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SOURCES OF INCREASED WAGE DIFFERENTIALS IN THE FINNISH PRIVATE SECTOR*

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This paper explores the sources underlying the marked increase in the dispersion of private-sector wages in Finland since the mid-90s by use of a recently proposed method to decompose changes along the whole wage distribution over a period of time into several factors contributing to those changes. The results suggest that changes in the way individual and workplace attributes are valued in the labour market have been the driving force behind both real wage growth and increasing wage dispersion. This finding holds true most strongly for white-collar manufacturing workers, who dominate the higher-paid segment of the Finnish private sector. This phenomenon is less pronounced for services sector workers and, eventually, disappears when moving towards the lower end of the sector's wage distribution. Taken together, these findings are well in line with international evidence stating that changes in the way attributes are rewarded in the labour market tend to drive the growth in wage dispersion in the upper tail of the distribution while changes in the workforce composition are likely to be a notably stronger force behind widening wage differentials in the lower tail of the distribution. (JEL: J31)

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1. Introduction

The dispersion in wages has increased remarkably in the Finnish private sector since the mid-90s (Asplund and Böckerman, 2008). However, this increase in wage differentials has been very prominent with respect to total wages, while the distribution of basic wages has widened to a much lesser extent, if at all. Combined with the fact that the growth in total real wages has widely outperformed the growth in basic real wages, this implies that most of the observed increase in private-sector wage differentials originates in an increasingly uneven distribution of various performance-pay related items and fringe benefits. Accordingly it is hardly surprising that the rise in wage dispersion has for the most part occurred in the upper half of the wage distribution.

This trend of increasing wage differentials does not encompass all private-sector employees, though. Most strongly it has concerned those working in the services sector. Also white-collar workers in manufacturing have seen their wage differentials grow but the increase has been more moderate than among services sector workers, whereas the wage dispersion of blue-collar manufacturing workers has remained practically unaffected. Moreover, the widening in services sector wage differentials was much more pronounced in the late 1990s than in the early 2000s with the situation being rather the opposite among white-collar manufacturing workers, who saw the growth in their wage differentials accelerate after the turn of the century.

This paper attempts to explore the sources underlying the marked increase in the dispersion of white-collar manufacturing wages and, especially, services sector wages by use of a recently proposed method to decompose changes in wage distributions over a period of time into several factors contributing to those changes. The basic idea of this method is to undertake the decomposition 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). More precisely, it starts with an estimate of the whole conditional wage distribution using quantile regression techniques[1], then estimates the corresponding unconditional distribution by integrating the conditional distribution over the range of covariates investigated and, finally, decomposes the changes in distribution into two major factors: coefficients (price effect) and covariates (composition effect).[2]

The particular decomposition procedure based on quantile regression applied in the present paper follows that of Melly (2006). This methodology is described also in, for instance, Machado and Mata (2005) and Melly (2005a). A noteworthy difference between the decomposition implemented here and the decomposition proposed by Autor, Katz and Kearney (2005) or Melly (2005b) concerns the treatment of the estimation error, that is, the residuals. More precisely, while the latter solution provides a decomposition into three distinct parts – coefficients, characteristics and residuals – the former method assumes that the linear quantile regression model is correctly specified and that, asymptotically, the residual component vanishes.[3] An entirely different approach would be to use the kernel re-weighting estimator proposed by DiNardo, Fortin and Lemieux (1996) and extended by Lemieux (2002, 2006). However, while the decomposition procedure based on quantile regression can be seen as more appealing in the sense that it offers a natural economic interpretation of each estimation step, both methods have been shown to

[1] A comprehensive review of quantile regression is provided by Koenker (2005). Estimating the entire wage distribution has a clear advantage over scalar measures such as Gini coefficients, which not only mask details in the wage distribution but also place different inherent weights on different parts of the distribution (cf. the discussion in e.g. DiNardo, Fortin and Lemieux (1996)).

[2] While decomposition procedures based on quantile regression have been used in a growing number of studies on changes in wage structures over time, the methodology is increasingly applied also in studies of the gender wage gap (see e.g. Chzhen and Mumford (2009) and the references therein) but, occasionally, also in studies of private–public sector wage differentials (e.g. Melly (2005a)).

[3] In Melly (2006), as in most of the theoretical and applied research using quantile regression, the linear model for conditional quantiles is assumed to be correctly specified. In this case, any crossing of conditional quantile functions would simply be due to a pure finite sample problem. However, if the crossing arises from misspecification, then the interpretation of quantile regression estimates becomes more complicated. This question is addressed extensively by Angrist, Chernozhukov and Fernández-Val (2006).

reach similar conclusions despite the different underlying assumptions (Melly, 2006).[4,5] The extent to which these alternative approaches have, so far, been applied empirically is next briefly illustrated.

Melly (2005b) uses his method to disentangle the sources of changes in the distribution of US male wages between 1973 and 1989. His results indicate that changes in characteristics explain about half of the observed growth in US (male) wage inequality over this particular time period while, in contrast to most previous US studies, residuals are found to account only for about 20 per cent. This much smaller role for residuals he explains by taking into proper account the dependence that commonly prevails between characteristics (e.g. education and experience) and residuals and, hence, also between changes in these two factors. Using his extended re-weighting estimator Lemieux (2006) reaches, in effect, much the same conclusion: mechanical changes in the workforce composition account for a large fraction of the growth in residual (male) wage inequality in the USA between 1973 and 1987, and for all of it between 1988 and 2003. The method proposed by Melly (2006) has recently been applied also by Dustmann, Ludsteck and Schönberg (2007), who investigate the evolution of the (full-time male) wage structure in West Germany over the years 1979 to 2001. They conclude that changes in workforce composition play a more important role than changes in skill prices and that this holds true especially at the upper end of the wage distribution.

Machado and Mata (2005) apply their quantile regression decomposition method to explore the change in the (full-time) wage distribution in Portugal between 1986 and 1995, and conclude that shifts in coefficients and covariates have contributed to this change in roughly equal proportions. The Machado–Mata method has also been applied to data for Germany, India and the USA. Kohn (2006) investigates the change in the East and West German wage structures between 1992 and 2001. His findings support those of Dustmann, Ludsteck and Schönberg (2007) in that changes in worker characteristics explain to a great extent the disproportionately large wage increases in the upper half of the wage distribution of men working full-time in West Germany. While this finding also holds for their female counterparts, the corresponding results for East Germany point to the opposite with the price effect dominating over an almost negligible composition effect. Azam (2009) studies changes in the (full-time regular) wage structure of urban India in the period 1983–2004 and finds that the price effect has been the driving force behind wage growth across the entire wage distribution and, especially, at the higher end of the distribution.

Autor, Katz and Kearney (2005, 2008) reassess the conclusions drawn by Lemieux (2006) using both the re-weighting estimator of Lemieux (2006) for the USA and an extended version of the quantile decomposition technique proposed by Machado and Mata (2005). Both estimators produce results indicating that the changes in workforce composition have operated primarily on the lower half of the US (male) wage distribution, although countervailed by significant lower-tail price compression, whereas the dramatic rise in upper-tail wage dispersion is almost entirely explained by changes in labour market prices. Gosling, Machin and Meghir (2000), finally, show using their specific quantile regression-based decomposition method that increases in educational differentials in combination with cohort effects explain two-thirds of the sharp rise in (male) wage dispersion in the UK from 1966 to 1995.

