How does labour market history influence the access to hiring interviews?

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Abstract

Purpose – The purpose of this paper is to provide evidence of the effect of labour market status on the current probability to be invited to a hiring interview. The authors compare the effect of periods of unemployment, part-time job and short-term contracts (STCs).

Design/methodology/approach – Correspondence tests were conducted for accountants and sales assistants. The authors estimate the discrimination components from the response rate of each candidate by the asymptotic least squares method.

Findings – The authors find that men with a part-time profile suffer discrimination in both professions. Other differences of treatment are specific: for accountants, the authors find that the probability of success decreases with the time spent in unemployment, while for sales assistants the probability of success is smaller with a history of STCs.

Originality/value – This study compares the effect of different dimensions of career history (part-time versus full-time, permanent versus short-term, unemployment versus employment) for experienced job candidates. It also proposes an alternative way to exploit the design of a correspondence experiment.

Keywords France, Unemployment, Discrimination, Discrimination in employment, Part-time workers, Hiring, Labour market history, Part-time job

Paper type Research paper

1. Introduction

Since the beginning of the Great Recession in 2008, the French labour market has been deeply transformed. Between the first semester of 2008 and the third semester of 2015, the number of unemployed people has increased by 54.3 per cent. The unemployment rate reached 10.2 per cent of the active population (Beck and Vidalenc, 2017). In the same time, the duration of unemployment has approximately doubled: the average number of days in unemployment has risen from 237 to 472 days (De Visme, 2017). As a consequence, atypical employment positions have developed (Barlet et al., 2014). These facts question the ability of both the unemployed people and the people who were on atypical job contracts to reintegrate the labour market.

Many studies indicate that the current occupation (employment, unemployment) influences the subsequent trajectory of people in the labour market (Givord, 2005; Fremigacci and Terracol, 2013; Fontaine and Rochut, 2014). Having a poor quality job can reduce the chances of getting a good job in the future. Therefore, the workers who have taken part-time or short-term jobs may face the risk to fall in a “bad job trap” while the workers who
decline these job offers may face long-term unemployment. The crisis would amplify
the dualism of the labour market between stable (good) jobs and unstable (poor) jobs.
This phenomenon has also been identified for decades as an unemployment persistence factor
at the macroeconomic level (Blanchard and Summers, 1986).

Dualism is the subject of renewed attention in the context of the Great Recession. In the USA,
recent studies have shown that among workers who experienced six months of unemployment
between 2008 and 2012, only 11 per cent have found a stable job 15 months later (Krueger
et al., 2014). The chances of returning back to work are highly dependent on the time spent out
of work, especially the first eight months of searching and when the local labour markets are in
turmoil (Kroft et al., 2013). The crisis may well have reinforced this negative correlation between
returning to work and the duration of unemployment (Kroft et al., 2016). It seems to have altered
the cyclical properties of the American economy, making it less resilient to shocks.

Theoretically, the relationship between the current labour market status and the
subsequent trajectory in the labour market can be explained by human capital (Becker, 1994)
and signalling (Spence, 1973). According to the first mechanism, employment is a vocational
experience that alters human capital, and it modifies the cognitive or non-cognitive abilities,
like a person’s motivation. According to the second mechanism, even when human capital is
unchanged, having a bad job provides information that can be used by future recruiters as far
as it can be interpreted as an employability or a productivity indicator.

In practice, it is difficult to distinguish a signalling effect from a human capital effect.
The chances of exiting unemployment and getting a high-quality job depend on many
factors. Among them, it is particularly complicated to identify the specific effect of an
individual’s previous occupation or past duration of unemployment, both of which depend
on the same factors. We must guard ourselves against selection and endogeneity biases.
This is the subject of an extensive microeconometric literature, which applies duration
models to the analysis of state dependence in unemployment (Heckman and Borjas, 1980;
Lynch, 1985; Van den Berg and van Ours, 1994; Reed et al., 1999; Imbens and Lynch, 2006;
Lesner, 2015). It is even more difficult to break down this effect according to the mechanism
at play, human capital or signalling. One solution for identifying the cause of discrimination
is the use of laboratory experiments. Van Belle et al. (2017) found that a long unemployment
period may be interpreted as a lack of motivation by the recruiters.

