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WAGE FORMATION AND GENDER WAGE GAPS: THE CHANGING ROLE OF HUMAN CAPITAL IN THE FINNISH TECHNOLOGY INDUSTRY

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ABSTRACT: Both academia and policymakers express a strong belief in higher average education levels exerting a narrowing impact on wage inequality in general and gender wage gaps in particular. The present paper scrutinizes whether or not this effect extends to R&D- and export-intensive branches such as the technology industry. The answer seems to be a cautious 'no'. Indeed, while changes in standard human capital endowments can explain little, if anything, of the growth in real wages or the widening of wage dispersion among the Finnish technology industry's white-collar workers, a new job task evaluation scheme introduced in 2002 seems to have succeeded, at least in part, to make the wage-setting process more transparent by re-allocating especially the industry's female white-collar workers in a way that better reflects their skills, efforts and responsibilities. One crucial implication of this finding is that improving the standard human capital of women closer to that of men will not suffice to narrow the gender wage gap in the advanced parts of the economy and, hence, not also the overall gender wage gap. The reason is obvious: concomitant with rising average education levels, other skill aspects have received increasing attention in working life. Consequently, a conscious combination of formal and informal competencies as laid down in well-designed job task evaluation schemes may, in many instances, offer a more powerful path to tackling the gender wage gap.

Key words: decomposition, gender wage gap, human capital, job task evaluation, technology industry, wage formation
JEL-codes: J16, J31

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TIIVISTELMÄ: Sekä akateemisessa maailmassa että poliittisten päättäjien keskuudessa vallitsee vahva usko siihen, että väestön keskimääräisen koulutustason nousu kaventaa palkkaeroja ja erityisesti sukupuolten välisiä palkkaeroja. Tässä paperissa selvitetään, ulottuuko tämä vaikutus nykypäivän tutkimus- ja kehitysintensiivisille vientitoimialoille kuten teknologiateollisuuteen. Vastaus tähän kysymykseen näyttäisi olevan varovainen 'ei'. Tuloksemme osoittavat, että teknologiateollisuuden toimihenkilöiden perinteisellä tavalla mitatun inhimillisen pääoman rakenteessa tapahtuneet muutokset pystyvät selittämään vain murto-osan, jos lainkaan, heidän palkkarakenteessaan tapahtuneista muutoksista. Tämä koskee yhtä lailla reaalipalkkojen kasvua kuin palkkaerojen (eli palkkahajonnan) suurentumista. Sen sijaan vuonna 2002 käyttöön otettu tehtävien vaativuustasoluokitus on ainakin osittain tehnyt teknologiateollisuuden toimihenkilöiden palkanmuodostuksesta aiempaa selvästi läpinäkyvämpää. Erityisen selkeästi tämä muutos näkyy kaikista osaavimpien ja kilpailukykyisimpien naistoimihenkilöiden kohdalla, jotka aiempaa paremmin näyttäisivät siirtyneen omia taitojaan ja ponnistuksiaan vastaaviin tehtäviin. Tutkimuksemme keskeinen johtopäätös onkin, että naisten perusosaamisen nostaminen lähemmäksi miesten tasoa ei riitä kaventamaan sukupuolten välisiä palkkaeroja kansainvälisillä, vahvasti tutkimukseen ja kehitykseen panostavilla toimialoilla, joissa erityisosaamisen merkitys tuottavuuden ja kannattavuuden edistämisessä on ratkaisevaa. Tämä johtuu siitä, että työelämässä on enenevässä määrin ryhdytty palkitsemaan työssä hankittua pätevyyttä. Toisin sanoen, varsinkin näillä toimialoilla on palkkatason ja palkkaerojen huomattavasti keskeisemmäksi määrittäjäksi noussut perinteisen osaamisen sijaan työn vaativuus. Näin ollen huolellisesti suunniteltu tehtävien vaativuustasoluokitus eli muodollisen ja epämuodollisen osaamisen tarkkaan mietitty yhdistäminen näyttäisi monessa tilanteessa tarjoavan tehokkaamman välineen sukupuolten välisten palkkaerojen kaventamisessa.

Avainsanat: dekomponointi, sukupuolten välinen palkkaero, inhimillinen pääoma, tehtävien vaativuuden arviointi, teknologiateollisuus, palkanmuodostus
JEL-koodit: J16, J31

1. INTRODUCTION

The technology industry has over the past few years attracted much attention in Finland. The reasons are multifold. First, the technology industry has been an integrated part of the so-called Nokia miracle and has, as a consequence, become the leader of technical progress in the Finnish economy. Second, because of the technology industry's fundamental – mainly globalization-induced – restructuring, including outsourcing and off-shoring, also its workforce has undergone substantial changes, the most conspicuous being a clear strengthening in the dominance of high-educated employees. Third, in 2002 the technology industry introduced an innovative system for evaluating job tasks – in a similar fashion across all of the industry's establishments – by the skills, efforts and responsibilities required for performing the working tasks related to each job. Based on this radically new evaluation system, the personnel of each establishment were ranked according to a 4-level hierarchy which, by definition, is independent of the job holder's occupation category.[1] Last, but not least, the technology industry has been a forrunner not only in developing job-task evaluation schemes but also in adopting and implementing performance-related pay schemes. Indeed, the growing use within the technology industry of various modes of performance-related pay has resulted in an increasingly diverging trend between the employees' basic (normal) and total wages.

These major changes within Finland's most R&D- and export-intensive industry raise questions about the present-day role of standard measures of human capital (formal education, work experience) in setting the industry's wages and, especially, in promoting gender wage equality, as compared to emerging new ways of evaluating individual labour market-relevant competencies. This paper attempts to address these questions, which evidently have resonance also to other advanced industries as well as to other advanced economies, by use of a decomposition method based on quantile regression recently proposed by Melly (2006). A clear advantage of this approach is that the decomposition can be undertaken along the whole wage distribution as compared to the traditional way of decomposing wage differentials at the mean. Hence, the methodology can be seen as an extension to Oaxaca (1973), Blinder (1973) as well as Juhn, Murphy and Pierce (1993).

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[1] This new occupation-independent 4-level job task hierarchy distinguishes between 'management', 'senior specialists', 'specialists' and 'auxiliary staff'. Previous to 2002, the system used for categorizing job tasks into hierarchies (levels) was entirely different: the white-collar workers were assigned into specific job-task groups comprising a varying number of distinct job-task levels (from one up to, at most, six levels) which, moreover, were not comparable across job-task groups.

While decomposition procedures based on quantile regression have been used in a growing number of studies on changes in wage structures over time (see e.g. Asplund, 2010, for a brief review), the use of the methodology within other fields of study is only emerging. So far the method has spread, albeit in a limited fashion, mainly to studies of gender wage gaps (see e.g. Chzhen and Mumford, 2009, and the references therein) and occasionally also to studies of private–public sector wage differentials (Melly, 2005a). The present paper contributes to this restricted literature by presenting multifaceted results on the sources underlying the gender wage gaps observed in Finland in the early 2000s.