This brief review also shows that the existing empirical evidence on the sources underlying observed changes in the wage structure, ob-

[4] *As emphasised by an anonymous referee, similar conclusions are reached only if all parametric assumptions underlying the two methods are satisfied. In case of misspecification, the outcomes may, of course, be different.*

[5] *More elaborated procedures are presented in Chernozhukov, Fernández-Val and Melly (2009) but, so far, the companion software does not extend to the decomposition stage. Indeed, their procedures are shown to cover not only the quantile regression estimators of Gosling, Machin and Meghir (2000) and Machado and Mata (2005) as special cases but encompasses, inter alia, also duration regression such as the approach developed and applied by Donald, Green and Paarsch (2000) for investigating and comparing sources of wage inequality for full-time male workers between Canada and the United States in 1989. Compared to this approach, the recent work by Firpo, Fortin and Lemieux (2009) proposes a clearly different method for estimating the impact of changes in the distribution of explanatory variables.*

tained by using alternative approaches for decomposing these changes along the whole wage distribution, is still confined to a limited number of countries. Indeed, different decomposition approaches have, so far, been applied to data only for Germany and the USA. Nonetheless, the overall impression mediated by these analyses is that similarities or dissimilarities in results are not driven primarily by the use of different decomposition methods but rather by differences in other key aspects such as data sources used, including the quality of the available wage measure, the set and definition of characteristics considered, and the time period covered.

This paper adds to the rather scarce present-day knowledge within this particular field of research by reporting decomposition results obtained from using the method proposed by Melly (2006) for a country representing the Nordic model of a compressed wage structure. The main advantages of the data employed are a large sample size, precise measurement of wages, and a time horizon extending over a fairly homogeneous economic context (1996 to 2006). The results suggest that changes in the way individual and workplace attributes are valued in the labour market have been the driving force behind both real wage growth and increasing wage dispersion within the category of white-collar manufacturing workers. The outcome is much the same for services sector workers. The only exception concerns the lower half of the sector's wage distribution, where the rise in wage dispersion seems to have been driven primarily by changes in the composition of attributes rather than by changes in the remuneration of these attributes. Taken together, these findings are well in line with international evidence stating that the price effect tends to drive the rise in wage dispersion in the upper tail of the distribution while the composition effect is likely to be a much stronger force behind widening wage differentials in the lower tail of the distribution.

The paper is organised as follows. The next section offers a brief outline of the Melly (2006) decomposition method. Section 3 presents the data and set-up, including key descriptive statistics. Quantile regression results are reported and discussed in Section 4 while Section 5 presents decomposition outcomes. Concluding remarks are gathered into Section 6.

2. Estimation method

The estimation method applied in the subsequent analysis encompasses a total of three steps: estimation of the conditional wage distribution using quantile regression techniques, integration of this conditional distribution over the range of covariates considered and, finally, decomposition of changes over time in the estimated counterfactual distribution into two major factors capturing the contribution of changes in coefficients and covariates, respectively. Next, each step is described in some more detail.[6]

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[7]

$$(1)\quad F^{-1}_{y|x}(\tau|x_i) = x_i\beta(\tau),\ \forall\tau\in\,]0,1[,$$

where $F^{-1}_{y|x}(\tau|x_i)$ 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 $(i=1,\ldots,N)$ drawn from some population. Koenker and Bassett (1978) further show that $\beta(\tau)$ can be estimated, separately for each quantile τ, by

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

where $1(\cdot)$ is the indicator function. Since the dependent variable is the (natural) logarithm of wages, equation (2) produces a vector of coefficients which can be interpreted as wage effects

[6] *For a comprehensive outline, see e.g. Machado and Mata (2005) and Melly (2005a, 2006).*

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

of the different covariates 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 $j=1,...,J$. This procedure results in a vector, $\hat{\beta}$, comprising a finite number of QR coefficients, $\hat{\beta}(\tau_1),..., \hat{\beta}(\tau_j),..., \hat{\beta}(\tau_J)$

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 generalised to hold for the total sample population by integrating it over the whole range of the distribution of the covariates included in the first (QR) step. In brief, this can be done by replacing each conditional estimate $F^{-1}_{y|x}(\tau_j|x_i)$ 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

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

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 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 covariates had been distributed as in year t. More specifically, equation (3) needs to be re-estimated with the covariates 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 covariates (x), coefficients ($\hat{\beta}$) and residuals. However, as already noted in the outline, the present application assumes that the linear quantile regression model is correctly specified. In the absence of specification error, the residual component vanishes asymptotically and the decomposition of the changes in the dispersion of wages between t–1 and t is given by

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

where the first two terms on the right-hand side give the effect of changes in coefficients and the last two terms the effect of changes in the distribution of covariates between year t and t–1. Since estimates can be produced for the counterfactual distribution as a whole, a decomposition in line with equation (4) can be undertaken at any point along the wage distribution (e.g. 25th, 50th (median) or 75th percentile), as well as for all commonly used dispersion and inequality measures (e.g. interquantile differences, standard deviation, coefficient of variation, Gini coefficient).

3. Data and set-up

The data employed covers the full 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 combination of fairly broad coverage of private-sector employment[8] and highly reliable sources for the original database provides a trustworthy platform for the estimation and decomposition of counterfactual distributions using quantile regression techniques as described in the previous section.

As indicated already in the outline, the analysis focuses on two large groups of private-sector employees: white-collar manufacturing workers and services sector employees. The reason for overlooking the manufacturing sector's blue-collar workers is simply that the dispersion of their wages, however measured, has remained practically unchanged (Asplund and Böckerman, 2008). In contrast, the dispersion in white-collar manufacturing wages and, especially, in services sector wages has widened substantially since the mid-90s. Moreover, apart from having been of different strength, the growth in the wage dispersion of these two worker categories also unveils a clearly different time profile. More precisely, the increase in services sector wage differentials occurred mainly in the late 1990s, whereas the growth in the dispersion of white-collar manufacturing wages accelerated only after the turn of the century. This difference in both the strength and the timing of widening wage differentials justifies a split between white-collar manufacturing workers and services sector workers. Additionally it offers a well-motivated choice of years to be compared: 1996 to 2001 and 2001 to 2006.[9]

The analysis is further restricted to those in full-time employment only. With respect to white-collar workers in manufacturing, this restriction is of minor importance as the share of white-collar part-time jobs is still negligible (around 2 per cent in 2006). The situation is totally different in the services sector, where a considerable proportion is working on a part-time basis (18 per cent in 2006). These part-timers are typically young people working mainly in the retail trade while studying. Hence, retaining this relatively large number of workers with an obviously rather loose attachment to the labour market would most likely have spurious effects on the outcome of the wage analysis undertaken. Simultaneously the exclusion of all part-time workers also from the analysis of the services sector wage structure improves the comparability of results across the two worker categories.

