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# New Technologies and the Gender Wage Gap
## Evidence from France
# Nuevas tecnologías y brecha de géneros en el salario
## Evidencia de Francia
# Nouvelles technologies et différences salariales selon les sexes en France

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Article abstract

This paper focuses on the impact of information and communication technologies (ICT) on the gender pay gap along the wage distribution. Our empirical analysis relies on two complementary French surveys conducted in 1998 and 2005 on a large sample of employees. We estimate quantile regressions and use a difference-in-difference strategy to assess the effect of new technologies. Both in 1998 and 2005, we find that the gender gap estimated for the group of ICT-users is not really different from the gap for non-users. Among ICT-users, wage differentials between men and women are mostly explained by a divergence in the rewards to identical characteristics.

# New Technologies and the Gender Wage Gap

## Evidence from France

**Eva Moreno-Galbis**
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*This paper focuses on the impact of information and communication technologies (ICT) on the gender pay gap along the wage distribution. Our empirical analysis relies on two complementary French surveys conducted in 1998 and 2005 on a large sample of employees. We estimate quantile regressions and use a difference-in-difference strategy to assess the effect of new technologies. Both in 1998 and 2005, we find that the gender gap estimated for the group of ICT-users is not really different from the gap for non-users. Among ICT-users, wage differentials between men and women are mostly explained by a divergence in the rewards to identical characteristics.*

The effect of information and communication technologies (ICT) on wage inequalities between skilled (ICT-users) and unskilled (ICT-non-users) workers has been analyzed by a considerable amount of literature (see, among others, Beaudry and Green, 2005; Lee and Kim, 2004; Krusell *et al.*, 2000; Krueger, 1993). In contrast, the impact of novel technologies on the gender wage gap has been less studied. Using two surveys conducted

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in France in 1998 and 2005, this paper seeks to gain insight on the consequences of ICT adoption on earnings inequalities between women and men along the wage distribution. More precisely, we analyze the gender gap within the group of ICT users and the group of non-users. We refer to both populations respectively as modern and traditional workers.

The economic literature has traditionally analyzed average earnings differences between women and men resulting from divergences in work experience, years of schooling and types of jobs occupied by women and men (see Blau and Kahn, 1996, 2000, for an analysis on various OECD countries). Based on Albrecht, Björklund and Vroman (2003), there starts though to appear an emerging literature interested in the pay gap observed along the wage distribution rather than in average wage differentials between women and men. Moreover, there begins to be a common consensus among the economic profession on the existence of a "glass ceiling" effect.[1] This effect implies that women manage to do quite well in the labour market up to a point after which there is an effective limit on their prospects, *i.e.* women's wages fall behind men's more at the top of the wage distribution than at the middle or the bottom.

In their seminal paper on Sweden, Albrecht, Björklund and Vroman (2003) find that the gender log wage gap increases along the wage distribution and accelerates at the upper tail, suggesting the presence of a glass ceiling effect. Similar studies have been conducted in Germany (Fizenberger and Wunderlich, 2002), Denmark (Datta-Gupta, Oaxaca and Smith, 2006) and Spain (de la Rica, Dolado and Llorens, 2008) among other countries. For instance, the gender gap in Spain expands at the top of the wage distribution for high-educated people, while for the low-educated group, the gap is more significant at the bottom of the distribution.

In France, Ponthieux and Meurs (2006) have shown that the average gender wage gap is about 16 percent, once working time is controlled for. Only two contributions have recently focused on a distributional approach. On the one hand, using matched worker-firm data for about 130,000 employees and 14,000 employers, Jellal, Nordman and Wolff (2008) show that accounting for firm-related characteristics significantly reduces the gender earnings gap at the top of the distribution, but the gender gap still remains much higher at the top than at the bottom. On the other hand, using a large sample of employees working in a French private company from the Defense and Aerospace sector, Barnet-Verzat and Wolff (2008) obtain a gender wage gap of about 8% when controlling for age,

1. Sociologists have also devoted a lot of attention to the glass ceiling phenomenon. See for instance the contribution of Spilerman and Petersen (1999).

experience, qualification and location, which remains rather flat along the wage distribution.

To the best of our knowledge, the existing literature on wage differentials between men and women has not yet considered the effect of novel technologies on the gender gap along the wage distribution. Therefore, our paper attempts to fill this gap. Is the gender pay gap more or less significant among ICT users than among non-ICT-users? Does the gender gap follow the same path in the traditional and modern populations? Is the nature of these wage differentials the same in both populations? From a theoretical viewpoint, our position is that the effect of novel technologies on the gap is uncertain, on a priori grounds.

On the one hand, if one assumes that ICT tend to exacerbate the returns to human capital (Davis and Haltiwanger, 1991; Krueger, 1993; Autor, Katz and Krueger, 1998; Krusell *et al.,* 2000; Lee and Kim, 2004; Beaudry and Green, 2005), we can expect that technological adoption will promote an increase in the gender gap. Women have frequently less years of schooling and less work experience than men, since their professional career is often interrupted by maternity and child care. Thus, with respect to men, their wages are likely to be relatively deteriorated if the market starts giving a premium on human capital.

On the other hand, we can think the other way round and claim that the introduction of ICT has deteriorated men's comparative advantage in certain types of jobs. Because novel technologies require essentially intellectual abilities rather than physical abilities and novel technologies have been introduced in the production process, we can expect a reduction of the men's comparative advantage (in terms of physical force) in many tasks. This should reduce their relative wages with respect to women and promote a fall in the gender gap.

To study the effect of novel technologies on the gender gap, we use individual data obtained from the French Labour Force Survey and the Complementary Survey on Working Conditions for 1998 and 2005. For these two years, we divide our sample into two groups, one made up of individuals employing novel technologies at their job (modern group) and another one comprising individuals not employing them (traditional group). Note that the use of a novel technology is likely to result from the discretionary choice of a worker, this choice being based on potential wages so that estimates of the returns to labour market characteristics of ICT users and non users may be biased.[2] However, we do not compare wages of traditional and modern workers, but we focus instead on wage

2. Entorf, Gollac and Kramarz (1999) show that controlling for selectivity bias is not so important in France when investigating the impact of ICT on wages and employment.

differentials between men and women within the high-tech group and within the low-tech group.

