Evaluating the effects of new technologies on wage inequality *

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Abstract

Using individual data from the French Labor Force Survey and the Complementary Survey on Working Conditions for 1998, we analyze earnings inequalities along the wage distribution between workers using novel technologies (ICT) at their job and those not using them. We estimate quantile regressions with technological dummies and carry out a decomposition analysis to identify the fraction of the technological premium attributable to differences in the labor market characteristics between ICT-users and not users, and the fraction due to diverging returns to identical characteristics. We conclude that divergences in the labor market characteristics between both workforces are the main factor responsible for the observed technological premium. The French labor market seems therefore to have become segmented between workers having the required skills to use novel technologies and those not having these skills. The intra-wage inequality analysis confirms this result.

Keywords: Technological wage gap, information and communication technologies, quantile regressions

JEL Classification: J31, J71, O33

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1 Introduction

The introduction of information and communication technologies (ICT hereafter) over the past decades has fostered an upturn in the returns to human capital, and more particularly in the rewards to workers using novel technologies at their job. Most of the existing literature on the subject focuses on the effects of ICT on average wage inequalities between skilled and unskilled workers or between workers using and not using novel technologies. In this paper, we seek to provide a more complete picture of the effects of modern technologies on earnings inequalities by analyzing the technological gap between ICT-users and not users along the whole wage distribution.

Many papers studying the evolution of the skill-premium over the past decades point towards biased technological progress and the complementary relationship between new technologies and skilled labor as the main factor responsible for the increasing trend observed in high-skilled relative wages. Krueger (1993) claims that workers using computers at their job earn 10-15% higher wages than non-users. Furthermore, the tremendous expansion of computers during the 80s accounts for one-third to one-half of the rise in the returns to education. Lee and Kim (2004) confirm Krueger's findings for the nineties. They conclude that the computer premium has been persistent during this decade, while the Internet premium decreased sharply between 1997 and 2001.

Autor, Katz, and Krueger (1998) or Davis and Haltiwanger (1991) also underline the role of skill-biased technological progress as the driving force of wage inequalities in the U.S. since the second half of the twentieth century. Using U.S. data, Krusell et al. (2000) find that during the 90s, the development of better and cheaper capital equipment being more complementary with skilled labor drove down wages of unskilled workers. Finally, concerning European countries, Caroli and Van Reenen (2001), working with French and British data, estimate that the increase in earnings inequalities inside firms between high- and low-skilled workers is due to the introduction of skill-biased technological and organizational practices.

On the other hand, the theoretical frameworks developed by Acemouglu (1999), Kremer and Maskin (1996) and Thesmar and Thoenig (2000) conclude that recent technological developments have fostered an increased segregation of the labor market, between high-tech firms employing high-skilled workers and low-tech firms employing low-skilled workers. This tendency towards homogenization in the firms' workforce should reduce wage dispersion within firms and increase wage inequality across firms. This result is empirically confirmed by Bartel and Sichermann (1999) who based on U.S. data find that the observed education premium in high-tech industries is due to sorting of highly educated individuals based on their unobserved characteristics in high-tech industries. Bailey, Berg, and Sandy (2001) using survey data on 45 U.S. establishments, or Doms, Dunne, and Troske (1997) and Dunne and Schmitz (1995), working also with American data, confirm that plants using advanced production methods employ a higher share of non production workers and pay higher wages.

In sum, there is a common agreement in the literature on the fact that novel technologies increase the returns to education and the rewards to ICT-users. However, while one stream of literature considers that these effects have increased wage inequalities within plants (between skilled and unskilled workers), another stream insists on the idea that ICT adoption leads to an increase in earnings inequalities across firms since it promotes a labor market segregation between high-tech firms employing skilled labor and low-tech firms employing unskilled labor.

Our paper aims at providing a more complete picture on the effects of novel technological practices on wage inequality by analyzing the evolution of the technological premium along the wage distribution, and not only for the mean wage level. Our analysis uses individual data obtained from the French Labor Force Survey and the Complementary Survey on Working Conditions during the 90s.

We first distinguish between workers using ICT (modern workers) and those not using them (traditional workers). Second, we investigate the extent to which the "technological premium" or "technological gap"[1] observed at various points of the wage distribution can be explained by divergences in labor market characteristics between modern and traditional workforces. We then examine if rewards to observed labor market characteristics are the same for both types of workers. Third, we carry out a decomposition analysis seeking to identify the extent to which the technological wage gap responds to differences in the workers' characteristics or to differences in the returns to these characteristics. This decomposition is implemented for both, the average wage differential and the wage differential observed along the distribution. Finally, we analyze earnings inequalities inside each group of workers.

Even if returns to identical labor market characteristics cannot be assumed to be equal for ICT-users and non-users, the decomposition analysis points rather to divergences in labor market characteristics as the main factor responsible for the observed wage gap, discrimination playing only a minor role. We conclude therefore that the labor market is segmented between workers having the required skills to use ICT (who are likely to be employed in high-tech sectors) and workers not having the required skills. Moreover, the intra-wage inequalities analysis, implemented using the Lorenz's curves and an interquantile range regression, confirms this result.

The remainder of this paper is organized as follows. Section 2 describes the data sources, the used variables, and it also provides a descriptive analysis of our sample. Section 3 implements a quantile regression analysis similar to the one used by Albrecht, Björklund, and Vroman (2003) when studying the gender gap in Sweden. We determine the differences in labor market characteristics between modern and traditional workforces and then compare the rewards to these

[1] We define the technological gap as the wage differential observed between ICT-users and non-users.

characteristics between both groups. We also decompose the technological premium between two components: one due to differences in the workers' labor market characteristics and another one explained by differences in the rewards to these characteristics (discrimination). Intra-wage inequalities are studied in section 4, and an historical comparison is implemented in section 5. Section 6 concludes.

2 Data and variables

2.1 The data sources

We use the French Labor Force Survey and the Complementary Survey on Working Conditions for 1991 and 1998. In the Labor Force Survey, a representative sample of 135000 individuals (belonging to 65000 households) aged of more than 15 years old is annually interviewed and questioned on their personal and professional status. The survey contains information concerning the main activity of the individual during the survey week, seniority at a job, occupation, wage, size of the firm, age, marital status, number of children, education, nationality and so forth. Every year, a third of the sample is renewed implying that each individual is interviewed only 3 times. The rate of sampling is 1/300.

The Complementary Survey on Working Conditions is conducted every seven years on a representative sample of 21000 employed workers interviewed by the Labor Force Survey. This survey covers four fields of interest: (*i*) organization and timetable of working days, (*ii*) workplace organization and job content, (*iii*) working risks, and (*iv*) degree of harmfulness of the job. We focus on the second field, where we dispose information concerning the use of new technologies by the workers. Given that the introduction of these novel practices took place along the nineties it is not striking to find much more information regarding the use of ICT in the 1998's cross-section of the Complementary Survey on Working Conditions than in the 1991's wave, where most of these technologies (internet, intranet, etc.) had not even been adopted by firms.

Because our paper seeks to analyze earnings inequalities between ICT-users and non-users, we eliminate from the sample all individuals working in the public sector, where wages are fixed by law and do not respond to productivity reasons. We also eliminate all individuals who are not full-time workers (so as to avoid preference issues problems, since for partial time workers it is not always a choice to be at part time) and those working in firms employing less than 10 people where people are more likely to be paid at the minimum wage. Finally, we eliminate individuals for whom there are missing observations. Our remaining sample covers exactly 7051 individuals for 1998.

Of course, we apply the same selections for 1991 and 1998. We restrict our attention to workers in the private sector and to full-time jobs. This allows us to shed light on the effects of ICT on wages that are explicitly linked to individual productivity.

2.2 The variables

We adopt the log of the monthly wage as our dependent variable. We classify every worker as modern or as traditional depending on whether she uses or not novel technologies. The Complementary Survey on Working Conditions provides information on the following variables:

- COMPUTER1: The worker uses a computer connected to an internal or external network.
- COMPUTER2: The worker uses a computer not connected to any network.
- TERMINAL: The worker uses a console.
- INTERNET: The worker uses internet with a professional objective.
- ROBOT: The worker uses robots or other machine tools being able to move autonomously.
- OTHERS: The worker uses other informatics material.
- ORDERINT: The worker receives internal orders from a computer.
- ORDEREXT: The worker receives external orders from a computer.

We build an indicator variable called MODERN adopting the unitary value when the individual uses at least one of the novel technologies (and MODERN is equal to 0 otherwise). Working with individual data instead of plant data, limits the possibility of our econometric study to capture the positive productivity spillovers that someone not using ICT but being employed in a plant where everybody uses them may receive.

In what follows, the attention of the paper is focused on the 1998 wave of the Labor Force Survey and the Complementary Survey on Working Condition, an historical comparison being introduced in section 5. The descriptive statistics summarized in Table 1 reflect an important upturn (from 41.8% to 56.3%) in the proportion of workers using at least one novel technology at work between 1991 and 1998. As expected, the probability to use a computer connected to a network has strongly increased during the 90s.

Insert Table 1 here

2.3 The sample characteristics

The existence of wage differentials between modern and traditional workers is clearly displayed in Table 2. An ICT-user earns in average 32.2% (9.214-8.892=0.322) more than a non-user. Besides, the technological premium increases along the distribution. In the first decile, modern workers earn 14.70% more, in the first quartile they earn 22.30% more, in the second quartile this difference raises to 29.70%, in the third quartile it attains 38.40% and in the ninth decile of the distribution 50.20%. The wage gap between both types of workforces reaches therefore a maximum at the top of the distribution.

The representation of the kernel density estimates of the log wage (see Figure 1) reveals that the modern workers distribution is rightward shifted with respect to the traditional workers distribution, that is, ICT-users receive higher wages than non-users. This finding is confirmed by Figure 2 where we represent the evolution of the technological wage gap along the distribution. From the sixth decile, the growth rate of the wage premium accelerates, the standard deviation being very significant. According to the descriptive statistics, earnings inequalities rise thus as we approach the upper tail of the distribution[2].

Insert Figure 1 here

Insert Figure 2 here

Evidently, the next question that arises is whether this technological wage gap stands for differences in the labor market characteristics between the high-tech and low-tech workforces or responds rather to differences in the rewards to these characteristics. Section 3.3 analyzes in detail this question, however, the descriptive statistics summarized in Table 2 permit to anticipate that, in average, ICT-users are younger but have more seniority than non-users. In terms of years of schooling the share of highly-educated workers (undergraduate, graduate and postgraduate diploma) is also more important inside the modern group of workers. Finally, workers occupying executive, intermediary or technician positions are more likely to use modern technologies at their job.

Insert Table 2 here

[2]Nevertheless, it may be that individual characteristics are more strongly different at the top of the distribution between ICT and non-ICT users.

