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Jérémy HERVELIN
Crest-Ensae

Cecile BALLINI
Dares

Mathilde GAINI
Drees

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Jérémy Hervelin† Cécile Ballini‡ Mathilde Gaini§

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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.

Keywords: School dropouts, Active labor market policies, Field experiment
JEL codes: J08, J24, M51

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†CREST-ENSAE. Contact at jeremy.hervelin@ensae.fr
‡DARES. Contact at cecile.ballini@travail.gouv.fr
§DREES. Contact at mathilde.gaini@sante.gouv.fr

I 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., 2010). 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.[1] 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

[1]The experiment was conducted under the patronage of the *Sécurisation des parcours professionnels* Chair (http://www.chaire-securisation.fr), the partners of which are the Ministry of Labor, Pôle emploi (Public Employment Service), UNEDIC (Public Unemployment Insurance), Alpha Group (Consultancy firms specialized in labor relations), Sciences Po and CREST. The Chair's executive committee, composed of representatives of these institutions, approved this experiment without imposing any constraint on the design proposed by the authors.

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 II.B 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. (2019) 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, 2016). 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., 2018; 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, 1999). In the current French context, our paper argues for active labor market policies that combine *both* on-the-job training and 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 VI.B. Upstream work on possibly less costly and easier-to-implement programs that prevent youths from dropping out of the school system should not be forgotten either (Björklund and Salvanes, 2011).

The paper is organized as follows. Section II presents the French employment public policies and the situation of dropouts in the French labor market, in order to legitimate our experimental setting. Section III describes the experimental design. Section IV presents the main findings. Section V presents robustness checks that confirm our main results. Section VI discusses the potential mechanisms and the external validity of our experiment. Section VII concludes.

II 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.

II.A 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.[2] 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 II.B), 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 A.1.1 in Appendix A.1 presents descriptive statistics on the training undertaken by youths registered at *Pôle emploi*. It appears that 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.[3] Table A.1.2 in Appendix A.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).

II.B Profile of school dropouts

We use a sample of the TRAJAM[4] database to follow youths who have been flagged as dropouts and avoid certain composition effects among the different labor market status dis-

[2] Go to https://www.education.gouv.fr/bcp/mainFrame.jsp?p=1 for more open data.
[3] Go to http://poem.travail-emploi.gouv.fr/ for more trends.
[4] *TRAjectoires des Jeunes Appariés aux Mesures actives du marché du travail.*

Table I
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.

cussed 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.[5] 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 A.1.3 in Appendix A.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 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.

[5] 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.

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 I 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.

III 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.

III.A 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 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.[6] 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

[6]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.

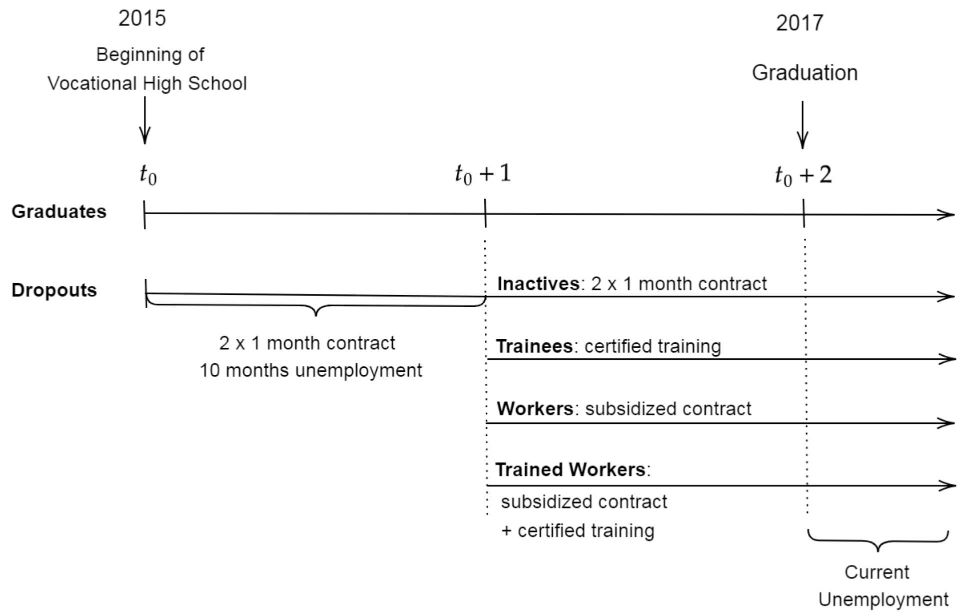

Figure 1: Diagram of Treatment Profiles

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.

