within the first twenty days.
Lecture: More than 5% of graduated applicants were called back by employers one day at most after they sent their applications, against 2% for dropout applicants.

TABLE 3.14
Effects of Labor Market Experiences on Propositions for Interview

Proposition	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Inactive	-0.1736***	-0.1769***	-0.1753***	-0.1896***	-0.1362***
	(0.0139)	(0.0140)	(0.0140)	(0.0157)	(0.0315)
Trainee	-0.0695***	-0.0730***	-0.0695***	-0.0799***	-0.0172
	(0.0142)	(0.0140)	(0.0139)	(0.0156)	(0.0317)
Worker	-0.0672***	-0.0702***	-0.0689***	-0.0727***	-0.0493**
	(0.0100)	(0.0099)	(0.0099)	(0.0112)	(0.0217)
Trained Worker	-0.0241*	-0.0241*	-0.0229*	-0.0290**	-0.0020
	(0.0125)	(0.0124)	(0.0124)	(0.0138)	(0.0279)
Graduate mean	0.2530***	0.2530***	0.2530***	0.2638***	0.2023***
	(0.0088)	(0.0088)	(0.0088)	(0.0098)	(0.0193)
Observations	8,600	8,600	8,600	7,024	1,576
R-squared	0.0129	0.0478	0.0600	0.0621	0.1176
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	No

Note: The dependent variable is a dummy variable equal to one if the application gets a proposition as a callback. Proposition corresponds to cases in which the fictitious candidate received a proposition for interview or hiring. Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, gender of the recruiter, and years of professional experiences. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.15
Effects of Labor Market Experiences using Within-Posting Variation

Proposition	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Inactive	-0.8176***	-0.8173***	-0.8173***	-0.8625***	-0.6012**
	(0.0706)	(0.0725)	(0.0726)	(0.0784)	(0.2379)
Trainee	-0.2243***	-0.2235***	-0.2236***	-0.2536***	-0.0779
	(0.0641)	(0.0657)	(0.0657)	(0.0728)	(0.1980)
Worker	-0.2552***	-0.2547***	-0.2547***	-0.2668***	-0.1974
	(0.0395)	(0.0405)	(0.0405)	(0.0448)	(0.1223)
Trained Worker	-0.1750***	-0.1748***	-0.1748***	-0.1710***	-0.1748
	(0.0558)	(0.0572)	(0.0573)	(0.0630)	(0.1791)
Graduate mean	0.6159***	0.6176***	0.6176***	0.6224***	0.5144***
	(0.0281)	(0.0287)	(0.0287)	(0.0320)	(0.1030)
Observations	2,140	2,140	2,140	1,776	364
R-squared	0.0922	0.1074	0.1079	0.1228	0.1621
Resume Couple	Yes	Yes	Yes	Yes	Yes
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The variation in profile treatment within job posting in each round offers the opportunity to examine within-posting variation in callback rates by profile treatment. The dependent variable is a dummy variable equal to one if the application gets a proposition callback. Proposition corresponds to cases in which the fictitious candidate received a proposition for interview or hiring. “Resume Couple” are demeaned dummy variables controlling for the pair of resumes sent to one job offer and the order of each resume (whether first or second). Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, gender of the recruiter, and years of professional experiences. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.16
Probability of Callbacks given Firm Characteristics for Cooks

	Firm Type		Firm Size	
Positive Callbacks	For-Profit	Not For-Profit	Small	Large
	(1)	(2)	(3)	(4)
Inactive	-0.1982***	-0.3428***	-0.1842***	-0.2668***
	(0.0186)	(0.0533)	(0.0245)	(0.0292)
Trainee	-0.0916***	-0.0774	-0.0831***	-0.1007***
	(0.0179)	(0.0616)	(0.0240)	(0.0291)
Worker	-0.0776***	-0.2099***	-0.0684***	-0.1338***
	(0.0125)	(0.0428)	(0.0168)	(0.0197)
Trained Worker	-0.0361**	0.0138	-0.0104	-0.0531**
	(0.0151)	(0.0552)	(0.0199)	(0.0251)
Graduate mean	0.2594***	0.3190***	0.2488***	0.3036***
	(0.0104)	(0.0366)	(0.0136)	(0.0172)
Observations	6,160	605	3,461	2,502
R-squared	0.0574	0.2835	0.0712	0.1095
Dep. & Month FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application for a cook position gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. For-profit firms are firms which sell products or services for profits. Small firms are firms with at most 10 employees. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.17
Probability of Callbacks given Firm Characteristics for Bricklayers

	Firm Type		Firm Size	
Positive Callbacks	For-Profit	Not For-Profit	Small	Large
	(1)	(2)	(3)	(4)
Inactive	-0.1701***	-	-0.1900***	-0.0678
	(0.0336)	-	(0.0415)	(0.0888)
Trainee	-0.0420	-	-0.0873**	0.0818
	(0.0342)	-	(0.0418)	(0.0673)
Worker	-0.0613**	-	-0.0689**	-0.0055
	(0.0239)	-	(0.0288)	(0.0504)
Trained Worker	-0.0009	-	-0.0203	0.1311**
	(0.0297)	-	(0.0360)	(0.0637)
Graduate mean	0.2013***	-	0.2130***	0.1727***
	(0.0197)	-	(0.0247)	(0.0362)
Observations	1,516	30	993	411
R-squared	0.1301	0.7917	0.1802	0.2605
Dep. & Month FE	Yes	-	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application for a bricklayer position gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. For-profit firms are firms which sell products or services for profits. Small firms are firms with at most 10 employees. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.18
Probability of Callbacks given Contract Characteristics for Cooks

