Knocking on closed doors?

Identifying the determinants of employer call-backs for unskilled youth

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Master in Economics

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Abstract

This paper uses experimental data collected during a correspondence study in France to investigate the determinants of job finding for unskilled youth. The fictitious applicants differ in their most recent labour market history, where a fraction dropped out of secondary education and benefited from subsidized employment and/or job training. The identified employer preferences reveal a clear negative effect of dropout, but which can be compensated through work experience and training post-dropout. Another main question is whether skilled workers crowd out unskilled youth when job competition increases. I present a stylised job matching model in which employers raise their hiring standards in slack labour markets which can be tested against our experimental data. However, I do not find significant and robust evidence of crowding out. This leads us to conclude that comprehensive active labour market policies can play a positive role in improving access to the labour market for this target population.

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Contents

1 Introduction

Since 2000, youth unemployment in France has consistently been above 20 percent, even right before the Great Recession. In comparison, the German youth unemployment rate has stayed below 10 percent for most of the last decade and was not significantly affected by recent economic downturns. Persistent youth unemployment in France and other European countries does not appear to be only cyclical but also structural. Unsurprisingly, the most affected are unskilled youth, all above those who dropped out of the educational system. Over the years, France has rolled out several active labour market policies attempting to improve the employment situation of unskilled youth. Interventions ranged from job search assistance to hiring credits, from job training schemes to thousands of publicly subsidized jobs. The present paper will focus on the latter two elements. In the literature, most recently Card et al. (2017), public job creation programmes have been found to generate little or no positive effect on the employment probability of their beneficiaries. The same study finds that overall, job training has a positive and lasting impact on job finding, especially in the medium to long run. Also, Kluve et al. (2016) find that programmes which incorporate multiple interventions, such as subsidized employment and training, are more effective. This highlights the potential complementarity of different policy schemes for job seekers. We will hereby focus on the *Emplois d'avenir* in France, a large-scale job creation policy implemented between 2012 and 2018, in which employers were also compelled to provide additional training to the beneficiaries.

Overall, however, the impact evaluation for these policies using administrative data sources remains challenging, which is perhaps why a clear trend fails to emerge in the literature. First, these such analyses will always suffer from potential biases due to unobservable characteristics, such as ability, motivation and the extent of individuals' social network, causing omitted variable bias. Second, job seekers can usually select into the treatment and anticipate its effects, which makes it difficult to identify an effect using quasi-experimental methods. Third, changes in the treated and control group over time (composition effects) could invalidate the results (Ballini et al. 2019). Equally, these approaches say little about the actual preferences of employers over candidates with different labour market histories, of which knowledge is crucial when assessing the effect on the probability of employment. For example, statistical discrimination could well be an issue at play in the setting of active labour market policies. Employers might have opinions on the expected productivity of workers benefiting from different programmes, and on dropouts versus graduates, which lead them to systematically reject applications from one group or another. This calls for the application of an experimental approach to evaluating labour market policies, which is implemented in the present study in the form of an audit correspondence study. Résumés and cover letters of fictitious applicants were sent to cook and mason jobs all over France. In the first wave of the experiment, advertised job offers were sampled and in the second, applications were e-mailed as spontaneous applications to a list of sampled firms over the course of 2017 and 2018. Just as other field experiments in economics, correspondence studies rely on randomized treatment. The randomized variable in our case is the labour market experience of our fictitious applicants, which includes subsidized employment, job training, dropout without further education or experience, and regular graduation from a vocational school. Apart from this variable, the résumés are strictly comparable in all dimensions, thus perfectly matched on all observable variables, allowing to identify a causal treatment effect. After recording employer call-backs, the data can be used to answer several research questions. First, what is the effect of school dropout on the likelihood of call-back? Second, does work experience matter as much as job training? Third, is the ranking of candidate profiles by employers robust to the choice of recruitment channel, or can differences be traced back to the medium of the application?

Several features of this study stand out in the literature on correspondence studies and labour market discrimination. Since their inception in the 1970s and 1980s,[1] correspondence studies have been widely used to analyse the effect of race, gender, religion and sexual orientation on employment.[2] In the specific context of the labour market, numerous experiments involved varying the length of current or past unemployment spells to identify duration dependence of unemployment (e.g. Kroft et al. 2013; Ghayad 2013; Eriksson and Rooth 2014; Farber et al. 2016; Nunley et al. 2017). Some of these studies let employment experience vary and find that underemployment or "interim" jobs during a period of unemployment have a negative impact on call-backs and do not compensate for unemployment spells. Overall, however, the studies do not agree on duration dependence. Fremigacci et al. (2016) investigate the impact of "atypical" work experience, such as a succession of fixed-term contracts, part-time work or unemployment spells on employer responses, finding a negative effect of fixed-term contracts and of part-time work for men. Some papers find positive effects of internship experience in tertiary education, such as Nunley et al. (2016) or Baert et al. (2019). Finally, there is some literature on correspondence studies where educational attainment is the treatment variable. Verhaest et al. (2016) find higher invitation rates for master than for bachelor graduates. In a study similar to the present one, Cahuc, Carcillo, and Minea (2017) estimate the impact of subsidized employment (with and without skill certification) on the call-backs of school dropouts in France. While they find a large positive effect of certification and no effect of subsidized employment, this analysis does not identify the effect of dropout, nor differences between labour market programmes with greater emphasis on training or on experience. Along with Ballini et al. (2019) whose experimental data is analysed further here, the present paper is able to provide several new insights on the qualitative rather than quantitative dimension of training and work experience. In fact, our applicants have similar educational attainment but differ widely in the types of skills they acquired in the classroom or in the workplace. Apart from the latter two publications, this paper is the only correspondence study to my knowledge with a particular focus on the labour market outcomes of unskilled youth. The comparison of call-backs from advertised jobs and spontaneous applications is also new in the literature and allows for additional insights

[1] For example, see Jowell and Prescott-Clarke (1970)

[2] For a review, see Bertand and Duflo (2017)

as well as greater external validity of the results. The first set of results from the correspondence study reveal a clear and robust ordering of profiles by employers. Dropouts receive fewer call-backs on average, but can make up for it especially through programmes involving both employment and training. Other types of programmes also partly compensate for the dropout, while youth without any experience post-dropout have the lowest chances of finding a job. The same hierarchy is found both for posted vacancies and unsolicited applications. In terms of policy, this confirms previous findings on the value-added of combining education and experience and on the lower effectiveness of job training and job creation programmes. These results can also be taken as evidence that on average, employers set clear hiring standards based on the perceived average productivity of potential employees.

Another obstacle for unskilled youth entering the labour market is competition with skilled unemployed workers. In a setting with increased job competition, the unskilled youth considered in our test could be crowded out by other workers, landing at the back of "job queues". If this hypothesis was verified, labour market policies aiming at upgrading the employability of low-skilled youth might not be sufficient to boost their chances of job finding when the labour market is saturated with more skilled unemployed workers. The idea of "job competition" already dates back to the 1970s and a seminal contribution by Thurow (1975). In his model, employers' hiring standards are constant over the business cycle but skilled workers land at the front of job queues because they are viewed as more trainable than unskilled workers. Since our concrete experimental setting measures employer preferences, it is more strongly related to Okun (1981), who stated that employers increase their hiring standards when unemployment is high instead of lowering wages. In both cases, more educated or experienced workers take the jobs previously occupied by less educated workers. Job competition has also been incorporated in job matching models. Van Ours and Ridder (1995) propose a model in which it is optimal for skilled workers to look for jobs in lower segments of the labour market if the lower-segment labour market is sufficiently tight. Other matching approaches rely on *a priori* assumptions on the segmentation of skilled and unskilled jobs, for example that skilled workers can perform unskilled jobs but not vice-versa, to feature crowding-out effects (Dolado et al. 2000; Decreuse 2010). However, these models are conceptually ill-suited to be tested with experimental data, as we do not observe the fraction of skilled relative to unskilled workers in our sample. Instead, it is possible to measure how employer preferences over different types of unskilled workers change with local labour market conditions. I present a stylized job matching model in which firms raise their reservation hiring productivity in response to an increase in entry costs in the labour market, which can be interpreted as a sign of adverse labour market conditions. In equilibrium, firms in areas with higher unemployment have more selective hiring standards. I hereby address the frequent lack of theoretical explanations of the findings of experimental studies on labour market discrimination (Bertand and Duflo 2017). In our data, this should be reflected in a decrease in call-back premia for the "most skilled among the unskilled" youth, as they are the principal workers being displaced by more skilled workers at the margin. The empirical literature on labour-market crowding out has found mixed results on crowding out. Van Ours and Ridder (1995) found that job competition only occurs between tertiary-level and higher vocational degree holders. Gautier et al. (2002) conclude in their analysis that crowding out is more outflow than inflow driven, meaning that in recessions, firms hang on to their skilled workers and lay off unskilled workers first. In an influential paper, Crépon et al. (2013) conduct a randomised experiment to analyse the displacement effects of job search assistance programmes. They find that externalities do exist and that they are stronger in slack labour markets, in economically depressed areas and when the beneficiaries of the programme compete mainly with other eligible workers. Some theoretical considerations around the equilibrium effects of active labour market policies are presented in this paper and in Cahuc and le Barbanchon (2010). Still, the literature identifying crowding out effects in the labour market is scarce and finds mixed results. Also, to date, data from correspondence studies has not been used to investigate crowding out of unskilled by more skilled workers. Therefore, I use cross-sectional variation in local unemployment and call-back rates to estimate the fall in call-back premia attributable to local job competition. Unfortunately, despite finding some negative effects of job competition on call-back premia, most results are statistically insignificant. This leads us to conclude that while crowding out cannot be ruled out, it is not clearly identifiable, nor does it make us question the benefits of active labour market policies for unskilled youth.

This paper will proceed as follows. Section 2 gives some context on the French active labour market policies examined. Section 3 goes over the design of the correspondence study and addresses some of its limitations. Sections 4 and 5 present the empirical results on the relative effect of education and experience on call-backs and on crowding-out, respectively. Section 6 concludes.

2 Background

This section provides supplementary information on French active labour market policies, stressing the relevance of analysing the determinants of job access of unskilled youth. Also, since our experimental study considers more than one recruitment channel, I detail the distribution of these channels among employers and job seekers.

2.1 Youth unemployment and high school dropout in France

After completing lower secondary education and obtaining the *Brevet des collèges* diploma, French pupils have several educational options. Those who do not continue to obtain the general baccalaureate in three years can enrol in vocational upper secondary institutions (*lycées professionnels)* delivering the main vocational degree, the *certificat d'aptitude professionnelle* (CAP). The CAP can also be obtained as part of an apprenticeship. Mandatory schooling, however, ends at age 16 and every year, slightly below 100 000 high school dropouts are recorded in France, according to the Ministry of education.[3] In 2018, the French National Institute for Statistics and Economic Studies (INSEE) recorded an unemployment rate of 43.4 percent for dropouts in the first four years after leaving the educational system. This number is far above the national average of 17 percent for the same post-education period,[4] and the unemployment rate of 20.8 percent for 15-24 year-olds.[5]

2.2 Subsidized employment and job training schemes

In order to fight high unemployment among unskilled youth at the height of the economic crisis of the early 2010s, the administration under president Francois Hollande introduced a programme of publicly subsidized jobs called *Emplois d'avenir*. The policy was enacted on 26 October 2012 and remained in place until the end of 2017, when it was phased out by the government under Emmanuel Macron. Over this period, more than 300 000 contracts were signed according to the French employment ministry (Rostam 2016). The policy targets youth aged between 16 and 25, with a low level of education (lower than the French baccalaureate), who are unemployed and who have been actively searching for a job for six months. Employers in the market sector receive a subsidy of 35% of the minimum wage and the subsidy is increased to 75% for employers in the non-market sector. In fact, a majority of jobs were created in the non-market sector which mainly includes non-profit organisations, local and central administrative bodies (Rostam 2016). The main goal of the policy is not only to provide youth with a first work experience, but also to upgrade their skills through training. Training has to be provided by employers but it can take different forms. It can be either on-the-job or in classrooms, and involve certification or not. About half of the beneficiaries followed a training programme delivering an official certificate, around 15% of whom obtain a recognized educational degree during their first year in the contract, i.e. a baccalaureate, a vocational (CAP) or equivalent (*titre professionnel de niveau V*) degree. Other types of training are rather centred on basic literacy and numeracy, work attitude or also job counseling and may or may not receive certification (Rostam 2016). Therefore, the evaluation of this policy must take into account the heterogeneity in training provided. Ballini et al. (2019) have further calculated that youth without an upper secondary degree made up 24% of all the recipients of the policy and 57% of recipients under 18 years old. Cahuc, Carcillo, and Minea (2017) report that, between 2014 and 2016, a share ranging from 10 to 20% of high-school dropouts were in a subsidized employment relationship.[6] For our chosen occupations, a third of youth under 18% in cook positions have contracts for one year or less, which is the case for almost two thirds of masons (Ballini et al. (2019)). Overall, it results that the main feature of the *Emplois d'avenir* is

[3] More information can be found on https://www.education.gouv.fr/cid55632/la-lutte-contre-le-decrochage-scolaire.html .

[4] The data can be found on https://www.insee.fr/fr/statistiques/2429772 .

[5] https://www.insee.fr/fr/statistiques/2489498

[6] The calculations are made from pooled Labour Force Survey data (*Enquête Emploi*) for 2014-2016.

that they provide complementary work exposure and skills upgrading, unlike simple job training or job search assistance programmes sponsored by the Public Employment Service. In this paper, we will compare youth in these subsidized jobs to youth in job training programmes (*formation professionnelle*) which deliver a CAP or equivalent degree but with a much less work exposure.[7] These schemes are delivered in specific public or private job training centres under the supervision of administrative regions and the Public Employment Service *Pôle emploi*.

