Why are the older workers discriminated?

Laetitia Challe* Emmanuel Duguet†
François Langot‡ Yannick L'Horty§
Loic Du Parquet¶ Pascale Petit‖

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Abstract

This paper emphasizes on the foundations of three statistical discriminations that are specific to the older workers: employers can think that a senior is characterized by *(i)* a shorter distance to the retirement age, *(ii)* a larger distance to the technological frontier, and/or *(iii)* a smaller ability to move from old toward new occupations than a younger worker. We design a specific controlled experiments in order to test each of these statistical discriminations. We also present a "pure" discrimination equilibrium and a controlled experiments specific to this assumption. Our empirical results, based on data collected between mid-January and mid-August 2015 in France, support the view that the older worker are discriminated in the hiring process via these four channels. This suggests that the French gap in the employment rate of the older workers is partly explained by significant discriminations.

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*ERUDITE-TEPP, Université Paris-Est-CNRS
†ERUDITE-TEPP, Université Paris-Est Créteil & Cepremap
‡GAINS-TEPP, Université du Mans-CNRS & Paris School of Economics & Cepremap & IZA
§ERUDITE-TEPP, Université Paris-Est-CNRS
¶GAINS-TEPP, Université du Mans-CNRS
‖ERUDITE-TEPP, Université Paris-Est-CNRS & Cepremap

1 Introduction

In all European countries, the 90s have been the times of the reforms of the pension system: the retirement age has been postponed or the number of contributive periods has been extended (see Gruber and Wise (1999), (2007) and (2010)). These reforms are motivated by the increase of the lifetime expectation, and thus of the dependance ratio, leading the SS system to be unsustainable without any reform. These policy changes must induce the populations to work longer and thus mechanically, must increase the employment rates of the older workers. There was controversies when these reforms are been implemented[1]: can we ask older people to work longer, while they are less likely than other groups of workers to have a job? If the labor demand addressed to older workers is low, incentives to work longer by postponing the retirement age would not be enough: in a world where technologies change, it must first put the seniors on the technological frontier to make them employable, or/and allow them to perform more easily job transitions.

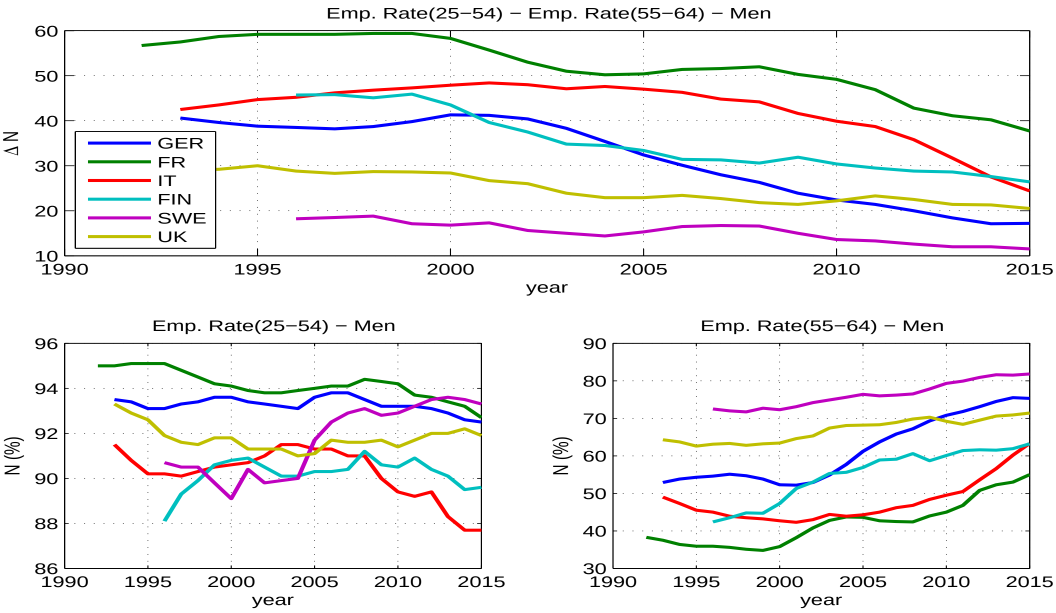
What can it be observed if we look at the aggregate data? The Figure 1 shows that the increase of the employment rate of the older workers is underway[2]: the period at which the employment gaps are reduced between prime-age and older workers depends on the country-specific year of the reform, but it is clear that these gaps have been reduced, mainly because the employment rates of the older workers have increased. The great recession has not stopped these trends. So, this is a long run phenomenon, observed in countries that share the same technologies. Another major feature of the figure 1 are the different speeds among countries to fill these gaps. This suggests that, beyond these reforms and these technological changes, the age discrimination on labor markets can explain these heterogenous performances. This paper deals with this type of discrimination, by focusing on the hiring process: the foundations of the statistical age discriminations are explained, and each channel is tested using controlled experiments.

We focus on the hiring process because these employment gaps per age can come from two phenomena: *(i)* after 60 year old (the lowest age to leave in retirement), the employees keep their jobs and thus contribute mechanically to the increase of the employment rate for the 55-64, and *(ii)* before the age of retirement (ie. before 60 years old), the employment rate increases in order to prepare this increase of the working duration. For our propose, this last option is the most interesting because it implies a selection process through the hiring decision: older workers are in competition with other workers to obtain new jobs. At this stage, a discrimination process can reduce their wishes to be employee. The figure 2 shows that the employment rates of the 50-59 increase in all countries, but this adjustment seems be very slow for some countries, in particular in France. Hence, the labor markets of older worker have became more active since the middle of the 90s, by giving more chance to be employed, but some countries seems to be behind the times in this process, particulary France. Indeed, this trend remains slow and limited

[1]See Hairault and Langot (2016) for a survey on this literature.

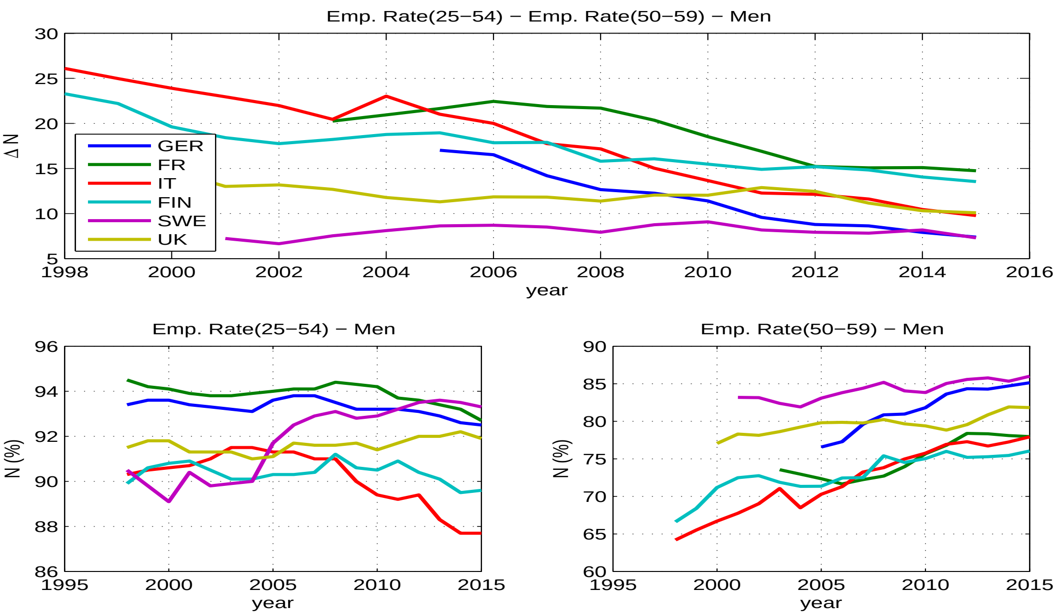
[2]In order to control from the increasing trend of the women participation, this figure displays the data for men, only.

Figure 1: Employment Rates by Age: European Countries



Data source: EuroStat EU-LFS (`lfsi-emp-a`)

Figure 2: Employment Rates by Age: European Countries



Data source: EuroStat EU-LFS (`lfsi-emp-a`) in France where the employment gaps between prime-age and older workers remain the largest. Hence, for some countries, and particularly in France, the changes in labor market institutions, or in pension system, as well as the increased number of policies directed to older people are still insufficient in removing all obstacles that reduce their chance to find and retain employment.

This is why discrimination against older workers on the French labor market is worthy of analysis: this is the objective of this paper. We first emphasize on the foundations of the statistical discrimination that are specific to the older workers. We distinguish 3 channels: *(i)* the distance to the retirement age, *(ii)* the distance to the technological frontier, and *(iii)* the ability to move from old toward new occupations. Secondly, we design a specific controlled experiments in order to test each source of statistical discrimination against older workers. At the end of the paper, we also present a "pure" discrimination equilibrium and a controlled experiments specific to this assumption. All our theoretical analysis are based on extended versions of the search and matching model à la Diamond-Mortensen-Pissarides (DMP) where life-cycle features are introduced as it is done in Hairault, Langot and Sopraseuth (2010), Cheron, Hairault and Langot (2011) and (2013), Menzio et al (2015) or Kitao, Ljungqvist and Sargent (2016). All our empirical investigations are based on controlled experiments that consist to send fictitious applications and CV at employers of the French area the most dense in employment (Paris-Ile de France). Hence, this paper innovate on two points. On the one hand, it overcomes difficulty inherent in the age discrimination measure and on the other hand, it can identify the causality of this discrimination beyond the initial measure.

From a methodological point of view, our evaluation of the discrimination in recruitment consists of constructing a controlled experiment on the labor market (Riach and Rich, (2002) and Petit (2003)). The "testing" method consists of creating two fictitious application (CVs and cover letters), perfectly similar in terms of career and qualifications. The only significant distinction between the two candidates will be the attribute whose effect on access to employment is to be evaluated. These two CVs will then be sent simultaneously in response to the same job vacancies. Since the two candidates are perfectly similar with the exception of one attribute, any significant disparity in attaining job interviews will only be imputable to the effect of this attribute on the access to employment. The experimental data collected during testing are, as a result, free of selection bias and unobserved heterogeneity.[3] These are the primary contributions of this experimental method.[4] As it is underlined by Neumark, Burn and Button (2015), the main difficulty with the age discrimination comes from the correlation between age and experience:

[3]On the two phases of recruitment, we test only, the access to the job interview and not the result of this interview itself. Indeed, this second phase is subject to biases influenced by the personality and the appearance of candidates.

[4]The principal limitation of the controlled experiment method is, however, that it does not provide a measure of recruitment discrimination on the labor market (Heckman (1998)). Indeed, contrary to survey data, and even to administrative data, the test results are partial (some occupations tested), occasional (some months of experimentation) and localized (some employment areas examined). The measure of discrimination thus does not refer to a representative cross-section of the labor market. Precautions need to be taken in regard to the generalization of the results.

by comparing two workers that only differ with respect to the age, the senior with the same experience than the younger can be perceived as an atypical worker, not really attach to the labor market. This method thus can lead to over-estimates the discrimination against the older workers. Hence, following Riach and Rich (2010), Neumark, Burn and Button (2015) propose to correct this bias by giving an experience "commensurate with age". We follow this idea for the construction of our fictitious CVs. Moreover, our theoretical investigations underline the multidimensional aspect of age. Its "backward" dimension is highly correlated with the experience, the education, and thus to the gap between the technological frontier and the human capital of workers. The "forward" dimension of the worker age provides an indication on the expected joint-profits of the matches and can be directly linked to the "normal" retirement age in a society. Hence, more than the age, what matter is a distance, at the time of the hiring, between the first flow-profit and the last one, given that the horizon of the match is bounded. This bound can come from the SS rules, the obsolescence of the worker knowledge or from the high learning costs for displaced workers. From the view point of the statistical discrimination, these channels are different, but can act negatively on the employment rate of the older workers.