We rely on a difference-in-difference strategy to investigate whether the gender wage gap is different between ICT-users and non-users. We also study whether, within each group of workers, returns to labour market characteristics are the same for females and males. Finally, we carry out a quantile decomposition analysis seeking to identify the extent to which the pay gap observed along the wage distribution responds to differences between women's and men's characteristics or to differences in the returns to these characteristics. Again, this analysis is implemented for the high-tech and low-tech workforces.

Our main results are that the gender gap increases along the wage distribution in both populations. However, wage differentials are not really different among ICT-users and non-users. In the modern group of workers, the divergence in the rewards to identical characteristics mainly explains the gender gap all along the distribution, while it plays a predominant role only at the top of the distribution in the traditional group.

The remainder of this paper is organized as follows. In the next section, we describe the data sources as well as the variables used. The third section includes our econometric results obtained from quantile regressions, a difference-in-difference estimator implemented in order to know whether the gender gap statistically diverges between ICT-users and non-users, and a quantile decomposition of the gender wage gap. The fourth section concludes.

## *DATA AND VARIABLES*

### *The Data Sources*

Our empirical analysis is based on two joint surveys conducted in France respectively in 1998 and 2005 under the supervision of the National Statistical Institute (INSEE). Specifically, we use for these two years the French Labour Force Survey and the Complementary Survey on Working Conditions.

In the Labour Force Survey, a representative sample of 135,000 individuals (belonging to 65,000 households) older than age 15 years is annually interviewed and questioned on their personal and professional status. The survey contains information related to 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. The rate of sampling is 1/300.

The Complementary Survey on Working Conditions is conducted every seven years on a representative sample of 21,000 employed workers interviewed by the Labour 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, which contains information on the use of new technologies (such as computers, consoles, internet, intranet, etc.) by the workers. Even if the number of questions concerning the use of novel technologies is much larger in the 2005 wave, we have selected only those questions having their exact equivalent in the 1998 wave. This will allow us to classify the 1998 and 2005 workforces between modern (high-tech) and traditional (low-tech) workers according to the same criteria.

Because our intent is to analyze the gender wage gap in the high-tech and the low-tech groups, we eliminate from the sample all individuals working in the public sector, where wages are normally fixed by strict French legislation and should not respond to productivity or discrimination reasons. We also eliminate all individuals working in firms that employ less than 10 people and all those for whom there are missing observations. Our remaining sample covers 7,418 individuals for the 1998 wave, having either a full-time or a part-time job, and 4,303 workers for the 2005 wave.[3]

### *The Variables*

We adopt the log of the hourly wage of the worker as our dependent variable in order to control for the divergence in the number of hours worked by each employee. The classification of the individuals between traditional and modern workforces is based on their use of new technologies. To obtain a coherent classification of the labour force between modern and traditional workers for 1998 and 2005, we have used the following ICT variables appearing in both waves of the survey on Working Conditions:

- COMPUTER 1: The worker uses a computer connected to an internal or external network.
- COMPUTER 2: The worker uses a computer not connected to any network.
- LAPTOP: The worker uses a laptop at her job.

3. The size of the sample is significantly lower in 2005 because the size of the firm is missing for many workers in this wave. In our empirical analysis, we have decided to delete these observations as the size of the firm is likely to be strongly related with the use of ICT. For the sake of robustness, we have also included these observations with missing size when estimating the regressions, with an additional dummy picking up the effect of the unknown firm size. This does not affect our results.

- TERMINAL: The worker uses a console.
- INTERNET: The worker uses internet with a professional objective.

We classify as modern any worker employing at least one of the previous technologies (indicator MODERN). To assess the sensitivity of our results to the definition of the classification variable, we have also constructed two additional, more restrictive indicators, where the worker is considered as modern if she employs at least two ICT (MODERN2) or at least three ICT (MODERN3). In the sequel, we will mainly focus, however, on the classification provided by the indicator MODERN.

Unfortunately, we work with individual data and not with plant data. Thus, we are not able to control for unobserved firm heterogeneity and we will miss the positive externality on the productivity perceived by those workers that, in spite of not using ICT, are employed in firms where other workers use novel technologies. This is a drawback of our approach, since we may include people having labour market characteristics much closer to the modern workforce in the group of traditional workers (people employed in high-tech firms, but not using novel technologies). However, because this classification problem concerns both women and men in the traditional group, the analysis of the gender gap within the group should not be affected by it.

Panel A of Figure 1 displays the observed log hourly wage differential between men and women within each type of workers (modern vs. traditional) along the wage distribution for 1998 and 2005.[4] Whereas within the high-tech workforce the gender gap follows a continuously upward trend for both years, 1998 and 2005, wage differentials between men and women inside the traditional group of workers seem to have evolved along the considered period. While there was not a clearly defined trend in 1998, the gender gap follows a decreasing path along the distribution in 2005.

