The male-female wage gap in France: an analysis using non-parametric methods

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Abstract

We use a non-parametric method to decompose the difference in male and female wage densities into two parts–one explained by characteristics and one which is attributable to differences in returns to characteristics. We learn substantially more about the gender wage gap in France through this analysis that we do through comparable parametric techniques. In particular, we find that there are no unexplained differences in male and female earnings distributions in the bottom fifth of the data. Occupation and part-time status are the most important determinants of the wage gap for all workers. In contrast with parametric methods, we find that education plays no role in the wage gap once we account for occupation.

1 Introduction

The headline of *Le Monde* on 8 March 2004 proclaimed "Male-Female inequalities are persisting in the French labor market" attesting to the continuing concern in France about gender wage inequality. The 2003 report on gender parity published by the French National Statistics Institute (L'Institut national de la statistique et des études économiques, INSEE) shows that, on average, wages of French women are only about 80% of male wages in the private and semi-public sectors (85% in the public sector). That gender inequality in general remains a problem for France is further documented by the United Nation's most recent Gender-related development index, where France ranks 17th, behind many of its continental neighbors, the U.S., the U.K. and Australia.

Only a few econometric studies (Meurs and Ponthieux (2000), Meurs and Meng (2001), Meurs and Meng (2004), and Dupray and Moullet (2002)) investigate the nature of this wage gap. All of these studies use the standard Oaxaca decomposition which splits the average gender wage gap into two components, one attributable to differences in wage-generating characteristics and one attributable to differences in returns for the same endowment of these characteristics.

Barsky et al. (2001) highlight two main limitations in this standard decomposition methodology. First, it is based on parametric assumptions about the form of the conditional expected earnings function which can induce specification errors. Secondly, the gender earnings gap is measured at the mean, thereby ignoring the differences in the form of the entire earnings distribution.

In this study, we implement a non parametric procedure to analyze the influence of workers' productive characteristics on gender differences in the distribution of wages. In doing so, we adapt the methodology developed by DiNardo et al. (1996)). Hence, instead of focusing on average wages (as in the Oaxaca decomposition), we examine the entire density of wages. The main estimation problem is thus to construct a counterfactual wage density that would prevail for women if they had men's distribution of characteristics (and vice versa). This counterfactual density can be estimated by applying standard nonparametric kernel density estimation techniques to a re-weighted sample of women.

Using the French data set *2002 Employment Survey* conducted by INSEE, this paper aims to shed light on the nature of the gender wage differential, exploring the added value of a non-parametric analysis over previous knowledge based on parametric estimates.

We find that the non-parametric analysis illuminates several features of the male-female wage gap which are not evident from the parametric analysis. We also find some striking differences with the parametric results. The first finding is that there are important differences in the shape of the density of male and female wages. Female wages are much more concentrated than male wages and the proportion of female wages in the very-low wage part of the distribution is more than twice as great as for males. The modal wage for females is quite a bit lower than for males. The second finding is that occupation and part-time status are the two main characteristics which contribute to the wage gap between men and women. In combination, these two characteristics completely account for differences in the bottom quartile of the male and female wage distributions. While we find that the proportion of the overall wage gap which is explained by different characteristics of men and women is roughly the same as that in the parametric analysis, the differences are all in the upper part of the wage distribution. In the lower part of the wage distribution there is no unexplained wage inequality (i.e., wage inequality that is due to different returns for the same skills). The third interesting finding is that once occupational segregation and part-time status are accounted for, education plays no significant role in the wage gap. These results are in stark contrast to the parametric results and the standard wisdom.

The next section briefly reviews the main parametric tools used in the literature to analyze the gender wage differential and the results from previous papers which have applied these techniques to French wage data. In section three, we discuss the data set which we use, present some labor market statistics, and review the outcome of the parametric decomposition of the French gender wage gap applied to this data. In section four, we discuss the non-parametric technique and results. We briefly discuss policy implications in the concluding section.

2 Gender wage differential

2.1 Parametric estimation

Most studies of the gender wage gap consider the gap in mean wages between men and women where those wages depend upon a set of human capital characteristics. The gap may be written as

$$g = \int w f_m \left(w | x_1, \ldots, x_k \right) dw - \int w f_f \left(w | x_1, \ldots, x_k \right) dw \tag{1}$$

where $f_m\left(w|\cdot\right)$ and $f_f\left(w|\cdot\right)$ are the conditional densities of male and female wages, respectively, and $x_1, \ldots, x_k$ are labor market and human capital characteristics.

Consider the male conditional wage density $f_m\left(w|x_1, \ldots, x_k\right)$ and note that it can be found by integrating out the effect of the characteristics from the joint density of wages and characteristics

$$
\begin{aligned}
f_m(w|x_1,\ldots,x_k) &= \int\limits_{x_1}\ldots\int\limits_{x_k} f_m(w,x_1,\ldots,x_k)dx_1\ldots dx_k \\
&= \int\limits_{x_1}\ldots\int\limits_{x_3} f_m(w|x_1,\ldots,x_k)f_m(x_1,\ldots,x_k)dx_1\ldots dx_k \qquad (2)
\end{aligned}
$$

By replacing $f_m(w|x_1,\ldots,x_k)$ in (1) with the above expression we can now express the gender wage gap as

$$
\begin{aligned}
g =& \int\limits_{w} w \int\limits_{x_1}\ldots\int\limits_{x_3} f_m(w|x_1,\ldots,x_k)f_m(x_1,\ldots,x_k)dx_1\ldots dx_k dw \\
&- \int\limits_{w} w \int\limits_{x_1}\ldots\int\limits_{x_3} f_f(w|x_1,\ldots,x_k)f_f(x_1,\ldots,x_k)dx_1\ldots dx_k dw \qquad (3)
\end{aligned}
$$

Estimating separate regressions for men and women and then calculating the mean gender wage gap from the fitted values of those regressions reproduces the gap found in the data. In order to understand what fraction of the gap is due to different returns to characteristics and what fraction is due to a difference in the distribution of characteristics, Oaxaca (1973) proposed a decomposition technique which exploits the relationship in (3).

So for example, an estimate of the wage gap due to differences in the distribution of characteristics is given by

$$
\begin{aligned}
\widehat{g}_a(s=f) = & \widehat{f}(w; s_w = f, x_1 = m, \ldots, x_k = m) \\
& - \widehat{f}(w; s_w = f, x_1 = f, \ldots, x_k = f) \\
=& \int\limits_{w} w \int\limits_{x_1}\ldots\int\limits_{x_3} \widehat{f}_f(w|x_1,\ldots,x_k)\widehat{f}_m(x_1,\ldots,x_k)dx_1\ldots dx_k dw \\
&- \int\limits_{w} w \int\limits_{x_1}\ldots\int\limits_{x_3} \widehat{f}_f(w|x_1,\ldots,x_k)\widehat{f}_f(x_1,\ldots,x_k)dx_1\ldots dx_k dw \qquad (4)
\end{aligned}
$$

where $\widehat{f}_f(w|x_1,\ldots,x_k)$ is an estimate of the conditional mean function for women (the regression coefficients from the wage regression using only women's wage data) and $\widehat{f}_f(x_1,\ldots,x_k)$ and $\widehat{f}_m(x_1,\ldots,x_k)$ are the empirical distributions of characteristics from the data. We use the notation $\widehat{f}(w; s_w = f, x_1 =$

$m, \ldots, x_k = m)$ to indicate the (estimated) conditional distribution of wages using the female wage structure and the male attributes or characteristics.[1] $\widehat{g}_a(s = f)$ is the gap in wages due to attributes using the female wage structure.

An estimate of the wage gap due to differences in the return to characteristics would be estimated as

$$\widehat{g}_r(s = f) = \widehat{g} - \widehat{g}_a(s = f) \tag{5}$$

where $\widehat{g}$ is the estimate of (3).

A large literature has evolved regarding the choice of "reference wage structure". Oaxaca (1973) and Blinder (1973) propose two reference wage structures, depending on whether one estimates what a woman would receive if she faced the male wage structure ($\widehat{f}_m(w|x_1, \ldots, x_k)$) or one assesses how much a man would earn if he were paid according to the female wage structure ($\widehat{f}_f(w|x_1, \ldots, x_k)$). The decomposition can be quite sensitive to which wage structure is used but neither is a priori preferable to the other. One might argue that the reference structure should lie somewhere between the male and female structures.

Reimers (1983) and Cotton (1988) assume that the reference wage structure should be a weighted average of the observed structures of males and females. Reimers gives each a weight of .5, whereas Cotton proposes weights equal to the sample fraction of males and females. Both are somewhat arbitrary. Neumark (1988) develops an alternative procedure, from the Becker model of discriminatory tastes (Becker (1971)). Oaxaca and Ransom (1994) show that this result implies weighting the male coefficient estimates by $(\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'_m\mathbf{X}_m)$ and the female coefficient estimates by $I - (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'_m\mathbf{X}_m)$ where X is the observation matrix (of attributes) for the pooled sample, X_m is the observation matrix for the male sample, and I is the identity matrix of appropriate dimension.

These wage decomposition techniques suffer from two main limitations. First, they are based on parametric assumptions about the form of the conditional expected earnings function (most of the time linear-in-logs or some simple non-linear specification that includes quadratic terms for education, age or experience) which can induce specification errors. Secondly, the gender earnings gap is measured at the mean, potentially ignoring important differences in the

[1]Where separate linear regressions are estimated for men ($\widehat{w}^{(m)} = X_m\widehat{\beta}_m$) and women ($\widehat{w}^{(f)} = X_f\widehat{\beta}_f$), (4) is equivalent to $\widehat{\beta}_f\left(\bar{X}_m - \bar{X}_f\right)$.

earnings distribution. This paper relaxes those assumptions by using a non-parametric decomposition of the French gender wage differential, inspired by the methodology developed by DiNardo et al. (1996).

Before we discuss that technique and our results, we briefly review the main studies which have applied the parametric wage decomposition to French data.

2.2 The gender wage gap in France

If research on gender wage inequalities in France has been quite large in the past decade (Bayet (1996), Colin (1999), Silvera (1996) and Simmonet (1996)), only a few econometric studies attempted to decompose the gender wage gap (Meurs and Ponthieux (2000), Meurs and Meng (2001), Meurs and Meng (2004), and Dupray and Moullet (2002)).

Though the main focus of these last four papers is to estimate the part of the gender wage gap attributed to male/female differences in observable individual (and firm) characteristics–the 'explained' part–and the part accounted for by differences in the returns to these characteristics–the 'unexplained' part–they diverge substantially on the assumptions and the methodologies used.

Their common point is to use the parametric, Oaxaca-Blinder methodology which decomposes the gender wage gap at the mean by employing assumptions on the reference wage structure. Meurs and Ponthieux (2000) and Meurs and Meng (2001) follow the Oaxaca and Ransom (1994) approach, Dupray and Moullet (2002) use the Reimers (1983) assumption, whereas Meurs and Meng (2004) choose to compare the results obtained with three different wage structures.

Meurs and Meng (2001) use the method of Brown et al. (1980) to account for the occupational attainment differences between males and females and find that the largest part of the wage gap is explained by wage differences within occupation. They find that a large part of the wage gap, between 54% and 62%, remains unexplained.

Meurs and Ponthieux (2000) conduct wage decompositions for all workers together as well as separately for full-time workers. For the latter, a correction for selectivity into full-time jobs is introduced in the wage equation and a complementary term is added to the right-hand side of the traditional wage decomposition equation. Their primary result is that 15% of the gender gap remains unexplained for the whole sample of workers whereas for full-time workers the unexplained part increases to 48% of the wage gap. When the Heckman procedure for selection in full time jobs is included, there is very little change–the unexplained portion of the wage gap decreases slightly to 44%.

In Dupray and Moullet (2002), the focus is on gender differences among employees in the private sector. They use a sample of individuals who left the schooling system in 1998 and look at their wage in 1998 (for their first job) and in 2001. Their principal conclusion is that the gender wage gap in the private sector has increased substantially between 1998 and 2001 due to growth in the difference between males and females in returns to productive characteristics. The part of the wage gap accounted for by differences in returns increases from about 20% in 1998 to 76% in 2001. This last figure is mainly attributable to the selection effect into private employment. We view these results with caution as the change seems incredibly large for such a short time period and the sample is fairly restrictive.