Our results, based on data collected between mid-January and mid-August 2015,[5] support the view that the older worker are discriminated in the hiring process. The section 3 shows that there exist 3 potential sources of statistical discriminations à la Arrow (1972) and Phelps (1972), and all of them can not be rejected by the data: employers expect that *(i)* the job duration will be shorter when the normal age of retirement is coming up, *(ii)* the distance to the technological frontier is larger for an older workers, and *(iii)* the ability to learn a new job is lower for an older worker. Moreover, the section 4 shows that a taste discrimination ("pure" discrimination) process a la Becker (1957) can not be rejected. All these results are presented after a brief presentation of the related literature (section 2), and before the conclusion (section 5).

2 Related Literature

Over the last thirty years, in almost OECD countries, a lot of research measures discrimination in access to employment, by using controlled experiments as correspondence tests, without being always able to identify the causes, taste or statistical discrimination (Riach and Rich (2002)). But, there have been very few applied studies on labor market discrimination that considered age as a criterion. To our knowledge, only four correspondence tests of access to the recruitment interview, measure the age discrimination. The main reason lies in the difficulty to measure the age discrimination. It comes to comparing access to employment of individuals with different ages, but with the same productive attributes. Nevertheless, the age and some productive attributes, such as experience are necessarily correlated.

[5]For all tested hypotheses, 6361 applications have been sending allocated on seven occupations and twenty-eight profiles.

In the United States, Bendick et al. (1997) compare the chances of candidates of the same sex, one 32 years of age and another 57, in two occupations (computing for men and administration for women). They bring to light a strong age discrimination against older workers. Riach and Rich (2010) consider, on the English labor market the chances of two candidates, one 27 years of age and another 47 in three occupations (administration and sales for women, food service for men). Strong age discrimination was highlighted against older workers on administration jobs, one more moderate on food service jobs and age discrimination in favor of women on sales jobs.[6]

More recently, Neumark, Burn and Button (2015) explore the age discrimination in twelve US towns allocated in eleven States, which are distinguishing by the rate of seniors in the population and a law against discrimination more or less severe. Almost 40 000 fictitious applications of men and women have been sending in response to the low-skilled job offers: sales and casher (men or women), caretakers and cleaning persons (men), safety officers (men), secretary and administrative assistant (women). The fictitious candidates are differentiated by their age (30, 50, 65 years old), and for candidates aged of 50 and 65 years old, by their professional experience: low (as the candidate aged 30), or then higher. In the second case, Neumark, Burn and Button (2015) make to vary the professional career of fictitious candidates. At the moment where they apply, two candidates of 50 and 65 years old are in the continuity of their career: they are skilled on the kind of jobs. Two other candidates of 50 and 65 years old, by contrast, were previously occupied on a higher skilled jobs in the same sector of activity. For them, it is a downgrading in their professional position, a transitional job. Finally, for another candidate who is aged of 65 years, this downgrading did act 10 years earlier. Their main results are following: firstly, the age discrimination put more the candidates which are close to retirement (65 versus 50 years old). This discrimination against them appears, also, in the strategy of downgrading. Secondly, if the age discrimination appears systematically in their results for the women, it is more ambiguous for men. If in all tested occupations, women suffer age discrimination, this is not the case for men. Thirdly, the age discrimination appears more limited in the States where the law against discrimination is more binding: when it is more severe for offenders, the access to employment of the older workers is higher.

3 The statistical discrimination based on the worker age

Why does the age matter at the time of the hiring? There is two dimensions in the age which give a particular value of a job occupied by an age-a worker, denoted $J(a)$. Indeed, the age contains an information on the experience of the worker, ie. the number of years between the current meeting and the age at which worker enters in the labor market: this is the "backward dimension"

[6] To permit comparison with the young candidate and the senior, Riach and Rich (2010) use two strategies. The first strategy is to allocate candidates with experience in different fields (unrelated to the post they are applying for) at the beginning of their careers, to equalize the number of experience years between young and senior candidates in the tested occupation. The second is to mention in the application of senior candidate the length of career breaks, for example, in order to care for his children.

of the age (the initial condition for $J(a)$). The current age also contains an information on the number of years that employer can expect to retain the worker before her retirement age: this is the "forward dimension" of the age (the terminal condition for $J(a)$. All the employers, at the time of the selection process between the applications use age to forecast these two dimensions of the worker age: when there exist fixed hiring costs associated to each hiring (denoted by K), this expected capitalization value of the job ($J(a)$) must recoup them. But, the computations of these two forecasts can be biased at the level of the individual simply because employers have an imperfect information. For example, if it is possible to know the complete career of a worker, and hence her social security wealth, the age at which she reaches the full rate pension age can be only considered as an imperfect estimate of the effective retirement age because it is possible for her/him to retire sooner or later than this "rational" age.[7] In the same way, even if an employer observes perfectly the age at which a worker begins her career, all of them are victim of the same obsolescence of their human capital, but this phenomena is heterogenous among workers. This imperfect information leads usual statistical discrimination à la Arrow (1972) and Phelps (1972).

In what follows we use the traditional model à Pissarides (2000), extended to account for life-cycle features as proposed in Cheron, Hairault and Langot (2011) and (2013), in order to give some foundations to the statistical discriminations based on age. Two simplifications are introduced:

- firstly, the wage do not depend on the labor tightness, in the spirit of the wage bargaining solution discussed in Hall and Milgrom (2008).
- secondly, the matching process is not directed per age, and all the candidates have the same chance to be draw.[8]

The rate of job matching is $H = h\left(v, \int_a u(a)da\right)$ where $\int_a u(a)da = u$ and $\theta = \frac{v}{u}$ are respectively the aggregate unemployment and the labor market's tightness, the workers' arrival rates of job offers are $\lambda(a) = \max\{p(\theta), 0\}$ whereas the transition rate at which vacancy jobs are filled is:$q(\theta) = h\left(1, \theta^{-1}\right)$. In the case of an undirected matching function, the value of a vacancy is given by

$$rV = \gamma + q(\theta) \int_a \frac{u(a)}{u} \max\{J(a) - K, 0\} da \tag{1}$$

where γ is the search cost for the firm. The free-entry condition on the labor market leads to $V = 0$. Moreover, the optimal choices of the employers lead them to select workers allowing them to recoup their fixed hiring costs: $\max\{J(a) - K, 0\} = J(a) - K$ for a s.t. $J(a) \geq K$ and $\max\{J(a) - K, 0\} = 0$ for a s.t. $J(a) < K$. Let denoted by $\widetilde{a}$ the threshold age satisfying

[7]See Hairault, Langot and Zylberberg (2015) for search and matching models where the retirement choices are endogenous, and Bi and Langot (2016) where they are imperfectly observed.

[8]This assumption is in accordance with the laws prohibiting the age discrimination applied in a large number of OECD countries. In the last section of the paper, we come back to this assumption in order to introduce an equilibrium with taste discrimination based on the worker age.

$J(\widetilde{a}) = K$ (the "reservation age"), the equation (1) gives the "job creation" curve:

$$\frac{\gamma}{q(\theta)} = \int_{\widetilde{a}} \frac{u(a)}{u}[J(a) - K]da \tag{2}$$

The undirected search assumption leads to $\lambda(a) = p(\theta)$, $\forall a < \widetilde{a}$ and $\lambda(a) = 0$ for $a \geq \widetilde{a}$. Given that θ is shared by all workers, we discuss in what follow only an $J(\widetilde{a}) = K$, ie. on the reservation age.[9]

In the following sections, we propose a theoretical framework, an empirical protocol and estimates that allow us to test successively 3 hypotheses: the distance from retirement (section 3.1), the gap between human capital and new technologies (section 3.2) and the difficulties of professional retraining following an occupational change (section 3.3).

3.1 Does the distance to retirement matter at the time of hiring?

In this section, we focuss on the distance between the current age a and the retirement age R, ie. the "horizon" before the retirement $(R - a)$. Hence, we assume that all the agents are identical and that their productivities and wages do not depend on their ages. It is then shows that the age per se does not matter, contrary to the "horizon" before the retirement. But the retirement age R is an uncertain event at the time of the hiring. Hence, the employer can use the public information on SS rules in order to predict the number of years until the "normal" retirement age of the worker. This statistical discrimination à la Arrow (1972) and Phelps (1972) can lead to discriminate against older workers. More precisely, this discrimination process, if it exists, exclude from the hiring process the candidate with a short horizon, whereas some of them will choose to work after this "normal" retirement age.

3.1.1 Theoretical Analysis

Let denoted by r the interest rate, y the productivity, w the wage, δ the exogenous separation rate and R the retirement age. The retirement age R depends on SS rules shared by all agents, but also on preferences which are at contrary specific to each agents. Hence, it would be predicted by the employer: this predicted retirement age must then be view as the "normal" retirement age. The value of a job occupied by a worker of age a is given by[10]

$$rJ(a) = y - w - \delta J(a) + \dot{J}(a) \quad \Rightarrow \quad J(a) = \frac{y - w}{r + \delta}\left[1 - e^{-(r+\delta)(R-a)}\right]$$

[9] In the following, we also extend the model to account for a more smoothed discrimination process, instead of the process where all workers share the same contact rate before a and zero after.

[10] Remark that if the productivity and the wage grow at the rate g, then this equation is not modified, except that the interest rate is now net of the growth rate g: $J(a) = \frac{y-w}{r-g+\delta}\left[1 - e^{-(r-g+\delta)(R-a)}\right]$. Hence, for simplicity we omit the growth without loss of generality.

The last term shows that $J(a)$ is non-stationary. This is due to the existence of a retirement age. Indeed, if $R \to \infty$, the value is stationary and homogenous among jobs. It is given by $\frac{y-w}{r+\delta}$. At the opposite, when R is bounded, $J(a)$ is a decreasing function of age: the capitalization of profits is made on a shorter horizon. The term $\frac{y-w}{r+\delta}$ is the product of the profit instantaneous $(y-w)$ by the average length of employment unconditional to the retirement event $(1/\delta)$, the interest rate reducing the value of the future periods. The term $e^{-(r+\delta)(R-a)}$ is the probability that the job still exists at the period $R-a$, all periods being discounting by r.

