Gender Wage Differences across Quantiles accounting for Sample Selection [1]

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Very preliminary and incomplete – do not quote!

Abstract: This paper analyzes empirically the development of the gender wage gap for different skill groups and full- and part-time employees in the U.K. using quantile regression accounting for sample selection. The empirical analysis is based upon the General Household Survey from 1975 to 1995. First, a linear probability model for employment status is estimated distinguishing between full–time, part–time, and nonemployment. Second, the estimated probilities for full–time and part–time are then using to take account of sample selection by a second order polynomial series expansion when estimating quantile regressions, see Newey (1999) for nonparametric series estimation to account for sample selection in a mean regression. Our goal is to analyze whether the level of the gender wage gap across the distribution of wage are identified. Based on the concept of identification at infinity, the level of female full–time and part–time wages can not be identified and therefore the same holds true for the level of the gender wage gap. However, it is found that wage gap between full-time employed females and full-time employed males has closed considerably during the observation period. The gap has closed mostly in the lower part of the wage distribution. In contrast, part-time employed women did not catch up relative to full-time employed men. While sample selection affects the estimated age profile for female wages, the estimated time trend in the gender wage gap is for the most part not affected by sample selection for female workers.

Keywords: Gender Wage Gap, Quantile Regression, Cohort Analysis

JEL Classification: J16, J31, J71

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1 Introduction

In recent years, numerous studies on the gender wage gap in the U.K.[1] have been presented and it has been documented that on average the gender wage gap for full–time employed females has been decreasing since the 70's, while no improvement for part–time employed females has been found. Based on international comparisons, Blau and Kahn (1996, 1997) argue that the gender wage gap has been decreasing in most industrialized countries despite a tendency for increasing wage dispersion among male workers, see also Altonji and Blank (1999). Since average formal educational attainment is lower for females than for males one would expect an increasing gender wage gap when wage inequality among males rises. Thus, Blau and Kahn (1997) interpret the reduction in the gender wage gap as women "swimming upstream".

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The empirical strategy of the paper builds on our earlier paper Fitzenberger and Wunderlich (2001) which focussed on identifying cohort effects for males and female workers. When defining cohorts by year of birth and dealing with the inherent identification problem between age, time, and cohort effects, that earlier study finds that wages for women can be described by a separable model in age and time whereas wages for male workers with low or medium skill level involve significant additional separable cohort effects, see tables 2–4 in Fitzenberger/Wunderlich (2001). The earlier paper is descriptive in the sense that selection effects are not accounted for. In this paper, I estimate the wage equations for females accounting for selection effects but otherwise taking the same specifications as in Fitzenberger/Wunderlich (2001). For the comparison with male workers, I use the descriptive models for males estimated in the earlier paper not taking account of sample selection. The issue of sample selection into employment distinguishing full–time and part–time is much more important for women and part–time employment is rarely observed for male workers.

2 The Gender Wage Gap in Britain

The traditional strategy of investigating the gender pay gap (first proposed by Blinder, 1973 and Oaxaca, 1973 and extended by Juhn/Murphy/Pierce, 1993) is to decompose the mean wage differential between males and females into differences due to observed individual wage determining characteristics, differences in rewards to these characteristics, and an unexplained share. This strategy, which is usually based on Mincer-type earnings equations, is applied to the British case in various studies (for a brief overview see Joshi/Paci, 1998: pp34). Changes in the gender wage gap are then identified by looking at changes of these components or comparing the relative wage position of females within the male wage distribution between at least two points in time. The findings obtained by previous studies differ, because they use different data and model

[1]See, for example, Bell and Ritchie (1998), Harkness (1996), Joshi and Paci (1998), Manning and Robinson (1998), and some of the papers in Gregg and Wadsworth (1999a).

specifications and compare cross sections in different years.[2] But in general, they find that the average full-time gender gap has narrowed substantially between the 70's and the 90's, whereas the average part-time gender gap remained constant at best.

Gender related policy changes have occurred during the observation period, starting with the decisive Equal Pay Act of 1970 ratified in 1975 which attempted to prevent gender related wage differences for the same work. These policies appear to have contributed to reducing gender wage differentials in the British labor market.[3] In addition, the overall gap in educational attainment has closed, as younger and better educated female cohorts replaced older and less educated cohorts dropping out of the labor force. But according to Desai et al. (1999) there is now a clear distinction between the levels of qualification of full-time and part-time employed women. Another trend influencing pay rates decisively is that average employment tenure increased tremendously for females. Maternity Rights legislation (1987, amended in 1993) has enabled far more women than before to return to the same employer after the birth of children (Desai et al. 1999, Gregg/Wadsworth 1999b).