Taken together, our findings indicate that improvements in the standard human capital endowments of women can go some way in narrowing the overall male–female wage gap. Raising the skill levels of women closer to those of men is not, however, likely to dissolve the gender wage gap problem. Concomitant with rising average education levels, other skill dimensions have received increasing attention in working life. In research focusing on traditional measures of human capital, this tends to show up in expanding wage differentials between (observably) equally skilled individuals (within-group wage dispersion). Our results suggest that carefully designed job-task evaluation schemes can provide at least part of a solution in the sense that an individual's ranking will then be determined by use of consciously combined formal (easily measurable) and informal (mostly unquantifiable) competencies, thus making the wage-setting process in the workplace more transparent. Additionally, such schemes can be expected to revive the role of formal education and cumulated work experience in wage formation by strengthening their indirect, if not their direct, effect on wage levels and trends. Having said this, our results, however, also show that making job-task evaluation schemes work successfully to promote the narrowing of gender wage gaps across the whole wage distribution is a most challenging task.

The rest of the paper is organized as follows. The next section presents the data used. It also provides descriptive statistics for the dependent variable (total hourly wages) and the key explanatory variables included in the estimated models with the focus being on comparing levels and trends within and across genders. Section 3 introduces the estimation method and framework applied in Section 4 for unveiling, separately for each gender, the main sources underlying real wage growth and changing wage dispersions. In Section 5, the same approach is used to compare the sources underlying the observed gender wage gaps and, especially, to identify changes over time in the relative importance of these sources. In both these sections presenting major results, particular attention is paid to the role played by standard human capital endowments as compared to the job task evaluation scheme introduced in 2002. Section 6 concludes.

2. DATA AND DESCRIPTIVE STATISTICS

The data comes from the administrative records of the Confederation of Finnish Industries. The confederation gathers, on a regular basis, information on wages and worker attributes directly from its member companies. Additionally, these files are supplemented with information on, *inter alia*, completed educational degrees as recorded in the official registers of Statistics Finland.

The particular dataset used in the subsequent analysis covers practically all white-collar workers employed in the technology industry in Finland. The estimation data is restricted to those in full-time employment only, as the share of part-timers is almost non-existent (less than 1.5 per cent still in 2007). It comprises a cross-section of 52,273 observations for 2002 and of 57,072 observations for 2007. While the technology industry is an expanding branch, it is also an increasingly male-dominated one (cf. Table 1 below).

The major reasons for focusing on the time period 2002–2007 are as follows. The year 2002 is chosen as the starting point because it is the first year of the new job task evaluation system. The year 2007 is, in turn, the most recent year readily available in our database. Moreover, these years represent a period of steady economic growth and declining unemployment rates. Also the institutional setting remained largely unchanged, although the traditional comprehensive collective bargaining framework did give increasingly way to more localized bargaining as a growing number of issues in sectoral agreements were made negotiable at a local level.[2] Pay systems such as performance-related pay and profit-sharing schemes have never been regulated by collective agreements in Finland, though.

The evolution of wage differentials within and between male and female white-collar workers in the Finnish technology industry is analyzed by use of total hourly wages.[3] Hence, the wage concept used as the dependent variable throughout the subsequent analysis includes any performance-pay items and/or fringe benefits paid on top of

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[2] For more details, see e.g. Asplund (2007).

[3] The use of hourly wages rules out the possibility that at least part of the change in wage dispersion or in the gender wage gap is caused by changes in the difference in the number of hours worked (cf. Lemieux, 2006).

the normal (basic) hourly wage. Focusing on total wages is well-motivated as the dispersion of the industry's white-collar normal wages remained practically unchanged in the years investigated, irrespective of gender. Accordingly, it is hardly surprising that no major changes are discernible in the gender wage gap when measured by the normal wage.[4] The total hourly wage is deflated by the official consumer price index. It is calculated using information on total monthly earnings and normal weekly working hours (as recorded in the files of employers[5]). Table 1 gives descriptive statistics concerning the level and dispersion of total hourly real wages for, respectively, male and female white-collar workers employed on a full-time basis in the technology industry.

In brief, Table 1 shows that the technology industry's white-collar total wages are substantially more dispersed among those earning above the median. This holds true for both genders. The dispersion in especially top-end wages widened further between 2002 and 2007 while the dispersion in below-median wages remained practically unchanged. This pattern is discernible also across both genders. Particularly striking is the finding that the dispersion in total wages among the industry's top-earning white-collar workers was larger among its female employees already in 2002. Additionally, they saw their wage differentials increase over the next few years to a broader extent than did their male counterparts. For the rest of the distribution, the total wages of females remained less dispersed, as did also the overall dispersion in their wages. However, despite the dispersion in female total wages having moved closer to that of male total wages, the overall gender wage gap was substantial still in 2007 (about 19 per cent at the mean) and, in effect, increasing when moving up the wage scale.

The subsequent statistical analysis will pay particular attention to the role of standard human capital endowments as compared to alternative ways of measuring competencies (here represented by the technology industry's new job task evaluation scheme) in explaining the within- and between-gender patterns and trends unveiled in Table 1. A major reason for this particular focus is that both academia and policymakers continue to express a strong belief in higher average education levels exerting a positive influence on wage inequality in general and gender wage gaps in particular. Are such straightforward effects discernible in today's R&D- and export-intensive branches or should the attention be increasingly turned to other ways of identifying key competencies at least when it comes to the more advanced parts of the economy?

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[4] Results obtained from using the basic hourly wage instead of the total hourly wage can be obtained from the authors upon request.

[5] The records refer to December of each year.

Table 1. Descriptive statistics for the dependent variable (total hourly real wage)

	Males		Females		Females vs. males	
	2002	2007	2002	2007	2002	2007
Level (2007 Euros)						
Mean	21.52	24.91	16.84	20.15	0.78	0.81
Standard deviation	7.70	9.19	5.92	7.46	0.77	0.81
Percentiles						
P10	14.23	16.25	11.54	13.54	0.81	0.83
P25	16.17	18.55	12.94	15.32	0.80	0.83
P50	19.58	22.44	15.19	17.97	0.78	0.80
P75	24.84	28.82	19.02	22.70	0.77	0.79
P90	31.13	36.60	24.28	29.53	0.78	0.81
Interpercentiles						
ln(P90) – ln(P10)	0.78	0.81	0.74	0.78	0.95	0.96
ln(P75) – ln(P25)	0.43	0.44	0.38	0.39	0.90	0.89
ln(P90) – ln(P50)	0.46	0.49	0.47	0.50	1.01	1.02
ln(P90) – ln(P75)	0.23	0.24	0.24	0.26	1.08	1.10
ln(P75) – ln(P50)	0.24	0.25	0.22	0.23	0.94	0.93
ln(P50) – ln(P10)	0.32	0.32	0.27	0.28	0.86	0.88
ln(P50) – ln(P25)	0.19	0.19	0.16	0.16	0.84	0.84
ln(P25) – ln(P10)	0.13	0.13	0.11	0.12	0.90	0.93
Number of observations	37 711	41 821	14 562	15 251	52 273	57 072
Share of females (%)					27.9	26.7

In order to answer this intricate question, the (natural) logarithm of total hourly real wages is first regressed on a set of characteristics representing traditional measures of individual human capital: formal education, work experience and seniority. As already noted, the information on formal education is from the official education register administered by Statistics Finland. It gives the highest single degree completed by an individual. These degrees are turned into years of schooling using the transformation key of Statistics Finland. Work experience measuring total years in the labour market is not available in the data and is, therefore, defined as age[6] minus years of schooling minus age at school start (7), thus referring to potential work experience. Seniority is derived from direct information in the data records on the starting year of the current employment relationship. In a second step, the estimated models are supplemented with dummy indicators capturing the 4-level job task evaluation scheme introduced in 2002 and, in a final step, with dummy indicators for aggregated occupation categories.[7]

[6] The sample population is restricted to those aged 18 to 65.