Meurs and Meng (2004) introduce variables on firm characteristics and estimate their contribution to the explanation of the gender wage gap. They find that the firm effect reduces the gender wage gap by 15%. The endowment effect (the effect of characterisitics) and the return effect explain respectively 49% and 65.8% of this gap.

It is difficult to determine how much these various studies differ from one another since only Meurs and Ponthieux (2000) present standard errors for the different elements of the decomposition. However, the finding that around 50% of the wage gap (for full-time workers) remains unexplained is fairly robust.

The aim of the parametric estimates of the wage decomposition which we present below is not to add complexity and confusion to the existing studies, but to provide a point of comparison with the non-parametric decompositions displayed afterwards. Although we use a different data set, our parametric results are roughly similar to those reviewed above. Before presenting those results, we discuss the data we use.

3 Data

The data are derived from the 2002 Employment Survey conducted by the French National Statistics Institute (L'Institut national de la statistique et des études économiques, INSEE). The survey covers 175,939 individuals. Our estimation sample is 60,274 individuals, after removing people outside legal working age, inactive, unemployed, self-employed, military conscripts, and observations with missing data.

3.1 Construction of hourly wage

Survey respondents provided information on their monthly salary (including annual bonus converted into monthly data) before income tax. This is the net salary after *cotisations sociales* have been taken out. These *cotisations sociales* represent tax levies which are directed toward specific purposes such as funding government provided medical care, unemployment insurance, and pensions. *Cotisations sociales* represent the bulk of taxes which individuals in France pay on their gross salary and for an average worker constitute around 25% of the gross salary. The French typically discuss salaries net of the *cotisations sociales*, hence the survey question is framed in these terms. Income taxes are then deducted from this net wage. Income tax is calculated on the net wage less 10% (for work-related expenses) and is progressive. For example, a single person with gross annual wage of 28,000 € will have about 7,000 deducted for *cotisations sociales* and will then pay income tax of 1,600 € on the remaining income.

To abstract from the effect of variations in hours worked, the earnings data were converted into an hourly wage using the information given by workers on the number of hours they usually work per week. For those who failed to report the usual number of hours they worked (about 12% of the sample), we used the number of hours worked in the previous week, if available. This latter figure would tend to introduce excess variation into the salary data so we prefer the question regarding usual hours worked. We conducted the analysis presented below dropping this latter group and the results are unaffected.

We find, as others do, that hourly wages constructed in this manner are smaller than we would expect. It seems that people tend to over-report the number of hours they work and under-report their salary. In our data, median male hourly wage is 8.54 €. For females it is 7.52 €. Mean hourly wages are 10.31 € for men and 8.97 € for women (see Table 6 below.) These are less than those provided in the official statistics, which claim that in 2001 men made 11.68 € per hour relative to women's 9.50 € per hour (INSEE (2003)). The ratio between the two is roughly the same in our data as in the official statistics, although the gap in mean wages appears slightly smaller in our data. It may be that men over-report hours more than women. Table 1 and Figure 1 show information on the distribution of wages in the sample.

Table 1: Quantiles of Hourly Wage[2]

	Sample size: 60,274		
Quantile	All	male	female
0.005	1.41	1.61	1.26
0.010	1.81	2.19	1.66
0.025	3.00	3.61	2.53
0.050	4.22	4.89	3.58
0.100	5.23	5.63	4.83
0.500	8.11	8.59	7.54
0.900	14.66	15.70	13.57
0.950	18.31	19.67	16.67
0.975	22.87	24.35	20.91
0.990	30.77	32.86	28.78
0.995	39.86	44.80	35.97

The hourly equivalent of the French minimum wage (SMIC) is 6.83 €. (It has been increased in 2003 to 7.19 €.) This is the gross wage, however, and if we adjust for the *charges sociales* at this income level (about 21%) we find that the minimum hourly wage is 5.39 €. In the reduced sample of 60,274, we find 7.5% of men and 15.6% of women reporting a wage level that is below this amount. We think that the number of workers who are actually earning less than the SMIC is much less than this[3]. Those reporting wages lower than the SMIC who are not in a category that could legally be paid below the minimum are primarily concentrated in clerical work. This may indicate that individuals are given tasks which force them to work more hours than those recognized by their employers.

[2] All descriptive statistics and density estimates provided in the paper use survey weights.

[3] Workers below age 18 with less than 6 months of experience, youth in apprenticeships, individuals in internal training programs, and some disable workers are the only ones who could legally be paid less than the SMIC. There are few of these in the data

3.2 Some labor market statistics

The tables below present some statistics on labor force participation, employment, nature of employment and wages. Substantial differences between women and men are highlighted by sex.

Table 2: Labour Force Status of population age 15-65

	Female	Male
Inactive	7,446,172 (38%)	4,918,753 (25.6%)
Active	12,148,653 (62%)	14,296,950 (74.4%)
Employed	10,965,854 (56%)	13,206,361 (68.7%)
Unemployed	1,182,799 (6%)	1,090,589 (5.7%)
(unemployment rate)	(9.7%)	(7.6%)
Total	19,594,825	19,215,703

Female activity rate (62%) remains quite low by US standards where more than 70% of women participate to the labor force, but is near the average participation rate of the European Union (60%). Female participation has greatly increased during the past three decades in France while the male participation rate has steadily decreased. The gender employment gap (12.4%) is substantial though lower than the average of the OECD countries (around 20%)[4]. These global employment rates hide large gender disparities in the nature of the occupied jobs. Tables 2, 3 and 4 go further into the description of the features of employment by sex.

Table 3: Employed workers[5]

	Female	Male
Self-employed	811,495 (7.6%)	1,703,498 (13.2%)
Wage earner	9,930,474 (92.4%)	11,237,937 (86.8%)
Full Time	6,936,886 (64.6%)	10,674,758 (82.5%)
Part Time	2,993,588 (27.9%)	563,179 (4.4%)
Total	10,741,969	12,941,435

More than 28% of women work part time whereas only 4% of men do. Indeed, part-time jobs are prevalent in the sectors where women are highly represented, such as trade, restaurant, and individual services. Women's part-time employment rate in France is close to the OECD average of 24%.

[4] Statistics from US, European Union, and OECD countries are from OECD (2002)

[5] The total in Table 3 is not equal to the number of employed in Table 1 because of missing observation on wage and hours of work.

Table 4: Wage earners

	Female	Male
Outsourcing	174,649 (1.8%)	337,137 (3.0%)
Apprenticeship	82,632 (0.8%)	185,334 (1.6%)
Temporary contract(private sector)	515,956 (5.2%)	371,187 (3.3%)
Other private employment	5,949,757 (59.9%)	8,131,968 (72.4%)
Internship or "favored contracts"	262,483 (2.6%)	157,507 (1.4%)
Civil servants	2,944,997 (29.7%)	2,054,804 (18.3%)
Total	9,930,474	11,237,937

Non-standard forms of employment (outsourcing, temporary work, "favored contracts") have been increasing in France during the past two decades. A larger proportion of females than males work with temporary or favored contracts, which provide flexible labour to the employers and often pay lower wages than "regular" jobs[6]. However, men are more numerous in subcontracted jobs. Almost 30% of women work in the public sector, where higher average wages prevail (see Table 6). The public sector may also offer job characteristics such as stability and flexibility attractive to women with children.

Table 5: Occupations of wage earners

	Female	Male
Manager and Professional	1,155,113 (11.6%)	1,978,048 (17.6%)
Semi-professional	2,304,374 (23.2%)	2,624,797 (23.4%)
Clerk	5,262,230 (53.0%)	1,681,533 (15.0%)
Laborer	1,208,757 (12.2%)	4,953,559 (44.1%)
Total	9,930,474	11,237,937

Turning to occupational attainment, Table 5 shows that more than half of female employment is concentrated in the clerk category. Gender segregation is particularly high in these occupations as for instance, 98% of French secretaries are women. Suffering from low status, these occupations are also often

[6] What we are calling favored contracts are known in France as *contrat aidé*. These include *contrat d'apprentissage, contrat de qualification jeune, contrat de qualification adulte, contrat d'adaptation*, or *contrat initiative emploi*. Private firms receive a fixed amount of money from the State as well as exoneration from paying the *cotisations sociales* when they hire people using one of these types of contracts. The stated purpose of these contracts is to help young people obtain experience during their training (*contrat d'apprentissage, contrat de qualification jeune*) or to help the unemployed improve their job propsects (*contrat de qualification adulte, contrat d'adaptation, contrat initiative emploi*). In the *contrat d'apprentissage* and *contrat de qualification jeune* the wage earned by the young worker is only a fraction of the official minimum wage (SMIC).

characterized by weak career prospects. However, men are over-represented in laborer jobs which share some of the same features. Furthermore, whereas men still have better access to high-skilled jobs, women almost reach equality in occupations such as lawyer, magistrate, professors etc. (see D'Intignano (1999))

This job segregation is likely to have a major impact on the gender wage gap. Indeed, the male/female ratio of hourly wages increases as one goes down the hierarchical scale. This appears to favor women as far as laborers are concerned. More generally, gender differences in monthly average wages amount to 34%. However, once one controls for the working hours, the gender gap decreases to 15%. The biggest gender gap occurs among private, long-term employees with men earning on average 21% more than women.

Table 6: Male-female hourly wage differences by various categories

	Male	Female	Ratio (Male/Female)
All wage earners (monthly average wage)	10.31 (1691.53)	8.97 (1261.46)	115.0% (134.1%)
Full-time	10.37	9.34	111.1%
Part-time	9.15	8.13	112.6%
Outsourcing	7.23	6.74	107.3%
Apprenticeship	3.23	3.84	84.2%
Temporary contract (private sector)	8.28	6.92	119.8%
Other private employment	10.43	8.63	120.9%
Internship or "favored contracts"	5.34	5.53	96.5%
Public sector	11.75	10.61	110.7%
Manager and professional	16.98	15.78	107.6%
Semi-professional	11.16	10.79	103.4%
Clerk	8.38	7.22	116.0%
Laborer	7.86	6.60	119.0%

Gender inequalities in France are substantial even though not dramatic by international standards. They also indicate the way one should deal with econometrics on wages. The next section investigates, in a parametric analysis, the nature of the gender wage gap. These will provide a basis of comparison both with previous studies and with the non-parametric analysis that follows.

3.3 Parametric estimate of the gender wage gap

We estimate separate linear regressions for men and women using the log of the hourly wage as the dependent variable. The explanatory variables include standard human capital measures, individual characteristics, and job characteristics: diploma (7 categories), experience, experience squared, tenure, tenure squared, marital status, nationality (6 categories), part-time status, occupation (10 categories), private sector, industrial sector (11 categories), type of contract (6 categories) and 4 location dummy variables. Appendix Table A1 provides descriptive statistics and descriptions of the variables.

The results from the parametric wage decompositions are presented in Table 7. We transform the predicted values from the regressions into consistent predictions of the level of the hourly wage and use these predictions to calculate the wage gap in levels for easier comparison with the non-parametric results. We split these differences into those due to characteristics ("explained") and returns ("unexplained") as described above. Standard errors appear in parentheses.[7]

Table 7: Parametric decompositions of the gender wage gap

	Gender Gap	Characteristics		Returns	
		Level	%	Level	%
Full Sample	1.39 (.07)				
Reference Wage Structure:					
Pooled		0.85 (.03)	61%	0.54 (.06)	39%
Male		0.73 (.08)	53%	0.66 (.09)	47%
Female		0.28 (.05)	20%	1.11 (.08)	80%
Full-time workers only[8]	1.07 (.07)				
Pooled		0.46 (.04)	43%	0.61 (.07)	57%
Male		0.30 (.05)	28%	0.77 (.08)	72%
Female		−0.02 (.06)	-2%	1.09 (.08)	102%

There are several results worth noting. Characteristics explain roughly 60% of the wage variation in the full sample (using the pooled wage reference struc-

[7] All standard errors in the paper are based upon 200 bootstrap replications from clusters to maintain the correlation structure in the data. The differences between the clustered bootstrap and a naive bootstrap, treating the sample as i.i.d., were very small. This isn't surprising since clustering was done on workplace and each workplace sample generally included a broad range of occupation categories and wages.