If an open position requires an installation cost K, which does not depend on the age of the worker contacted to perform the task, then there exists an age $\widetilde{a}$ s.t. $J(\widetilde{a}) = K$. This threshold age $\widetilde{a}$ is given by:

$$\widetilde{a} \quad = \quad R - \frac{1}{r+\delta} \log\left(\frac{y-w}{y-w-(r+\delta)K}\right) \tag{3}$$

Thus, for all ages $a > \widetilde{a}$, there will be no hiring. Employees having an age $a > \widetilde{a}$ and who will suffer from a job separation (at a rate δ) will never be rehired. After controlling by characteristics such as productivity, age and job separation rate, the statistical discrimination can occurs if the employer expects that the worker can retire sooner: $\widetilde{a}(R_1) < \widetilde{a}(R_2)$ for $R_1 < R_2$. Hence, the signal of a short horizon, whatever the worker age leads the employer to prefer an alternative candidate with a longer horizon.[11]

Proposition 1. *If $K > 0$, the firms discriminate older workers because age can indicate a short distance between the retirement age and the current age.*

Proof. The Equation (3) shows that the arbitration condition determines indeed $R-\widetilde{a}$, for $K > 0$. But, for $K \to 0$, we have $\widetilde{a} \to R$ showing that the distance to retirement is not used to select workers. □

Hence, the forward looking behaviors underline the crucial role of the horizon of the workers. But this forward looking behavior has an impact on the current decision only if the hiring is an investment, ie. only if $K > 0$. If this decision is static ($K \to 0$), the worker horizon does not matter for the value of the firm and thus is not used to select among the workers. The proposition 1 shows that at the same age, the individual paths on the labor market can lead to an heterogeneity in R which depends on the SS rule, namely the eligibility of the worker to a full-rate pension. Hence, the signal of a short horizon can be a source of a statistical discrimination.

[11] Remark that individuals with age a s.t. $a > \widetilde{a}$ were hired before they age $\widetilde{a}$, then they can remain employed until retirement if their jobs are not destroyed.

3.1.2 Empirical Test

Data collection. In order to analyze distance from retirement age hypothesis, two similar level professions were assessed: call-center agent, and sales assistant. The former involve more often than the latter the funding of a training by the employers who expect a return on investment: K must be larger for the hiring of a called-center agent than for a sales assistant.[12] Hence, by comparing these two types of jobs, we are able to control for an observed training cost (the called-centers agent). For each of the two occupations, three fictitious applications were built and sent to answer the same job offers. They involve two senior men of the same age (56) and a younger man aged 29. The first one entered the labor market at age 15, and thus, is entitled to retire before legal age of 62. He specified in his resume that he has 41 years of experience and specified in his covering letter that he's entitled to retire in about one year. The second one is the same age, but entered the labor market when he was 21. He mentioned in his resume that he has 34 years of experience. The third fictitious applicant is a 29-year-old man who has 13 years of experience. All applications are otherwise similar in all remaining points. In both occupations[13], the three fictitious applicants hold the same diploma (a "Certificate of Professional Competence" in sales). Since they entered the labor market, they have accumulated significant experience in the kind of job they are applying for. For the two older workers and for the younger worker, within their professional experience as sales assistant, the call-center agents have two experiences as call-center agents (the second experience being longer than the first one): following Neumark, Burn and Button (2015), we thus give an experience "commensurate with age", but identical whatever the age for the specific task of the job. As for the sales assistants, they only have experiences in retail business.[14]

Results. Under the distance from retirement age hypothesis we should empirically find out that employers prefer the 29-year-old candidate, and among 56-year old candidates, that they prefer the one further from retirement. This distinguished expected effect for both applicants over 50 should be more important in the call-center agent occupation, as it involves, in most cases, a training funded by the employer (see appendix E.1, table 17).

We assessed about 300 job offers for each of both occupations. As far as call-center agents were concerned, 20.6% of tested job offers received a positive answer to, at least, one of the three fictitious candidates. Sales assistants got a lesser overall answer rate with 13.9% of employers who

[12] Remark that this information is a necessary condition to obtain a significant "horizon effect" for the called-center agents but not for the sales assistants. Nevertheless, it can exist some other fixed hiring costs, different from an explicit period of training. In the appendix E.1, table 17, we show that on this tested sample of job offers, the proportion of job offers mentioning the funding of training by the employer is higher for the call-center agents than for the sales assistants. At the same time, the average duration of this training, when it is mentioned in the job offer, is also more important for the call-center agents.

[13] We present, in appendix C, table 12, the main average and modal attributes of individuals working in those two occupations, as extracted from the French Labor Force Survey (Enquête Emploi-INSEE).

[14] Additions to the protocol are provided in Appendix D. Examples of fictitious applications are available upon request.

responded positively to, at least, one of the fictitious candidates. These differences in percentages between occupations translate two traits. First, a high percentage means an important tension in this occupation. Then, it suggests a good match between the application profiles we built and the employer's expectations. We also find out that on this tested sample of job offers, the proportion of job offers mentioning the funding of training by the employer is higher for the call-center agents than for the sales assistants (table 17). At the same time, the average duration of this training, when it is mentioned in the job offer, is also more important for the call-center agents.

Table 1: Gross rate of success on the same job offers

	Call-center agents			Sales assistants		
	Positive answers rate (p-value)	90% Conf. interval L. bound	90% Conf. interval U. bound	Positive answers rate (p-value)	90% Conf. interval L. bound	90% Conf. interval U. bound
56 years old long distance	10.00%*** (0.000)	7.15%	12.85%	3.99%*** (0.000)	2.13%	5.84%
56 years old short distance	8.33%*** (0.000)	5.69%	10.98%	2.99%*** (0.002)	1,39%	4.59%
29 years old	17.00%*** (0.000)	13.43%	20.57%	12.62%*** (0.000)	9.50%	15.75%
% of job offers with a positive answer for at least a fictitious candidate[1]	20.67%			13.95%		
♯ of job offers	300			301		

[1]: Percentage of jobs offers for which at least one of 3 fictitious candidates has received a positive answer from the employer (for the access to job interview).
Example of lecture: on the 300 tested job offers of call-center agents, the senior man with a long distance from retirement age has obtained a job interview in 10% of cases.
P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

The table 1 detailed the access rates to a job interview according to profiles while the table 2 provides a comparison of these rates of success. Basically, the access rate to a job interview is higher for the 29-year-old candidate if compared to senior profiles (table 1). It is 17% for call-center agents, and almost 13% for sales assistants.[15] The senior candidate with a longer distance from retirement age (10% and 4%) has a success rate higher than that of the senior candidate with a shorter distance to retirement (8,33% and 3%). However, the difference between the access rates to a job interview of the two senior candidates is not statistically significant at a conventional threshold of 10% (table 2).[16]

[15]In both occupations, preference expressed by employers for the 29-year-old candidate confirms on jobs offered with a permanent contract (Appendix E, Table 18).

[16]Among 56-year-old candidates (call-center agents or sales assistants), employers with a permanent contracts

Table 2: Differences in success rates on the same job offers

	Call-center agents			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-7.00***	0.001	-10.41%	-3.59%
56 years old-short distance versus 29 years old	-8.67***	0.000	-12.03%	-5.31%
Effect of the distance 56 years old short distance versus 56 years old long distance	-1.67	0.160	-3.62%	0.29%
♯ of job offers	300			
	Sales assistants			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-8.64***	0.000	-11.54%	-5.74%
56 years old-short distance versus 29 years old	-9.63***	0.000	-12.49%	-6.78%
Effect of the distance 56 years old short distance versus 56 years old long distance	-1.00	0.371	-2.83%	0.84%
♯ of job offers	301			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

In sale assistant occupation, preference expressed for the 29-year-old candidate also emerges for jobs which offered wage is higher than the average of overall sample (Appendix E, Table 19). At the same time, for this relatively better paid type of job, chances for a 56-year-old candidate to access a job interview are significantly higher if his distance from retirement age is further (gap of 4 points in percentage). If we compare the differences in success rates among older workers and between job, the "distance effect" reduce the change by 1.67 pp for the call-center agents, whereas the success rate is only reduced by 1pp for the sales assistants: the training costs seem to play in the right way.

Nevertheless, these first results are not statistically significant. Hence, if we simply approximate the chance to access a job interview by the number of reply of the employers, it seems that the distance from retirement does not statistically matter. But, all replies are not identical: for the same number of positive replies, the chances of a candidate are significantly lower than an other if this first is always called after one or two other candidate, whereas the second is always called first. In the table 3 we report the rank of the replies addressed to candidates, when they are in competition with one or two other different candidates. This experiments shows that of the 63% (Call-center agent)/50% (Sales Assistant) of the all the replies addressed to a 56 years

to offer tend to favor the one further from retirement; however, this preference is not significant at conventional thresholds.

Table 3: Rank of each candidate when employers have called him with at least one other candidate

		Rank 1		Rank 2		Rank 3	
		CC	SA	CC	SA	CC	SA
56 year old long distance	2 candidates called	63.64	50.00	36.36	50.00	0	0
	3 candidates called	33.33	0	26.67	33.33	40.00	66.67
56 year old short distance	2 candidates called	11.11	33.33	88.89	66.66	0	0
	3 candidates called	26.67	33.33	46.67	66.66	26.67	0
29 year old	2 candidates called	75.00	57.14	25.00	42.86	0	0
	3 candidates called	40.00	66.67	26.67	0	33.33	33.33

CC: Call-center Agent. SA: Sale Assistant.
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

old candidate with a long distance of retirement, are replies where this candidate is called first, the others 36%/50% being replies where she/he is called in second. At the opposite, when the distance to retirement is short, in 89%/66% of the cases, the candidate is called after at least another candidate that not share this short distance to retirement.

Hence, if is not possible to distinguish statistically between the two fictitious candidates of 56 years old on the basis of the number of replies, it is clear that their rankings in the hiring process, approximated by the rank of the reply when several candidates are in competition, supports the view that a short distance to retirement is used against the older candidates during the hiring process. Moreover, the call-center agents seems to be more discriminated than the sales assistants, as it is suggested by the theory and the measure of the training costs at the time of the hiring. We conclude that it exists a statistical discrimination, based on distance to retirement, that excludes from the hiring process the candidate with a short horizon, whereas some of them will choose to work after the "normal" retirement age.

3.2 Does human capital obsolescence matter for the hiring process?

Another disadvantage of the older workers can come from their human capital. For example Aubert, Caroli and Roger (2004) show that both organizational and technological change allows to identify a ”technological age” which is a distance between the education of the older workers and the knowledge required to use new technology. Moreover, in Saint-Paul (2010), it is underlined that the abilities (measured by the dexterity) of the older workers are significantly lower than the ones of the 25-34 year-old workers.[17] But all workers are not affected by a decline of their productivities at the end of their life cycle. So, Garibaldi, Martins, and van Ours (2010) show that older workers are generally considered to be more consistent, cautious, conscientious and less "risky" (fewer accidents, less likely to quit, less absent than younger workers). Furthermore, Garibaldi, Martins, and van Ours (2010) also show that the older workers can maintain their level of productivity to the extent that this only depends on cognitive skills, while they lose some part of productivity depending on physical strength. But, this is not the age dynamics

[17]The estimates comes from Avolio and Waldman (1994) paper.

of productivity as such that matters for employability, but rather the wage-productivity gap (A competitive labor market leaves no gap). Thus, we focus on situations where the wage is rigid at the end of the life cycle, as it is suggested by Lazear (1979), by an argument of long-term contract, or by Ljungqvist and Sargent (2008), by an argument based on unemployment benefits.[18] Hence, this section focusses on the potential disadvantage of the older workers driven by a productivity-wage gap. But, as in the previous section, all the older workers do not suffer from the same distance to the technology. Hence, the employers must predict the employee specific technological gaps. This leads to a statistical discrimination à la Arrow-Phelps. As previously, we present the theoretical foundations of this argument and its test.