3 The technological premium: a quantile regression analysis

3.1 Pooled quantile regression with technological dummy

We begin investigating the extent to which the gap in the log wage distribution between modern and traditional workforces can be attributed to differences in the labor market characteristics of these workers, such as age, years of schooling, seniority, nationality, etc. The effects of the covariates on the location, scale and shape of the conditional wage distribution can be easily estimated using a quantile regression framework. This is a major advantage compared to the least square model, which leads only the effects on the location (the conditional mean of the distribution). Since the quantile regression framework allows characteristics to have different returns at different quantiles, at each point of the distribution it can control more fully for differences between wages paid to ICT-users and non-users that are attributable to divergent labor market characteristics. More precisely this technique estimates the θ^{th} quantile of a variable conditional on covariates. The θ^{th} quantile of a random variable y (the monthly wage in our case) conditional on x is the value of q_θ such that $P[y \leq q_\theta/x] = 0$ for $\theta \epsilon (0, 1)$. The quantile regression model assumes that q_θ is linear in x, that is $q_\theta = x\beta(\theta)$[3].

We carry out a series of quantile regressions on a pooled 1998 dataset (resulting from combining the dataset of modern workers with the dataset of traditional workers). Importantly, these pooled quantile regressions impose the restriction that the returns to included labor market characteristics are the same for ICT-users and non-users. More precisely, let w_i be the log wage of individual i and x_i a vector of explanatory variables excluding the "technological dummy" MODERN (which is equal to one when the worker uses at least one of the novel technologies). The model we seek to estimate is:

$$q_\theta(w_i|x_i) = x_i'\beta(\theta) + MODERN\gamma(\theta) \tag{1}$$

where $q_\theta(w_i|x_i)$ is the θ^{th} conditional quantile of w_i. The set of coefficients $\beta(\theta)$, provides the estimated rate of return to the covariates at the θ^{th} quantile of the log wage distribution. We introduce as covariates in the quantile regression a gender dummy, the age of the worker, a quadratic profile of the age, seniority, a quadratic profile of seniority, years of schooling, nationality of the worker, 5 occupational categories, the firm's size and 35 sectoral dummies. The estimated technological dummy (MODERN) coefficients indicate the extent to which the technological wage gap remains unexplained at the various quantiles when we control for differences in the characteristics of modern and traditional workers.

Table 3 summarizes the estimated technological dummy coefficients and the returns to the considered labor market characteristics at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles using the pooled 1998 data. We first comment the results concerning the explanatory variables.

[3]For further detail on the quantile regression method, see the recent book of Koenker (2005).

Insert Table 3 here

The negative effect of gender increases as we move up the wage distribution, which is consistent with the existing literature on the gender gap (see Albrecht, Björklund, and Vroman (2003) or Arulampalam, Booth, and Bryan (2004))[4]. The impact of age and age squared decreases as we move up towards the top of the wage distribution, whereas the influence of seniority remains roughly constant all along the distribution. Rewards to education vary depending on the considered diploma. While returns to CAP−BEP diploma initially decrease and then recover, rewards to the Baccalaureate decrease along the distribution, returns to undergraduate diplomas are U shaped (they reach a minimum in the second quartile) and returns to graduate and postgraduate diplomas raise as we move to the top of the distribution. The effect of nationality is not significant and the rewards associated to each occupation increase both along the distribution and when moving from production to non production occupations.

Recalling that the dummy MODERN captures the wage gap that cannot be attributed to differences in the labor market characteristics between ICT-users and non-users, we find that the technological premium remains fairly stable and small along the wage distribution, at around 6%. This indicates that when controlling for differences in the labor market characteristics between both workforces, we manage to explain most of the observed technological wage gap. Furthermore, the 95% confidence intervals associated to these coefficients overlap all along the distribution, underlining that the coefficients are not statistically different. In sum, when controlling for differences in labor market characteristics and when assuming that modern and traditional workers are equally rewarded for identical characteristics, wage differentials between ICT-users and non-users are greatly reduced, and the upward trend displayed by the observed gap (see Table 2) disappears.

Nevertheless, the previous finding is based on a very restrictive constraint, i.e. the equality in the returns to included labor market characteristics between modern and traditional workers. The following section tests the validity of this hypothesis and proposes an alternative approach to analyze the technological premium.

3.2 Quantile regression by type of worker

In order to test whether the rewards to different labor market characteristics can be assumed to be equal between the modern and the traditional workforces, we implement a quantile regression analysis distinguishing between the common effect affecting both types of workers, which is represented by means of the individual covariate variables, and the specific effect exclusively

[4]This is the so-called glass ceiling effect, according to which women are prevented from reaching top positions. Using matched employer-employee data, Jellal, Nordman, and Wolff (2005) show that the glass ceiling effect is valid in France even once one controls for firms' characteristics.

associated to ICT-users. This last effect is captured through the introduction of crossed explicative variables resulting from multiplying the dummy MODERN by the corresponding covariates. If these crossed terms are significant, we cannot accept the hypothesis of equality in the returns to labor market characteristics since there are significant specific effects linked to the use of ICT[5].

Table 4 summarizes results of our estimates. The individual explanatory variables capture the returns that are common to both types of workers, whereas crossed terms reflect the specific rewards linked to the use of novel technologies. First of all, we remark that the value of the joint F-test is always very significative, implying that the hypothesis of equal returns to labor market characteristics has to be rejected. Therefore, we cannot measure the technological gap from the pooled sample including both types of workers and results provided in the previous section may be misleading.

Insert Table 4 here

Besides, the analysis of the crossed explicative variables (crossed column) permits to determine the labor market characteristics being rewarded differently for modern and traditional workforces. On average, i.e. according to estimates from OLS regression, only returns to gender and to occupation vary between ICT-users and non-users. When studying the rewards to labor market characteristics along the wage distribution, we observe that in the first decile differences in the returns are mainly linked to age and occupation. In the first quartile, the only specific effects being significant are those linked to higher education, occupation and economic sector. The specific effects linked to occupation and economic sector remain significant in the second quartile, where age is also better paid for ICT-users.

In the third quartile, the specific returns associated to occupation and economic sector keep their significance, and those associated to females arise also as significant. In the last decile, only returns to graduate and postgraduate diplomas as well as the specific rewards to various occupations are significant. It is interesting to remark that, at the ninth decile of the distribution, the crossed-term associated to graduate and postgraduate diplomas presents a negative and significant coefficient. Highly qualified ICT-users are worse paid for their schooling diploma than non-users. This may result from the scarcity of high-skilled labor among the traditional workforce[6].

Table 5 presents the quantile log wage regressions by type of worker. Because we cannot assume that ICT-users and non-users are equally rewarded for their labor market characteristics,

[5] Specifically, to assess the joint significativeness of the different crossed terms, we rely on a F-test for each quantile regression.

[6] Indeed, Table 2 shows that only 1.3% of traditional workers has a graduate or postgraduate diploma. It may be that these individuals have reach high top positions, which would be imperfectly measured by the current occupational dummies.

we proceed now to implement a series of quantile regressions analysis over the separate samples of modern and traditional workers. More precisely, Table 5 estimates the effect of gender, age, seniority, education, nationality, occupation, firm's size and economic sector separately for each type of worker at the various percentiles. Since regressions are implemented over different samples, results are not strictly comparable[7].

Insert Table 5 here

Estimations summarized in Table 5 suggest that the negative impact of being a woman on wages is more important among ICT-users along the distribution. The rewards to age are less important for modern workers at bottom of the distribution but this situation is reverted from the first quartile. In contrast, seniority is systematically better rewarded for high-tech users.

As already mentioned in Section 1, a considerable amount of literature has investigated to which extent the adoption of novel technologies promotes an increase in the returns to human capital (see Beaudry and Green (2005), Lee and Kim (2004) or Krueger (1993)). It seems thus interesting to verify that most educational levels are better rewarded for modern workers than for traditional ones all along the distribution. The returns to the CAP−BEP diploma constitute though an exception to this finding. This vocational training diploma is better rewarded on average and at the top of the distribution for low-tech workers.

Another striking exception is represented by the returns to postgraduate diploma which, as previously signaled, are higher for traditional workers at the ninth decile of the wage distribution. However, the last column of Table 5 reveals that in average rewards to graduate and postgraduate diplomas are more important for ICT-users, which seems more coherent with the existing literature on the subject. Furthermore, on average, only returns to the vocational training diploma (CAP−BEP) are more important for the traditional workforce, which suggest that ICT-users have seen their returns to education improved.

3.3 Quantile regression decomposition

We now turn to a quantile regression analysis decomposing the divergence in the log wage distributions of modern and traditional workers into one component that is due to differences in the labor market characteristics between ICT-users and non-users, and another component that responds to differences in the rewards to these characteristics. Specifically, we implement the decomposition at each quantile of the wage distribution following the recent technique developed in Machado and Mata (2005)[8].

[7] However, the significant crossed variables displayed in Table 4 signal which labor market characteristics are differently rewarded for ICT-users and non-users.

[8] Such quantile decompositions have been recently used in the gender gap literature. See for instance Albrecht, Björklund, and Vroman (2003) or Arulampalam, Booth, and Bryan (2004).

Let us briefly describe this decomposition analysis. Let β^t and β^m denote respectively the returns to individual characteristics x^t and x^m in the traditional and the modern group of workers. The decomposition of the technological wage gap can be expressed as follows:

$$x^m\beta^m(\theta) - x^t\beta^t(\theta) = (x^m - x^t)\beta^m(\theta) + x^t(\beta^m(\theta) - \beta^t(\theta)) \tag{2}$$

or :

$$x^m\beta^m(\theta) - x^t\beta^t(\theta) = x^m(\beta^m(\theta) - \beta^t(\theta)) + (x^m - x^t)\beta^t(\theta)) \tag{3}$$

where $(x^m - x^t)\beta^m(\theta)$ and $(x^m - x^t)\beta^t(\theta)$ stand for the part of the technological premium explained by differences in labor market characteristics between the high-tech and low-tech workforces. The terms $x^t(\beta^m(\theta) - \beta^t(\theta))$ and $x^m(\beta^m(\theta) - \beta^t(\theta))$ correspond to the fraction of the premium attributable to differences in the returns to these characteristics. In the first case, i.e. $x^t(\beta^m(\theta) - \beta^t(\theta))$, we are assuming that all workers have the traditional workforce labor market characteristics and we capture the gap attributable to a divergence in the rewards to these characteristics. Conversely, in the second case $x^m(\beta^m(\theta) - \beta^t(\theta))$, we do the same, but consider instead that all workers have the high-tech workforce characteristics. Both terms are interpreted as resulting from a discrimination by the labor market, since individuals with identical characteristics are paid differently.

Thus, when using the Machado-Mata approach we generate two counterfactual densities. We proceed in the following way to generate the first density $x^t\beta^m$:

1. Draw n numbers at random from (0, 1), say θ_1, θ_2, ..., θ_n
2. Using the modern group dataset, estimate the quantile regression coefficient vectors, $\beta^m(\theta_i)$, for $i = 1, .., n$.
3. Make n draws at random with replacement from the traditional group dataset, denoted by x_i^t, for $i = 1, ...n$.
4. The counterfactual density is then generated as $\{y_i = x_i^t\beta^m(\theta_i)\}$ for $i = 1, ..., n$, i.e. we have modern workers having the labor market characteristics of traditional ones but being paid as ICT-users.

In order to get standard errors for the counterfactual gap, we replicate 40 times the decomposition. The second counterfactual density (modern workers paid for their own characteristics as traditional ones) can be estimated by simply reversing the roles of traditional and modern workers in steps 2 and 3[9].