[8] The full-time sample is 50,267 observations.

ture). However, one of the characteristics included in the regression is part-time status. When we separate out full-time workers, we explain only 43% of the wage gap. Part-time status clearly has a large effect. We also considered only those full-time workers in the private sector, and the amount of the gap explained increases to about half.

The other interesting result is that the choice of reference wage structure has a huge impact. We explain the most variation using the pooled wage structure, although the male wage reference structure gives similar results. We explain almost no variation when we use the female wage reference structure.

It is worth noting that correcting for sample selection does not change the results. Selection only contributes to narrow the observed gender wage gap by about 1.5%. Furthermore, this change is not significant. In general, for both males and females, we find that people who select themselves into wage employment would potentially earn higher wages than those who do not, but the male/female disparities in the selection process are not large enough to contribute to explain the gender wage gap.[9]

We also separately considered private and public sector workers. Not surprisingly, the wage gap in the private sector (1.76 € per hour) is significantly larger than that in the public sector. However, the gap in the public sector is not significantly smaller than that for all workers. In both sectors, we explain about 60% of the gap by different characteristics, using the pooled wage structure, and the pattern using male and female wage structures is the same as that observed for all workers.[10]

In order to shed more light on the origin of this gender wage gap, Table 8 provides a break-down of the contribution of the wage determinants to the "characteristics" component. We do not present results for women for full-time workers since the characteristics gap is essentially zero.

[9] Neuman and Oaxaca (2001) discuss several approaches to conducting wage decompositions with selectivity-corrected wage equations where selection may occur at both the stage of joining the employed labor force and when choosing a specific occupation or job status.

[10] Separate results for the private and public sectors and the estimates accounting for sample selection are available from the authors.

Table 8: Contribution of explanatory variables to the "characteristics gap"

Reference Wage Structure:	Pooled	Male	Female
	Full Sample		
Characteristics Gap	0.85 (.03)	0.73 (.08)	0.28 (.05)
Occupation	72.1% (2.7%)	58.2% (5.6%)	107.1% (16.6%)
Sector	25.2% (2.3%)	30.0% (4.8%)	38.7% (11.6%)
Education	−9.9% (1.5%)	−14.6% (2.4%)	−31.8% (10.7%)
Part-time	4.8% (1.8%)	17.6% (6.8%)	−22.1% (8.6%)
Contract Status	2.1% (0.5%)	2.2% (0.9%)	7.2% (2.5%)
Public Sector	−10.1% (1.1%)	−11.9% (2.4%)	−28.8% (7.8%)
Night Work	10.2% (1.0%)	10.7% (1.6%)	14.6% (6.0%)
Other Characteristics	2.6% (1.1%)	1.4% (1.4%)	11.2% (4.3%)
	Full-time workers only		
Characteristics Gap	0.46 (.04)	0.30 (.05)	
Occupation	87.3% (6.4%)	74.7% (12.5%)	
Sector	46.2% (5.0%)	76.1% (14.3%)	
Education	−40.9% (5.6%)	−70.9% (15.7%)	
Contract Status	3.7% (1.1%)	5.4% (2.2%)	
Public sector	−21.7% (3.1%)	−34.7% (8.9%)	
Night Work	19.5% (2.3%)	25.7% (5.0%)	
Other Characteristics	−2.7% (2.7%)	−1.3% (4.6%)	

First of all, we note that we do not find many differences between the sample of all workers and the sample of only those who are working full time. Occupation, sector, and night work–in order of importance–contribute to widening the wage gap. Schooling and public sector employment act to narrow the wage gap. Contract status and other characteristics are often not significant, and when they are, their effect is small.

Part-time employment has the effect of widening the wage gap when we consider the pooled or the male wage reference structure. However, when we use the female reference structure, it appears that part-time work actually contributes to narrowing the wage gap. The main reason for this is that part-time female workers in general have better human capital characteristics than their full-time counterparts. The converse is true for men.

Next we turn to a non-parametric analysis of this wage data and the gap between men and women.

4 Nonparametric estimation of wage gap

We will use the method of DiNardo et al. (1996) to construct a non-parametric decomposition of the wage gap. This will allow us to examine the impact of each set of characteristics on the distribution of wages for men and women and their differences.

4.1 Estimation of counter-factual densities of wages

Consider again the wage gap as represented by (3)

$$\begin{aligned} g = & \int_w w \int_{x_1} \dots \int_{x_3} f_m(w|x_1, \dots, x_k) f_m(x_1, \dots, x_k) dx_1 \dots dx_k dw \\ & - \int_w w \int_{x_1} \dots \int_{x_3} f_f(w|x_1, \dots, x_k) f_f(x_1, \dots, x_k) dx_1 \dots dx_k dw. \end{aligned}$$

The key assumption that we will make use of in decomposing the wage gap characteristic-by-characteristic is that the density of wages conditional on attributes for each sex does not depend upon the density of attributes for that sex. Consider, for example, the male distribution of attributes $f_m(x_1, \dots, x_k)$. Using Bayes' rule, we can factor this into the product of a conditional and an unconditional density

$$f_m(x_1, \dots, x_k) = f_m(x_1, \dots, x_{k-1}|x_k) f_m(x_k). \tag{6}$$

The distribution of male wages, conditional on attributes, can thus be written as

$$\begin{aligned} & f_m(w|x_1, \dots, x_k) = \\ & \int_{x_1} \dots \int_{x_3} f_m(w|x_1, \dots, x_k) f_m(x_1, \dots, x_{k-1}|x_k) f_m(x_k) dx_1 \dots dx_k. \end{aligned} \tag{7}$$

Using (7) we can construct "counter-factual" densities such as the male wage density with the male distribution of characteristics 1 through $k-1$ and the female distribution of characteristic k

$$f(w; s_w = m, x_1 = m, \dots, x_{k-1} = m, x_k = f) = \int_{x_1} \dots \int_{x_3} f_m(w|x_1, \dots, x_k) f_m(x_1, \dots, x_{k-1}|x_k) f_w(x_k) dx_1 \dots dx_k. \tag{8}$$

To implement (8), note that

$$f(w; s_w = m, x_1 = m, \dots, x_{k-1} = m, x_k = f) = \int_{x_1} \dots \int_{x_3} f_m(w|x_1, \dots, x_k) f_m(x_1, \dots, x_{k-1}|x_k) f_m(x_k) \frac{f_w(x_k)}{f_m(x_k)} dx_1 \dots dx_k$$
$$= f_m(w|x_1, \dots, x_k) \frac{f_w(x_k)}{f_m(x_k)}. \tag{9}$$

This counter-factual distribution is the conditional distribution of male wages re-weighted by the fraction of the female density of the kth attribute to the male density of the kth attribute. (9) may also be written as

$$f_m(w|x_1, \dots, x_k) \frac{f(f|x_k) f(m)}{f(m|x_k) f(f)}. \tag{10}$$

where $f(f)$ and $f(m)$ are the sample proportions of female and male workers and $f(s|x)$ are the probabilities of being of sex s, conditional on attribute x. This allows us to eliminate the problem of regions of x for which $f_s(x_k)$ are very small and allows us to apply the technique to a vector of attributes.

Using the nonparametric, kernel density estimator of Rosenblatt (1956) and Parzen (1962), we can estimate the density of wages for men by

$$\widehat{f}_m(w) = \frac{1}{n_m h} \sum_{i=1}^{n_m} K\left(\frac{w - w_i}{h}\right) \tag{11}$$

where n_m is the number of males in the sample, h is a smoothing parameter sometimes called a bandwidth, and $K(\cdot)$ is a kernel function which gives large weight to points w_i near w and small weight to points which are far from w. This provides a consistent estimate of $f(w; s_w = m, x_1 = m, \dots, x_k = m)$ and it (implicitly) uses the empirical distribution of the attributes for men. To estimate the counter-factual $(w; s_w = m, x_1 = m, \dots, x_{k-1} = m, x_k = f)$ we use

$$\widehat{f}_m(w; s_w = m, x_1 = m, \dots, x_{k-1} = m, x_k = f) = \frac{1}{n_m h} \sum_{i=1}^{n_m} \widehat{\psi}_x(x_k) K\left(\frac{w - w_i}{h}\right) \tag{12}$$

where $\widehat{\psi}_x(x_k)$ is an estimate of $\frac{f(f|x_k)f(m)}{f(m|x_k)f(f)}$ from (10).

We use the fourth-order kernel with smoothly declining derivatives proposed by Müeller (1984). The bandwidths are chosen to undersmooth the densities– we calculate the optimal bandwidth for the data as if the data under the 99th percentile were normally distributed (which would tend to oversmooth the densities) and then divide this number by 4. We find that this works well and furthermore that the results are not sensitive to bandwidth choice. We include the survey weights in the density estimation although ignoring the weights provides nearly identical estimates.

4.2 Results

Before embarking upon a detailed discussion of the non-parametric results, we briefly preview the main outcomes of the analysis. There are many points of agreement between the parametric and non-parametric results. In both cases, we find a large role for occupation and part-time status in explaining the wage gap. We also find that when we use the female reference wage structure that the amount of the wage gap we are able to explain is much less than when we use the male structure. We take this as evidence that there are many more unobservable factors (flexibility, proximity to child-care and school, family-friendly workplace policies) which influence women's choice of work than men's. In both analyses, we find the role of public sector employment in reducing the wage gap to be small but significant and the effect of contract status to be insignificant. The overall amount of the gap that is explained by all observable characteristics is roughly the same in both the parametric and non-parametric methods.

There are several important ways in which our non-parametric analysis diverges from the parametric results. Directly examining wage densities provides a richer set of information than focusing only on the mean. Perhaps the most interesting feature is a small, but important group of women making a very low wage–less than 5 € per hour. There are no almost no men in this wage range. We further examined the data regarding this group of women and find that they are concentrated in clerical work. They are frequently part-time. However, the vast majority of them are not in job categories which would allow employers to pay them less than minimum wage (trainees, apprentices, etc.) This is probably reflecting women who spend many more hours on the job than those for which they are paid.

Education, which plays a large role in reducing the gender wage gap in the parametric analysis, has almost no effect in the non-parametric analysis once the occupational segregation has been taken into account. While women have more education, there is no additional return to that education in the occupational structure of men. Sector appears to contribute to the wage gap in the parametric analysis, but in the non-parametric analysis it is acting to reduce the wage gap. Night work matters much more in exacerbating the wage gap in the parametric analysis than it does in the non-parametric analysis where its effect is very small.

Figure 1 presents the density of wages for males and females considered separately. There are three striking features of this graph. First, the male density lies everywhere to the right of the female density, indicating that men have higher wages than women. Secondly, the mode of the density for men is roughly 2 € higher than that for women and male wages are much less concentrated around this mode than female wages are around their mode. Thirdly, there is a substantial group of female workers in the very low wage part of the distribution (below 5 € per hour). There are very few men in this part of the distribution. A parametric analysis ignores the second and third features of these densities.

In order to understand the effect of characteristics, we will progressively introduce female characteristics into the male wage density using the technique described above. (This is equivalent to the parametric case of using the male reference wage structure.) If characteristics, and not returns, are to explain the wage gap, then once we have introduced all observable female characteristics into the male density, the 'counter-factual' density of male wages with female characteristics should be identical to that of female wages.

We subdivide the characteristics into eight groups: occupation, sector, education, part-/full-time status, contract status, public/private sector, night/day work, and remaining characteristics. Remaining characteristics include marital status, county of birth, experience and tenure.

The advantage of the non-parametric decomposition is to move the focus away from a summary statistic measure (the gap at the mean) towards an analysis of the full distribution. However, to facilitate comparison with the parametric results presented earlier, we find it useful to provide some summary measures of the results from the non-parametric decompositions. For each counter-factual distribution we consider 4 summary measures (exact details of their calculation may be found in the appendix): the mean, median, six other quantiles, and the integrated absolute distance between the two densities using the empirical density to weight each point. We use all of the data for the density estimates, but the summary measures are calculated over the interval 1 € to 41 € . This allows us to avoid problems of small numbers of observations outside of this interval.