3.2.1 Theoretical Analysis

Assume that the productivity of a worker, $y(a)$, is a decreasing function of her age a, such that $ye^{-\theta a}$. This age-specific technological gap is attached to the worker[19]: it can be interpreted as the distance between the schooling knowledge and the current technology or by the continuous decline of the dexterity with the worker age as it is suggested by Saint-Paul (2010). Hence, the age can give two signals: its forward dimension can give a measure of the "horizon" effect (the distance between the current age and the retirement age), whereas its backward dimension can measure the obsolescence of the human capital. The value of a job occupied by a-age worker is given by:

$$rJ(a) \quad = \quad y(a) - w - \delta J(a) + \dot{J}(a)$$

The new component in $J(a)$ is the age-decreasing productivity $y(a)$. This non-stationary component of the instantaneous profits (the "technological gap") implies that there is an age a_D such that $y(a_D) - w = 0$, which is given by

$$a_D = \frac{\log(y) - \log(w)}{\theta}$$

This equation shows that the larger will be θ, the lower will be a_D: a large "speed" of obsolescence leads to low threshold age.

If the match has been formed when the worker age is such that $a < a_D$, this threshold indicates the age at which the worker is fired by the firm, this last having no interest to hoard this worker because the obsolescence phenomena is irreversible. These fired workers will be unemployed until they become eligible to the SS system at the age R.[20]

[18] For simplicity, these two arguments are summarized by our assumption of a constant wage.

[19] Here θ must be interpreted as a characteristic of each worker, given the worker-specific technological age. Hence, given the distribution of the θ, the employer must predicts the worker productivity.

[20] This unemployment at the end of the life-cycle is not the same than the one described by Aghion and Howitt (1994) or Mortensen and Pissarides (1998). Indeed, the unemployment spell is not a productive event allowing to reallocate the worker from low to high productive activities. In our case, the unemployment is an

Does this "technological age" matter? In the hiring process, we deduce from the previous remark that all the workers older than a_D are excluded from the selection process. If $a_D < R$, the worker horizon is bounded by his "technological age".[21] In this case, the "social age", defined as the distance to retirement age, gives no information on the match value. Nevertheless, the forward behavior of the employers leads them to be more restrictive in the hiring process than for the layoffs. Indeed, in the case where $a_D < R$, the job value becomes:

$$J(a) = \int_a^{a_D} e^{-(r+\delta)(\tau-a)}[y(\tau)-w]d\tau$$

Using this value, one can defined the threshold age at which firms stop to hire, $J(\widetilde{a}_D) = K$:

$$K = \frac{ye^{-\theta\widetilde{a}_D}}{r+\delta+\theta}\left[1-e^{-(r+\delta+\theta)(a_D-\widetilde{a}_D)}\right] - \frac{w}{r+\delta}\left[1-e^{-(r+\delta)(a_D-\widetilde{a}_D)}\right] \qquad (4)$$

The first term on the RHS shows that the obsolescence has two effects on the value of a worker hired at the age $\widetilde{a}_D$. Firstly, her gap to the technological frontier at the age of the hiring reduces the potential productivity by the factor $e^{-\theta\widetilde{a}_D}$. Secondly, the firm capitalizes declining productivities until the separation at the age a_D.

Proposition 2. *When obsolescence leads firms to fire workers before the retirement age ($a_D < R$), (i) the distance to the retirement does not matter and (ii) the age at which they decide to exclude the older worker from the hiring process is still lower than a_D.*

Proof. Straightforward using the Equation (4): if $\widetilde{a}_D > a_D$ then $J(a) < 0$ and thus can not be equal to $K > 0$, whereas if $\widetilde{a}_D < a_D$ then $J(a) > 0$ and thus can be equal to $K > 0$. This is true for parameters insuring that $a_D = \frac{\log(y)-\log(w)}{\theta} < R$. □

In the proposition 2, the same mechanisms are at work than in proposition 1, except that now the terminal condition is a "technological age" (a_D) driven by the obsolescence process, whereas in the proposition 1, the terminal condition is given by the retirement age (R). But, $\widetilde{a}_D$ and $\widetilde{a}$ share the property of amplifying the selection process against the older workers. Indeed, when the obsolescence reduces the labor productivity, the multiplier effect is larger.

Corollary 1. *When obsolescence matters, the hiring discrimination is stronger for tasks where new technologies are used intensively.*

Proof. When a task uses new technologies intensively, the obsolescence of the human capital of the older increases: $d\theta > 0$. Using the equation (4), we can define $K \equiv F(\widetilde{a}_D, a_D(\theta), \theta)$, with

unproductive event during which agents wait for the retirement age. They never come back on the productive sectors/occupations: all the workers older than a_D are excluded from the hiring process and quit the labor market at age R.

[21] Remark, if $a_D > R$, there is no firing due to the obsolescence of the worker knowledge, and thus the hiring process is also not affected by a_D. This implies that the exclusion of the workers older than a_D is due to a discrimination based on the distance to the retirement age (previous section).

$F_1'(\widetilde{a}_D, a_D(\theta), \theta) < 0$, $F_2'(\widetilde{a}_D, a_D(\theta), \theta) > 0$ and $F_3'(\widetilde{a}_D, a_D(\theta), \theta) < 0$. Then, we have

$$\frac{d\widetilde{a}_D}{d\theta} = -\frac{F_3'(\widetilde{a}_D, a_D(\theta), \theta)}{F_1'(\widetilde{a}_D, a_D(\theta), \theta)} - \frac{F_2'(\widetilde{a}_D, a_D(\theta), \theta)}{F_1'(\widetilde{a}_D, a_D(\theta), \theta)} \frac{da_D}{d\theta} < 0$$

because $\frac{da_D}{d\theta} = F_1' < 0$. Hence, for $\theta \to 0$ we have $\widetilde{a}_D \to \widetilde{a}$, leading to $a_D - \widetilde{a}_D \approx R - \widetilde{a}$ whereas for $\theta > 0$ we deduce that $a_D - \widetilde{a}_D > R - \widetilde{a}$. $\square$

The corollary 1 underlines that the impact of the obsolescence comes from two channels that magnify its effect: the first magnifies the impact of the ”horizon” effect because it reduces both the current profits (the first term in the Equation (4)), and the second reduces the horizon during which firm can recoup the hiring cots (a_D).

Hence the obsolescence leads to *(i)* fire the workers sooner (a_D decreases with θ), and *(ii)* the age at which firms stop to hire is also smaller. Hence, if an exogenous separation hits a worker after the age $\widetilde{a}_D$, it is not possible for him to find another job. Both phenomena reduce the employment rate at the end of the life cycle.

3.2.2 Empirical Test

Data collection. To test this hypothesis, we target two occupations with similar skill levels (Master degree /Executive position) and with no relationship with customers. To test the impact of θ on the hiring selection process, two tasks are selected on the base of their exposures to their specific speeds of human capital obsolescence: technological gap can be more important for IT project managers and IT developers than for management accountants and accountants, ie. θ can be larger for IT project managers and IT developers than for management accountants and accountants. If the "human obsolescence" does not matter for the management accountants and accountants, then the discrimination on this labor market is driven by the horizon to retirement, described in the previous subsection. Three fictitious applications are submitted in answer to job offers in each of both occupations: three men holding a Master degree, respectively aged 32, 42 and 52. Their experience tends to increase with age. Based on French Labor Force Survey data (see appendix C, table 13), the applications are made realistic.

Results. The number of tested job offers for IT project managers and IT developers is 302, while job offers for management accountants and accountants amount to 308. As far as IT project managers and IT developers are concerned, 33.4% of tested job offers were answered positively to, at least, one out of three, which means an important tension in this occupation, as well as a good match between employer’s expectations and fictitious candidates profiles. As for management accountants and accountants, they obtain a lesser overall answer rate with 11% companies that positively responded to, at least, one of the fictitious candidates. Table 4 details of job interview access rates for each candidate, while table 5 compares success rates.

Table 4: Gross rate of success on the same job offers

	IT Project Manager and Developer			Accountant Manager and Accountant		
	Positive answers rate (p-value)	90% Conf. interval L. bound	90% Conf. interval U. bound	Positive answers rate (p-value)	90% Conf. interval L. bound	90% Conf. interval U. bound
52 years old	10.26%*** (0.000)	7.39%	13.14%	1.95%*** (0.011)	0.63%	3.27%
42 years old	17.88%*** (0.000)	14.23%	21.53%	4.22%*** (0.000)	2.35%	6.09%
32 years old	30.79%*** (0.000)	26.51%	35.08%	7.47%*** (0.000)	4.99%	9.95%
% of job offers with a positive answer for at least a fictitious candidate[1]	33.44%			11.04%		
♯ of job offers	302			308		

[1]: Percentage of jobs offers for which at least one of 3 fictitious candidates has received a positive answer from the employer (for the access to job interview).
P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 5: Differences in success rates on the same job offers

	IT Project Manager and Developer			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	90% Conf. interval U. bound
Effect of the age				
52 years old versus 32 years old	-20.53***	0.000	-24.51%	-16.55%
42 years old versus 32 years old	-12.91***	0.000	-16.48%	-9.35%
52 years old versus 42 years old	-7.62***	0.000	-10.66%	-4.57%
♯ of job offers	302			
	Accountant Manager and Accountant			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	90% Conf. interval U. bound
Effect of the age				
52 years old versus 32 years old	-5.52***	0.000	-7.99%	-3.05%
42 years old versus 32 years old	-3.25***	0.049	-5.96%	-0.53%
52 years old versus 42 years old	-2.27***	0.092	-4.49%	-0.05%
♯ of job offers	308			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Results show that the success rate strongly and regularly decreases in function of age for the IT project managers and IT developers who are exposed to a more rapid human capital obsolescence, while it decreases in lesser proportions for the management accountants and accountants. Thus, this seems to validate the obsolescence hypothesis: the IT project managers and IT developers are discriminated more early during there life cycle ($a_D < R$ and thus $\widetilde{a}_D < \widetilde{a}$), whereas for the accountant managers and accountants, the older workers are less discriminated, suggesting that only the distance to retirement matters for this last type of tasks. Beyond the fact that these results are robust to the contract type (permanent or not) or at the level of the wage offer (higher than median, see appendix E, tables 20 and 21), this analysis based on the type of contract gives some support to the opposition between the types of the hiring discriminations at work on the two labor markets. As the gap in the success rate is unsignificant between the 42 and 32 years old, whereas it becomes between the 52 and 42 years old for the accountant Managers and accountants, this clearly suggests the presence of the hiring discriminations driven by the "horizon to retirement" effect. This is not the case for the IT project managers and IT developers where the premia to the youth appears early.

The specific profile of the position to be filled (management accountant versus accountant in one situation; IT project manager versus IT developer in the other one) does not really affect those results (see appendix E, tables 22 and 24). Finally, it seems that the profile of the employer does not change these results (see appendix E, table 23). Hence, the employers think that, despite a more important experience, older workers are less adaptable to new technologies: their general human capital would be obsolete, despite of their on-the-job training.

We should find out a more important detrimental difference in job interview access for older candidates when occupations are intensive in new technologies, such as IT developer. This is the case, but there also exists some significant gaps in occupations less intensive in new technologies, such the accountants. Does the quantitative results of the table 5 conceal the two different channels of hiring discriminations at work in the two labor market?