III.B 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.[7] 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 A.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.[8] For both occupations, the

[7]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.

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

profiles are then in line with real applicants that employers encounter, even though "Trained Workers" are less usual.

III.C 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).[9] 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.[10] The surnames, Petit and Dubois, were respectively ranked 6 and 7, according to the *Fichier patronymique* (INSEE).[11] 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.[12] Since the diploma is national, there is no information about the 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)[13] 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.

[9] 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.

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

[11] The same method was done for surnames.

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

[13] 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.

III.D 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.[14] The templates were based on different samples taken from the *Pôle emploi CVthèque*,[15] 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.[16]

Job offers for both occupations were mainly identified using the *Pôle emploi* website.[17] 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.[18] 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.

III.E Data collection

In total, 10,938 applications were sent from 22 January 2018 to 13 July 2018[19]. This sample size largely satisfied our power calculations. The overall sample size was chosen to detect a minimum effect of ± 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

[14]See appendix A.2 for examples of resumes and cover letters.

[15]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.

[16]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).

[17]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.

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

[19]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.

Table II
Randomization Tests

	Graduates	Dropouts							
		Inactives		Trainees		Workers		Trained Workers	
	(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)
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.

Houndolo (2016).[20] We then made sure that the job offer characteristics were not correlated with the different profiles. Table II 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.

IV Results

Table III 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.

IV.A 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:

$$y_{ij} = \alpha + \beta_k T_{i=k} + x_j' \gamma + \varepsilon_{ij} \tag{1}$$

where y_{ij} is a dummy variable equal to one if applicant i gets called back for job j. $T_{i=k}$

[20] 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 III
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 $H_0 : \{\Delta = \text{callback[graduates] - callback[dropouts]} = 0\}$ vs $H_1 : \{\Delta \neq 0\}$.

Table IV
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.

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 III.A. 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 (1) are reported in Table IV.[21] 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".[22] 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 $\beta_{k=Inactive}$ param-

[21] To address concerns about non-linear effects, we report the results of Table A.3.1 replacing the OLS (linear probability) model with a Probit model in Appendix A.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.

[22] The results also hold when considering the more restrictive definition of callback "propositions" as presented in Table A.3.2 in Appendix A.3.

eter 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", 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.[23]

IV.B Training and experience as partial compensations only

While Table IV 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.[24] Although firms could have received more than our two applications for their job vacancies, Table V gives a second view on the ranking of profiles by recruiters.

Table V presents the same specifications as in Table IV. We additionally control for the pair of resumes sent to a specific job offer.[25] The difference in the probability of being called back among dropout profiles and graduates 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 IV.A. When applying the same

[23]This result is also valid when one looks at the survival rate of an application as depicted in Figure A.3.1 in Appendix A.3. "Graduate" and "Trained Worker" applications received more callbacks sooner and for a longer period of time than of "Inactive", "Trainee" and "Worker" applications.

[24]67% of firms did not respond to any profile, while 13% responded to both.

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

Table V
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.

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 A.3.3 in Appendix A.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.

IV.C 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 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

Table VI
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.

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 VI 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.[26] Large firms seem to consider applicants without skills certified by any diploma to a lesser extent than applicants who do. Tables A.3.4 and A.3.5 in Appendix A.3 indicate similar results for cooks and not that much for bricklayer positions, probably because of too few observations.

[26]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 VII
Probability of Callbacks given Contract Characteristics

Positive Callbacks	Type of Contract		Required Experience	
	Temporary	Permanent	≤ 1y	> 1y
	(1)	(2)	(3)	(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.

IV.D 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 VII 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 A.3.6 and A.3.7 in Appendix A.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:

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

V 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.

V.A 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.[27]

For each job vacancy that received an application, we recorded the location of the job. Since, as stated in III.C, 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

[27] 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 VIII
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.

mean unemployment rate is 8.9%. Following Athey and Imbens (2017), we demeaned our two continuous variables and fully interacted them with our profile variables to ensure unbiased estimates.

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

V.B Speculative applications

It appears that a high proportion of job vacancies was managed by temporary work agencies during the experiment, especially for bricklayer positions.[28] 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.[29] 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.[30] 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

[28] 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.

[29] 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.