The implied mean wage for men is 9.93 € per hour, while for women it is 8.68 € per hour. The gap is therefore 1.25 € per hour as shown in the second row of Table 9.[11] Table 9 contains the implied mean from the 'counter-factual' density estimates for one decomposition. The order of the decomposition can be seen in the left-hand column and the characteristics are added cumulatively. When we introduce women's occupations into the male wage structure, mean wages fall to 9.41 €, a reduction in the wage gap of 41.5%. When we introduce women's sector in addition to occupation, we find that mean wages actually increase to 9.48 € , a marginal increase of 9.2% in the gap after accounting for occupation of .73 € . Occupation and sector combined reduce the gap between men and women by 36.1%, as indicated in the final column. The figures in square brackets in the tables are 95% confidence intervals. These are calculated using the clustered bootstrap with 200 replications.

As shown in Table 10, the implied median for men is 8.64 € per hour while that for women is 7.60€ per hour. The gap in median wages, 1.04 € per hour, is slightly smaller than that in mean wages. Table 11 contains six other quantiles from the two distributions and the various counter-factuals. Asterisks indicate a significant difference at the 95% level between the quantile for women and that for the counter-factual male distributions using female characteristics. The characteristics are included cumulatively across the table. First we consider male wages with female occupations only. Then we consider male wages with female occupation and sector, etc.

[11] Recall that this is calculated conditional on being in the range 1 € to 41 € so this will tend to provide a slightly smaller mean gap between men and women than that found in the data because more men are in the upper tails of the wage distribution.

Table 9: Mean wages implied from non-parametric decompositions

Male wages with Female Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	9.93 [9.87,9.98]	1.25 [1.17,1.32]		
Occupation	9.41 [9.34,9.48]	0.73 [0.65,0.81]	−41.5% [−46.2%,−36.8%]	
Sector	9.48 [9.39,9.56]	0.80 [0.71,0.89]	9.2% [4.2%,14.3%]	−36.1% [−41.9%,−30.2%]
Education	9.49 [9.41,9.57]	0.81 [0.72,0.90]	1.7% [−0.8%,4.2%]	−35.0% [−40.7%,−29.3%]
Part-/Full-time	9.22 [9.06,9.38]	0.54 [0.37,0.70]	−33.6% [−50.2%,−16.9%]	−56.8% [−69.1%,−44.5%]
Contract status	9.29 [9.12,9.46]	0.61 [0.44,0.78]	13.9% [4.1%,23.7%]	−50.8% [−63.6%,−38.0%]
Public/private	9.27 [9.10,9.45]	0.59 [0.42,0.77]	−3.5% [−7.1%,0.2%]	−52.5% [−65.8%,−39.3%]
Night work	9.30 [9.11,9.49]	0.62 [0.43,0.82]	5.3% [−6.2%,16.7%]	−50.0% [−64.6%,−35.5%]
All characteristics	9.37 [9.16,9.57]	0.69 [0.48,0.89]	10.7% [−0.5%,21.8%]	−44.7% [−60.4%,−28.9%]

Table 10: Median wages implied from non-parametric decompositions

Male wages with Female Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	8.64 [8.59,8.69]	1.04 [0.97,1.11]		
Occupation	8.36 [8.28,8.44]	0.76 [0.67,0.85]	−26.9% [−33.9%,−19.9%]	
Sector	8.36 [8.28,8.44]	0.76 [0.67,0.85]	0.0% [−6.9%,6.9%]	−26.9% [−34.3%,−19.5%]
Education	8.36 [8.27,8.45]	0.76 [0.67,0.85]	0.0% [−4.9%,4.9%]	−26.9% [−34.5%,−19.3%]
Part-/Full-time	8.00 [7.88,8.12]	0.40 [0.27,0.53]	−47.4% [−62.4%,−32.3%]	−61.5% [−73.4%,−49.7%]
Contract status	8.08 [7.95,8.21]	0.48 [0.34,0.62]	20.0% [5.4%,34.6%]	−53.8% [−66.1%,−41.6%]
Public/private	8.08 [7.94,8.22]	0.48 [0.34,0.62]	0.0% [−7.9%,7.9%]	−53.8% [−67.0%,−40.7%]
Night work	8.12 [7.98,8.26]	0.52 [0.37,0.67]	8.3% [−6.3%,23.0%]	−50.0% [−63.5%,−36.5%]
All characteristics	8.20 [8.05,8.35]	0.60 [0.45,0.75]	15.4% [4.2%,26.6%]	−42.3% [−56.5%,−28.1%]

Figure 2 graphs the distance between the two densities. The first row of Tables 12 shows the integrated absolute distance between these two lines, weighted by the estimated female density.

Table 11: Quantiles

Unadjusted			Male wages with female characteristics			
	Female	Male	Occupation	Sector	Education	Part-/Full-time
5 %	3.84	4.96 *	4.28 *	4.28 *	4.24 *	3.64
10 %	4.88	5.64 *	5.24 *	5.24 *	5.24 *	4.80
20 %	5.64	6.48 *	6.08 *	6.12 *	6.12 *	5.68
50 %	7.60	8.64 *	8.36 *	8.36 *	8.36 *	8.00 *
80 %	11.08	12.52 *	11.88 *	11.92 *	11.96 *	11.72 *
90 %	13.64	15.76 *	14.84 *	15.04 *	15.16 *	15.20 *
95 %	16.64	19.52 *	18.28 *	18.80 *	18.92 *	19.44 *
			Contract status	Public/private	Night work	All characteristics
5 %			3.76	3.72	3.76	3.72
10 %			4.88	4.84	4.88	4.88
20 %			5.76 *	5.76 *	5.76	5.76
50 %			8.08 *	8.08 *	8.12 *	8.20 *
80 %			11.80 *	11.76 *	11.80 *	11.96 *
90 %			15.24 *	15.24 *	15.28 *	15.36 *
95 %			19.60 *	19.52 *	19.56 *	19.72 *

Table 12: Integrated Absolute Distance (weights=$10\widehat{f}_{female}(wage)$)

Male density with Female Characteristics	Gap	Marginal change	Percentage of total gap explained
Unadjusted	0.241 [0.225,0.258]		
Occupation	0.171 [0.149,0.193]	−29.2 [−36.0%,−22.5%]	
Sector	0.177 [0.155,0.200]	4.0% [−1.2%,9.2%]	−26.4% [−33.7%,−19.1%]
Education	0.172 [0.149,0.194]	−3.3% [−5.8%,−0.7%]	−28.8% [−36.1%,−21.5%]
Part-/Full-time	0.108 [0.079,0.137]	−36.9% [−52.4%,−21.5%]	−55.1% [−67.1%,−43.1%]
Contract status	0.118 [0.088,0.148]	9.0% [0.1%,18.0%]	−51.0% [−63.4%,−38.6%]
Public/private	0.121 [0.088,0.153]	2.3% [−1.9%,6.5%]	−49.9% [−63.2%,−36.5%]
Night work	0.125 [0.087,0.163]	3.3% [−6.4%,12.9%]	−48.2% [−63.6%,−32.8%]
All characteristics	0.138 [0.098,0.179]	10.8% [4.8%,16.8%]	−42.7% [−59.3%,−26.0%]

Figure 3 presents the first counter-factual density which we consider. We compare female wages to male wages with the female occupation structure. All other characteristics for men retain the male distribution. We can see three things happening. First, the density moves to the left indicating that if males had the female occupation distribution that their wages would be lower than they currently are. This is reflected in the mean wage gap which now falls from

1.25 to 0.73 € per hour (Table 9, third row). As seen from Table 10, the gap in the median wage falls from 1.04 to 0.76 € per hour.

From Table 5 we see that males are heavily over-represented in the laborer category while females are heavily over-represented in the clerical category. Men are also over-represented in the manager and professional category. This characteristic alone accounts for 41% of the mean wage gap and 27% of the gap in median wages.

The fact that the gap between male wages with female occupations and female wages is smaller than the gap between male and female wages may be interpreted as evidence that occupation is acting to increase the wage gap between men and women in the data. Once we give both groups the same occupational distribution, the wage gap is seen to shrink. For the summary measures, negative numbers in the marginal change column can be interpreted as indicating that the variable explains part of the wage gap. Positive numbers can be interpreted as indicating that the distribution of that variable in the data is actually helping to reduce the actual wage gap between men and women.

The second interesting feature of Figure 3 is the movement in the lower tail of the density. The male density is now much more similar to the female density. This (relatively) large group of female workers at very low wages is thus explained considerably by occupation. In Table 11 we see that once female occupation is introduced into male wages, the 5% quantile drops from 4.96 to 4.28 € per hour. This is still significantly different from 3.84 € per hour, the 5% quantile of female wages.

The third striking feature of Figure 3 is that the mode of male wages with female occupations is not too dis-similar to the mode of female wages. The peak is not nearly as high, however.

Figure 4 presents the differences in the two densities. Introducing the female occupation structure into the male wage structure has clearly changed the densities quite a bit. But is this counter-factual density 'closer' to the female density? Given that the gap in the two densities is now much closer to zero at all points in the distribution, every measure of distance must show that the densities are closer. Table 12 shows that the integrated absolute distance, weighted by female density, has decreased by 29%.[12]

Figure 5 presents the result of introducing the female distribution of occupation and sector into the male wage structure, keeping other male characteristics the same. Figure 5 shows that in fact the counter-factual distribution for males actually shifts slightly to the right. While the combined effect of occupation and sector is to reduce the gap between male and female wages (36% lower for the mean–see the last column of Table 9), the marginal effect is to make the male and female distributions more unequal. The effect is very small. The mean wage gap grows from 9.41 to 9.48 € per hour (Table 9). This marginal change, while small, is significant at the 5% level. We find no significant change in median wages or integrated distance. At the mean, therefore, the distribution of men and women in various activity sectors seems to be acting to keep the wage gap down slightly. This result is in contrast to the parametric case where we find that sector contributes to exacerbating the wage gap.

Figure 6 provides the results from adding women's educational distribution, along with occupation and sector, to the male wage distribution. Quite surprisingly, education has no significant effect on the wage gap. This is in stark contrast to the parametric results where education was found to be one of the significant factors in reducing the wage gap between men and women.

Figures 7 and 8 provide the results from including women's part-time status, along with occupation, sector and education, to the male wage distribution. The results are again rather striking. Given women's part-time status, the male wage density shifts quite a bit to the left. So if men had women's part-time status their wages would be quite a bit lower than they are. We also see that this introduces a bi-modality in the male 'counter-factual' wage distribution. Thirdly, we note that in the lower tail (below 5 € per hour) that male 'counter-factual' wages are actually slightly worse than female wages.

The top panel of the last column of Table 11 presents the quantiles for this counter-factual distribution. At the 5%, 10% and 20% quantiles we now find no significant differences between the female wage distribution and the male wage structure with female occupation, sector, education and part-time status.

[12] We also considered unweighted measures of absolute distance as well as weighted and unweighted integrated squared distance measures and the results are roughly comparable. See the discussion below about the effects of weighting the absolute distance measure.

However, the quantiles for men at the median and above remain significantly different. The mean wage gap is reduced by 57% and the gap in the median wage is reduced by 62%. The absolute distance measure in Tables 12 shows that the two densities are now much closer as is evident from Figure 8.

Figures 9 through 11 present the progressive introduction of female contract status, public/private sector distribution, and finally all remaining observable characteristics including night work. Surprisingly, neither the public/private sector split nor night work (which is mostly men and which is paid a premium) contribute significantly to the wage gap. Contract status pushes the counter-factual male distribution slightly further away from the female distribution (indicating that contract status contributes to reducing the wage gap in the data). The effect is small however, 0.07 € per hour for the mean gap and 0.08 € per hour for the median gap. In the parametric case, we found a large contribution of night work to the wage gap, whereas in the non-parametric decompositions we find little effect of night work on the wage gap.