In order to assess the signalling effect of labour market history, we need to control for
human capital. An efficient way to control for it is to collect experimental data, since it
allows accounting for both the observable characteristics of the job applicants and
unobservable heterogeneity. The first study that used an experimental method in order to
measure the effects of unemployment duration on the chances of obtaining a job was carried
out in Switzerland in 1999 (Oberholzer-Gee, 2008). It has been followed by several studies on
the American labour market (Kroft et al., 2013). These studies have found both human
capital and signalling effects, a weakening in the chances of exiting unemployment after six
months only. Birkelund et al. (2017) found a negative effect of long-term unemployment in
the Norwegian labour market, stronger for women. Baert and Verhaest (2014) reached a
similar conclusion for the Belgian labour market, after one year in unemployment. However,
some studies have made other findings. A study carried out in Sweden with the same type of
method indicates that the effects of past employment and unemployment situations are
rather insignificant compared to the current situation of the applicant (Eriksson and
Rooth, 2014). Cahuc et al. (2017) found that unemployment has no effect on a population of
French high school drop-outs. In this context, one originality of our research is to be the first
in France to study the situation of experienced workers.

We have made a correspondence test in order to identify the effect of the past and current
occupations on the chances to be invited to a hiring interview. We have selected two
professions with a tight labour market: accountants and sales assistant. Our applicants have
five different profiles: long-term contracts (LTCs), short-term contracts (STCs), short-term unemployment, long-term unemployment and part-time jobs. We find that men with a part-time profile suffer discrimination in both professions. For accountants, we find that the probability of success also decreases with the time spent in unemployment. For sales assistants, we find that a history of STCs reduces the chances to get a hiring interview.

2. Experiment
We wish to evaluate the answer that an applicant gets with his characteristics and the answer he would have got with other characteristics. The most convenient way to collect such data is to perform an experiment. We construct a set of applications with similar characteristics except for the history in the labour market.

Correspondence studies are best suited to measure the effect of an individual characteristic on the chances of getting a job (Baert et al., 2016; Riach and Rich, 2002; Neumark, 2012, 2016). It consists in building fictitious applications that are practically identical apart from the trait whose effect we want to evaluate, and then to send them simultaneously in response to the same job offers. One can then evaluate how the chances of success vary between the fictitious applicants. This method eliminates the unobservable heterogeneity of job applicants and the self-selection bias. Its main limitation is related to the necessarily limited size of the experiment. Evaluations from correspondence tests produce a one-time measurement for specific professions (Heckman, 1998). However, it reveals information that no other data source can provide: the answers that were given by the recruiters to several competitors for the same job.

2.1 Choice of professions
We chose professions which satisfy two criteria: a tight labour market and a large number of offers. A tight labour market, characterised by a large number of job offers per job seeker, was chosen both to have a high response rate and to obtain a lower bound estimate of discrimination (Baert et al., 2015). If discrimination occurs in a tight labour market, it should be worse in the professions sharing common characteristics. The second criterion, a large number of job offers, allows for decreasing the risk of detection by reducing the share of the experimental applicants in the total applicants.

2.2 Choice of candidates
For the two professions, the applicants are male in order to avoid gender discrimination (Duguet and Petit, 2005) single and childless. They are between 31 and 33 years old, which corresponds to experienced workers. Their first and last names are sounding French in order to avoid ethnic discrimination (Duguet et al., 2015). They live inside Paris (13th, 14th and 15th districts) in order to avoid address discrimination (Duguet, Gray, L'Horty, Du Parquet, Petit, 2017). Finally, they have a driving licence and a car, which correspond to mobile workers (Duguet, Du Parquet, L'Horty and Petit, 2017). From this basis, we define the five following profiles:

(1) LTCs profile: it is the benchmark situation, where no discrimination is expected. This candidate has 12 years of experience with four LTCs. These contracts have had an increasing duration over time. The last position is held since 2011.

(2) Part-time contracts (PTC) profile: this profile is close to the previous one, with LTCs only, but includes two periods of PTC. The worker starts with three years and a half on a full-time job, then one year on a part-time job, then five years and a half on a full-time job, and moved on a part-time job over the last two years before the test period. Overall, it makes only three years with a part-time job, but the two last years may matter more for the recruiter. Since the worker has no child, it could indicate either health problems, or the will to spend more time on leisure or on another business.
Short-term unemployed (STU) profile: this profile is similar to the LTC profile but includes a short unemployment period at the end. The unemployment period starts in October 2014. Since the test is made between February and May 2015, the unemployment duration is between 4 and 7 months.

Long-term unemployed (LTU) profile: this profile is similar to the LTC profile but includes a period of unemployment starting in January 2014. The unemployment duration is therefore between 13 and 17 months.

STCs profile, on full-time jobs: this profile is the most different from the baseline case. It includes seven periods of employment because the contracts are shorter. The worker has started with two STCs, moved to a LTU of five years, and then to a series of four STCs. The last contract started in May 2014.