Desai et al. (1999)[4] find that the average wage gap of all men and full-time employed women has narrowed from 43 percent in 1975 to 24 percent in 1995.[5] In terms of the aforementioned Blinder–Oaxaca decomposition, the characteristics component has declined from 12 percent to 5 percent, the rewards component has declined from 28 percent to 12 percent, and the unexplained part of the gap increased from 3 percent to 7 percent. In contrast, the mean wage gap between all men and part-time employed women has risen from 46 percent in 1975 to 55 percent in 1995. The share of the pay gap due to differences in characteristics increased from 3 percent to 15 percent, the share due to their rewards increased from 33 percent to 53 percent.[6]

Gender wage differentials are partly related to differences in actual labor market experience which contributes to the individual's human capital. An additional explanation for age-earnings profiles is offered by Manning (2000). Using a simple search model, he shows that a substantial share of the rise in earnings over the life cycle and virtually all the earnings gap between men and women can be explained in this way. In this framework, the narrowing of the gender wage gap has to be attributed to the convergence of male and female labor market transition rates.

When investigating the gender wage gap, it is necessary to make a distinction between full-time and part-time employment, because the latter jobs are primarily female and might, for various reasons, exhibit a "systematic" wage penalty. It is often assumed that gross hourly wage offers are independent from hours worked (with the exception

[2] Most studies use cross sectional micro data, see for comparatively new evidence, inter alia, Desai et al. (1999), Blackaby et al. (1997), and Harkness (1996). The studies of Makepeace et al. (1998) and Joshi/Paci (1998) are based on cohort data. To our knowledge, the only recent studies using panel data are Bell/Ritchie (1998) using the New Earnings Survey and Manning/Robinson (1998) using the British Household Panel Study.

[3] See Wright/Ermish (1991) for an overview of the studies investigating this in the 70's and 80's.

[4] We use this study as reference because it is congruent with our data and observation period.

[5] Using the General Household Survey and controlling for education, age, job tenure, industry, region, and children.

[6] The latter result is somewhat confusing, because adding both numbers leads to a negative unexplained share of 13 percent.

of overtime hours). But this is not necessarily the case. Ermish/Wright (1991) find strong evidence that women receive lower wage offers in part-time jobs than in full-time jobs. When controlling for self selection into these two types of jobs, they show that a woman with given education and employment characteristics generally receives a lower wage in part-time than in full-time employment.

Trying to explain this finding, Ermish/Wright (1991) argue that the supply function for part-time workers may be distinct from that of full-timers: Several characteristics of part-time jobs, such as a better possibility to reconcile family and employment allow a substitution of higher wages for these characteristics.[7] This causes a compensating wage differential due to unmeasured characteristics of the job or workplace. Further arguments for a full-time/part-time wage gap are based on higher fixed costs for part–time jobs, labor market segmentation after having worked full– or part–time for a while, stronger monopsony power of employers in local labor markets because of a lower mobility of part–time workers, and the impact of different individual characteristics on the choice to work full–time or part–time.

In their overview on the gender gap in the British labor market, Desai et al. (1999, for a more detailed analysis see Harkness, 1996) emphasize that the pattern of change in the gender pay gap depends very much on whether a woman works full-time or reduced hours. All the relative gain in pay made by women compared to men is due to full-time employed women. In 1974 full-time employed women earned, on average, 60 percent, whereas part-time employed females earned 65 percent of male average wages. In 1994, full-timers reached nearly 80 percent and part-timers still remained at 65 percent of the average male wage. Harkness (1996) finds that when estimating different specifications for full-time and part-time employed women, supply and demand factors completely explain the wage gap between these two groups. That is, the gap is due to differences in characteristics.

A deficiency of a descriptive analysis of the change in the average gender pay differentials is that the findings may be caused by selection or composition effects. This might be due to a changing distribution of individual characteristics like education and tenure, or to a changing self selection regarding employment in general as well as full-time and part-time jobs over time (e.g. if the availability of child care facilities or individual mobility has improved). Demand side factors, such as structural and technological change, market power, or union coverage (see Bell/Ritchie, 1998) are important as well. Furthermore, rising wage inequality could mean that simple comparisons of average wages of men and women give a misleading impression of the change in the labor status of women (Desai et al. 1999: 177). Blau/Kahn, (1997) convincingly argue that wage dispersion and gender wage differentials are closely linked. For instance, if returns to human capital rise, women will see a fall in their relative earnings due to their lower stock of human capital. Additionally, the wage gap differs across the entire wage distribution, and the various quantiles progress differently over time (for a descriptive analysis see Harkness, 1996). Overall wage inequality has changed as well as have returns to education, experience, and job tenure (e.g. Gosling et al. 2000, Gregg/Wadsworth, 1999b, and Manning, 2000). Moreover, (re)entry wages have declined (Gregg/Wadsworth, 2000).

[7] Individuals jointly maximize their utility from working over the wage rate and other attributes of the job or workplace.

In contrast to the numerous studies using the traditional average wage gap decomposition technique, little attempt has been undertaken to account for differences in the gender gap across the entire wage distribution. Blackaby et al. (1997) extend the method of Juhn/Murphy/Pierce (1993) and analyze the gap at the 10% and the 90% percentile for the time period from 1973 to 1991. Their results indicate that the wage gap has narrowed mostly in the lower part of the wage distribution (see also Harkness, 1996). This is particularly striking in light of the strong increase in wage dispersion for males (Gosling et al. 2000) suggesting that British women are indeed "swimming upstream" (Blau/Kahn, 1997). When the dynamics of the gender wage gap differ across the distribution, results on the average gender gap can be quite misleading.