Positive Callbacks	Type of Contract: Temporary	Type of Contract: Permanent	Required Experience: $\leq 1y$	Required Experience: $> 1y$
	(1)	(2)	(3)	(4)
Inactive	-0.2146***	-0.2097***	-0.2586***	-0.1427***
	(0.0229)	(0.0258)	(0.0240)	(0.0244)
Trainee	-0.0813***	-0.0904***	-0.0957***	-0.0646***
	(0.0225)	(0.0252)	(0.0230)	(0.0234)
Worker	-0.0986***	-0.0743***	-0.1037***	-0.0629***
	(0.0154)	(0.0180)	(0.0157)	(0.0172)
Trained Worker	-0.0249	-0.0456**	-0.0343*	-0.0335
	(0.0189)	(0.0220)	(0.0191)	(0.0211)
Graduate mean	0.2750***	0.2472***	0.3093***	0.1907***
	(0.0128)	(0.0151)	(0.0131)	(0.0141)
Observations	4,252	2,772	4,289	2,735
R-squared	0.0710	0.0872	0.0662	0.0802
Department & Month FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application for cooks gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. "1y" stands for one year experience in the occupation. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.19
Probability of Callbacks given Contract Characteristics for Bricklayers

Positive Callbacks	Type of Contract: Temporary	Type of Contract: Permanent	Required Experience: $\leq 1y$	Required Experience: $> 1y$
	(1)	(2)	(3)	(4)
Inactive	-0.1361**	-0.1562***	-0.2184***	-0.1400***
	(0.0556)	(0.0441)	(0.0659)	(0.0381)
Trainee	-0.0595	0.0169	-0.0313	-0.0558
	(0.0491)	(0.0491)	(0.0623)	(0.0375)
Worker	-0.0774**	-0.0333	-0.0930**	-0.0349
	(0.0354)	(0.0321)	(0.0388)	(0.0292)
Trained Worker	0.0487	-0.0195	0.0413	-0.0398
	(0.0436)	(0.0423)	(0.0580)	(0.0324)
Graduate mean	0.1942***	0.2096***	0.2514***	0.1680***
	(0.0276)	(0.0270)	(0.0325)	(0.0234)
Observations	730	846	626	950
R-squared	0.2219	0.1629	0.2548	0.1717
Department & Month FE	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application for bricklayers gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. "1y" stands for one year experience in the occupation. Department and month fixed effects are demeaned dummies. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

3.8.4 Potential mechanisms

TABLE 3.20
Effects of Certification for Dropout Workers on Callbacks

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Worker w/ Public Certificate	0.0637***	0.0649***	0.0643***	0.0612***	0.0680*
	(0.0161)	(0.0160)	(0.0158)	(0.0177)	(0.0379)
Worker w/ Private Certificate	0.0146	0.0107	0.00939	0.00871	0.00717
	(0.0154)	(0.0155)	(0.0154)	(0.0174)	(0.0375)
Constant ($\approx$ Worker w/ no certificate mean)	0.213***	0.214***	0.214***	0.222***	0.187***
	(0.0108)	(0.0108)	(0.0107)	(0.0146)	(0.0278)
Observations	4,301	4,301	4,301	3,513	788
R-squared	0.004	0.051	0.068	0.072	0.154
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. “Private Certificate” indicates that the youth got an attestation from his previous employer certifying acquisition of skills (included in “Worker” in previous specifications). While “Public Certificate” indicates that the youth got a diploma from the Ministry of Education certifying acquisition of skills (“Trained Worker” in previous specifications). Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, years of professional experiences, and gender of the recruiter. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

TABLE 3.21
Effects of Unemployment Duration on Callbacks

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Unemployment Duration	-0.00658***	-0.00817***	-0.00800***	-0.00854***	-0.00607***
	(0.000729)	(0.000734)	(0.000729)	(0.000819)	(0.00161)
Constant	0.326***	0.345***	0.343***	0.356***	0.280***
	(0.0111)	(0.0112)	(0.0111)	(0.0130)	(0.0257)
Observations	8,600	8,600	8,600	7,024	1,576
R-squared	0.009	0.048	0.065	0.068	0.126
Dep. & Month FE	No	Yes	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes	Yes

Note: The dependent variable is a dummy variable equal to one if the application gets a positive callback. Positive callback corresponds to cases in which the fictitious candidate received a request for complementary information or a proposition for interview or hiring. “Unemployment duration” is the total duration of non-employment situations in months for any applicant, i.e. since they left school until the end of the experiment. Department and month fixed effects are demeaned dummies. Job characteristics include dummies for the type of contract, working time, years of professional experiences, and gender of the recruiter. All columns report OLS linear probability model estimates. Robust standard errors are clustered at the firm level and reported below the coefficients. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

Providing Information to young NEETs

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

Based on: *Providing Information to NEETs about Nearby Public Assistance Agencies: Evidence from a Text Messaging Experiment*
Keywords: NEET, Information provision, Public assistance, Field experiment
JEL codes: D04, D83, D64, J68

4.1 Introduction

Every month in France, a number of young people are identified as not in employment, education, or training (NEET) during "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 so as to enroll greater numbers.

Nowadays, most individuals communicate through text messaging on a daily basis. Whether texts are sent to relatives to maintain relationships (Ling, 2010), by private firms to purchase their goods (Rettie et al., 2005), or by medical centers to sustain individuals' efforts in combating substance abuse (Mason et al., 2015), texts 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?

Nonetheless 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 by 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 authority and test new ways of delivering information to young NEETs.[1] 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 with equal probability. They received information on the nearest *mission locale* agency. The first group did not receive any text 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

[1] 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.

