WORKING PAPER

N° 2022-15

EXTRACTING THE DISCRIMINATION COMPONENTS FROM THE CALLBACK RATES

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www.tepp.eu

TEPP – Theory and Evaluation of Public Policies - FR CNRS 2042

Extracting the discrimination components from the callback rates*

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July 2022

Abstract

In order to measure hiring discrimination, researchers perform correspondence tests. Several fake job candidates ("testers") are sent on the same job offer, and the comparison of their callback rates measures discrimination. This method reaches some limits when several discrimination mechanisms are at work. We propose a methodology applicable to all correspondence tests, which allows for clarifying identification issues and perform an optimal estimation. We apply this method to gender discrimination in construction jobs: masonry, plumbing and electricity. We find that each job exhibits a different discrimination type.

JEL: C51, C93, J16, J24, J71 .

Keywords: Hiring discrimination, Field experiments, Gender, Identification, Asymptotic Least Squares, France .

*We thank Souleymane Mbaye for research assistance and Sébatien Roux for helpful comments. We also thank the participants to the 6th TEPP Winter School (Aussois, 2016) and the 13th TEPP Conference on Policy Evaluation (La Réunion, 2016). Corresponding author: Emmanuel Duguet, Université Paris Est, Mail des Mèches, 61 avenue du Général de Gaulle, 94010 Créteil Cedex, France. emmanuel.duguet@u-pec.fr

Introduction

Over the last decades, women have increased their qualification level and their activity rates (OECD [2012]). However, the strong inequalities between women and men in the labour market remain a major societal challenge (Bertrand [2011]). Inequality persists in terms of working time, working conditions, occupation and sector. This leads to income inequality.

Women employment suffers both from a vertical segregation, the glass ceiling, and from a horizontal segregation, gendered occupations (Baert et al. [2016]). Therefore, despite of the development of new technologies, women and men continue to specialize in different occupations in the USA (Hegewisch et al. [2010]) and in Europe (Bettio et al. [2009]). For instance, according to OECD [2012], more than 70% of the workers in education, health and social services are women. This is of consequence in France, since the half of the gender hourly wage gap, estimated at 18.4%, can be explained by occupation differences (Chamkhi [2015]).

Notwithstanding some progress in occupation balancing, only 17% of occupations in the French labour market included at least 40% of women or men (Naves and Wisnia-Weill [2014]). These occupations represented 16% of French employment over 2009-2011. One of the sector were women are especially at a disadvantage is construction. In 2014, they represented 5% of this sector's total employment, even though the environment was favourable. Indeed, the French Construction Federation had announced its will to triple women employment, counting on a change in mentalities, strong needs of qualified personnel and less physically demanding working conditions. At the same time, communication campaigns by public authorities are accompanying this decision by the Construction Federation. The goal of these private and public actions is to correct the over-representation of men in the construction sector. It originates both from demand and supply factors.

On the supply side, the disequilibrium could come from the under-representation of women in the construction training fields. Since few women choose the construction training channels, few candidate and get the jobs. And girls indeed make different choices than boys. According to the French Ministry of Education (of Education [2019]), girls represented 1% of the pupils or apprentices in the building-construction-roofing trainings in 2010, and 9% in the building-construction-finishing trainings. The same year, the proportion of girls in office secretary training reached 92%, and 91% in health and social occupations. On the demand side, a low proportion of women could come from hiring discrimination (Heckman [1998]). Several discrimination mechanisms may be at work. First, taste discrimination from employers, the other workers or customers may reduce the access of women to some occupations (Becker [1957]). The second mechanism, statistical discrimination, is based on beliefs about the discriminated group (Arrow [1973], Phelps [1972], Spence [1973]). At the hiring stage, an employer may not observe the productivity of the candidate perfectly well and, for this reason, forms an anticipation from both objective and subjective elements. At the hiring stage, women may be discriminated because of an increased risk of career interruption (maternity leaves) and, in the construction sector, because of the beliefs of the employer regarding the productivity of women in this field. In this paper, we focus on labor demand. We examine whether there is a gender discrimination in three occupations of the construction sector. We have performed correspondence tests designed to address this issue (Firth [1982], Neumark et al. [1996], Riach and Rich [2002]).

We propose a methodology for extracting discrimination components from field experiments (Neumark [2018] for a survey). It relies on the construction of a model that includes the discrimination component in a consistent way for all the candidates and labour contract types. We relate the callback rates to a discrete choice model with unobserved heterogeneity. This step allows for establishing a relationship between the callback rates and the unknown discriminatory components. When the component can be retrieved from the callback rates the system is (over)identified and we proceed to the estimation step. We show that the discrimination components can be estimated by the Asymptotic Least Squares (ALS) method, which also provide an overidentification test. In the terminology of ALS, the callback rates are the auxiliary parameters and the discrimination coefficients are the parameters of interest. We illustrate the method with an application to construction jobs, and show how to apply the method when the restrictions involved by the estimates lead to change the estimation benchmark.

The first section presents the experiment which produces the main statistics. The second section is about the identification of the discrimination components. In the third section we present an original application to gender discrimination in construction jobs.