[9] This means that we use the traditional dataset to estimate the quantile regression coefficients and make bootstrap draws from the modern dataset.

So, we obtain two counterfactual densities, one indicating the wages that high-tech workers would earn if they had the labor market characteristics of low-tech ones (x^t) but were paid as modern workers ($\beta^m(\theta)$), and another one indicating the wages that high-tech workers would earn if they had their own characteristics but were paid as traditional workers. Evidently, in the absence of discrimination, we should find that both types of workers are equally remunerated for the same labor market characteristics. Table 6 compares the technological wage gap observed when using our original sample with the fictitious technological gap arising when we consider that modern workers have the traditional workforce characteristics, but are rewarded as ICT-users (column 3) and with the fictitious gap arising when we consider that ICT-users are paid as traditional workers (column 4).

Column 3 of Table 6 reveals that the fictitious technological premium arising when modern workers are considered to have the traditional workforce characteristics, increases smoothly from the first quartile of the distribution, reaching a maximum at the ninth decile where it attains 11.54%. When comparing this fictitious technological premium with the observed one, we remark that discrimination (i.e. the fact that workers with identical characteristics are paid differently) explains at most 23% of the observed gap (at the top of the distribution) implying that earnings divergences between ICT-users and non-users mainly respond to differences in the labor market characteristics.

Insert Table 6 here

A similar conclusion holds when focusing on the fourth column of Table 6. When modern workers are assumed to have their own characteristics but get paid as traditional workers, we find a reduced fictitious gap which falls along the distribution. Therefore, here again, discrimination is not the main factor responsible for the observed technological premium along the distribution, which is more likely to be due to differences in the workers characteristics.

The wage gap between ICT-users and non-users observed along the distribution seems then to respond to a divergence in the labor market characteristics between modern and traditional workers. Discrimination explains only a very reduced fraction of this gap. Furthermore, we evidence that the predicted gap when we assume that modern workers have the traditional workforce characteristics but are paid as modern is larger than when considering that they keep their own characteristics but are rewarded as traditional workers. This suggests that the observed wage inequality between the two labor forces results from a segmentation of the labor market between workers having the required skills and characteristics to use novel technologies, and those workers not having them.

3.4 Mean decomposition of the wage gap

Our previous quantile decompositions assume first that modern workers have the traditional workforce characteristics but are paid as ICT-users, in which case the modern workers wage structure corresponds to the non discriminatory wage structure. When assuming that ICT-users have their own characteristics but are paid as non-users, the traditional wage structure stands for the non discriminatory structure. However, as noticed by Oaxaca and Ransom (1994), the nondiscriminatory structure should lie somewhere "between" the modern and the traditional wage structures.

To get further results using decomposition methods, we restrict our attention to the mean wage gap in the sequel. Following Oaxaca and Ransom (1994), we define the (unadjusted) wage differential (g_{mt}) as:

$$g_{mt} = \frac{w_m}{w_t} - 1 \tag{4}$$

where w_m represents the wages of modern workers ("advantaged" group) and w_t represents the wages of non ICT-users ("disadvantaged" group). In the absence of labor market discrimination the modern/traditional wage differential would reflect pure productivity differences (q_{mt}):

$$q_{mt} = \frac{w_m^0}{w_t^0} - 1 \tag{5}$$

where 0 denotes the absence of labor market discrimination. The market discrimination coefficient denoted by d_{mt} may be defined as the proportionate difference between $g_{mt} + 1$ and $q_{mt} + 1$:

$$d_{mt} = \frac{\frac{w_m}{w_t} - \frac{w_m^0}{w_t^0}}{\frac{w_m^0}{w_t^0}} \tag{6}$$

Equations (4)-(6) imply the following logarithmic decomposition of the gross wage differential:

$$ln(g_{mt} + 1) = ln(d_{mt} + 1) + ln(q_{mt} + 1) \tag{7}$$

This means that the market discrimination coefficient reveals only the relative wage effects of market discrimination, masking how much of the adjusted differential can be attributed to overpayment of modern workers and how much corresponds to underpayment of traditional workers. It is straightforward then to partition the discrimination coefficient into modern overpayment and traditional underpayment components:

$$ln(d_{mt} + 1) = ln(\delta_{m0} + 1) + ln(\delta_{0t} + 1) \tag{8}$$

where $\delta_{m0} = \frac{w_m}{w_m^0} - 1$ is the differential between modern workers current wages and the wages that they would receive in the absence of discrimination, and $\delta_{0t} = \frac{w_t^0}{w_t} - 1$ is the differential between the wage that traditional workers would have received in the absence of discrimination and their current wages. Finally, upon substitution in (7) we obtain:

$$ln(g_{mt}+1) = ln(\delta_{m0}+1) + ln(\delta_{0t}+1) + ln(q_{mt}+1) \quad (9)$$

As remarked by Oaxaca and Ransom (1994), considering the decomposition given by (9) within the framework of semi-logarithmic wage equations estimated by ordinary least squares from cross-section data leads to[10] :

$$ln(g_{mt}+1) = \overline{x'_m}(\widehat{\beta_m} - \beta^*) + \overline{x'_t}(\beta^* - \widehat{\beta_t}) + (\overline{x_m} - \overline{x_t})'\beta^* \quad (10)$$

where $\overline{x}$ is the vector of mean values of the regressors, $\widehat{\beta}$ is the conforming vector of estimated coefficients, and β^* is the estimated non discriminatory wage structure.

The decompositions specified by equations (9) and (10) cannot be made operational without some assumption about what the wage structure would be in the absence of discrimination. Hence, a versatile representation of the estimated nondiscriminatory wage structure is given by:

$$\beta^* = \Omega\,\widehat{\beta_m} + (I - \Omega)\widehat{\beta_t} \quad (11)$$

where Ω is a weighting matrix.

Several cases can then be considered. When the modern workers wage structure is assumed to be the nondiscriminatory structure, then $\Omega = I$, whereas when the traditional workers wage structure is assumed to be the nondiscriminatory one $\Omega = 0$. Reimers (1983) chooses the weighting matrix $\Omega_R = (0.5)I$ for the wage decomposition, while Cotton (1988) adopts a weighting matrix $\Omega_C = l_m I$, where l_m is the fraction of the sample made up by the majority group[11]. Both solutions present the drawback of choosing the weight in an arbitrary manner. Hence, Oaxaca and Ransom (1994) propose a more general weighting matrix specified by:

$$\Omega_0 = (x'x)^{(-1)}(x'_m x_m) \quad (12)$$

where x is the observation matrix for the pooled sample and x_m is the observation matrix for the modern workers' sample. The interpretation of Ω_0 as a weighting matrix is readily seen by noting that $x'x = x'_m x_m + x'_t x_t$, where x_t is the observation matrix for the traditional workers sample. Oaxaca and Ransom (1994) show then that:

$$\widehat{\beta} = \Omega_0\widehat{\beta_m} + (1 - \Omega_0)\widehat{\beta_t} \quad (13)$$

Table 7 summarizes the various results obtained when applying the alternative methods of constructing the weighting matrix Ω. The first row corresponds to the case where $\Omega = 0$,

[10] We consider $ln(\widetilde{w_m}) = \overline{x'_m}\widehat{\beta_m}$ and $ln(\widetilde{w_t}) = \overline{x'_t}\widehat{\beta_t}$

[11] Remark that Reimers weighting matrix is a special case of Cotton's when the modern and traditional sample sizes are the same.

the second row stands for $\Omega = I$, in the third row we use a weighted average as in Cotton (1988) and in the fourth row we use the method proposed in Oaxaca and Ransom (1994) where $\Omega = (x'x)^{(-1)}(x'_m x_m)$.

Insert Table 7

When the traditional workers wage structure is taken as the non discriminatory wage structure, i.e. $\Omega = 0$, we observe that 75.6% of the average gross wage differential ($ln(g_{mt} + 1)$) responds to differences in the labor market characteristics of the workforce fostering a productivity gap ($ln(q_m + 1)$), while only 25% of the wage premium results from discrimination. Similarly, when the modern workers' wage structure is taken as the nondiscriminatory reference (i.e. when $\Omega = I$), the divergence in the workforces productivity manages to explain 87.3% of the mean wage differential.

The intermediary solutions proposed by Cotton (1988)) and Oaxaca and Ransom (1994), do not really change our findings. When using a weighted average matrix, we find that discrimination only justifies 19.2% of the observed wage differential between ICT-users and non-users, while the divergence in the labor market characteristics between both workforces explains the 80.7% left. The pooled sample approach presented by Oaxaca and Ransom (1994) leads to equivalent results, since discrimination explains 12.7% of the average wage gap and productivity differences 87.8%.

In sum, decomposing the mean gross wage differential observed between the modern and the traditional workforces, permits to conclude on the importance of productivity differences between both workforces as a main factor responsible for wage divergence. ICT-users and non-users seem to have clearly differentiated labor market characteristics fostering a wage gap where discrimination plays only a minor role.

4 Intra-wage inequalities: the Lorenz curve

When analyzing wage inequalities between low-tech workers and high-tech ones, we conclude that the observed technological wage gap is mainly due to differences in the labor market characteristics of the workforces, rather than to differences in the rewards to identical labor market characteristics. Differences in the labor market characteristics between the modern and the traditional workforces are likely to result from a segmentation process of the labor market between workers having the required skills to use novel technologies (generally employed in high-tech firms) and unskilled workers employed in low-tech firms.

According to Acemouglu (1999), Kremer and Maskin (1996) and Thesmar and Thoenig (2000), the progressive segregation of the labor market between high-tech firms employing skilled workers and low-tech firms employing unskilled workers, should lead to an increased wage inequality across firms and to a reduced wage dispersion within firms. This section focuses on wage inequalities inside the modern and the traditional workforces. Figure 3 represents the Lorenz curves associated to the wage distribution of both groups.

Insert Figure 3 here

These curves capture whether wages are uniformly distributed among workers or if they are rather more concentrated in certain segments. The farther the curve is from the principal diagonal of the figure, the more concentrated is the wage distribution. In Figure 3, the modern workers curve is below the one associated to the traditional group, so that wage inequalities are more important among ICT-users (since the distribution of wages is more concentrated).

We estimate in Table 8 the interquantile wage differentials along the distribution. More precisely, in the first column of this table, we consider wage dispersion within the wage range covering the distance between the ninth decile and the first decile. In the second column, we analyze how spread are wages at the middle of the distribution, since the considered range covers the difference between the third and the first quartile. Introducing the dummy MODERN permits to capture if the use of novel technologies influences or not intra-wage dispersion.

Insert Table 8 here

We obtain a positive coefficient for the MODERN dummy, which makes sense with the descriptive findings. However, the corresponding estimate remains insignificant at conventional levels, meaning that intra-wage inequalities are mainly due to differences in observed characteristics. So, we conclude that the use of novel technologies does not affect the dispersion of wages along the wage distribution. Differences in the number of years of schooling and in the occupation positively influence the dispersion of wages, whereas age negatively affects it. Finally, intra-wage inequality is more reduced among women.

In summary, even if the Lorenz curves represented in Figure 3 suggest that wages are more concentrated among ICT-users, a detailed analysis of intra-wage dispersion controlling for age, gender, seniority, education, occupation, firm's size and economic sector, reveals that the use of novel technologies does not affect wage dispersion. Wage inequality is thus important between ICT-users and non-users, while within wage inequality does not differ between both groups.