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 state clearly the existence 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 greater 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 duration analyses and linear regression analyses indicate that the texts had no overall effect. Nor did 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 seemed 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 did 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 be not relevant for this population. Second, the time delay 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 because 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,[2] 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 about 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 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 course. 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. However, Duzgun and Yamamoto (2016) find no effects from SMS promotional campaign sent to more than 90,000 individuals by a Turkish mobile operator to induce them to buy a new smartphone. 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.

[2]Reviews by Card et al. (2018b) and Caliendo and Schmidl (2016b) 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. (2013b) show the existence of negative spillover effects leaving youth unemployment barely or completely unchanged.

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. However, they find that texts have positive effects on students' well-being, though the results are mostly driven by students "feeling a greater sense of belonging at UofT". 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, Armour (2018) finds positive effects from information letters on disability insurance take-up for workers subject to professional constraints. Finkelstein and Notowidigdo (2019) find a positive effect from similar letters on social security subscription, and Liebman and Luttmer (2015) find an increase in labor force participation from letters correcting misconceptions about social security earnings. 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. Bhargava and Manoli (2015) find a positive effect of between 14% and 31% on the demand for tax credits by re-mailing the information letter sent by the IRS about the EITC. Gerber et al. (2008) find a positive effect of about 30% on voting for political elections when the information in the letter threatens to reveal the individual's electoral attitude to the neighborhood. 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 Mexico, Bertrand et al. (2010) and Seira et al. (2017) find little or no positive effects on the demand for bank credits after sending letters revealing the possibility of bargaining over established debt contracts. In Germany, 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. 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. 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, texts are stylized and draw on an extensive literature in psychology and neuroscience about communication. The study tests 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 4.2 presents the relevant French institutions and some characteristics of young NEETs. Section 4.3 describes the experimental design. Section 4.4 shows and discusses the results of the experiment. Section 4.5 presents the conclusions.

4.2 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*.

4.2.1 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).[3]

Young people attend the army day once atfer receiving an official invitation from the Ministry of the Army, generally between their registration at the town hall and their eighteenth birthday.[4] 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 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.[5]

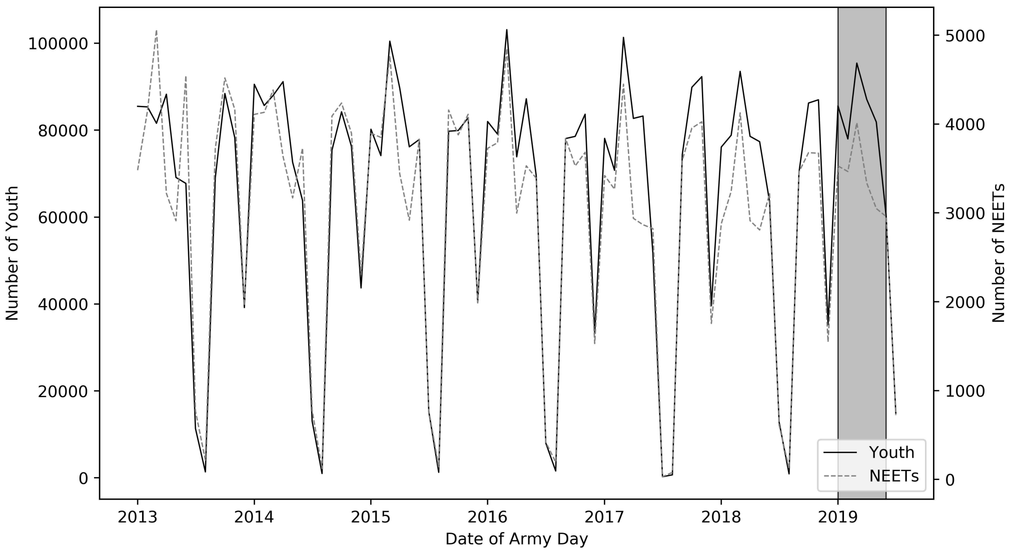
Every year about 800,000 young people participate in army days. According to a report from the French general accounting office, 96% of all French-born individuals do their army day before they turn 25 (Courdescomptes, 2016). Figure 4.1 shows the numbers attending the army days per month from January 2013 to July 2019. A cyclical pattern

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

[4] 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.

[5] 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.

FIGURE 4.1: Evolution of the number of youths and NEETs attending army days per month



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

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.

4.2.2 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 4.1 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.[6]

[6]Eckstein and Wolpin (1999a) 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., 2010b, Hervelin et al., 2020b). 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).

TABLE 4.1
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.

4.2.3 *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.

4.2.4 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 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 4.1 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 4.6 in Appendix 4.6.1 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.[7] From these results, it follows that the remaining share of young NEETs who do not go to a *missions locale* agency is still

[7] 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.

large. These considerations were taken into account in the field experiment presented in the next section.

4.3 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.

4.3.1 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 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 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 4.2[8]. 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).[9]

[8]Table 4.7 in Appendix 4.6.2 shows the text contents in the original version and Figure 4.4 shows how they are displayed on a smartphone screen.

[9]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.

TABLE 4.2
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.

4.3.2 Structure of the texts

Table 4.3 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.[10] 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 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

[10] 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.

TABLE 4.3
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.

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).[11] 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).[12] 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.[13]. 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

[11] *"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.

[12] 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.

[13] *"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).

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 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.

4.3.3 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 4.1. 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;[14]

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 group received the first text

[14] It appears that about 65% to 75% provided a (valid) phone number.

on the following Wednesday morning around 10 am.[15] The second texts were sent seven days later at the same time.[16] 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 4.6.4 in Appendix 4.6.4 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 $\pm$4.5 pp at the 5% significance level and about $\pm$3.7 pp at the 10% significance level, considering a power of 80%.[17].

To conclude this section, Table 4.8 in Appendix 4.6.3 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.