The wage concept used as the dependent variable measures the total hourly wage deflated by the official consumer price index.[10] This total hourly real wage is calculated using information on total monthly earnings and normal weekly working hours (as recorded in the files of employers[11]) and comprises any bonuses and/or fringe benefits paid on top of the basic wage. Table 1 gives descriptive statistics concerning the level and dispersion of total hourly real wages for white-collar manufacturing workers and services sector workers, respectively. Apart from illustrating the aforementioned difference in both the strength and the timing of widening wage differentials within the two worker categories, the table also displays a clear wage gap in favour of white-collar manufacturing workers which, moreover, appears across the whole wage distribution. Additionally the table indicates that in the 10-year period under study, this gap in wage levels has remained roughly unchanged with respect to high-paid workers, whereas lower down the wage scale it has widened further due to real wages having increased clearly faster for white-collar manufacturing workers than for services sector workers. Indeed, a common feature of the two worker categories is that the rise in wage dispersion is for the most part explained by disproportionately larger increases in total real wages in the upper half of the distribution. Among white-collar manufacturing workers, this evolution at the top end of the wage distribution has been accompanied by a steady increase also in lower-tail wage differentials, whereas a corresponding change is almost undetectable among services sector workers.

[8] *The data complied by the Confederation of Finnish Industries covers about half of all private-sector employees.*

[9] *The economic context remained unchanged from 1996 up to 2006 in the sense that these years represent a period of almost steady economic growth and declining unemployment rates. The institutional setting continued to be dominated by collective bargaining but this traditional comprehensive collective bargaining framework gave increasingly way to more localised bargaining from the mid-90s as a growing number of issues in sectoral agreements were made negotiable at a local level, a process that could be characterised as centralised decentralisation (see Asplund (2007) for a review). Since the focus of the present paper is on the total wage, thus comprising also performance-pay items as well as fringe benefits, it should, however, be emphasised in this context that pay systems such as performance-related pay and profit-sharing schemes have never been regulated by collective agreements in Finland.*

[10] *The use of hourly wages rules out the possibility that at least part of the change in wage dispersion is caused by changes in the spread of hours worked (cf. Lemieux (2006)).*

[11] *For white-collar manufacturing workers the records refer to December of each year (August for 1996), and for services sector workers to October.*

The (natural) logarithm of total hourly real wages is regressed on a set of covariates representing human capital (formal education, work experience, seniority), gender, employer attributes (size) and industry. 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 as well as the corresponding field of study. These degrees are turned into years of schooling using the transformation key of Statistics Finland. Indeed, all results reported in the next sections are based on this continuous years-of-schooling variable. This saves precious space especially as estimations including a detailed set of indicators for degree and field do offer a more nuanced (although also a less easily interpretable) picture of the heterogeneity of educational wage effects, but also prove to produce no substantial changes in key results. Work experience measuring total years in the labour market is not available in the data and is, therefore, defined as age[12] minus years of schooling minus age at school start (7), thus referring to potential experience. Seniority is derived from direct information in the data records on the starting year of the current employment relationship. Size measures number of employees in the firm with a distinction made between four size categories: 1–19, 20–99, 100–249 and 250+. Industry, which actually refers to the branch line in collective bargaining, is covered by a total of 49 indicators for white-collar manufacturing workers and no less than 56 indicators for services sector workers. Although the inclusion of this broad set of industry indicators adds only marginally to the explanatory power of the estimated regressions (after the addition of size indicators) and also leaves the coefficient estimates for the other covariates roughly unchanged, retaining industry as an explanatory variable in the estimations can be justified by a simple Wald chi square test of the joint significance of industry effects for the determination of both white-collar manufacturing and services sector wages.

Table 2 presents descriptive statistics for gender, years of schooling, work experience, seniority and employer size, thus leaving out the long list of industry branches. The table shows that the composition of both white-collar manufacturing workers and services sector workers has changed since the mid-90s. In both categories, women represent a decreasing proportion of the workforce with most of this decline having occurred in the late 1990s. Another common feature is a clear increase in the average length of schooling, especially in the early 2000s. In both

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

	White-collar manufacturing workers			Services sector workers		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
Level (2006 Euros)						
Mean	14.39	15.52	18.21	11.89	12.87	14.58
Standard deviation	5.46	5.85	7.44	4.75	5.74	6.77
Percentiles						
P10	9.24	9.92	11.24	8.03	8.40	9.29
P25	10.55	11.50	13.26	8.99	9.40	10.42
P50	12.88	14.08	16.30	10.68	11.22	12.57
P75	16.73	17.86	21.00	12.72	14.03	16.12
P90	21.56	23.10	27.73	17.68	19.74	22.61
Dispersion						
ln(P90) – ln(P10)	0.85	0.85	0.90	0.79	0.85	0.89
ln(P75) – ln(P25)	0.46	0.44	0.46	0.35	0.40	0.44
ln(P90) – ln(P50)	0.52	0.49	0.53	0.50	0.57	0.59
ln(P90) – ln(P75)	0.25	0.26	0.28	0.33	0.34	0.34
ln(P75) – ln(P50)	0.26	0.24	0.25	0.17	0.22	0.25
ln(P50) – ln(P10)	0.33	0.35	0.37	0.29	0.29	0.30
ln(P50) – ln(P25)	0.20	0.20	0.21	0.17	0.18	0.19
ln(P25) – ln(P10)	0.13	0.15	0.17	0.11	0.11	0.12
No. of observations	123 993	185 105	181 347	137 051	166 239	196 681

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

categories, the workers have on average relatively long experience from the labour market and also from their current employer. While the former shows a minor, if any, increase, the latter reveals a clearly decreasing trend thereby suggesting increased turnover in private-sector employment. Finally, the distribution of workers across differently sized employers has undergone only marginal changes between 1996 and 2006, the most prominent being a further strengthening of the dominance of firms with 250 employees or more.

4. Quantile regression results

This section reports key findings from the first estimation step, that is, for the quantile regressions (QR).[13] For convenience, the effects on wage levels and wage dispersion of the different individual and workplace attributes under study are presented separately by covariate. The wage effects resulting from QR estimations are displayed for a total of five quantiles: the 10th percentile (P10) representing the lowest point along the wage distribution, the 25th percentile (P25), the 50th percentile (P50) or median, the 75th percentile (P75) and the 90th percentile (P90), thus representing the highest point at the wage distribution. For comparison purposes, the corresponding wage effects obtained from mean regression (OLS) are also reported. The effect of each covariate on the dispersion of wages, finally, is measured by means of the difference between the QR coefficients of the 90th and the 10th percentile, $\hat{\beta}(0.90) - \hat{\beta}(0.10)$. As argued by Melly (2005b), this interquantile difference should not be significantly different from zero if the error term is independent of the covariate under scrutiny. If, on the other hand, the difference between the 90th and 10th percentile coefficients on a covariate is positive, then a higher value of this attribute tends to increase wage differentials within this particular group. Correspondingly, a negative difference has the opposite (compressing) impact on wage dispersion.