5 Comparing the situations in 1991 and 1998

The introduction of novel technological practices in Europe, and particularly in France, started in the middle 80s and continued all during the nineties. It is thus interesting to compare wage inequalities in 1991 with the situation in 1998. We use the 1991 wave of the Labor Force Survey and the Complementary Survey on Working Conditions. As remarked in sections 2.1 and 2.2, this wave includes less information on the use of ICT, probably due to the fact that these technologies were not yet sufficiently diffused among French establishments. However, we do have data on the use of computers, consoles, robots and other informatics material by the worker in 1991[12], so we can still define a modern worker as a worker using at least one of these technologies.

As for the 1998 dataset, we only consider full time workers employed in the private sector, in firms employing more than 10 people. We keep the same explanatory variables as in 1998, which are gender, age, seniority, nationality, education, occupation, size of the firm and 35 sectoral dummies. We finally eliminate individuals for whom there are missing observations. After this selection process our 1991 sample is reduced to 5248 individuals. We can compare now the situation in 1991, where ICT were less expanded, with the situation in 1998[13].

Figure 4 presents the distribution of the observed and the estimated technological wage gap in 1991 and 1998. The observed gap stands for the wage differential directly provided by our sample, while the estimated gap is computed using quantile regressions with controls for gender, age, seniority, education, nationality, occupation, size of the firm and economic sector. Figure 4 reflects an increasing observed technological premium as we move up the distribution for both 1991 and 1998. However, once we control for the labor market characteristics, the estimated technological gap remains rather flat along the wage distribution. Finally, the observed and the estimated gaps are both more important in 1998 than in 1991.

Insert Figure 4 here

To what point these differences in the technological premium between 1991 and 1998 are significant? Table 9 tests the significativeness of these differentials at all points of the distribution. It represents the observed and estimated technological premium at each percentile of the log wage distribution in 1991 and 1998. We compute a difference-in-difference estimator to determine whether the technological premium increased (which leads to a positive sign) or not during the nineties. A bootstrapping method is used to find the standard errors of the difference-in-difference estimates and build confidence intervals at the 95% level to study if the null hypothesis (same technological gap for both periods) can be accepted or not. When the zero value is not included in the interval, we have to accept that the technological gap is larger in 1998 than in 1991. Conversely, if zero is included, we cannot accept the hypothesis of a rise in the technological premium.

[12] See Table 1 for the comparison between 1991 and 1998.

[13] The comparison is not implemented from a dynamic perspective, since the lack of information on the institutional changes between 1991 and 1998, makes the dynamic analysis incorrect.

Insert Table 9 here

From the upper part of Table 9 we conclude that the observed technological premium is significantly larger at all points of the distribution (except from the first decile) in 1998 with respect to 1991. Furthermore, even when we control for gender, age, seniority, education, nationality, occupation, firm size and economic sector, the estimated technological premium increases significantly between 1991 and 1998 from the middle of the distribution. In the second quartile of the distribution the estimated technological premium is 3.5 points of percentage higher in 1998, in the third quartile this differential equals 2.5 points of percentage and in the ninth decile it attains 3.0 points. In the 10th and 25th percentile of the distribution, zero is included in the confidence interval, indicating that we cannot accept an increase in the estimated technological premium between 1991 and 1998.

The diffusion of novel technologies along the nineties accelerated wage differentials between ICT-users and non-users at the top of the wage distribution[14]. This suggests a clear divergence between the labor market characteristics of the modern and the traditional workforces (segmentation of the labor market). This result is confirmed by Table A1 in the appendix: when assuming that identical characteristics are equally rewarded independently on the use of ICT, most of the technological premium existing in 1991 is explained by differences in the labor market characteristics between the the high-tech and the low-tech workforces. Again, the part of the unexplained gap is significant, but very reduced. Hence, our findings are evidence of a segmentation of the labor market between ICT and non-ICT users during the 90s.

What about intra-wage inequalities? Table 10 provides the decile ordinates of the Lorenz curve for 1991 and 1998, which permits to compare the evolution of wage concentration during these years inside each type of workforce. Concerning the traditional group of workers, Table 10 reveals a slight reduction in intra-wage inequalities in 1998 with respect to 1991. For instance, at the beginning of the nineties, the 10% of the better paid workers concentrated 21.49% of the wage bill while at the end of the decade they cumulated 19.10%. In the modern workers case, intra-wage inequalities along the distribution remain almost constant between 1991 and 1998. There is therefore a persistence in intra-wage inequalities along the nineties in spite of the large diffusion of novel technologies during this period (both types of labor forces remain homogeneous)[15].

The last column of Table 10 compares the variation in intra-wage inequalities inside the traditional and the modern group between 1991 and 1998. For the first half of the distribution, we conclude that the evolution of earnings inequalities is roughly similar for both types of workforces. From the seventh decile of the Lorenz curve, we observe that the reduction in

[14]Then, our results stand in contrast with evidence from the U.S., where Doms, Dunne, and Troske (1997) find a persistence of the technological premium along the nineties.

[15]Table A2 in the appendix confirms that the use of novel technologies does not affect intra-wage dispersion.

intra-wage inequalities has been more important among traditional workers.

Insert Table 10 here

The historical comparison points towards a progressive segmentation of the labor market fostering an increase in the technological premium between 1991 and 1998. The labor markets characteristics of people using novel technologies at their job have become increasingly different with respect to those of non-ICT users, yielding an upturn in the wage gap between both workforces. Conversely, because each group has become increasingly homogenous, especially among the traditional workforce, we observe that intra-wage inequalities remain fairly constant and are even slightly reduced.

6 Conclusion

The purpose of this paper was to gain insight on the effects of new technologies on wage inequalities, using very detailed data collected in France during the 90s. There are two main streams in the economic literature analyzing the consequences of technological adoption on earnings inequality. The first one, represented by Krusell et al. (2000), Autor, Katz, and Krueger (1998), Krueger (1993) or Davis and Haltiwanger (1991), underlines the role of skill-biased technological progress as the driving force of wage inequalities between skilled and unskilled workers inside firms. The second stream, represented by Kremer and Maskin (1996), Thesmar and Thoenig (2000), Bartel and Sichermann (1999), Bailey, Berg, and Sandy (2001) or Dunne and Schmitz (1995), suggests that ICT adoption has fostered a segregation process in which the labor market has become increasingly divided between one segment composed by modern firms employing high-skilled labor, and a second segment including traditional firms employing low-skilled labor. According to this stream, the new labor market structure should lead to important wage inequalities between firms but reduced intra-wage inequalities. For both streams, ICT are expected to stimulate returns to human capital.

Working with the French Labor Force Survey and the Complementary Survey on Working Conditions for 1998, we have analyzed earnings inequalities between ICT-users and non-users along the wage distribution. We find that the observed technological wage gap is more important at the top of the distribution than at the bottom of the distribution. However, insights from quantile regressions and various decomposition analyses indicate that most of this gap results from a divergence in the labor market characteristics between high-tech and low-tech workforces.

The historical comparison confirms this result. The diffusion of novel technologies along the nineties has promoted a progressive segmentation of the labor market between ICT-users and non-users. The increasingly differentiated labor market characteristics between both groups has led the upturn in the technological premium between 1991 and 1998. Finally, the intra-wage inequality analysis reveals that the use of ICT does not significantly affect wage dispersion, the degree of wage concentration inside the traditional and the modern workforces remaining roughly constant between 1991 and 1998.

In summary, our results tend to support the idea that the introduction of ICT over the past decades has promoted a segmentation of the labor market between ICT-users and non-users in France. Inter-wage inequalities between both groups have raised, whereas intra-wage inequalities do not differ between both groups workers. A worthwhile question would be to investigate the impact on the technological premium due to the persistent expansion of novel technologies since the beginning of the 2000s, and we leave this issue for future research.

References

Acemouglu, D. 1999. "Changes in Unemployment and Wage Inequality: an Alternative Theory and Some Evidence." *American Economic Review*, no. 89:1259–1278.

Albrecht, J., A. Björklund, and S. Vroman. 2003. "Is there a Glass Ceiling in Sweden?" *Journal of Labor Economics* 21:145–177.

Arulampalam, W., A.L. Booth, and M.L. Bryan. 2004. "Is There Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wages Distribution." *IZA Discussion Paper*, no. 1373.

Autor, D.H., L.F. Katz, and A.B. Krueger. 1998. "Computing inequality: Have computers changed the labour market?" *Quarterly Journal of Economics* 113:1169–1213.

Bailey, T., P. Berg, and C. Sandy. 2001. "The Effect of High Performance Work Practices on Employee Earnings in the Steel, Apparel and Medical Electronics and Imaging Industries." *Industrial and Labor Relations Review* 54 (2A): 525–543.

Bartel, A., and N. Sichermann. 1999. "Technological Change and Wages: An Interindustry Analysis." *The Journal of Political Economy* 107 (2): 285–325 (April).

Beaudry, P., and D.A. Green. 2005. "Changes in US wages, 1976-2000: Ongoing Skill Bias or Major Technological Change." *Journal of Labor Economics* 23 (3): 609–648 (July).

Caroli, E., and J. Van Reenen. 2001. "Skilled Biased Technological Change? Evidence from a Pannel of British and French Establishments." *Quarterly Journal of Economics* 116 (4): 1449–1492.

Cotton, J. 1988. "On the Decomposition of Wage Differentials." *Review of Economics and Statistics* 70:236–243.

Davis, S., and J. Haltiwanger. 1991. "Wage Dispersion between and within U.S. Manufacturing Plants." *Brookings Papers on Economic Activity. Microeconomics* 1991:115–200.

Doms, M., T. Dunne, and K. Troske. 1997. "Workers, Wages and Technology." *The Quarterly Journal of Economics* 112 (1): 253–290 (February).

Dunne, T., and J.A. Schmitz. 1995. "Wages, Employment Structure and Employer Size-Wage Premia: Their Relationship to Advanced Technology Usage at US Manufacturing Establishments." *Economica* 62:89–107.

Jellal, M., C. Nordman, and F.C. Wolff. 2005. "Theory and evidence on the glass ceiling effect using matched worker-firm data." *Mimeo, University of Nantes.*

Kremer, M., and E. Maskin. 1996. "Wage inequality and segregation by skill." *NBER Discussion Paper*, no. 5718.

Krueger, A. 1993. "How Computers Have Changed the Wages Structure: Evidence from Microdata, 1984-1989." *The Quarterly Journal of Economics* 108 (1): 33–60 (February).

Krusell, P., L.E. Ohanian, J.V. Rios-Rull, and G.L. Violante. 2000. "Capital skill complementarity and inequality: A macroeconomic analysis." *Econometrica* 68 (5): 1029–53.

Lee, S.H., and J. Kim. 2004. "Has the Internet Changed the Wage Structure too?" *Labour Economics* 11:119–127.

Machado, J.A.F., and J. Mata. 2005. "Counterfactual Decomposition of Changes in Wage Distribution using Quantile Regression." *Journal of Applied Econometrics* 20 (4): 445–465.

Oaxaca, R., and M. Ransom. 1994. "On Discrimination and the Decomposition of Wage Differentials." *Journal of Econometrics* 61:5–21.