4.4 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 at a *mission locale* on NEETs' take-up. Then, I turn to the probability of going to a *mission locale* agency over time.

4.4.1 Linear analyses

To analyze the overall effect of the texts, I estimate the following linear probability model with Ordinary Least Squares (OLS) estimators:

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

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 $k \in \{$Neutral, Distance, Enrollment, Distance + Enrollment$\}$ as depicted in Section 4.3.1. 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

[15]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".

[16]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.

[17]The expected sample size was about 10,000 youths so as to detect a minimum effect of $\pm$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 4.4
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.

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 4.4. 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.[18] 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.[19] In addition, I re-run the same

[18]To address concerns about non-linear effects, I report the estimate of β with a Probit model. Table 4.9 in Appendix 4.6.5 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.

[19]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

TABLE 4.5
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.

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 4.4 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 4.10, 4.11, and 4.12 in Appendix 4.6.6 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[20], the type of city, the unemployment rate, and the number services, schools, forms of transports, and leisure facilities.[21]

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.

their texts in 2018 when a name was provided. Overall, the average treatment effects on the treated (ATT) should be similar to the ITT.

[20]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.

[21]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).

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 the randomization inference procedure deliver non-significant effects of the treatment text.[22]

As complementary elements, Table 4.5 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.

4.4.2 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.[23] Figure 4.2 shows the survival curve associated with each group obtained after a Kaplan-Meier estimation of the respective survival rate, assuming random censoring.[24] 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.

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.[25] 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 4.13 in Appendix 4.4.2 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 4.6 in Appendix 4.4.2 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

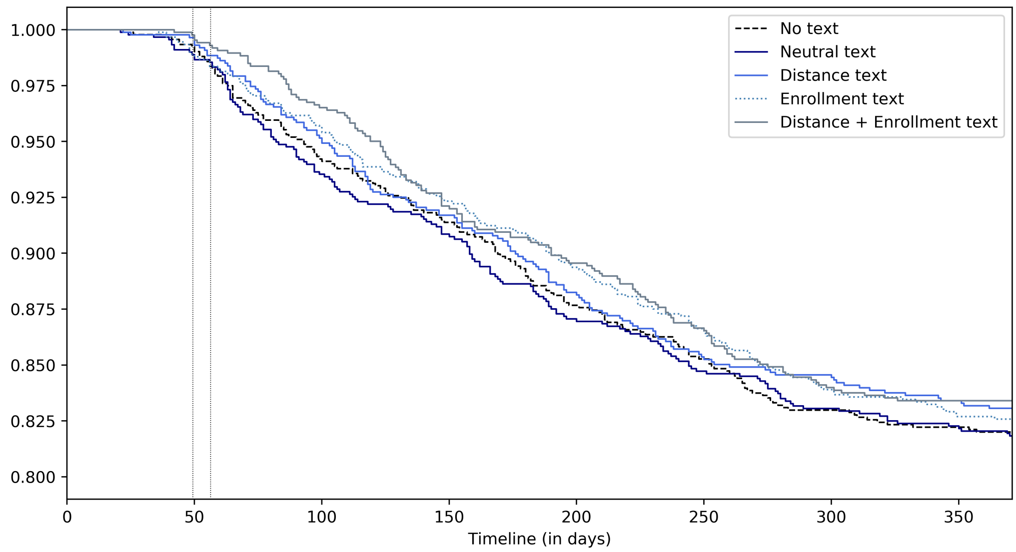
[22] It should be noted that the experiment was not designed to test heterogeneous effects in the first place.

[23] 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.

[24] 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.

[25] 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.

FIGURE 4.2: 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).

to a public agency at a particular date after the army day, controlling for time and individual characteristics.[26] The proportional hazard model is estimated with a Cox regression and results are shown in Table 4.14 in Appendix 4.6.8. The effect of the treatment groups are separately shown in Figure 4.3 for easier representation.[27] 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.

4.4.3 Interpretation

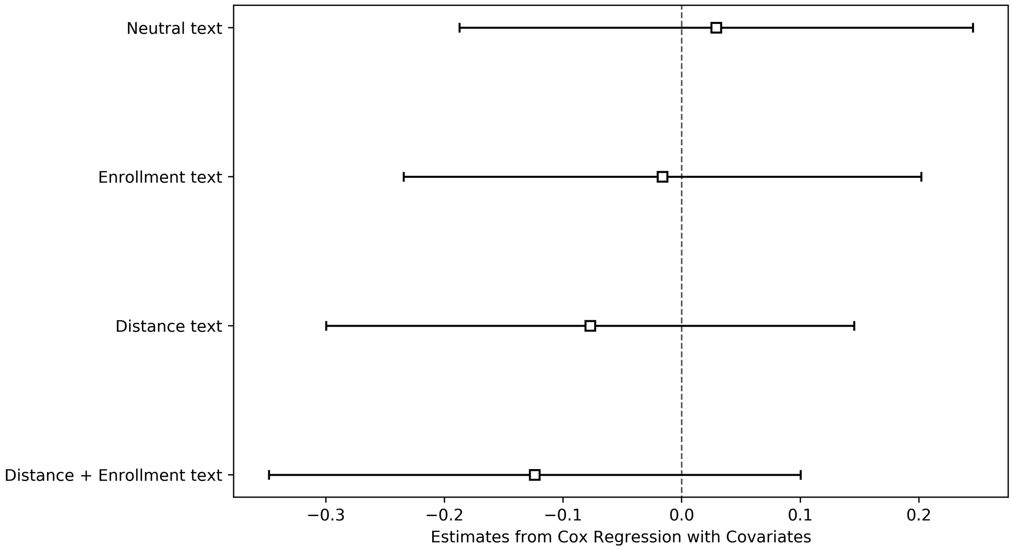
Overall, the treatment texts have a non-significant effect on the probability of going to a *mission locale* agency, whether they are written in the simplest way or stylized according to how youths communicate. They also have a non-significant effect in relation to various characteristics, whether at 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 results.