Table 2. Descriptive statistics for key covariates

	White-collar manufacturing workers			Services sector workers		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
Females, %-share	39	35	35	72	68	67
Average schooling years	13.04	13.06	13.42	12.02	11.78	12.58
Work experience, years	20.24	20.73	21.20	20.95	21.33	21.03
Seniority, years	11.74	11.76	11.50	10.44	9.41	9.34
Firm size, %-share						
1 – 19	4	4	4	16	15	15
20 – 99	18	15	15	18	17	18
100 – 249	16	16	17	16	15	14
250+	61	65	65	51	52	53
No. of observations	123 993	185 105	181 347	137 051	166 239	196 681

Note: Additionally, the covariates comprise industry of employment detailed over 49 industries for white-collar manufacturing workers and 56 industries for services sector workers.

[13] *In line with previous studies using the Machado and Mata (2005) or the Melly (2005a, 2005b, 2006) decomposition of changes in the wage distribution over time, 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 the private sector and, moreover, to full-time working individuals of two particular – albeit broad – worker categories, and from relying on individual and workplace attributes which are likely to involve various choices (education, employer size, industry). Overlooking these aspects is partly due to the structure of the data employed but mainly to the method applied. (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.) Accordingly, the analysis presented in this paper can be characterised as a description of the wage distribution conditional on being employed on a full-time basis as a white-collar manufacturing worker or as a services sector worker while being endowed with given individual and workplace-related attributes.*

Table 3. Gender (female share) effects on wage levels and wage dispersion

	White-collar manufacturing workers			Services sector workers		
	1996	2001	2006	1996	2001	2006
OLS (mean)	–0.251***	–0.207***	–0.196***	–0.239***	–0.224***	–0.200***
QR(P10)	–0.203***	–0.170***	–0.162***	–0.093***	–0.091***	–0.079***
QR(P25)	–0.218***	–0.184***	–0.176***	–0.136***	–0.127***	–0.119***
QR(P50, median)	–0.238***	–0.201***	–0.191***	–0.215***	–0.195***	–0.181***
QR(P75)	–0.270***	–0.221***	–0.207***	–0.316***	–0.277***	–0.240***
QR(P90)	–0.295***	–0.237***	–0.218***	–0.369***	–0.334***	–0.283***
QR(P90) – QR(P10)	–0.093***	–0.067***	–0.056***	–0.275***	–0.244***	–0.204***

Note: *** indicates that the estimated coefficient is significant at the 99.9 per cent level.

Standard errors for these interquantile differences are estimated by bootstrapping the results 100 times.[14] Stars indicate the level of significance of the reported estimates.

The estimated negative coefficients for gender, as reported in Table 3, indicate that women earn less than men also after detailed control for differences in human capital assets, employer size and industry of employment. The table also reveals that the gender wage gap increases considerably when moving up through the wage distribution. This finding implies that the mean (OLS) estimate provides a rather crude picture of the male–female wage gap, especially for services sector workers. However, the table also shows that the average pay penalty of women has declined in both worker categories over the 10-year period investigated, reaching approximately the same level by 2006 (about 20 log wage points). Moreover, while this decline in the male–female wage gap is visible throughout the wage distribution, it has been relatively stronger in its upper tail. As a consequence, there has been a clear narrowing in the spread of the gender wage gap across the wage distribution. Taken together, these effects imply that the female wage distribution has shifted to the right on the wage scale, closer to that of men. Simultaneously it has also become more dispersed although by far not as dispersed as that of men. Put differently, the hampering impact on overall wage dispersion of a larger proportion of females in the workforce has weakened.

Table 4 turns the focus to the effect on wage levels and wage dispersion of completed years of schooling after account has been made for differences in gender, labour market experience, seniority, employer size and industry of employment. The average return to an additional year of schooling unveils a declining trend among white-collar manufacturing workers. Moreover, this decline in educational returns has concerned mainly those earning median or above-median wages and, as a consequence, has resulted in a marked compression of returns to investments in education across the distribution of white-collar manufacturing wages. In other words, the same education was still in 2006 better rewarded in higher-paid jobs but the wage gain was clearly lower than in 1996. Among services sector workers, the trend has rather been the opposite with rising returns especially at the top end of the wage distribution. Hence, while larger proportions of better educated workers tend to increase wage dispersion, this effect seems to have weakened among white-collar manufacturing workers, whereas it has strengthened substantially among services sector workers.

Work experience entered the regressions with both a linear and a quadratic term. However, although being statistically highly significant, the coefficient estimated for the quadratic term is persistently very small. This outcome suggests that the experience–wage profile has remained approximately linear across the entire wage distribution after accounting for worker differences in gender, formal education, seniority, employer size and industry of employment. For this very reason, Table 5 only reports the coefficient estimates obtained for the linear term. The table displays a remarkable increase in the rewarding

[14] *Compared to the bootstrap simulation technique applied in the Machado and Mata (2005) approach, the method proposed by Melly (2006) is computationally easier as the estimation of the quantile regressions per se does not require bootstrapping.*

of labour market experience among white-collar manufacturing workers, but only after the turn of the century. Additionally this increase has been relatively stronger for those in high-paid jobs, which has strengthened the positive (increasing) effect of accumulated labour market experience on white-collar manufacturing wage differentials. Again an opposite direction of change is discernible among services sector workers who have seen the value of their labour market experience decline especially in more recent years. As this decline has affected the whole wage distribution, the difference in estimated work experience effects between high-paid and low-paid services sector workers has remained roughly unchanged. Hence, unlike the situation among white-collar manufacturing workers, the wage dispersion increasing effect of this particular human capital attribute has, broadly speaking, neither strengthened nor weakened among services sector workers.

Also seniority entered the regressions with both a linear and a quadratic term. Both terms are persistently statistically highly significant, but compared to the wage effect of labour market experience also the initial impact (linear term) of seniority on wage levels is minor (Table 6), occasionally even negative, while the seniority–wage profile (quadratic term) reveals an even weaker curvature than the experience–wage profile. Among white-collar manufacturing workers, the wage effect of seniority is, *ceteris paribus*, strongest in low-paid jobs, where it has also remained practically unchanged. Higher up the distribution, in contrast, seniority turns out to exert a non-negligible negative impact on wage levels. Moreover, this negative influence has strengthened further over the investigated time period. A similar pattern of increasingly negative seniority wage effects when moving up through the wage distribution characterised also services sector workers in the mid-90s. The same overall pattern prevailed also at the turn of the century. By 2006, however, the effect of seniority on services sector wages had turned positive across the entire distribution, albeit with the effect still being strongest in the lower tail of the distribution. This reversed effect, which appears to prevail in both worker categories, implies that seniority has a weakly negative (compressing) effect on wage dispersion. However, while this trend has strengthened

Table 4. Education (years of schooling) effects on wage levels and wage dispersion

	White-collar manufacturing workers			**Services sector workers**		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
OLS (mean)	0.079***	0.075***	0.072***	0.060***	0.048***	0.066***
QR(P10)	0.065***	0.067***	0.065***	0.032***	0.025***	0.032***
QR(P25)	0.070***	0.071***	0.070***	0.040***	0.031***	0.041***
QR(P50, median)	0.078***	0.076***	0.075***	0.053***	0.041***	0.056***
QR(P75)	0.084***	0.079***	0.076***	0.062***	0.051***	0.070***
QR(P90)	0.086***	0.079***	0.076***	0.068***	0.058***	0.081***
QR(P90) – QR(P10)	0.022***	0.012***	0.011***	0.035***	0.032***	0.050***

Note: *** indicates that the estimated coefficient is significant at the 99.9 per cent level.