Given that these applications were sent simultaneously in response to the same job offers, the applications had to include elements of differentiation. These differences concern the resume presentations, i.e. font type, font size and page layout, all the while remaining standard in form. The applicants offer experiences acquired in real companies. These firms differ, but are comparable in terms of their activities, size, market power, etc. The applicants’ leisure activities are different as well, while also remaining very typical and impersonal (team sports, individual sports, cinema, reading, music, etc.). The short e-mails sent along with the resumes were also worded differently, while remaining standard in style. An address, a cell phone number and an e-mail address were attributed to each applicant. These resumes were compiled based on the expertise of representatives from each of the vocational fields in question. They were consulted for their opinions about whether the applications appear realistic or not.

Another important point in order to avoid detection is the number of candidates who reply on each job post in the real labour market. The more the better. The only reliable data that we could find were about executives. Since the jobs in our study are less qualified than these, we interpret the executives’ number of applicants as lower bounds for our professions. According to APEC (2017), each job post for sales executives received on average 44 candidates in the first quarter of 2015 and 54 candidates in the second quarter. For accounting executives, the figures are, respectively, 57 and 52 for each offer. Overall, considering that these figures are lower bound, our experiment is likely to have avoided detection.

2.3 Responses to job offers
The candidates have responded to online job offers between February and May 2015. We carried out a simple job interview test by sending electronic applications or by regular mail for the same job offer shortly after the job was posted online. This way, no applicant had to undergo the interview in person. This method was chosen for two reasons. First, interviews introduce a bias on the part of recruiters related to the applicants’ physical appearance and personality. These unavoidable biases are not perceptible by researchers and are impossible to control. We assume that since interviews generate a cost, the recruiter would invite for an interview only applicants who objectively have a chance to obtain the position. No photographs were added to written applications. Second, since the data collection process is less burdensome and is completed within a given time period, we were able to constitute a larger sample. Our outcomes are callback rates in a broad sense (see Baert et al., 2015), either an invitation to a job interview or a request for more information or to contact the recruiter.

In order to ensure that the formatting or content of a specific application would not systematically influence companies’ choices of a particular applicant (in spite of the precautions taken when the applications were created), we interchanged the resume layouts and cover letters between the STC profile and the LTC profile, between the STU profile and...
the LTU profile and between the LTC profile and the PTC profile. Finally, we randomized the order of candidates for each job offer.

In order to implement our estimation method, we need both to identify the contract term (short, long) and full-time jobs. STCs are defined by durations strictly lower than 12 months. LTCs are defined as either undefined term contracts or contracts for 12 months and more. We keep full-time jobs because they represent almost all the offers for accountants and sales assistants. Our method could be easily adapted to part-time jobs if there were enough observations.

Table I summarises the data available. Most of the posts include enough information for our discrimination analysis. We also report two important independence tests. The first test checks whether the answer of the recruiter depends on the sending order. The second test examines whether the answer depends on the address of the candidates. We find that the answers do not depend on the sending order. Therefore, the number of candidates that we have sent does not seem to have diminished the callback rates. We also find that the Paris districts were adequately chosen since the addresses of the candidates did not influence significantly the answers of the recruiters. The overall success rate is close to one-third, which indicates a tight labour market in France.

3. Model

We can summarise the success probabilities of the candidates by the following system. The letter $L$ refers to the offers of LTCs. The subscript $i$ refers to the job post. It is useful to point up the post-level unobservable heterogeneity $u_{L,i}$. For each job post $i$, we have the following callback probabilities:

$$
\begin{align*}
Pr(\text{LTC}, \text{L}) &= \theta_L + u_{L,i} \\
Pr(\text{STU}, \text{L}) &= \theta_L + \delta_U + u_{L,i} \\
Pr(\text{LTU}, \text{L}) &= \theta_L + \delta_U + \delta_L + u_{L,i} \\
Pr(\text{PTC}, \text{L}) &= \theta_L + \delta_P + u_{L,i} \\
Pr(\text{STC}, \text{L}) &= \theta_L + \delta_S + u_{L,i} \\
E(u_{L,i}) &= 0.
\end{align*}
$$

The candidate with a history of LTCs, the (LTC, L) case, should experience no discrimination when he replies to a LTC offer since he has no characteristic susceptible to attract it.

<table>
<thead>
<tr>
<th>Contract</th>
<th>Sales assistant</th>
<th>Profession</th>
<th>Accountant</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full time</td>
<td>Part time</td>
<td>n/a</td>
</tr>
<tr>
<td>Long term</td>
<td>237</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Short term</td>
<td>57</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>n/a</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Posts used</td>
<td>294</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,470</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$\text{Independence of the callback with^a}$

<table>
<thead>
<tr>
<th></th>
<th>Sending order</th>
<th>Paris district</th>
<th>Overall success rate^b (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.88</td>
<td>0.57</td>
<td>34.2</td>
</tr>
</tbody>
</table>

$\text{Notes:}$ n/a, not available. $^a$p-value of the $\chi^2$ test of independence; $^b$percentage of posts with at least one positive answer.
His average probability of success is $\theta_L$, a measure of labour market tightness for LTCs. To this component, we add $u_{L,i}$, an unobserved heterogeneity term at the job post level. This heterogeneity term may be correlated with the characteristics of the candidates, so that we have to eliminate it by differencing in order to get unbiased estimates. We set $E(u_{L,i}) = 0$ without loss of generality because the model includes a constant term $\theta_L$.