Reimers, C. 1983. "Labor Market Discrimination Against Hispanic and Black Men." *Review of Economics and Statistics* 65:570–579.

Thesmar, D., and M. Thoenig. 2000. "Creative Destruction and Firm Organization Choice." *Quarterly Journal of Economics* 115 (5): 1201–1237 (November).

Table 1. Percentage of workers using new technologies

Variable	1991	1998
COMP1	23.13%	41.58%
COMP2		19.84%
TERMINAL	25.61%	22.54%
INTERNET	-	7.23%
ROBOT	2.79%	3.47%
OTHER	4.77%	8.85%
ORDERINT	-	31.48%
ORDEREXT	-	17.88%
MODERN	41.79%	56.30%

Source: Surveys CT 1991 and CT 1998.

For 1991, there is no detailed data specifying whether the computer is connected or not to a network. The survey does not contain neither any question on the use of internet (which was probably absent from most French establishments by that time) or the computer means used to transmit orders to the workers.

Table 2. Description of the sample

Variables	Traditional workforce	Modern workforce	All
Dependent variable : Log wage			
Mean	8.892	9.214	9.074
Decile 1	8.575	8.722	8.633
Quartile 1	8.700	8.923	8.780
Quartile 2	8.860	9.157	9.008
Quartile 3	9.063	9.447	9.290
Decile 9	9.290	9.792	9.627
Explanatory variables			
Female	0.269	0.365	0.323
Age	39.34	38.83	39.05
Seniority	10.85	12.34	11.69
Education : No diploma	0.435	0.149	0.274
Education : BEPC	0.063	0.066	0.065
Education : CAP – BEP	0.394	0.315	0.350
Education: Baccalaureate	0.061	0.177	0.126
Education: Undergraduate	0.034	0.167	0.109
Education: Graduate-Postgraduate	0.013	0.126	0.077
French citizenship	0.906	0.973	0.943
Occupation : Executive	0.025	0.203	0.125
Occupation : Intermediary	0.060	0.150	0.111
Occupation : Technician	0.063	0.162	0.119
Occupation : Employee	0.125	0.251	0.196
Occupation : Skilled worker	0.488	0.188	0.319
Occupation : Non-skilled worker	0.239	0.045	0.130
Number of observations	3081	3970	7051

Source: Survey CT 1998.

Table 3. Quantile regression estimates of the log wage – pooled sample

Variables	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean (OLS)
Constant	7.144***	7.646***	7.983***	8.191***	8.342***	7.602***
	(68.59)	(105.59)	(132.85)	(134.90)	(82.38)	(125.20)
Modern	0.062***	0.054***	0.066***	0.061***	0.074***	0.066***
	(5.31)	(6.07)	(8.51)	(7.56)	(5.51)	(8.38)
Female	-0.097***	-0.100***	-0.129***	-0.152***	-0.179***	-0.130***
	(7.54)	(10.70)	(16.34)	(19.40)	(14.40)	(16.32)
Age	0.048***	0.032***	0.026***	0.026***	0.021***	0.040***
	(10.50)	(10.51)	(10.03)	(9.79)	(4.67)	(15.29)
Age² (10e-2)	-0.053***	-0.034***	-0.026***	-0.023***	-0.016***	-0.040***
	(9.73)	(9.08)	(8.10)	(7.12)	(2.89)	(12.47)
Seniority	0.011***	0.013***	0.013***	0.012***	0.010***	0.012***
	(6.44)	(9.52)	(10.69)	(9.47)	(4.44)	(9.83)
Seniority ² (10e-2)	-0.016***	-0.022***	-0.022***	-0.022***	-0.017***	-0.021***
	(3.25)	(5.55)	(6.16)	(6.02)	(2.64)	(5.85)
Education : BEPC	0.068***	0.065***	0.070***	0.070***	0.097***	0.077***
	(3.44)	(4.26)	(5.17)	(5.09)	(4.42)	(5.62)
Education : CAP – BEP	0.078***	0.062***	0.059***	0.066***	0.062***	0.077***
	(6.51)	(6.81)	(7.30)	(7.95)	(4.55)	(9.47)
Education: Baccalaureate	0.107***	0.077***	0.070***	0.088***	0.080***	0.107***
	(6.22)	(5.97)	(6.09)	(7.43)	(4.17)	(9.25)
Education: Undergraduate	0.158***	0.147***	0.139***	0.161***	0.167***	0.172***
	(8.00)	(9.99)	(10.74)	(12.15)	(7.53)	(13.20)
Education: Graduate-Postgraduate	0.179***	0.158***	0.205***	0.299***	0.299***	0.261***
	(7.00)	(8.50)	(12.65)	(18.14)	(10.68)	(15.93)
French citizenship	0.019	0.018	0.020	0.025*	-0.004	0.013
	(0.94)	(1.20)	(1.52)	(1.82)	(0.19)	(0.98)
Occupation : Executive	0.592***	0.646***	0.718***	0.774***	0.896***	0.718***
	(23.62)	(34.58)	(44.93)	(49.00)	(33.72)	(44.55)
Occupation : Intermediary	0.260***	0.281***	0.334***	0.374***	0.458***	0.336***
	(11.29)	(16.51)	(22.71)	(25.25)	(19.19)	(22.61)
Occupation : Technician	0.250***	0.255***	0.275***	0.324***	0.349***	0.292***
	(11.71)	(15.85)	(19.88)	(23.36)	(15.82)	(20.94)
Occupation : Employee	0.095***	0.082***	0.110***	0.144***	0.176***	0.118***
	(4.56)	(5.43)	(8.34)	(10.89)	(8.28)	(8.95)
Occupation : Skilled worker	0.084***	0.086***	0.084***	0.098***	0.104***	0.098***
	(5.25)	(7.11)	(7.98)	(9.31)	(6.07)	(9.16)
Pseudo R^2	0.332	0.377	0.423	0.466	0.495	0.648

Source: Survey CT 1998.

The sample comprises 7051 observations. The different regressions also include 5 dummies for firm's size and a set of 35 sectoral dummies. Significance levels are respectively 1% (***), 5% (**) and 10% (*). Reference categories are respectively 'No diploma' for education and 'Non-skilled worker' for occupation.

Table 4. Quantile regression estimates of the log wage – pooled sample

Variables	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile		Mean (OLS)	
	Primary	Crossed	Primary	Crossed	Primary	Crossed	Primary	Crossed	Primary	Crossed	Primary	Crossed
Constant	6.863***		7.648***		7.873***		8.087***		8.375***		7.553***	
	(53.76)		(74.64)		(89.56)		(80.28)		(56.39)		(88.73)	
Modern firm	0.834***		0.212		0.168		0.008		-0.119		0.196	
	(4.47)		(1.39)		(1.29)		(0.05)		(0.55)		(1.56)	
Female	-0.095***	-0.012	-0.090***	-0.013	-0.095***	-0.040**	-0.132***	-0.038**	-0.167***	-0.026	-0.109***	-0.031*
	(4.61)	(0.47)	(5.46)	(0.62)	(6.90)	(2.31)	(8.58)	(1.97)	(8.14)	(1.02)	(8.29)	(1.86)
Age	0.062***	-0.030***	0.028***	0.002	0.020***	0.009	0.025***	0.007	0.015***	0.014	0.040***	-0.001
	(10.53)	(3.65)	(6.29)	(0.33)	(5.54)	(1.55)	(6.10)	(1.15)	(2.76)	(1.64)	(11.47)	(0.10)
Age² (10e-2)	-0.070***	0.038***	-0.030***	0.001	-0.022***	-0.003	-0.026***	0.000	-0.012*	-0.007	-0.043***	0.007
	(10.03)	(3.83)	(5.67)	(0.16)	(4.78)	(0.48)	(5.21)	(0.02)	(1.73)	(0.68)	(10.02)	(1.07)
Seniority	0.010***	0.004	0.011***	0.002	0.012***	0.002	0.009***	0.003	0.006**	0.004	0.012***	-0.000
	(4.14)	(1.21)	(5.25)	(0.80)	(6.41)	(0.77)	(4.55)	(1.03)	(2.07)	(1.09)	(6.93)	(0.17)
Seniority² (10e-2)	-0.014**	-0.008	-0.019***	-0.004	-0.021***	-0.006	-0.015**	-0.013	-0.007	-0.019	-0.023***	0.001
	(2.14)	(0.87)	(3.00)	(0.42)	(3.73)	(0.84)	(2.37)	(1.42)	(0.82)	(1.52)	(4.26)	(0.13)
Education : BEPC	0.033	0.040	0.060**	0.011	0.047**	0.024	0.067***	-0.003	0.069**	0.019	0.056***	0.022
	(1.22)	(1.05)	(2.50)	(0.33)	(2.29)	(0.84)	(2.87)	(0.10)	(2.22)	(0.44)	(2.82)	(0.79)
Education : CAP – BEP	0.090***	-0.031	0.049***	0.017	0.054***	0.003	0.068***	-0.010	0.061***	-0.011	0.078***	-0.017
	(5.92)	(1.35)	(3.79)	(0.85)	(4.86)	(0.17)	(5.35)	(0.52)	(3.49)	(0.40)	(7.33)	(1.00)
Education: Baccalaureate	0.135***	-0.044	0.074***	0.017	0.065***	0.021	0.072***	0.009	0.063*	0.033	0.101***	-0.000
	(4.75)	(1.25)	(2.94)	(0.55)	(3.01)	(0.77)	(2.97)	(0.31)	(1.83)	(0.77)	(4.86)	(0.00)
Education: Undergraduate	0.144***	0.005	0.110***	0.049	0.115***	0.048	0.162***	0.010	0.164***	0.027	0.156***	0.021
	(3.39)	(0.10)	(3.09)	(1.21)	(3.79)	(1.38)	(4.65)	(0.26)	(3.26)	(0.47)	(5.34)	(0.64)
Education: Graduate-Postgraduate	0.144**	0.037	0.048	0.133**	0.165***	0.075	0.206***	0.078	0.586***	-0.275***	0.248***	0.023
	(2.40)	(0.56)	(0.91)	(2.29)	(3.56)	(1.48)	(3.90)	(1.36)	(7.99)	(3.41)	(5.59)	(0.47)
French citizenship	0.024	0.003	-0.006	0.028	-0.002	0.005	0.006	-0.011	-0.014	-0.001	-0.004	0.017
	(1.07)	(0.07)	(0.30)	(0.79)	(0.11)	(0.17)	(0.31)	(0.32)	(0.51)	(0.03)	(0.22)	(0.58)
Occupation : Executive	0.724***	-0.169***	0.739***	-0.122**	0.799***	-0.139***	0.914***	-0.176***	0.864***	-0.106	0.830***	-0.168***
	(14.88)	(2.84)	(17.18)	(2.33)	(21.64)	(3.10)	(22.12)	(3.53)	(16.42)	(1.62)	(23.23)	(3.89)
Occupation : Intermediary	0.304***	-0.092*	0.322***	-0.054	0.398***	-0.096***	0.458***	-0.112***	0.524***	-0.183***	0.395***	-0.104***
	(8.27)	(1.86)	(10.52)	(1.29)	(15.29)	(2.69)	(15.39)	(2.76)	(12.26)	(3.24)	(15.92)	(3.04)
Occupation : Technician	0.274***	-0.082*	0.292***	-0.063	0.334***	-0.095***	0.390***	-0.099***	0.396***	-0.161***	0.353***	-0.109***
	(9.10)	(1.85)	(10.84)	(1.62)	(14.55)	(2.87)	(15.18)	(2.68)	(11.63)	(3.24)	(16.01)	(3.44)
Occupation : Employee	0.048	0.030	0.025	0.077**	0.065***	0.056*	0.108***	0.047	0.211***	-0.105**	0.084***	0.026
	(1.44)	(0.67)	(0.98)	(2.10)	(3.09)	(1.78)	(4.47)	(1.32)	(6.30)	(2.18)	(4.19)	(0.87)
Occupation : Skilled worker	0.097***	-0.059*	0.086***	-0.020	0.101***	-0.039	0.115***	-0.040	0.133***	-0.098**	0.115***	-0.054**
	(5.28)	(1.69)	(5.59)	(0.67)	(7.62)	(1.49)	(7.76)	(1.35)	(6.63)	(2.46)	(9.06)	(2.18)
Test : crossed effects=0 F-value (prob.)	3.58 ; 0.000		2.37 ; 0.000		3.64 ; 0.000		3.81 ; 0.000		3.41 ; 0.000		2.84 ; 0.000	
Pseudo R^2	0.343		0.386		0.434		0.476		0.506		0.656	

Source: Survey CT 1998.