[30] 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 IX
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.

new academic year and to avoid too strong a negative signal associated with the duration of unemployment.

Results are shown in Table IX. We consider the same outcome variable and specifications as in section IV. 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. 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.

VI 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).

VI.A Potential mechanisms

We think of two potential mechanisms that may explain what drives the negative sign of our dropout treatment profiles.[31] The first mechanism concerns the negative signal that dropping out of the school system entails for youths. Their doing so may suggest 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). 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. (2019), or only classroom training. Indeed, Table A.4.1 in Appendix A.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.[32]

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. (2013) 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

[31] 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.

[32] 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.

months of unemployment. In Switzerland, Oberholzer-Gee (2008) finds adverse effect after thirty months. For France, as shown in Table A.4.2 in Appendix A.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.

VI.B 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 (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., 2013).

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, 2018). 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.

VII 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.

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A Appendix

A.1 Related descriptive statistics

Table A.1.1
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 A.1.2
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 A.1.3
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.

A.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.

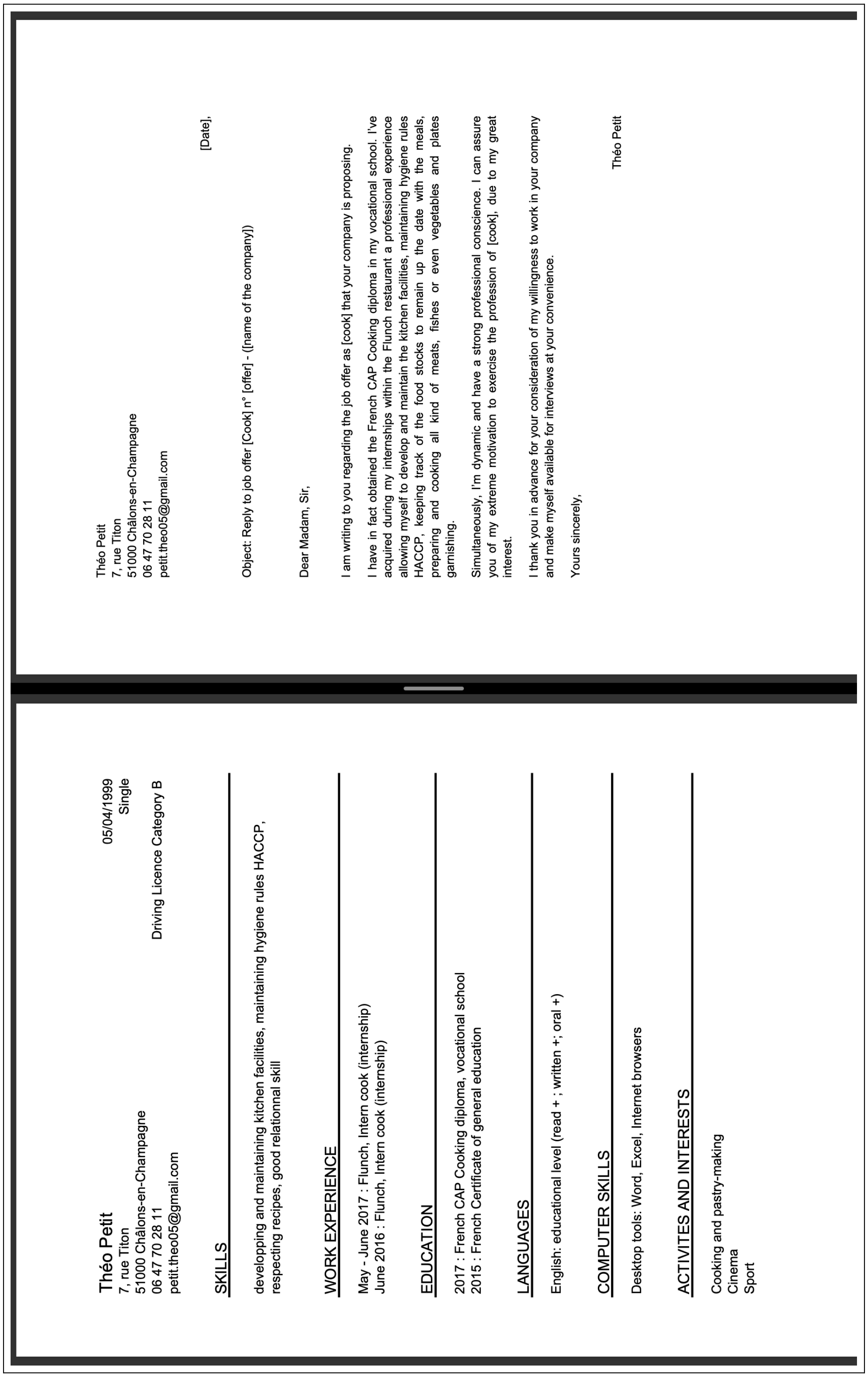
With kind regards,
Alexis Dubois

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



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.