The candidate with one year of unemployment (STU, L) faces a specific effect $\delta_U$. Its sign is undetermined: on the one hand, unemployed workers are immediately available in a tight labour market so that firms could prefer STU workers to candidates with a LTC because the latter must respect a notice period between one and three months ($\delta_U > 0$) and, on the other hand, unemployed workers could experience a statistical discrimination on their expected productivity ($\delta_U < 0$). The argument may be stronger for the LTU and they could suffer from a specific stigma $\delta_L$. The total effect for the LTU workers is $\delta_U + \delta_L$, the sum of the unemployment and stigma effects.

There remains two profiles that we wish to test: long-term PTC (PTC, L) and the STCs (STC, L). $\delta_P$ is the potential statistical discrimination against the workers with a long history of PTC. According to Pak (2013), the male workers who have decided to work part time did it for the following reasons: the inability to find a full-time contract (37 per cent), another professional or training activity (18 per cent), health problems (11 per cent), the will to have free time (11 per cent) and helping family members (7 per cent). Since there is almost no part-time job offer in the two professions that we test, we can disregard the inability to find a full-time job. The four other reasons have one point in common: they imply a lower work involvement in the job than full-time workers. The recruiter may therefore have doubts about the ability of the candidate to shift easily from a part-time to a full-time job or to accept overtime, and rank the candidate with a part-time history below the other workers and we should find $\delta_P < 0$. Last, the workers with a long history of STCs (STC, L) could be discriminated against because they have not successfully found a stable job by the age of 30, and this may generate doubts about their professional skills. In fact the issue is a bit more complicated since, in France, STC benefit from a specific legal premium (the “precariousness bonus”) equal to 10 per cent of the total wage of the contract period, so that workers could prefer STCs because they want to earn more. The workers with these profiles would trade their job stability for a 10 per cent wage bonus. We denote the reaction of the recruiter as $\delta_S$.

We go further by considering the job posts for STCs (denoted $S$). Here, we will consider that every candidate with a former long term contract could suffer from a “bad transition” statistical discrimination. On the one hand these workers lose the security of their previous contract and the recruiter may wonder why the candidate accepts this situation but, on the other hand, it may also indicate the will to get the 10 per cent wage bonus at the end of the contract period. We denote $\delta_R$ the effect associated with a contract term reduction. The five probabilities become:

\[
\begin{align*}
\text{Pr}(\text{LTC}, S) &= \theta_S + \delta_R + u_{S,i} \\
\text{Pr}(\text{STU}, S) &= \theta_S + \delta_U + u_{S,i} \\
\text{Pr}(\text{LTU}, S) &= \theta_S + \delta_U + \delta_L + u_{S,i} \\
\text{Pr}(\text{PTC}, S) &= \theta_S + \delta_R + \delta_P + u_{S,i} \\
\text{Pr}(\text{STC}, S) &= \theta_S + u_{S,i} \\
E(u_{S,i}) &= 0,
\end{align*}
\]

where $\theta_S$ is the tightness in the labour market for STCs and $u_{S,i}$ the post-level unobserved heterogeneity on the probabilities of success for the STCs. One difference appears with the
previous case for the STCs: it is not a source of discrimination for short-run contracts, since it involves a continuity of the labour market status.

The aim of this application is to estimate the interest parameters \((\theta_L, \delta_U, \delta_L, \delta_P, \delta_S, \theta_S, \delta_R)\) from the raw success proportions of the candidate. We explain how in the next section.

4. Method

The method both solves an overidentification issue and provides a minimum variance estimator. The problem was originally created by the need to separate the posts on short- and long-run contracts. It had for consequence to provide two estimators for the parameters \(\delta_U, \delta_L,\) and \(\delta_P\). We fix this problem by first testing the equality of the different estimators and, since the test is conclusive in our application, we provide the minimum variance estimates of the discrimination parameters.

This method may be of a more general interest. Indeed, the disturbances of the linear probability models commonly used in the literature are heteroskedastic. Correcting the standard errors allows for a correct inference, but OLS is still not the best estimation method in this case. Using a Probit model estimated by maximum likelihood may provide an asymptotically optimal inference under the normality of the disturbances, but this assumption cannot be tested. With our method, optimality is explicitly addressed, and the normality properties of the estimates results from the law of large numbers, not from an assumption.