Table 11 provides a similar story for the quantiles. Giving women's occupation, sector, education and part-time characteristics to men, makes the distribution between men and women the same at the 20% quantile and below. There is no additional movement in the quantiles as we add the remaining characteristics. And the quantiles for men at the median and above remain significantly different even after we introduce all observable female characteristics. Nor is there any effect on the mean or median gap as can be seen in Tables 9 and 10.

In Tables 9 through 12 and Figures 1 through 11, we considered a comparison between the estimated density of female wages and the 'counter-factual' densities of male wages with the introduction of different female characteristics. One question that might be asked is whether the results are sensitive to the choice of reference wage structure. What if we compare male wages to 'counter-factual' densities of female wages with the introduction of different male characteristics? Figures 12 through 15 present a portion of these results. We do not show separate graphs for each characteristic since many of them have no visible effect on the distribution. Tables 13 through 16 contain the summary statistics for this decomposition.

Table 13: Mean wages implied from non-parametric decompositions

Female wages with Male Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	8.68 [8.63,8.73]	1.25 [1.17,1.32]		
Occupation	9.05 [8.97,9.12]	0.88 [0.80,0.96]	−29.5% [−34.9%,−24.1%]	
Sector	9.05 [8.96,9.14]	0.87 [0.77,0.97]	−0.7% [−6.5%,5.2%]	−30.0% [−37.1%,−22.8%]
Education	9.05 [8.95,9.14]	0.88 [0.78,0.98]	0.8% [−1.7%,3.3%]	−29.4% [−36.7%,−22.1%]
Part-/Full-time	9.10 [9.01,9.19]	0.83 [0.73,0.93]	−5.8% [−10.6%,−1.1%]	−33.5% [−40.7%,−26.3%]
Contract status	9.08 [8.99,9.17]	0.85 [0.74,0.95]	2.0% [−0.5%,4.4%]	−32.2% [−39.6%,−24.8%]
Public/private	9.10 [9.01,9.20]	0.82 [0.72,0.92]	−2.7% [−3.8%,−1.5%]	−34.0% [−41.3%,−26.7%]
Night work	9.20 [9.07,9.33]	0.73 [0.59,0.87]	−11.6% [−20.8%,−2.4%]	−41.6% [−52.4%,−30.9%]
All characteristics	9.08 [8.94,9.21]	0.85 [0.71,0.99]	16.9% [8.5%,25.2%]	−31.8% [−42.6%,−21.0%]

Table 14: Median wages implied from non-parametric decompositions

Female wages with Male Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	7.60 [7.55,7.65]	1.04 [0.97,1.11]		
Occupation	7.72 [7.64,7.80]	0.92 [0.83,1.01]	−11.5% [−19.3%,−3.8%]	
Sector	7.80 [7.70,7.90]	0.84 [0.73,0.95]	−8.7% [−16.1%,−1.3%]	−19.2% [−29.1%,−9.4%]
Education	7.80 [7.69,7.91]	0.84 [0.72,0.96]	0.0% [−4.7%,4.7%]	−19.2% [−29.5%,−9.0%]
Part-/Full-time	7.88 [7.76,8.00]	0.76 [0.64,0.88]	−9.5% [−16.6%,−2.5%]	−26.9% [−37.4%,−16.4%]
Contract status	7.88 [7.77,7.99]	0.76 [0.64,0.88]	0.0% [−5.0%,5.0%]	−26.9% [−37.4%,−16.4%]
Public/private	7.88 [7.77,7.99]	0.76 [0.64,0.88]	0.0% [−4.8%,4.8%]	−26.9% [−37.4%,−16.4%]
Night work	8.00 [7.86,8.14]	0.64 [0.49,0.79]	−15.8% [−27.7%,−3.9%]	−38.5% [−51.6%,−25.3%]
All characteristics	7.88 [7.73,8.03]	0.76 [0.60,0.92]	18.8% [7.0%,30.5%]	−26.9% [−41.2%,−12.7%]

Figure 12 shows the female counter-factual wage distribution including male occupation. The mode of the distribution is higher and slightly to the right and the density of very low wage workers has fallen. However the decrease in the gap is less substantial than what we observed in Figure 3. This is born out by Tables 13 and 14, where we see that including male occupation in the female wage structure decreases the gap by 30%. The gap in the median drops 12%.

This is reminiscent of the parametric case where we were less able to account for the wage gap when using the female reference wage structure. In this case, as in the parametric case, the explanation is that the effect of unobservables in the distribution of female wages is much larger than that for males. This is not surprising since women with children are more likely to consider non-wage aspects of the job such as location and flexibility.

Table 15: Quantiles

Unadjusted			Female wages with male characteristics			
	Male	Female	Occupation	Sector	Education	Part-/Full-time
5 %	4.96	3.84 *	4.60 *	4.56 *	4.56 *	4.80 *
10 %	5.64	4.88 *	5.20 *	5.20 *	5.20 *	5.36 *
20 %	6.48	5.64 *	5.84 *	5.84 *	5.84 *	6.00 *
50 %	8.64	7.60 *	7.72 *	7.80 *	7.80 *	7.88 *
80 %	12.52	11.08 *	11.48 *	11.60 *	11.56 *	11.52 *
90 %	15.76	13.64 *	14.44 *	14.44 *	14.44 *	14.32 *
95 %	19.52	16.64 *	17.84 *	17.60 *	17.68 *	17.56 *
			Contract status	Public/private	Night work	All characteristics
5 %			4.72 *	4.76 *	4.76 *	4.72 *
10 %			5.32 *	5.36 *	5.36 *	5.32 *
20 %			5.96 *	5.96 *	5.96 *	5.92 *
50 %			7.88 *	7.88 *	8.00 *	7.88 *
80 %			11.52 *	11.52 *	11.64 *	11.48 *
90 %			14.32 *	14.32 *	14.60 *	14.32 *
95 %			17.56 *	17.56 *	17.84 *	17.56 *

Table 16: Integrated Absolute Distance (weights=$10\widehat{f}_{male}(wage)$)

Female density with Male Characteristics	Gap	Marginal change	Percentage of total gap explained
Unadjusted	0.196 [0.183,0.210]		
Occupation	0.211 [0.189,0.234]	7.5 [−2.6%,17.6%]	
Sector	0.201 [0.179,0.223]	−4.8% [−9.4%,−0.3%]	2.3% [−7.5%,12.2%]
Education	0.204 [0.181,0.226]	1.4% [−0.6%,3.5%]	3.8% [−6.4%,14.0%]
Part-/Full-time	0.192 [0.168,0.216]	−5.6% [−9.8%,−1.4%]	−2.1% [−12.9%,8.8%]
Contract status	0.191 [0.167,0.215]	−0.9% [−2.4%,0.7%]	−2.9% [−13.9%,8.1%]
Public/private	0.187 [0.163,0.211]	−2.0% [−3.0%,−1.1%]	−4.9% [−16.0%,6.2%]
Night work	0.170 [0.140,0.199]	−9.2% [−18.0%,−0.3%]	−13.6% [−28.1%,0.9%]
All characteristics	0.187 [0.157,0.218]	10.5% [4.3%,16.6%]	−4.6% [−19.7%,10.5%]

Interpreting the numbers which summarize the area between the two curves is difficult without making reference to the graphs. Consider Figure 12 in combination with Table 16. Introducing the male occupation distribution into the female wage structure brings the two distributions closer together in the tails (below 5 € and above 14 € approximately) but further apart in the peak of the female wage distribution (between 6 € and above 8 € approximately). When we calculate the absolute distance of this gap, giving equal weight to each point, we find that the female counter-factual distribution is slightly closer to the male wage distribution. When we weight by the male density (Table 16), we find that they are actually more dis-similar after introducing male occupation into the female wage structure. However, this is nonetheless consistent with the large decrease in the wage gap since the major effect involved in introducing male occupation is to move the part of the female wage distribution which falls below 5 € up into the 6 to 8 € area.

Figures 13 and 14 present the results from introducing male occupation, sector, education and part-time status into the female wage distribution. Sector has the effect of increasing the wage gap in the data when we use the female wage structure, contrary to what we found when we used the male wage structure. (This effect is insignificant for the mean, but significant for the median.) When we used the male wage structure, we found that this group of characteristics completely eliminated the wage gap in the bottom part of the distribution. For the female wage structure, looking at Figure 14, the two distributions do not appear to be very different below about 7 € per hour. However, from Table 15 we see that there remains a significant difference between all the quantiles, even those in the lower part of the distribution. Part-time status again has a significant negative affect, but the magnitude is smaller in the female wage structure than it was when we used the male wage structure.

Figure 15 shows the female 'counter-factual' distribution when all male characteristics have been introduced. This distribution is still quite different from the distribution of male wages. Although much of the bump in the density at very low wages has been eliminated and the density has shifted out towards the right slightly, the mode of 'counter-factual' wages is still well below that of male wages. In contrast to the earlier results, we find that night work contributes to reducing the gap.

Looking at Figure 15 and Table 16, it is a curious result that the absolute distance measure shows no significant difference between the gap between the original male-female wage distributions and the gap between the male distribution and the female wage distribution with all observable male characteristics. This is partly because improvements in part of the distribution (below 5 € and above 10 €) are offset by increased gaps between the two densities in the middle of the distribution where most of the data is.

Globally, looking at Figure 11 and Figure 15, there are many aspects of the distribution that remain unexplained after introducing all observable characteristics. In the parametric case, we explained 53% and 20%, respectively, of the wage gap using the male and female reference wage structures. Looking at the implied mean from the non-parametric distributions in Tables 9 and 13, we see that 45% and 32% of the wage gap is explained in the analogous cases. So the overall picture is comparable to the parametric case, but the individual contribution of particular characteristics is quite different.

4.3 Results for full-time workers

Given the importance of part-time employment in explaining the wage gap, particularly in the non-parametric decompositions, we wish to explore the consequences of conducting the analysis on the sample of full-time workers only. Figures 16 through 21 and Tables 17 through 20 summarize these results.

The most striking result is that for both the male density with all female characteristics and the female density with all male characteristics, we are unable to explain any of the wage gap–the last row of Tables 17 and 20 show that although the gap is decreased, the result is insignificant. However, some of the individual characteristics are significant. The pattern does not change much from the full sample. For the male reference structure, occupation has a large effect on causing the wage gap at the mean. Sector and education have small effects on reducing the wage gap. For the female wage structure, most individual characteristics are insignificant, although the pattern is roughly as it was in the full sample. Night work has a significant effect on the wage gap.

Table 17: Mean wages implied from non-parametric decompositions
Full-time workers only

Male wages with Female Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	9.99 [9.89,10.08]	0.94 [0.85,1.03]		
Occupation	9.78 [9.69,9.87]	0.73 [0.66,0.80]	−22.1% [−28.6%,−15.5%]	
Sector	9.88 [9.78,9.98]	0.83 [0.75,0.91]	13.2% [8.0%,18.3%]	−11.8% [−20.0%,−3.7%]
Education	9.92 [9.82,10.02]	0.87 [0.79,0.95]	4.6% [2.0%,7.2%]	−7.8% [−16.5%,1.0%]
Contract status	9.90 [9.80,10.00]	0.85 [0.77,0.93]	−1.7% [−3.8%,0.3%]	−9.4% [−18.0%,−0.7%]
Public/private	9.86 [9.77,9.96]	0.82 [0.74,0.90]	−4.2% [−5.6%,−2.8%]	−13.2% [−21.6%,−4.7%]
Night work	9.90 [9.80,10.01]	0.85 [0.77,0.94]	4.6% [0.9%,8.4%]	−9.1% [−18.6%,0.3%]
All characteristics	9.98 [9.87,10.09]	0.93 [0.84,1.02]	8.8% [4.1%,13.4%]	−1.2% [−11.7%,9.4%]