2.3 Distribution of recruitment channels

An often neglected but important determinant of the success of job search is the recruitment channel. The recruitment process depends strongly on how much and on the medium through which information on the applicant and the employer is conveyed. As conceptualised by Spence (1973), hiring is an investment under uncertainty, where employers make decisions based on observable signals of the employee's marginal productivity. De Larquier and Rieucau (2015) compare the particularities of different recruitment channels in this respect. When public intermediaries, such as *Pôle emploi*, are activated in the job search, candidates have to make "form investments" to comply with the existing codes and practices of recruitment. This can be characterized as a formal process. In informal channels such as personal networks or job forums, applicants can convey information more directly to employers through personal interactions and recommendations by others. In the case of unsolicited applications, defined as applications which are not sent in response to job advertisements, the procedure tends to be more formal than informal if there is no network connection between the employer and the applicant. From the firms' perspective, the choice of recruitment channels is also relevant. Depending on the public it wants to appeal to, the timeline in which it wants to hire and the financial and human resource means at its disposal, firms might resort to public intermediaries, their networks and to open calls to applications more or less frequently (see Bessy and Marchal 2009). For instance, accepting speculative applications can widen the pool of potential applicants, while resorting to informal methods allows the firm to better identify suitable candidates. Also, speculative applications allow hiring at almost zero advertisement cost, much to the contrary of public intermediation. The distribution of recruitment channels is important for policymakers as well, since informal job search and spontaneous applications are not directly observable in the data provided by public employment agencies. If signals are valued differently depending on the search format, some policies might be more or less effective. In a 2016 inquiry on employer recruiting methods, the "Enquête Ofer" (*Offre d'emploi et recrutement*), 68% of employers said that they examine spontaneous applications, but only accounting for 21% of effective hires. Personal and professional networks were invoked by 53% of employers, while public intermediaries were only activated in 36% of all cases. The latter two accounted for 27% and 13% of effective

[7]These programmes only feature a two-month internship period. The same is alos valid for students enrolled in vocational schools.

hires, respectively (Bergeat and Rémy 2017). Using data from the *Enquête emploi* between 2005 and 2012, de Larquier and Rieucau (2015) reveal the following pattern of search activity among job seekers: 84% respond to published job offers, 74% use speculative applications, 63% contact public intermediaries and 63% use personal and professional contacts. They also find that spontaneous applications are used more often when unemployment is high. One could also think that this form of recruitment is more important for young people without a network and less aware of the help proposed by employment agencies, especially in unskilled segments of the labour market.

3 Experimental design

We use the experimental setting of a correspondence study to identify the effect of various educational and/or employment pathways on employer call-backs. The method consists of sending fictitious résumés and cover letters of job applicants only differing in their type of education and experience, while keeping other observable characteristics constant. These applications were either sent out to posted vacancies or as unsolicited applications to a list of sampled firms all across France over the course of 2018. For both waves of the study, employer call-backs were subsequently recorded and compared across the different groups. To ensure the correct identification of the treatment effects on employer preferences, the design of the correspondence study has to address potential sources of bias. The fictitious candidate profiles and résumés, the choice of occupations as well as the application procedure are therefore described in detail in this section. The experimental design is similar to Cahuc, Carcillo, and Minea (2017), but differs in key dimensions such as the choice of treatment groups and job search channels.

3.1 The candidate profiles

Our fictitious candidates are all male, 19 years old, unemployed at the time of their application, and identical except for their educational and employment history. All candidates have completed lower secondary education (*Brevet des collèges*) before their personal trajectories diverge in the following two years. Some candidates obtain a CAP degree, either in a vocational school (*lycée professionnel*) or in specialized apprenticeship centres (*centre de formation d'apprentis*). I will hereafter refer to this group as T1, or non-dropouts. The rest of our pool of individuals drops out of the school system after completing middle school. During the first year following dropout, they are unemployed except for two short one-month work periods in fields unrelated to the occupations considered in our experiment. After the first year of dropout, they then receive three different types of interventions:

1. A first fraction benefit from a subsidized employment scheme (*Emploi d'avenir*) in the relevant

field and gain work experience for one year (T2).[8]

2. A second fraction benefit from an *Emploi d'avenir* but also obtained a CAP degree through additional job training (T3).

3. A third fraction enrols in a public job training programme delivering a certification equivalent to a CAP degree. These individuals are not in an employment relationship during this period (T4).

Our control group (C) consists of individuals remaining unemployed for another year, except for two more one-month employment spells in unrelated fields. These youths did not gain relevant work experience or training after leaving the school system. Thus, the sample contains four treatment groups (T1-T4), differing in the combination of relevant education and work experience, and one control group. On the educational dimension, T1, T3 and T4 have the same educational attainment (all have a CAP or equivalent degree), but the résumés for T3 and T4 also contain the negative signal of school dropout. T2 and T3 have more work experience relative to T1 and T4, who received more formal education and only completed internships during their curriculum. The exception are the candidates in T1 who obtained their degree through an apprenticeship and therefore spent a majority of their time in their apprenticeship firms. However, we include them in the non-dropouts group since our main focus is on how education and work experience can improve the employability of school leavers, not of upper secondary graduates. It should be noted that the size of the different groups is not identical. Most profiles were doubled before the randomization took place, depending on whether the *emploi d'avenir* or the mandatory internships for non-dropouts were in the market or non-market sector.[9] As a result, the control group as well as T3 are, respectively, roughly a fourth and half the size of the other groups. Overall there were 13 different profiles to randomly draw from.

A necessary condition for the identification of causal effects of educational and employment pathways on employer call-backs is the "strict comparability" across groups on observable information (Bertand and Duflo 2017). These include age, gender, personal background, residence location, unemployment duration at the time of application, foreign languages, general skills and hobbies. Hence, to ensure that differences in call-backs are only caused by the manipulation of the treatment variable, the résumés are carefully constructed to make candidates identical in all dimensions except the treatment, and to avoid interference between the treatment signal and any other piece of information which could bias employer responses. As already mentioned, all applicants are 19 year-old males, with common French names and surnames to eliminate signals related to the candidate's ethnic or religious background. The chosen names, *Alexis Dubois* and *Théo Petit*, are sufficiently

[8] Note that our candidates satisfy the eligibility criteria for subsidized jobs: being between 16 and 25 years old, having a low level of education, and having been unemployed during the six previous months.

[9] Profiles were also doubled in T4 to account for two different public job training programmes, which still deliver equivalent vocational degrees.

common so that employers could not personally identify the candidates on the Internet.[10] The school dropout is not explicitly mentioned and can only be inferred by noticing that the applicant had not been in education the year following the dropout. Another important signal to which recruiters react is the length of the current unemployment spell. As previous studies (see Kroft et al. 2013; Ghayad 2013; Eriksson and Rooth 2014; Farber et al. 2016; Nunley et al. 2017) have provided some evidence of duration dependence, the education and employment timelines are harmonized such that all applicants within the same "wave" of applications have equal unemployment spells. Further, to rule out reputation effects, the school names do not appear on the résumés. To preserve the anonymity of the employers with whom candidates gained prior work experience and exclude personal ties between previous and prospective recruiters, we limit our choice of training firms to large firms located all over France.[11] This also has the practical advantage that the résumés can be re-used in any geographical area. Candidates live in the administrative capital (*préfecture*) of the *département* of the vacancy so as to reduce the chance of a negative call-back due to commuting distance. Finally, to provide more detailed information on the candidates' suitability for the job, which might otherwise be unobservable by the employers, we include a general skills section listing some concrete technical and *soft* skills acquired in previous jobs. These skills were equivalent for all individuals in the treatment groups. Without this mention, employers might otherwise have false doubts about the qualifications of applicants in a given treatment group and not react to the treatment signal itself, especially if they lack information on the content of specific labour market policies.

3.2 Choice of occupations and application procedure

Choosing which occupation to send applications to is important to ensure that the study models a realistic setting. As we are focusing on specific active labour market and education policies, we must select employers for whom the candidates' pathway looks credible. This minimises the risk of detection of the correspondence study and avoids biased responses directed at "atypical" profiles. Using the 2017 French Employment Survey (*emquête emploi en continu*), two types of jobs were selected according to the following criteria:

- The jobs are in different industries.
- At least 10% of the youth currently employed in these occupations are high school dropouts.
- At least 10% of the youth currently employed in these occupations obtained a vocational (CAP or BEP) degree before turning 20. Among them, between 10 and 90% received the degree as part of an apprenticeship.

[10] The first names and surnames were chosen randomly among the top 20 most names in 1999, the birth year of our cohort, from INSEE name registers.

[11] Flunch and Hippopotamus for cooks and Bouygues Construction and Lafarge for construction workers.

- The specialisation chosen by the largest number of the workers holding a CAP degree matches their current job. This ensures that employers in these fields recruit among a pool of applicants not only with similar degrees, but also well-defined and certified specialisations.
- The age difference between apprentices and regular vocational school graduates in these occupations is under one year, and under 2 years between dropouts and non-dropouts.
- Within the profession, at least 1% of contracts are publicly subsidized.
- The profession is performed both in the market and non-market sectors.
- There are sufficiently many vacancies posted on the Public Employment Service's website.[12]

Cooks and masons were ultimately chosen as being sufficiently representative of the employment chances of our fictitious youth profiles in this segment of the labour market. It is clear that within these occupations, all our applicants are relatively inexperienced. They will thus compete with other unemployed workers with higher levels of experience and technical skills, especially in regions with high local unemployment. However, this should not be an issue for the purpose of our study as we seek to assess the determinants of job finding specifically for young people entering the labour market, and the role of specific policies following school dropout. Furthermore, since we only examine entry-level candidates, we will be able to investigate indirectly whether more experienced workers harm young workers' employment prospects when local unemployment is high (see section 5).

Posted vacancies were sampled on the *Pôle Emploi* website for each *département.* We restricted ourselves to job offers accepting applications from private e-mail accounts. To reduce the risk of detection, we excluded offers from temporary employment agencies (who might create résumé databases) and never applied to the same employer twice, even if the vacancies were posted in different regions. We sent two applications on consecutive working days to the same offer in order to increase our sample size. For this purpose, we created two different, but standard, layouts and wordings for the résumés and cover letters. We thereby drew upon résumé and cover letter templates found online on the *Pôle emploi* CV database. The first application is drawn uniformly from the 13 different profiles. The résumé and cover letter formats, the applicant name and his address were drawn randomly from two possible options for the first application. We also chose to always include one application with subsidized employment (either T2 or T3) in each pair. Hence, if the first draw was either T2 or T3, we drew the second one randomly from C, T1 and T4 and vice-versa. In summary, each firm received applications with distinct layouts from two candidates with different names and profiles. For our sample of speculative applications, potential recruiters of masons and cooks were scraped from two websites, *Qualibat* and *La bonne boîte. Qualibat* is an organization certifying construction firms and *La bonne boîte* is a website run by *Pôle emploi* listing

[12]Section 3.3 contains more information on the calculation of the minimal sample size for each group.

employers who might hire within the next 6 months. As before, previous employers, duplicate firms, firms already contacted in the first wave of the experiment and interim job offers were excluded. This time, only one application was sent per firm such that recruiters would not become suspicious of receiving two spontaneous applications over a short time interval. As the mailing was automated, the date and time at which applications would be sent was also drawn randomly.

10 938 applications (8848 cooks and 2090 masons) were sent to posted vacancies from January 23 to July 13, 2018. The large discrepancy between occupations arose because of an unexpectedly high number of interim job offers for masons. Our sample of speculative applications consists of 14125 observations (7810 cooks and 6315 masons). Applications for masonry jobs were sent over two periods, in July 2017 and in October 2018, while cook applications were mailed in November and December 2018. Therefore, the end date of the candidates' last employment or education spell was adjusted to either June 2017 or June 2018. The adjustment was made to ensure that candidates had not been unemployed for more than four months before applying for jobs. Still, unemployment duration is slightly shorter in the sample of speculative applications than the sample of posted vacancies, for which it ranges between six and twelve months. During the experiment, employer responses were recorded by phone or e-mail. We included several categories of our dependent variable to cover the cases of non-response, negative call-back, invitations to job interviews, hiring offers and information requests.[13] Any positive offer for an interview or a position was subsequently denied to minimize the burden for employers.

3.3 Statistical power

In this section, I report the power calculations underlying the sample sizes of the different groups. In field experiments, the aim is not only to find significant treatment effects, but also to design an experiment capable of detecting an effect when there actually is one. This is referred to as the sensitivity of a design, or its statistical power. From Athey and Imbens (2017), the minimal sample size in a completely randomized experiment can be calculated as

$$N = \frac{(t_\beta + t_\alpha)^2\, \sigma^2}{\tau^2\, \gamma(1-\gamma)},$$

where t_β and t_α are the critical values of the standard Normal distribution corresponding to the power and significance levels, respectively. σ^2 is the variance of the outcome variable conditional on treatment, τ is the minimal treatment effect we wish to detect, and γ is the fraction of treated individuals in the sample. Since the treatment group is drawn independently from a Uniform distribution, all groups should be equally large and we can set $\gamma = 0.5$. We set $\tau = 0.3$ and calculate σ^2 as $\mu\,(1-\mu)$, where μ is the supposed proportion of the population having 1 as an

[13] We further distinguish between information requests relative to job mobility, education, experience, administrative matters and unclassified requests.

outcome in the absence of treatment (set to 0.07). With a power level $\beta = 0.8$, a significance level $\alpha = 0.05$, and assuming that the expected effect is positive, the minimal sample size per profile should be around 1,000. This target is easily achieved four all treatment groups (table 1), since many of the 13 possible profiles are aggregated together in defining these sub-samples. Solely the control group in the sample of posted vacancies is slightly below the target.

Table 1: Sample sizes by group

	Posted vacancies	Spontaneous applications
Control	799	1,702
Non-dropouts (T1)	3,110	4,076
Employed (T2)	3,673	3,286
Employed with degree (T3)	1,796	1,691
Job training (T4)	1,560	3,370

3.4 Balancing tests

To ensure that the randomisation was successful, I report the mean of a selected range of covariates across treatment and control groups, as well as the p-values of a two-sided difference-in-means t-test. Systematic differences in summary statistics across groups would be a worrisome indicator of non-random treatment, even if the researcher is not directly involved in matching applications to vacant jobs. For our subsequent analyses in section 5, it is important to ensure that profiles were randomized well across geographical areas. Because the randomised trial is not stratified, meaning that vacancies were not first sampled to be balanced across geographical areas, and profiles randomly drawn afterwards, I test whether certain profiles were over- or underrepresented in areas with few observations and in areas with unemployment above the median. Here, the nature of the bias would be linked to the (perhaps non-random) distribution of job offers across the French territory. Overall, table 2 shows that the randomization in the first wave of the trial was successful. Except for a higher number of observations by *département* for T3, the treatment does not seem correlated with local labour market conditions, the regional sample size, and the occupation. The table in Appendix 7.2 performs additional balancing tests for firm, vacancy and sector-related covariates. Apart from few exceptions, which can always be expected, the randomisation is successful. For spontaneous applications (table 3), we observe that the control group is overrepresented in areas with high unemployment (significant at the 10% level), and that non-dropouts were drawn more often during the months of July and August 2017 (only for masons). Also, the group of non-dropouts is underrepresented among cooks. Otherwise, balancing across all groups seems to have been achieved.

Table 2: Balancing table (posted vacancies)

	Control	Non-dropouts		Employed		Employed with degree		Job training	
	Mean	ΔMean	p	ΔMean	p	ΔMean	p	ΔMean	p
Cook (vs. mason)	0.800	0.018	0.264	0.004	0.773	0.019	0.266	-0.003	0.866
Obs. by *departement*	174.706	2.526	0.579	-0.400	0.928	10.601**	0.032	6.229	0.213
Obs. by commuting zone	85.166	0.079	0.977	-1.447	0.586	2.637	0.364	-0.537	0.856
Obs. by commuting zone > 30	0.221	-0.007	0.685	0.005	0.752	-0.022	0.233	0.002	0.935
Unemployment (departement) > median	0.498	0.011	0.572	0.006	0.755	0.026	0.215	0.022	0.304
Unemployment (comm. zone) <median	0.512	0.006	0.783	-0.002	0.919	0.027	0.233	0.014	0.532

Note: *p<0.1; **p<0.05; ***p<0.01
The first column reports the covariate mean for the control group. Other column pairs report the difference in covariate means for the treatment groups, and the p-value of a two-sided difference-in-means test.