First, information on distance and past enrollment may be not relevant for this population. Figures 4.8 and 4.9 in

[26] 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 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.

[27] The impact of all covariates are represented graphically in Figure 4.7 in Appendix 4.6.8.

FIGURE 4.3: 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 4.14.

Appendix 4.6.9 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.[28] Young NEET may try to use their private and informal networks to gain 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.

4.5 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,

[28] 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.

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.

4.6 Appendix

4.6.1 Military guidance

TABLE 4.6
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$\times$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).

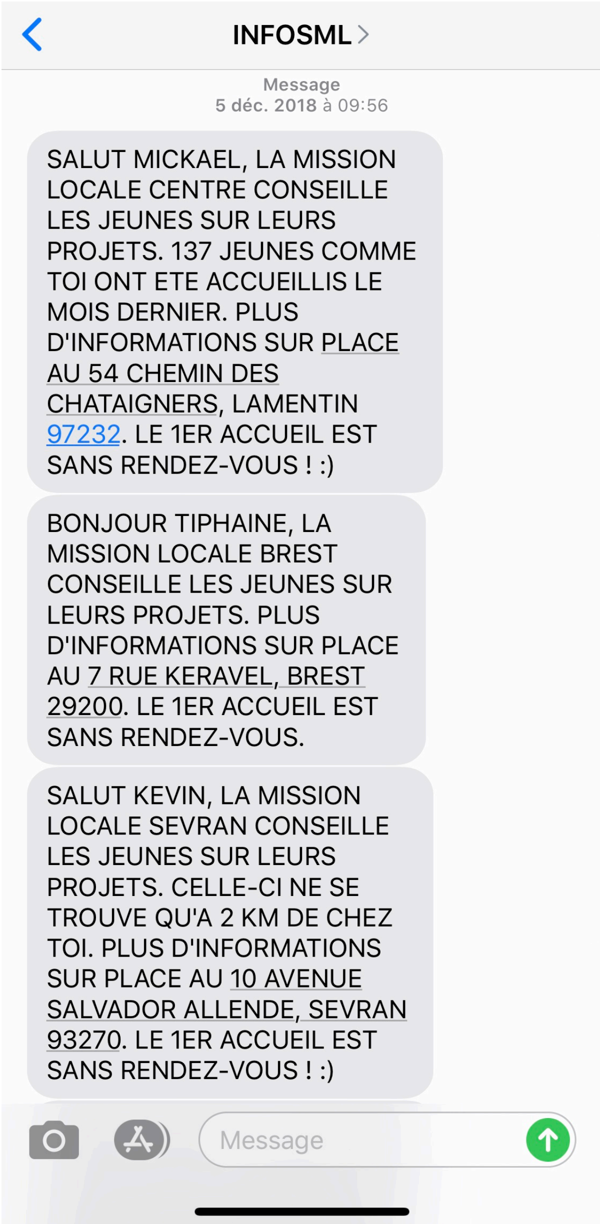
4.6.2 Original version of the texts

TABLE 4.7
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 4.4: 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.

4.6.3 Randomization tests

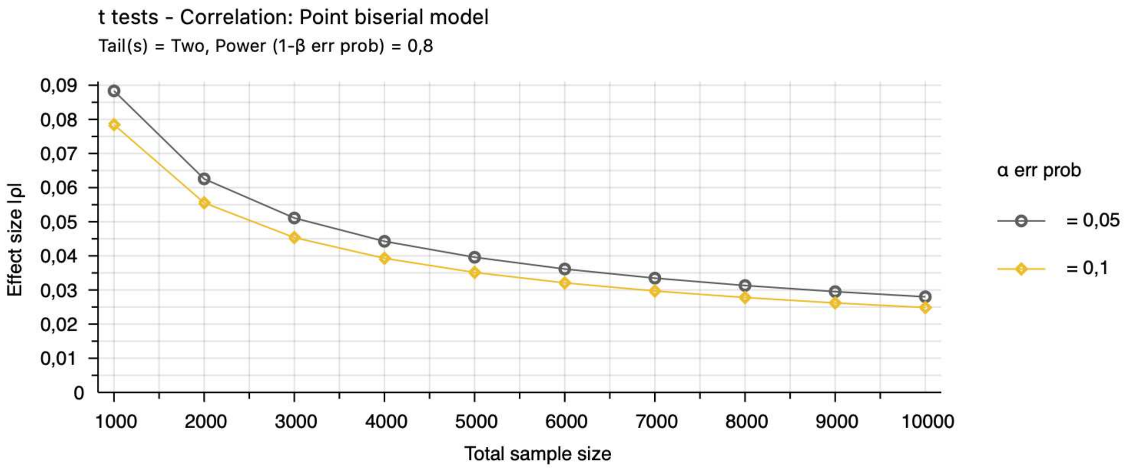
TABLE 4.8
Randomization Tests

	Control	Treatments							
		Neutral		Distance		Enrollment		Dist. + Enroll.	
Characteristics	(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.

4.6.4 Power of the experiment

FIGURE 4.5: 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%.

4.6.5 Non-linear model estimates

TABLE 4.9
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.

4.6.6 Heterogeneous intention-to-treat effects

TABLE 4.10
Intention-to-treat effects across individual characteristics

OLS Estimates	Gender		Age		Literacy		Guided	
	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 (≈ 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 4.11

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 4.12
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.