1 The experiment

We have collected data about the construction sector in the Paris area between February and July 2015. We have replied to all the full-time jobs posts for electricians, plumbers and masons. This includes both short term and long term contracts.

Candidates. Four candidates were sent in reply to each offer: a woman and a man with the standard qualification, and a man and a woman with an excellence qualification. Table 1 indicates the identity of the candidates. All the candidates have French sounding first and last names,[1] are either 23 or 24 years old, childless and own a driving licence and a car.[2] They had a vocational training certificate (CAP) in the same profession, in 2008 or 2009 (depending on their age). They have three professional experiences in small companies, did not experience any unemployment period and are searching on the job.[3]. They live inside the city of Paris, in districts ("arrondissements") with comparable socio-economic characteristics.[4] Overall, we have given to our candidates the characteristics which are the most favourable in the French labour market according to the previous applied discrimination literature, except for the three characteristics that we wish to test (gender, qualification, maternity). We did not use any photograph to avoid appearance biases (see Rich [2018]), used standard and impersonal hobbies (sport, cinema, reading, music) and have included some differencing elements in the CV layout. We have randomized the differencing elements among the candidates.

The CAP (Cerfificat d'Aptitude Professionnelle, literally "professional capacity certificate") is a vocational training certificate which grants a qualified worker/employee degree. It exists for around 200 professions. 188,386 CAP have been granted in France in 2015. We focus on three professions: electricity, plumbing and masonry. This basic diploma is often demanded by the construction firms in their posts. We indicate it as the standard qualification level in our statistical model.

In order to implement our methodology, we need to distinguish short and long contracts. After examining the distribution of the labor contracts duration, it appears that our method is applicable if we keep, on the one hand, the contracts of 6 months or less and, on the other

[1]A foreign origin can reduce the callback rates in the French labour market, see Duguet et al. [2015].
[2]Mobility can influence the callback rates, see Duguet et al. [2018a].
[3]Past unemployment period can interfere with the callback rates, see Duguet et al. [2018b].
[4]For evidence of address discrimination, see Duguet et al. [2019].

Table 1: Experiment candidates

Candidates	Plumbing	Masonry	Electricity
Woman, Standard	Aurélie DUVAL	Juliette LEROY	Anaïs DUBOIS
Woman, Excellence	Pauline LEMAIRE	Laura BONNET	Elodie FOURNIER
Man, Standard	Thomas ROUX	Alexandre PETIT	Julien GUERRIN
Man, Excellence	Jonathan MOREL	Jérémy MOREAU	Anthony DURAND

Standard: standard vocational training diploma (CAP, "Certificat d'Aptitude Professionnelle")
Excellence: "best French apprentice" (MAF) or "Worldskills competition" (OM) regional laureates

hand, the contracts of 12 months or more (including the permanent contracts).[5]

Excellence qualifications (MAF and OM). The MAF ("un des Meilleurs Apprentis de France", literally "one of the best French apprentices") is a prize created in 1986 by the MOF National Society (MOF, "un des Meilleurs Ouvriers de France" means literally "one of the best French craftsmen"), in 104 professions. Its goal is to "promote among apprentices ... the taste of well done work, asserting their personality, their passion, spirit of initiative, progress in their applied competencies, obtaining the fair reward of their effort and to testify with pride about the efficiency of their training to manual professions". Depending on their profession, the candidates must either make a craft work during 5 months or pass a trial. The best apprentices obtain a medal. The contest takes place in three steps: first, at the département level.[6] The best apprentices get a bronze, silver or gold medal. The silver and gold medal at this level can compete at the regional level.[7]. A the regional level, the best apprentices can get a gold or silver medal. Finally, the regional gold medals can compete at the national level, where gold medals only are awarded. In 2015, there were 5196 participants (in all professions). There were 3472 laureates at the departement level, 1517 at the regional level. 817 apprentices went in final, and 316 were rewarded. The national level of the competition would send too strong a signal and cause detection because the laureates are invited to a ceremony by the President of the Senate. We indicate a gold medal at the regional level, which represent 13% of the total number of candidates.

The OM ("Olympiade des Métiers" or "Worldskills Competition") is organized by the Regional Councils in partnership with the professional and training organisms in 50 professions. It is a three-stage contest. First, at the French regional level; second, at the national level where a team is made for each profession; third, the national teams are sent at the Worldskills Competition, organized every two years. In 2015, the competition took place in Sao-Paulo. There were 1000 finalists from 59 countries. About 6000 French apprentices have participated to this competition. In order to avoid detection, we cannot use the national level selection, because the team is received by the President of the French Republic. We indicate a selection at the regional level, which represent 800 candidates out of 6000. The selection rate is therefore 13.3%, close to the MAF selection level. Overall, our excellence qualifications indicate candidates if the first decile of the competitors. This achievement could be used for international comparisons because it exists in many countries.

[5]Therefore, we have excluded the contracts of 7 to 11 months from all the computations.
[6]Metropolitan France is divided into 95 département.
[7]Metropolitan France is divided into 22 regions

Experiment and protocol tests. Table 2 provides some sample statistics. We have data 133 posts for masonry, 141 for electricity and 288 for plumbing. This corresponds to the dispatch of 2248 CVs (4× 462 posts). The global callback rates are high, at least one of the four candidates gets a callback in 29.8% of the cases for electricity, 36.1% for plumbing and 24.8% for masonry.