Table 6: Rank of each candidate when employers have called him with at least one other candidate

	32 years old		42 years old		52 years old	
	IT	AA	IT	AA	IT	AA
One job interview	45.16%	69.57%	9.26 %	61.54%	9.68 %	50.00%
Two job interviews	26.88%	26.09%	42.59%	30.77%	6.45 %	33.33%
Three job interviews	27.96%	4.35 %	48.15%	7.69 %	83.87%	16.67%

IT: IT Project Manager and Developer. AA: Accountant Manager and Accountant.
Source: TEPP-CNRS testing data, Ile de France, mid-January and mid-August 2015.

How to read the first column? Of all tested offers for which the 32-year candidate was called, in 45.16% of cases positive for him, this candidate has been called alone; in 26.88% of cases positive for him, he was called with another type of candidate (a worker aged of 42 or 52 years old); in 27.96% of cases positive for him, the other two types of candidates were also contacted by the employer.

The table 6 presents a qualitative analysis of the replies of the employers. If we measure the quality of the job interview by the fact that the employer concentrates its recruiting efforts on this particular individual, the large reduction of the priority accorded to the youth decreases starting from the 42 years old for the IT project managers and IT developers, whereas it declines only from the 52 years old for the management accountants and accountants. Hence, we can conclude that the discriminations against older workers, based on the "human capital obsolescence" are more present for tasks more intensive in new technologies.

3.3 Does the ability to learn a new task matter for the hiring process?

As it is suggested by Neumark et al (2015) "*a significant share of any increase in employment among seniors would be expected to come from new employment in part-time or shorter-term "partial retirement" or "bridge jobs", rather than continued employment of workers in their long-term career jobs*" (p.1). This phenomena is highly linked to technological change that drives the job polarization described by Autor and Dorn (2013) and Acemoglu and Autor (2011): a large part of experimented workers, in the middle of the wage distribution, shows their tasks replaced by new technologies, and must be reallocated toward new activities. Thus, a first characteristic of these workers is the obsolescence of their human capital: as in the previous section, the productivity of a worker is a decreasing function of her age, interpreted as the distance between the schooling knowledge and the current technology. For these displaced workers, ie. workers who move from their old occupations toward new tasks, there are incentives to learn, because the human capital used in their previous tasks can not be useful for the new ones. Their best reactions consist to accumulate specific skills which are learned by doing their new jobs. Because this human capital is specific, it is not transferable after a reallocation choice. Hence, the hiring process depend on the credibility of the ability to learn on-the-job. The employer can then use statistical information to predict this worker-specific characteristic: as previously, we provide some foundations to this statistical discrimination à la Arrow-Phelps of the older workers.

3.3.1 Theoretical Analysis

This section focusses on the case where new employees (the displaced workers) have access to a learning-by-doing production process after their hirings: their productivities, becomes $y(a, v) = ye^{-\theta a}e^{\lambda(a-v)}$ where v is the age at the time of the hiring. This productivity can be rewritten as follow: $y(a, v) = ye^{-\theta v}e^{(\lambda-\theta)(a-v)}$, where $e^{-\theta v}$ accounts for the technological gap at the hiring age, and $e^{(\lambda-\theta)(a-v)}$ the evolution of this human capital during the period $a - v$. If $\lambda > \theta$, the learning process is efficient because the accumulation of the specific human capital compensates the depreciation of the general human capital, whereas if $\lambda < \theta$, the learning process is not able to compensate the depreciation of the general human capital. Thus, the job value is

$$rJ(a, v) \quad = \quad y(a, v) - w - \delta J(a, v) + \dot{J}(a, v)$$

There is two cases, depending if the "technological gap" can be compensated or not by the learning-by-doing process. We focus on this last case which gives clear foundations to a statistical discrimination against the older workers.[22] In the case of a low ability to learn a new task, $\lambda < \theta$, the compensation induced by the learning is partial. The productivity is age-decreasing and thus it exists a "technological age", denoted by $a_L(v)$ such as $y(a_L(v), v) - w = 0$. This age is given by

$$a_L(v) = v + \frac{\log(ye^{-\theta v}) - \log(w)}{\theta - \lambda}$$

This equation shows that $a_L(v) > v$ if $\log(ye^{-\theta v}) > \log(w)$ because $\theta > \lambda$. At the opposite, if the distance to the technology is too large at the age of the hiring, implying that the first profit is lower than zero ($\log(ye^{-\theta v}) < \log(w)$), then this technological gap excludes the older workers.[23] This could be the case for large value of θ implying that the technological age bounded the worker horizon ($a_D < R$). This is not the case if θ is small enough to ensure $a_D > R$ and thus $a_L(v) > v$. Then, we have

$$a_L(v) \equiv a_D + \frac{\lambda}{\theta - \lambda}(a_D - v) > a_D$$

using $\log(y) - \log(w) = a_D\theta$. This last equation shows that the learning process can postpone the age at which the profits become negative. Indeed, when $a_D > R > a_L(v)$, the job value at the age of the hiring ($v = a$) is given by:

$$J(a, a) \quad = \quad \int_a^{a_L(a)} e^{-(r+\delta)(\tau - a)}[y(\tau, a) - w]d\tau$$

Using this value, the threshold age at which firms stop to hire, $J(\widetilde{a}_L, \widetilde{a}_L) = K$, is:

$$K \quad = \quad \frac{ye^{-\theta\widetilde{a}_L}}{r + \delta + \theta - \lambda}\left[1 - e^{-(r+\delta+\theta-\lambda)\frac{\theta}{\theta-\lambda}(a_D - \widetilde{a}_L)}\right] - \frac{w}{r+\delta}\left[1 - e^{-(r+\delta)\frac{\theta}{\theta-\lambda}(a_D - \widetilde{a}_L)}\right] \qquad (5)$$

As in the case without learning-by-doing, the first term on the RHS shows that the obsolescence generates two effects on the production of a worker hired at the age $\widetilde{a}_L$. Firstly, her gap to the technological frontier at the age of the hiring reduces the potential productivity by the factor $e^{-\theta\widetilde{a}_L}$. Secondly, the firm capitalizes declining productivities until the separation at the age $a_L(\widetilde{a}_L)$. With respect to the case without learning-by-doing, the parameter λ indicates how the obsolescence is dampened: when $a_L(\widetilde{a}_L) > a_D$, the firm expects to capitalize over a longer employment duration.

Proposition 3. *When $\theta < \lambda$, the firms reject applications of workers younger than the "technological age" (a_D), ie. $\widetilde{a}_L < a_D$.*

Proof. Straightforward using the Equation (5): if $\widetilde{a}_L > a_L(\widetilde{a}_L)$ then $J(a, a) < 0$ and thus can

[22]See the appendix A for the case where the high ability to learn can make disappear the statistical discrimination against the older workers.

[23]Indeed, staring with a initial profit lower than zero, and given that the expected productivity declines with the worker age, due to the low efficiency of the learning process, the learning process does not matter.

not be equal to $K > 0$, whereas if $\widetilde{a}_L < a_L(\widetilde{a}_L)$ then $J(a) > 0$ and thus can be equal to $K > 0$. Given that $a_L(\widetilde{a}_L) = a_D + \frac{\lambda}{\theta-\lambda}(a_D - \widetilde{a}_L) \Rightarrow a_L(\widetilde{a}_L) - \widetilde{a}_L = \frac{\theta}{\theta-\lambda}(a_D - \widetilde{a}_L)$, we have $J(a) > 0$ when $0 < a_L(\widetilde{a}_L) - \widetilde{a}_L \Leftrightarrow a_D > \widetilde{a}_L$. □

Hence the proposition 3 shows that the ability to learn is not sufficient to fight against the discriminations against the older workers during the hiring process.

Corollary 2. *When obsolescence matters, the strong hiring discrimination is damped by the ability to learn a new task.*

Proof. Equation (5) can be rewritten as follows $K \equiv G(\widetilde{a}_L, a_D(\theta), \theta, \lambda)$, with $G'_1(\widetilde{a}_D, a_D(\theta), \theta, \lambda) < 0$, $G'_2(\widetilde{a}_D, a_D(\theta), \theta, \lambda) > 0$, $G'_3(\widetilde{a}_D, a_D(\theta), \theta, \lambda) < 0$, and $G'_4(\widetilde{a}_D, a_D(\theta), \theta, \lambda) > 0$. This gives the solution for $\widetilde{a}_L$ as a function of $\{\theta, \lambda\}$. Using the properties of G, we deduce $\frac{d\widetilde{a}_D}{d\theta} < 0$ and $\frac{d\widetilde{a}_D}{d\lambda} > 0$. □

The rise of the depreciation of the human capital θ reduces the maximum age at which firms hire though two channels: the direct one which reduces the current productivity and the indirect negative impact transiting by a reduction of the "technological age" a_D. On the contrary, the rise of the efficiency of the learning process increases the maximum age at which firms hire though these two same channels, but in the opposite direction. The empirical analysis consists to evaluate if the employers expect different values for the parameters λ, contingent to another type of the workers. For example, if we consider reallocation from routine tasks toward manual tasks, and more particularly the "personal care services", the men can be victim to discrimination given their low share in this type of jobs.

3.3.2 Empirical Test

Data collection. Three occupations are assessed for which we purposely haven't taken all other discriminating factors into account, to keep the "other things being equal" principle: low skills and no costly training. They are personal care services: home help (domestic staff, and domestic help), cleaning persons and caretakers. For each job offer, four fictitious applications are built and sent. Each candidate has gone through a long period of unemployment after working for many years in a declining industry: as in the theoretical analysis, these workers are victim to an obsolescence of their human capital ($\theta > 0$). Without any opportunities in the labor markets of their previous tasks, they choose to move toward an occupation in tension, implying for us a professional learning. Their expected ability to learn, ie. the perceived value of λ, is at the heard of our test. There are two 50-year-old (51 and 52), still far from retirement and two 30-year-old (35 and 36). The only difference between them lies in gender: one is a man, the other one a woman. This gender difference can be a signal used by the employers to discriminate against the men who are less present in this type of activity: their abilities to learn can then be expected to be lower than those of women.

After having neutralized the distance from retirement age, potential obsolescence and training funding, if the senior man has less chances to get a job interview (thus preventing his retraining) than a woman with a similar profile, we can conclude that a stereotype does exist, in which social standard, a senior man can't retrain in feminized and lower skilled occupations, such as personal care services. Adding two younger applications allows confirming that retraining argument is an issue exclusively related to senior population.[24] .

Results. We present job interview access rates for the four fictitious candidates in table 7, incorporating the different occupations. 381 job offers were tested in the personal care services occupation profession group. An overall 42% of these job offers received a positive response to, at least, one of the four fictitious candidates, confirming the high tension in this family of occupations, and a good match between employers' expectations and the profiles of built applications. Table 8 compares job interview access rates of each fictitious candidate, with a pairwise comparison on the same job offers.

Table 7: Gross rate of success on the same job offers

	Personal Care Services			
	Positive answers rate	p-value	90% Conf. interval L. bound	U. bound
30 years old - Man	17.85%***	0.000	14.62%	21.08%
50 years old - Man	12.07%***	0.000	9.29%	14.85%
30 years old - Woman	26.77%***	0.000	23.08%	30.46%
50 years old - Woman	25.98%***	0.000	22.24%	29.72%
% of job offers with a positive answer for at least a fictitious candidate[1]	41.99%			
♯ of job offers	381			

[1]: % of jobs offers for which at least one of 3 fictitious candidates has received a positive answer from the employer.
P-values and conf. intervals: bootstrapped 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, mid-January/mid-August 2015.