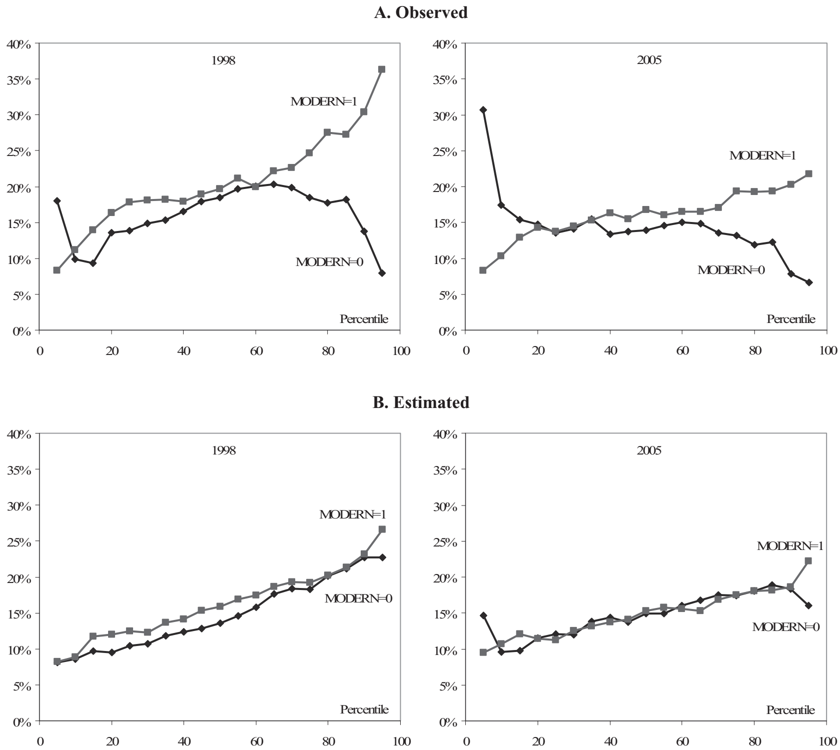
### *The Sample Characteristics*

This divergence in the gender gap observed for each population may result from a divergence of the labour market characteristics between females and males within high-tech workers and low-tech ones. Table 1 summarizes these main characteristics for each population segment.

4. The adopted indicator is MODERN. Main results of this descriptive analysis hold when classifying workers according to MODERN2 or MODERN3. We only observe a remarkable difference in 1998 for MODERN3 = 0, for which the gender gap follows an upward trend at the top of the wage distribution, while this trend is decreasing when considering MODERN or MODERN2. However, it should be noted that the proportion of workers with MODERN3 = 1 is very low in 1998 (10.6%).

FIGURE 1

**Gender Hourly Wage Gap in 1998 and 2005, by Type of Worker**




Source: Surveys CT98 and CT05.

According to the Working Conditions surveys, men belonging to the traditional group of workers have more seniority than women (particularly in 1998), lower diploma levels, higher hourly wage, work less often as partial time workers and are less often employed in very large firms (more than 500 employees) than women. In contrast, while in the 1998 wave traditional men were around the same age as women, in the 2005 wave they are younger on average.

Concerning the modern group of workers, differences in age and seniority between male and female are more pronounced in 1998, where men are slightly older and have more seniority. For both years, there are fewer men with baccalaureate and undergraduate diplomas, but men are more numerous to have a postgraduate diploma. They also have a higher hourly wage and work less often as partial time workers. Finally, contrarily to the traditional group, men are less often employed in firms with less than 500 employees and more often in large firms. The difference between males and females remains though moderate concerning the firm's size (particularly for 2005).

To finish this descriptive approach, it should be noted that in both waves (1998, 2005), women represent around 35% of the workforce being classified as traditional, whereas their representation rises to 44% in 1998 and 47% in 2005 when considering the modern workforce. This tends to support the idea that women may benefit from a comparative advantage in the use of novel technologies, where physical force is not required. Therefore, they are becoming more present within the modern group of workers.

Keeping in mind these differences in the labour market characteristics between women and men depending on the use of novel technologies at work, we now turn to an econometric analysis. We rely on quantile regressions since our descriptive statistics suggest that the gender hourly wage gap varies along the wage distribution.

## ***ECONOMETRIC RESULTS***

### *Pooled Quantile Estimates with Gender Dummies*

We begin by investigating the extent to which the gender gap inside the traditional and modern workforces can be attributed to differences in the labour market characteristics between women and men (such as age, years of schooling, seniority, etc). The effects of the covariates on the location, scale and shape of the conditional wage distribution can be easily estimated using the quantile regression model proposed by Koenker and Bassett (1978).[5] This specification allows individual characteristics to have different returns at different quantiles, so that it can control more fully for differences between wages attributable to labour market characteristics at each percentile of the distribution.

To examine the gender differentials along the wage distribution in the modern and traditional workforces, we carry out for each group of workers a series of quantile regressions on a pooled 1998 dataset and on a pooled 2005 dataset (resulting from combining the dataset of women and men). These pooled quantile regressions impose the restriction that the returns to included labour market characteristics are the same for women and men. We also estimate standard OLS models to study the gender gap at the mean hourly wage.

5. A technical appendix on quantile regressions and quantile decomposition is available from the authors upon request.

TABLE 1

**Description of the Samples**

| *Variables* | *1998* | | | | *2005* | | | |
|---|---|---|---|---|---|---|---|---|
| | *MODERN = 0* | | *MODERN = 1* | | *MODERN = 0* | | *MODERN = 1* | |
| | *Male* | *Female* | *Male* | *Female* | *Male* | *Female* | *Male* | *Female* |
| Age | 39.13 | 39.11 | 38.76 | 38.36 | 42.36 | 44.37 | 41.43 | 41.36 |
| Seniority | 10.98 | 9.47 | 12.66 | 11.62 | 13.18 | 12.72 | 13.85 | 13.71 |
| Education: No diploma | 0.416 | 0.461 | 0.143 | 0.134 | 0.383 | 0.421 | 0.122 | 0.101 |
| Education: BEPC | 0.057 | 0.075 | 0.060 | 0.083 | 0.056 | 0.087 | 0.075 | 0.068 |
| Education: CAP – BEP | 0.440 | 0.290 | 0.329 | 0.298 | 0.439 | 0.309 | 0.274 | 0.222 |
| Education: Baccalaureate | 0.055 | 0.081 | 0.166 | 0.205 | 0.090 | 0.101 | 0.175 | 0.238 |
| Education: Undergraduate | 0.021 | 0.074 | 0.165 | 0.175 | 0.020 | 0.054 | 0.174 | 0.228 |
| Education: Graduate-Postgraduate | 0.012 | 0.018 | 0.138 | 0.104 | 0.012 | 0.029 | 0.180 | 0.144 |
| Number of worked hours per month | 157.67 | 134.74 | 163.51 | 147.40 | 149.95 | 128.79 | 161.04 | 140.71 |
| Part-time job | 0.046 | 0.332 | 0.022 | 0.208 | 0.048 | 0.332 | 0.021 | 0.232 |
| Hourly wage (ln) | 1.970 | 1.815 | 2.312 | 2.107 | 2.213 | 2.087 | 2.521 | 2.363 |
| French citizenship | 0.892 | 0.927 | 0.975 | 0.980 | 0.944 | 0.955 | 0.973 | 0.991 |
| Firm's size: 10–49 employees | 0.378 | 0.305 | 0.201 | 0.277 | 0.385 | 0.329 | 0.204 | 0.235 |
| Firm's size: 50–499 employees | 0.370 | 0.397 | 0.324 | 0.334 | 0.367 | 0.341 | 0.321 | 0.312 |
| Firm's size: 500–999 employees | 0.069 | 0.085 | 0.096 | 0.090 | 0.069 | 0.105 | 0.091 | 0.091 |
| Firm's size: > 1000 employees | 0.182 | 0.213 | 0.379 | 0.299 | 0.179 | 0.226 | 0.383 | 0.362 |
| Number of observations | 2324 | 1264 | 2149 | 1681 | 988 | 554 | 1458 | 1303 |