Table 2: Sample Statistics

The table reports the p values for all the tests.

Profession	Electricians	Masons	Plumbers
Short term	72	70	108
Long term	69	63	180
Total	141	133	288
Observations	564	532	1152
Callback rate	0.298	0.248	0.361
Qualifications callback equality test			
Women	0.896	0.472	0.215
Men	0.278	0.907	0.149
Independence test:			
Sending order	0.571	0.986	0.982

We need to perform two tests in order to validate our experimental protocol. First, we check that the rotation of CVs was efficient, by performing a chi-squared test of independence between the sending order of the candidates and their callback status. Second, in order to avoid detection, we cannot send two MAF or two OM candidates. We send two CAP, one MAF and one OM candidates. This raises the issue of differentiated effects of MAF and OM candidates, and we need to test this hypothesis.

The tests are reported in Table 2. We never reject the independence assumption between the sending order and the callback status at the conventional levels (p-value between 0.571 and 0.986). In order to test the homogeneity of the excellence characteristics, we have performed the following test. We first compute the callback rate difference between the MAF candidates and the CAP candidate on the same posts; this difference eliminates (additive) unobserved heterogeneity. We get an estimate of the MAF advantage over the standard qualification. Then, we perform the same operation for the OM candidate and get an estimate of the callback rate advantage of the OM candidate over the standard candidates on the same posts. Finally, we test the equality of these two differences, separately for each gender and profession. This is a difference-in-differences test. The results are presented in Table 2: we never reject the homogeneity effect at conventional levels of significance (p-values between 0.149 and 0.907). For this reason, we will regroup the OM and MAF characteristics under the "excellence" appellation in the statistical model.

The raw callback rates are reported in Table 3. We will show below that they mix all the effects of the components model and, for this reason, are hard to interpret. Overall, men tend to be called more often than woman, so that some discrimination may be at work. In electricity, men enjoy an advantage on long term contracts, but not women. Something must restrain the hiring of women on long term contracts. For masonry, women are almost always ranked behind their male counterpart. For plumbing, men are not preferred to women for the strongest qualification, but this can happen for low qualifications. Something reduces the hiring of standard qualification women.

Table 3: Callback rates

Proportions.

Profession	Electrician	Mason	Plumber
Short term contracts:			
woman, standard	0.111	0.057	0.148
woman, excellence	0.139	0.100	0.231
man, standard	0.167	0.143	0.120
man, excellence	0.153	0.171	0.167
Long term contracts:			
woman, standard	0.116	0.111	0.161
woman, excellence	0.145	0.063	0.206
man, standard	0.246	0.079	0.222
man, excellence	0.261	0.159	0.200
Global	0.298	0.248	0.361

$*$: reference used in the components model.

2 Identification and Estimation

We wish to distinguish taste discrimination from statistical discrimination. There are two types of statistical discrimination against young women: first, the employer may question their professional skill; second, the candidate could be pregnant in a near future. Our methodology allows for estimating these two types of statistical discrimination separately.

The identification of these discrimination components relies on the differences between them.[8] Taste discrimination, like sexism, should apply to all women. It is not the case of the two other discrimination types. Statistical discrimination on skills may only apply to the women with the standard skills, not to the women with excellence qualifications. Here, we use an excellence marker, which indicate workers at the top of their profession. Therefore we can assume that statistical discrimination on skills apply to the standard qualification level only. There remains to isolate statistical discrimination on pregnancy. Here, it should apply to all the women, like taste discrimination, but there is one way to isolate its effects. We use information about the length of the labour contract. If the contract is very short, the probability that a maternity could affect the firm is negligible, since the firm has anticipated the end of the contract. We consider contracts whose duration is lower than 6 months, and compare them to contracts of 12 months and more. Therefore we do not suppress the maternity characteristic from the candidates, since it is impossible, but its consequences for the firm. Notice that this method can be easily applied to all correspondence tests: adding an extra qualification to some candidates is straightforward, and the term of labour contracts is indicated in almost all job offers. In order to clarify the important identification issue, we use a component model. We also use this model in order to discuss the issues of unobserved heterogeneity and optimal estimation.

[8] For an alternative approach, see Neumark [2012].

2.1 Identification

We model the probability of a callback.[9] For any candidate j on job ad i we let v_{ij}^* be the recruiter's gain associated with a callback:

$$v_{ij}^* = m_{ij} + \alpha_i + \varepsilon_{ij}$$

where m_{ij} is the model for candidate j on job i. It form depends on each experiment and includes the discriminatory components we wish to estimate. The α_i term is the job ad correlated effect (or "fixed effect") , since the same recruiter replies to all the candidates and ε_{ij} is the idiosyncratic error term, typically a white noise. We observe the callback dummy :

$$v_{ij} = \begin{cases} 1 & \text{if } v_{ij}^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