Table 3: Balancing table (spontaneous applications)

	Control	Non-dropouts		Employed		Employed with degree		Job training	
	Mean	ΔMean	p	ΔMean	p	ΔMean	p	ΔMean	p
Cook	0.575	-0.087***	0.000	0.008	0.594	-0.009	0.586	0.009	0.550
Obs. by *departement*	227.665	-3.747	0.304	-3.349	0.373	-6.197	0.154	-2.613	0.486
Obs. by commuting zone	137.878	0.350	0.943	-0.903	0.858	-5.361	0.349	0.397	0.937
Obs. by commuting zone <30	0.180	0.007	0.523	0.004	0.739	0.007	0.617	-0.002	0.866
Unemployment (departement) > median	0.530	-0.018	0.216	-0.018	0.227	-0.010	0.574	-0.012	0.411
Unemployment (comm. zone) > median	0.550	-0.037**	0.012	-0.029*	0.063	-0.032*	0.068	-0.027*	0.082
Month = July 2017	0.156	0.101***	0.000	0.002	0.880	0.005	0.681	-0.011	0.295
Month = August 2017	0.031	0.030***	0.000	-0.004	0.390	0.004	0.541	0.007	0.182

Note: *p<0.1; **p<0.05; ***p<0.01
The first column reports the covariate mean for the control group. Other column pairs report the difference in covariate means for the treatment groups, and the p-value of a two-sided difference-in-means test.

3.5 Advantages and potential limitations of the design

In the literature on economic field experiments, correspondence studies have been praised for solving some of the problems arising in the context of audit studies, in which pairs of testers are sent to interact with potential employers in person. Audit studies raise many questions on the difficulty to match auditors on both physical and behavioural aspects. Also, there might be "demand effects" where test persons consciously or subconsciously act to generate the desired results (Bertand and Duflo 2017). With fictitious applicants, the matching on observables is much more accurate because the researcher can control what the employer observes in the application files. The method also suppresses demand effects and allows for larger sample sizes thanks to its low marginal cost. However, correspondence studies have shortcomings when it comes to correctly identifying market discrimination. The most prominent critique has been put forward by Heckman (1998). This is why a discussion of potential limitations of this experiment, as well as the way in which we address these issues, is in order.

First, it is important to bear in mind that correspondence studies allow less general conclusions on hiring discrimination compared to audits because the only observable outcome is employer call-back and not the final hiring decision. We have to assume that differences in call-backs are highly correlated with differences in actual job finding between groups. On this point, the price to pay seems rather small considering the many pitfalls of conducting job interviews in person with auditors. It seems unlikely that employers would invite a person to an interview if they saw no possibility of hiring her. Further, it has also been criticized that the outcome variable is binary, and that as a result, it would be wrong to infer "equal treatment" from employers who do not respond to any candidate (Bertand and Duflo 2017; Riach and Rich 2002). A second common critique of correspondence studies is the fact that by applying to all firms and vacancies found online, which can be considered a random sample of employers, the correspondence study estimates market discrimination through "discrimination encountered by a randomly selected person [...] at a randomly selected firm" (Heckman 1998. In reality, Heckman argues, discrimination is not an average outcome but occurs at the margin, i.e. among a smaller number of firms who receive applications from both treated and non-treated groups and only choose one of them. This point also relates to the search strategies of applicants: usually, individuals do not apply randomly but optimally select into jobs where they see the highest chance of being hired. This point is often raised in context with racial or ethnic discrimination where, for example, there might be assortative matching between recruiters and workers of the same ethnicity or from the same neighbourhood.[14] We however argue that this problem is of little importance in our setting, and that the job search process constructed in or experiment reflects the actual experience of youth in these educational and professional segments. As we focus on a well-delimited group of youths with similar skills, we can assume that all groups are likely to target the same vacancies.[15]Since their personal and professional networks are probably limited, youths are restricted to formal recruitment channels through public intermediaries or speculative applications (see section 2). Moreover, if the search for vacancies was not random, our design would suffer from experimenter bias (Lahey and Beasley 2009). The similarity of search strategies within our sample is also underlined by the fact that youth usually follow very standard procedures building their résumés and cover letters, often with

[14]This issue could also arise when some of the fictitious candidates are over- or underqualified, as it seems unlikely that they might sort into the same jobs as appropriately qualified workers.

[15]The only exception to the representativity of job search could be apprentices being hired by their apprenticeship firms and who are counted as non-dropouts in the experiment. Also, youths on subsidized, fixed-term contracts usually do not go on to work in the same firms for several reasons. First, many of these jobs were created in the non-market sector. Second, fixed-term contracts can only be renewed twice in France and have a maximum cumulative duration of 18 months. So, the fact that individuals in groups T2 and T3 are searching normally for a job is not a bad signal in itself (Cahuc, Carcillo, and Minea 2017).

the help of online resources, counselors at school or the Public Employment Service. We confirmed the representativity of our résumés with actual employers in food services and construction and with counselors from *Pôle emploi*. It is important to remember overall that our goal in this paper is to look at employer preferences and policies for a very specific demographic. We are thus not making large claims about discrimination on the market for all types of workers, as is often the case in other studies on racial discrimination, for example.

I finish by focusing on two important aspects raised by Heckman (1998). First, to ensure that the treatment effect is correctly identified, an implicit assumption made by correspondence studies is that mean differences in unobservable productivity across groups is zero. This simply amounts to saying that the treatment variable is uncorrelated to the error term, as otherwise, differences in callbacks can be attributed to mean differences in unobservable productivity and not to the signal on the résumé. Second, when the dependent variable is non-linear in productivity,[16]differences in the group variance of unobserved productivity (i.e. in its within-group distribution) can generate biased estimates or, even worse, spurious evidence in favour of or against discrimination. We must therefore assess whether all groups have the same distribution in their unobserved productivity. What can be said is that the precise definition of our target population guarantees that our groups, perhaps with the exception of the control group, are not "vertically" differentiated along their levels of skills and employability but "horizontally" along the mix of education and work experience. It also helps that we included a detailed skills section in our résumés to inform employers about the actual skills of the candidates. Hence, it is not unreasonable to assume that the distributions of unobserved productivity are not statistically different. A potential solution is outlined in Neumark (2012), who shows that if the résumés contain observables that are correlated with the probability of hiring, an unbiased estimate of discriminating behaviour can be recovered. A future way to implement this solution in our study would be to include random variation in the quality of applications, such as introducing a lower-quality application with poor spelling and/or layout (see also Aeberhardt et al. 2011).

4 The effect of dropout, education and experience on call-backs

This section reports the effects of school dropout as well as different labour market histories on the probability of call-back of our fictitious applicants. Table 4 presents the average call-back probabilities by group. For both samples, the difference in call-backs between the treated groups and the control group is clear, as is the larger premium associated to non-dropouts compared to the other groups. However, these estimates do not allow to control for (non-randomized) variation across

[16]Nonlinearity arises in a realistic setting in which employers send positive call-backs to individuals above a reservation productivity threshold, which can also be thought of as a "reservation profile" within a linear ordering of profile types.

geographical areas and between different months of the year. To include these as fixed effects, I estimate a linear probability model, where the dependent variable is the binary indicator for a "positive call-back". Before presenting the results, I discuss the choice of the linear probability model over other discrete choice models in econometrics, as well as potential issues which need to be solved during the estimation. In addition to the analyses performed on the sample of posted vacancies in Ballini et al. (2019), I fully analyse the experimental data from spontaneous applications. Potential differences in employer preferences could then be linked to the recruitment channel. I finish by presenting a range of robustness checks.

Table 4: Descriptive call-backs by profile type

	Posted vacancies			Spontaneous applications		
	N	%	Call-back	N	%	Call-back
Control	799	7.3	0.100	1,702	12.0	0.043
Non-dropouts (T1)	3,110	28.4	0.279	4,076	28.9	0.075
Employed (T2)	3,673	33.6	0.210	3,286	23.3	0.057
Employed with degree (T3)	1,796	16.4	0.261	1,691	12.0	0.073
Job training (T4)	1,560	14.3	0.219	3,370	23.9	0.062

4.1 A linear probability model

We model the probability of call-back as a linear function of observable applicant characteristics and several control variables:

$$\Pr(Y_{ij} = 1|T_i, Z_j) = \alpha + \beta\, T_i + Z_j'\gamma_j + \epsilon_{ij}$$

Y_{ij} is the dependent variable and equal to one if applicant i receives a positive call-back from employer j. In the baseline specification, a positive call-back is defined as a non-negative reaction from employers, excluding only negative responses and non-responses and including additional information requests (see section 3.2). T_i denotes the treatment status of individual i. Z_j is a vector of employer control variables. In the baseline specification, the controls include fixed effects for the region (either *département* or commuting zone) in which the job offer is located and the month in which the application was sent to employer j. Month fixed effects are included to account for variation in call-backs due to the increase in the duration of the candidates' current unemployment spell as well as, for example, periodic variations in recruitment activity. Area fixed effects account for time-invariant local economic conditions affecting the rate of call-backs directly.

Standard econometrics textbooks often highlight the drawbacks of linear probability models (LPM) compared to other binary response models, such as the Probit and Logit model. The LPM relies on the assumption that the relationship between the call-back probability and the regressors is linear over the range of probabilities considered. Linearity implies that the estimated marginal effects of the regressor on the probability are constant over the probability domain. This could be an important issue in the presence of nonlinearities, especially for probability values close to 0 or 1. While the probability of call-back is low overall, being below 10 percent for most of the sample of spontaneous applications, nonlinearities are not a significant issue when considering a discrete treatment variable. The LPM is still well-suited to analyse the effects of different treatments on call-backs. Moreover, the LPM has a clear advantage over non-linear models as the coefficient estimates are easily interpretable as the marginal change in probability in response to the treatment, holding all other variables constant. Nevertheless, caution is required on a few points. First, due to the linearity assumption, some of the predicted call-back rates could lie below 0 or above 1, rendering the estimates implausible. This eventuality needs to be checked to ensure that only a negligible fraction of the sample is concerned. The second, more relevant issue are heteroskedastic standard errors. In fact, since the dependent binary variable is the outcome of a Bernoulli trial, its variance is a function of the regressors X. [17] Furthermore, as applications were sent out to posted vacancies in pairs, the outcomes might be correlated with each other within each pair, and also within the same geographical area. Thus, to correctly estimate the residuals, we consider robust standard errors which are clustered at the job offer level for posted vacancies, and at the *département* or commuting zone level for speculative applications.

4.2 Baseline results

In the following, I perform several baseline regressions to estimate the impact of résumé characteristics on call-back rates. I follow closely the work by Ballini et al. (2019) on the sample of posted vacancies and replicate some of their analyses on the whole sample of speculative applications. This allows to answer several interesting questions. First, are the effects of school dropout, as well as education and experience on invitation rates robust for the sample of spontaneous applications? Can we conclude that the hierarchy of profiles that we identify has external validity and thus policy implications? Finally, can we impute differences in the results across waves of the experiment to the recruitment channel that is used?

[17] Applying the variance formula for a Bernoulli.distributed random variable, we have

$$\mathrm{Var}(Y|X) = P(Y|X)\ (1 - P(Y|X)) = X\beta\ (1 - X\beta); \quad X = (T, Z).$$

4.2.1 The effect of school dropout on call-backs

Table 5 shows that compared to non-dropouts, dropouts are significantly less likely to be called back by prospective employers. The negative effect of the signal is a drop in probability of 6.8 percentage points when responding to job offers, and of 1.7 points for speculative applications. Relative to non-dropouts, dropouts are, respectively for each job prospection channel, 20.4 and 27.4 percent less likely to be contacted. The effect thus seems robust and of similar magnitude in both samples.

Table 5: The effect of school dropout on call-backs

	Probability of call-back	
	Posted vacancies	Spontaneous applications
Constant	0.333***	0.062***
	(0.035)	(0.011)
Dropout	−0.068***	−0.017***
	(0.009)	(0.005)
Observations	10,938	14,125
R^2	0.035	0.018

Note: *p<0.1; **p<0.05; ***p<0.01.
This table reports the coefficient estimates of a LPM, where *dropouts* is a treatment dummy. The regression includes *departement* (reference: Gironde) and month (reference: May 2018) fixed effects. Standard errors are clustered at the firm level for posted vacancies and at the *departement* level for spontaneous applications.

4.2.2 The relative importance of training and work experience on call-backs

The estimates in table 5 mask considerable heterogeneity within the group of dropouts. We can expect that public job training and employment schemes help dropouts compensate the negative signal, while youth who did not benefit from these schemes are more strongly disadvantaged. In table 6, I estimate the average treatment effects associated with each of the four treatment groups (T1-T4). In both samples, a clear hierarchy of profiles can be established: non-dropouts remain the most preferred group by employers, followed by workers on a subsidized employment contract and a vocational degree. The premia associated with these two profiles, compared to the control group of inactive workers, are not statistically different from each other. Over the whole sample, these groups have a higher probability of success of 16-18 percentage points for posted vacancies, and about 3 points for spontaneous applications. Workers on a subsidized employment contract or a job training programme (but not both) have lower but still significantly positive call-back premia. Again, the premia of this pair are within a close margin of each other, at roughly 11 and 2 percentage points, respectively, but significantly lower than for the previous pair. The ranking of candidate profiles also holds within each occupational category, confirming that our results are not driven by one profession only. The main insight from the regressions (1) and (4) is that subsequent educational or work experience helps reduce the negative signal of dropout in all cases. However, spells of employment augmented with training (T3) seem to "double" the amount of positive signals on résumés, prompting employers to respond more positively and practically compensating for the dropout. The consistent relative callback premia of above 80 percent in table 7 show that employed workers with a degree are consistently almost as likely to be contacted back as non-dropouts. Youth with either additional experience or training can at best compensate for two thirds of the dropout. Table 6 reveals some heterogeneity in call-back premia by profession. In levels, call-back rates are clearly inferior for masons that for cooks, as demonstrated by the constant term being approximately 18 and 4 points below the reference value for cooks. This could either reflect a difference in overall labour market conditions in the construction sector, or also a strong distaste of construction firms for youth in our control group with no relevant training or experience. This could perhaps be related to the very specific manual skills needed in this occupation, which decreases the trainability of inactive workers. Furthermore, speculative applications for masonry jobs only seem to be considered seriously for non-dropouts and trained workers (T3), whereas workers with "unidimensional" profiles (T2 and T4) do not differ significantly from the control group. This could reinforce the idea that in rather technical jobs, speculative applications need to boast a strong positive signal for employers to consider hiring a worker without advertising the job beforehand. Still, employers' preference orderings over our five groups remain similar across samples and occupations.