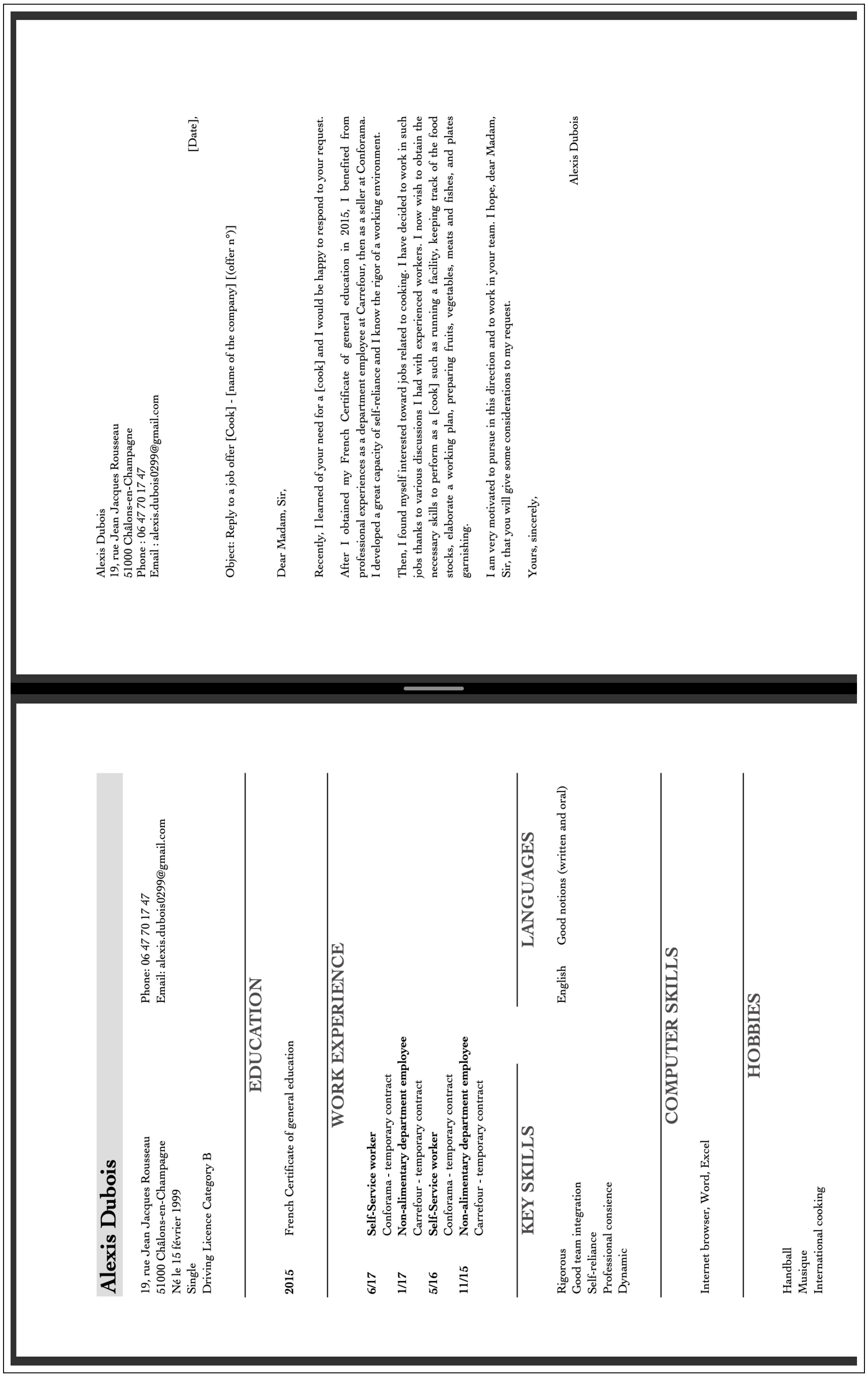
Simultaneously, I'm dynamic and have a strong professional conscience. I can assure you of my extreme motivation to exercise the profession of [cook], due to my great interest.