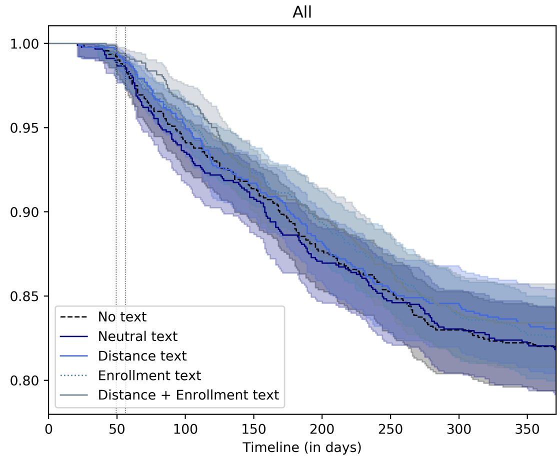
4.6.7 P-values and monthly survival curves

TABLE 4.13
P-values for log rank tests

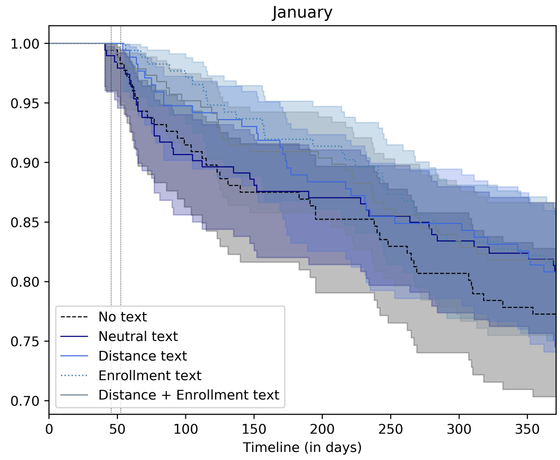
Type of text	No	Neutral	Distance	Enrollment	Dist. + Enroll.
	(1)	(2)	(3)	(4)	(5)
No	-	.8537	.5578	.6910	.3963
Neutral	.8537	-	.4399	.5645	.3037
Distance	.5578	.4399	-	.8442	.7870
Enrollment	.6910	.5645	.8442	-	.6462
Dist. + Enroll.	.3963	.3037	.7870	.6462	-

Note: This table reports the p-values associated to the log rank tests associated to the estimated survival functions in Section 4.4.2.

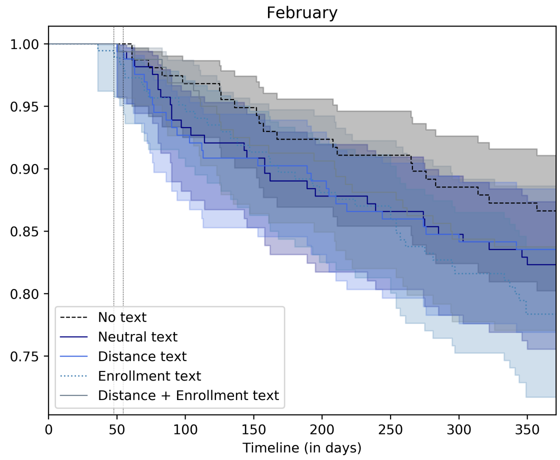
FIGURE 4.6: Monthly survival curves



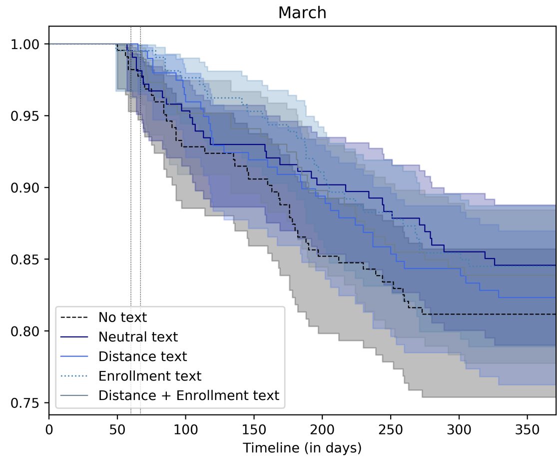
(A) Survival rates



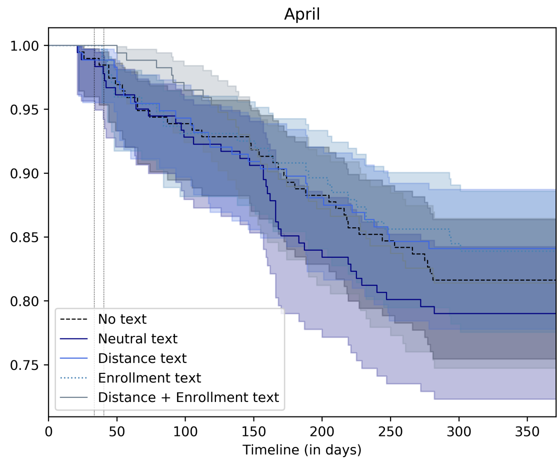
(B) Survival rates in January



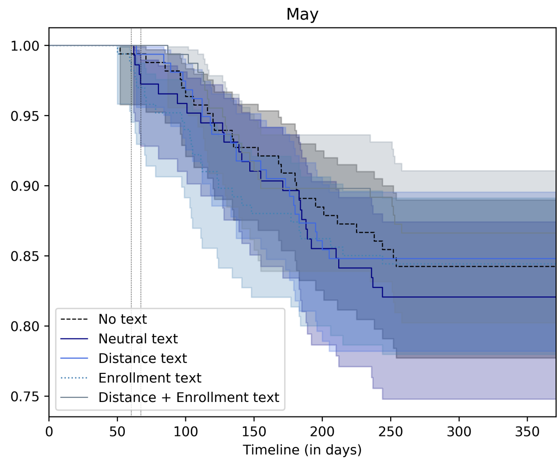
(C) Survival rates in February



(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.