Our earlier study Fitzenberger/Wunderlich (2001) contributes descriptive evidence on the development of the gender wage gap for different skill groups and full- and part-time employees in the U.K. The empirical analysis is based upon the General Household Survey from 1975 to 1995 (the same data as in this study) and therefore provides evidence on an exceptionally long period. The focus of the earlier stuy is to identify the macroeconomic trends of wages apart from life cycle and cohort effects implementing a model which takes into account the impact of age, time, and birth cohort simultaneously. Moreover, quantile regression is used to distinguish between various points of the entire wage distribution. We conclude that the wage gap between full-time employed females and full-time employed males has closed considerably during the observation period. The gap has closed mostly in the lower part of the wage distribution. In contrast, part-time employed women did not catch up relative to full-time employed men. However, this study neglects the issue of sample selection. One goal of this paper is to analyze as to whether the results in our earlier study remain robust when taking sample selection into account.

3 The General Household Survey (GHS)

The General Household Survey (GHS) was started in 1971. It is conducted by the Office of Population Censuses and Surveys based on a random sample of the population living in private (post-coded) households in the U.K. and it covers around 10,000 households. Between 1971 and 1996/97 interviews were carried out annually. Each household member above age 15 is interviewed. The survey response rate amounts to roughly 66 per cent. For this study, we use the repeated annual cross–sections from 1975 to 1995/96. The GHS data are often used for analyses of wages because they contain consistent information on usual weekly earnings, the individual's highest formal education level, and various other important individual characteristics.

We use data on individuals between age 20 (age 25 for high skilled individuals) and 60 for whom valid information on educational attainment, wage, age, gender, working hours, and employment is available. All other observations are dropped. The age interval for high skilled persons is reduced because these individuals usually finish full time education in their mid twenties. We compute log weekly earnings deflated to 1975 by the consumer price index and we distinguish three groups by gender and employment status: full-time employed men (M), full-time employed women (F(F)), and part-time employed women (F(P)).

We use the usual weekly earnings and working hours reported in the GHS (see Manning, 2000).[8] Full-time employment is defined as working more than 35 hours a week. The part-time share within the group of females with valid wages varies between 30.30 and 37.22 percent and the share of women amongst all employees with valid wages, irrespective of wether the job is full- or part-time, varies between 42.06 and 52.31 percent. Both shares grow over time.

The GHS provides detailed information about each respondent's educational background. Information on the highest educational qualification of each person is available for the period 1975 to 1982. From 1983 the GHS contains a list of all qualifications each individual has obtained. The questions about obtained qualifications changed slightly in 1988 and again in 1994. From this information we extracted the highest qualification of each person. However, the skill variable exhibits two structural breaks in 1983 and 1994 which results in an increase of missing answers between the two years. There is also a change in the questionnaire for 1988, but this is not visible in the data. Unsurprisingly, the non–response behavior is correlated across several questions, namely employment, wage, qualification, and working time. Thus, dropping individuals with missing wages reduces missing observations in qualification as well. We split the employment status groups by skill level into

(U) low skilled individuals who report to have no or an "other" qualification,

(H) high skilled individuals with qualifications above A–level, and

(M) medium skilled individuals who constitute the remaining category.

The skill composition of the work force has changed remarkably during the observation period. The share of low skilled men and women (according to our definition) amongst employed persons with valid wage information dropped from 59.40 percent in 1975 to 21.35 percent in 1995. The share of the high skilled increased from 10.23 percent in 1975 to 27.48 percent in 1995.

The sizes of our subsamples, defined by gender, employment status, and skill level, varies between 6,132 observations (high skilled full-time working women) and 34,474 observations (medium skilled full-time employed males). Table 1 in the appendix shows the detailed numbers of observations by year, gender, skill level, and employment status. In our subsequent empirical analysis, we pool all cross–sections from 1975 to 1995.

4 Descriptive Evidence

Note: Figures in this section refer to Fitzenberger/Wunderlich (2001)!

This section presents the basic trends in wages for full–time working males, and for full–time and part–time working females over the time period from 1975 to 1995. At

[8] Even though we can define employment status based on working hours, it is not possible to construct hourly wages which are consistently defined over time, see Gosling et al. (2000).

this point, we develop an overall picture about wage trends over this period. Therefore we do not control for participation changes and composition bias which presumably are serious problems for females in general and even more so for part–time working females. The unconditional curves discussed in this section portray a combination of time, age, and cohort effects. In the course of the paper, we will show how the composition of these effects differs across skill groups, various quantiles of the conditional wage distribution, and male as well as female full-time and part-time employees.

Figures 1 to 3 (see appendix) depict the trends in unconditional weekly log wages and cumulated growth rates of log wages of full-time working men, full–time working women, and part-time working women (cumulated growth rates are relative to 1975). Within each group, we distinguish the 20%–, 50%–, and 80%–quantiles of the wage distribution. This gives an impression of what happened at different points of the distribution and offers some provisional evidence of the development of wage dispersion.