Basically, age only affects chances to access a job interview for men: chances of a 50-year-old are lesser than that of a 30-year-old one (gap of 6 points in percentage). However, for women, age seems effectless: a 30-year-old and a 50-year-old have roughly the same chances of getting a job interview. Also, regardless of their age, women are significantly more successful than men. However, this gender preference is more important among senior population. There is a 9 point gap in percentage among the 30-year-old, and a 14 point one among the 50-year-old. This suggest that employers expect that the displaced women can rapidly learn the specificities of

[24]French Labor Force survey data were used to build credible profiles: see appendix C, table 14

Table 8: Differences in success rates on the same job offers

Pairwise comparison on the same job offers	Personal Care Services			
	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
Men: 50 years old versus 30 years old	-5.77***	0.001	-8.61%	-2.93%
Women: 50 years old versus 30 years old	-0.79	0.733	-4.59%	3.01%
Effect of the gender				
50 years old: Women versus Men	8.92***	0.000	4.88%	12.96%
30 years old: Women versus Men	13.91***	0.000	10.02%	17.80%
♯ of job offers	302			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

these manual tasks (personal care services), whereas this is not the case for the men. We reach the same results when we reduce the scope to higher quality job offers: permanent positions (appendix E, table 25) and wages higher than sample median value (appendix E, table 26).

Thus, as stated by the hypothesis of professional retraining difficulties, men undergo a specific age-related penalty, women don't. Chances for men to get a job interview decrease by one third over 50, other things being equal. Women are preferred to men for personal care services, especially over 50. This empirical test suggests that the employers expect that the man's ability to learn (λ in the theoretical model) a manual task, after an experience on a routine task, is lower than the one of a women. Hence, the largest share of the women in these activities gives more credibility at the new female candidates.

4 The taste discrimination based on the worker age

A last argument that can explain the discrimination against the older worker is the subjective preferences of the employers for the younger workers à la Becker (1957). In order to isolate this phenomena, the initial investment of the firm at the time of hiring must zero ($K = 0$), and hence the value of each job is static: young and older workers generate exactly the same profit $y - w$. We then focus on the hiring process where a discrimination process can be introduced if the entrepreneur ranks the applications of the candidates. We then use an urn-ball model that turns out to be particularly useful when one deals with ranking or discrimination in a search-matching framework, i.e. when firms receive more than one application and rank or discriminate among them.[25]

[25]The seminal paper on discriminations in the matching process is Blanchard and Diamond (1994), that focus on short term versus long term unemployed workers. For the discrimination between black and white worker or between male or female workers, see e.g. Rosen (1997), Moen (1999) or Rocheteau and Zenou (2001).

4.1 Theoretical Analysis

The idea of the urn-ball model consists to represent the firms as urns and the workers as balls.[26] An urn becomes "productive" whenever it has a ball in it. There are u unemployed workers and v vacancies. Suppose that each of the u unemployed visits one employer (or vacancy) chosen at random and takes the job if available. If more than one worker appears, one is chosen at random for employment. A way of formulating this urn-ball model is to use a Binomial distribution. This will be very useful when we deal with ranking and discrimination.[27]

In this search-matching framework, the discrimination process consists, when firms receive more than one application, to rank or to discriminate among them. We focus on two types of workers, say young and old workers. We assume that there is a discrimination against older workers. This means that if a vacancy receive several applications and if among them one comes from a younger worker, then the employer will always prefer to hire this younger worker. Let us denote by u_O and u_Y the unemployment level of older and younger workers respectively. Consider a given vacancy and let N_O (N_Y) be the number of young (old) applicants received in a period of time. Thus N_O is a random variable that represents the number of older applicants to a firm in the u_O repeated independent Bernoulli trials and N_Y is a random variable that represents the number of young applicants to a firm in the u_Y repeated independent Bernoulli trials. The random variables N_O and N_Y are independent. Then, N_O follows a Binomial distribution $B(1/v, u_O)$ and N_Y follows a Binomial distribution $B(1/v, u_Y)$. Then, assuming u and v are large number, we use the Poisson approximation (see appendix B) for the Binomial distribution. We thus have:

$$P\left[N_i = n\right] = \frac{\left(\frac{u_i}{v}\right)^n}{n!} e^{-\frac{u_i}{v}} \quad \text{for } i = Y, O$$

Therefore, the probability that a vacancy is filled with a young applicant is given by:

$$P\left[N_Y \geq 1\right] = 1 - P\left[N_Y = 0\right] = 1 - e^{-\frac{u_Y}{v}}$$

Let us now calculate the probability that a vacancy is filled with an old applicant. This is more tricky since we have to be sure that no young applicant apply for the job. This probability is thus equal to:

$$P\left[N_Y = 0 \cap N_O \geq 1\right] = P\left[N_Y = 0\right] P\left[N_O \geq 1\right] = e^{-\frac{u_Y}{v}} - e^{-\frac{u}{v}}$$

This implies that the number M_Y (M_O) of younger (older) workers matches per period is:

$$M_Y = v\left(1 - e^{-\frac{u_Y}{v}}\right) \qquad M_O = v\left(e^{-\frac{u_Y}{v}} - e^{-\frac{u}{v}}\right)$$

[26] The standard urn-ball model in discrete time, introduced in the search-matching literature by Butters (1977), Hall (1979), Pissarides (1979).

[27] See the appendix B for a brief presentation of the usual urn-ball model without discriminations.

As a result, the probabilities to find a job for an old and a young worker are respectively equal to:

$$\frac{M_O}{u_O} = \frac{v}{u_O}\left(e^{-\frac{u_Y}{v}} - e^{-\frac{u}{v}}\right) \qquad\qquad \frac{M_Y}{u_Y} = \frac{v}{u_Y}\left(1 - e^{-\frac{u_Y}{v}}\right)$$

Finally, the general matching function of the economy which gives the total number of matches per period $M(u,v) = M_Y + M_O$ is given by:

$$M(u,v) = v\left(1 - e^{-\frac{u}{v}}\right) = v\left(1 - e^{-\frac{1}{\theta}}\right) \quad \Rightarrow q(\theta) = \frac{M}{v} = \left(1 - e^{-\frac{1}{\theta}}\right)$$

which is obviously the same one than in an economy without discrimination against older workers (see appendix B).

Hence, if there are only two age groups in the economy, the value of a vacancy is:

$$rV \;=\; -\gamma + \left[\frac{M_Y}{v}(y-w) + \frac{M_O}{v}(y-w)\right] = -\gamma + q(\theta)(y-w)$$

Using the free-entry condition $V = 0$, we obtain $\frac{\gamma}{q(\theta)} = y - w$. With or without discrimination, the labor market tightness is the same, but the hiring probability for each group are different. In particular, given the solution for θ, and assuming that $u_Y = \alpha u$ and $u_O = (1-\alpha)u$, we have

$$\begin{aligned}
\frac{M_O}{u_O} &= \theta\frac{u}{u_O}\left(e^{-\frac{u_Y}{u}\frac{1}{\theta}} - e^{-\frac{1}{\theta}}\right) = \theta\frac{1}{1-\alpha}\left(e^{-\alpha\frac{1}{\theta}} - e^{-\frac{1}{\theta}}\right)\\
\frac{M_Y}{u_Y} &= \theta\frac{u}{u_Y}\left(1 - e^{-\frac{u_Y}{u}\frac{1}{\theta}}\right) = \theta\frac{1}{\alpha}\left(1 - e^{-\alpha\frac{1}{\theta}}\right)
\end{aligned}$$

Proposition 4. *It always exists equilibrium with "taste" discrimination if employers select this free strategy.*

Proof. We have $\frac{M_O}{u_O} < \frac{M_Y}{u_Y}$ iff $\frac{e^{\alpha}-\alpha}{1-\alpha} < e^{\frac{1}{\theta}}$. Given that θ is the solution of $\frac{\gamma}{q(\theta)} = y - w \Leftrightarrow \frac{1}{\theta} = \log\left(\frac{y-w}{y-w-\gamma}\right)$, we deduce that the share of the young workers α must satisfy $f(\alpha) \equiv \frac{e^{\alpha}-\alpha}{1-\alpha} < \frac{y-w}{y-w-\gamma}$. As $\frac{y-w}{y-w-\gamma} > 1$ and $f(\alpha) \in (1,\infty)$, for $\alpha \in (0,1)$, we deduce that α always exists. □

Hence, if employers decide to rank the applications via ad hoc preference for the younger workers, an equilibrium can exist where the hiring rate of the older workers is always lower than for the younger workers. This equilibrium is sustainable in the long run.

4.2 Empirical Test

Data collection. The social norm sends back to Becker and its theory of "taste" discrimination (also called pure discrimination). In our case, this is an "anti-senior culture". In accordance with our theoretical approach, we choose occupations doesn't need investments in the human capital from the employer's part. The characteristics of the employees must have a potential impact on their production (the belief of the employers). According to these criteria, we kept the salesman occupation.

On each job offer, we build and send four fictitious applications. The individuals are distinguished from their gender and age: a man and a woman, respectively 49 and 48 years old, a man and a woman respectively 52 and 53 years old. We built their experiences in order to get them as fairly far from retirement, accordingly to their experiences too (like the protocol obsolescence) knowing that the oldest (the one who is 53 years old) is still far from retirement. At the same period of time, all they entire in the labor market.[28]

Results. The table 9 presents the access rates to a job interview for four fictitious candidates on 301 tested job offers of sales assistant. The table 10 makes a pair wise comparison on the same job offers.

Table 9: Gross rate of success on the same job offers

	Sales Assistant			
	Positive answers rate	p-value	90% Conf. interval L. bound	U. bound
40 years old - Man	6.98%***	0.000	4.57%	9.38%
50 years old - Man	4.65%***	0.000	2.63%	6.67%
40 years old - Woman	11.96%***	0.000	8.88%	15.04%
50 years old - Woman	8.31%***	0.000	5.73%	10.88%
% of job offers with a positive answer for at least a fictitious candidate[1]	17.28%			
♯ of job offers	301			

[1]: % of jobs offers for which at least one of 3 fictitious candidates has received a positive answer from the employer.
P-values and conf. intervals: bootstrapped 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, mid-January/mid-August 2015.

Even if a very few years separate the candidates in our controlled experience, aging lowers the chances to access to an job interview for a man or a woman, with an effect a little more marked for these last ones (more than 3%). In the occupation of sales assistants, a discrimination related to the gender appears, which goes against men, among the forty years old and fifty years old candidates. In both cases, women have a higher chance than men with the same age, but this effect is higher for the forty years old candidates (differences of 5% in favor women). So the hypothesis that, the social norm discriminates older workers in the employment can not be

[28]We verify with the French Labor Force Survey that the characteristics of candidates are realistic. See appendix C, table'15.