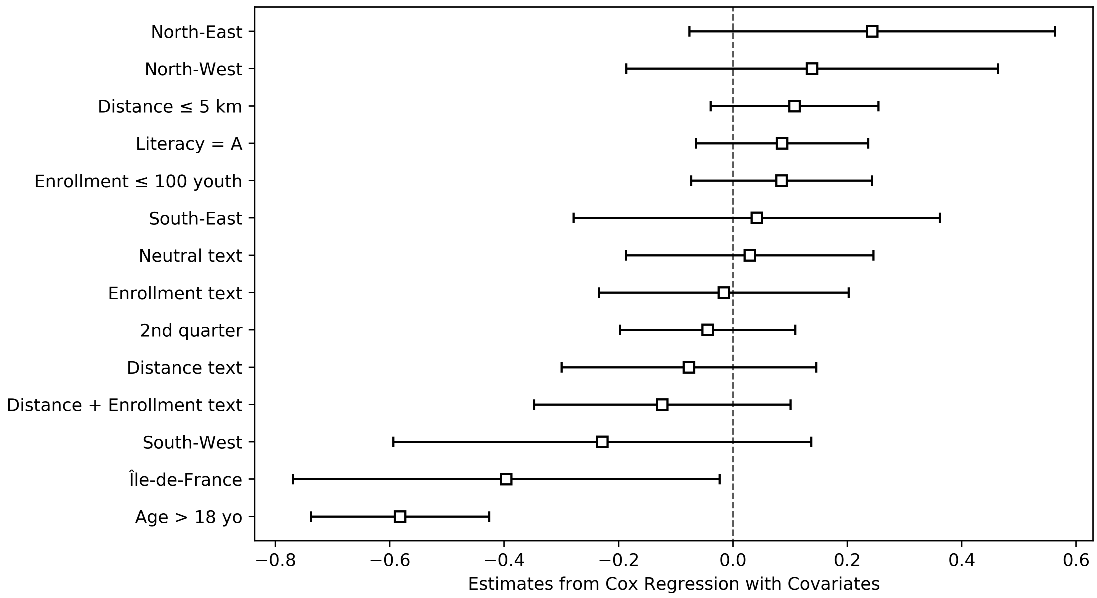
4.6.8 Proportional hazard model outputs

TABLE 4.14
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.

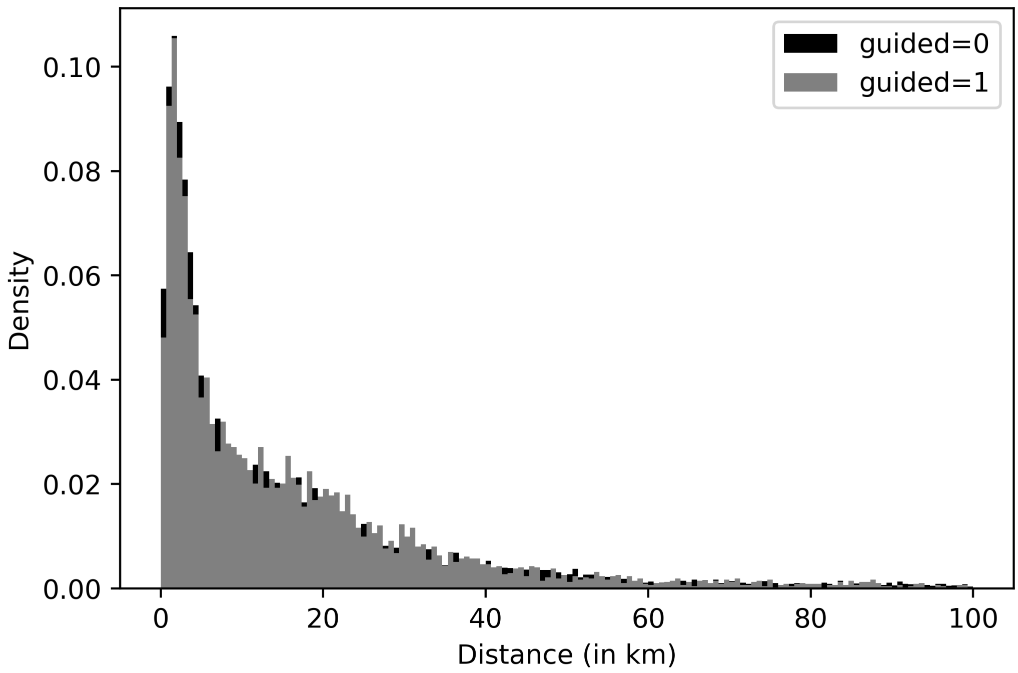
FIGURE 4.7: Estimates of treatment and covariate effects on the hazard ratios



Note: Estimates of covariates on the hazard ratios are obtained with a proportional hazard model estimated by Cox regression shown in Table 4.14.