Source: Surveys CT98 and CT05.

We introduce as covariates in the various regression age and seniority of the worker (with a quadratic profile in both cases), six dummies corresponding to the level of diploma, two dummies for part-time job and French citizenship, firm's size and 16 sector dummies.[6] We also add a dummy variable which is equal to one when the worker is a woman, and to zero otherwise. In the various regressions, the estimated gender dummy coefficients indicate the extent to which the gender gap, for both the traditional and modern sectors, remains unexplained at the various percentiles when we control for differences in the observed characteristics between women and men.

To completely isolate the effect of gender, we could also take into account the fact that some occupations are more technologically intensive than others. However, as remarked by Albrecht, Björklund and Vroman (2003), introducing occupations as a covariate may create an endogeneity problem since these occupations are also the result of the glass ceiling effect. This would be, for instance, the case if employers prevent women from reaching top positions in their firms such as managerial or executive positions. Therefore, in what follows, we do not control for these occupations in the different regressions.

In Table 2, we summarize the estimated coefficients for the OLS regressions using the 1998 and 2005 data. The estimated average gender gap amounts to 14.4% in 1998 and to 14.2% in 2005, when considering the traditional group of workers. In contrast, in the modern group of workers, the gender gap amounts to 17.0% in 1998 and to 15.4% in 2005. Wage differentials explained by the fact of being a woman are thus more important within ICT users independently on the wave we consider, but we also note that the magnitude of the gender gap has decreased over time.

In average (OLS), the sign of the coefficients associated to each of the covariates responds to what could be expected in both populations and both years. Returns increase with age, seniority and the diploma level. The size of the firm is significant in 1998, where working in a larger firm is always better rewarded independently of the considered group of workers. Conversely, in 2005, working in a large firm is better paid only for modern workers.

Panel B of Figure 1 displays the estimated coefficients associated to the gender dummy variable at the various percentiles for the high-tech and low-tech groups using the pooled 1998 and 2005 datasets and the MODERN

6. To test the robustness of our results, we have also implemented these regressions without controlling for the economic sector. Again, this has little influence on our different econometric results. All these additional results are in an appendix available from the authors upon request.

TABLE 2

**OLS Estimates of the Gender Log Wage Gap, by Type of Worker**

| *Variables* | *1998* | | *2005* | |
|---|---|---|---|---|
| | *MODERN = 0* | *MODERN = 1* | *MODERN = 0* | *MODERN = 1* |
| Constant | 0.957*** | 0.851*** | 1.298*** | 1.293*** |
| | (7.78) | (7.67) | (6.40) | (10.31) |
| Female | –0.144*** | –0.170*** | –0.142*** | –0.154*** |
| | (11.33) | (16.18) | (7.23) | (11.17) |
| Age | 0.038*** | 0.048*** | 0.022*** | 0.037*** |
| | (7.86) | (8.83) | (2.76) | (6.55) |
| $Age^2$ (/100) | –0.040*** | –0.043*** | –0.018* | –0.033*** |
| | (6.63) | (6.18) | (1.88) | (4.69) |
| Seniority | 0.017*** | 0.014*** | 0.006* | 0.009*** |
| | (9.35) | (6.72) | (1.76) | (3.53) |
| $Senirity^2$ (/100) | –0.031*** | –0.024*** | –0.006 | –0.010 |
| | (5.32) | (3.82) | (0.61) | (1.45) |
| Education: BEPC | 0.076*** | 0.135*** | 0.108*** | 0.088*** |
| | (3.18) | (6.33) | (2.76) | (2.97) |
| Education: CAP – BEP | 0.112*** | 0.094*** | 0.122*** | 0.092*** |
| | (10.40) | (6.60) | (6.52) | (4.31) |
| Education: Baccalaureate | 0.197*** | 0.189*** | 0.215*** | 0.164*** |
| | (9.16) | (11.56) | (6.74) | (7.19) |
| Education: Undergraduate | 0.393*** | 0.331*** | 0.403*** | 0.311*** |
| | (10.23) | (18.39) | (9.29) | (13.28) |
| Education: Graduate- | 0.585*** | 0.592*** | 0.560*** | 0.498*** |
| Postgraduate | (7.79) | (28.17) | (5.39) | (19.54) |
| Part-time job | –0.045** | –0.041** | 0.067** | –0.017 |
| | (2.49) | (2.41) | (2.01) | (0.87) |
| French citizenship | 0.015 | –0.029 | 0.000 | –0.030 |
| | (0.93) | (0.83) | (0.01) | (0.54) |
| Firm's size: 50–499 | 0.023** | 0.041*** | 0.022 | 0.002 |
| employees | (2.06) | (3.19) | (1.17) | (0.09) |
| Firm's size: 500–999 | 0.059*** | 0.051*** | –0.052 | 0.064*** |
| employees | (3.27) | (2.73) | (1.31) | (2.82) |
| Firm's size: > 1000 | 0.080*** | 0.076*** | 0.014 | 0.066*** |
| employees | (5.36) | (5.69) | (0.59) | (3.85) |
| Number of observations | 3588 | 3830 | 1542 | 2761 |
| $R^2$ | 0.33 | 0.48 | 0.21 | 0.34 |

Source: Surveys CT98 and CT05.