Table 5. Work experience (in years, linear term) effects on wage levels and wage dispersion

	White-collar manufacturing workers			**Services sector workers**		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
OLS (mean)	0.025***	0.022***	0.031***	0.025***	0.024***	0.019***
QR(P10)	0.015***	0.013***	0.018***	0.016***	0.014***	0.009***
QR(P25)	0.017***	0.015***	0.022***	0.017***	0.015***	0.011***
QR(P50, median)	0.023***	0.020***	0.028***	0.020***	0.019***	0.015***
QR(P75)	0.031***	0.027***	0.038***	0.025***	0.024***	0.021***
QR(P90)	0.038***	0.035***	0.046***	0.032***	0.033***	0.026***
QR(P90) – QR(P10)	0.023***	0.022***	0.029***	0.015***	0.019***	0.017***

Note: *** indicates that the estimated coefficient is significant at the 99.9 per cent level.

slightly among white-collar manufacturing workers, it has weakened among services sector workers.

The wage effects of employer size are captured by means of three size indicator variables with a staff of less than 20 employees forming the reference group. In order to keep the amount of results down, Table 7 only reports for each size group the coefficient estimated for the median (P50) and the spread around this median as measured by the difference in the coefficient estimates for the two tails of the wage distribution, that is, for the highest (P90) and the lowest (P10) percentile. The median wage effects displayed in the table clearly suggest that the size of the employer has an independent impact also after controlling for gender, human capital endowments and industry of employment. Moreover, this effect strengthens with the size of the employer, i.e. workers with the same attributes, including industry of employment, are typically paid more in larger firms. This tendency seems to be notably stronger among white-collar manufacturing workers than among services sector workers. When it comes to the contribution of employer size to wage dispersion, the effect is clearly positive (increasing), albeit not always significantly so. The strength of the impact reveals no clear-cut pattern across size categories, worker groups or years investigated. Indeed, it is by no means self-evident from Table 7 that wages paid by larger firms tend not only to be higher but also to show a wider spread.

5. Decomposition results

The quantile regression results reported in the previous section were based on a large number of observations for both white-collar manufacturing workers and services sector workers (see Table 1 above). The use of such a broad dataset was possible because quantile regression estimates were produced for a very limited number of values along the wage distribution. As already noted, even with a much smaller sample size, estimation of the whole quantile regression process is simply not possible.

Following the STATA programme for decomposition of differences in distributions using

Table 6. Seniority (in years, linear term) effects on wage levels and wage dispersion

	White-collar manufacturing workers			Services sector workers		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
OLS (mean)	0.001*	0.000***	–0.001***	–0.001***	0.002***	0.005***
QR(P10)	0.005***	0.005***	0.005***	0.003***	0.006***	0.008***
QR(P25)	0.003***	0.003***	0.002***	0.001***	0.004***	0.006***
QR(P50, median)	0.001***	0.000***	–0.001	–0.001***	0.001***	0.004***
QR(P75)	–0.002***	–0.003***	–0.005***	–0.004***	–0.001*	0.003***
QR(P90)	–0.005***	–0.007***	–0.008***	–0.007***	–0.003***	0.003***
QR(P90) – QR(P10)	–0.011***	–0.012***	–0.013***	–0.010***	–0.009***	–0.006***

Notes: *** indicates that the estimated coefficient is significant at the 99.9 per cent level, * at the 95 per cent level.

Table 7. Employer (firm) size effects on median wage levels and wage dispersion

	White-collar manufacturing workers			Services sector workers		
	1996	**2001**	**2006**	**1996**	**2001**	**2006**
QR(P50, median)						
20 – 99	0.019***	0.033***	0.034***	0.056***	0.048***	0.039***
100 – 249	0.025***	0.053***	0.046***	0.072***	0.075***	0.052***
250+	0.069***	0.097***	0.104***	0.050***	0.078***	0.050***
QR(P90) – QR(P10)						
20 – 99	0.016	0.054***	0.022**	0.032***	0.036***	0.018***
100 – 249	0.020*	0.046***	0.013	0.049***	0.098***	0.040***
250+	0.011	0.042***	0.040***	0.010	0.048***	0.010*

Notes: Reference group is 1–19 employees. *** indicates that the estimated coefficient is significant at the 99.9 per cent level, * at the 95 per cent level.

quantile regression (*rqdeco*) developed by Melly (2006), a smaller sample was used for 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. More precisely, the decomposition results presented in this section are, for each pair of years investigated, based on a 30 per cent sample drawn randomly from the data employed in the previous section. This sample size has two advantages. First, it is large enough to produce quantile regression estimates that are both qualitatively and quantitatively almost identical to those reported in Tables 3 to 7, an outcome that also serves as a robustness check of the quantile regression estimates on which the decomposition results are based. Second, it is small enough to keep the computation time at a reasonable level.[15]

Next, the estimated effects on changes in wage distributions of changes in coefficients and in the composition of the workforce are first displayed in a number of graphs and then summarised using a set of selected statistics. The plotted decomposition results are obtained by applying the decomposition procedure outlined in Section 2 at each of 99 different quantiles along the estimated counterfactual (unconditional) log wage distribution ($\theta = 0.01, 0.02, \ldots, 0.99$) with standard errors computed by bootstrapping the results 100 times. While the plots do not display confidence intervals, it should be noted that the estimates are highly precise throughout the distribution, including its two tails. The effect of the residuals is persistently negligible, thus indicating the good fit of the models, and is therefore not depicted in these graphs.

Figure 1 presents decomposition results for white-collar manufacturing workers for the two periods under scrutiny. The curve depicting the total factual change in the unconditional log wage distribution of white-collar manufacturing workers repeats the story already told by Table 1: compared to the evolution in the late 1990s, real wage growth has, after the turn of the century, not only been stronger throughout the wage distribution but has also been characterised by disproportionately larger increases higher up the distribution and, especially, at its top end. Despite these distinct differences in real wage growth patterns between the late 1990s and the early 2000s, the overall picture mediated by the decomposition results is strikingly similar. Across the whole distribution, the growth in white-collar manufacturing real wages is to most part explained by changes in coefficient estimates, that is, how white-collar manufacturing workers' individual and workplace attributes are rewarded in the labour market. Conversely, while also changes in the workforce composition have contributed positively to real wage growth at all estimated points along the wage distribution, the effect of changing attributes has persistently been substantially smaller than the effect of contemporary changes in the remuneration of these attributes. Moreover, in both periods there appears to have been only minor variation across the wage distribution in the absolute magnitude of this wage increasing effect of changing white-collar manufacturing workers' attributes. In relative terms, on the other hand, the composition effect has maintained a somewhat stronger role in the lower half of the wage distribution. Put differently, the relative importance of the price effect is not only stronger throughout the wage distribution but its dominance over the composition effect also tends to strengthen further when moving up through the wage distribution, albeit this tendency has weakened slightly after the turn of the century. For example, in both periods the price effect explained some 75 per cent of real wage growth at the 10^{th} percentile, whereas the corresponding share at the 90^{th} percentile was about 82 per cent for 2001/2006 compared to almost 92 per cent for 1996/2001.