Table 10: Differences in success rates on the same job offers

Pairwise comparison on the same job offers	Sales Assistant			
	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
Men: 50 years old versus 40 years old	-2.33***	0.088	-4.57%	-0.08%
Women: 50 years old versus 40 years old	-3.65***	0.046	-6.67%	-0.64%
Effect of the gender				
50 years old: Women versus Men	4.98***	0.005	2.06%	7.91%
40 years old: Women versus Men	3.65***	0.020	1.08%	6.23%
♯ of job offers	301			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

rejected. But the attributes of job offers has a significant impact. If the job offer is a permanent contract, the employers seem to be less sensitive to age: they still prefer forty years old candidates but this difference is significant, only for women (See appendix E, table 27). When they have a vacant job to fill with a permanent contract, employers consider indifferently a man which is a little bit younger or older than 50. Along with the kind of jobs, among the forty years old candidates, the employers discriminate men, but this trend is not significant among the fifty years old candidates. Finally, on the job offers offering a wage above to the median value of the sample, no age or gender effects appear in the statistically significant (See appendix E, table 28).

Table 11: Rank of each candidate when employers have called him with at least one other candidate

		Rank 1	rank 2 or more
Men, 40 years old	2 candidates	57.14%	42.86%
	3 candidates or more	20%	80%
Men, 50 years old	2 candidates	0%	0%
	3 candidates or more	30%	70%
Women, 40 years old	2 candidates	45.45%	54.55%
	3 candidates or more	30%	70%
Women, 50 years old	2 candidates	50%	50%
	3 candidates or more	50%	50%

Source: TEPP-CNRS testing data, Ile de France, mid-January and mid-August 2015.

These results might suggest that pure discrimination à la Becker is not robust in our case. However, a qualitative analysis of the employer responses to CVs (see table 11) shows that men, aged 50 years old, are always put in competition with at least two other candidates, and have then a higher rank in the second. In contrast, women are more than 50 years called in rank 1, compared to women 40 years. This seems to reinforce the interpretation of the age discrimination, conditional to the sex of the workers.

5 Conclusion

The French gap in the employment rate of the older workers is significant, and initially (the beginning of the 90s) very large: *(i)* the normal retirement age is lower than in the other OECD countries (60 years old), *(ii)* there are numerous pre-retirement schemes, and *(iii)* there exist larger intergenerational differences in skills in comparison with other countries (see the international survey of adult skills PIAAC of the OECD (2014)), underlining the inefficiency of the vocational training for the seniors.[29] Our study suggests that these institutional arrangements lead the older workers to be perceived as less employable individuals: the employers perceive them as more risky workers because they can have *(i)* a short horizon before (pre-)retirement, *(ii)* a long distance to the technological frontier, and *(iii)* a high difficulty to learn new tasks. These expectations drive the statistical discrimination against older workers and can only be fight via a large increase of the speed of the reforms: a more rapid and larger increase of the normal retirement age, and a reinforcement of the vocational training directed to the older workers. Finally, concerning the discrimination à la Becker, these institutional changes aiming to keep seniors in the labor market, and thus to share the same rules than the other workers, could also fight this taste anti-senior.

[29]The poor performance in the adult skills for France comes from the results for persons aged 45-65. At the opposite, French workers aged 16-44 reach scores closer to (but still below) the average.

A Learning on-the-job: the case of a high ability to learn a new task: $\lambda \geq \theta$.

If the learning process is efficient, ie. $\theta < \lambda$, the productivity is age-increasing on-the-job. Even in this case, one must to check if the worker horizon is sufficient to ensure that potential losses at the beginning of the employment spell can be compensated by positive profits before a separation or retirement. Hence, a worker is not excluded from the hiring if her productivity, at the end of her career (here the retirement age R) is larger than her wage w: at age $a = R$ one must have $y(R, v) > w$. Hence, it appears that there exists a threshold age $\overline{v}$ such that $y(R, \overline{v}) = w$. Only workers younger than $\overline{v} = R - \frac{\theta}{\lambda}(R - a_D)$ years old can be selected for the hiring process.[30] For a worker hired at an age $a < v$, the job ends when she reaches the retirement age R. The value of this job at the age of the hiring a is given by:

$$J(a, a) = \int_a^R e^{-(r+\delta)(\tau-a)}[y(\tau, a) - w]d\tau \quad \text{for } a < R - \tfrac{\theta}{\lambda}(R - a_D)$$

Using this value, the threshold age at which firms stop to hire is defined by $J(\widetilde{a}_L, \widetilde{a}_L) = K$. Given that $\widetilde{a}_L < R - \frac{\theta}{\lambda}(R - a_D)$ in order to allow the learning process to have time to compensate the initial depreciation, the solution for $\widetilde{a}_L$ is given by:

$$K = \frac{ye^{-\theta\widetilde{a}_L}}{r+\delta+\theta-\lambda}\left[1 - e^{-(r+\delta+\theta-\lambda)(R-\widetilde{a}_L)}\right] - \frac{w}{r+\delta}\left[1 - e^{-(r+\delta)(R-\widetilde{a}_L)}\right] \qquad (6)$$

When the leaning-by-doing process is expected to be efficient, the first term on the RHS shows that the obsolescence two opposite effects on the production of a worker hired at the age $\widetilde{a}_L$. Firstly, as in the previous cases, her gap to the technological frontier at the age of the hiring reduces the potential productivity by the factor $e^{-\theta\widetilde{a}_L}$. Secondly, the firm capitalizes increasing productivities until the separation at the age R. With respect to the case without learning-by-doing or with an inefficient learning process, we have now $\theta - \lambda < 0$: this indicates how the productivity gains are accumulated, whereas $R > a_L(\widetilde{a}_L) > a_D$ shows that the firm expects to capitalize over a longer employment duration.

Proposition 5. *When $\lambda > \theta$, the age at which firms stop to hire can be larger than the "technological age" a_D, and is only bounded by the retirement age R.*

Proof. Because $\lim_{\lambda\to\infty}[R - \frac{\theta}{\lambda}(R - a_D)] = R$, the the admissible values for $\widetilde{a}_L$ are bounded by R. □

When $\lambda > \theta$, the capitalization effect of the specific human capital growth reduces the discrimination against the older workers. Nevertheless, the perception of this new accumulated knowledge

[30] For an hiring age higher that $\overline{v}$, the current profits are always negative: $\overline{v}$ is thus the maximum age at which firms hire. Remark that this threshold age is such that $\overline{v} < R$ iff $R > a_D$.

must to lead to forget that the older workers are hired with a large part of their general human capital that is obsolete. This initial unfavorable initial condition can be compensated only if the learning-by-doing effect is large.

Corollary 3. *When obsolescence matters, the hiring discrimination against older workers can disappear if the learning-by-doing process is highly efficient.*

Proof. Equation (6) can be rewritten as follows $K \equiv H(\widetilde{a}_L, \theta, \lambda)$, with $H'_1(\widetilde{a}_L, \theta, \lambda) < 0$, $H'_2(\widetilde{a}_L, \theta, \lambda) < 0$, and $H'_3(\widetilde{a}_L, \theta, \lambda) > 0$. We deduce from the implicit relation given by H the relation $\widetilde{a}_L = \Psi(\theta, \lambda)$, with $\Psi'_1 < 0$ and $\Psi'_2 > 0$. Given that the life-cycle is bounded by the retirement age, we have $\lim_{\lambda \to \infty} \widetilde{a}_L = R$. □

The corollary 3 can explain why some workers can be hired despite the large between their general human capital and the frontier of this knowledge. Indeed, some individuals can be perceived as highly productive few periods after their hirings. In this case, each candidate provides some surplus for the firm, and then the discrimination against a particular group is irrational.

B The urn-ball model without discrimination

Let N be a random variable that represents the number of applicants to a firm in the u repeated independent Bernoulli trials. Then, N follows a Binomial distribution $B(1/v, u)$, where $1/v$ is the probability of success, i.e. the probability that a given worker will visit the firm and u is the number of trials, i.e. the number of unemployed. Then,

$$P(N = n) = \begin{pmatrix} u \\ n \end{pmatrix} \left(\frac{1}{v}\right)^n \left(1 - \frac{1}{v}\right)^{u-n}$$

and $E[N] = \frac{u}{v} = \frac{1}{\theta}$. Thus, the probability that a given firm will be visited by at least one worker (or, equivalently, the probability that a given firm will receive at least one application) is

$$P(N \geq 1) = 1 - P(N = 0) = 1 - \left(1 - \frac{1}{v}\right)^u$$

If u and v approach to infinity in such a way that $u/v = 1/\theta$ remains constant, then we can approximate a Binomial distribution by a Poisson distribution so that

$$\lim_{V \to \infty, U \to \infty} P(N = n) = \frac{e^{-\frac{1}{\theta}} \left(\frac{1}{\theta}\right)^n}{n!}$$

Hence, when u and v are large, it is straightforward to see that:

$$P(N \geq 1) = 1 - P(N = 0) = 1 - e^{-u/v} = 1 - e^{-\frac{1}{\theta}}$$

This implies that the matching function is given by:

$$M = v\left(1 - e^{-u/v}\right) = v\left(1 - e^{-\frac{1}{\theta}}\right) \quad \Rightarrow \quad \begin{cases} q(\theta) & = & \frac{M}{v} & = & \left(1 - e^{-\frac{1}{\theta}}\right) \\ p(\theta) & = & \frac{M}{u} & = & \theta\left(1 - e^{-\frac{1}{\theta}}\right) \end{cases}$$

C Descriptive Statistics based on the French Labor Force Survey

Table 12: Average and modal attributes of call-center agents and sales assistants

Characteristics	Call-center agents	Sales assistants
Nationality (mode)	French	French
Region of residence (mode)	Nord-Pas de Calais	Ile-de-France
School leaving age (average)	20 years old	20 years old
Highest qualification obtained (mode)	BTS	BEP
Potential experience, in years (average)	12 years old	16 years old
Rate of women (percentage)	76	75

Source: French Labor Force Survey 2008-2012 (INSEE).
Field: Employed workers having finished their studies.
Sales assistants by correspondence,
Telemarketers: code profession 555a, nomenclature PCS 2003
Non-specialized sales assistants: code profession 553a de la nomenclature PCS 2003

Lecture: Between 2008 and 2012, the call-center agents having finished their studies were most often French women who live in the "Nord-Pas-de-Calais". In average, they are 20 years old at the end of their studies. The highest qualification obtained by these workers is most often the "BTS", (a degree corresponding of the 2 first years of the bachelor). Finally, in average, the surveyed call-center agents have accumulated 12 years of potential experience on the labor market for the end of their initial studies.