It equals 1 when recruiter calls the candidate back, and zero otherwise. We wish to estimate the model from a sample of dummy variables and the characteristics of the candidate, chosen by the researcher who runs the experiment. First, we need to eliminate the unobserved heterogeneity term α_i. Let F_ε be the c.d.f. of ε, we get the theoretical callback probability:

$$P_{ij} = \Pr(v_{ij} = 1) = \Pr(v_{ij}^* > 0) = 1 - F_\varepsilon\left(-(m_{ij} + \alpha_i)\right).$$

These probabilities have empirical counterparts and, with an assumption on on F_ε, we can estimate the model. Notice that the fit of several distributions can be compared with our method. In order to eliminate the α_i terms, we need to compare the answers to two candidates on the same job ad. Let $j = 1$ be a freely chosen reference candidate, with no loss of generality, we eliminate α_i with the following differencing:

$$D_{ij} = F_\varepsilon^{-1}(1 - P_{i1}) - F_\varepsilon^{-1}(1 - P_{ij}) = m_{ij} - m_{i1}.$$

By definition of the callback probabilities, the difference $m_{ij} - m_{i1}$ term contains the discrimination terms that we wish to estimate. Simplification occurs when ε is assumed to have a symmetric distribution. In this case we get:[10]

$$P_{ij} = F_\varepsilon\left(m_{ij} + \alpha_i\right)$$

and we can take the difference:

$$\Delta_{ij} = F_\varepsilon^{-1}(P_{ij}) - F_\varepsilon^{-1}(P_{i1}) = m_{ij} - m_{i1}.$$

Two well-known cases are worth commenting. First, the default case of correspondence studies is the linear probability model, which leads to a direct comparison of the callback probabilities. Assuming a uniform distribution, $F_\varepsilon(\varepsilon) = \varepsilon$, we get:

$$\Delta_{ij} = P_{ij} - P_{i1}.$$

and the coefficients can be interpreted as percentage points. Another case encountered is the logit model. It has the advantage to constrain the estimated probabilities in the $[0,1]$ interval.

[9] This is the first paper where we have developed this method. The linear variant of this method has been used later in Duguet et al. [2019] and Duguet et al. [2018b].

[10] The method can be applied without this assumption.

Assuming a logistic distribution, $F_\varepsilon(\varepsilon) = 1/(1+\exp(-\varepsilon))$, we must take the difference of the log odds ratios of the two candidates:

$$\Delta_{ij} = \ln \frac{P_{ij}}{1-P_{ij}} - \ln \frac{P_{i1}}{1-P_{i1}}.$$

and the coefficients are to be interpreted as log-odds ratios. Finally, with the normit/probit model, we get :

$$\Delta_{ij} = \Phi^{-1}(P_{ij}) - \Phi^{-1}(P_{i1})$$

where Φ is the cdf of the standard normal distribution, and the coefficients are more difficult to interpret as in the two previous cases.

Now that the unobserved heterogeneity term has been eliminated, we discuss the identification of the discriminatory components. In our applications, we have four candidates that we send to both short term (less than 6 months) and long term contracts (12 months and more). We denote the four candidate by a number and the contract type by a letter (s for short term, ℓ for long term. Gender is denoted by w and m (woman, man) and the qualification by r and e (required, excellence). The definition of the candidate is given in the following table:

Table 4: Candidates and modelling

Contract type	Gender	Qualification	index
short term	male	standard	$s1$
short term	male	excellence	$s2$
short term	female	standard	$s3$
short term	female	excellence	$s4$
long term	male	standard	$\ell 1$
long term	male	excellence	$\ell 2$
long term	female	standard	$\ell 3$
long term	female	excellence	$\ell 4$

The models for the short term contracts are described by the following equations. In a linear probability model, it would be the theoretical representation of the probabilities, in a logit model, the representation of the log odds ratios. The model depends on i through the contract term only. For short term contracts, we set:

$$\begin{aligned} m_{s1} &= \theta_s \\ m_{s2} &= \theta_s + \theta_e \\ m_{s3} &= \theta_s + \delta_T + \delta_Q \\ m_{s4} &= \theta_s + \theta_e + \delta_T \end{aligned}$$

The two first candidates are men. The first term $m_{s1} = \theta_s$ represents the job opportunities in the labour market for short term jobs, labour market tightness, since it represents the average probability of success for a man with the standard qualification. By definition, this candidate should not suffer from discrimination and provides a natural benchmark for the comparisons to follow. The second probability concerns the male candidate with an excellence certificate. We set $m_{s2} = \theta_s + \theta_e$ where θ_e is the effect of excellence on the chances to be called back. We expect $\theta_e \geq 0$. The third and fourth candidates are women. We start from the benchmark model