Broadly speaking, the decomposition results obtained for services sector workers paint much the same picture but in reversed order (Figure 2). First and as already concluded from Table 1 above, the rise in services sector wage dispersion was notably stronger in the late 1990s than

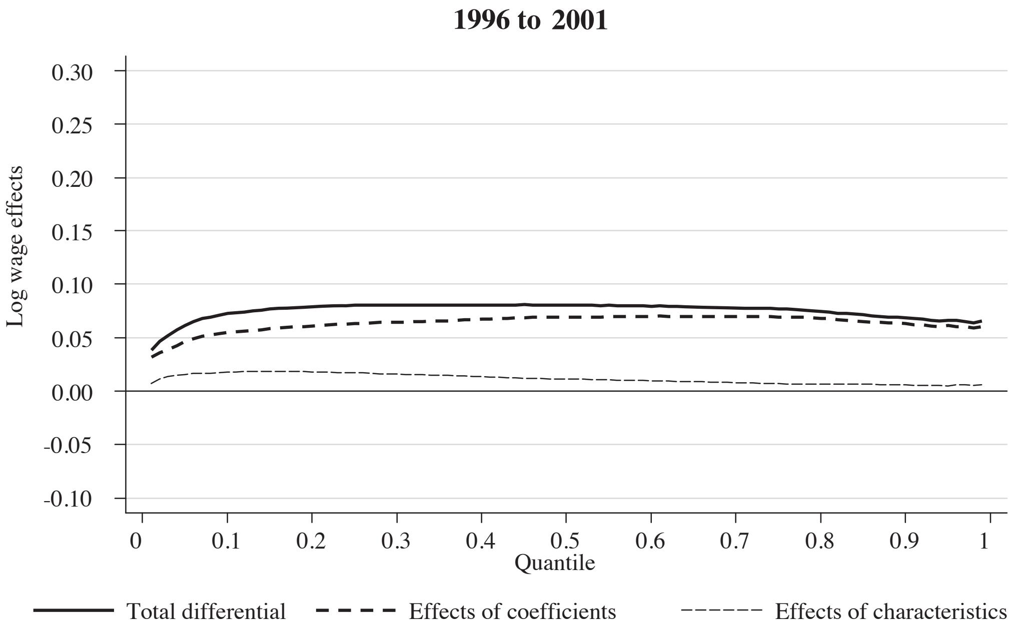
[15] The decomposition procedure is computationally intensive because of the use of bootstrapping for calculating the standard errors of the estimates. As formally shown by Chernozhukov, Fernández-Val and Melly (2009), an alternative approach would be to continue with the full sample for the estimations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

in the early 2000s due to conspicuous differences in real wage growth between the upper and lower tails of the distribution. Second, the effect of changes in coefficients has, in both periods, been quantitatively more important than the effect of changes in the composition of attributes at each of the estimated points along the wage distribution. The dominating role of the price effect was, however, clearly more pronounced in the late 1990s than in the early 2000s also among services sector workers. However, unlike the evolution within the category of white-collar manufacturing workers, the relative importance of changing remuneration of attributes seems to have weakened across the entire wage distribution, not only in its upper half. At the 90th percentile, the price effect explained the lion's share of the real wage growth between 1996 and 2001 (or almost 92 per cent, as among white-collar manufacturing workers) compared to just below two-thirds for 2001/2006 (corresponding to a much stronger decline than for their white-collar manufacturing counterparts). At the 10th percentile, the change in the price effect was even larger: from having accounted for almost 177 per cent of real wage growth between 1996 and 2001, it was down at about 70 per cent for 2001/2006 (slightly less than for their white-collar manufacturing counterparts). The high percentage estimated for the 1996/2001 price effect implies that the growth in real wages at this particular quantile would have been much stronger unless counteracted by concomitant compositional changes. Indeed, as shown in the upper graph of Figure 2, the compositional changes that the services sector workforce underwent in the late 1990s acted as a countervailing force on real wage growth across most of the distribution. This negative contribution from changing compositions of attributes turned into, at most, marginal gains only towards the top end of the wage distribution. Simultaneously this finding stands out as the most conspicuous difference in decomposition results between the two worker categories, as displayed in Figures 1 and 2. By the early 2000s, the composition effect had turned positive and more similar in absolute magnitude also across the services sector wage distribution.

More details are provided in Table 8 which, following Melly (2005b), presents decomposition results for changes in various measures of wage dispersion: for the standard deviation as well as for selected interquantile differences along the log wage distribution. For comparison purposes, the table provides corresponding results for both the mean and the median. Standard errors computed by bootstrapping the results 100 times are given in parentheses.

Table 8 repeats in many respects what has already been concluded based on the results presented in Figures 1 and 2. The notable widening in the unconditional distribution of services sector wages in the late 1990s and of white-collar manufacturing wages in the early 2000s is reflected in substantial increases in all measures of wage dispersion displayed in the table and, especially, in those capturing changes in the upper half of the wage distribution. The results reported for the mean and the median, in turn, describe the overwhelming effect on real wage growth of (positive) changes in the remuneration of worker and workplace attributes, a finding that holds for both worker categories and persists over both time periods investigated. The table also unveils, however, the peculiar feature of the composition of services sector workers changing, on average, in a real-wage decreasing way between 1996 and 2001, with this effect being notably stronger in the lower than in the upper tail of the distribution.

Most interesting in Table 8 are the results obtained from decomposition of changes in wage dispersion as measured by interdecile and interquartile gaps of the underlying log wage distribution. All five measures of wage dispersion indicate that the marked widening in the dispersion of white-collar manufacturing wages in the early 2000s can for the most part be explained by changes in the rewarding of worker and workplace attributes. Conversely, the contribution of changes in the distribution of these attributes has been close to negligible. On the other hand, this outcome is only to be expected in view of the similarity in the absolute magnitude of the composition effect across the white-collar manufacturing wage distribution (cf. Figure 1 above). Indeed, the increase in the 90–10 log wage gap after the turn of the century is es-