Even though differences in relative call-back premia attributable to recruitment channels in table 7 cannot be directly identified by simply comparing the two waves of the experiment, we can observe a few tendencies. Job finding through spontaneous applications is more difficult for employed workers without additional training (T2) and trainees (T4) who have a weaker signal of employability on their résumé. These two groups are consistently 10 to 20 percent less likely to receive a response from recruiters through a spontaneous candidature. This could be interpreted as employers paying less attention to weaker signals when examining an incoming stream of unsolicited applications. To the contrary, the data does not support the idea that a spontaneous application might be a positive signal of extra motivation for less qualified candidates, causing employers to discriminate less between profiles (Bonoli and Hinrichs 2012). Overall, spontaneous applications remain a very formal channel of job search where lower-quality applications struggle to be noticed. This might of course be different if these candidates applied spontaneously to employers within

Table 6: The effect of training and work experience on call-backs

	Probability of call-back					
	Posted vacancies			Spontaneous applications		
	All	Masons	Cooks	All	Masons	Cooks
	(1)	(2)	(3)	(4)	(5)	(6)
Control	0.099***	−0.010	0.187***	0.029***	0.005	0.040**
	(0.028)	(0.063)	(0.040)	(0.011)	(0.016)	(0.016)
Non-dropouts (T1)	0.181***	0.156***	0.189***	0.032***	0.029***	0.036***
	(0.013)	(0.030)	(0.015)	(0.006)	(0.010)	(0.009)
Employed (T2)	0.111***	0.099***	0.116***	0.014**	0.006	0.019**
	(0.013)	(0.028)	(0.014)	(0.006)	(0.010)	(0.009)
Employed with degree (T3)	0.164***	0.152***	0.168***	0.029***	0.031**	0.028***
	(0.015)	(0.033)	(0.017)	(0.008)	(0.012)	(0.011)
Job training (T4)	0.119***	0.107***	0.125***	0.018***	0.014	0.022***
	(0.015)	(0.032)	(0.017)	(0.006)	(0.010)	(0.009)
Observations	10,938	2,090	8,848	14,125	6,315	7,810
R^2	0.042	0.106	0.045	0.019	0.030	0.025

Note: *p<0.1; **p<0.05; ***p<0.01.

This table reports the treatment effects estimated by a LPM. Regressions (1)-(6) include *departement* and month fixed effects. Standard errors are clustered at the firm level for posted vacancies and at the *departement* level for spontaneous applications.

their social network, yet this eventuality can not be captured in our experimental setting.

Table 7: Relative call-back premia

	Posted vacancies			Spontaneous applications		
	All	Masons	Cooks	All	Masons	Cooks
Employed (T2)	0.610	0.640	0.620	0.430	0.210	0.530
Employed with degree (T3)	0.900	0.970	0.890	0.910	1.100	0.800
Job training (T4)	0.650	0.680	0.660	0.560	0.480	0.630

Note: The table reports the call-back premia of T2-T4 divided by the call-back premium of non-dropouts (T1).

4.3 Robustness checks

To assess the robustness of our previous results, and ensure that they are not driven by omitted variables in the baseline specification of our linear probability model, I present the results from several robustness checks. First, I re-estimate the basic LPM with a more restrictive definition of positive call-backs, only including interview and hiring propositions and excluding information requests. This procedure is often applied in the literature on correspondence studies. The absolute call-back rates are expected to be lower than before, but the ranking of applicant profiles and the size of the premium of each profile should ideally remain the same, confirming that we do not confound employers' genuine interest in a candidate with information requests which might not even lead to an interview invitation. For the sample of advertised job offers, 434 out of 2530 positive call-backs (17.1%) are excluded. For the sample of unsolicited applications, we remove 147 out of 896 positive call-backs (16.4%). The results in table 8 show that the ordering of profiles is robust to a "strictu sensu" definition of call-backs. Again, we can discern two "pairs" of nearly equivalent résumé types, namely non-dropouts and employed workers with a degree on the one hand, and employed workers and trainees on the other hand. Compared to table 6, the premia are an average of two points lower in columns (1)-(3) and of the same order of magnitude in (4)-(6), where differences are even slighter due to the low level of the coefficients. The decline in premia for posted vacancies, however, is not necessarily worrisome as it can be expected that all profiles are equally affected by a more restrictive consideration of call-backs.

Throughout the experiment, information was also collected on the vacancy and firm characteristics to which the applications were sent. An additional robustness check is thus to include these controls in the linear probability model and assess whether they capture some of the effect

Table 8: Call-back premia (restrictive definition)

	Probability of call-back					
	Posted vacancies			Spontaneous applications		
	All	Masons	Cooks	All	Masons	Cooks
	(1)	(2)	(3)	(4)	(5)	(6)
Control	0.069***	−0.008	0.134***	0.017*	0.006	0.021
	(0.026)	(0.055)	(0.037)	(0.010)	(0.015)	(0.014)
Non-dropouts (T1)	0.160***	0.125***	0.170***	0.035***	0.030***	0.038***
	(0.012)	(0.028)	(0.014)	(0.006)	(0.009)	(0.008)
Employed (T2)	0.099***	0.073***	0.108***	0.018***	0.003	0.029***
	(0.011)	(0.026)	(0.013)	(0.006)	(0.008)	(0.007)
Employed with degree (T3)	0.144***	0.117***	0.151***	0.033***	0.030***	0.035***
	(0.014)	(0.031)	(0.015)	(0.007)	(0.011)	(0.009)
Job training (T4)	0.102***	0.094***	0.106***	0.022***	0.017*	0.028***
	(0.014)	(0.031)	(0.015)	(0.006)	(0.009)	(0.007)
Observations	10,938	2,090	8,848	14,125	6,315	7,810
R^2	0.039	0.090	0.041	0.019	0.031	0.024

Note: *p<0.1; **p<0.05; ***p<0.01.

This table reports the treatment effects estimated by a LPM. the dependent variable is equal to 1 only if the employer response includes an explicit invitation to an interview or a direct hiring proposition. Regressions (1)-(6) include *departement* and month fixed effects. Standard errors are clustered at the firm level for posted vacancies and at the *departement* level for spontaneous applications.

of dropout, education and experience on job finding. The process of randomisation in fact cannot control for these factors since the quantity and types of vacancies that are posted are not in the researcher's control. A change in the call-back rates dictated by résumé, firm, vacancy or sector characteristics could invalidate the random assignment of the treatment. Table 14 in appendix 7.3.1 unequivocally shows the robustness of all treatment effects to the inclusion of control variables, as there is only very little variation compared to the baseline estimates in table 6. While individual covariates such as distance from work, required work experience or applying to a small or medium-sized firm have a significant impact on the call-back probability (see table 15 in appendix 7.3.1), this impact is likely the same for all treated groups. It is also worth noting that for both posted vacancies and speculative applications, résumé characteristics such as the applicant name and the layout are not significant for speculative applications. For posted vacancies (table 15), I find that "Théo Petit" is 1.6 percentage points more likely to be called back than "Alexis Dubois" (p-value = 0.052). However, this difference is likely due to very small standard errors and is also economically negligible compared to the magnitude of the call-back premia.

Finally, criticism directed at audit studies often points out that audit studies only identify average discrimination in the sample, whereas hiring discrimination occurs at the margin (Heckman 1998). In other words, if firms facing applications from candidates from different groups systematically preferred one type of candidate over the other, we would be able identify the true extent of discrimination on the labour market in this subsample of firms. Since we sent out pairs of job applications to posted vacancies, it is possible to get a sense of discrimination at the margin. This is not possible for speculative applications for which, due to reasons previously enunciated, each firm only received one résumé.[18] Appendix 7.3.2 reports the estimates calculated by Ballini et al. (2019) on the restricted sample of employers who responded to only one of the two fictitious candidates. Again, the ordering appears to be the same, but the premium associated to non-dropouts (the reference category) is considerably higher. Employed workers with a CAP degree have significantly lower chances of call-back than graduates, as well as the other groups. It is also striking that the disadvantage of "inactives" (C) is much larger compared to the estimates on the entire sample. This indicates that while employers' preference orderings identified on the entirety of sampled firms are robust, our estimates are likely to only give a lower bound of the true extent of youths' challenges in accessing the labour market.

4.3.1 Policy implications

The results presented in this section give a clear indication that active labour market policies with both a training and an employment dimension send the strongest signal to employers and largely compensate for school dropout. This fact should be relevant in the implementation of future

[18] Also, Riach and Rich (2002) argue that with only one application per firm, we identify "preferential treatment" instead of clear-cut discrimination.

policies, especially those targeted at youth with the lowest employability. One can imagine that if an early school-leaver was willing and able to work and complete a full traineeship, he is not only more qualified but also signals higher motivation and employability. Of course, in this case the subsidized employment policy should allow for recipients to choose whatever form of training he finds most attractive or useful. Ensuring this access to vocational training also presupposes sufficient training facilities and monitoring by the administration. Lastly, caution should be applied when interpreting these results. In fact, the correspondence study only informs us about discrimination at the invitation stage, not about true hiring discrimination. Despite a larger cost of doing so, employers might invite a large number of candidates to interviews, but when in doubt always choose a candidate who did not drop out of school. This discrimination at the hiring stage can be large (see Cahuc, Carcillo, Minea, and Valfort 2019) and is not observed in our case.

5 Crowding out effects

The results from section 4 hide some heterogeneity in the treatment effects depending on local labour market conditions. In slack labour markets with more competition from other, potentially higher-skilled workers, active labour market policies might not be sufficient to "push" unskilled youth sufficiently to the front of job queues to have a realistic chance of being hired. The same could be true for non-dropouts, who could find themselves behind candidates with already a few years of work experience. We can expect to see compensating effects for the dropout in tight labour markets, while in slack markets, recruiters could increase their hiring standard as the pool of unemployed workers widens, crowding out both dropouts and non-dropouts. In this section, I begin by presenting a simple matching model in which firms increase their hiring standard when labour market conditions worsen. The model's qualitative prediction can then be tested against our experimental data, using cross-sectional variation in measures of labour market tightness across French *départements* and commuting zones. If skilled workers drove unskilled workers out of the job market through a shift in employer selectivity, we would observe a decrease in all call-back premia when the labour market is more competitive, i.e. tightness is lower.

5.1 A simple matching model

The model presented here is a job matching model with one type of job and workers differing in productivity. Firms hire an unemployed worker only if she has a level of productivity above a given threshold. The model departs from the common assumption of free entry in equilibrium and assumes a positive entry cost for firms wishing to open a vacancy. This assumption allows to model how an exogenous variation in entry costs affects firms' reservation productivity and the equilibrium level of unemployment. The model predicts that higher entry costs, which constrain firms in the number of vacancies they can create, cause employers to raise their hiring standards, which increases unemployment.

5.1.1 The matching function

I consider a standard matching function $M(u, v)$ as in the Pissarides (2000) model relating the number of job matches to the rate of unemployment, u, and the number of available vacancies, v. It is assumed that $M(.)$ is increasing and concave in both arguments and homogeneous of degree one. Labour market tightness, $\theta = v/u$, is defined as the ratio of the number of vacancies to the number of unemployed. Since the labour market is frictional and unemployed workers and unfilled vacancies coexist, we can characterize the probabilities of filling a vacancy and of exiting unemployment. The vacancy filling rate equals the total number of matches over the number of vacancies: $m(\theta) \equiv \frac{M(u,v)}{v} = M(u/v, 1) = M(1/\theta, 1)$. It is decreasing in the level of θ, as more vacancies relative to unemployed workers increase congestion on the firm side. The job finding rate is equal to the total number of matches over the number of unemployed: $f(\theta) \equiv \frac{M(u,v)}{u} = M(1, u/v) = M(1, \theta) = \theta m(\theta)$. It is increasing in θ, as unemployed workers have access to more job opportunities.

5.1.2 Job creation

I assume that the unemployed differ in their level of productivity on the job, y, which is increasing in their level of skills. The robust hierarchy of profiles identified in section 4 supports the argument that employers extract signals from workers' applications to rank them according to their perceived productivity. Productivity within the pool of unemployed workers is distributed according to the cumulative distribution function $G(y)$. The firm decides to open a vacancy only if it meets a worker with a productivity above a unique reservation productivity, R. In addition, the firm faces an advertisement cost per unit of time, h, as long as the vacancy remains unfilled. Once a job is filled, the expected profit for the firm ($J(y)$) is given by the worker's productivity minus the labour cost (w), plus the expected change in profits if the job is destroyed and becomes vacant, which occurs at an exogenous rate q. For simplicity, I assume that all workers are paid a legally binding minimum wage w regardless of their level of productivity.[19] The values of a vacancy (1) and a filled job (2) are described by the following Bellman equations:

$$rV = -h + m(\theta) \max_R \int_R^\infty (J(y) - V)\, dG(y) \tag{1}$$

$$rJ(y) = y - w + q(V - J(y)) \tag{2}$$

[19]This assumption eliminates the Nash wage bargaining part of the standard matching model. It can be justified by the fact that the data collected from the experiment is mainly for entry-level jobs at the bottom of the wage distribution.

In (1), The firm chooses its reservation productivity R in order to maximise the expected profit of filled job relative to a vacancy. It thus faces a trade-off between increasing the productivity of its new workers and maintaining a sufficiently large pool of potential job candidates, namely a fraction $(1 - G(R))$ of all unemployed which are above the threshold R. Differentiating the integral with respect to R, we obtain the following first-order condition:

$$J(R^*) = V. \tag{3}$$

The firm will choose R^* such that the value of a job at the reservation productivity is equal to the value of keeping the vacancy open, i.e. such that it is indifferent between hiring a new worker and leaving the vacancy unfilled. Solving for $J(y)$ in (2), we can re-express the value of a filled job and solve for $J(y) - V$:

$$J(y) = \frac{y - w + qV}{r + q} \;\Leftrightarrow\; J(y) - V = \frac{y - w - rV}{r + q}.$$

Using the optimality condition (3), the reservation productivity level is:

$$R^* = w + rV. \tag{4}$$

The value of a vacancy (equation (1)) then writes:

$$rV = -h + m(\theta) \int_{w+rV}^{\infty} \frac{y - w - rV}{r + q}\, dG(y). \tag{5}$$

5.1.3 Equilibrium

In the standard matching model by Pissarides (2000), $V = 0$ in equilibrium (the free-entry-condition) and firms create vacancies as long as its value is positive. However, if there are no entry costs for firms, the equilibrium level of reservation productivity will be constant and thus independent of labour market tightness. In fact, equation (4) would dictate that $R^* = w$, which is fixed. Therefore, I assume that there is a positive entry cost, C. In equilibrium, $V = C > 0$ and firms adjust their level of vacancies until the value of a vacancy covers the entry cost. The entry cost can be thought of as any exogenous factor which constrains firms in opening new vacancies, such as a sectoral economic shock making new jobs less profitable for firms. With the entry cost, equation (5) can be rewritten:

$$rC = -h + m(\theta) \left[\int_{w+rC}^{\infty} \frac{y - w}{r + q}\, dG(y) - \frac{rC}{r + q}(1 - G(w + rC)) \right] \tag{6}$$

Equation (6) is just a generalised version of the labour demand equation in the Pissarides (2000) model.[20] Because wages are exogenous, this equation pins down labour market tightness

[20] If we set $C = 0$, we can recover the standard labour demand relation

$$\int_{w}^{\infty} \frac{y - w}{r + q}\, dG(y) = \frac{h}{m(\theta)},$$

where the LHS is the expected profit of a filled job, and the RHS is the expected cost of a vacancy (recruitment cost times expected duration of recruitment).