The first thing to do is to eliminate unobserved heterogeneity since its presence can bias the estimates. All the \(\delta\) parameters will be estimated from differences and are, therefore, corrected for unobserved heterogeneity. Only the \(\theta\) estimates are obtained from the levels and are influenced by the unobserved heterogeneity, but they do not measure discrimination. In what follow, we focus on the estimation of the discrimination components.

For the LTCs, the elimination of the unobserved heterogeneity is done by differencing from the baseline case (LTC, L), except for long-term unemployment, where differencing with the short-term unemployment case is more relevant. We take the following differences, in order to identify the discrimination parameters:

\[
\begin{align*}
D_{STU,L} & = \Pr(STU,L) - \Pr(LTC,L) = \delta_U \\
D_{LTT,U} & = \Pr(LTU,L) - \Pr(STU,L) = \delta_L \\
D_{PTC,L} & = \Pr(PTC,L) - \Pr(LTC,L) = \delta_P \\
D_{STC,L} & = \Pr(STC,L) - \Pr(LTC,L) = \delta_S.
\end{align*}
\]

For the STCs, we eliminate the heterogeneity terms by differencing from the most relevant case in the same post:

\[
\begin{align*}
D_{LTC,S} & = \Pr(LTC,S) - \Pr(STC,S) = \delta_R \\
D_{STU,S} & = \Pr(STU,S) - \Pr(STC,S) = \delta_U \\
D_{LTT,U} & = \Pr(LTU,S) - \Pr(STU,S) = \delta_L \\
D_{PTC,S} & = \Pr(PTC,S) - \Pr(LTC,S) = \delta_P.
\end{align*}
\]

Overall, the eight probability differences allow for the identification of the five discrimination parameters \(\delta = (\delta_U, \delta_L, \delta_P, \delta_S, \delta_R)\), so that we have three degrees of freedom. They come from the fact that there are two different ways to compute the three parameters \((\delta_U, \delta_L, \delta_P)\). The model is overidentified, and we will have to test that these additional constraints are satisfied. The previous identification constraints provide our estimating equations for the method of asymptotic least squares (henceforth ALS) presented below. The theoretical
relationships can be written under a more convenient matrix form, by stacking all the constraints together:

\[
\begin{pmatrix}
D(STU, L) \\
D(LTU, L) \\
D(PTC, L) \\
D(STC, L) \\
D(LTC, S) \\
D(STU, S) \\
D(LTU, S) \\
D(PTC, S)
\end{pmatrix}
= \begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
\delta_U \\
\delta_L \\
\delta_P \\
\delta_S \\
\delta_R
\end{pmatrix},
\]

or:

\[
\pi = A \delta,
\]

where \( \pi \) is the vector of the theoretical differed probabilities (i.e. the auxiliary parameters in the ALS terminology), \( A \) is the identification matrix and \( \delta \) regroups the theoretical discrimination coefficients (i.e. the parameters of interest in the ALS terminology). We easily obtain a CAN estimator of \( \pi \) from the empirical probabilities[1]. It is estimated from the raw success percentages of the candidates. When we replace the theoretical probabilities by their empirical counterpart, we get an error term \( \omega \) defined by:

\[
\omega = \hat{\pi} - \pi, \quad \text{with} \quad \operatorname{Plim} \sqrt{N}(\hat{\pi} - \pi) = 0, \quad \text{where} \quad N \text{ is the sample size. Inserting } \omega \text{ in the previous equation gives:}
\]

\[
\hat{\pi} = A \delta + \omega
\]

since \( \hat{\pi} \) and \( A \) are observable, we can estimate this relationship by FGLS in one stage only[2]. This is the ALS method[3]. Let \( \Omega \) be the estimated covariance matrix of \( \hat{\pi} \), we get the optimal estimator of the discrimination coefficients:

\[
\hat{\delta} = \left( A' \hat{\Omega}^{-1} A \right)^{-1} A' \hat{\Omega}^{-1} \hat{\pi}
\]

with estimated covariance matrix:

\[
\hat{V}(\delta) = \left( A' \hat{\Omega}^{-1} A \right)^{-1}
\]

The overidentification statistic is simply a norm computed on the estimated error term of our relationship, \( \hat{\omega} = \hat{\pi} - A \hat{\delta} \). Therefore, we get:

\[
S = \hat{\omega}' \hat{\Omega}^{-1} \hat{\omega}
\]

and under the null hypothesis (\( \pi = A \delta \)), it is asymptotically \( \chi^2(3) \) distributed.