Absolute values of t statistics are in parentheses. Significance levels are respectively 1% (***), 5% (**) and 10% (*). The different regressions also include a set of 16 dummies related to the firm's sector.

indicator.[7] For both years, once we have controlled for the observable labour market characteristics, we find that the proportion of the wage explained by the simple fact of being a man increases continuously along the wage distribution. The gender wage gap is about twice higher at the top of the wage distribution than at the bottom. Also, we note that the estimated gender gap is larger within the modern workforce in 1998, while there are no remarkable differences in the estimated gender gap in 2005 between the high-tech and low-tech workforces.

Independently of the year and of the group of workers we consider, we conclude that men significantly out earn women and that wage differentials follow an upward trend. It matters to control for the divergence in labour market characteristics, as this considerably affects the results we observed for the traditional group of workers where the gender gap did not display a clear trend in 1998 and was decreasing in 2005. In contrast, for the modern group of workers, results are only slightly modified when we control for the objective characteristics. Nevertheless, we observe a reduced magnitude in the gender wage gap.

Our econometric results suggest that the estimated wage gap between men and women is more significant among ICT-users than among non-users in 1998, whereas in 2005 results are more ambiguous. Hence, a question worth asking is to know whether these differences in the estimated gender gap in the high-tech and the low-tech groups are significant. To test this point, we rely on a difference-in-difference strategy. Let $\gamma_T$ and $\gamma_M$ be the estimates associated to the gender dummy variable respectively for traditional and modern workforces. At various points of the distribution, we compute the difference $\Delta\gamma = \gamma_M - \gamma_T$. We rely on a bootstrapping method to compute standard errors and to obtain a confidence interval of our estimator (Efron and Tibshirani, 1993).[8]

The values of the difference-in-difference estimates are described in Panel A of Table 3 for the MODERN indicator. Our conclusions are twofold. First, the gender gap can be accepted to be equal in the traditional and modern workforces all along the distribution when we consider the year 2005. In contrast, for 1998, wage differentials between men and women can be accepted to be equal at the bottom (first decile and quartile) and upper part (third quartile and ninth decile) of the wage distribution. In the

7. For the sake of place, we only focus here on the role of the gender dummy variable along the wage distribution, whose estimates are in Table 3. Results from the different quantile regressions are available upon request.

8. Specifically, we use 50 bootstrap replications and confidence intervals are bias corrected.

middle of the distribution (second quartile), the gender gap is estimated to be slightly more important within the modern workforce.

The situation is different if we consider tighter indicators of modernity. When using MODERN2, the gender gap in the high-tech workforce is significantly larger than in the low-tech group from the middle of the distribution for 1998. In 2005, the only significant difference between the gender gap arises in the second quartile. Finally, when the total population is classified according to MODERN3, no divergence in the gender gap computed for modern and traditional workers arises for 1998. In 2005, the gap is significantly different between both groups only at the first quartile.

In sum, the use of novel technologies does not seem to significantly improve or deteriorate earnings inequality between women and men. Independently of the modernity indicator we use, the gender gap estimated for the modern workforce is not systematically higher or lower than the gap estimated for the traditional workforce.

### ***Pooled Quantile Regressions with Interacted Variables***

The main restriction imposed by the previous series of quantile regressions is that the returns to observable labour market characteristics are the same for women and men. In order to test the validity of this assumption, we implement a similar regression analysis but introducing a set of interacted explanatory variables, so that the individual covariates capture the effect that is common to men and women, and the interacted terms refer to the specific returns linked to the fact of being a female.[9] We then use a F-test to test the joint significativeness of the crossed variables. If they are significant, we cannot accept the hypothesis of equality in the returns to labour market characteristics since there do exist significant female specific effects.

Results of the regressions including both the individual covariates and the interacted terms reveal that, apart from the third quartile of the modern workforce in 2005, where the interacted variables are not jointly significant (there are no women specific effects), in the rest of the regressions (modern and traditional workforces in 1998 and 2005) the interacted terms arise as jointly significant.[10]

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9. The interacted explanatory variables result from multiplying the female dummy by the different control variables.

10. These results are not reported in the present version of the paper, but they are available upon request.

TABLE 3

**Difference-in-Difference Estimates of the Gender Wage Gap**

***A. With the MODERN indicator***

| *Variables* | *1998* | | | *2005* | | |
|---|---|---|---|---|---|---|
| | *Gender dummy MODERN = 0* | *Gender dummy MODERN = 1* | *Difference in difference* | *Gender dummy MODERN = 0* | *Gender dummy MODERN = 1* | *Difference in difference* |
| Percentile 10 | –0.086 (0.019) | –0.089 (0.013) | –0.003 (0.023) | –0.096 (0.029) | –0.107 (0.017) | –0.011 (0.037) |
| | | | [–0.040;0.040] | | | [–0.083;0.036] |
| Percentile 25 | –0.104 (0.011) | –0.125 (0.012) | –0.021 (0.013) | –0.121 (0.019) | –0.112 (0.014) | 0.009 (0.023) |
| | | | [–0.044;0.000] | | | [–0.039;0.038] |
| Percentile 50 | –0.136 (0.009) | –0.159 (0.009) | –0.023 (0.014) | –0.149 (0.016) | –0.153 (0.014) | –0.004 (0.023) |
| | | | [–0.053;–0.001] | | | [–0.047;0.049] |
| Percentile 75 | –0.183 (0.013) | –0.192 (0.016) | –0.009 (0.024) | –0.174 (0.019) | –0.175 (0.016) | –0.001 (0.023) |
| | | | [–0.055;0.023] | | | [–0.036;0.040] |
| Percentile 90 | –0.227 (0.022) | –0.232 (0.020) | –0.005 (0.032) | –0.183 (0.042) | –0.186 (0.026) | –0.003 (0.037) |
| | | | [–0.067;0.042] | | | [–0.068;0.035] |
| Mean | –0.144 (0.012) | –0.170 (0.010) | –0.027 (0.016) | –0.142 (0.020) | –0.154 (0.013) | –0.012 (0.023) |
| | | | [–0.061;0.004] | | | [–0.063;0.032] |