θ_s and we add a first discriminatory component associated to gender, denoted δ_T. Here we prefer a taste discrimination interpretation for the following reason. Firstly, it affects all female candidates, with or without an excellence certificate. Secondly, the short term contracts are often used as trial periods in the French labour market. Therefore, a rejection of female candidates on these contracts should reflect the will to avoid all contact with the candidates. In a statistical discrimination framework, the situation should be different, since the rejection of the candidates relies on imperfect information. Under imperfect information, a trial period is a way to solve the asymmetry of information and the female candidates should not be systematically rejected on short term contracts. We expect a negative value for δ_T. Finally, we introduce a component susceptible to measure statistical discrimination, denoted δ_Q. The recruiters with preconceptions should think that the women with a standard qualification are less competent than the men with the same qualification. But this effect should be restricted to a part of the women only, contrary to the taste discrimination component, since an excellence certificate makes the preconception doubtful. This distinction plays an important role for identification. Taking the differences from the benchmark candidate $s1$, we get :

$$\Delta_{s2} = m_{s2} - m_{s1} = \theta_e$$
$$\Delta_{s3} = m_{s3} - m_{s1} = \delta_T + \delta_Q$$
$$\Delta_{s4} = m_{s4} - m_{s1} = \theta_e + \delta_T$$

It is readily seen that the parameters $(\theta_e, \delta_T, \delta_Q)$ can be retrieved by $(\Delta_{s2}, \Delta_{s4} - \Delta_{s2}, \Delta_{s3} - \Delta_{s4} + \Delta_{s2})$. However, these components also appear in the long term contracts, so that, globally, they will be overidentified. For this reason, we do not estimate them directly and we adapt our estimation method. For the long term labour contracts, three modifications must be made to the model. First, the labour market tightness may be different. Second, we must account for statistical discrimination related to the maternity leaves (denoted δ_M). Notice that these contracts are from different job ads than the short term contracts, so that the differencing is performed separately for the two types of contracts. We get:

$$m_{\ell 1} = \theta_\ell$$
$$m_{\ell 2} = \theta_\ell + \theta_e$$
$$m_{\ell 3} = \theta_\ell + \delta_T + \delta_Q + \delta_M$$
$$m_{\ell 4} = \theta_\ell + \theta_e + \delta_T + \delta_M$$

The callback probability of the benchmark candidate (male with standard qualification) measures the labour market tightness θ_ℓ and the excellence candidates gets an advantage θ_e. For women, there can be both taste discrimination (δ_T), statistical discrimination on the competencies (δ_Q) and statistical discrimination on maternity (δ_M). The differencing from the benchmark candidate gives :

$$\Delta_{\ell 2} = m_{\ell 2} - m_{\ell 1} = \theta_e$$
$$\Delta_{\ell 3} = m_{\ell 3} - m_{\ell 1} = \delta_T + \delta_Q + \delta_M$$
$$\Delta_{\ell 4} = m_{\ell 4} - m_{\ell 1} = \theta_e + \delta_T + \delta_M$$

Women with the standard qualifications ($\ell 3$) can be discriminated both because they are woman (δ_T), because the recruiter doubts their qualification (δ_Q) or because the recruiter anticipates a career interruption caused by maternity (δ_M). Women with an excellence qualification can be discriminated only because they are woman (δ_T) or because the recruiter anticipates a maternity (denoted δ_M). We now show how to estimate the structural parameters ($\theta_e, \delta_T, \delta_Q, \delta_M$) in an optimal way.

2.2 Estimation

The callback probabilities have empirical counterparts, so that we can estimate the Δ terms. These estimators are CAN (Consistent and Asymptotically Normal). In addition, there exists a theoretical relationship between the callback probabilities and the structural parameters of the model. Therefore we can use the empirical probabilities to estimate the structural parameters. The optimal estimation of the structural parameters is given by the Asymptotic Least Squares method, which was originally developed in Chamberlain [1982], Chamberlain [1984] and Gouriéroux et al. [1985]. In this literature, the transformation of the callback probabilities (Δ_{ij}) are called the auxiliary parameters and the structural parameters are called the parameters of interest. The identification constraints can be rewritten:

$$\underbrace{\begin{pmatrix} \Delta_{s2} \\ \Delta_{s3} \\ \Delta_{s4} \\ \Delta_{\ell 2} \\ \Delta_{\ell 3} \\ \Delta_{\ell 4} \end{pmatrix}}_{\pi} = \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 \end{pmatrix}}_{A} \underbrace{\begin{pmatrix} \theta_e \\ \delta_T \\ \delta_Q \\ \delta_M \end{pmatrix}}_{\beta}$$

or

$$\pi = A\beta$$

The auxiliary parameter π is easily estimated from the data, β is the interest parameter, and is not directly observable. In order to estimate β, we need to replace π with an estimate $\hat{\pi}$. Let:

$$\hat{\pi} = \pi + \omega$$

where ω is the estimation error on the auxiliary parameter. Substituting into the identification constraints, we get an equation that can be used for estimation:

$$\hat{\pi} = A\beta + \omega$$

where $\hat{\pi}$ and A are observable, so that a minimum distance estimation is feasible. Let $\Omega = \mathrm{V}(\omega)$, its diagonal elements are the variances of the auxiliary parameters estimators, and the off diagonal term, the covariance between the estimators. They are correlated because the answers to all the candidates come from the same recruiter. The optimal estimator of β is the Feasible Generalized Least Squares (FGLS) estimator:

$$\hat{\beta} = (A'\hat{\Omega}^{-1}A)^{-1}A'\hat{\Omega}^{-1}\hat{\pi}$$

It is asymptotically normal and its asymptotic covariance matrix can be estimated by the following statistic:

$$\mathrm{V}(\hat{\beta}) = (A'\hat{\Omega}^{-1}A)^{-1}$$

where $\hat{\Omega}$ is a consistent estimate of Ω. The overidentification statistic, denoted S, is simply an estimate of the norm on the identification constraints, we get:

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

with $\hat{\omega} = \hat{\pi} - A\hat{\beta}$. Under the null hypothesis ($\mathrm{H}_0 : \pi = A\beta$), it is $\chi^2(2)$ distributed. More generally, for an overidentified system, the degrees of freedom equal the difference between the number of auxilliary parameters and the number of structural parameters. This statistic or its p-value can be used as a choice rule for F_ε. Indeed, π depend on the callback probabilities and on the specific functional form F_ε. Taking the distribution with the highest p-value is therefore equivalent to take the distribution which fits the best the identification constraints. Table 5 presents the statistics of our application. The uniform distribution is the only one that passes all the tests at the 5% level. The logistic distribution is close to the uniform, but the normal distribution performs poorly for electricians and plumbers. Notice that the uniform case is the most common encountered in the literature since it is equivalent to compare callback rates directly.

Table 5: Overidentification statistics

Distribution	Electrician	Mason	Plumber
Uniform	0.26	5.37	3.63
p-value	0.876	0.068	0.163
Logistic	0.29	6.11	3.70
p-value	0.864	0.047	0.157
Normal	0.52	35.9	8.86
p-value	0.770	0.000	0.012

3 Application

Electricians. We illustrate the practice of the method with electrician jobs. We have selected this occupation because it provides a good overview of all the estimation issues that one can encounter. We will use a uniform distribution, so that our comments will be based on the callback rate differences. An important point is that we need to proceed by backward elimination. Indeed, when a coefficient is not significant, it can involve that the theoretical callback rates of several candidates are equal. In this case, it is possible to improve on the efficiency of the estimation method by regrouping the candidates before to compute their callback rate. In other words, a constraint on a parameter can involve a larger number of observations available to estimate a given parameter. We will show how to aggregate the callback rates in this case. The starting model is:

$$\begin{aligned}
m_{s1} &= \theta_s \\
m_{s2} &= \theta_s + \theta_e \\
m_{s3} &= \theta_s + \delta_T + \delta_Q \\
m_{s4} &= \theta_s + \theta_e + \delta_T \\
m_{\ell 1} &= \theta_\ell \\
m_{\ell 2} &= \theta_\ell + \theta_e \\
m_{\ell 3} &= \theta_\ell + \delta_T + \delta_Q + \delta_M \\
m_{\ell 4} &= \theta_\ell + \theta_e + \delta_T + \delta_M
\end{aligned} \tag{1}$$

The estimation results are presented in Table 6. Column (1) reports that the lowest Student statistics (0.19) is associated with $\hat{\theta}_e$. Therefore, we set $\theta_e = 0$ in the system (1) and the components model becomes:

$$\begin{aligned}
m_{s1} &= \theta_s \\
m_{s2} &= \theta_s \\
m_{s3} &= \theta_s + \delta_T + \delta_Q \\
m_{s4} &= \theta_s + \delta_T \\
m_{\ell 1} &= \theta_\ell \\
m_{\ell 2} &= \theta_\ell \\
m_{\ell 3} &= \theta_\ell + \delta_T + \delta_Q + \delta_M \\
m_{\ell 4} &= \theta_\ell + \delta_T + \delta_M
\end{aligned} \tag{2}$$

Table 6: Electricians, ALS estimates

Estimation by the Asymptotic Least Squares method. Asymptotic Student statistics between parentheses († significant at 10%, $*$ significant at 5%)

Components	(1)	(2)	(3)	(4)
θ_e	-0.005			
	(0.19)			
δ_T	-0.017	-0.021		
	(0.49)	(0.62)		
δ_Q	-0.036	-0.028	-0.036	
	(1.07)	(1.04)	(1.36)	
δ_M	-0.088	-0.088	-0.104*	-0.128*
	(1.52)	(1.52)	(2.03)	(2.67)
S	0.27	0.00	0.06	0.59
degrees of freedom	2	1	1	1
p-value	0.88	0.98	0.81	0.44

Under $\theta_e = 0$, we see that the male candidates should be regrouped both on short term ($s1$ and $s2$) and long term contracts ($\ell 1$ and $\ell 2$). This grouping should be done with equal weight because we have send the same candidates on all the job ads, so that their number of observations are equal.[11] We get:

$$\begin{aligned}
\frac{1}{2}(m_{s1}+m_{s2}) &= \theta_s \\
m_{s3} &= \theta_s + \delta_T + \delta_Q \\
m_{s4} &= \theta_s + \delta_T \\
\frac{1}{2}(m_{\ell 1}+m_{\ell 2}) &= \theta_\ell \\
m_{\ell 3} &= \theta_\ell + \delta_T + \delta_Q + \delta_M \\
m_{\ell 4} &= \theta_\ell + \delta_T + \delta_M
\end{aligned}$$

and the difference model becomes:

$$\begin{aligned}
\Delta_{s3} &= m_{s3} - \frac{1}{2}(m_{s1}+m_{s2}) = \delta_T + \delta_Q \\
\Delta_{s4} &= m_{s4} - \frac{1}{2}(m_{s1}+m_{s2}) = \delta_T \\
\Delta_{\ell 3} &= m_{\ell 3} - \frac{1}{2}(m_{\ell 1}+m_{\ell 2}) = \delta_T + \delta_Q + \delta_M \\
\Delta_{\ell 4} &= m_{\ell 4} - \frac{1}{2}(m_{\ell 1}+m_{\ell 2}) = \delta_T + \delta_M
\end{aligned}$$