5. Results
The raw call-back rates are reported in Table AI. The ALS results are presented in Table II. We proceed by backward elimination, suppressing sequentially the parameter which has the smallest \( t \)-statistic. However, this method has different implications with ALS than...
with the OLS method for the following reason. When a parameter is not significant, it means that candidates from different groups have the same success probability. Therefore, we should regroup them and estimate a global probability in order to increase the efficiency of the estimation. Interestingly, if we regroup two sets of candidates, we double the number of observations and this diminishes the standard errors of our estimates. The backward selection mechanism in our study is therefore very different from the standard regression case. We give a full account of the backward elimination process for this reason.

Regrouping candidates is equivalent to take the average probability because we send exactly the same number of people in each profile. Consider two groups of sample size $N$ with a success dummy variable $d_i$ (1 if success, 0 otherwise), $i \in G_1$ for Group 1 and $i \in G_2$ for Group 2, with respective success probabilities $\hat{p}_1 = N^{-1}\sum_{i \in G_1} d_i$ and $\hat{p}_2 = N^{-1}\sum_{i \in G_2} d_i$, the global success probability is equal to:

$$\hat{p} = \frac{1}{2N} \sum_{i \in G_1 \cup G_2} d_i = \frac{N}{2N} \left( \frac{1}{N} \sum_{i \in G_1} d_i + \frac{1}{N} \sum_{i \in G_2} d_i \right) = \frac{1}{2} (\hat{p}_1 + \hat{p}_2),$$

and the argument extends to any number of groups. One simply has to take the average of the probabilities. When we estimate the model for sales assistants, reported in Column (1), we first find $\delta_R = 0$. Replacing $\delta_R$ in the identification constraints modifies the equations of the STCs only. We get that $\Pr(LTC, S) = \Pr(STC, S)$, the success is the same on STC for the candidates who already have a LTC or a STC. Therefore, we take the average of these probabilities and use the following new

<table>
<thead>
<tr>
<th>Backward elimination</th>
<th>Sales assistant</th>
<th>Profession</th>
<th>Accountant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levels</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$\theta_L$</td>
<td>0.190*</td>
<td>0.190*</td>
<td>0.190*</td>
</tr>
<tr>
<td>SD</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
</tr>
<tr>
<td>$\theta_S$</td>
<td>0.211*</td>
<td>0.219*</td>
<td>0.219*</td>
</tr>
<tr>
<td>SD</td>
<td>0.054</td>
<td>0.051</td>
<td>0.051</td>
</tr>
</tbody>
</table>

| Differences           |                |            |            |
| $\delta_U$           | 0.024          | 0.023      | 0.016      | 0.065*     | 0.074*     | 0.072*     |
| SD                   | 0.023          | 0.023      | 0.020      | 0.022      | 0.020      | 0.020      |
| $\delta_L$           | -0.015         | -0.015     | 0.020      | -0.071*    | -0.075*    | -0.080*    |
| SD                   | 0.020          | 0.020      | 0.024      | 0.024      | 0.024      | 0.024      |
| $\delta_P$           | -0.062*        | -0.063*    | -0.063*    | -0.073*    | -0.044*    | -0.037**   | -0.045*    |
| SD                   | 0.020          | 0.020      | 0.019      | 0.021      | 0.019      | 0.018      |
| $\delta_S$           | -0.032         | -0.033     | -0.032     | -0.042*    | -0.019     |            |
| SD                   | 0.024          | 0.024      | 0.024      | 0.023      |            |
| $\delta_R$           | 0.012          | 0.042      | 0.048      |
| SD                   | 0.035          | 0.039      | 0.038      |

Overidentification p-value | 0.634       | 0.684      | 0.576      | 0.270      | 0.081      | 0.154      | 0.604      |

| Long-term posts      | 237          |            |            |
| Short-term posts      | 57           |            |            |
| Total posts           | 284          |            |            |
| Observations          | 1,470        |            |            |

Notes: *, ** Significant at 5 and 10 per cent levels, respectively

Table II.

Discrimination components estimates—asymptotic least squares

Labour market history
set of identification constraints:
\[
\frac{1}{2} (\text{Pr}(LTC, S) + \text{Pr}(STC, S)) = \theta_S + u_{S,i}
\]
\[
\text{Pr}(STU, S) = \theta_S + \delta_U + u_{S,i}
\]
\[
\text{Pr}(LTU, S) = \theta_S + \delta_U + \delta_L + u_{S,i}
\]
\[
\text{Pr}(PTC, S) = \theta_S + \delta_P + u_{S,i}.
\]