Table 13: Average and modal characteristics of IT Project managers and management accountants

Characteristics	IT Project managers	Management accountants
Nationality (mode)	French	French
Region of residence (mode)	Ile-de-France	Ile-de-France
School leaving age (average)	23 years old	23 years old
Highest qualification obtained (mode)	master of engineering	masters of accounting
Potential experience, in years (average)	15 years old	15 years old
Part of permanent contract (percentage)	99	98
25-29 years old (percentage)	19	18
30-34 years old	11	25
35-39 years old	17	16
40-44 years old	25	13
45-49 years old	16	12
50-54 years old	5	7
55-59 years old	3	6

Source: French Labor Force Survey 2008-2012 (INSEE)
Field: Employed workers having finished their studies

Table 14: Average and modal characteristics of employed workers in personal care services

Characteristics	Household employee	Household helper	Cleaning person	Caretaker	All
Nationality (mode)	French	French	French	French	French
Region of residence (mode)	Ile-de-France	Ile-de-France	Ile-de-France	Ile-de-France	Ile-de-France
School leaving age (average)	17 years old	18 years old	18 years old	16 years old	17 years old
Highest qualification (mode)	No degree	No degree	No degree	No degree	No degree
Potential experience (average)	32 years old	27 years old	26 years old	33 years old	28 years old
% of women	91	98	70	64	82
Average age	48 years old	45 years old	44 years old	49 years old	45 years old
♯ of days of the unemp.	800	664	750	577	724
before the actual job	(2y & 2m)	(1y & 9m)	(2y)	(1y & 6m)	(1y & 11m)
% of unemployed	18	25	27	18	25
Age groups (in %)					
25-29 years old	3	6	7	3	6
30-34 years old	5	7	8	4	7
35-39 years old	9	10	11	8	10
40-44 years old	14	14	16	13	15
45-49 years old	17	17	18	17	18
50-54 years old	19	18	17	18	18
55-59 years old	19	15	13	23	15

French Source: Labour Force Survey 2008-2012 (INSEE)
Field: Employed workers having finished their studies

Table 15: Average and modal attributes on sales assistants

	Sales assistants		
Characteristics	Man	Woman	All
25-29 years old (percentage)	7	15	22
30-34 years old	4	12	15
35-39 years old	3	10	13
40-44 years old	3	8	11
45-49 years old	2	7	9
50-54 years old	1	6	7
55-59 years old	1	5	6

French Source: Labour Force Survey 2008-2012 (INSEE)
Field: Employed workers having finished their studies

D Data Collection for the 4 protocols

In a same campaign of testing, the fictitious candidates are distinguishing; only, by the attribute whose we want to test the effect on the chances to access to job interview. They are, also, the same characteristics. All of them, are French, the sound of their first name and name indicate a French origin. They are the driving license with a car, and live in Paris and suburbs, in neighborhood similar across socio-economic perspectives. All of them are employed when they apply and explain, in their CVs, have at least a similar experience to that required for tested job offers.

Internet is the main source used to collect the job offers where the fictitious applications have been sending. Specialized web-sites have been using for some occupations ("jobanque" for the management accountant, "jobtic" for the computing) as a complement to normal generalists web-sites ("Pôle Emploi", "Monster", "cadremploi", "cadresonline", "keljob", "boncoin", "vivastreet"). For most of the applications have been sent by e-mail either "Pôle emploi", or private placement operator, or, directly, company, the same day as the publishing date of the job offers. For a same job offer, the applications have been sent the same day with a different random sending order according to job offers. The collected job offers cover exclusively permanent and fixed-term contracts (full-time and part-time for low-skilled occupations) on the region Ile-de-France.

Table 16: Differences in success rates on the same job offers offering a permanent contract

Tested Occupations Tested Occupations	♯ of build profiles	♯ of tested job offers	♯ of sending applications
"Distance of the retirement" hypothesis			
Call-center agent	3	300	900
Sales assistant	3	301	903
Sub-total " distance of the retirement "	6	601	1803
"Obsolescence" hypothesis			
IT project manager and IT developer	3	302	906
Management accountant and accountant	3	308	924
Sub-total " obsolescence "	6	610	1830
"Professional retraining" hypothesis			
Household employee and household helper	4	189	756
Cleaning person	4	169	676
Caretaker	4	23	92
Sub-total " professional retraining "	12	381	1524
"Social norm" hypothesis			
Sales assistant	4	301	1204
Sub-total " social norm "	4	301	1204
General Total	28	1893	6361

E Complementary Results

E.1 Distance to retirement hypothesis

Table 17: Reference to the funding of training by the employer in the job offers of the call-center agents and the sales assistants

	Number of job offers	Rate of job offers indicating the funding of the training	Average length of training given in the job offer
Call-center agent	300	14.67% (N=44)	29.72 days (N=9)
Sales assistants	301	8.31% (N=25)	16 days(N=3)

Source: TEPP-CNRS testing data
Ile de France, between mid-January and mid-August 2015.

Table 18: Differences in success rates on the same job offers offering a permanent contract

	Call-center agents			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-6.70***	0.011	-11.06%	-2.34%
56 years old-short distance versus 29 years old	-8.25***	0.001	-12.42%	-4.03%
Effect of the distance 56 years old short distance versus 56 years old long distance	-1.55	0.313	-4.07%	0.97%
♯ of job offers	194			
	Sales assistants			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-11.44***	0.000	-15.30%	-7.59%
56 years old-short distance versus 29 years old	-12.94***	0.000	-16.87%	-9.00%
Effect of the distance 56 years old short distance versus 56 years old long distance	-1.49	0.251	-3.63%	0.65%
♯ of job offers	201			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 19: Differences in success rates on the same job offers offering a wage above the median value of the sample

	Call-center agents			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	90% Conf. interval U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-5.41***	0.104	-10.87%	0.06%
56 years old-short distance versus 29 years old	-5.41***	0.108	-10.93%	0.12%
Effect of the distance 56 years old short distance versus 56 years old long distance	0.00	1.00	-2.12%	2.12%
♯ of job offers	111			

	Sales assistants			
Pairwise comparison on the same job offers	Gap (in % points)	p-value	90% Conf. interval L. bound	90% Conf. interval U. bound
Effect of the age				
56 years old-long distance versus 29 years old	-7.83***	0.005	-12.42%	-3.23%
56 years old-short distance versus 29 years old	-12.17***	0.000	-17.21%	-7.14%
Effect of the distance 56 years old short distance versus 56 years old long distance	-4.35	0.023	-7.50%	-1.20%
♯ of job offers	115			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

E.2 Obsolescence hypothesis

Table 20: Differences in success rates on the same job offers offering a permanent contract

	IT Project Manager and Developer			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-19.78***	0.000	-24.04%	-15.51%
42 years old versus 32 years old	-12.31***	0.000	-16.11%	-8.51%
52 years old versus 42 years old	-7.46***	0.000	-10.67%	-4.26%
♯ of job offers	268			
	Accountant Manager and Accountant			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-4.62***	0.002	-7.12%	-2.11%
42 years old versus 32 years old	-1.54	0.346	-4.23%	1.15%
52 years old versus 42 years old	-3.08**	0.019	-5.23%	-0.92%
♯ of job offers	260			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 21: Differences in success rates on the same job offers offering a wage above the median value of the sample

	IT Project Manager and Developer			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-21.82***	0.000	-30.94%	-12.70%
42 years old versus 32 years old	-14.55***	0.002	-22.29%	-6.80%
52 years old versus 42 years old	-7.27**	0.038	-13.05%	-1.50%
♯ of job offers			55	
	Accountant Manager and Accountant			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-23.81**	0.012	-39.36%	-8.26%
42 years old versus 32 years old	0.00	1.00	-15.72%	15.72%
52 years old versus 42 years old	-23.81***	0.010	-39.09%	-8.53%
♯ of job offers			21	

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 22: Differences in success rates on the same job offers: IT Project managers versus other occupations in the computing

	IT Project Manager			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-23.46***	0.000	-29.18%	-17.73%
42 years old versus 32 years old	-12.96***	0.000	-18.16%	-7.77%
52 years old versus 42 years old	-10.49***	0.000	-14.74%	-6.25%
♯ of job offers			162	
	Other occupations in the computing			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-17.14***	0.000	-22.95%	-11.34%
42 years old versus 32 years old	-12.86***	0.000	-17.84%	-7.85%
52 years old versus 42 years old	-4.29	0.104	-8.63%	0.05%
♯ of job offers			140	

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 23: Differences in success rates on the same job offers for IT Project Manager and Developer: SSII versus other kind of employer

	SSII			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-20.56***	0.000	-27.37%	-13.75%
42 years old versus 32 years old	-7.48**	0.030	-13.13%	-1.83%
52 years old versus 42 years old	-13.08***	0.000	-18.94%	-7.23%
♯ of job offers	107			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 24: Differences in success rates on the same job offers: management accountants versus other occupations in the accounting

	Management Accountants			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-5.63***	0.000	-8.64%	-2.61%
42 years old versus 32 years old	-3.90**	0.046	-7.11%	-0.68%
52 years old versus 42 years old	-1.73	0.245	-4.18%	0.72%
♯ of job offers	231			
	Other occupations in the accounting			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
52 years old versus 32 years old	-5.19**	0.042	-9.39%	-1.00%
42 years old versus 32 years old	-1.30	0.654	-6.06%	3.47%
52 years old versus 42 years old	-3.90	0.182	-8.70%	0.91%
♯ of job offers	77			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

E.3 Professional retraining hypothesis

Table 25: Differences in success rates on the same job offers offering a permanent contract

	Personal Care Services			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
Men: 50 years old versus 30 years old	-6.58***	0 .004	-10.37%	-2.80%
Women: 50 years old versus 30 years old	-1.65	0.575	-6.48%	3.19%
Effect of the gender				
50 years old: Women versus Men	11.11***	0.001	5.63%	16.59%
30 years old: Women versus Men	16.05***	0.000	10.76%	21.34%
♯ of job offers	302			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 26: Differences in success rates on the same job offers offering a wage above the median value of the sample

	Personal Care Services			
Pairwise comparison on the same job offers	Gap		90% Conf. interval	
	(in % points)	p-value	L. bound	U. bound
Effect of the age				
Men: 50 years old versus 30 years old	-5.59**	0.048	-10.23%	-0.95%
Women: 50 years old versus 30 years old	3.11	0.393	-2.88%	9.09%
Effect of the gender				
50 years old: Women versus Men	9.32***	0.009	3.43%	15.20%
30 years old: Women versus Men	18.01***	0.000	12.22%	23.80%
♯ of job offers	302			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

E.4 Social norm hypothesis

Table 27: Differences in success rates on the same job offers offering a permanent contract

Pairwise comparison on the same job offers	Sales Assistant			
	Gap(in % points)	p-value	90% Conf. interval	
			Lower bound	Upper bound
Effects of the age				
Men: Fifty-years-old versus Forty-years-old	-1.99	0.286	-5.06%	1.07%
Women: Fifty-years-old versus Forty-years-old	-3.98*	0.056	-7.40%	-0.56%
Effects of the gender				
Forty-years-old: Woman versus Man	4.98**	0.011	1.78%	8.17%
Fifty-years-old: Woman versus Man	2.99	0.155	-0.47%	6.44%
♯ of job offers	201			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.

Table 28: Differences in success rates on the same job offers offering a wage above the median value of the sample

Pairwise comparison on the same job offers	Sales Assistant			
	Gap(in % points)	p-value	90% Conf. interval	
			Lower bound	Upper bound
Effects of the age				
Men: Fifty-years-old versus Forty-years-old	-0.87	0.656	-4.08%	2.34%
Women: Fifty-years-old versus Forty-years-old	-2.61	0.328	-6.99%	1.77%
Effects of the gender				
Forty-years-old: Woman versus Man	4.35	0.131	-0.39%	9.09%
Fifty-years-old: Woman versus Man	2.61	0.256	-1.17%	6.39%
♯ of job offers	115			

P-values and confidence intervals were calculated using the bootstrap method based on 5,000 draws.
* 10% significance level; ** 5% significance level;*** 1% significance level
Source: TEPP-CNRS testing data, Ile de France, between mid-January and mid-August 2015.