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 A.2.1: Example of CV and Cover Letter (Cook Student - layout 1)



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.

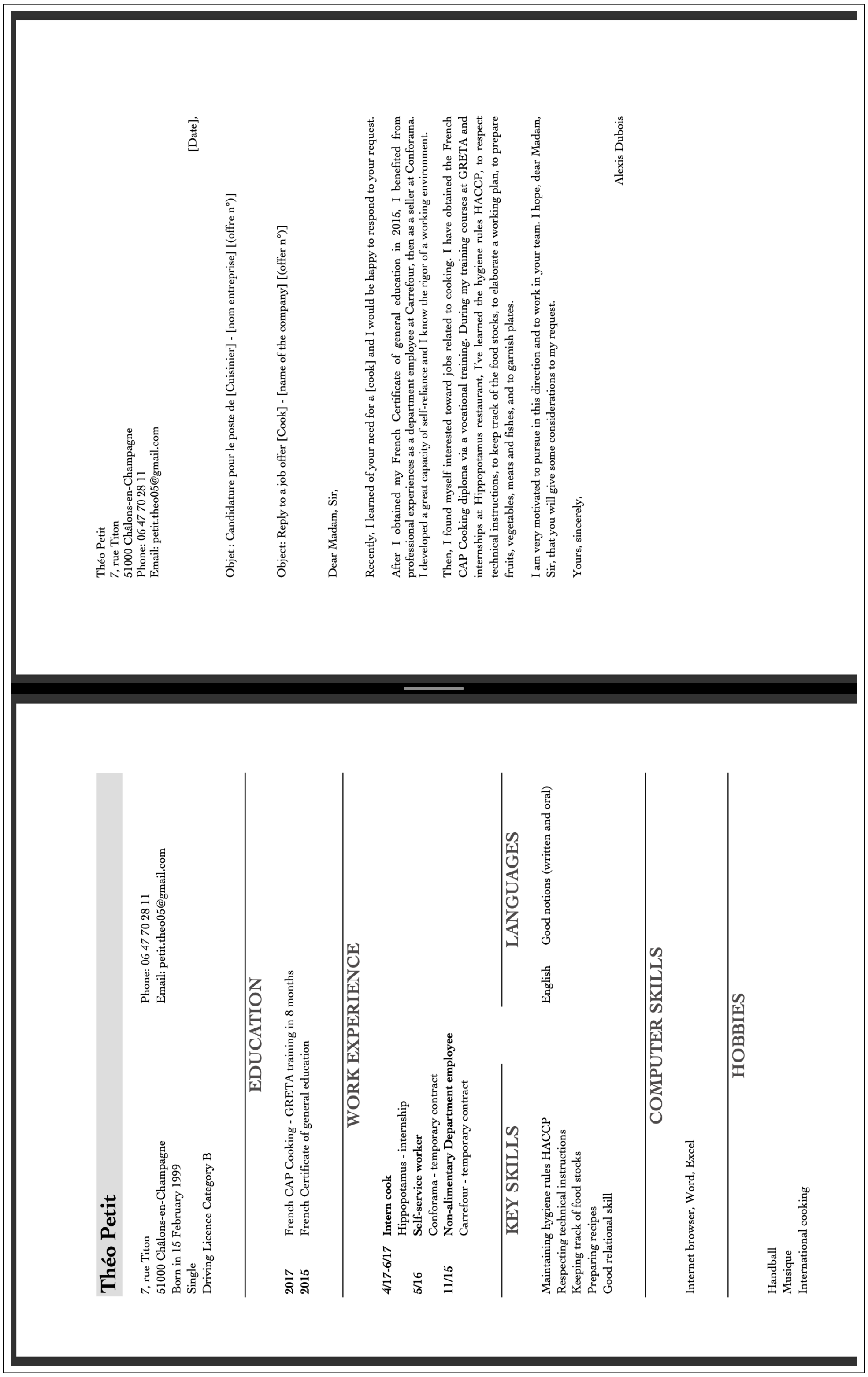
Then, I found myself interested toward jobs related to cooking. I have decided to work in such jobs thanks to various discussions I had with experienced workers. I now wish to obtain the necessary skills to perform as a [cook] such as running a facility, keeping track of the food stocks, elaborate a 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 A.2.2: Example of CV and Cover Letter (Cook Inactive - 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.