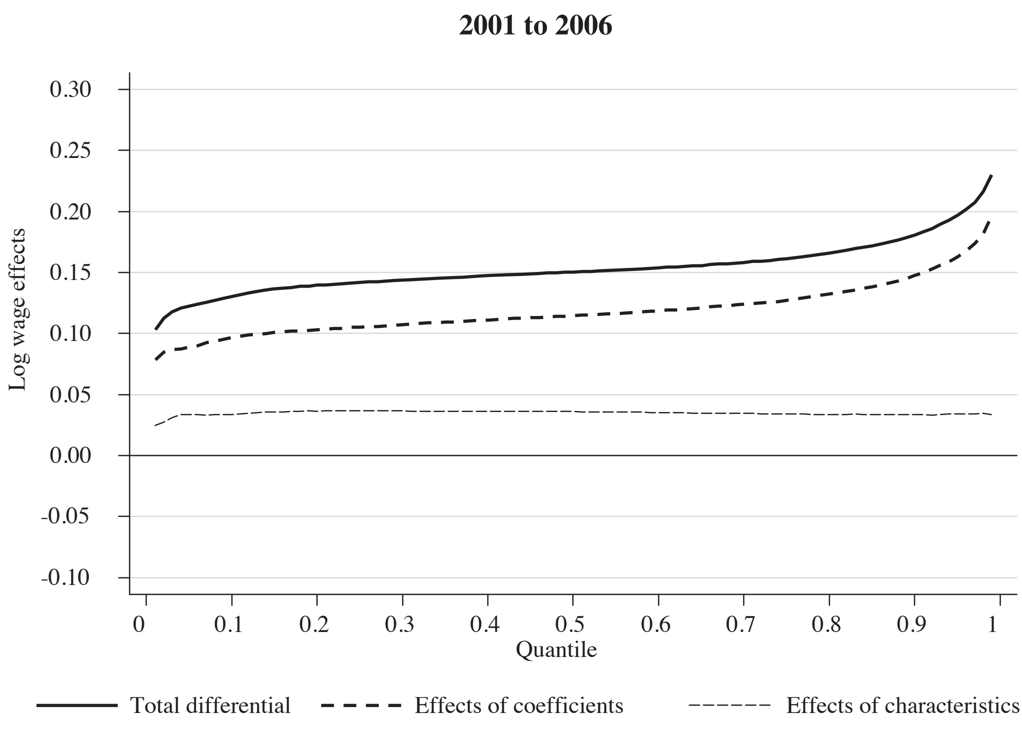


Figure 1. Decomposition of changes in the distribution of white-collar manufacturing wages

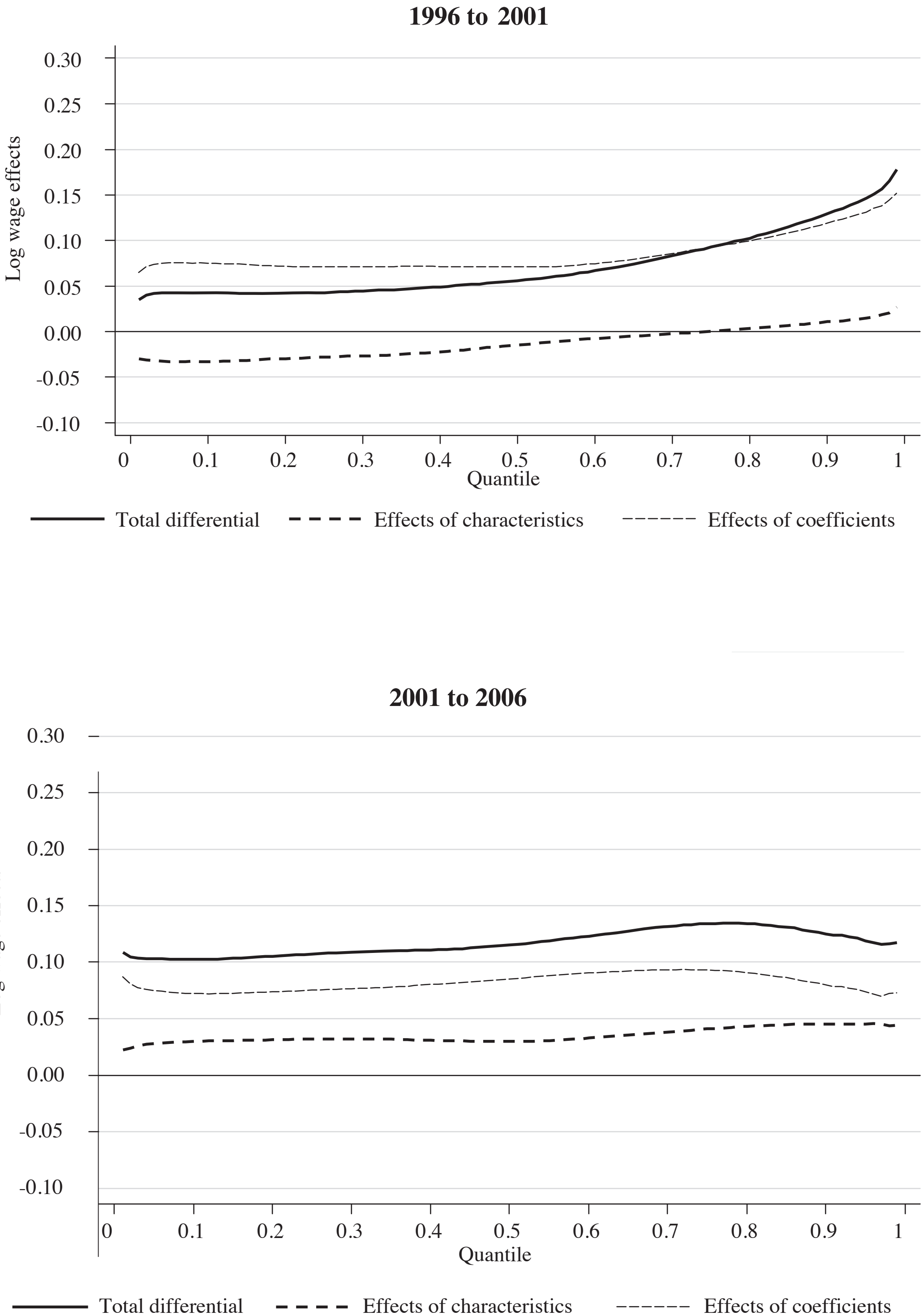


Figure 2. Decomposition of changes in the distribution of services sector wages

Table 8. Decomposition of changes in distribution using various measures of wage dispersion

	1996/2001			2001/2006		
	Total factual change	**Composition effects (covariates)**	**Price effect (coefficients)**	**Total factual change**	**Composition effect (covariates)**	**Price effect (coefficients)**
White-collar manufacturing workers						
Mean	7.55 (.07)	1.15 (.04)	6.40 (.07)	15.36 (.20)	3.48 (.02)	11.88 (.20)
Median	8.07 (.06)	1.13 (.09)	6.95 (.09)	15.07 (.15)	3.60 (.04)	11.47 (.17)
Standard deviation	0.75 (.10)	0.45 (.02)	0.76 (.09)	2.09 (.22)	0.18 (.03)	2.10 (.22)
90–10	–0.39 (.11)	–1.21 (.04)	0.81 (.29)	5.03 (.77)	–0.04 (.01)	5.06 (.74)
50–10	0.79 (.11)	–0.65 (.09)	1.44 (.27)	1.99 (.38)	0.23 (.03)	1.76 (.32)
90–50	–1.18 (.06)	–0.56 (.09)	–0.63 (.09)	3.04 (.67)	–0.26 (.03)	3.30 (.66)
75–25	–0.35 (.17)	–0.99 (.08)	0.63 (.07)	1.98 (.31)	–0.26 (.02)	2.23 (.34)
Services sector workers						
Mean	7.18 (.34)	–1.26 (.16)	8.43 (.20)	11.71 (.11)	3.52 (.06)	8.19 (.08)
Median	5.62 (.42)	–1.45 (.35)	7.07 (.11)	11.54 (.21)	3.03 (.03)	8.51 (.14)
Standard deviation	3.49 (.28)	1.62 (.09)	2.00 (.20)	1.07 (.05)	0.61 (.03)	0.75 (.03)
90–10	8.71 (.92)	4.33 (.24)	4.38 (.69)	2.26 (.11)	1.52 (.07)	0.74 (.06)
50–10	1.37 (.42)	1.81 (.34)	–0.44 (.10)	1.28 (.20)	–0.01 (.05)	1.29 (.13)
90–50	7.34 (.89)	2.52 (.35)	4.82 (.66)	0.99 (.20)	1.53 (.05)	–0.55 (.13)
75–25	4.97 (.77)	2.86 (.24)	2.11 (.56)	2.66 (.22)	0.88 (.21)	1.78 (.13)

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

timated to be totally due to disproportionate changes at the two tails of the wage distribution in the remuneration of key attributes. Concomitantly, the compositional changes have rather had a (marginally) compressing effect on the evolution of white-collar manufacturing wage differentials.