Table 18: Quantiles
Full-time workers only

Unadjusted			Male wages with female characteristics			
	Female	Male	Occupation	Sector	Education	Contract status
5 %	4.24	5.08 *	4.72 *	4.72 *	4.72 *	4.80 *
10 %	5.24	5.76 *	5.52 *	5.56 *	5.56 *	5.56 *
20 %	6.00	6.56 *	6.40 *	6.44 *	6.44 *	6.40 *
50 %	8.04	8.72 *	8.68 *	8.72 *	8.72 *	8.72 *
80 %	11.44	12.52 *	12.32 *	12.40 *	12.48 *	12.48 *
90 %	13.96	15.76 *	15.36 *	15.64 *	15.76 *	15.72 *
95 %	17.00	19.48 *	18.84 *	19.40 *	19.56 *	19.52 *
			Public/private	Night work	All characteristics	
5 %			4.76 *	4.84 *	4.80 *	
10 %			5.52 *	5.56 *	5.56 *	
20 %			6.36 *	6.40 *	6.44 *	
50 %			8.68 *	8.68 *	8.76 *	
80 %			12.44 *	12.48 *	12.56 *	
90 %			15.68 *	15.76 *	15.92 *	
95 %			19.48 *	19.60 *	19.80 *	

Table 19: Integrated Absolute Distance (weights=$10\widehat{f}_{female}(wage)$)
Full-time workers only

Male density with Female Characteristics	Gap	Marginal change	Percentage of total gap explained
Unadjusted	0.148 [0.127,0.169]		
Occupation	0.140 [0.119,0.160]	−5.5 [−16.5%,5.5%]	
Sector	0.145 [0.123,0.168]	4.0% [−1.9%,9.9%]	−1.7% [−14.2%,10.8%]
Education	0.141 [0.119,0.162]	−3.2% [−5.8%,−0.7%]	−4.9% [−17.3%,7.6%]
Contract status	0.130 [0.109,0.151]	−7.7% [−10.1%,−5.3%]	−12.2% [−24.2%,−0.2%]
Public/private	0.124 [0.102,0.145]	−4.8% [−6.6%,−3.0%]	−16.4% [−28.6%,−4.2%]
Night work	0.126 [0.103,0.149]	1.9% [−3.3%,7.1%]	−14.8% [−28.3%,−1.4%]
All characteristics	0.138 [0.115,0.161]	9.8% [5.3%,14.2%]	−6.5% [−20.9%,7.8%]

Table 20 presents results for the mean using the female reference distribution.

Table 20: Mean wages implied from non-parametric decompositions
Full-time workers only

Female wages with Male Characteristics		Gap	Marginal change	Percentage of total gap explained
Unadjusted	9.05 [8.95,9.14]	0.94 [0.85,1.03]		
Occupation	9.10 [9.00,9.21]	0.89 [0.81,0.96]	−5.8% [−14.1%,2.6%]	
Sector	9.13 [9.02,9.25]	0.85 [0.76,0.94]	−3.7% [−9.2%,1.9%]	−9.2% [−18.9%,0.4%]
Education	9.14 [9.02,9.26]	0.85 [0.75,0.94]	−0.6% [−3.7%,2.5%]	−9.8% [−19.7%,0.1%]
Contract status	9.16 [9.04,9.28]	0.83 [0.73,0.92]	−2.6% [−4.2%,−1.0%]	−12.1% [−22.0%,−2.2%]
Public/private	9.19 [9.07,9.31]	0.80 [0.71,0.89]	−3.1% [−4.2%,−1.9%]	−14.8% [−24.6%,−5.0%]
Night work	9.29 [9.13,9.44]	0.70 [0.57,0.83]	−12.6% [−22.9%,−2.3%]	−25.5% [−39.3%,−11.8%]
All characteristics	9.15 [8.99,9.30]	0.84 [0.71,0.98]	20.4% [11.2%,29.6%]	−10.3% [−24.9%,4.3%]

4.4 Robustness to different orderings

This non-parametric decomposition technique is not insensitive to ordering. One reasonable question might be whether or not these results are driven by the order of the decomposition which we employed. To check this, we conducted the analysis using ten different orderings. Occupation and part-time status always had large and significant effects on the wage gap irrespective of where they were placed in the ordering. Sector, likewise, was always found to be acting to decrease the actual wage gap in the data. Education and public/private sector, when placed first in the ordering, both were found to have a negative impact on the actual wage gap. This result is what we found in the parametric analysis. In both cases, however, the impact is smaller than that of occupation, sector, or part-time status.

Any time that education appears after occupation in the ordering, its effect is entirely eliminated. The opposite is not true and occupation still has a large effect after accounting for education. It would seem that occupational segregation is a much more important influence on the wage gap than education.

Figure 22 shows the effect of adding female public/private sector status only to the male wage structure. There is no influence in the bottom part of the distribution, but there is a shift from the mode outwards towards the upper tail. Figure 23 shows the effect of adding the female education distribution only to the male wage structure. Again there is no effect on the group of low-wage workers, but we can see a slight movement from the mode out towards the upper tail. Figure 24 shows the effect of adding the distribution of female contract status to the male wage distribution and there is almost no effect on the distribution, nor on the mean, as shown in the last row of Table 21.

Table 21: Consequences of changing ordering of decompositions
Effect of each set of variables when placed first in decomposition
Mean wages: Full sample

Male wages with Female Characteristics		Gap	Percentage of gap explained
Unadjusted	9.93 [9.87,9.98]	1.25 [1.17,1.32]	
Occupation	9.41 [9.34,9.48]	0.73 [0.65,0.81]	−41.5% [−46.2%,−36.8%]
Sector	10.53 [10.43,10.62]	1.85 [1.74,1.96]	48.3% [43.0%,53.6%]
Public/private	10.14 [10.08,10.19]	1.46 [1.38,1.53]	16.9% [15.0%,18.8%]
Part-/Full-time	9.54 [9.44,9.64]	0.86 [0.75,0.98]	−30.8% [−37.4%,−24.1%]
Education	10.12 [10.06,10.18]	1.44 [1.37,1.51]	15.4% [11.5%,19.3%]
Night work	9.93 [9.88,9.98]	1.25 [1.18,1.33]	0.4% [−0.9%,1.8%]
Contract status	9.89 [9.83,9.95]	1.21 [1.13,1.29]	−2.8% [−4.3%,−1.2%]

5 Conclusion

The non-parametric analysis adds considerable value to the parametric results. The effect of different characteristics in explaining the wage gap is strikingly different at different points in the distribution. Some characteristics, such as education and night work, appear not particularly important in the non-parametric analysis. Occupation and part-time status, revealed as important in the parametric analysis, are found to be particularly key in explaining differences amongst low-wage workers.

It is not clear that the government would want to implement policies to reduce the wage gap between men and women. Certainly if the gap arose out of efficiently functioning labor markets, the government might be loath to intervene.[13] However, if the gap were seen to arise from discrimination, our paper points to three areas of concern

1. A substantial fraction of workers report a wage below the legal minimum wage. While this is no doubt due partially to measurement error, these individuals are concentrated in part-time and clerical work where the possibility that individuals are actually working more hours than for which they are paid does arise. For workers paid a piece-meal rate, the government could be more aggressive in making sure that these rates reflect reasonable work expectations. This problem may not be linked to discrimination, per se, but it certainly affects many more woman (fifteen percent) than men (seven percent.)

2. Discrimination may be taking the form of occupational segregation. While women have had some success at penetrating into predominantly male occupations, those occupations which have traditionally been female-dominated continue to be very segregated. Clerical work in particular is striking in our data. This also tends to be very low wage work. The government might look to trying to policies to increase wages in these traditionally female occupations.

3. If one rejects the story of occupational discrimination and treats occupation as simply another characteristic, then our results show that in the bottom fifth of the wage distribution, there is no difference in the return to characteristics between men and women. That premise would lead one to conclude that the entire wage gap is driven by workers in the top 75 to 80 percent of the wage distribution. Any government programs to affect the wage gap should thus focus on this group.

[13] See Cain (1990) and Altonji and Blank (1999) for a review of models which give rise to gender wage gaps both with and without discrimination.

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Appendix

Using the estimated densities for male and female wages, we calculate the summary statistics in the following way

Mean

$$\int_{1}^{41} w\widehat{f}_{male}\left(w\right)dw - \int_{1}^{41} w\widehat{f}_{female}\left(w\right)dw$$

For the male wage structure with female characteristics progressively introduced, we then calculate the mean gap in a similar fashion. For example, when we introduce only the female occupation into the male wage structure, we have

$$\int_{1}^{41} w\widehat{f}_{male}\left(w; S = male, x_o = fem, x_R = male\right)dw - \int_{1}^{41} w\widehat{f}_{female}\left(w\right)dw$$

Median

We also present the gap in the median wage. We solve for the median by solving

$$\int_{1}^{z} \widehat{f}_{male}\left(w\right)dw = .5 \tag{13}$$

for z. We then calculate the gap as

$$\int_{1}^{\widehat{z}_{male}} \widehat{f}_{male}\left(w\right)dw - \int_{1}^{\widehat{z}_{fem}} \widehat{f}_{fem}\left(w\right)dw$$

Quantiles

For the quantiles, we solve (13) for the appropriate value.

Integrated Absolute Distance, weighted

$$\int_{1}^{41} \widehat{f}_{fem}(w)\left|\widehat{f}_{male}\left(w; S = male, x_o = fem, x_R = male\right) - \widehat{f}_{fem}(w)\right|dw$$

For weights we use the estimated density of the female wage distribution when we are comparing female wages with male 'counter-factual' distributions that incorporate female characteristics. In the converse case we use the estimated male density.

Figure 1
French wage distribution

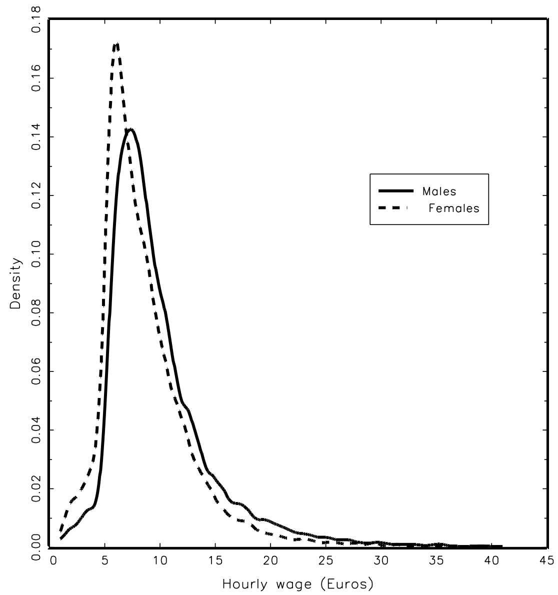

Figure 2
French wage distribution: actual differences (male−female)