[7] The data originally contains 18 main occupation categories (as constructed from a total of 55 single occupations) which were, however, re-classified into 11 occupation categories, as some of the categories comprised very few or occasionally no observations at all.

Table 2 presents, separately for 2002 and 2007, gender-specific descriptive statistics for years of schooling, potential work experience and seniority, for job-level distributions as well as for occupation categories. In brief, the table shows that the average schooling level is high and increasing with the technology industry's female white-collar workers being on average only marginally less educated than their male colleagues. Needless to say, the reversed gender gap in the average length of work experience follows from work experience referring to its potential (rather than its actual) length. A common feature of the industry's male and female white-collar workers, however, is that their average labour market experience is relatively long and increasing, as is also their experience with the current employer.

Table 2. Descriptive statistics for key characteristics

	Males		Females		Females vs. males*	
	2002	2007	2002	2007	2002	2007
Basic human capital attributes						
Average schooling, years	14.2	14.4	13.6	13.9	0.96	0.97
Standard deviation	2.3	2.3	2.4	2.3	1.03	1.02
Work experience, years	17.1	18.5	18.3	19.7	1.07	1.07
Standard deviation	10.2	10.3	10.4	10.7	1.02	1.04
Seniority, years	9.0	9.7	8.9	9.7	0.99	1.00
Standard deviation	9.3	9.7	9.6	10.0	1.03	1.03
Distribution across job task evaluation levels, %						
1 (highest)	6.4	11.0	1.9	5.3	10.4	14.9
2	36.0	39.2	18.8	24.0	16.8	18.2
3	47.5	42.6	41.1	41.7	25.1	26.3
4 (lowest)	10.1	7.2	38.1	29.0	59.4	59.6
Distribution across aggregated occupation categories, %						
Business management and development	0.9	0.9	0.9	0.7	26.1	22.3
Research and development	46.0	43.5	19.4	17.8	14.0	13.0
Quality control	3.3	3.3	3.5	4.3	28.8	32.2
Manufacturing and construction	17.2	17.4	4.3	5.8	8.8	10.8
Transport and storage	2.7	1.8	6.0	5.0	46.3	49.7
Information processing	7.9	6.4	6.8	5.2	24.8	23.1
Maintenance and repair	3.0	4.8	0.4	0.6	5.2	4.5
Sourcing	3.2	3.8	4.8	6.4	36.7	37.8
Sales, marketing and communication	12.3	14.8	14.0	17.3	30.5	30.0
Legal, environmental and financial management	1.9	2.3	14.2	15.1	73.9	70.8
Administration, health care and security	1.4	1.1	25.9	21.7	87.4	88.2
Number of observations	37 711	41 821	14 562	15 251	52 273	57 072

Note: * For the job task evaluation levels as well as for the aggregated occupation categories, the numbers give the relative share of women at each level and in each occupation category, respectively.

The distribution of male and female white-collar workers across the four job task evaluation levels reveals a male dominance at the higher levels and a female dominance especially at the lowest level (4). The most conspicuous change compared to the initial situation in 2002 is an increase in the relative share of women at the highest level (1), from 10.4 to nearly 15 per cent. Finally, the technology industry is characterized by strong segregation of its male and female white-collar workers into specific occupations. As the time period under scrutiny is rather short, it is hardly surprising that the gender distribution across occupations reveals only minor changes.

3. ESTIMATION METHOD AND FRAMEWORK

The estimation method applied in the subsequent analysis encompasses a total of three steps: estimation of the whole conditional wage distribution using quantile regression techniques[8], estimation of the corresponding unconditional distribution by integrating this conditional distribution over the range of characteristics covered and, finally, decomposition of changes over the particular dimension considered (time and gender, respectively) in the estimated counterfactual distribution into two major factors capturing the contribution of changes in coefficients (price effect) and in characteristics (composition effect). Next, each step is described in more detail.[9]

While ordinary least squares (OLS) techniques provide estimates for the conditional mean only, quantile regression (QR) techniques allow the whole conditional wage distribution to be estimated. Moreover, while QR estimates capture changes in the shape, dispersion and location of the distribution, OLS estimates do not. Assume, following Koenker and Bassett (1978), who first proposed the QR technique, that[10]

$$F_{y|x}^{-1}(\tau|x_i) = x_i\beta(\tau), \quad \forall\, \tau \in \left]0,1\right[\,, \tag{1}$$

where $F_{y|x}^{-1}(\tau|x_i)$ is the τ^{th} quantile of the log wage distribution y conditional on a $K \times 1$ vector of relevant covariates x_i with (y_i, x_i) representing an independent sample $i = 1,\dots,N$ drawn from some population. Koenker and Bassett (1978) further show that $\beta(\tau)$ can be estimated, separately for each quantile τ, by

[8] A comprehensive review of quantile regression is provided by Koenker (2005).

[9] For a full outline, see e.g. Machado and Mata (2005) and Melly (2005a, 2005b, 2006).

[10] The notation is simplified by suppressing the dependence on the time and the gender dimension, respectively. The notation]0,1[in eq. (1) indicates that, formally, the quantile regression is not defined at 0 or 1, implying that $0 < \tau < 1$.

$$\hat{\beta}(\tau) = \underset{b \in \Re^K}{\arg\min} \frac{1}{N} \sum_{i=1}^{N} (y_i - x_i b)(\tau - 1(y_i \leq x_i b)), \tag{2}$$

where $1(\cdot)$ is the indicator function. Since the dependent variable is the (natural) logarithm of wages, eq. (2) produces a vector of coefficients which can be interpreted as the wage effects of the different characteristics at a particular quantile of the conditional wage distribution.

By definition, an infinite number of quantile regressions along the wage distribution could be estimated. With a large number of observations, however, the estimation of the whole quantile regression process bogs down. It simply becomes too time consuming. A feasible solution then is to estimate a specific number of quantile regressions uniformly distributed over the wage distribution. These specific quantile regressions are taken to capture those points along the wage distribution where the solution, that is the wage effects, changes. Accordingly, the coefficients estimated at a given point, $\hat{\beta}(\tau_j)$, are presumed to remain unchanged on a certain interval, from τ_{j-1} to τ_j for $j = 1,\ldots,J$. This procedure results in a vector, $\hat{\beta}$, comprising a finite number of QR coefficients, $\hat{\beta}(\tau_1),\ldots\hat{\beta}(\tau_j),\ldots,\hat{\beta}(\tau_J)$.

In the next step, these conditional quantiles, τ, of y are turned into estimates of unconditional quantiles, θ, of y. Put differently, the conditional wage distribution is generalized to hold for the total sample population by integrating it over the whole range of the distribution of the characteristics accounted for in the first (QR) step. In brief, this can be done by replacing each conditional estimate $F_{y|x}^{-1}(\tau_j | x_i)$ by its consistent estimate $x_i\hat{\beta}(\tau_j)$. More formally, the sample population's θ^{th} quantile of y can be estimated by

$$\hat{q}(\hat{\beta}, x) = \inf\left\{ q : \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{J} (\tau_j - \tau_{j-1}) 1(x_i \hat{\beta}(\tau_j) \leq q) \geq \theta \right\}, \tag{3}$$

where taking the infimum guarantees that the finite sample solution is unique.