TABLE 3 (continued)

***B. With the MODERN2 indicator***

| *Variables* | *1998* | | | | | | *2005* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Gender dummy MODERN2 = 0* | | *Gender dummy MODERN2 = 1* | | *Difference in difference* | | *Gender dummy MODERN2 = 0* | | *Gender dummy MODERN2 = 1* | | *Difference in difference* | |
| Percentile 10 | –0.077 | (0.014) | –0.110 | (0.022) | –0.033 | (0.028) | –0.100 | (0.022) | –0.116 | (0.026) | –0.016 | (0.029) |
| | | | | | [–0.102;0.013] | | | | | | [–0.045;0.037] | |
| Percentile 25 | –0.098 | (0.010) | –0.103 | (0.016) | –0.005 | (0.022) | –0.104 | (0.014) | –0.128 | (0.018) | –0.024 | (0.020) |
| | | | | | [–0.044;0.027] | | | | | | [–0.055;0.022] | |
| Percentile 50 | –0.126 | (0.010) | –0.169 | (0.015) | –0.043 | (0.022) | –0.125 | (0.014) | –0.159 | (0.018) | –0.034 | (0.023) |
| | | | | | [–0.092;–0.019] | | | | | | [–0.082;–0.005] | |
| Percentile 75 | –0.160 | (0.012) | –0.192 | (0.021) | –0.032 | (0.020) | –0.156 | (0.017) | –0.174 | (0.017) | –0.018 | (0.034) |
| | | | | | [–0.071;–0.002] | | | | | | [–0.075;0.051] | |
| Percentile 90 | –0.183 | (0.018) | –0.244 | (0.047) | –0.061 | (0.031) | –0.141 | (0.036) | –0.179 | (0.035) | –0.038 | (0.060) |
| | | | | | [–0.095;–0.016] | | | | | | [–0.106;0.049] | |
| Mean | –0.127 | (0.009) | –0.178 | (0.015) | –0.051 | (0.019) | –0.125 | (0.015) | –0.156 | (0.016) | –0.031 | (0.021) |
| | | | | | [–0.087;–0.012] | | | | | | [–0.063;0.019] | |

TABLE 3 (continued)

***C. With the MODERN3 indicator***

| *Variables* | *1998* | | | | | | *2005* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Gender dummy MODERN3 = 0* | | *Gender dummy MODERN3 = 1* | | *Difference in difference* | | *Gender dummy MODERN3 = 0* | | *Gender dummy MODERN3 = 1* | | *Difference in difference* | |
| Percentile 10 | –0.073 | (0.012) | –0.067 | (0.027) | 0.006 | (0.059) | –0.089 | (0.017) | –0.110 | (0.048) | –0.021 | (0.041) |
| | | | | | [–0.073;0.102] | | | | | | [–0.052;0.056] | |
| Percentile 25 | –0.102 | (0.009) | –0.100 | (0.028) | 0.002 | (0.019) | –0.105 | (0.010) | –0.176 | (0.041) | –0.071 | (0.031) |
| | | | | | [–0.026;0.031] | | | | | | [–0.099;–0.026] | |
| Percentile 50 | –0.128 | (0.008) | –0.122 | (0.025) | 0.006 | (0.029) | –0.124 | (0.010) | –0.149 | (0.018) | –0.025 | (0.027) |
| | | | | | [–0.024;0.040] | | | | | | [–0.054;0.041] | |
| Percentile 75 | –0.163 | (0.011) | –0.166 | (0.041) | –0.003 | (0.032) | –0.146 | (0.014) | –0.163 | (0.030) | –0.017 | (0.041) |
| | | | | | [–0.051;0.058] | | | | | | [–0.085:0.059] | |
| Percentile 90 | –0.201 | (0.016) | –0.179 | (0.038) | 0.023 | (0.076) | –0.136 | (0.023) | –0.219 | (0.046) | –0.083 | 0.064 |
| | | | | | [–0.084;0.112] | | | | | | [–0.176;0.029] | |
| Mean | –0.136 | (0.008) | –0.153 | (0.026) | –0.017 | (0.028) | –0.121 | (0.012) | –0.168 | (0.028) | –0.047 | (0.032) |
| | | | | | [–0.073;0.015] | | | | | | [–0.104;0.010] | |

Source: Surveys CT98 and CT05.
Standard errors are in parentheses, confidence intervals at the 95 percent level are in brackets. Standard errors of the difference estimator are obtained via bootstrapping (with 50 bootstrap replications), and confidence intervals are bias corrected.

These results differ only for the modern workforce in 2005 when we consider tighter definitions of modernity. When working with the indicator MODERN2,[11] women specific effects arise as significantly different from zero in 1998 and 2005 when considering the traditional workforce (apart from the 90$^{th}$ percentile in 2005). In contrast, for the modern group of workers, we can only admit the presence of gender effects in 1998 (apart from the 90$^{th}$ percentile). In 2005, even if in average (OLS regression) women are differently rewarded for identical characteristics, along the distribution the interacted terms do not arise as being significantly different from zero (apart from the 50$^{th}$ and 90$^{th}$ percentiles).