Figure 1 shows wage levels and cumulated wage growth for the three groups by employment status and gender. Here, we pool the three skill groups. The left panel of the graphs shows the usual picture of wage level differences between the status groups with full-time employed men showing the highest wage level at every quantile and every point in time, followed by full-time employed females. The wage levels of part-time working females are the lowest. This is to be expected, since we investigate weekly wages. The wage distribution of full-time working females is more compressed than the distribution of males and part-time working females.

Cumulated wage growth is depicted in the right panel of figure 1. It is evident that wage growth was typically positive for all status groups and that wage dispersion has increased for all groups (because wage growth is higher at higher quantiles). There is a small spike in the curves in the beginning of the observation period. This spike is also found in other studies based on different data sets (for example, see Blackaby, 1997: 258 and Machin, 1999: 190). In the upper two graphs (full-timers), wage dispersion started to increase in the beginning of the eighties, whereas for part-timers we observe growing dispersion over the entire period. Full-time working women have made the largest gains over time. Their cumulated growth rates amount to 50 percent (in logarithms) at the 20%–quantile, 55 percent at the median, and 75 percent at the 80%–quantile. For full-time employed men and part-time employed women, the growth rates are roughly the same at the different quantiles. They amount to about 25 percent at the 20%–quantile, 40 percent at the median, and 50 percent at the 80%–quantile.

Among other things, wage dispersion may increase or decrease with a change in the distribution of skills which are paid differently.[9] Figure 2 exhibits wage trends by educational level. It is apparent that aggregating different skill levels within employment status groups hides important differences in growth rates. The location of wage distribution is positively related with skill level for all three status groups. Wage dispersion increases considerably less within skill groups compared to the trends shown in figure 1. For high skilled males, all skill groups of full-time employed females, and medium skilled part-time employed females wage dispersion does not change by an important magnitude. Thus, in the case of full-time employed females wage inequality increases

[9] For an overview on the debate about increasing wage dispersion in the U.K., see Blackaby et al. (1997).

for the most part not within, but between skill groups.

Furthermore, we find that especially for full-timers wage growth is strongest for high skilled individuals: High skilled full-time working females gain around 60 percent (in logarithms) with only small differences across the distribution. High skilled men exhibit a cumulated growth rate of 40 percent at all three quantiles in 1995. In contrast to high skilled men, wage inequality has risen for medium and low skilled men. For full-time employed medium and low skilled females, the pictures are nearly identical. Both groups exhibit a wage growth of around 40 percent at all three quantiles in 1995 and wage inequality has risen only marginally. It has to be emphasized that wage growth of high skilled full-time employed females is one third larger than wage growth of medium and low skilled full-time working females.

Part-time working women of all skill groups exhibit the weakest wage growth over time in comparison to male and female full-timers. Except for the medium skilled, the curves seem to have more pronounced ups and downs compared to the other groups. The growth rate of high skilled females varies the most at the lowest quantile. The cumulation rate amounts to 25 percent (in logarithms) in 1981 and decreases by nearly 40 percentage points in in the following three years. Nevertheless, in 1995 cumulative wage growth of part-timers is always positive. The low skilled face growth rates of 5 percent at the 20%–quantile, 13% at the median, and 26 percent at the 80%–quantile. Wage inequality has therefore increased within this group. The growth rates of the medium skilled amount to 25 percent at 20% quantile and median, and 20 percent at the 80% quantile. Because the ranking of the quantiles often reverses during the observation period, there is no indication of changing wage inequality.

As mentioned before, wage growth of high skilled part-timers is very volatile. Starting in 1985, the curves of the median and the 80% quantile exhibit more continuity. In 1995 the 80% quantile exhibits a growth rate of 30 percent, median and 20% quantile 20 percent. The comparison of cumulative wage growth of males and females with the same educational level shows that the gender wage gap has narrowed for full-timers and has increased for part-timers. This finding is in line with previous studies referred to in section 2.

Figure 3 exhibits the differences in cumulated growth rates of full-time employed females versus full-time employed males, and part-time employed females versus full-time employed males. These differences are calculated separately for the three skill levels and the three quantiles. The effects in the lower part of the wage distribution of full-timers are particularly interesting with women at the 20%–quantile gaining the most. For all skill groups the cumulated wage growth is roughly 20 percentage points higher compared to full-time employed males at the 20%–quantile. This is in line with Blackaby et al. (1997: 258) who find that the reduction in the gender wage gap is strongest at the lowest quantiles of the earnings distribution.

Also, the median of low and medium skilled full-time employed females exhibits stronger growth than males. The cumulated difference amounts to roughly 10 percentage points. In the case of high skilled females, wage growth at the median and the 20%–quantile are 20 percentage points ahead of their male counterparts. For the low skilled and the high skilled, changes at the 80%–quantile are less than changes for the median and the 20%–quantile during the whole period whereas in the group of medium skilled, the median and the 80%–quantile move in a very similar fashion below the 20% quantile.