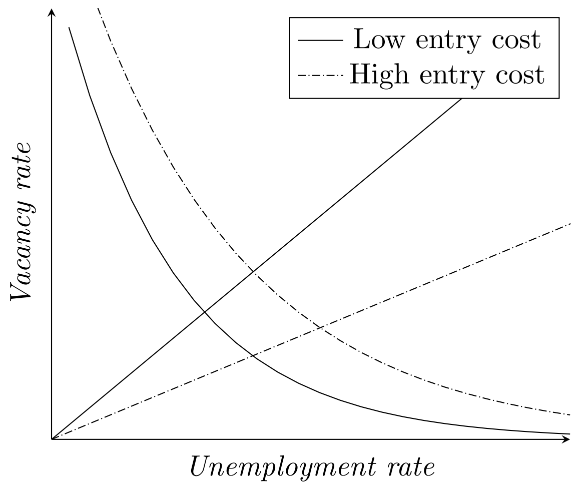
in equilibrium as a function of C. Since $m(\theta)$ is a decreasing function, tightness is increasing in the entry cost ($\frac{d\theta}{dC} < 0$).[21] Moreover, reservation productivity is increasing in C since firms must compensate for higher entry barriers by hiring more productive workers.

While firm behaviour pins down equilibrium labour market tightness, we need to determine the equilibrium level of unemployment. In equilibrium, inflows into unemployment equal exits from unemployment. While employed workers separate from their employers at rate q, unemployed workers match with employers if their productivity is above R^*, hence with probability $\theta m(\theta)(1 - G(R^*))$. Steady-state unemployment is thus defined by:

$$u\ (1 - G(R^*))\ \theta m(\theta) = q\ (1-u) \ \Leftrightarrow \ u = \frac{q}{q + (1 - G(R^*))\theta m(\theta)} \tag{7}$$

5.1.4 Comparative statics

The model can be used to derive a theoretical prediction that firms in slack labour markets have a higher reservation productivity (i.e. hiring standard). Consider an exogenous increase in C. From equation (6), we know that this will decrease equilibrium tightness and the job finding probability for workers, as firms create less vacancies. For any level of R^*, equilibrium unemployment increases. Equation (4) tells us that the firm will also increase its reservation productivity. The increase in R^* causes an upward shift of the Beveridge curve, signalling a fall in match efficiency: firms now have to post more vacancies for a given level of unemployment. The shift of the Beveridge curve amplifies the increase of unemployment in equilibrium.



The new equilibrium features higher unemployment (lower tightness) and higher hiring standards. Unproductive workers are crowded out by more productive workers when firms face larger entry barriers, as recruiters become less prone to inviting low-skilled workers to job interviews.

[21] This presupposes that the term in square brackets on the RHS of equation (6) is positive. Remember that this term represents $\int_{R^*}^{\infty} J(y) - V\, dG(y)$. In equilibrium, $y \geq R^*$, $J(R^*) = V$, $J(y)$ is increasing in y so therefore, $J(y) \geq V$. Integrating this positive function yields a positive value.

This qualitative prediction can be tested with experimental data as we can measure the variation of call-back premia across regions with different local economic conditions, hence different entry costs and levels of unemployment. We can thus compare different local labour market equilibria.

5.2 Empirical analysis

Identifying crowding out effects involves measuring by how much call-back premia associated with each profile vary with labour market tightness. Measuring the degree of competition between unskilled and skilled workers, in local labour markets, and for specific occupations only is difficult: publicly available data on unemployment rates by *département* or by commuting zones do not differentiate by age, sex or educational level. We are therefore unable to use a measure of unemployment of only skilled workers in a given area as an indicator of higher job competition. Data on the number of vacancies by sector or occupation in a local labour market, revealing differences in job creation across France, are not available either. In order to measure labour market tightness, I therefore rely on two indicators. The first one is the overall local unemployment rate (by *département* and commuting zone) which is published by INSEE on a quarterly basis. The second measure is the average call-back rate by geographical unit. In the second case, some econometric challenges, such as simultaneity bias, must be dealt with, especially in areas with only few observations.

5.2.1 Local unemployment rates

The experimental data is merged with INSEE unemployment data by *département* and by commuting zone. Commuting zones (*zones d'emploi*) are officially defined as local labour pools in which a majority of the workforce lives and works, and where businesses source most of their employees from. The current delimitations of commuting zones date back to 2010, and there are currently 321 commuting zones, which is more than the 96 *départements* in metropolitan France. The merging with the commuting zone database is performed using municipality names. Due to the merging of numerous municipalities in recent years, in total, 888 and 851 observations could not be matched with commuting zone information through this identifier for each sample. Further, I split the sample into several groups depending on the level of unemployment. All areas with a level of unemployment above the median across all areas are considered as having a high level of unemployment, and all observations within the same area are attributed to the same group. Due to fluctuations in the number of observations by group, the two groups are not exactly balanced, but this allocation by geographical entity allows to treat commuting zones in particular as independent labour markets. I estimate the following equation in order to compare call-backs by profile depending on whether the unemployment rate of the *département* or commuting zone is above the median:

$$\Pr(Y_{ij} = 1 | T_i, Z_j, U_j) = \alpha + \beta_1 T_i + \beta_2 T_i \times U_j + \delta U_j + Z_j' \gamma_j + \epsilon_{ij}$$

U_j is a dummy variable equal to 1 if unemployment in the area of firm j is above the median. As in every linear regression model, we must ensure that none of the regressors is correlated with the error term. First, we can safely assume that a positive hiring decision of a firm in any area does not reversely affect the local unemployment rate. Second, there could omitted variables affecting both unemployment and call-backs, such as the closure of a large local employer increasing local unemployment and decreasing labour demand of firms in all sectors. However, since the unemployment rate covers all sectors of the local economy, I will argue that it is a sufficiently good measure of the overall condition of the labour market, absorbing most of the effect of other omitted variables. As such, there should not be any correlation between error terms within a given area either. I will return to potential omitted variables in section 5.2.3 and compare the results obtained here with those from alternative specifications.

Crowding-out is identified if β_2 is negative for some or all profile categories. Also, one should expect β_2 to be more strongly negative for the "best" profiles within our sample, namely non-dropouts and employed workers with a degree, indicating that employers treat them increasingly as "inferior" profile categories. Thus, the call-back rates of all treated profiles should converge. Table 9 presents the results both for posted vacancies and spontaneous applications, and for unemployment measured at the *département* and commuting zone level. Column (1) supports the hypothesis of crowding-out effects, with call-back premia being negatively affected by a high level of unemployment. The call-back rate decrease for every treated group that is attributable to unemployment is approximately 6 points. Interestingly, the control group does not experience a significant decrease in call-backs, meaning that the call-back probabilities of the treated and control individuals are closer together. This can support the idea that employers become more selective when the local labour market is slack. In column (2), where we consider a finer grid of commuting zones, the sign of β_2 is still negative for all profiles (including the control), but not significantly so. This calls for additional robustness checks to see whether the data actually supports crowding-out. The coefficients are not significantly negative nor positive for regressions (3) and (4) on spontaneous applications. I identify two potential reasons for this discrepancy. First, because differences in call-back rates are much lower for speculative applications, we need higher statistical power to detect small changes. In fact, the number of observations was calculated to detect a mean difference in call-backs of 0.03 or more, which is below the magnitude of potential crowding-out effects. In the present regression, by interacting the treatment and unemployment dummies, our groups are too small to detect small significant differences in call-backs. Second, the nature of the recruitment channel itself may play a role. Unlike job advertisements, which are clearly correlated with firm and sector-level labour demand, hires through spontaneous applications are likely not. In fact, they could occur anytime

Table 9: Crowding-out effects by local level of unemployment

	Probability of call-back			
	Posted vacancies		Spontaneous applications	
	DEP	ZE	DEP	ZE
	(1)	(2)	(3)	(4)
Control	0.106***	0.116***	0.058***	0.053***
	(0.018)	(0.019)	(0.008)	(0.008)
Non-dropouts (T1)	0.213***	0.209***	0.029***	0.037***
	(0.020)	(0.021)	(0.010)	(0.011)
Employed (T2)	0.139***	0.129***	0.014	0.019*
	(0.018)	(0.020)	(0.010)	(0.011)
Employed with degree (T3)	0.194***	0.188***	0.023*	0.026**
	(0.022)	(0.024)	(0.013)	(0.013)
Job training (T4)	0.153***	0.135***	0.018*	0.024**
	(0.022)	(0.024)	(0.010)	(0.011)
Unemployment > median	−0.008	−0.024	−0.028***	−0.017*
	(0.021)	(0.022)	(0.010)	(0.010)
Non-dropouts (T1) × (Unemployment > median)	−0.064**	−0.045	0.008	−0.008
	(0.027)	(0.028)	(0.013)	(0.013)
Employed (T2) × (Unemployment > median)	−0.056**	−0.025	0.001	−0.007
	(0.025)	(0.027)	(0.013)	(0.013)
Employed with degree (T3) × (Unemployment > median)	−0.061**	−0.045	0.015	0.008
	(0.030)	(0.031)	(0.016)	(0.017)
Job training (T4) × (Unemployment > median)	−0.066**	−0.029	0.003	−0.004
	(0.030)	(0.031)	(0.013)	(0.013)
Observations	10,938	10,050	14,069	13,274
R^2	0.022	0.020	0.004	0.004

Note: *p<0.1; **p<0.05; ***p<0.01.

This table reports the estimated coefficients from a LPM. Regressions (1)-(4) include month fixed effects. "DEP" denotes *départements*, and "ZE" commuting zones. Standard errors are clustered at the firm level for posted vacancies and at the *departement* or commuting zone level for spontaneous applications.

and the inflow of speculative applications to firms could be fairly stable over the business cycle. Response rates to spontaneous applications should then depend less on the unemployment rate. Still, higher unemployment significantly decreases the baseline call-back rate by an average of 2 points for spontaneous applications.

5.2.2 Local average call-back rates

As previously discussed, another measure of tightness is the average employer invitation rate in a region. As an in-sample measure, the average call-back rate has the advantage to be a more precise indicator of labour demand in the construction and food services sector. Zones with higher call-back rates should have a lower level of unemployment. For *départements*, a one-point increase in the unemployment rate decreases the average call-back rate by 1.1 points (significant at 1%). For commuting zones, the estimate over the whole sample is -0.7 points. When removing outliers, i.e. commuting zones with average call-backs equal to 0 or superior to 0.3, which occurs when the number of observations per commuting zone is very low, the estimate becomes more negative and reaches -0.9 points. I report these estimates in table 13 (appendix 7.1). In table 10, I re-estimate the previous equation by replacing the unemployment rate dummy by an indicator equal to one if the average call-back rate is below the median of all *départements* or commuting zones. For advertised jobs (columns 1-3), the results are ambiguous. At the commuting zone level, call-back premia are significantly decreasing for most profiles, while the estimated decrease in call-backs is weaker at the *département* level. In the upper panel, the call-back premia stay consistent with the ordering of section 4. In column 3, where we restrict ourselves to commuting zones with more than 30 observations (removing most zones with zero or implausibly high call-back rates), significance levels decrease for all interaction terms. This could also be an indication of reverse causality bias (see section 5.2.3), as with more observations, the reverse effect of one positive call-back on mean call-backs is reduced. For spontaneous applications (columns 4-6), the fall in call-backs for non-dropouts and employed workers with a degree is the strongest and always significant. This seems consistent with the prediction that employers increase hiring standards, which affects non-dropouts the strongest at the margin.

Table 10: Crowding-out effects by local average call-back rates

	Probability of call-back					
	Posted vacancies			Spontaneous applications		
	DEP	ZE	ZE	DEP	ZE	ZE
	(1)	(2)	(3)	(4)	(5)	(6)
Control	0.135***	0.153***	0.142***	0.062***	0.064***	0.062***
	(0.019)	(0.020)	(0.023)	(0.009)	(0.008)	(0.010)
Non-dropouts (T1)	0.195***	0.220***	0.226***	0.047***	0.046***	0.055***
	(0.021)	(0.022)	(0.025)	(0.011)	(0.011)	(0.013)
Employed (T2)	0.134***	0.139***	0.144***	0.028**	0.024**	0.032**
	(0.020)	(0.021)	(0.024)	(0.011)	(0.011)	(0.013)
Employed with degree (T3)	0.189***	0.197***	0.206***	0.046***	0.041***	0.055***
	(0.023)	(0.025)	(0.028)	(0.014)	(0.013)	(0.016)
Job training (T4)	0.133***	0.127***	0.133***	0.024**	0.030***	0.031**
	(0.023)	(0.025)	(0.028)	(0.011)	(0.011)	(0.013)
Average call-back < median	−0.063***	−0.099***	−0.087***	−0.034***	−0.046***	−0.036***
	(0.021)	(0.022)	(0.025)	(0.010)	(0.009)	(0.011)
Non-dropouts (T1) × (Average call-back < median)	−0.035	−0.072***	−0.059*	−0.026**	−0.030**	−0.035**
	(0.027)	(0.027)	(0.031)	(0.013)	(0.012)	(0.015)
Employed (T2) × (Average call-back < median)	−0.054**	−0.050*	−0.041	−0.026*	−0.019	−0.027*
	(0.025)	(0.026)	(0.029)	(0.013)	(0.012)	(0.015)
Employed with degree (T3) × (Average call-back < median)	−0.059**	−0.071**	−0.053	−0.031*	−0.026*	−0.033*
	(0.029)	(0.030)	(0.034)	(0.016)	(0.015)	(0.019)
Job training (T4) × (Average call-back < median)	−0.037	−0.019	−0.018	−0.010	−0.019	−0.016
	(0.030)	(0.031)	(0.035)	(0.013)	(0.012)	(0.015)
Restrict No. Obs > 30	No	No	Yes	No	No	Yes
Observations	10,938	10,050	7,860	14,125	13,274	10,846
R^2	0.032	0.048	0.041	0.015	0.020	0.018
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: *p<0.1; **p<0.05; ***p<0.01.
This table reports the estimated coefficients from a LPM. Regressions (1)-(6) include month fixed effects. "DEP" denotes *départements*, and "ZE" commuting zones. Columns (3) and (6) remove all commuting zones from the sample with less than 30 observations. Standard errors are clustered at the firm level for posted vacancies and at the *departement* or commuting zone level for spontaneous applications.