Two conclusions can thus be drawn from our analysis. First, as far as the definition of modern worker is not too tight, identical labour market characteristics are differently rewarded between men and women along the wage distribution for traditional and modern workers in 1998. Second, in 2005, women specific effects are systematically significant (independently of the modernity indicator we consider) for the traditional workforce, whereas for the modern workforce they only arise as significant along the wage distribution when considering the indicator MODERN.

Whereas the F-test permits to determine whether women specific effects are jointly significant, the analysis by individual interacted variables permits to underline more precisely the labour market characteristics being paid differently for men and women. It seems interesting to compare if these discriminatory characteristics (in the sense that they are differently rewarded depending on the gender) are the same for ICT users and non users.

In average, there are no particular labour market characteristics being rewarded differently for men and women in 2005, neither in the traditional or the modern workforce. When studying the rewards to labour market characteristics along the wage distribution, we realize that for modern workers, women employed in part time jobs are less paid along the first half of the wage distribution. When focusing on the low-tech workforce, there are no characteristics presenting a systematic significant woman specific effect along the distribution. However, in the ninth decile of the wage distribution, we find that seniority is less rewarded for women whereas age and postgraduate diplomas are more rewarded.

In 1998, the baccalaureate, the graduate and postgraduate diplomas and the fact of working in a firm of more than 1000 employees are in average less rewarded for modern women. In contrast, in the traditional group of

11. When considering the tightest modernity indicator, MODERN3, a convergence problem arises when focusing on the modern workforces due to the scarcity of observations. However, women specific effects arise as significant when considering the traditional group of workers for 1998 and 2005.

workers, female specific effects are in average negative when considering age and CAP-BEP diploma and positive for undergraduate diplomas and a firm's size between 50–499.

When studying the rewards to labour market characteristics in 1998 along the wage distribution, we find that within modern workers graduate and postgraduate diplomas are less paid for women along the first half of the distribution. In contrast, modern women employed in firms having between 50 and 499 workers are better paid along the first quartile of the distribution and less paid in the ninth decile.

Concerning the traditional workforce, age is less rewarded along the wage distribution and the CAP-BEP diploma in the middle of the distribution. In contrast women holding an undergraduate diploma or being employed in a firm having between 50 and 499 workers are better paid almost all along the distribution.

So, the main conclusion of these quantile regressions with interacted variables is that assuming that men and women are equally rewarded for identical labour market characteristics does not seem appropriate.

### *A Quantile Regression Decomposition*

Part of the observed gender gap may be explained by objective differences in the labour market characteristics between men and women, whereas another part of the gap may be due to a divergence in the rewards to identical labour market characteristics. In this subsection, we develop a quantile decomposition analysis which allows us to decompose the gender wage gap into these two components, i.e. the divergence in the labour market characteristics and the difference in the rewards to these characteristics. The decomposition is implemented at each quantile of the wage distribution using the technique developed in Machado and Mata (2005).[12]

The Machado-Mata approach allows generating a counterfactual density of the female log wage that would arise if women were given men's labour market characteristics, but continued to be "paid like women". In the absence of discrimination against women, we should find that both types of workers are equally remunerated for the same labour market characteristics. In Table 4, we decompose, for the three modern indicators, the gender gap between a component responding to differences in objective characteristics, denoted by $\Delta X$, and an unexplained component that we interpret as resulting from the divergence in the rewards to identical characteristics, denoted by $\Delta\beta$.

12. Quantile decomposition techniques have been recently adopted by the gender gap and glass ceiling literature (Albrecht, Björklund and Vroman, 2003). The quantile decomposition is an extension of the well-known Oaxaca-Blinder decomposition, which is implemented at the mean of the sample.

Independently on the year or the modernity indicator we consider, estimated results reveal that, in average, the part of the gender gap resulting from the divergence in the rewards to identical characteristics represents more than 80% of the total gap, for both the modern and traditional workforces. Results are though modified as soon as we consider the decomposition by quantiles.

Let us start with the 2005 wave. When the population is classified according to the indicator MODERN, we find that the $\Delta\beta$ component explains almost the total gender gap estimated for the high-tech workforce along the distribution. In contrast, when focusing on the traditional workforce, we realize that for the first decile and quartile of the distribution, objective differences between men and women explain the total estimated gender gap, whereas they explain 50% of the pay gap corresponding to the second quartile. At the top of the distribution (3$^{rd}$ quartile and 9$^{th}$ decile), the $\Delta\beta$ component stands for all the estimated gap. Results remain quite robust when considering tighter indicators of modernity, particularly for the high-tech group. For the traditional group of workers, the tighter the indicator we consider, the more important is the fraction of the estimated gender gap at the bottom of the distribution explained by the divergence in the rewards to identical characteristics.

Concerning 1998, the fraction of the estimated pay gap responding to a divergence in the returns to identical characteristics is increasing along the wage distribution of modern workers independently of the modernity indicator we consider. It systematically explains more than the half of the gap. In contrast, when considering the traditional workforce, we find that, for the various modernity indicators, differences in the objective labour market characteristics between men and women explain most of the estimated gap along the first half of the wage distribution. From the median of the distribution, the $\Delta\beta$ component stands again for most of the estimated gap.

In conclusion, our decomposition analysis shows that within the high-tech group, the gap along the wage distribution results mainly from a divergence in the rewards to identical characteristics. Conversely, in the traditional group, differences in the objective characteristics of men and women explain most of the estimated gap along the first half of the wage distribution, but the unexplained component plays a prominent role in the third quartile and ninth decile.