These results indicate that, for all skill groups of full-time employees, the gender wage gap has narrowed mostly in the lower part of the wage distribution. The literature often attributes the narrowing of the gender wage gap to policy changes which were implemented in the beginning of the 70's: "It can be seen [...] that the gender gap only began to narrow around 1973 most probably reflecting the fact that the [Equal Pay] Act gave employers a five year time scale to bring wages for comparable jobs into line" (Blackaby et al., 1997: 258). Nevertheless, it is puzzling that these policies should have been most successful in the lower parts of the wage distribution for all skill groups considered. Also, the gains for females were not concentrated in the 70's making it unlikely to attribute them (solely) to the Equal Pay Act.

The comparison of wage growth rates of part-time females and full-time males shows a completely different pattern: The gender gap has increased but the pattern of growth differences varies across skill levels. One may speculate that, because of the female dominance within the part-time segment of the labor market, institutional restrictions apply to a much smaller extent, which allows employers to pay females a lower wage over time compared to the mostly full-time working males.

5 Empirical Analysis

Selection model:

Employment status full–time employed FT=1 and PT=0

Employment status part–time employed FT=0 and PT=1

Linear Probability model for employment status $FT_i = 0, 1$ and $PT_i = 0, 1$:

(1) $$FT_i = x'_{1,i}\alpha_{FT} + u_{FT,i} \quad \text{with} \quad P(FT_i = 1) = x'_{1,i}\alpha_{FT}$$

and

(2) $$PT_i = x'_{1,i}\alpha_{PT} + u_{PT,i} \quad \text{with} \quad P(PT_i = 1) = x'_{1,i}\alpha_{PT}$$

< Plan to estimate a trivariate probit model >

Potential Wages

(3) $$ln(wage_i^{FT}) = x'_{2,i}\beta_{FT} + \epsilon_{FT,i}$$

and

(4) $$ln(wage_i^{PT}) = x'_{2,i}\beta_{PT} + \epsilon_{PT,i}$$

Observation rule:

1. $ln(wage_i^{FT})$ observed if $FT_i = 1$ ($ln(wage_i^{PT})$ not observed)
2. $ln(wage_i^{PT})$ observed if $PT_i = 1$ ($ln(wage_i^{FT})$ not observed)
3. Both $ln(wage_i^{FT})$ and $ln(wage_i^{PT})$ not observed if $FT_i = PT_i = 0$

5.1 Employment status of women

I distinguish between full–time employment (FT=1), part–time employment (PT=1), and nonemployment (NE=1) as the three possible employment states, see 18 for the variable definitions. To analyze the employment status of women, I estimate a linear probability model for the three states. The estimated equations for observation i are given by equation 1 and 2. The equation for nonemployment is implied by these two equations since $NE = 1 - FT - PT$. The system is estimated as system of seemingly unrelated regressions (SURE estimation) separately by skill level. I combine the observations with low skill level and missing skill information, see table 1 in the appendix, and I provide separate estimates for low/missing, medium, and high skill levels. Family background variables (children in household, number and age of household members), information on non–labor income for the women, and information on the health status are strong determinants of employment status which are assumed not to affect the potential wage of the women. The specification of the employment equations involve a lot of interaction effects in order to reduce the number of cases where the fitted employment probabilities (FT and PT) are below zero. It proved particularly important to allow for a number of interaction effects for married women. The estimation results are found in tables 3–5.

The estimates for the year dummies indicate a strong decline in FT employment among low–skilled women, a slower decline for women with medium skill level, and a strong increase for high–skilled women.

< to be completed >

5.2 Quantile regressions for wages accounting for sample selection

I estimate quantile regressions (20%–, 50%–, and 80%–quantile) of the following wage equation for women

$$(5) \qquad ln(wage) = a_1 age + a_2 age^2 + a_3 age^3 + b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + \sum_j \kappa_j DY_{j,t} + g(\hat{P}(FT_i = 1), \hat{P}(PT_i = 1))$$

where *wage* are real weekly earnings in full–time or part–time employment, the age polynomial is of order 2, the time polynomial of order 4, and I include cyclical year dummies $DY_{j,t}$ which are orthogonalized with respect to (≡uncorrelated with) the polynomial in time.[10] In addition, the each wage equation involves a selection correction term $g(\hat{P}(FT_i = 1), \hat{P}(PT_i = 1))$ which is specified as a second order polynomial expansion in $\hat{P}(FT_i = 1)$ and $\hat{P}(PT_i = 1)$. In order to identify the level of potential wages, I normalize $g(\hat{P}(FT_i = 1), \hat{P}(PT_i = 1)) = 0$ when $\hat{P}(FT_i = 1) = 1$ for full–time employed women and $\hat{P}(PT_i = 1) = 1$ for part–time employed women, respectively. This yields identification at infinity by the chosen functional form. Therefore, the selection correction term is given by