Estimation then proceeds by differencing in order to eliminate the unobserved heterogeneity term \( u_{S,i} \) and applying ALS to the differences. The results are reported in Column (2). We find that \( \delta_L = 0 \). This time, it has consequences for the two blocks of the identification constraints (long term and short term). For the long-term block, the two types of unemployed workers now share the same success probability \( (\text{Pr}(STU, L) = \text{Pr}(LTU, L)) \) so that we will use their average value. We get:
\[
\text{Pr}(LTC, L) = \theta_L + u_{L,i}
\]
\[
\frac{1}{2}(\text{Pr}(STU, L) + \text{Pr}(LTU, L)) = \theta_L + \delta_U + u_{L,i}
\]
\[
\text{Pr}(PTC, L) = \theta_L + \delta_P + u_{L,i}
\]
\[
\text{Pr}(STC, L) = \theta_L + \delta_S + u_{L,i}.
\]

For the STCs, it will add one average to the already existing one:
\[
\frac{1}{2} (\text{Pr}(LTC, S) + \text{Pr}(STC, S)) = \theta_S + u_{S,i}
\]
\[
\frac{1}{2} (\text{Pr}(STU, S) + \text{Pr}(LTU, S)) = \theta_S + \delta_U + u_{S,i}
\]
\[
\text{Pr}(PTC, S) = \theta_S + \delta_P + u_{S,i}.
\]

Estimation now proceeds by first differencing separately inside each block, because the heterogeneity terms \( u_{L,i} \) and \( u_{S,i} \) are different in the two blocks, and then applying ALS to the differences. The result is reported in Column (3). We find \( \delta_U = 0 \). The two blocks are strongly modified by this result. For the long-term block, we have \( \text{Pr}(LTC, L) = \text{Pr}(STU, L) = \text{Pr}(LTU, L) \) and for the short-term block, we have \( \text{Pr}(LTC, S) = \text{Pr}(STU, S) = \text{Pr}(LTU, S) = \text{Pr}(STC, S) \). Averaging the relevant probabilities, we get the following identification constraints for the long-term block:
\[
\frac{1}{3} (\text{Pr}(LTC, L) + \text{Pr}(STU, L) + \text{Pr}(LTU, L)) = \theta_L + u_{L,i}
\]
\[
\text{Pr}(PTC, L) = \theta_L + \delta_P + u_{L,i}
\]
\[
\text{Pr}(STC, L) = \theta_L + \delta_S + u_{L,i}
\]

and the following constraints for the short-term block:
\[
\frac{1}{4} (\text{Pr}(LTC, S) + \text{Pr}(STU, S) + \text{Pr}(LTU, S) + \text{Pr}(STC, S)) = \theta_S + u_{S,i}
\]
\[
\text{Pr}(PTC, S) = \theta_S + \delta_P + u_{S,i}.
\]

Estimation proceeds by two separate block differencing followed by ALS, reported in Column (4). All the remaining coefficients are significant at the 5 per cent level. We comment on the outcome of this backward elimination process.
First, the tightness on sales assistant jobs is the same for STCs and LTCs ($\theta_L = \theta_S$). The two corresponding statistics are independent since LTCs and STCs come from different posts, and we can perform the standard t-test of equality between the two tightness coefficients (20.1 and 22.4 per cent). We cannot reject equality at the 5 per cent level.

We now comment on the discrimination coefficients. The standard (LTC) candidate has a success rate around 20 per cent. It receives, on average, one positive answer for five applications. We find that two types of candidates suffer from statistical discrimination. The part-time contract candidate has much less chances to be recruited ($-7.3$ points). This may reflect the belief of the employers about the reason why these male candidates have a part-time job. Considering the reasons given by Pak (2013), we may explain this results by the motivations of part-time jobs for men: having another job or being in training, the will to have free time, health problems and the need to help family members. These activities could send bad productivity or involvement signals and motivate a rejection since other candidates are available. More precisely, if health is the cause of the previous part-time job, one cannot exclude a probability of failure. Baert et al. (2016) provided evidence of discrimination against men with one year of depression. More generally, statistical discrimination would cause the rejection of the candidate. Finally, helping family members can imply to be less available for a full-time job. The recruiter may anticipate a potentially lower involvement in the job and prefer another candidate.

The second significant effect affects workers with a previous history of STCs. Since the contracts in this profession are mostly LTCs, 76 per cent of the posts, this history could indicate either a bad potential productivity or a will to get the 10 per cent precariousness bonus. Here, the result may be explained by the age of the candidate, around 30, and by firms’ common practice of using the STCs as trial periods. At this age, the hypothesis of a failure to find a stable job may be favoured by the recruiters. The recruiters may expect that the workers with a long history of STCs have failed to convince their previous employers to recruit them on a LTC. We could not use this argument for younger workers because STCs are common at the beginning of the career, but here the candidates have been in the labour market over the last 12 years and the failure hypothesis may be favoured by the a significant part of the recruiters. Overall, we find that it results in a penalty of $-4.2$ points ($\delta_S$).