The estimates of this new model show that $\hat{\delta}_T$ has a Student t equal to 0.65, so that we can set $\delta_T = 0$ in the model (2), regroup and compute the difference from the new benchmark. More precisely, the model reduces to:

$$\begin{aligned}
m_{s1} &= \theta_s \\
m_{s2} &= \theta_s \\
m_{s3} &= \theta_s + \delta_Q \\
m_{s4} &= \theta_s \\
m_{\ell 1} &= \theta_\ell \\
m_{\ell 2} &= \theta_\ell \\
m_{\ell 3} &= \theta_\ell + \delta_Q + \delta_M \\
m_{\ell 4} &= \theta_\ell + \delta_M
\end{aligned} \tag{3}$$

so that we regroup ($s1$,$s2$,$s4$) for the short term contracts and ($\ell 1$,$\ell 2$) for the long term contracts. Wet get the differences:

$$\begin{aligned}
\Delta_{s3} &= m_{s3} - \frac{1}{3}(m_{s1}+m_{s2}+m_{s4}) = \delta_Q \\
\Delta_{\ell 3} &= m_{\ell 3} - \frac{1}{2}(m_{\ell 1}+m_{\ell 2}) = \delta_Q + \delta_M \\
\Delta_{\ell 4} &= m_{\ell 4} - \frac{1}{2}(m_{\ell 1}+m_{\ell 2}) = \delta_M
\end{aligned}$$

We find that δ_Q, is not significantly different from 0 (Asymptotic Student t: 1.36). Imposing the constraint $\delta_Q = 0$ implies that there is no significant discrimination among the short term contracts. Therefore, we will rely on the long term contracts only, for estimating δ_M. The estimating

[11] This point has to be adapted to each application. The weight of each callback rate is equal to the number of observations of the candidate divided by the number of observations of all the candidates that have been regrouped.

equations reduce to :

$$\Delta_{\ell 3} = m_{\ell 3} - \frac{1}{2}(m_{\ell 1} + m_{\ell 2}) = \delta_M$$
$$\Delta_{\ell 4} = m_{\ell 4} - \frac{1}{2}(m_{\ell 1} + m_{\ell 2}) = \delta_M$$

and we get an estimated effect of maternity at -12.8 percentage points with an asymptotic Student t of 2.67. Electricity is characterized by a statistical discrimination attributable to maternity leaves.

Masons. The application is similar to the electricians. Backward eliminations leads to tastes discrimination against women (table 7). Being a woman reduces the callback rate by 5.8 percentage points.

Plumbers. The application to plumbers is different since an effect vanishes through backward elimination (δ_T). This comes from the fact that, when we eliminate parameters, the benchmark group is redefined so that some probability differences may be smaller with the new benchmark group. The backward elimination method clearly favors the δ_Q component, which measures statistical discrimination on the competencies of women.

Table 7: Masons, ALS estimates

Estimation by the Asymptotic Least Squares method. Asymptotic Student statistics between parentheses († significant at 10%, ∗ significant at 5%)

Components	(1)	(2)	(3)	(4)
θ_e	0.055	0.021		
	(1.58)	(1.08)		
δ_T	-0.107*	-0.080*	-0.081*	-0.058*
	(2.91)	(2.78)	(2.77)	(2.69)
δ_Q	0.044			
	(1.17)			
δ_M	0.059	0.058	0.051	
	(1.37)	(1.35)	(1.16)	
S	5.37	6.75	4.31	5.66
degrees of freedom	2	3	2	3
p-value	0.068	0.080	0.116	0.130

Table 8: Plumbers, ALS estimates

Estimation by the Asymptotic Least Squares method. Asymptotic Student statistics between parentheses († significant at 10%, $*$ significant at 5%)

Components	(1)	(2)	(3)	(4)
θ_e	0.007			
	(0.35)			
δ_T	$0.068^{\dagger}$	0.071^{*}	0.033	
	(1.86)	(2.06)	(1.33)	
δ_Q	$-0.053^{\dagger}$	-0.059^{*}	-0.059^{*}	-0.038^{*}
	(1.81)	(3.15)	(3.14)	(2.20)
δ_M	-0.063	-0.067		
	(1.48)	(1.57)		
S	3.63	1.01	3.48	0.44
degrees of freedom	2	1	2	1
p-value	0.163	0.315	0.175	0.509

Conclusion

We proposed an estimation methods that allows both to clarify the discrimination components and allow for their optimal estimation. This methods is flexible and allows for analyzing complex forms of discrimination. It could also readily be extended to more complicated empirical cases, where all the candidates are not sent to all the job offers.