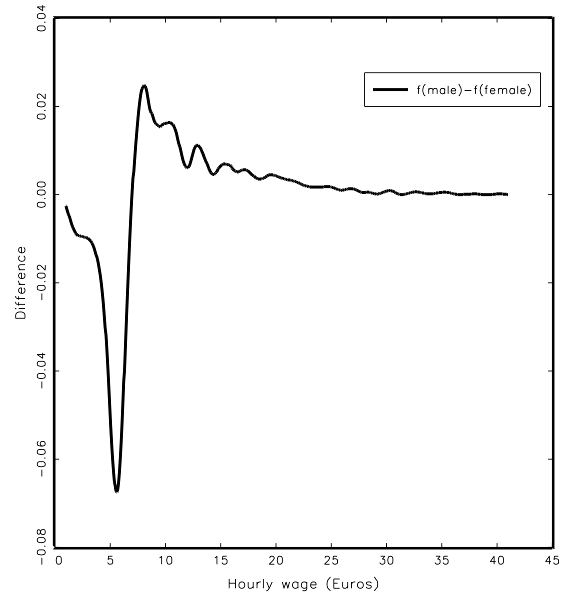

Figure 3
Differences from occuption

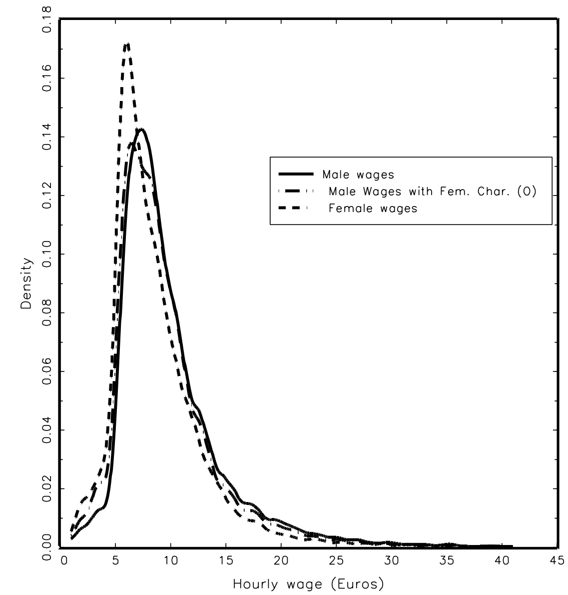

Figure 4
French wage distribution: differences from occupation

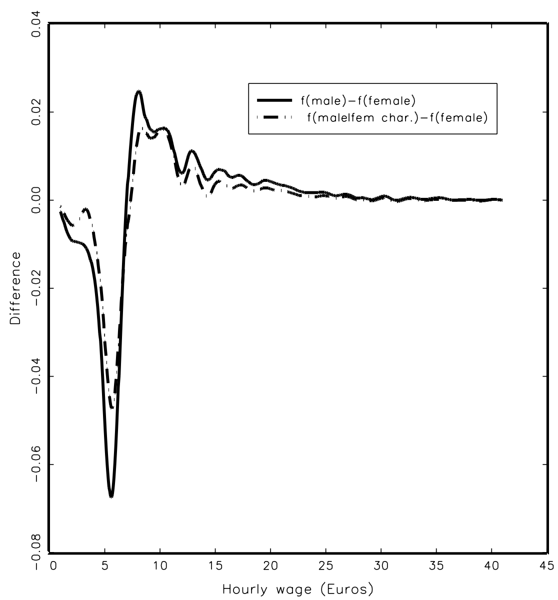

Figure 5
Differences from occuption and sector

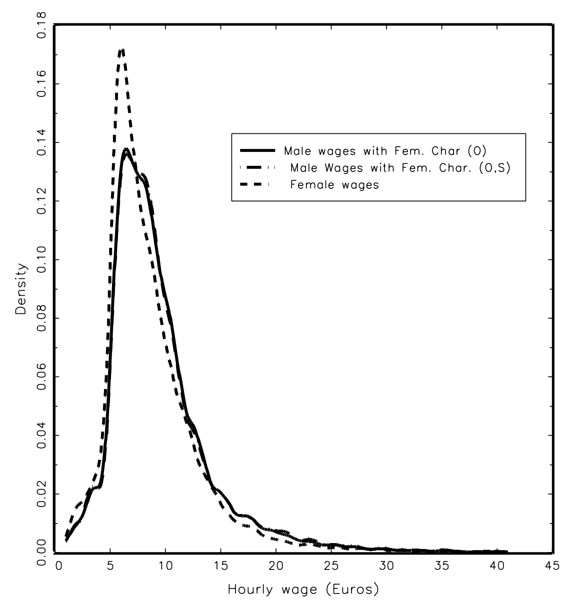

Figure 6
Differences from occuption, sector and education

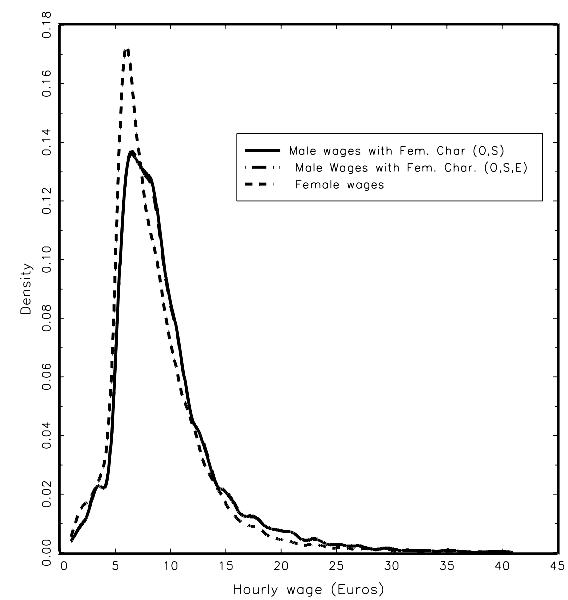

Figure 7
Differences from occuption, sector, education, and part-time status

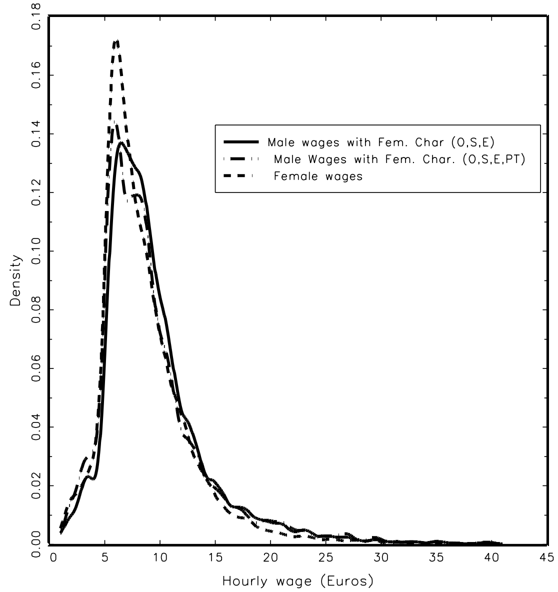

Figure 8
Differences from occupation, sector, education, and part-time status

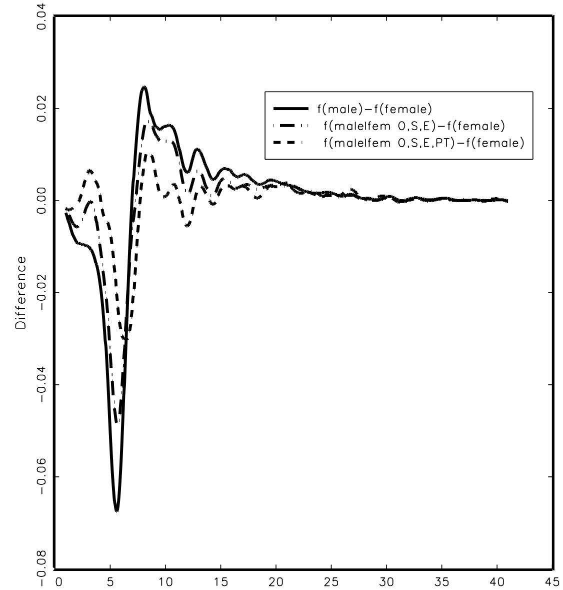

Figure 9
Differences from occupation, sector, education, part-time status,
and contract status

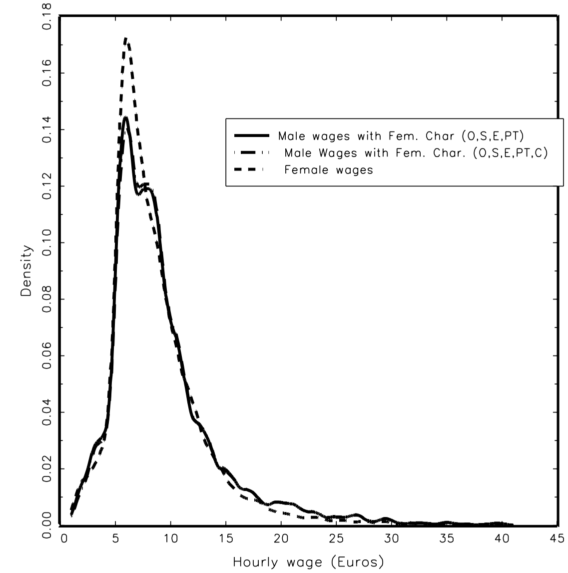

Figure 10
Differences from occuption, sector, education, part-time status,
contract status and public/private status