In the final step, this framework for simulating the whole counterfactual distribution is used for decomposing, say, changes in the dispersion of wages over a period of time. This is done by estimating the counterfactual wage distribution that would have prevailed in year $t-1$ given that the characteristics accounted for had been distributed as in year t. In this case, eq. (3) needs to be re-estimated with the characteristics now referring to year t and the estimated coefficients to year $t-1$. By combining the results obtained from steps two and three, the method allows a change in the wage distribution to be decomposed into the effects of changes in characteristics (x), coefficients $(\hat{\beta})$ and residuals. The final decomposition over time may then be written as

$$\begin{aligned} q(\beta^t, x^t) - q(\beta^{t-1}, x^{t-1}) = & \left[\left(q(\beta^t, x^t) - \hat{q}(\hat{\beta}^t, x^t)\right) + \left(\hat{q}(\hat{\beta}^{t-1}, x^t) - q(\beta^{t-1}, x^{t-1})\right)\right] \\ & + \left(\hat{q}(\hat{\beta}^t, x^t) - \hat{q}(\hat{\beta}^{t-1}, x^t)\right) + \left(\hat{q}(\hat{\beta}^{t-1}, x^t) - \hat{q}(\hat{\beta}^{t-1}, x^{t-1})\right), \end{aligned} \tag{4}$$

where the terms in the first line on the right-hand side give the effect of changes in residuals, while the terms in the second line give the effect of changes in coefficients and in the distribution of characteristics between year t and $t-1$.

This decomposition in three parts is implemented by, for instance, Autor, Katz and Kearney (2005) and Melly (2005b). The present application – as most of the theoretical and applied research using quantile regression – assumes instead that the linear quantile regression model is correctly specified. In the absence of a specification error, the residual component in the first line of eq. (4) vanishes asymptotically and a decomposition into two parts – coefficients and characteristics – will provide a true picture of the changes in the dispersion of wages between $t-1$ and t. As will become evident later on, the effect of the residuals is, indeed, persistently negligible, thus indicating the good fit of the models estimated. Moreover, since estimates can be produced for the counterfactual distribution as a whole, a decomposition in line with eq. (4) can be undertaken at any point along the wage distribution, as well as for all commonly used dispersion and inequality measures. Additionally, by simply replacing the time dimension in eq. (4) with the gender dimension, the same estimation framework can be used for estimating and decomposing, for selected years, the gender wage gap along the whole wage distribution.

The next two sections will report key findings from the final estimation step, that is, the decomposition exercise thus overlooking all results from the first estimation steps.[11] It should also be noted that in line with previous studies using the Machado and Mata (2005) or the Melly (2005a, 2005b, 2006) decomposition method, no attempt is made to account for the possible presence of sample selection or endogeneity problems. In the present context these may arise from including women in the analysis, from confining the analysis to full-time working individuals of a particular worker category (white-collar workers) in a specific industry (technology), and from relying on individual and job-related attributes which are likely to involve various choices and selections. Overlooking these aspects is partly due to the structure of the data used but mainly to

[11] These results are available upon request from the authors.

the method applied.[12] Hence, the subsequent analysis can be characterized as a description of, respectively, the wage distribution and the gender wage gap conditional on being employed on a full-time basis as a white-collar worker in the technology industry while being endowed with given individual and job-related attributes.

The particular estimation framework applied is the STATA programme for decomposition of differences in distributions using quantile regression (*rqdeco*) developed by Melly (2006). More precisely, the decomposition results reported in the next two sections are produced by estimating a grid of 100 different quantile regressions distributed uniformly between the two tails of the wage distribution or, more formally, between 0 and 1. Estimation of a grid of this dimension on the full estimating data (as shown in Tables 1 and 2) would, however, be computationally very time-consuming.[13] Hence, in order to keep the computation time at a reasonable level, smaller (50 per cent) samples are drawn randomly from the full estimating data and used in the decomposition exercises.[14] These smaller datasets are, nonetheless, large enough to produce quantile regression estimates that are both qualitatively and quantitatively very similar to those obtained from using the total number of observations available. Indeed, this outcome can simultaneously serve as a robustness check of the quantile regression estimates on which the reported decomposition results are actually based.

4. SOURCES UNDERLYING REAL WAGE GROWTH AND INCREASED WAGE DIFFERENTIALS: DECOMPOSITION RESULTS BY GENDER

The effects of changes in coefficients (price effect) and in workforce characteristics (composition effect) on the observed changes in the distribution of total hourly real wages among, respectively, male and female white-collar workers employed in the Finnish technology industry are first estimated by inclusion of merely standard human capital measures as explanatory variables. Hence, the decomposition results plotted in the two graphs of Figure 1 are obtained after account is made only for years of schooling, poten-

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[12] It is noteworthy, though, that sample selection is increasingly accounted for in studies of the gender wage gap also when the decomposition is undertaken across the entire wage distribution (see Chzhen and Mumford, 2009, and the references therein). However, positive selection into employment by women has been shown to be no serious problem in studies of the Finnish labour market (e.g. Asplund, 2001).

[13] It is worth noting that even with much smaller sample sizes, estimation of the whole quantile regression process would simply not be possible.

[14] The decomposition procedure is computationally intensive because of the use of bootstrapping for calculating the standard errors of the estimates. As formally shown by Chernozhukov, Fernández-Val and Melly (2009), an alternative approach would be to continue with the full sample for the estimations and to use subsamples for inference only. As the estimator is root n consistent, the standard errors can then be corrected accordingly.

tial work experience and seniority. The effect of the residuals is persistently negligible and is therefore not depicted in these graphs. Additionally, while the plots do not display confidence intervals, it should be noted that the estimates are highly precise throughout the wage distribution, except for its two tails. As a consequence, no results are shown for quantiles below 0.05 and above 0.95.

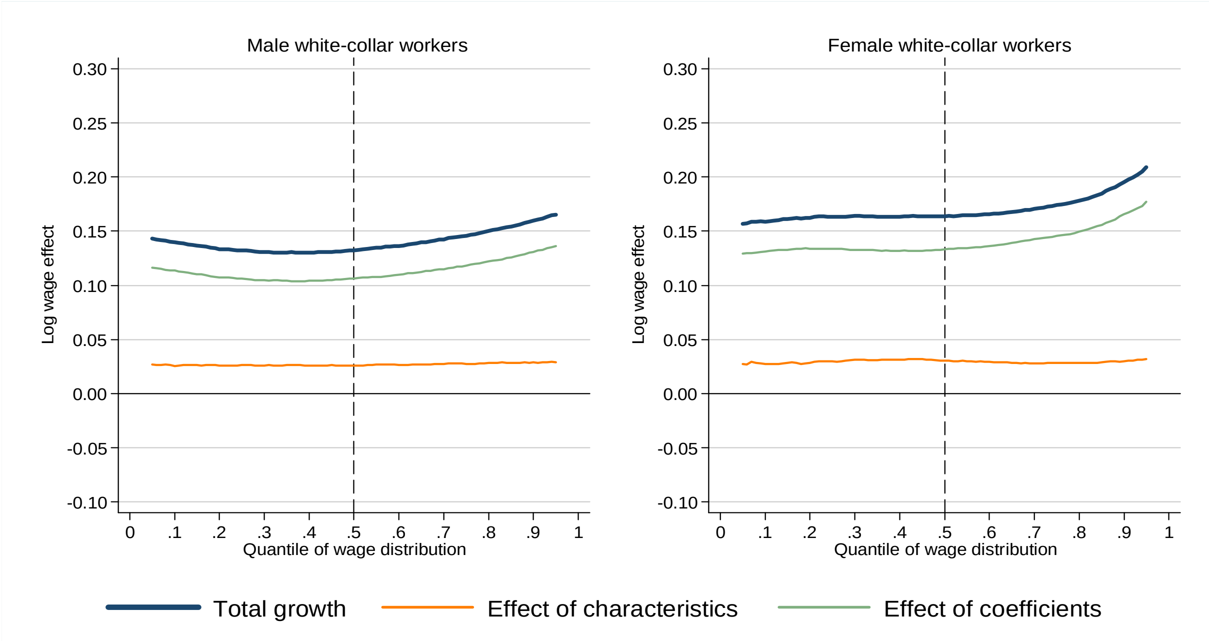
The curve depicting the total factual change from 2002 to 2007 in the unconditional log total hourly real wage distribution of the technology industry's male and female white-collar workers, respectively, repeats the story already told by Table 1: total hourly real wages have grown throughout the wage distribution, but the growth rate has been stronger higher up the distribution. This pattern has been more pronounced among the industry's female white-collar workers.