$$\begin{aligned} g^{FT}(PFT, PPT) &= s_0 + s_1 \cdot (1 - PFT) + s_2 \cdot PPT + s_3 \cdot (1 - PFT)^2 + s_4 \cdot PPT^2 \\ &+ s_5 \cdot (1 - PFT) \cdot PPT + \sum_{j=1}^{3} s_{5+j} \cdot age^j (1 - PFT) + \sum_{j=1}^{3} s_{8+j} \cdot age^j PPT \end{aligned}$$

for full–time employed women and by

$$\begin{aligned} g^{PT}(PFT, PPT) &= s_0 + s_1 \cdot PFT + s_2 \cdot (1 - PPT) + s_3 \cdot PFT^2 + s_4 \cdot (1 - PPT)^2 \\ &+ s_5 \cdot PFT \cdot (1 - PPT) + \sum_{j=1}^{3} s_{5+j} \cdot age^j PFT + \sum_{j=1}^{3} s_{8+j} \cdot age^j (1 - PPT) \end{aligned}$$

for part–time employed women, where $PFT = \hat{P}(FT_i = 1)$ and $PPT = \hat{P}(PT_i = 1)$. $s_0, s_1, ..., s_5$ denote the estimated coefficients, see Buchinsky (1998, 2001). The estimated probabilities from the linear probability model PFT and PPT turn out to lie below zero for a small number of cases. When the estimated probabilities are negative, zero is used instead. Thus, I define $PFT \equiv \hat{P}(FT_i = 1) = max(x'_{1,i}\hat{\alpha_{FT}}, 0)$ and $PPT \equiv \hat{P}(PT_i = 1) = max(x'_{1,i}\hat{\alpha_{PT}}, 0)$. It never occurs that one of the two probabilities PFT and PPT lies above one. In fact, the largest probabilities obtained are about 0.85 for PFT and 0.78 for PPT, see table 14. Since no probability close to one is obtained, it is not credible that the estimated quantile regressions identify the level of the wage distribution.

Depending upon whether the selection effect changes over time, it is possible to identify the time trend in wages. As discussed below, I find evidence that the selection effects do not changes over time.

Tables 6–11 provide the estimated quantile regressions with and without the sample selection correction. Bootstrapping simultaneously the first stage (linear probability model) and second stage (quantile regressions of wages) of the estimation approach, standard errors automatically take account of the fact that the selection correction terms involve estimation error. It is found that the selection effects are jointly significant and that the estimated age profiles seem strongly affected by accounting for selection effects. In contrast, figures 2 and 3 indicate that in most cases the estimated time trends (implied by the estimated fourth order polynomial in time) do not depend upon selection correction.

Based on the estimated models for males[11] in tables 15–17 , figures 4 and 5 provide the estimated change in the gender wage gap by skill group and quantile. The latter is

[10] $DY_{j,t}$ are constructed such that $\sum_t DY_{j,t} \cdot t^k = 0$ for all $k = 0, 1, ..., 4$ and $j = 1975, ..., 1990$ (1990=1995-4-1).

[11] The specification is taken from Fitzenberger/Wunderlich (2001) except for using here a fourth order polynomial in time instead of a fifth order polynomial. The estimated model is not changed because the time dimension is completly saturated due to the orthogonalized year dummies.

exactly identified if sample selection does not change over time. Table 13 provides the results of Wald tests for the significance of interaction terms of the sample terms with the polynomial time trend. In order to test this, we add the additional regressors

$$t^j \cdot (1 - PFT) \quad \text{and} \quad t^j PPT \quad \text{with } j = 1, ..., 4$$

for full–time employed women and the additional regressors

$$t^j \cdot PFT \quad \text{and} \quad t^j \cdot (1 - PPT) \quad \text{with } j = 1, ..., 4$$

for part–time employed women. Table 13 reports the Wald test statistics when testing for joint significance of these additional regressors both separately and jointly for the three quantiles considered. The hypothesis that the selection effect does not change over time can not be rejected in any cases. I conclude that the polynomial time trend in potential wages for women and, therefore, the change in the distributional gender wage gap regarding the distribution of potential wages are identified. Here it is assumed that selection into full–time employment is not an issue for males.

< to be completed >

6 Conclusions

Selection effects affect the age profiles but not the time trend for female wages. Since selection effects do not seem to depend upon time, one can estimate the change in the gender wage gap.

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A Appendix

A.1 Block Bootstrap Procedure for Inference

In the context of this study, we allow for the error terms being dependent across individuals within cohort–year–cells and across adjacent cohort–year–cells. The dependence is assumed to take the form of rectangular m–dependence across time and across cohorts. We use a flexible Block Bootstrap approach allowing for standard error estimates, which are robust against fairly arbitrary heteroskedasticity and autocorrelation of the error term (see Fitzenberger (1998) for this method in the time series context as well as Fitzenberger and Wunderlich (2000) and Fitzenberger et al. (2001) for applications in the context of estimating wage equations). The Block Bootstrap approach employed here extends the standard bootstrap procedure in that it draws blocks of observations to form the resamples. For each observation in a block, the entire vector comprising the endogenous variable and the regressors is used (design–matrix bootstrap), i.e. we do not draw from the estimated residuals. We draw two–dimensional blocks of observations with a block length of eight in the cohort and six in the time dimension with replacement until the resample has become at least as large as the resample size. Accordingly, standard error estimation takes account of error correlation both within a cohort–year–cell and across pairs of cohorts and time periods which are at most seven years in the cohort dimension and five years in the time dimension apart. Contrasting the results discussed in section 5 with conventional standard error estimates (the latter are not reported here) indicates that allowing for correlation between the error terms within and across cohort–year–cells (when forming the blocks) changes the estimated standard errors considerably.