We find evidence of hiring discrimination against women in the construction sector. However, the discrimination types really are different from one profession to another, as well as their magnitude.

The Beckerian explanation seems to hold in masonry, where taste-based discrimination is at work. In this context all women should suffer from discrimination. Persuasive advertising campaigns could help in changing the attitudes in this field, as well as legal sanctions. The situation is different in the two other jobs that we have tested.

The occupation of plumber is characterized by a statistical discrimination on qualification. Here, the employer may doubt the competences of the female candidates. Informative advertising campaigns should give the employers the right information and contribute to reduce the discriminatory hiring gap. Increasing the internship length during the training of the apprentices may also contribute to reduce information asymmetry.

Eventually, we find that electrician jobs exhibits another type of discrimination. The anticipation of a maternity by the employer may hinder the chances of young women to get a job. Since the full cost of the maternity leave is incurred by the Sécurité Sociale, the issue may be about the birth-related career interruptions of women. This issue is difficult to tackle. One solution would be to increase the parental leave by men, so as to bring nearer the career interruptions of women and men.

A last result is about the magnitude of the discrimination coefficients. We find that the stronger effect is about maternity, far above the taste based discrimination. This suggests that the most obvious forms of discrimination may not be the most harmful.

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A Use of the callback probabilities

The data can be summarized by the estimated callback probabilities vector and their covariance matrix. Let $\hat{\mathbf{p}} = \{\hat{p}_j\}$ be the $J \times 1$ vector of the estimated callback probabilities and $\hat{\Omega}_{\mathbf{p}}$ their estimated covariance matrix. J denotes both the number of candidates and their index set.

Uniform case. If the distribution of ε is assumed uniform, we first need to take the difference from the benchmark probability $\hat{p}_1$. This is done by $\hat{\pi} = D\hat{\mathbf{p}}$ and $\hat{\Omega} = D\hat{\Omega}_{\mathbf{p}}D'$ where D is the following differencing matrix:

$$\underset{(J-1,J)}{D} = \begin{pmatrix} -1 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{pmatrix}$$

When there are two groups of ads, for short term and long term contracts, the observations are independent between these two groups. We take :

$$\hat{\pi} = \begin{pmatrix} D\hat{\mathbf{p}}_s \\ D\hat{\mathbf{p}}_\ell \end{pmatrix}$$

where $\hat{\mathbf{p}}_s$ and $\hat{\mathbf{p}}_\ell$ are the estimated callback probability vectors on short and long term contracts respectively. For the covariance matrix, we use :

$$\hat{\Omega} = \begin{pmatrix} D\hat{\Omega}_s D' & 0 \\ 0 & D\hat{\Omega}_\ell D' \end{pmatrix}$$

where $\hat{\Omega}_s$ and $\hat{\Omega}_\ell$ are the estimated covariance matrices of the empirical callback probabilities on short and long term contracts respectively.

Logistic case. In all the other cases, we need to apply the delta method. Consider one type of labour contract. The transformation of the callback probabilities is given by the differences of log odds ratios :

$$\underset{(J-1,1)}{\hat{\pi}} = \left\{ \ln\left(\frac{\hat{p}_j}{1-\hat{p}_j}\right) - \ln\left(\frac{\hat{p}_1}{1-\hat{p}_1}\right) \right\}_{j=2,\ldots,J}$$

and the covariance matrix will be estimated by $\hat{\Omega} = D(\hat{\mathbf{p}})\hat{\Omega}_{\mathbf{p}} D'(\hat{\mathbf{p}})$ with:

$$\underset{(J-1,J)}{D(\hat{\mathbf{p}})} = \frac{\partial \pi}{\partial \mathbf{p}'}(\hat{\mathbf{p}}) = \begin{pmatrix} -\frac{1}{\hat{p}_1(1-\hat{p}_1)} & \frac{1}{\hat{p}_2(1-\hat{p}_2)} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ -\frac{1}{\hat{p}_1(1-\hat{p}_1)} & 0 & 0 & \cdots & 0 & \frac{1}{\hat{p}_J(1-\hat{p}_J)} \end{pmatrix}$$

For two types of labour contracts, the estimators should be stacked as in the uniform case.

Normal case. We have:

$$\underset{(J-1,1)}{\hat{\pi}} = \left\{ \Phi^{-1}(\hat{p}_j) - \Phi^{-1}(\hat{p}_1) \right\}_{j=2,\ldots,J}$$

where Φ is the cdf of the standard normal distribution. The covariance matrix will be estimated by $\hat{\Omega} = D(\hat{\mathbf{p}})\hat{\Omega}_{\mathbf{p}} D'(\hat{\mathbf{p}})$ with:

$$\underset{(J-1,J)}{D(\hat{\mathbf{p}})} = \frac{\partial \pi}{\partial \mathbf{p}'}(\hat{\mathbf{p}}) = \begin{pmatrix} -\frac{1}{\varphi(\hat{p}_1)} & \frac{1}{\varphi(\hat{p}_2)} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ -\frac{1}{\varphi(\hat{p}_1)} & 0 & 0 & \cdots & 0 & \frac{1}{\varphi(\hat{p}_J)} \end{pmatrix}$$

where φ is the pdf of the standard normal distribution.

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