5.2.3 Leave-one-out average call-back rates

The results from table 10 are highly likely to suffer from simultaneity bias. With few observations in zone N_j, one additional positive call-back increases the average rate by $1/N_j$, which can be a large margin. The average call-back rate becomes a very volatile estimator of labour demand, with average call-back rates being artificially high or low.[22] In other words, there is a strong correlation between the average call-back rate and the error term, which mainly captures the unobservable determinants of firms' recruitment decision. A common way to solve reverse causality is to replace the simple average by the leave-one-out average over the $N_j - 1$ remaining observations. This solves the simultaneity issue, where the dependent variable has an effect on the explanatory variable. Whether the leave-one-out average is uncorrelated with the residual also depends on potential omitted variables. As a matter of fact, the average call-back rate is an imprecise measure of local economic conditions. Also, firm responses within a sector and region could be correlated with each other, violating the condition of no correlation between error terms. For instance, if the labour market is slack, all firms receive large numbers of applications, which mechanically pushes down the average call-back rate. An easy first remedy is therefore to control for the local unemployment rate, which is a better indicator of the local business environment. The regression model is the following:

$$\Pr(Y_{ij} = 1 | T_i, Z_j, R_j) = \alpha + \beta_1 T_i + \beta_2 T_i \times R_j + \delta R_j + Z_j' \gamma_j + \epsilon_{ij},$$

where

$$R_j = \begin{cases} 1 & if \quad \bar{Y}_{j,-i} < Median_j(\bar{Y}_{j,-i}) \\ 0 & otherwise \end{cases}$$

and

$$\bar{Y}_{j,-i} = \frac{1}{N_j - 1} \sum_{k,-i}^{N_j - 1} Y_{k,-i}$$

is the leave-one-out local average call-back rate and Z_j is a vector of controls consisting of the local unemployment rate and month fixed effects. Table 11 presents the results for both samples. With very few exceptions, the estimates for β_2 in the bottom panel are not significantly different from zero, despite being most often negative (as expected). Compared to table 10, the magnitude of the coefficients is clearly smaller, confirming the possibility that the negative crowding-out effect was overly inflated in the previous specification. It is also worth noting that when the unemployment rate is controlled for, the direct effect of the average rate of call-back is diminished. Thus, omitted variables could play a role even if they do not appear to affect the interaction terms which are of interest to us. By defining R_j as an indicator for when the leave-one-out average is below

[22] Some commuting zones had call-back rates between 0.25 and 0.5 because of one positive call-back among two to four applications. Likewise, most commuting zones with zero call-backs had fewer than 30 observations.

its median across geographical units (as for the "normal" average in table 10), the correction for endogeneity works through a "threshold effect". While the median remains unchanged, the "marginal" observations with a positive callback experience a decrease in the average call-back rate, since their own positive effect is not taken into account. For this reason, these observations are attributed to the group with $R_j = 1$, i.e. with a slack labour market while observations in the same area but with a negative call-back are attributed to the "tight" labour market group. Across all geographical units, this concerns between 5 and 11% of positive responses in both samples. Another way to measure crowding out, but avoiding counter-intuitive "threshold effects" is to interact the profile variable with the *continuous* leave-one-out average while still controlling for unemployment. The regression model is as follows:

$$\Pr(Y_{ij} = 1 | T_i, Z_j, \bar{Y}_{j,-i}) = \alpha + \beta_1 T_i + \beta_2 T_i \times \bar{Y}_{j,-i} + \delta \bar{Y}_{j,-i} + Z_j' \gamma_j + \epsilon_{ij}.$$

β_2 the identifies the effect of the call-back premia of an increase in the leave-one-out average call-back rate of one percentage point. As expected, the results in table 12 show positive effects of an increase in the average call-back rate,[23]yet there does not seem to be conclusive evidence of crowding out as most coefficients remain insignificant.

We can conclude that our improved identification strategy using leave-one-out average call-back rates does not sustain enough evidence for higher hiring standards in depressed labour markets. Overall, crowding-out effects initially detected by interacting the treatment with above-median unemployment are not robust to other measures of labour market tightness as soon as we address potential endogeneity. These results are in line with much of the empirical literature on labour market crowding out, which does not unanimously find evidence of crowding-out of unskilled by skilled workers. Moreover, as a decrease in labour market tightness does not have a positive effect on call-backs for certain groups either, we cannot infer that there is an increase in the relative call-back premium of non-dropouts versus dropouts, implying that they could crowd out the school dropouts *within* the sample. The existence of crowding-out might have important implications for designing active labour market policies. As van Ours and Ridder (1995) note, boosting the skills of unskilled youth might just redistribute unemployment to lower skill segments. According to our results, policies aiming at upgrading the skills of unskilled youth, through additional work experience but especially through a certified degree, do not have negative equilibrium effects on non-beneficiaries. Likewise, they do not seem to lose their effectiveness in the context of a depressed labour market. This could be an indication of positive labour demand effects of skills upgrading, where more skilled workers create more productive jobs, resulting in positive net job creation by firms (see also Decreuse 2010; Cahuc and le Barbanchon 2010). Such positive externalities do not appear in the stylised matching model presented here, and could be the subject of further empirical investigation.

[23]Note that due to the continuity of the interaction variable, the magnitude of β_2 is smaller than in previous tables.

Table 11: Crowding out effects, by leave-one-out average callback rates

	Probability of call-back									
	Posted vacancies					Spontaneous applications				
	DEP	DEP	ZE	ZE	ZE	DEP	DEP	ZE	ZE	ZE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Control	0.117***	0.283***	0.137***	0.217***	0.213***	0.059***	0.093***	0.054***	0.099***	0.094***
	(0.018)	(0.026)	(0.019)	(0.026)	(0.031)	(0.009)	(0.012)	(0.008)	(0.011)	(0.013)
Non-dropouts (T1)	0.169***	0.169***	0.197***	0.198***	0.219***	0.042***	0.043***	0.038***	0.038***	0.045***
	(0.019)	(0.019)	(0.021)	(0.021)	(0.025)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)
Employed (T2)	0.114***	0.114***	0.124***	0.124***	0.136***	0.027**	0.029***	0.023**	0.023**	0.031**
	(0.019)	(0.018)	(0.020)	(0.020)	(0.024)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)
Employed with degree (T3)	0.182***	0.183***	0.181***	0.181***	0.205***	0.042***	0.043***	0.034***	0.033***	0.046***
	(0.022)	(0.022)	(0.023)	(0.023)	(0.027)	(0.014)	(0.014)	(0.012)	(0.012)	(0.015)
Job training (T4)	0.116***	0.116***	0.121***	0.120***	0.125***	0.021**	0.024**	0.025**	0.025**	0.026**
	(0.022)	(0.021)	(0.023)	(0.023)	(0.027)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)
Average call-back < median	−0.029	−0.001	−0.072***	−0.058***	−0.051**	−0.027***	−0.017	−0.024**	−0.015	−0.018
	(0.021)	(0.021)	(0.022)	(0.022)	(0.025)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Local unemployment rate		−0.020***		−0.010***	−0.010***		−0.005***		−0.005***	−0.005***
		(0.002)		(0.002)	(0.003)		(0.001)		(0.001)	(0.001)
Non-dropouts (T1) × (Average call-back < median)	0.022	0.024	−0.022	−0.023	−0.041	−0.016	−0.018	−0.012	−0.013	−0.017
	(0.027)	(0.027)	(0.027)	(0.027)	(0.031)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)
Employed (T2) × (Average call-back < median)	−0.008	−0.006	−0.016	−0.016	−0.021	−0.023*	−0.026**	−0.017	−0.018	−0.026*
	(0.025)	(0.025)	(0.026)	(0.026)	(0.029)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)
Employed with degree (T3) × (Average call-back < median)	−0.042	−0.041	−0.035	−0.035	−0.048	−0.023	−0.024	−0.008	−0.008	−0.015
	(0.030)	(0.030)	(0.030)	(0.031)	(0.035)	(0.016)	(0.016)	(0.016)	(0.016)	(0.019)
Job training (T4) × (Average call-back < median)	0.003	0.006	−0.003	−0.002	0.001	−0.005	−0.008	−0.008	−0.009	−0.007
	(0.030)	(0.030)	(0.031)	(0.031)	(0.035)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)
Restrict No. Obs > 30	No	No	No	No	Yes	No	No	No	No	Yes
Control for local unemployment	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes
Observations	10,938	10,938	10,050	10,050	7,860	14,125	14,069	13,273	13,273	10,846
R^2	0.017	0.023	0.027	0.029	0.031	0.009	0.010	0.007	0.009	0.011

Note: *p<0.1; **p<0.05; ***p<0.01.
This table reports the estimated coefficients from a LPM. Regressions (1)-(10) include month fixed effects. "DEP" denotes *départements*, and "ZE" commuting zones. Columns (1) and (6) present estimates without controlling for local unemployment at the *département* level, columns (3) and (8) do the same at the commuting zone level. Columns (5) and (10) remove all commuting zones from the sample with less than 30 observations. Standard errors are clustered at the firm level for posted vacancies and at the *departement* or commuting zone level for spontaneous applications.

Table 12: Crowding out effects, by (continuous) leave-one-out average call-back rates

	Probability of call-back							
	Posted vacancies				Spontaneous applications			
	DEP	DEP	ZE	ZE	DEP	DEP	ZE	ZE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Control	0.017	0.128***	0.005	0.098***	0.014	0.069***	0.024***	0.093***
	(0.039)	(0.049)	(0.030)	(0.037)	(0.011)	(0.017)	(0.009)	(0.014)
Non-dropouts (T1)	0.116**	0.117**	0.165***	0.163***	0.029**	0.028**	0.042***	0.040***
	(0.048)	(0.048)	(0.035)	(0.035)	(0.014)	(0.014)	(0.011)	(0.011)
Employed (T2)	0.051	0.051	0.109***	0.108***	0.002	0.002	0.011	0.010
	(0.044)	(0.044)	(0.033)	(0.033)	(0.014)	(0.014)	(0.011)	(0.011)
Employed with degree (T3)	0.016	0.017	0.085**	0.084**	0.019	0.019	0.034**	0.033**
	(0.053)	(0.053)	(0.037)	(0.037)	(0.017)	(0.017)	(0.013)	(0.013)
Job training (T4)	0.062	0.062	0.101***	0.100**	0.019	0.018	0.027**	0.024**
	(0.053)	(0.052)	(0.039)	(0.039)	(0.014)	(0.014)	(0.011)	(0.011)
Average call-back < median	0.004**	0.002	0.004***	0.004***	0.005***	0.003*	0.003**	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Local unemployment rate		−0.009***		−0.009***		−0.005***		−0.007***
		(0.003)		(0.002)		(0.001)		(0.001)
Non-dropouts (T1) × Average call-back	0.003	0.003	0.001	0.001	0.001	0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employed (T2) × Average call-back	0.003	0.003	0.0003	0.0003	0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Employed with degree (T3) × Average call-back	0.006***	0.006***	0.003**	0.003**	0.002	0.002	−0.001	−0.0005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Job training (T4) × Average call-back	0.002	0.002	0.001	0.001	−0.00001	0.0002	−0.001	−0.0005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Control for local unemployment	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,938	10,938	10,050	10,050	14,125	14,069	13,273	13,273
R^2	0.028	0.029	0.033	0.034	0.008	0.009	0.004	0.007

Note: *p<0.1; **p<0.05; ***p<0.01.
This table reports the estimated coefficients from a LPM. Regressions (1)-(8) include month fixed effects. "DEP" denotes *départements*, and "ZE" commuting zones. Columns (1) and (5) present estimates without controlling for local unemployment at the *département* level, columns (3) and (7) do the same at the commuting zone level. Standard errors are clustered at the firm level for posted vacancies and at the *departement* or commuting zone level for spontaneous applications.

6 Conclusion

Against the backdrop of mass youth unemployment in France, this paper uses the experimental setup of a correspondence study to draw conclusions on the determinants of employer call-backs of unskilled youth. In two waves, 10,938 and 14,125 résumés differing only in candidates' last two years of labour market history were sent to posted vacancies and potential employers all around France. We are able to identify a clear negative effect of school dropout on the likelihood of call-back, but also positive compensating effects of following a job training programme or gaining relevant work experience post-dropout. Also, individuals combining both work experience and a certified vocational degree experience the largest increase in callbacks if we exclude non-dropouts. I find that employer preferences are robust to the recruitment channel, the definition of call-backs and the introduction of firm, vacancy and sector control variables. Another major insight of this study is the investigation of crowding out effects of unskilled youth by more skilled workers, as unemployment increases. A simple matching model would predict that in slack labour markets, firms raise their hiring standards to create more productive jobs and because they have access to a larger pool of applicants. However, I find little heterogeneity in profile-specific call-backs depending on local unemployment or average call-back rates, especially after taking into account endogeneity of the regressors. Thus, there is no clear evidence that skilled workers crowd out unskilled youth. These results do not support the presence of strong negative externalities of labour market policies, not do they question their effectiveness in adverse labour market conditions. I would therefore argue that subsidized employment and job training does improve the access of unskilled youth to a first job. The use of correspondence studies to identify crowding out is an innovative approach and it should be pursued further. A potential and necessary improvement for this correspondence study would be to implement a stratified design, such as to ensure that there is the same number of observations for each quantile of the local unemployment rate. A direct way of identifying crowding out would also be to include higher skilled manual workers in the sample as well, and to compare the relative call-back premia across unemployment levels. Through its special focus on unskilled youth, highlighting in particular the factors affecting the school-to-work transition of unskilled youth, this paper is of interest to the empirical literature and to policymakers for the implementation of effective policies to create job access for young people.

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7 Appendix

7.1 Average call-backs and local unemployment

Table 13: Average call-backs and local unemployment

	Average call-back rate		
	DEP	ZE	ZE
	(1)	(2)	(3)
Constant	0.165***	0.123***	0.161***
	(0.019)	(0.017)	(0.013)
Unemployment rate	−0.011***	−0.007***	−0.009***
	(0.002)	(0.002)	(0.001)
Restrict No. Obs > 30	No	No	Yes
Observations	96	304	212
R^2	0.226	0.042	0.157
Note:			*p<0.1; **p<0.05; ***p<0.01

7.2 Additional balancing tests (posted vacancies)

DIS-AGGREGATING RANDOMIZATION TESTS

	Graduates	Dropouts									
		All		Inactive		Trainees		Workers		Trained Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	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)	Sample mean	p-value (10)-(1)
Cook (vs bricklayer)	.8173	.8005	.1570	.7997	.2541	.7967*	.0908	.8042	.1699	.8184	.9219
For-profit	.9497	.9458	.4193	.9495	.9831	.9400	.1714	.9474	.6742	.9459	.5702
Not-for-profit	.0502	.0541	.4193	.0504	.9831	.0600	.1714	.0525	.6742	.0540	.5702
Primary sector	.0006	.0013	.3657	.0013	.5800	.0020	.2066	.0017	.2353	.0000	.2871
Secondary sector	.0003	.0006	.5226	.0000	.6122	.0013	.2214	.0008	.4015	.0000	.4466
Tertiary sector	.8398	.8265	.1034	.9213	.2189	.8160**	.0450	.8242*	.0956	.8426	.7951
Construction sector	.1591	.1714	.1304	.1773	.2253	.1806*	.0695	.1731	.1320	.1573	.8658
Small firm (vs large firm)	.6143	.6112	.7805	.6181	.8578	.6044	.5500	.6068	.5609	.6230	.5823
Permanent contract (vs temporary)	.4140	.4066	.4792	.4040	.6082	.4006	.3807	.4157	.8861	.3944	.1783
Full-time job	.9368	.9405	.4695	.9446	.4156	.9420	.4851	.9386	.7665	.9412	.5375
Part-time job	.0631	.0594	.4695	.0553	.4156	.0579	.4851	.0613	.7665	.0587	.5375
< 1-year required experience	.3541	.3610	.5015	.3906*	.0568	.3526	.9202	.3661	.3073	.3444	.4984
= 1-year required experience	.2228	.2060*	.0543	.1871**	.0295	.1990*	.0648	.2064	.1033	.2198	.8108
> 1-year required experience	.4230	.4329	.3504	.4222	.9671	.4482	.1035	.4274	.7192	.4356	.3931
No diploma required	.0534	.0558	.7175	.0792**	.0426	.0463	.4414	.0570	.6351	.0514	.8175
Cap required	.9174	.9107	.4146	.8857**	.0400	.9168	.9627	.9067	.2574	.9243	.5202
Bac required	.0291	.0333	.4025	.0349	.5283	.0368	.2977	.0361	.2330	.0241	.4507
Male recruiter (vs female)	.6174	.6265	.3853	.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. * significant at 10 percent, **significant at 5 percent.