A.2 Tables and Figures

Table 1: Numbers of observations used in employment status equations in tables 3–5 for women[a]

	Skill Level											
	U			M			H			Missing		
Year	FT[a]	PT[a]	NE[a]	FT[a]	PT[a]	NE[a]	FT[a]	PT[a]	NE[a]	FT[a]	PT[a]	NE[a]
1975	1240	2104	2493	590	755	876	142	304	170	79	96	154
1976	1112	2030	2561	607	787	886	157	258	182	79	80	171
1977	1046	1778	2067	572	755	848	196	350	209	42	24	77
1978	901	1734	2053	624	790	818	232	352	190	44	36	73
1979	868	1690	1868	659	764	795	214	330	244	46	48	62
1980	841	1738	1888	703	789	845	250	371	217	44	31	73
1981	775	1564	2056	772	888	959	228	370	234	51	36	83
1982	612	1269	1704	649	746	821	206	356	185	38	38	55
1983	554	1113	1668	630	734	952	201	309	213	60	44	91
1984	493	976	1501	630	735	927	270	324	226	66	45	107

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	Skill Level											
	U			M			H			Missing		
Year	FT[b]	PT[b]	NE[b]	FT[b]	PT[b]	NE[b]	FT[b]	PT[b]	NE[b]	FT[b]	PT[b]	NE[b]
1985	464	1021	1401	684	907	1002	305	288	207	57	42	99
1986	463	977	1335	777	967	971	304	388	240	56	48	72
1987	470	1053	1274	802	1005	967	379	386	221	63	53	90
1988	448	981	1172	858	950	951	362	362	201	65	17	93
1989	442	923	1125	873	1062	860	384	407	186	68	38	61
1990	394	886	1005	846	983	836	359	400	191	51	42	58
1991	431	808	1056	854	1047	973	418	364	224	64	38	75
1992	325	769	976	872	1174	1011	464	410	240	68	33	78
1993	264	722	1007	840	1145	940	412	412	233	91	40	90
1994	314	624	841	859	1171	973	396	380	211	116	67	209
1995	272	634	844	830	1165	944	506	390	232	114	85	196
Total	12730	25394	31895	15532	19320	19155	6384	7512	4456	1361	981	2067

Note: [a] Number of women aged 20 to 60 grouped by employment status, skill level, and year. This table contains observations with valid employment status information from the GHS. The skill information is possibly missing.
[b] FT: full–time employed, PT: part–time employed, NE: non–employed – see table 18.

Table 2: Numbers of observations for wage regressions in tables 6–8

	Males			Females					
	Full-time			Full-time			Part-time		
Year	U	M	H	U	M	H	U	M	H
1975	3357	1955	551	1168	556	132	1987	705	285
1976	3133	1970	537	1039	576	145	1908	727	242
1977	2713	1873	781	962	519	182	1638	687	312
1978	2570	1986	724	843	586	217	1616	733	316
1979	2438	1827	702	817	621	206	1606	715	314
1980	2186	1915	752	789	665	240	1650	745	353
1981	2137	1858	753	713	725	217	1477	829	346
1982	1674	1490	697	564	615	201	1207	703	342
1983	1434	1472	697	515	606	187	1060	701	295
1984	1222	1421	687	456	593	261	913	694	305
1985	1265	1280	1033	430	639	292	961	857	272
1986	1129	1562	876	428	750	297	924	931	377
1987	1152	1603	965	441	764	364	992	949	365
1988	1065	1544	885	423	821	353	926	901	343
1989	1031	1635	948	413	836	363	870	1018	398
1990	916	1489	876	360	793	341	825	935	389
1991	922	1549	879	397	819	407	754	1005	341

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	Males			Females					
	Full-time			Full-time			Part-time		
Year	U	M	H	U	M	H	U	M	H
1992	839	1562	909	303	850	454	738	1147	400
1993	661	1483	892	243	811	397	683	1119	398
1994	611	1529	797	287	817	385	577	1120	371
1995	565	1461	873	245	794	490	602	1109	377
Total	33020	34474	16814	11836	14756	6131	23914	18330	7141

Note: Number of individuals aged 20 to 60 grouped by sex, employment status, skill level, and year. The table contains observations with valid wage, skill level, and employment status information from the GHS, see table 18.