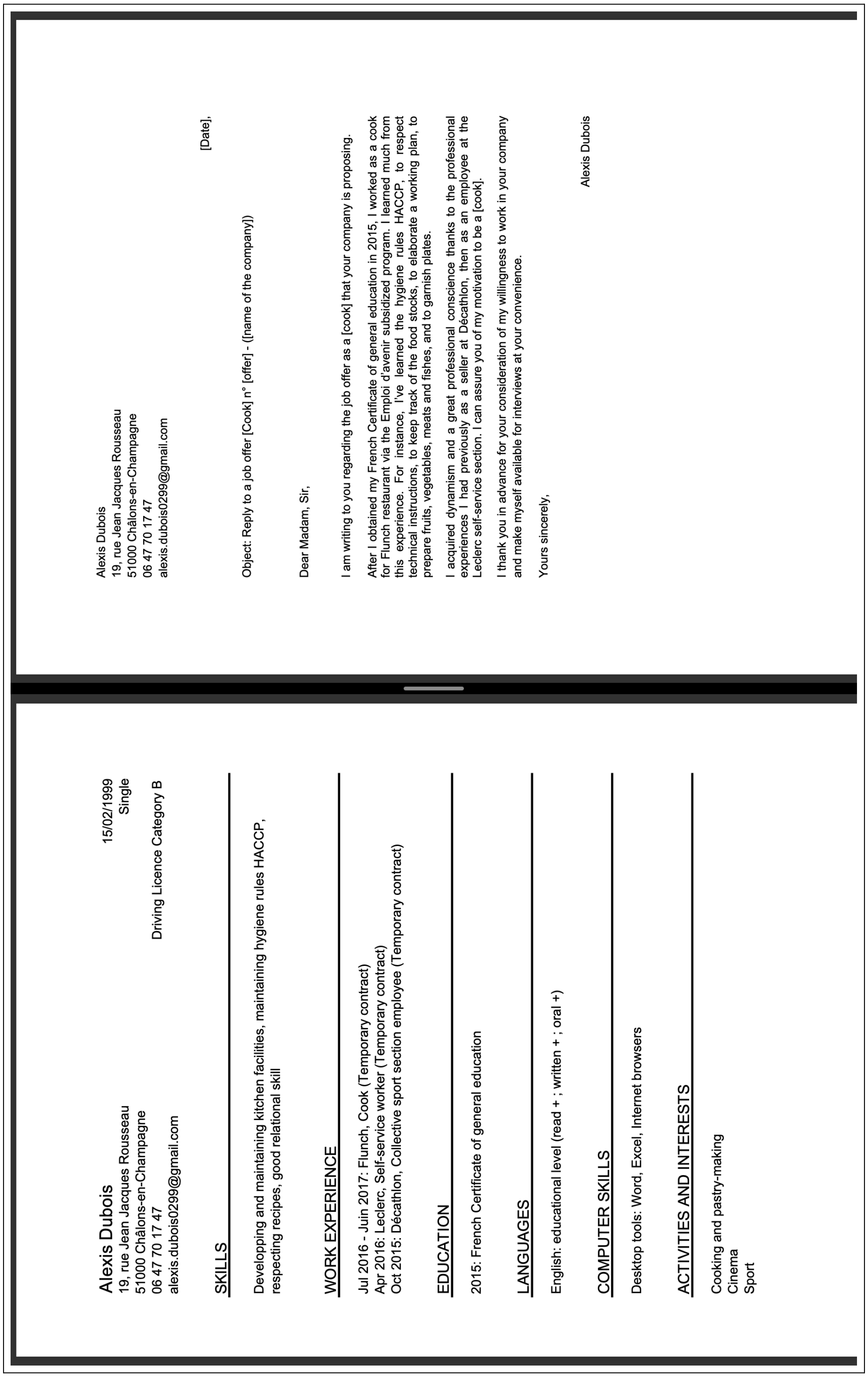
Then, I found myself interested toward jobs related to cooking. I have obtained the French CAP Cooking diploma via a vocational training. During my training courses at GRETA and internships at Hippopotamus restaurant, I've learned the hygiene rules HACCP, to respect technical instructions, to keep track 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

Figure A.2.3: Example of CV and Cover Letter (Cook Trainee - layout 2)



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 A.2.4: EXAMPLE OF CV AND COVER LETTER (COOK WORKER - LAYOUT 1)

A.3 Additional robustness checks

Table A.3.1
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.