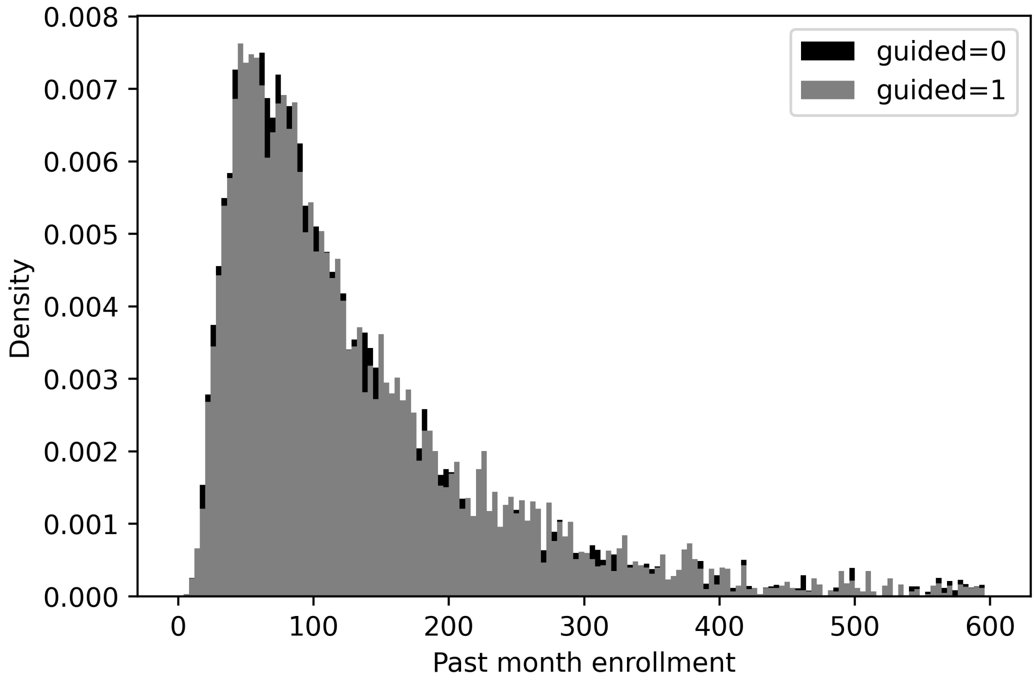
4.6.9 Histograms of distance and enrollment for compliers

FIGURE 4.8: 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 4.9: 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.

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ECOLE DOCTORALE

Titre : Transitions École-Emploi et Politiques Publiques Associées: Éléments d'Expériences en France

Mots clés : Transitions école-emploi, Politiques du marché du travail, Expériences de terrain

Résumé : Cette thèse se concentre sur les transitions école-emploi et les politiques du marché du travail qui y sont liées, en particulier pour les jeunes en difficulté. Basée sur des expériences de terrain menées en France en 2018 et 2019, elle comprend trois chapitres qui ajoutent de nouvelles preuves empiriques à la littérature économique.

Le premier chapitre apporte de nouveaux éléments sur la forte insertion professionnelle des apprentis. Il montre que le succès de l'apprentissage ne repose pas, dans le contexte français, sur un meilleur accès à l'emploi de ceux qui ne restent pas dans leur entreprise de formation. L'expansion de l'apprentissage a donc des effets très limités sur le chômage des jeunes si elle ne s'accompagne pas d'une augmentation de la rétention en entreprise de formation.

Le deuxième chapitre contribue à mieux comprendre les préférences des employeurs concernant des profils de jeunes décrocheurs scolaires. Il montre que les décrocheurs qui sont restés inactifs pendant plus de deux ans ont beaucoup moins de chances d'être rappelés pour un emploi que les diplômés du secondaire. L'emploi subventionné et la formation professionnelle augmentent les chances des décrocheurs, mais leurs chances restent encore faibles. Seule la combinaison de ces deux politiques permet aux jeunes décrocheurs de rattraper ceux qui n'ont pas abandonné l'école, réduisant les signaux négatifs associés au décrochage scolaire et à la durée d'inactivité.

Le troisième chapitre présente une expérience de terrain visant à analyser l'efficacité de SMS envoyés pour diriger des jeunes ni en emploi, ni en formation, vers des structures publiques d'aide. Tous les SMS ont été individualisés et comprenaient des informations spécifiques sur ces structures. Les résultats indiquent que les textes n'ont pas eu d'effet significatif sur la probabilité de s'adresser à ces structures. Ces résultats montrent que l'envoi de SMS à cette population n'est pas une stratégie efficace pour la diriger plus facilement vers une solution d'aide publique.

L'argument principal de cette thèse est donc de combler les écarts entre les écoles et les entreprises, afin qu'une proportion significative de jeunes puisse éviter une situation de non-emploi comme première expérience sur le marché du travail.

Title : School-to-Work Transitions and Related Public Policies: Evidence from Field Experiments in France

Keywords : School-to-work transitions, Labor market transition policies, Field experiments

Abstract : This thesis focuses on school-to-work transitions and related labor market policies designed to smooth these transitions, especially for young people in difficulty. Based on field experiments carried out in France in 2018 and 2019, it comprises three chapters that add new empirical evidence to the economic literature.

The first chapter brings new evidence on the higher employment rate of apprentices than vocational students after graduation. It shows that the success of apprenticeship does not rely, in the French context, on better job access to those who do not remain in their training firms. The expansion of apprenticeship thus has very limited effects on youth unemployment if this is not accompanied by an increase in the retention of apprentices in their training firm.

The second chapter contributes to the understanding of employers' preferences regarding young school dropout applicants. It shows that school dropouts who have remained inactive over two years have a significantly smaller chance of being called back for a job compared to non-dropout high school graduates. Subsidized employment and vocational training boost dropouts' chances, but their chances remain still lower. Only the combination of the two policies lets young dropouts to catch up with their non-dropout peers. Manipulation of the profiles indicates that both dropping out of school and inactivity duration entails negative signals for the employers.

The third chapter presents a field experiment designed to analyze the effectiveness of text messaging by public assistance agencies seeking to enroll young people who are not in employment, education, or training (NEET). All texts were individualized and included specific information about the agencies. Results indicate that the texts had no significant effect on the probability of going to those agencies. These findings show that sending texts to this population is not an effective strategy for enrolling it more easily.

The main argument of the thesis thus advocates closing gaps between schools and firms, so that a significant proportion of young people may avoid a non-employment situation as their first experience in the labor market.

Institut Polytechnique de Paris
91120 Palaiseau, France