The sample comprises 7051 observations. The different regressions also include 5 dummies for firm's size and a set of 35 sectoral dummies (all these variables being also crossed with the modern dummy). Significance levels are respectively 1% (***), 5% (**) and 10% (*). Reference categories are respectively 'No diploma' for education and 'Non-skilled worker' for occupation.

Table 5. Quantile regression estimates of the log wage – Traditional versus modern workforces

Variables	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile		Mean (OLS)	
	Traditional	Modern	Traditional	Modern	Traditional	Modern	Traditional	Modern	Traditional	Modern	Traditional	Modern
Constant	6.863***	7.697***	7.648***	7.859***	7.873***	8.042***	8.087***	8.095***	8.375***	8.256***	7.553***	7.750***
	(53.75)	(56.39)	(81.68)	(72.48)	(103.73)	(80.29)	(81.96)	(68.24)	(64.70)	(46.05)	(91.89)	(81.90)
Female	-0.095***	-0.107***	-0.090***	-0.103***	-0.095***	-0.135***	-0.132***	-0.170***	-0.167***	-0.194***	-0.109***	-0.140***
	(4.61)	(7.03)	(5.98)	(8.27)	(8.00)	(12.27)	(8.76)	(13.64)	(9.34)	(11.08)	(8.58)	(13.45)
Age	0.062***	0.031***	0.028***	0.030***	0.020***	0.029***	0.025***	0.032***	0.015***	0.030***	0.040***	0.039***
	(10.53)	(5.25)	(6.89)	(6.00)	(6.42)	(6.49)	(6.23)	(6.12)	(3.16)	(3.88)	(11.88)	(9.33)
Age^2 (10^e-2)	-0.070***	-0.031***	-0.030***	-0.029***	-0.022***	-0.025***	-0.026***	-0.026***	-0.012**	-0.020**	-0.043***	-0.036***
	(10.03)	(4.34)	(6.21)	(4.73)	(5.54)	(4.54)	(5.32)	(4.07)	(1.99)	(2.05)	(10.37)	(6.94)
Seniority	0.010***	0.014***	0.011***	0.013***	0.012***	0.014***	0.009***	0.012***	0.006**	0.010***	0.012***	0.012***
	(4.14)	(5.94)	(5.75)	(6.79)	(7.42)	(7.40)	(4.65)	(5.61)	(2.37)	(2.98)	(7.18)	(6.68)
$Seniority^2$ (10^e-2)	-0.014**	-0.022***	-0.019***	-0.022***	-0.021***	-0.027***	-0.015**	-0.028***	-0.007	-0.026**	-0.023***	-0.022***
	(2.14)	(3.40)	(3.28)	(3.97)	(4.32)	(5.08)	(2.42)	(4.27)	(0.94)	(2.55)	(4.42)	(4.30)
Education : BEPC	0.033	0.073***	0.060***	0.071***	0.047***	0.072***	0.067***	0.064***	0.069**	0.088**	0.056***	0.078***
	(1.22)	(2.76)	(2.74)	(3.21)	(2.65)	(3.46)	(2.93)	(2.63)	(2.55)	(2.48)	(2.92)	(3.98)
Education : CAP – BEP	0.090***	0.059***	0.049***	0.066***	0.054***	0.057***	0.068***	0.057***	0.061***	0.050**	0.078***	0.061***
	(5.92)	(3.35)	(4.15)	(4.43)	(5.63)	(4.10)	(5.47)	(3.49)	(4.01)	(2.07)	(7.59)	(4.66)
Education: Baccalaureate	0.135***	0.091***	0.074***	0.091***	0.065***	0.086***	0.072***	0.081***	0.063**	0.096***	0.101***	0.101***
	(4.75)	(4.33)	(3.22)	(5.22)	(3.48)	(5.18)	(3.03)	(4.18)	(2.10)	(3.34)	(5.03)	(6.46)
Education: Undergraduate	0.144***	0.148***	0.110***	0.159***	0.115***	0.163***	0.161***	0.172***	0.164***	0.191***	0.156***	0.177***
	(3.39)	(6.51)	(3.42)	(8.47)	(4.39)	(9.12)	(4.73)	(8.17)	(3.74)	(6.16)	(5.53)	(10.51)
Education: Graduate-Postgraduate	0.144**	0.181***	0.048	0.181***	0.161***	0.240***	0.206***	0.284***	0.586***	0.311***	0.248***	0.271***
	(2.40)	(6.34)	(0.99)	(8.05)	(4.03)	(11.26)	(3.99)	(11.32)	(9.17)	(8.17)	(5.79)	(13.52)
French citizenship	0.024	0.026	-0.006	0.024	-0.002	0.003	0.007	-0.005	-0.014	-0.015	-0.004	0.013
	(1.07)	(0.80)	(0.32)	(0.83)	(0.12)	(0.13)	(0.35)	(0.16)	(0.58)	(0.34)	(0.23)	(0.53)
Occupation : Executive	0.724***	0.555***	0.739***	0.617***	0.802***	0.660***	0.914***	0.738***	0.864***	0.758***	0.830***	0.662***
	(14.88)	(16.05)	(18.88)	(21.53)	(24.98)	(25.22)	(22.59)	(24.65)	(18.84)	(17.33)	(24.06)	(26.68)
Occupation : Intermediary	0.304***	0.213***	0.322***	0.268***	0.398***	0.302***	0.459***	0.347***	0.524***	0.341***	0.395***	0.291***
	(8.27)	(6.43)	(11.51)	(9.73)	(17.71)	(11.91)	(15.74)	(11.85)	(14.07)	(8.13)	(16.48)	(12.12)
Occupation : Technician	0.274***	0.192***	0.292***	0.230***	0.334***	0.240***	0.390***	0.291***	0.396***	0.235***	0.353***	0.244***
	(9.10)	(5.95)	(11.86)	(8.56)	(16.88)	(9.76)	(15.51)	(10.20)	(13.35)	(5.74)	(16.58)	(10.46)
Occupation : Employee	0.048	0.078**	0.025	0.102***	0.065***	0.121***	0.108***	0.154***	0.211***	0.106***	0.084***	0.110***
	(1.44)	(2.52)	(1.07)	(3.91)	(3.58)	(4.98)	(4.56)	(5.55)	(7.23)	(2.69)	(4.34)	(4.81)
Occupation : Skilled worker	0.097***	0.038	0.086***	0.066***	0.101***	0.062***	0.115***	0.075***	0.133***	0.035	0.115***	0.060***
	(5.28)	(1.26)	(6.12)	(2.63)	(8.82)	(2.66)	(7.94)	(2.78)	(7.60)	(0.90)	(9.39)	(2.73)
Pseudo R^2 - R^2	0.265	0.396	0.268	0.398	0.308	0.423	0.345	0.461	0.388	0.475	0.509	0.644

Source: Survey CT 1998.

The samples comprise respectively 3081 persons working in a traditional firm and 3970 persons working in a modern firm. The different regressions also include 5 dummies for firm's size and a set of 35 sectoral dummies. Significance levels are respectively 1% (***), 5% (**) and 10% (*). Reference categories are respectively 'No diploma' for education and 'Non-skilled worker' for occupation.

Table 6. Quantile decomposition of the modern-traditional wage differential

Distribution	Observed gap	Counterfactual gap	
		$\beta^m x^t$ - $\beta^t x^t$	$\beta^m x^m$ - $\beta^t x^m$
Percentile 10	0.1469	0.0791	0.0879
		(0.0216)	(0.0250)
Percentile 25	0.2231	0.0513	0.0541
		(0.0054)	(0.0077)
Percentile 50	0.2974	0.0746	0.0408
		(0.0034)	(0.0055)
Percentile 75	0.3840	0.0764	0.0297
		(0.0077)	(0.0043)
Percentile 90	0.5015	0.1154	0.0302
		(0.0103)	(0.0112)

Source: Survey CT 1998.
Standard errors obtained with 40 replications of the decomposition are in parentheses.

Table 7. Decomposition of the mean modern-traditional wage differential

Nondiscriminatory wage structure	$\ln(G^{mt}+1) = 0.3222$		$G^{mt} = 0.3801$			
	$\ln(D^{mt}+1)$	$\ln(Q^{mt}+1)$	Discrimination			Q^{mt}
			D^{mt}	δ^{mo}	δ^{t}	
Traditional	0.0785	0.2437	0.0816	0.0816	0.0000	0.2759
	(0.0090)	(0.0101)	(0.0096)	(0.0096)	(0.0000)	(0.0129)
Modern	0.0408	0.2813	0.0416	0.0000	0.0416	0.3249
	(0.0171)	(0.0179)	(0.0179)	(0.0000)	(0.0179)	(0.0236)
Weighted average	0.0620	0.2601	0.0640	0.0180	0.0451	0.2971
	(0.0091)	(0.0092)	(0.0097)	(0.0072)	(0.0047)	(0.0119)
Pooled	0.0392	0.2829	0.0400	0.0172	0.0223	0.3270
	(0.0049)	(0.0087)	(0.0050)	(0.0021)	(0.0028)	(0.0115)

Source: Survey CT 1998.
Bootstrapped standard errors are in parentheses, with 100 replications.