## *CONCLUSION*

The purpose of this paper was to gain insights on the effect of new technologies on the pay gap between women and men. Working with the French Labour Force Survey and the Complementary Survey on Working

TABLE 4

**OLS and Quantile Decompositions of the Gender Wage Gap**

***A. With the MODERN indicator***

| *Percentile* | *1998* | | | | | | *2005* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *MODERN = 0* | | | *MODERN = 1* | | | *MODERN = 0* | | | *MODERN = 1* | | |
| | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* |
| 10 | –0.168 | 0.045 | –0.123 | –0.074 | –0.065 | –0.139 | –0.207 | 0.034 | –0.174 | 0.000 | –0.114 | –0.114 |
| 25 | –0.081 | –0.040 | –0.121 | –0.062 | –0.115 | –0.177 | –0.144 | 0.015 | –0.128 | –0.021 | –0.122 | –0.142 |
| 50 | –0.046 | –0.103 | –0.149 | –0.046 | –0.164 | –0.210 | –0.064 | –0.063 | –0.127 | –0.007 | –0.150 | –0.157 |
| 75 | –0.018 | –0.170 | –0.188 | 0.005 | –0.240 | –0.236 | 0.004 | –0.115 | –0.112 | 0.011 | –0.194 | –0.183 |
| 90 | 0.025 | –0.200 | –0.175 | 0.019 | –0.294 | –0.276 | 0.019 | –0.106 | –0.087 | 0.029 | –0.205 | –0.176 |
| Mean | –0.051 | –0.102 | –0.154 | –0.037 | –0.168 | –0.205 | –0.049 | –0.078 | –0.126 | 0.011 | –0.168 | –0.158 |

***B. With the MODERN2 indicator***

| *Percentile* | *1998* | | | | | | *2005* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *MODERN2 = 0* | | | *MODERN2 = 1* | | | *MODERN2 = 0* | | | *MODERN2 = 1* | | |
| | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* | Δ*X* | Δβ | Δ*all* |
| 10 | –0.112 | 0.015 | –0.097 | –0.048 | –0.094 | –0.142 | –0.165 | 0.077 | –0.088 | –0.031 | –0.121 | –0.152 |
| 25 | –0.062 | –0.042 | –0.104 | –0.072 | –0.113 | –0.185 | –0.065 | –0.032 | –0.098 | –0.029 | –0.128 | –0.157 |
| 50 | –0.013 | –0.096 | –0.109 | –0.049 | –0.169 | –0.217 | –0.017 | –0.076 | –0.093 | –0.009 | –0.171 | –0.180 |
| 75 | 0.008 | –0.139 | –0.131 | –0.016 | –0.222 | –0.238 | 0.013 | –0.115 | –0.102 | 0.004 | –0.200 | –0.196 |
| 90 | 0.060 | –0.194 | –0.134 | 0.005 | –0.303 | –0.298 | 0.050 | –0.126 | –0.076 | 0.029 | –0.247 | –0.218 |
| Mean | –0.014 | –0.105 | –0.119 | –0.039 | –0.175 | –0.214 | –0.015 | –0.083 | –0.097 | –0.002 | –0.169 | –0.171 |

TABLE 4 (continued)

***C. With the MODERN3 indicator***

| *Percentile* | *1998* | | | | | | *2005* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *MODERN3 = 0* | | | *MODERN3 = 1* | | | *MODERN3 = 0* | | | *MODERN3 = 1* | | |
| | $\Delta X$ | $\Delta\beta$ | $\Delta all$ | $\Delta X$ | $\Delta\beta$ | $\Delta all$ | $\Delta X$ | $\Delta\beta$ | $\Delta all$ | $\Delta X$ | $\Delta\beta$ | $\Delta all$ |
| 10 | –0.100 | –0.004 | –0.104 | –0.037 | –0.094 | –0.132 | –0.090 | 0.008 | –0.082 | –0.158 | –0.014 | –0.172 |
| 25 | –0.061 | –0.043 | –0.104 | –0.046 | –0.094 | –0.140 | –0.013 | –0.058 | –0.071 | –0.022 | –0.172 | –0.193 |
| 50 | –0.010 | –0.112 | –0.122 | –0.019 | –0.154 | –0.174 | 0.015 | –0.096 | –0.081 | –0.008 | –0.182 | –0.190 |
| 75 | 0.013 | –0.163 | –0.150 | –0.020 | –0.171 | –0.191 | 0.043 | –0.136 | –0.093 | 0.039 | –0.226 | –0.187 |
| 90 | 0.042 | –0.189 | –0.147 | –0.019 | –0.221 | –0.240 | 0.082 | –0.153 | –0.071 | 0.072 | –0.286 | –0.213 |
| Mean | –0.013 | –0.118 | –0.130 | –0.033 | –0.141 | –0.174 | 0.024 | –0.103 | –0.079 | –0.012 | –0.172 | –0.184 |

Source: Surveys CT98 and CT05.

Note: $\Delta$ all is the estimated gender wage gap, $\Delta X$ is the part of the gap due to differences in objective characteristics and $\Delta\beta$ is the part of the gap due to differences in the rewards to identical characteristics.

Conditions for 1998 and 2005, we have studied earnings inequalities between women and men for the group of workers being ICT-users and for those being non-users by means of a quantile regression analysis. We find that in France, the gender gap is continuously increasing along the wage distribution independently on the considered group of workers. Furthermore, the difference in difference strategy reveals that, in general, there are not significant differences between the gender gap of the modern and traditional workforces along the wage distribution.

In spite of finding a gender gap of similar importance in the high- and low-tech group, the decomposition analysis reveals that the source of these earnings inequalities diverges among both groups. Within the modern group, the gap essentially results from women being paid less for identical labour market characteristics as men, while within the traditional group objective differences justify the gap estimated along the first half of the distribution. In that group, women are paid less than men for identical characteristics only at the top of the distribution.

Finally, two caveats have to be kept in mind when interpreting our results. First, we implicitly assume that the choice to use or not use ICT is set up in the same way for men and women. As stated in our introduction, it may be more or less difficult for women than for men to gain entry to the high technology sector. The problem here is that there is no clear instrument in the data sets that would have an effect on the probability for a woman to have a modern job, without influencing the log hourly wage. Secondly, we use data collected at the individual level, so that we are not able to control for the firms' characteristics in the regressions. It would be worthwhile to know whether our conclusions still hold with matched employer-employee data, an issue left for future research.

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