Figure 1: Balancing table for sector, firm and vacancy covariates (source: Ballini et al., 2019)

7.3 Robustness checks

7.3.1 LPM with controls

Table 14: Call-back premia with resume, sector, firm and vacancy controls

	Probability of call-back				
	Posted vacancies				Spont. applications
	(1)	(2)	(3)	(4)	(5)
Control	0.084***	0.079**	0.026	0.084	0.023**
	(0.029)	(0.037)	(0.045)	(0.280)	(0.012)
Non-dropouts (T1)	0.182***	0.181***	0.185***	0.189***	0.032***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.006)
Employed (T2)	0.111***	0.112***	0.112***	0.114***	0.014**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.006)
Employed with degree (T3)	0.164***	0.163***	0.162***	0.165***	0.030***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.008)
Job training (T4)	0.119***	0.119***	0.116***	0.120***	0.018***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.006)
Resume controls	Yes	Yes	Yes	Yes	Yes
Sector controls	No	Yes	Yes	Yes	No
Firm controls	No	No	Yes	Yes	No
Vacancy controls	No	No	No	Yes	No
Observations	10,938	10,938	9,966	9,836	14,125
R^2	0.043	0.047	0.053	0.068	0.020

Note: *p<0.1; **p<0.05; ***p<0.01.

This table reports the treatment effects estimated by a LPM. Regressions (1)-(5) include *departement* and month fixed effects as before. Standard errors are clustered at the firm level for posted vacancies and at the *departement* level for spontaneous applications.

Table 15: Detailed effects of covariates on the probability of call-back (posted vacancies)

	Estimate	p-value
Resume controls		
Layout 2	0.013	0.129
Theo Petit	0.016*	0.052
Sector controls		
Private, non-profit (vs. private, for-profit)	-0.064**	0.050
Public, for-profit	-0.076	0.284
Public, non-profit	-0.006	0.830
Agriculture	-0.113	0.391
Manufacturing	-0.243	0.149
Construction	-0.027**	0.042
Retail	-0.093***	0.003
Firm controls		
Medium-sized firm (vs. SME)	0.069*	0.078
Large firm	0.274	0.187
Micro-business	-0.024**	0.020
Female recruiter	0.004	0.686
Commuting distance (km)	-0.0004550***	0.005
Vacancy controls		
Permanent contract (vs. fixed-term)	-0.032***	0.001
Part-time contract (vs. full-time)	0.011	0.526
Education requirement: I-III (vs. V)	-0.196	0.135
Education requirement: IV	-0.011	0.746
Education requirement: VI	-0.001	0.982
Required experience (in years)	-0.031***	0.000

Note: *p<0.1; **p<0.05; ***p<0.01

7.3.2 Within-job call-backs (source: Ballini et al., 2019)

EFFECTS OF LABOR MARKET EXPERIENCES ON WITHIN-JOB CALLBACKS

Positive Callbacks	All Applicants			Cook	Bricklayer
	(1)	(2)	(3)	(4)	(5)
Inactive	-0.449***	-0.465***	-0.450***	-0.457***	-0.411***
	(0.0362)	(0.0386)	(0.0362)	(0.0400)	(0.0885)
Trainee	-0.141***	-0.149***	-0.141***	-0.149***	-0.104
	(0.0338)	(0.0360)	(0.0339)	(0.0373)	(0.0841)
Worker	-0.165***	-0.170***	-0.166***	-0.174***	-0.125
	(0.0334)	(0.0344)	(0.0335)	(0.0366)	(0.0840)
Trained Worker	-0.0901**	-0.0924**	-0.0904**	-0.103**	-0.0277
	(0.0383)	(0.0396)	(0.0383)	(0.0423)	(0.0929)
Constant	0.621***	0.614***	0.622***	0.627***	0.597***
	(0.0190)	(0.0234)	(0.0194)	(0.0212)	(0.0486)
Observations	2,248	2,248	2,248	1,858	390
R-squared	0.049	0.051	0.050	0.052	0.044
Department FE	No	Yes	Yes	Yes	Yes
Department × Month FE	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 positive callback. Positive callback corresponds to cases in which the fictitious candidate received a demand for complementary information or a proposition for interview or hiring. 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.

7.4 Résumé and cover letter examples

Application email messages (by layout)

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

Object: Candidature Offre n°XXX
Attached files: Curriculum_Vitae.pdf, Lettre_Motivation.pdf

Madame, Monsieur,

Suite à votre annonce XXX pour un poste de YYY, je souhaite vous envoyer ma candidature.
Veuillez trouver ci-joint ma lettre de motivation et mon curriculum vitae.
Je vous prie de croire, Madame, Monsieur, en l'expression de mes salutations distinguées.

Prénom Nom
Numéro de téléphone

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

Object: Candidature (annonce XXX)
Attached files: CV.pdf, LM.pdf

Madame, Monsieur,

Je me permets de vous soumettre ma candidature pour le poste de YYY suite à votre annonce XXX parue sur le site de Pôle emploi.
Je vous envoie en pièce jointe mon CV et ma lettre de motivation.
Veuillez croire, Madame, Monsieur, en l'expression de mes sentiments respectueux.

Prénom Nom
Numéro de téléphone

Application reply email messages (by candidate)

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

Bonjour,

Je souhaite vous remercier pour l'intérêt que vous portez à ma candidature. Je ne peux pourtant pas y répondre favorablement. En effet, j'ai accepté une autre offre d'embauche.

Bien à vous,
Alexis Dubois

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

Bonjour,

Je vous remercie pour votre réponse à ma candidature. Néanmoins, je viens d'accepter une autre proposition d'embauche.

Cordialement,
Théo Petit

Théo Petit 05/04/1999
7, rue Titon Célibataire
51000 Châlons-en-Champagne
06 47 70 28 11 Permis B
petit.theo05@gmail.com

COMPÉTENCES PROFESSIONNELLES

Préparation des aliments et repas, suivre l'état des stocks, règles d'hygiène HACCP, respect des fiches de recettes, bon relationnel

EXPÉRIENCES PROFESSIONNELLES

Sept 2015 - Juin 2017 : Flunch
Apprenti-cuisinier (Contrat d'apprentissage)

FORMATIONS

2017 : Diplôme CAP "Cuisine" en apprentissage
2015 : Brevet des collèges

LANGUES ÉTRANGÈRES

Anglais : niveau scolaire (lu + ; écrit + ; parlé +)

INFORMATIQUE

Outils bureautiques généraux : traitement de texte, tableur, internet

CENTRES D'INTÉRÊTS

Cuisine et pâtisserie
Cinéma
Sport

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

[Date],

Objet : Réponse à l'offre de [Cuisinier] n° [offre] - ([nom entreprise])

Madame, Monsieur,

Je vous adresse, par la présente, ma candidature au poste de [cuisinier] que vous proposez.

En effet, j'ai obtenu un CAP "Cuisine" en apprentissage. J'ai acquis pendant mon contrat d'apprentissage au sein du restaurant Flunch une expérience professionnelle me permettant d'entretenir et faire fonctionner des équipements de cuisine, respecter les règles d'hygiène HACCP, suivre les stocks d'aliments pour être à jour avec les menus, préparer et cuisiner les viandes, poissons ou encore légumes et dresser des plats.

En parallèle, je suis dynamique et doté d'une grande conscience professionnelle. Je peux vous assurer de mon extrême motivation à l'exercice du métier de [cuisinier], et ce, en raison de tout l'intérêt que je lui porte.

Vous souhaitant une très bonne réception, je reste, bien entendu, à votre entière disposition pour un entretien.

Je vous prie d'agréer, Madame, Monsieur, l'expression de mes salutations distinguées.

Théo Petit

Théo Petit 05/04/1999
7, rue Titon Célibataire
51000 Châlons-en-Champagne
06 47 70 28 11 Permis B
petit.theo05@gmail.com

COMPÉTENCES PROFESSIONNELLES

Préparation des aliments et repas, suivre l'état des stocks, règles d'hygiène HACCP, respect des fiches de recettes, bon relationnel

EXPÉRIENCES PROFESSIONNELLES

Mai - Juin 2017 : Flunch, Stagiaire cuisinier (Stage)
Juin 2016 : Flunch, Stagiaire cuisinier (Stage)

FORMATIONS

2017 : Diplôme CAP "Cuisine", lycée professionnel
2015 : Brevet des collèges

LANGUES ÉTRANGÈRES

Anglais : niveau scolaire (lu + ; écrit + ; parlé +)

INFORMATIQUE

Outils bureautiques généraux : traitement de texte, tableur, internet

CENTRES D'INTÉRÊTS

Cuisine et pâtisserie
Cinéma
Sport

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

[Date],

Objet : Réponse à l'offre de [Cuisinier] n° [offre] - ([nom entreprise])

Madame, Monsieur,

Je vous adresse, par la présente, ma candidature au poste de [cuisinier] que vous proposez.

En effet, j'ai obtenu un CAP "Cuisine" dans mon lycée professionnel. J'ai acquis pendant ma formation et mes stages au sein du restaurant Flunch une expérience professionnelle me permettant d'entretenir et faire fonctionner des équipements de cuisine, respecter les règles d'hygiène HACCP, suivre les stocks d'aliments pour être à jour avec les menus, préparer et cuisiner les viandes, poissons ou encore légumes et dresser des plats.

En parallèle, je suis dynamique et doté d'une grande conscience professionnelle. Je peux vous assurer de mon extrême motivation à l'exercice du métier de [cuisinier], et ce, en raison de tout l'intérêt que je lui porte.

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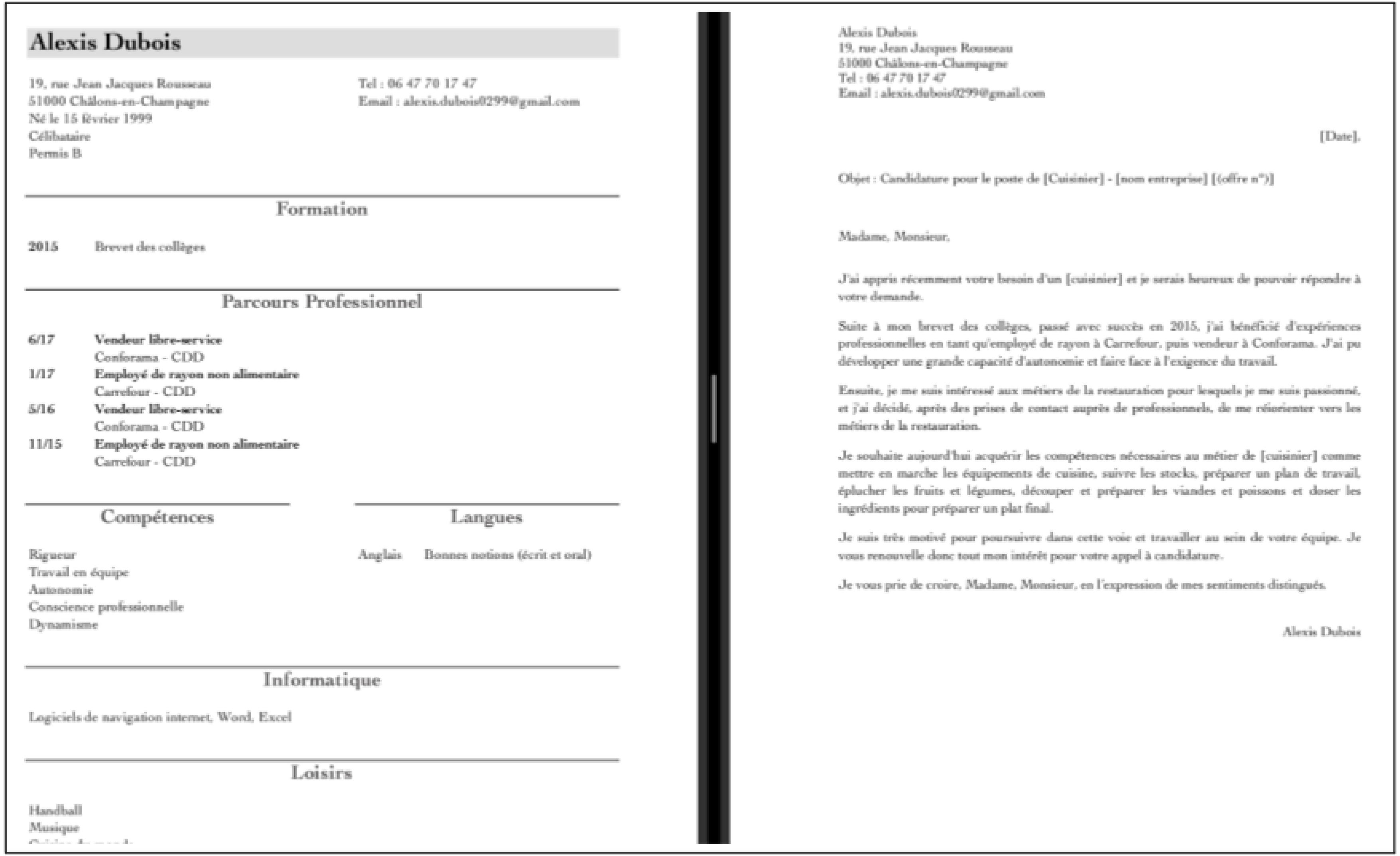
Théo Petit



Alexis Dubois

19, rue Jean Jacques Rousseau
51000 Châlons-en-Champagne
Né le 15 février 1999
Célibataire
Permis B

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

Formation

2015 Brevet des collèges

Parcours Professionnel

6/17 **Vendeur libre-service**
Conforama - CDD
1/17 **Employé de rayon non alimentaire**
Carrefour - CDD
5/16 **Vendeur libre-service**
Conforama - CDD
11/15 **Employé de rayon non alimentaire**
Carrefour - CDD

Compétences

Rigueur
Travail en équipe
Autonomie
Conscience professionnelle
Dynamisme

Langues

Anglais Bonnes notions (écrit et oral)

Informatique

Logiciels de navigation internet, Word, Excel

Loisirs

Handball
Musique

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

[Date].