Table 8. Interquantile regression estimates of the log wage

Variables	Interquantile range 10th percentile – 90th percentile	Interquantile range 25th percentile – 75th percentile
Constant	1.198***	0.544***
	(5.05)	(5.09)
Modern firm	0.013	0.007
	(0.60)	(0.51)
Female	-0.081***	-0.051***
	(4.40)	(3.26)
Age	-0.027***	-0.007**
	(2.95)	(2.00)
Age² (10e-2)	0.037***	0.011**
	(3.31)	(2.55)
Seniority	-0.002	-0.001
	(0.63)	(0.70)
Seniority ² (10e-2)	-0.001	-0.000
	(0.13)	(0.08)
Education : BEPC	0.029	0.005
	(1.06)	(0.29)
Education : CAP – BEP	-0.017	0.004
	(1.59)	(0.34)
Education: Baccalaureate	-0.027	0.010
	(1.39)	(0.94)
Education: Undergraduate	0.009	0.013
	(0.39)	(0.70)
Education: Graduate-Postgraduate	0.120***	0.141***
	(3.23)	(3.73)
French citizenship	-0.023	0.007
	(0.58)	(0.38)
Occupation : Executive	0.304***	0.129***
	(8.46)	(4.50)
Occupation : Intermediary	0.198***	0.093***
	(6.95)	(4.33)
Occupation : Technician	0.099***	0.069**
	(4.82)	(2.55)
Occupation : Employee	0.081***	0.061***
	(2.76)	(3.43)
Occupation : Skilled worker	0.020	0.012
	(1.10)	(0.80)

Source: Survey CT 1998.

The sample comprises 7051 observations. The estimated variance-covariance matrix of the estimators (VCE) is obtained via bootstrapping, with 20 bootstrap replications. The different regressions also include 5 dummies for firm's size and a set of 35 sectoral dummies. Significance levels are respectively 1% (***), 5% (**) and 10% (*). Reference categories are respectively 'No diploma' for education and 'Non-skilled worker' for occupation.

Table 9. Comparison of the technological log wage gap in 1991 and 1998

Log wage gap	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Mean (OLS)
Observed gap						
1991	0.145	0.182	0.249	0.336	0.436	0.261
	(0.006)	(0.017)	(0.009)	(0.015)	(0.025)	(0.011)
1998	0.147	0.223	0.298	0.384	0.501	0.322
	(0.011	(0.005)	(0.007)	(0.013)	(0.020)	(0.009)
Difference	0.003	0.034	0.048	0.048	0.065	0.060
	(0.014)	(0.018)	(0.023)	(0.031	(0.029	(0.016)
	[-0.013;0.020]	[0.005;0.072]	[0.001;0.077]	[0.000;0.087]	[0.024;0.097]	[0.019;0.087]
Estimated gap						
1991	0.039	0.036	0.031	0.036	0.044	0.035
	(0.009)	(0.009)	(0.007)	(0.011)	(0.017)	(0.008)
1998	0.062	0.054	0.066	0.061	0.074	0.066
	(0.012)	(0.009)	(0.008)	(0.008)	(0.013)	(0.008
Difference	0.023	0.017	0.035	0.025	0.030	0.031
	(0.016)	(0.010)	(0.012	(0.012)	(0.019)	(0.012)
	[-0.009;0.048]	[-0.003;0.032]	[0.017;0.056]	[0.002;0.046]	[0.005;0.060]	[0.004;0.047]

Source: Surveys CT 1991 and CT 1998.

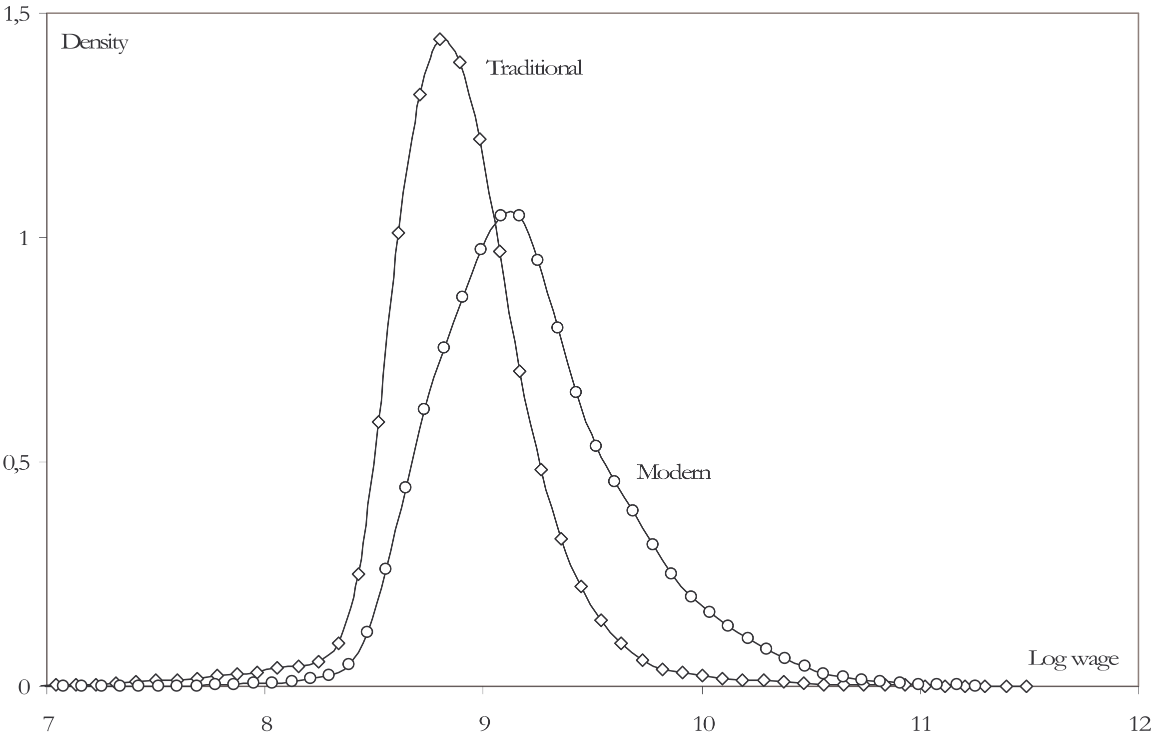
The samples comprise respectively 5248 observations in 1991, and 7051 observations in 1998. Asymptotic standard errors are in parentheses for the 1991 and 1998 estimations, standard errors of the difference-in-difference estimates are obtained via bootstrapping, with 50 bootstrap replications. Bias corrected confidence intervals at the 95 percent level are in brackets. When estimating the log wage gap, the covariates introduced into the regression control for gender, age, age squared, seniority, seniority squared, education, French citizenship, occupation, size of the firm, and sectoral dummies.

Table 10. Decile ordinates of the Lorenz curve, 1991 and 1998

Decile	Traditional workers			Modern workers			Difference in difference
	1991	1998	Difference	1991	1998	Difference	
1	5,84%	5,68%	-0,16%	4,97%	4,92%	-0,05%	0,11%
2	12,72%	12,83%	0,11%	10,93%	10,87%	-0,07%	-0,18%
3	20,08%	20,58%	0,50%	17,57%	17,57%	0,00%	-0,49%
4	27,98%	28,85%	0,88%	24,84%	25,02%	0,18%	-0,69%
5	36,49%	37,68%	1,19%	32,71%	33,17%	0,46%	-0,73%
6	45,53%	47,14%	1,61%	41,43%	42,08%	0,65%	-0,96%
7	55,32%	57,27%	1,95%	51,30%	51,99%	0,69%	-1,26%
8	66,10%	68,35%	2,24%	62,62%	63,39%	0,78%	-1,47%
9	78,51%	80,90%	2,39%	76,66%	77,48%	0,82%	-1,57%

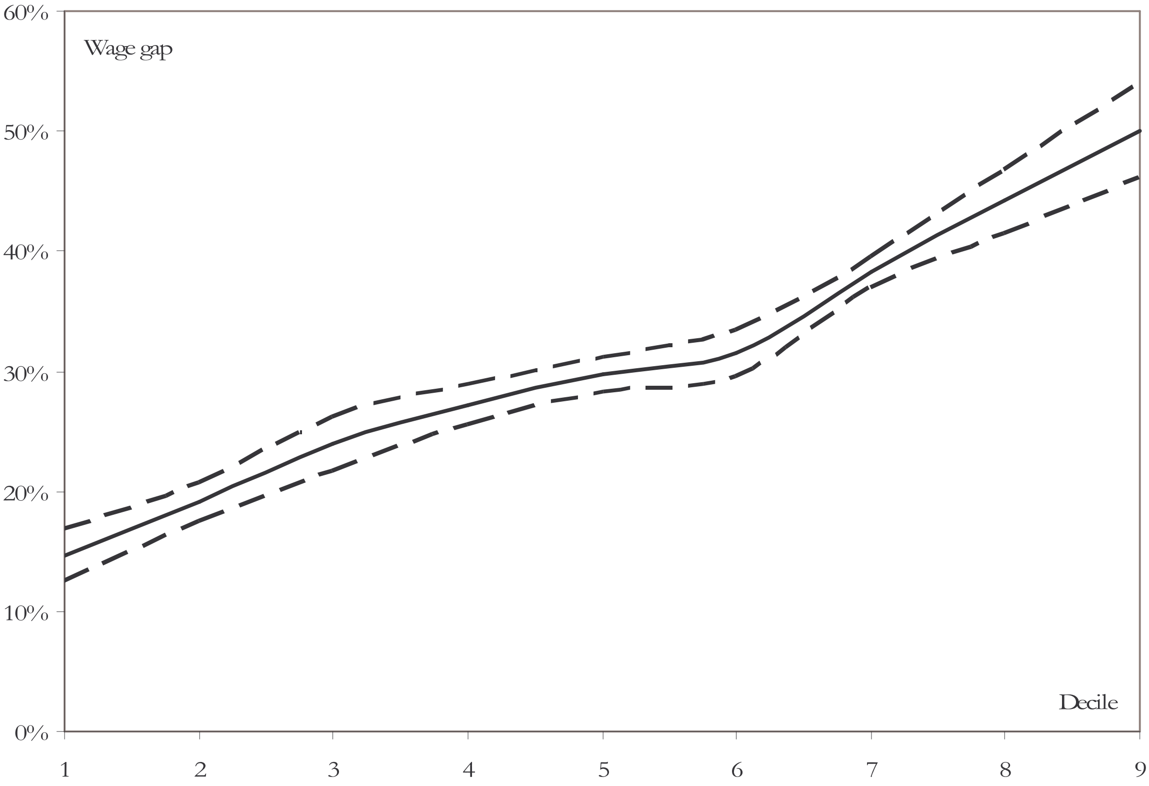
Source : Surveys CT 1991 and CT 1998.