An increasingly different value attached in the labour market to critical attributes is the driving force also behind the notable growth in the dispersion of services sector wages in the late 1990s, but only in the upper half of the distribution. Of the conspicuous increase in the 90–50 gap in log wages between 1996 and 2001, the price effect is estimated to have accounted for two-thirds and the composition effect for merely one-third. However, the relative importance of the composition effect strengthens markedly when moving down the services sector wage scale. More precisely, changes in the distribution of attributes explained an only slightly larger part of the rise in the 75–25 log wage gap in the late 1990s than did changes in the rewarding of these attributes. In contrast to these findings, the composition effect entirely dominated in these years the evolution of services sector wage differentials in the lower half of the wage distribution, as measured by the 50–10 gap in log wages.

All in all, the most conspicuous difference in wage dispersion decomposition results between white-collar manufacturing workers and services sector workers boils down to the contribution of the composition effect to widening wage differentials. In both worker categories, changes in the distribution of attributes have played a notably less important role than changes in the rewarding of these attributes in explaining the marked widening in wage differentials in the upper half of the distribution. Among white-collar manufacturing workers, the price effect has been the dominating factor behind the observed rise in wage dispersion also in the lower half of the distribution. Among below-median earning services sector workers, in contrast, this role is taken over by the composition effect with the price effect rather exerting a negligible (compressing) influence.

6. Concluding remarks

This paper has investigated major factors underlying the marked increase in the dispersion of private-sector wages in Finland since the mid-90s as measured by total hourly compensation; that is, with account made for various performance-pay related items as well as fringe benefits paid on top of the basic wage rate. The focus has thereby been on two distinct worker categories: white-collar manufacturing workers who have seen a remarkable increase in their wage differentials after the turn of the century, and services sector workers who experienced a much stronger widening in their wage distribution in the late 1990s than in the early 2000s. In both worker categories, the rise in wage dispersion has been concentrated to the upper half of the wage distribution.

The analysis was undertaken by applying a methodology recently proposed by Melly (2006), by means of which the observed changes in wage distributions can be decomposed into the effect of changes in covariates and in coefficients. The decomposition results for a selected grid of quantiles indicate that the price effect (changes in coefficients) has been quantitatively more important than the composition effect (changes in the distribution of attributes) at each of the estimated points along the log wage distribution. This pattern of real wage growth having been fuelled mainly by changes in the way key attributes are valued in the labour market holds true for both worker categories and for both time periods under scrutiny, albeit with the pattern being notably more pronounced in periods of larger increases in wage dispersion. This overall pattern, however, conceals conspicuous variation in the relative importance of the price and composition effects not only between but also within the two worker categories, which has implications for the driving forces behind the observed growth in wage dispersion.

Among white-collar manufacturing workers, increasingly different remuneration of major worker and workplace attributes comes out as the factor having contributed most strongly not only to overall growth in real wages but also to the notable rise in wage dispersion in the early 2000s. Indeed, the price effect is found to account for principally all of the widening in wage differentials in different ranges of the distribution. The roughly neutral contribution to increasing wage dispersion of changes in the composition of attributes is simply due to an almost non-existent variation in the (minor) absolute magnitude of the composition effect across the white-collar manufacturing wage distribution.

The outcome is distinctly different for services sector workers. More precisely, the results suggest that the price and composition effects have contributed in roughly equal proportions to the substantial increase in the dispersion of services sector wages in the late 1990s, as measured by the 90–10 gap in log wages. Closer inspection of this finding, however, reveals that these roughly equal contributions of changing distributions of attributes and changing remunerations of these attributes arise from opposite patterns in the upper and lower tails of the services sector wage distribution. Decomposition of the 90–50 log wage gap suggests that the price effect dominates over the composition effect, although less strongly when compared to the outcome for white-collar manufacturing workers. Decomposition of the 50–10 gap in log wages, in turn, results in a reversed situation with the increase in lower-tail wage differentials being entirely explained by compositional changes in attributes.

At first sight, these differences in decomposition results between white-collar manufacturing workers and services sector workers seem to suggest that the forces behind widening wage differentials are distinctly different in the two categories. This is not necessarily the case, however. When comparing the outcome for white-collar manufacturing workers with that for services sector workers, one should recall the gap in absolute wage levels that still prevails between the two worker categories across the entire wage distribution. More formally, on a horizontal wage scale the distribution of services sector wages has persistently been located to the left of the distribution of white-collar manufacturing wages. In other words, only a smaller portion of white-collar manufacturing workers is located at that particular segment of the overall wage distribution where the composition effect acts as the major driver of widening wage differentials. This being the case, the results for the Finnish private sector would seem to be well in line with those obtained for other countries according to which the price effect tends to dominate increases in wage dispersion at the top end of the wage distribution, with increases in wage dispersion at its lower end being explained mainly by changes in the composition of the workforce.

Having said this, it should, however, also be emphasised that the existing differences in wage levels and dispersions between white-collar manufacturing workers and services sector workers are by no means the only reasons underlying the different results obtained. A simple check by running the same models on the combined sample, with a dummy indicator included for being a services sector worker, produces decomposition results (not shown here) that differ in distinct ways from those obtained when undertaking the same estimations separately for the two worker categories. Merging the two datasets would, in other words, produce results that concealed important differences in the wage determination processes of white-collar manufacturing workers and services sector workers. More precisely, while support is obtained for differences in wage levels and dispersions playing a role, also other mechanisms seem to be at play. These other mechanisms relate especially to differences in how and when new performance-related pay schemes have been adopted and implemented in the two worker categories. Indeed, this is a question that would deserve particular attention in future research.

All in all, the findings reported in this paper highlight several crucial aspects of decompositions of changes in wage distributions using quantile regression. First, it is important to make a clear distinction between the contribution of the price and the composition effect to the growth of real wage levels at different points of the wage distribution, on the one hand, and to the evolution of wage dispersion, on the other hand. A dominating role of one effect for real wage growth does not necessarily imply that the same effect acts as the driving force also behind widening wage differentials. Second, the contribution of the price and the composition effect to changes in wage dispersion needs to be unveiled for different ranges of the wage distribution, not only for some overall measure of wage dispersion, as the relative importance of the two effects might vary substantially depending on the particular range considered. Last but not least, splitting the data employed into more homogeneous worker categories may provide a more nuanced picture not only of patterns and trends of real wage growth and wage dispersion but also of the absolute and relative importance of the forces underlying these patterns and trends.

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