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

Madame, Monsieur,

J'ai appris récemment votre besoin d'un [cuisinier] et je serais heureux de pouvoir répondre à votre demande.

Suite à mon brevet des collèges, passé avec succès en 2015, j'ai bénéficié d'expériences professionnelles en tant qu'employé de rayon à Carrefour, puis vendeur à Conforama. J'ai pu développer une grande capacité d'autonomie et faire face à l'exigence du travail.

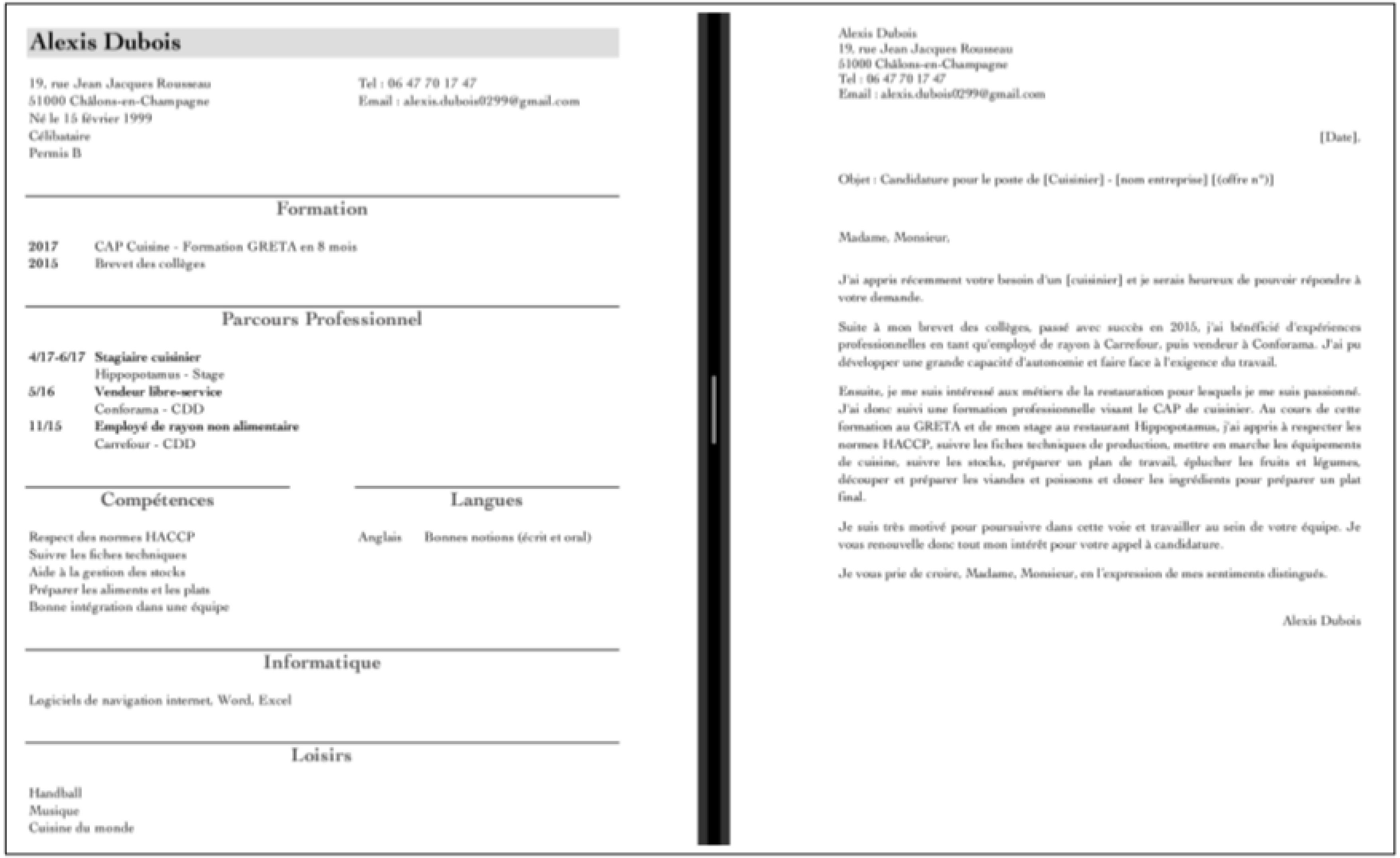
Ensuite, je me suis intéressé aux métiers de la restauration pour lesquels je me suis passionné, et j'ai décidé, après des prises de contact auprès de professionnels, de me réorienter vers les métiers de la restauration.

Je souhaite aujourd'hui acquérir les compétences nécessaires au métier de [cuisinier] comme mettre en marche les équipements de cuisine, suivre les stocks, préparer un plan de travail, éplucher les fruits et légumes, découper et préparer les viandes et poissons et doser les ingrédients pour préparer un plat final.

Je suis très motivé pour poursuivre dans cette voie et travailler au sein de votre équipe. Je vous renouvelle donc tout mon intérêt pour votre appel à candidature.

Je vous prie de croire, Madame, Monsieur, en l'expression de mes sentiments distingués.

Alexis Dubois



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Permis B

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

Formation

2017	CAP Cuisine - Formation GRETA en 8 mois
2015	Brevet des collèges

Parcours Professionnel

4/17-6/17	**Stagiaire cuisinier** Hippopotamus - Stage
5/16	**Vendeur libre-service** Conforama - CDD
11/15	**Employé de rayon non alimentaire** Carrefour - CDD

Compétences

Respect des normes HACCP
Suivre les fiches techniques
Aide à la gestion des stocks
Préparer les aliments et les plats
Bonne intégration dans une équipe

Langues

Anglais — Bonnes notions (écrit et oral)

Informatique

Logiciels de navigation internet, Word, Excel

Loisirs

Handball
Musique
Cuisine du monde

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

[Date].

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

Madame, Monsieur,

J'ai appris récemment votre besoin d'un [cuisinier] et je serais heureux de pouvoir répondre à votre demande.

Suite à mon brevet des collèges, passé avec succès en 2015, j'ai bénéficié d'expériences professionnelles en tant qu'employé de rayon à Carrefour, puis vendeur à Conforama. J'ai pu développer une grande capacité d'autonomie et faire face à l'exigence du travail.

Ensuite, je me suis intéressé aux métiers de la restauration pour lesquels je me suis passionné. J'ai donc suivi une formation professionnelle visant le CAP de cuisinier. Au cours de cette formation au GRETA et de mon stage au restaurant Hippopotamus, j'ai appris à respecter les normes HACCP, suivre les fiches techniques de production, mettre en marche les équipements de cuisine, suivre les stocks, préparer un plan de travail, éplucher les fruits et légumes, découper et préparer les viandes et poissons et doser les ingrédients pour préparer un plat final.

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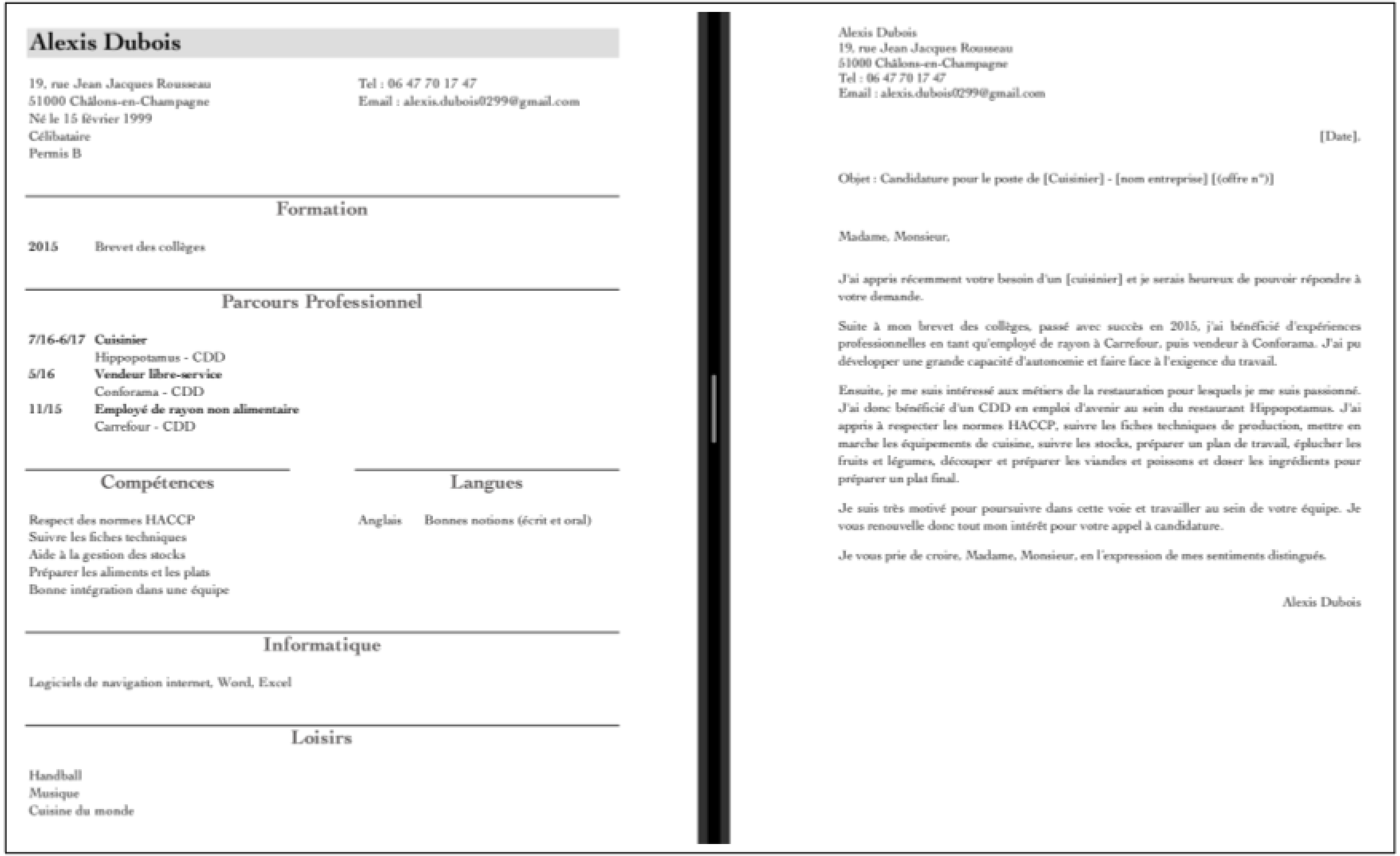
Je vous prie de croire, Madame, Monsieur, en l'expression de mes sentiments distingués.

Alexis Dubois



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51000 Châlons-en-Champagne
Né le 15 février 1999
Célibataire
Permis B

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

Formation

2015 Brevet des collèges

Parcours Professionnel

7/16-6/17 **Cuisinier**
Hippopotamus - CDD
5/16 **Vendeur libre-service**
Conforama - CDD
11/15 **Employé de rayon non alimentaire**
Carrefour - CDD

Compétences

Respect des normes HACCP
Suivre les fiches techniques
Aide à la gestion des stocks
Préparer les aliments et les plats
Bonne intégration dans une équipe

Langues

Anglais Bonnes notions (écrit et oral)

Informatique

Logiciels de navigation internet, Word, Excel

Loisirs

Handball
Musique
Cuisine du monde

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

[Date].

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

Madame, Monsieur,

J'ai appris récemment votre besoin d'un [cuisinier] et je serais heureux de pouvoir répondre à votre demande.

Suite à mon brevet des collèges, passé avec succès en 2015, j'ai bénéficié d'expériences professionnelles en tant qu'employé de rayon à Carrefour, puis vendeur à Conforama. J'ai pu développer une grande capacité d'autonomie et faire face à l'exigence du travail.

Ensuite, je me suis intéressé aux métiers de la restauration pour lesquels je me suis passionné. J'ai donc bénéficié d'un CDD en emploi d'avenir au sein du restaurant Hippopotamus. J'ai appris à respecter les normes HACCP, suivre les fiches techniques de production, mettre en marche les équipements de cuisine, suivre les stocks, préparer un plan de travail, éplucher les fruits et légumes, découper et préparer les viandes et poissons et doser les ingrédients pour préparer un plat final.

Je suis très motivé pour poursuivre dans cette voie et travailler au sein de votre équipe. Je vous renouvelle donc tout mon intérêt pour votre appel à candidature.

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Alexis Dubois

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51000 Châlons-en-Champagne
Né le 15 février 1999
Célibataire
Permis B

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

Formation

2017 CAP Cuisine - formation emploi d'avenir
2015 Brevet des collèges

Parcours Professionnel

7/16-6/17 **Cuisinier**
Hippopotamus - CDD
5/16 **Vendeur libre-service**
Conforama - CDD
11/15 **Employé de rayon non alimentaire**
Carrefour - CDD

Compétences

Respect des normes HACCP
Suivre les fiches techniques
Aide à la gestion des stocks
Préparer les aliments et les plats
Bonne intégration dans une équipe

Langues

Anglais Bonnes notions (écrit et oral)

Informatique

Logiciels de navigation internet, Word, Excel

Loisirs

Handball
Musique
Cuisine du monde

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

[Date].

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

Madame, Monsieur,

J'ai appris récemment votre besoin d'un [cuisinier] et je serais heureux de pouvoir répondre à votre demande.

Suite à mon brevet des collèges, passé avec succès en 2015, j'ai bénéficié d'expériences professionnelles en tant qu'employé de rayon à Carrefour, puis vendeur à Conforama. J'ai pu développer une grande capacité d'autonomie et faire face à l'exigence du travail.

Ensuite, je me suis intéressé aux métiers de la restauration pour lesquels je me suis passionné. J'ai donc bénéficié d'un CDD en emploi d'avenir au sein du restaurant Hippopotamus, associé d'une formation complémentaire m'ayant permis d'obtenir le CAP de cuisinier. J'ai appris à respecter les normes HACCP, suivre les fiches techniques de production, mettre en marche les équipements de cuisine, suivre les stocks, préparer un plan de travail, éplucher les fruits et légumes, découper et préparer les viandes et poissons et doser les ingrédients pour préparer un plat final.

Je suis très motivé pour poursuivre dans cette voie et travailler au sein de votre équipe. Je vous renouvelle donc tout mon intérêt pour votre appel à candidature.

Je vous prie de croire, Madame, Monsieur, en l'expression de mes sentiments distingués.

Alexis Dubois