Figure 1. Kernel density estimates of the log wage – Working in a traditional *versus* modern workforces



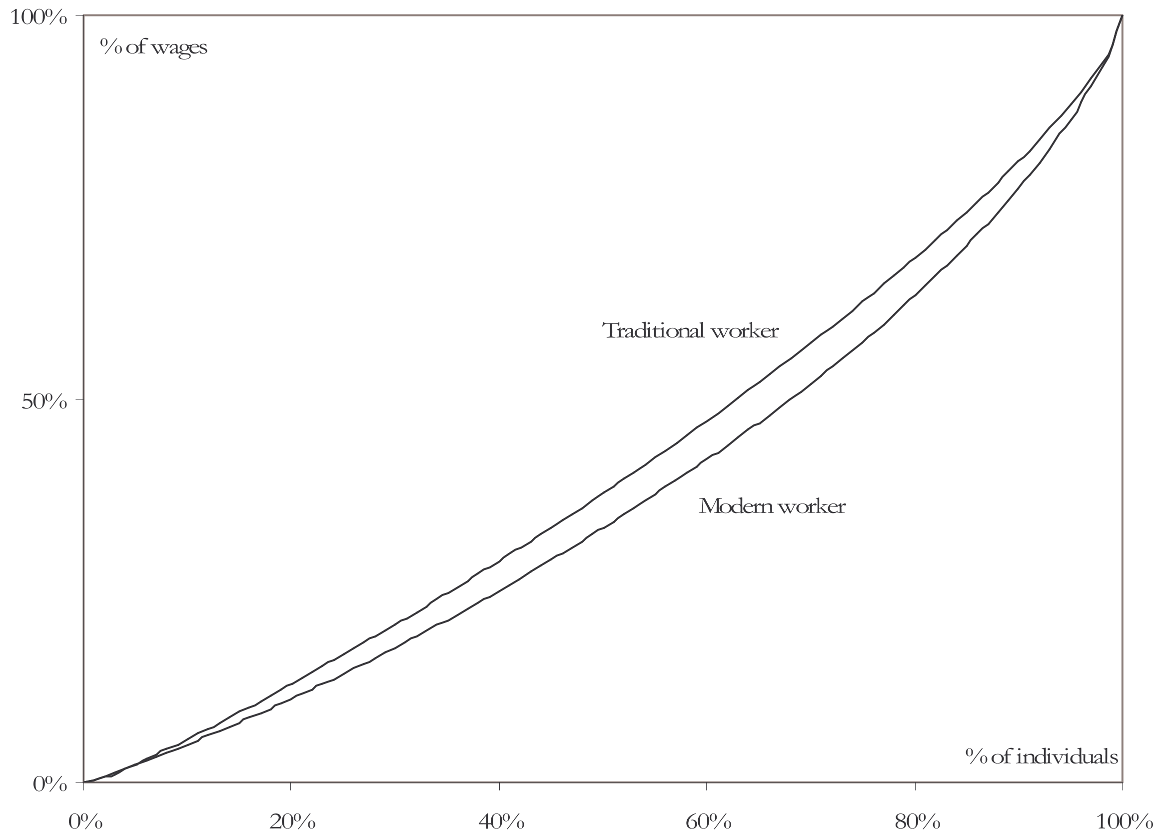
Source: Survey CT 1998.

Figure 2. Log wage gap between working in a traditional *versus* modern workforces



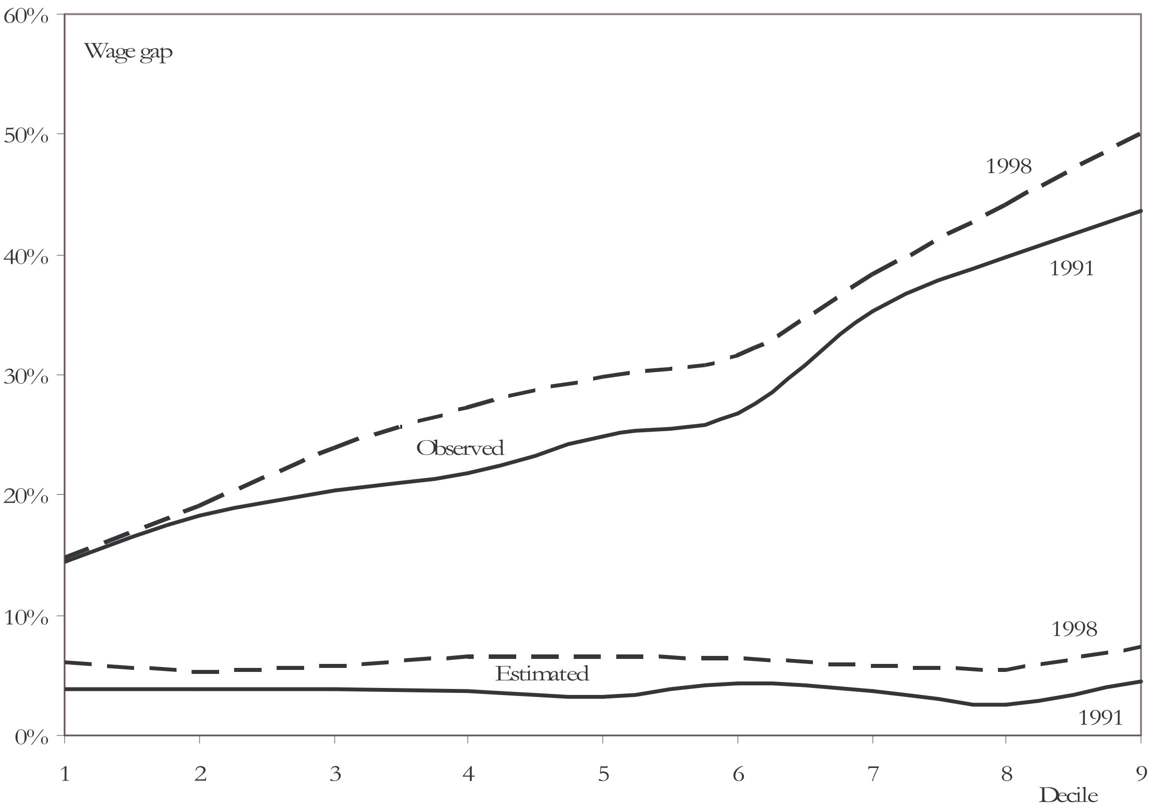
Source: Survey CT 1998.

Figure 3. Lorenz curves for wages, traditional versus modern forces



Source: Survey CT 1998.

Figure 4. Observed and estimated technological log wage gap, 1991 and 1998



Appendix

Table A1. Quantile regression estimates of the 1991 technological log wage gap – pooled sample

Variables	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	Mean (OLS)
Constant	7.446***	7.717***	7.831***	8.039***	8.144***	7.723***
	(95.66)	(115.00)	(140.81)	(97.43)	(63.38)	(117.83)
Modern firm	0.039***	0.036***	0.031***	0.036***	0.044***	0.035***
	(4.16)	(4.18)	(4.36)	(3.26)	(2.61)	(4.12)
Female	-0.105***	-0.100***	-0.112***	-0.134***	-0.192***	-0.129***
	(9.54)	(10.33)	(14.50)	(12.02)	(11.69)	(14.25)
Age	0.025***	0.023***	0.025***	0.023***	0.023***	0.026***
	(8.07)	(8.58)	(11.04)	(6.77)	(4.61)	(9.87)
Age^2 (10^{e}-2)	-0.027***	-0.024***	-0.024***	-0.021***	-0.020***	-0.025***
	(7.30)	(7.22)	(8.67)	(4.85)	(3.20)	(7.56)
Seniority	0.012***	0.009***	0.007***	0.006***	0.005*	0.008***
	(7.62)	(5.94)	(4.97)	(3.16)	(1.70)	(5.06)
Seniority ^{2} (10^{e}-2)	-0.018***	-0.012***	-0.009***	-0.007*	-0.005	-0.012***
	(5.77)	(3.80)	(3.08)	(1.81)	(0.79)	(3.43)
Education : BEPC	0.070***	0.063***	0.093***	0.109***	0.108***	0.092***
	(4.36)	(4.27)	(7.53)	(5.94)	(3.95)	(6.41)
Education : CAP – BEP	0.063***	0.067***	0.075***	0.065***	0.062***	0.071***
	(6.27)	(7.39)	(9.85)	(5.66)	(3.53)	(7.95)
Education: Baccalaureate	0.105***	0.109***	0.132***	0.117***	0.103***	0.114***
	(7.07)	(8.36)	(12.25)	(7.25)	(4.22)	(9.05)
Education: Undergraduate	0.135***	0.149***	0.160***	0.174***	0.150***	0.161***
	(7.22)	(8.98)	(11.65)	(8.27)	(4.66)	(9.93)
Education: Graduate-Postgraduate	0.186***	0.224***	0.247***	0.296***	0.292***	0.265***
	(8.22)	(11.14)	(14.37)	(11.22)	(7.33)	(13.13)
French citizenship	0.063***	0.025*	-0.002	-0.006	-0.006	0.020
	(4.14)	(1.79)	(0.21)	(0.37)	(0.24)	(1.45)
Occupation : Executive	0.671***	0.719***	0.775***	0.841***	1.067***	0.818***
	(30.98)	(38.51)	(51.05)	(37.73)	(32.76)	(45.88)
Occupation : Intermediary	0.288***	0.314***	0.364***	0.415***	0.509***	0.386***
	(14.69)	(18.42)	(26.20)	(20.07)	(16.32)	(23.71)
Occupation : Technician	0.319***	0.317***	0.337***	0.338***	0.350***	0.349***
	(17.50)	(19.76)	(25.66)	(17.44)	(12.14)	(22.66)
Occupation : Employee	0.133***	0.123***	0.136***	0.139***	0.205***	0.158***
	(8.14)	(8.36)	(11.43)	(7.90)	(7.65)	(11.32)
Occupation : Skilled worker	0.099***	0.098***	0.099***	0.098***	0.103***	0.112***
	(7.41)	(8.27)	(10.23)	(6.93)	(4.97)	(9.84)
Pseudo R^2 - R^2	0.321	0.381	0.433	0.478	0.516	0.653

Source: Survey CT 1991.

The sample comprises 5248 observations. The different regressions also include the firm's size and a set of 35 sectoral dummies. Significance levels are respectively 1% (***), 5% (**) and 10% (*).

Table A2. Interquantile regression estimates of the log wage: 1991

Variables	Interquantile range 10th percentile – 90th percentile	Interquantile range 25th percentile – 75th percentile
Constant	0.698***	0.322***
	(6.02)	(3.34)
Modern	0.005	-0.001
	(0.26)	(0.03)
Female	-0.087***	-0.034***
	(4.20)	(2.82)
Age	-0.002	-0.000
	(0.38)	(0.04)
Age² (10e-2)	0.008	0.004
	(1.14)	(0.77)
Seniority	-0.007**	-0.003
	(2.44)	(1.45)
Seniority ² (10e-2)	0.014**	0.005
	(1.97)	(0.90)
Education : BEPC	0.038	0.046**
	(1.42)	(2.00)
Education : CAP – BEP	-0.001	-0.001
	(0.07)	(0.09)
Education: Baccalaureate	-0.002	0.008
	(0.07)	(0.48)
Education: Undergraduate	0.015	0.026
	(0.28)	(0.84)
Education: Graduate-Postgraduate	0.105	0.072**
	(1.18)	(2.07)
French citizenship	-0.069**	-0.031
	(2.43)	(1.65)
Occupation : Executive	0.396***	0.122***
	(6.29)	(4.52)
Occupation : Intermediary	0.221***	0.101***
	(5.25)	(3.17)
Occupation : Technician	0.031	0.021
	(0.86)	(1.13)
Occupation : Employee	0.072*	0.017
	(1.88)	(0.67)
Occupation : Skilled worker	0.003	-0.000
	(0.17)	(0.01)

Source: Survey CT 1991.
The sample comprises 5248 observations. The estimated variance-covariance matrix of the estimators (VCE) is obtained via bootstrapping, with 20 bootstrap replications. The different regressions also include the firm's size and a set of 35 sectoral dummies. Significance levels are respectively 1% (***), 5% (**) and 10% (*).