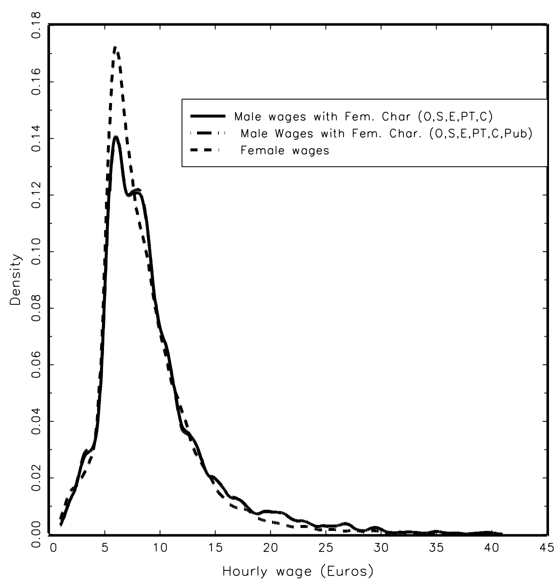

Figure 11
Differences from all observable characteristics

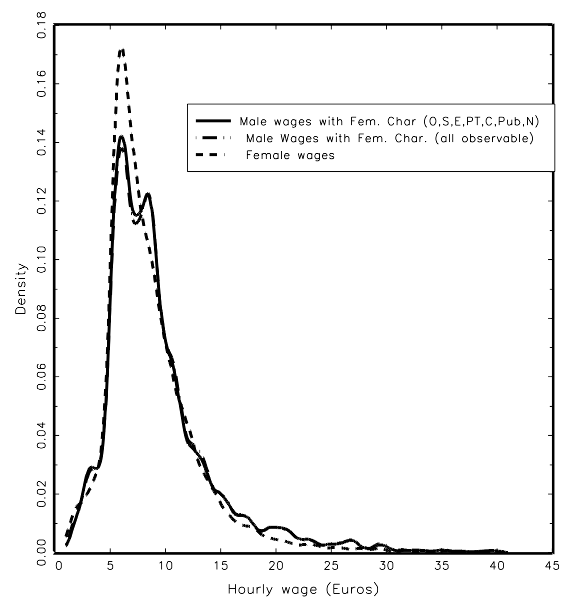

Figure 12
Differences from occuption

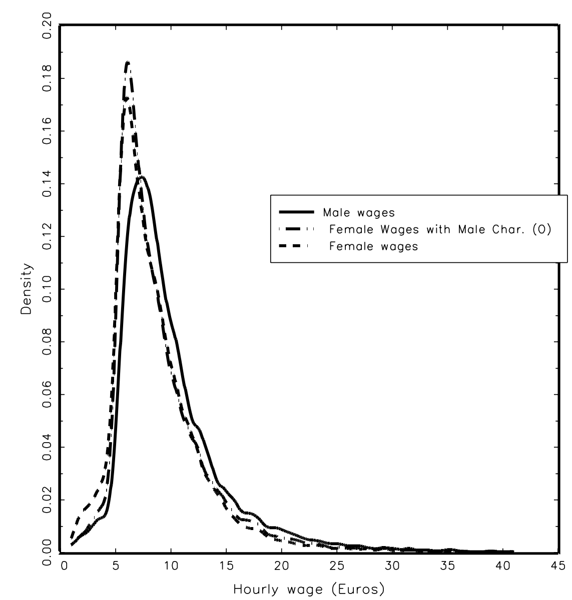

Figure 13
Differences from occupation, sector and education

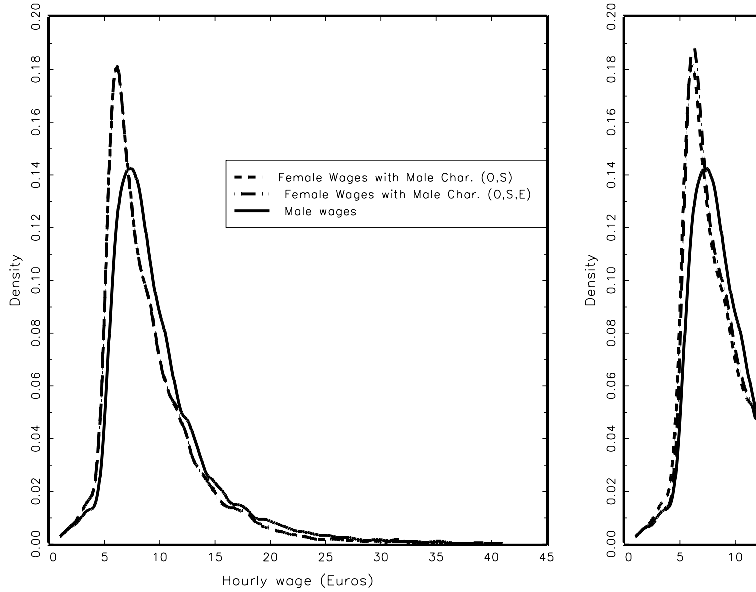

Figure 14
Differences from occupation, sector, education, and part-time status

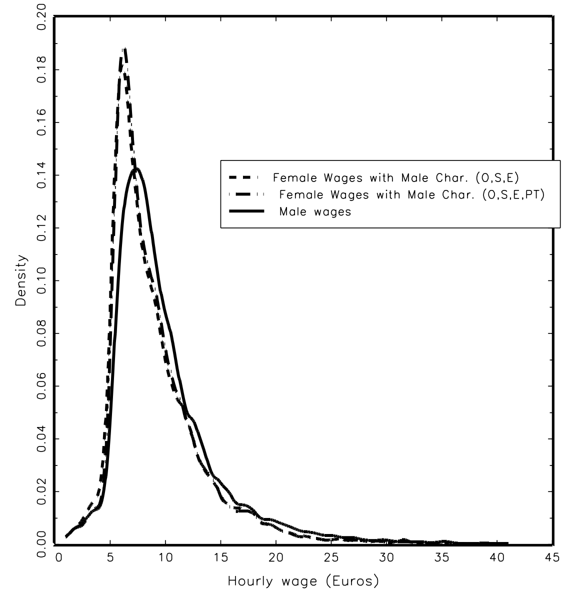

Figure 15
Differences from all observable characteristics

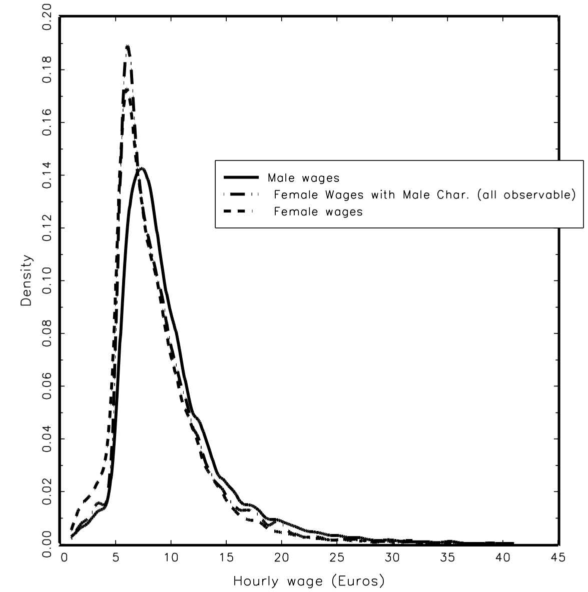

Figure 16
Full-time workers: Differences from occupation

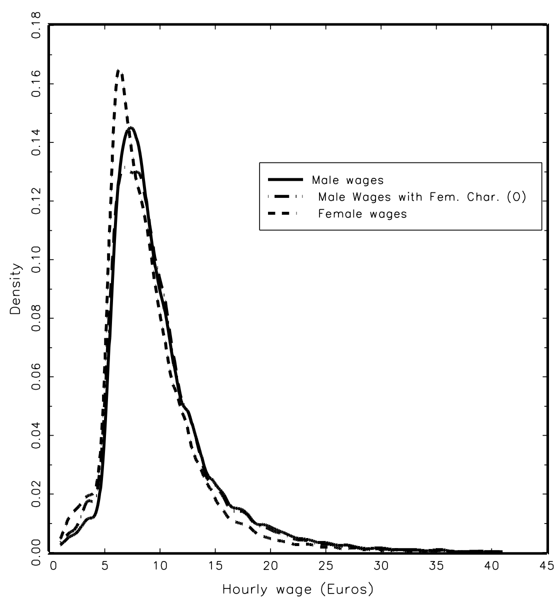

Figure 17
Full-time workers
Differences from occupation, sector and education

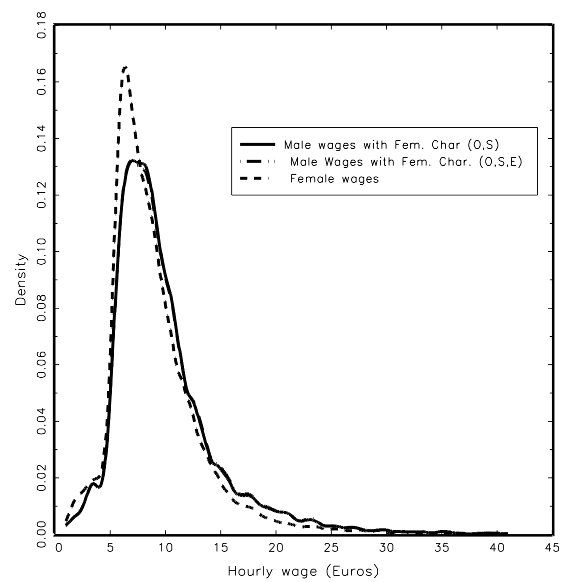

Figure 18
Full-time workers: Differences from occupation, sector,
education, contract, and public/private status

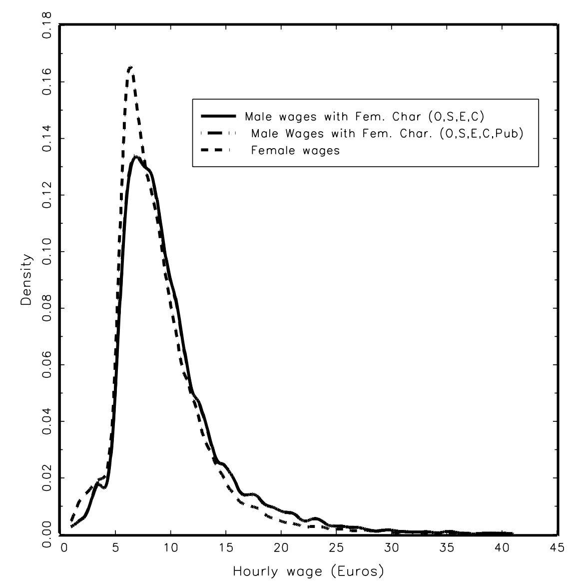

Figure 19
Full−time workers
Differences from all observable characteristics

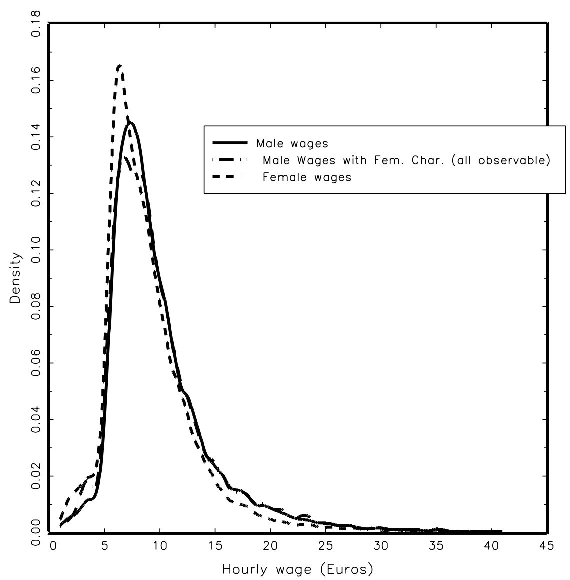

Figure 20
Full−time workers: Differences from occuption

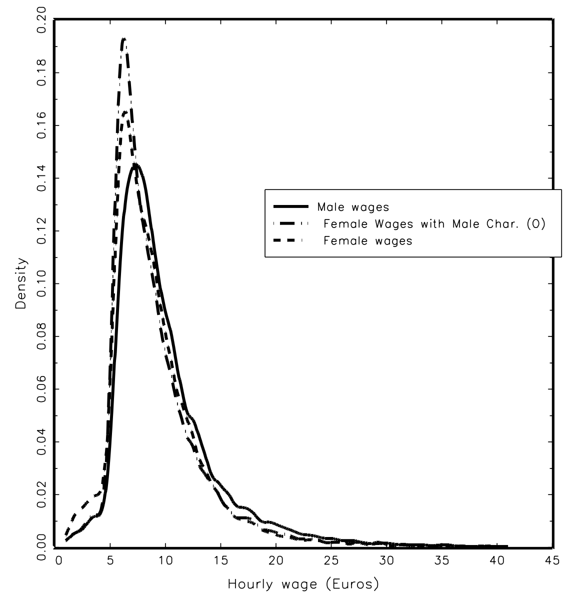

Figure 21
Full−time workers
Differences from all observable characteristics

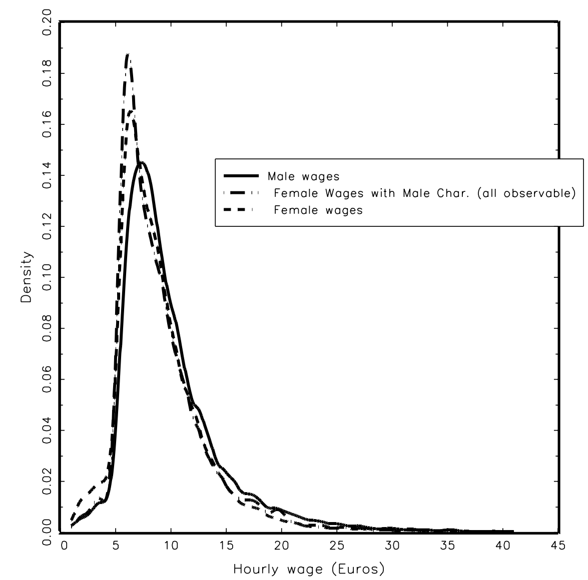

Figure 22
Differences from public/private employer

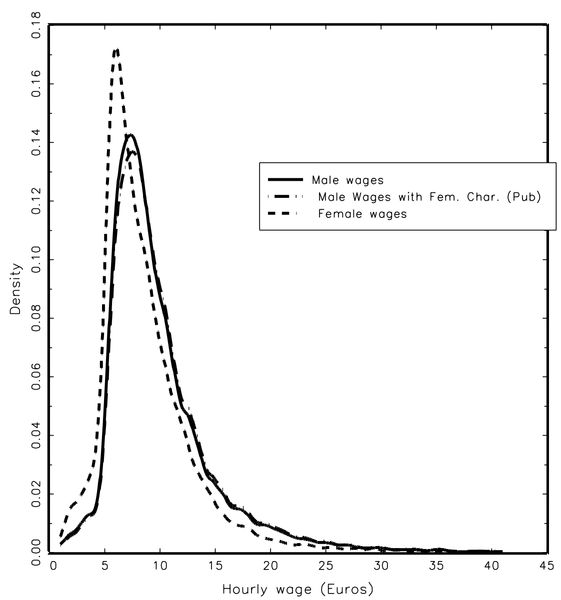

Figure 23
Differences from education

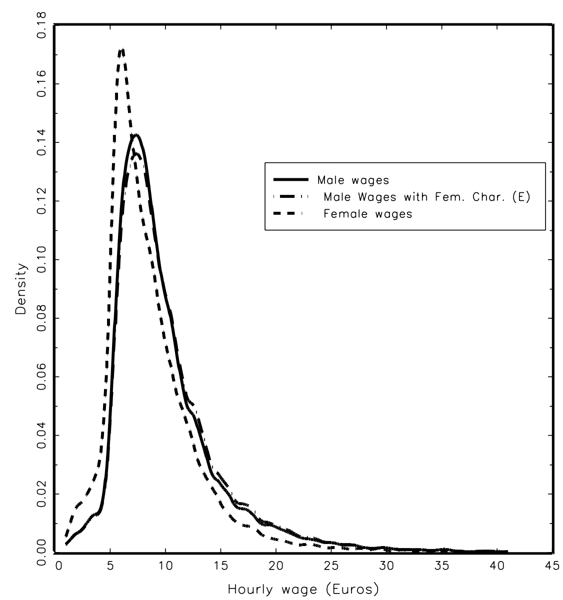

Figure 24
Differences from contract status