The decomposition results are strikingly similar across genders. While also changes in the industry's white-collar workforce composition have contributed positively to real wage growth at all estimated points along the distribution, this effect of changing standard human capital attributes has persistently been substantially smaller (and of a strikingly similar absolute magnitude across the whole wage distribution) than the effect of contemporary changes in the remuneration of these same attributes. Indeed, the relative importance of the price effect in explaining total hourly real wage growth is not only overwhelming throughout the wage distribution but its dominance over the composition effect tends to strengthen even further when moving up through the wage distribution. Accordingly, most of the increase in total wage differentials in the upper half of both of the male and the female wage distributions is explained by changes in the rewarding of formal education and accumulated work experience, whereas the contribution of changes in the composition of these attributes is close to negligible for both genders (Table 3).

The overall picture changes quite dramatically, however, when supplementing the estimated models with dummy indicators capturing changes between 2002 and 2007 in the distribution of the industry's white-collar workers across the four levels of the new job task evaluation scheme introduced in 2002. As shown in the two gender-specific graphs of Figure 2, accounting for the effect of distributional changes across the 4-level job task evaluation scheme strengthens both the absolute and the relative importance of the composition effect in explaining total hourly real wage growth, with the effect being strongest in the upper tail of the wage distribution but practically negligible in its lower tail. Hence, the implementation of this new scheme has made the wage-setting process more transparent, but mainly among the higher-paid. Additionally, this impact seems to have been more pronounced among the industry's female white-collar workers. The upward-sloping profile of the composition effect in combination with a downward-sloping profile of the price effect also changes fundamentally the decomposition results obtained for selected measures of wage dispersion: after accounting for distributional changes across the four job task evaluation levels the increased dispersion in the industry's white-collar total hourly wages is dominated by the compositional changes, whereas the changes in the rewarding of attributes have rather had a compressing effect on the growth in total-wage differentials (Table 4).

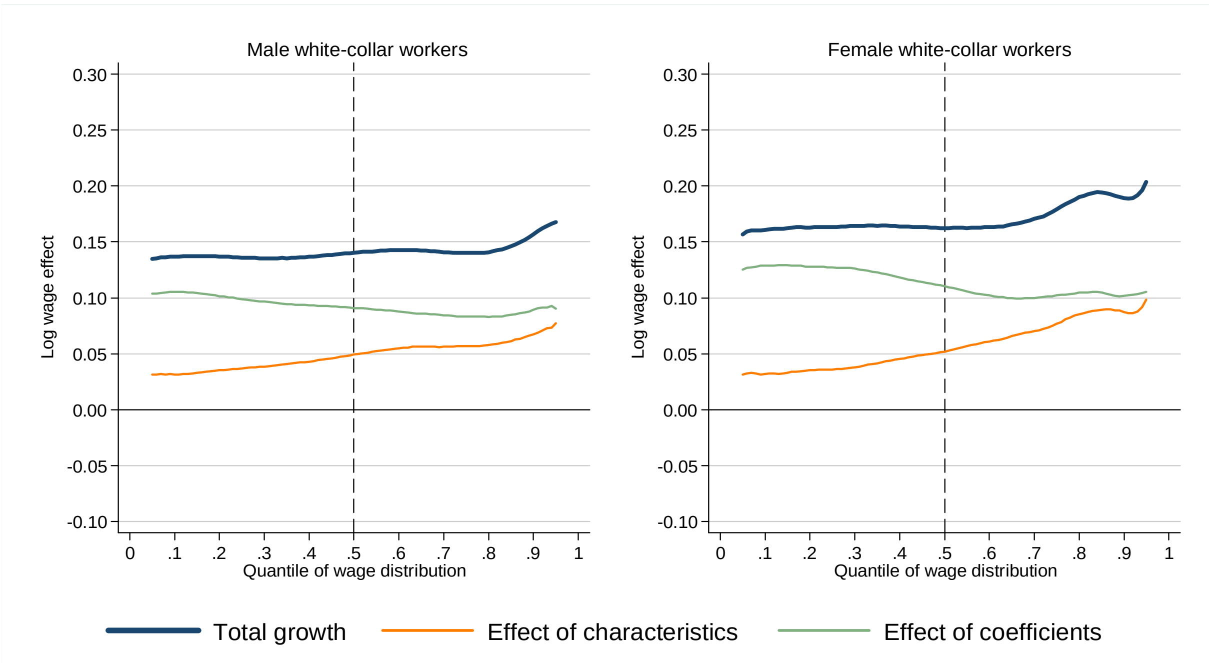
Finally it may be noted that the gender-specific decomposition results obtained when supplementing the estimated models with information on distributional changes across occupation categories were almost identical to those obtained when accounting for job task evaluation levels in addition to standard human capital measures (and are therefore not reported here). Moreover, this held true for both genders. Underlying this outcome is the combined effect of two basic features. As shown in Table 1, the occupational distribution of the technology industry's male and female white-collar workers has changed only marginally over the time period investigated. More important, the industry's establishments are to assign job task levels independently of the occupation category into which their white-collar workers are classified.

Figure 1. Decomposition of changes over time (2002/2007) in the distribution of total hourly real wages, by gender, after account is made for changes in traditionally measured human capital endowments only



Note: The plotted gender-specific decomposition results are obtained by applying the decomposition procedure outlined in the previous section at each of 99 different quantiles ($\theta = 0.01, 0.02, \ldots, 0.99$) along the counterfactual (unconditional) log total hourly real wage distribution, as estimated separately for each gender, with standard errors computed by bootstrapping the results 100 times.

Figure 2. Decomposition of changes over time (2002/2007) in the distribution of total hourly real wages, by gender, after account is made for changes in standard human capital endowments as well as job-level distributions



Note: See Figure 1.

Table 3. Decomposition of changes over time (2002/2007) in the distribution of total hourly real wages, by gender, at the mean and the median as well as for selected measures of dispersion after account has been made for changes in standard human capital endowments only

	Total factual change	Composition effect (characteristics)	Price effect (coefficients)
Male white-collar workers			
Mean	14.09 (.10)	2.68 (.01)	11.41 (.10)
Median	13.24 (.16)	2.60 (.01)	10.64 (.15)
Standard deviation	1.03 (.07)	0.14 (.02)	0.95 (.06)
90–10	2.01 (.28)	0.32 (.02)	1.70 (.28)
50–10	–0.72 (.16)	0.04 (.01)	–0.75 (.15)
90–50	2.73 (.27)	0.28 (.02)	2.45 (.26)
75–25	1.35 (.23)	0.14 (.03)	1.21 (.19)
Female white-collar workers			
Mean	17.08 (.14)	2.96 (.02)	14.12 (.14)
Median	16.38 (.05)	3.06 (.03)	13.33 (.07)
Standard deviation	1.46 (.16)	0.21 (.03)	1.39 (.14)
90–10	3.66 (.68)	0.23 (.03)	3.43 (.61)
50–10	0.51 (.11)	0.30 (.03)	0.20 (.07)
90–50	3.15 (.67)	–0.07 (.03)	3.22 (.59)
75–25	1.09 (.30)	–0.12 (.03)	1.21 (.28)

Notes: All numbers have been multiplied by 100. Standard errors computed by bootstrapping the results 100 times are given in parentheses.