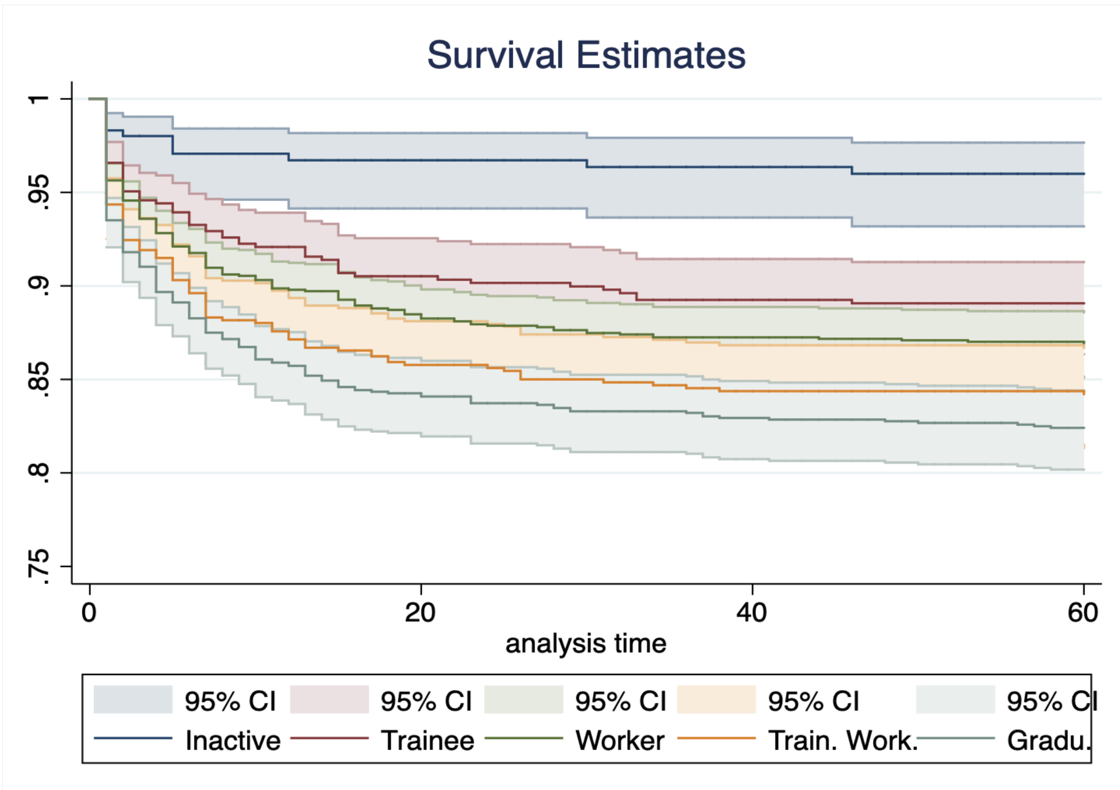


Figure A.3.1: Survival Rate of Applications
Note: The event relevant to non-survival is being called back for more information or a job interview or hiring. The timeline is in days. Most of the calls for a vacancy happen within the first twenty days.
Lecture: More than 5% of graduated applicants were called back by employers one day at most after they sent their applications, against 2% for dropout applicants.

Table A.3.2

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 A.3.3
Effects of Labor Market Experiences using Within-Posting Variation

Proposition	All Applicants (1)	(2)	(3)	Cook (4)	Bricklayer (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 A.3.4

Probability of Callbacks given Firm Characteristics for Cooks

Positive Callbacks	Firm Type		Firm Size	
	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 A.3.5

Probability of Callbacks given Firm Characteristics for Bricklayers

Positive Callbacks	Firm Type		Firm Size	
	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 A.3.6

Probability of Callbacks given Contract Characteristics for Cooks

Positive Callbacks	Type of Contract		Required Experience	
	Temporary	Permanent	$\leq$ 1y	> 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 A.3.7

Probability of Callbacks given Contract Characteristics for Bricklayers

Positive Callbacks	Type of Contract		Required Experience	
	Temporary	Permanent	$\leq$ 1y	> 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.

A.4 Potential mechanisms

Table A.4.1
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 (≈ 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 A.4.2

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.