We now turn to the accountant profession. The backward elimination process has also been used and is reported in Columns (5)–(7). We first find $\delta_R = 0$ (Column (5)) so that the workers previously on LTCs can be regrouped with the ones working on STCs. We get the following simplification for the long-term block:

$$\frac{1}{2}(\Pr(\text{LTC}, L) + \Pr(\text{STC}, L)) = \theta_L + u_{L,i}$$

$$\Pr(\text{STU}, L) = \theta_L + \delta_U + u_{L,i}$$
$$\Pr(\text{LTU}, L) = \theta_L + \delta_U + \delta_L + u_{L,i}$$
$$\Pr(\text{PTC}, L) = \theta_L + \delta_P + u_{L,i},$$

and for the short-term block, we find the additional constraint $\delta_R = 0$ (Column (6)) and get:

$$\frac{1}{2}(\Pr(\text{LTC}, S) + \Pr(\text{STC}, S)) = \theta_S + u_{S,i}$$

$$\Pr(\text{STU}, S) = \theta_S + \delta_U + u_{S,i}$$
$$\Pr(\text{LTU}, S) = \theta_S + \delta_U + \delta_L + u_{S,i}$$
$$\Pr(\text{PTC}, S) = \theta_S + \delta_P + u_{S,i},$$

and the final estimation is reported in column (7).
The success for the reference candidate (LTC, L) is higher for LTCs, but not significantly at the 5 per cent level. The main differences between the candidates come from the unemployment status and the term of the labour contract.

The workers with less than one year of unemployment are the most favoured candidate. They get an advantage of 7.2 points compared to the benchmark candidate. The reason may simply be that, on the one hand, they are immediately available and, on the other hand, their career interruption is too short to generate adverse beliefs about their productivity. We get a different result for the workers who have been unemployed for more than two years. They lose all the availability advantage of the STU. Compared to them, their hiring probability diminishes by 8 points. However, they do not lose all their capacity to get a hiring interview because these two effects offset each other. The total effect is close to zero and this means that the LTU have the same success probability than the workers with a LTC. But this very result shows an interesting point: the firms give the same chances to the LTC and the LTU, while the former workers will not be immediately available and the latter workers are immediately available[4]. This may reflect a better opinion about the on-the-job candidates.

Finally, we also find a negative effect for part-time workers, at 4.5 points. This result is similar to the one obtained on sales assistants jobs, and should also explain it by the anticipation of the employers about the future health and involvement of the candidate.

6. Conclusion
Labour market history has an impact on the current probability to be invited to a hiring interview. Workers with a profile of PTC have a significantly lower probability to be invited in both accountant and sales assistant jobs. This effect can be reasonably attributed to signalling. The workers who have chosen this type of job could be reputed to be less able or less willing to get involved in a full-time job. It could be related to health, like in Baert et al. (2016). For the sales assistant jobs, we find that the success probability is also smaller with a history of STCs. We also interpret it as a signalling effect. This result is in line with previous research (Biewen and Steffes, 2010) which accounts for a stigma effect of part-time work.

The results are different for accountants. Here, the probability of success decreases with the time spent in unemployment. While STU are favoured, due to their immediate availability in a tight labour market, the LTU lose this advantage. In this case, an anticipated depreciation of human capital could have motivated the recruiters.

Finally, the methodology is well suited when combinations of discriminations are at work. We plan to use it in order to disentangle three discrimination types against women: taste discrimination, statistical discrimination on labour quality and statistical discrimination on pregnancy.

Notes
1. CAN stands for consistent and asymptotically normal.
2. FGLS stands for feasible generalised least squares.
3. It was originally developed by Gouriéroux et al. (1985) and Chamberlain (1982, 1984).
4. A worker can leave after a compulsory legal notice of one to three months.

References


Further reading


### Appendix

#### Labour market history

<table>
<thead>
<tr>
<th>Path</th>
<th>Shortcut</th>
<th>Sales assistant Callback rate</th>
<th>SE</th>
<th>Accountant Callback rate</th>
<th>SE</th>
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<td><strong>Long-term contract offers</strong></td>
<td></td>
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<td>Long-term contract</td>
<td>(LTC, L)</td>
<td>0.190</td>
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<td>0.218</td>
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<td>0.027</td>
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<td>Long-term unemployed</td>
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<td>0.025</td>
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<td>Part-time contract</td>
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<td>0.181</td>
<td>0.025</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Long-term contract</td>
<td>(LTC, S)</td>
<td>0.228</td>
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<td>0.246</td>
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<td>0.105</td>
<td>0.041</td>
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</table>

Table AI: Raw callback rates

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