Table 4. Decomposition of changes over time (2002/2007) in the distribution of total hourly real wages, by gender, at the mean and the median as well as for selected measures of dispersion after account has been made for changes in both standard human capital endowments and job-level distributions

	Total factual change	Composition effect (characteristics)	Price effect (coefficients)
Male white-collar workers			
Mean	14.11 (.08)	4.90 (.13)	9.21 (.08)
Median	14.02 (.09)	4.92 (.29)	9.11 (.09)
Standard deviation	0.81 (.10)	1.35 (.10)	0.77 (0.5)
90–10	1.99 (.54)	3.60 (.37)	–1.61 (.10)
50–10	0.34 (.09)	1.76 (.28)	–1.42 (.08)
90–50	1.65 (.53)	1.84 (.41)	–0.19 (.11)
75–25	0.43 (.06)	1.98 (.15)	–1.55 (.17)
Female white-collar workers			
Mean	17.13 (.16)	5.91 (.28)	11.23 (.15)
Median	16.23 (.03)	5.20 (.38)	11.03 (.30)
Standard deviation	1.68 (.20)	2.77 (.42)	1.44 (.29)
90–10	2.87 (.24)	5.56 (.19)	–2.69 (.07)
50–10	0.17 (.11)	2.02 (.37)	–1.85 (.29)
90–50	2.70 (.21)	3.54 (.40)	–0.84 (.29)
75–25	1.58 (.72)	4.08 (.57)	–2.50 (.18)

Notes: All numbers have been multiplied by 100. Standard errors computed by bootstrapping the results 100 times are given in parentheses.

5. SOURCES UNDERLYING THE GENDER WAGE GAP: COMPARISON OF DECOMPOSITION RESULTS FOR 2002 AND 2007

Have these similarities and differentials in real total-wage growth and increased wage dispersions across genders affected the male–female white-collar total-wage gap of the Finnish technology industry? Most importantly, has the implementation of the job task evaluation scheme introduced in 2002 had a clear-cut impact on the industry's gender total-wage gap already by 2007? The approach used to answer these questions is identical to the one applied in the previous section: the effects of gender-specific differences in coefficients (price effect) and characteristics (composition effect) on the gender total hourly wage gap are first estimated with account being made for standard human capital endowments only, then by supplementing the estimated model with information on job task evaluation levels and, finally, with a set of occupation dummy indicators.

The curves in Figure 3 depicting the gender gap in total hourly wages in 2002 and 2007, respectively, tell the same story as Table 1. First, it widens when moving up the wage distribution. Second, it had, by 2007, narrowed across the whole distribution, most notably at its upper tail, which made the downward-sloping trend of the gender total-wage gap slightly less steep. However, the decomposition results suggest that these magnitudes of and changes in the gender total-wage gap can only marginally be explained by differences in standard human capital endowments between the industry's male and female white-collar workers. Instead, most of the industry's gender total-wage gap is explained by its male and female white-collar workers being differently rewarded for similar human capital attributes, a pattern that strengthens when moving up the wage distribution. These findings are illustrated in a simplified way in Figure 3 in the sense that it merely depicts the decomposition curve for the effect of gender differences in characteristics (the composition effect) as obtained for 2007.

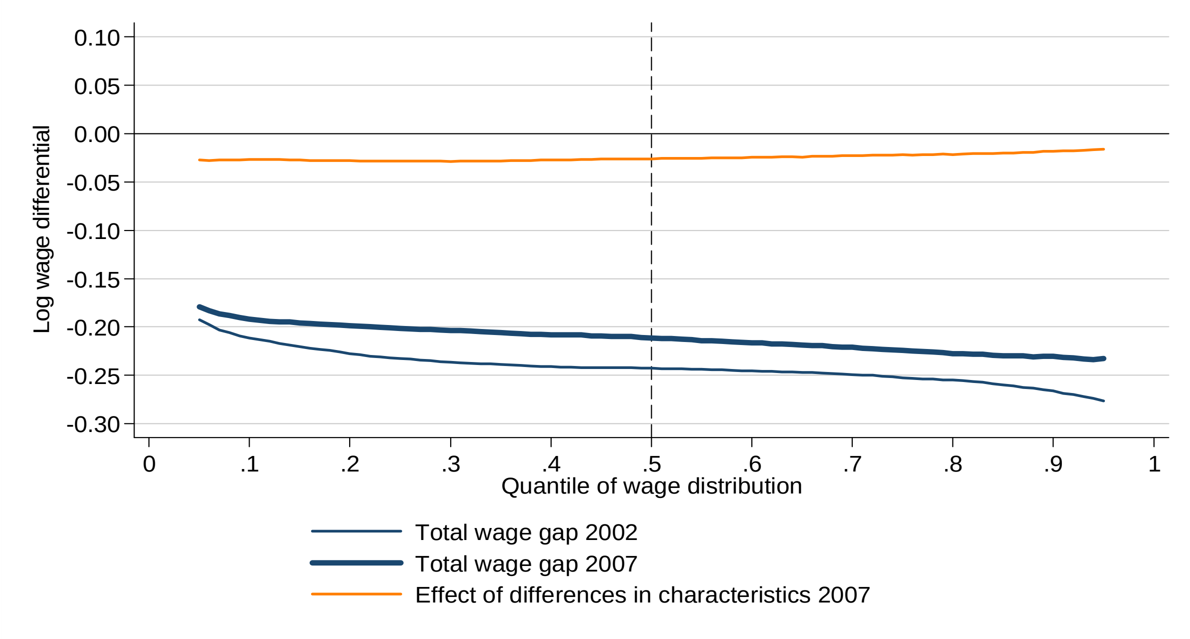
More details are given in Table 5, which shows that the overall picture mediated by the decomposition results involving only standard measures of human capital endowments has remained practically unchanged over the time period investigated. More precisely, both the gender gaps prevailing at the different points along the industry's white-collar wage distribution and the differences in the absolute magnitude of these gaps are for the most part explained by gender differences in the rewarding of similar human capital attributes.

The outcome changes quite radically, albeit merely in the upper half of the wage distribution, when adding information on the distribution of the industry's male and female white-collar workers across the four levels of the job task evaluation scheme adopted in 2002. As shown in Figure 4, this evaluation scheme has had a positive impact on the gender total-wage gaps prevailing among the industry's highest-paid white-collar workers, a tendency that has strengthened over the 5-year period under scrutiny. Figure 4, however, also indicates that it works in a less satisfactory way lower down the wage scale where, in fact, a majority of the industry's white-collar workers is located (cf. Table 1). While having had principally no effect on the gender total-wage gap amongst the lowest-paid white-collar workers, this new scheme seems to have widened the gender gap among those having a wage close to or slightly above the median.

From the decomposition results it may be concluded that the conspicuously different gender-gap impact of the job task evaluation scheme at the different parts of the industry's white-collar wage distribution arises from the combined effect of the job level-induced changes in the relative importance of the price and composition effects. This is illustrated for 2007 in the left-hand-side graph of Figure 5. The graph shows that, compared to the standard human capital outcome displayed in Figure 3, the job task evaluation scheme has weakened the relative importance of the price effect in explaining the prevailing gender total-wage gaps, but mainly in the upper tail of the wage distribution. Put differently, it has made the gender total-wage gap of the industry's high-paid white-collar workers more transparent in the sense that a larger part of the gap can be explained by differences in characteristics rather than by differences in their rewarding. This improved 'transparency' is discernible also in the middle part of the wage distribution. In contrast, however, to the situation higher up the wage scale, this evolution has for some reason not been accompanied by a concomitant decline in the relative importance of the price effect, which has rather boosted the overall gender gap. Finally, among the lowest-paid the price effect was quantitatively more important still in 2007. More details are given in Table 6.

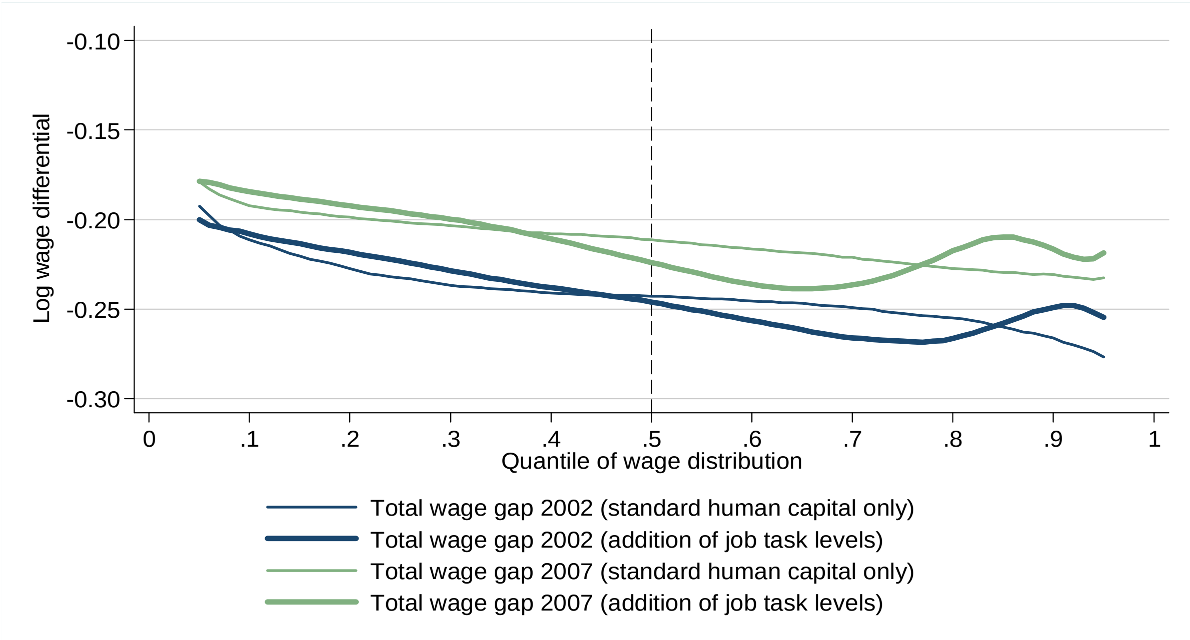
As a final point it may be noted that while the job task evaluation scheme introduced in 2002 seems to have a good potential to clarify and even narrow the gender wage gaps prevailing in the technology industry, strong segregation patterns continue to work in the opposite direction, thus mitigating the positive influence of the scheme. This phenomenon is illustrated for the year 2007 in the right-hand-side graph of Figure 5, which unveils the change in decomposition results when gender differences in occupational distributions are accounted for as well. Not surprisingly, the addition of occupational information re-increases the relative importance of the price effect in explaining the gap in total hourly wages between the industry's male and female white-collar workers.

Figure 3. Decomposition of gender gaps in total hourly wages for 2002 and 2007 after accounting for gender differences in standard human capital endowments only



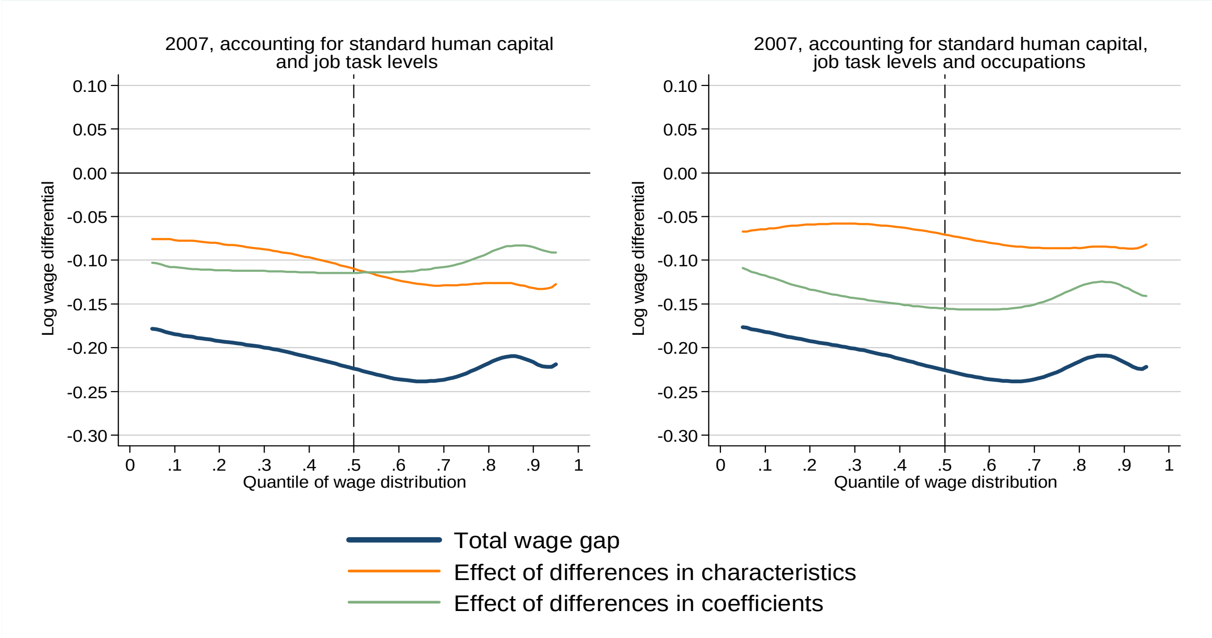
Notes: The plotted gender-gap decomposition results are obtained by applying the decomposition procedure outlined in Section 3 at each of 99 different quantiles ($\theta = 0.01, 0.02, \ldots, 0.99$) along the counterfactual (unconditional) log total hourly wage distribution with standard errors computed by bootstrapping the results 100 times. The effect of the residuals is persistently negligible, thus indicating the good fit of the gender-gap models and is therefore not depicted. While the plots do not display confidence intervals, the estimates are highly precise throughout the distribution, except for the two tails. Hence, no results are shown for quantiles below 0.05 and above 0.95.

Figure 4. Comparison of gender gaps in total hourly wages for 2002 and 2007 after accounting for gender differences in standard human capital endowments only and after also introducing gender differences in job-level distributions



Notes: See Figure 3.

Figure 5. Comparison of decompositions of gender gaps in total hourly wages for 2007 after accounting for gender differences in standard human capital endowments and job-level distributions and after also introducing gender differences in occupational distributions



Notes: See Figure 3.

Table 5. Decomposition of gender gaps in total hourly wages for 2002 and 2007 at the mean and the median as well as for selected measures of dispersion after accounting for gender differences in standard human capital endowments only

	Total factual gender wage gap	Differences in characteristics (composition effect)	Differences in coefficients (price effect)
Year 2002			
Mean	–24.03 (.20)	–3.41 (.06)	–20.62 (.24)
Median	–24.28 (.10)	–3.55 (.15)	–20.74 (.27)
Standard deviation	2.26 (.22)	0.60 (.03)	2.56 (.19)
90–10	–5.49 (.82)	1.07 (.10)	–6.56 (.78)
50–10	–3.15 (.45)	0.30 (.14)	–3.45 (.52)
90–50	–2.34 (.67)	0.77 (.16)	–3.11 (.58)
75–25	–2.01 (.38)	1.27 (.08)	–3.28 (.41)
Year 2007			
Mean	–21.05 (.16)	–2.44 (.04)	–18.60 (.18)
Median	–21.14 (.22)	–2.59 (.06)	–18.55 (.28)
Standard deviation	1.69 (.17)	0.38 (.03)	1.94 (.14)
90–10	–3.85 (.43)	0.83 (.10)	–4.68 (.47)
50–10	–1.93 (.22)	0.09 (.06)	–2.01 (.29)
90–50	–1.92 (.41)	0.74 (.10)	–2.67 (.44)
75–25	–2.28 (.27)	0.66 (.06)	–2.94 (.32)

Notes: All numbers have been multiplied by 100. Standard errors computed by bootstrapping the results 100 times are given in parentheses.

Table 6. Decomposition of gender gaps in total hourly wages for 2002 and 2007 at the mean and the median as well as for selected measures of dispersion after account has been made for gender differences in both standard human capital endowments and job-level distributions

	Total factual gender wage gap	Differences in characteristics (composition effect)	Differences in coefficients (price effect)
Year 2002			
Mean	–24.05 (.21)	–11.89 (.28)	–12.16 (.10)
Median	–24.61 (.33)	–12.04 (.56)	–12.58 (.15)
Standard deviation	2.22 (.13)	2.86 (.13)	1.00 (.09)
90–10	–4.11 (.37)	–6.92 (.29)	2.81 (.32)
50–10	–3.80 (.31)	–4.27 (.55)	0.47 (.14)
90–50	–0.30 (.40)	–2.65 (.54)	2.34 (.31)
75–25	–4.49 (.41)	–5.78 (.48)	1.29 (.14)
Year 2007			
Mean	–21.03 (.20)	–10.55 (.20)	–10.48 (.12)
Median	–22.40 (.25)	–10.97 (.57)	–11.43 (.10)
Standard deviation	1.94 (.10)	2.09 (.07)	1.11 (.08)
90–10	–3.23 (.31)	–5.49 (.10)	2.27 (.19)
50–10	–3.97 (.25)	–3.31 (.56)	–0.66 (.09)
90–50	0.74 (.30)	–2.19 (.55)	2.93 (.17)
75–25	–3.33 (.36)	–4.38 (.27)	1.05 (.44)

Notes: All numbers have been multiplied by 100. Standard errors computed by bootstrapping the results 100 times are given in parentheses.

6. CONCLUDING REMARKS

This paper has investigated major factors underlying the observed patterns and trends in male–female wages and wage gaps among white-collar workers employed in the Finnish technology industry. Special attention has thereby been paid to the role played by standard human capital endowments (years of schooling, work experience and seniority) as compared to alternative ways of measuring competencies (the technology industry's job task evaluation scheme). The methodology applied, which has recently been proposed by Melly (2006), allows the whole wage distribution to be decomposed into the effect of characteristics (composition effect) and of coefficients (price effect).

The dispersion in the technology industry's white-collar wages is found to have increased remarkably over the time period investigated (2002–2007) when measured by total wages; that is, with account being made for various types of performance-related pay as well as fringe benefits paid on top of the basic wage. In contrast, wage dispersion as measured by basic (normal) wages has remained almost unchanged. However, the increase in total-wage differentials has been entirely concentrated to the upper half of the industry's white-collar wage distribution, whereas the wage differentials among those earning below the median have remained practically unchanged.

A decomposition of the change in total-wage dispersion between 2002 and 2007 indicates that both the growth in real total wages and the increase in total-wage differentials among the technology industry's higher-paid white-collar workers are for the most part attributable to changes in the way acquired formal education and cumulated work experience are valued by the industry's establishments, and not to changes in the human capital composition of their workforce. However, the results change notably when account is also made for the 4-level job task evaluation scheme introduced in 2002. More precisely, this innovative scheme seems to have made the wage formation process of the industry's white-collar personnel more transparent, albeit mainly in the upper half of the wage distribution. Put differently, it has obviously induced important shifts of especially higher-paid white-collar workers across the four job task levels in a way that better reflects each employee's skills, efforts and responsibilities.

All these findings hold true for both male and female white-collar workers. Indeed, the observed trends and changes in the technology industry's white-collar wages and wage dispersions have in several respects been even more outstanding among its female than among its male white-collar workers. This concerns the growth in total real wages as well as the widening in wage differentials. Also the job task evaluation scheme seems to have had a stronger effect on the industry's female white-collar workers, which points to more competence-driven shifts across the four job task levels among women than among men.

These similarities and dissimilarities in wage developments across genders are shown to have affected also the male–female wage gap of the industry. First, the overall gender gap in total wages increases when moving up through the wage distribution. A comparison of the gender total-wage gap between 2002 and 2007 implies, however, that it has declined slightly at all points along the wage distribution with the decline having been relatively smallest among the lowest-paid and relatively largest among the highest-paid. Second, a decomposition of the gender total-wage gap into effects of characteristics and of coefficients suggests that male–female differences in standard human capital endowments can explain only a minor part of the overall gender gap in total wages. Conversely, most of the gender total-wage gap is found to be due to men and women being differently rewarded for similar human capital attributes. Moreover, this tendency strengthens when moving up through the wage distribution, and shows up for both 2002 and 2007. Third, the outcome changes considerably when account is also made for the distribution of males and females across the 4-level job task hierarchy adopted in 2002. Already in the first year of implementation, the allocation of men and women according to the skills, efforts and responsibilities required in their jobs had a conspicuous effect on the male–female total-wage gap, but only at the top-end of the wage distribution. By 2007, this positive effect had spread lower down the wage scale but was, nonetheless, still heavily concentrated to the upper half of the wage distribution.

Taken together, these findings indicate that improvements in the standard human capital endowments of women can go some way in narrowing the overall male–female wage gap. Raising the skill levels of women closer to those of men is not, however, likely to dissolve the gender wage gap problem. Concomitant with rising average education levels, other skill aspects have received increasing attention in working life. In research focusing on traditional measures of human capital, this shows up in expanding wage differentials between (observably) equally skilled individuals (within-group wage dispersion). Our results suggest that carefully designed job task evaluation schemes can provide at least part of a solution in the sense that an individual's ranking will then depend on a conscious combination of formal (easily measurable) and informal (unquantifiable) competencies, thus making the wage-setting process in the workplace more transparent. Additionally, such schemes can be expected to revive the role of formal education and cumulated work experience in wage formation by strengthening their indirect, if not their direct, effect on wage levels and trends. Having said this, our results, however, also show that making job task evaluation schemes work successfully across the whole wage distribution is a most challenging task.

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