Table 3: Estimation of linear probability model 1975-1995 for women with low or missing skill

	Full–Time		Part–Time		Nonemployment	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
Intercept	0.8121	(0.116)	0.3184	(0.099)	-0.1304	(0.123)
age	-0.1493	(0.084)	-0.2866	(0.077)	0.4359	(0.087)
age^2	0.0498	(0.021)	0.0935	(0.020)	-0.1433	(0.021)
age^3	-0.0056	(0.002)	-0.0087	(0.002)	0.0144	(0.002)
$age \cdot year$	-0.0009	(0.000)	0.0006	(0.000)	0.0003	(0.000)
Married (Dummy)	-0.1259	(0.077)	-0.1806	(0.072)	0.3065	(0.080)
Married · TwoAdults	0.0277	(0.018)	-0.0527	(0.018)	0.0251	(0.023)
Married · ThreeAdults	-0.0332	(0.019)	0.0282	(0.019)	0.0050	(0.023)
Married · HHKidslt5	0.0067	(0.038)	0.0731	(0.055)	-0.0798	(0.059)
Married · HHKids5t15	-0.0358	(0.034)	0.0562	(0.038)	-0.0204	(0.042)
Married · Kids0t2	-0.0415	(0.039)	-0.1116	(0.058)	0.1531	(0.062)
Married · Kids3t5	0.0493	(0.037)	-0.0820	(0.050)	0.0327	(0.058)
Married · Kids6t16	0.0123	(0.020)	0.0072	(0.027)	-0.0194	(0.030)
Married $\cdot age$	-0.0530	(0.039)	0.1662	(0.039)	-0.1132	(0.042)
Married $\cdot age^2$	0.0036	(0.005)	-0.0180	(0.005)	0.0145	(0.005)
Married $\cdot year$	0.0109	(0.001)	-0.0054	(0.001)	-0.0055	(0.002)
Widowed/Divorced (Dummy)	-0.2425	(0.092)	-0.1599	(0.098)	0.4024	(0.110)
Widowed/Divorced · HHKidslt5	0.0035	(0.035)	0.0293	(0.044)	-0.0328	(0.051)
Widowed/Divorced · HHKids5t15	-0.0467	(0.028)	0.0601	(0.028)	-0.0133	(0.030)
Widowed/Divorced · Kids0t2	0.0152	(0.024)	-0.0371	(0.036)	0.0219	(0.043)
Widowed/Divorced · Kids3t5	0.0686	(0.026)	-0.0721	(0.029)	0.0035	(0.037)
Widowed/Divorced · Kids6t16	-0.0178	(0.017)	-0.0092	(0.019)	0.0270	(0.023)
Widowed/Divorced $\cdot age$	0.0431	(0.048)	0.1169	(0.049)	-0.1600	(0.056)
Widowed/Divorced $\cdot age^2$	-0.0080	(0.006)	-0.0104	(0.006)	0.0184	(0.007)
Widowed/Divorced $\cdot year$	0.0067	(0.001)	-0.0050	(0.001)	-0.0017	(0.001)
TwoAdults (Dummy)	0.1837	(0.038)	0.0327	(0.033)	-0.2164	(0.044)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
TwoAdults ·*age*	-0.0408	(0.007)	0.0023	(0.007)	0.0386	(0.009)
ThreeAdults (Dummy)	0.0622	(0.040)	0.1249	(0.034)	-0.1872	(0.043)
ThreeAdults ·*age*	-0.0208	(0.008)	-0.0199	(0.008)	0.0408	(0.009)
OneAdult>60	-0.1090	(0.016)	-0.0560	(0.022)	0.1650	(0.023)
TwoAdults>60	-0.0449	(0.018)	-0.0142	(0.015)	0.0591	(0.020)
HHKidslt5 (Dummy)	-0.2351	(0.124)	0.3567	(0.147)	-0.1217	(0.173)
HHKids5t15 (Dummy)	-0.0382	(0.108)	0.0274	(0.101)	0.0108	(0.129)
Kids0t2 (Dummy)	-0.1239	(0.085)	-0.0234	(0.131)	0.1472	(0.145)
Kids3t5 (Dummy)	-0.0749	(0.070)	0.2495	(0.105)	-0.1746	(0.121)
Kids6t10 (Dummy)	0.2466	(0.076)	0.0101	(0.101)	-0.2567	(0.106)
Kids11t16 (Dummy)	0.4040	(0.077)	-0.2152	(0.080)	-0.1889	(0.095)
HHKidslt5 ·*age*	-0.0163	(0.064)	-0.1721	(0.081)	0.1884	(0.090)
HHKids5t15 ·*age*	-0.0706	(0.050)	0.0693	(0.054)	0.0014	(0.065)
HHKidslt5 ·age^2	0.0083	(0.008)	0.0216	(0.011)	-0.0299	(0.012)
HHKids5t15 ·age^2	0.0124	(0.006)	-0.0129	(0.007)	0.0005	(0.008)
Kids0t2 ·*age*	-0.0007	(0.046)	-0.0312	(0.074)	0.0319	(0.079)
Kids3t5 ·*age*	-0.0660	(0.038)	-0.0911	(0.053)	0.1571	(0.063)
Kids6t10 ·*age*	-0.1772	(0.038)	0.0688	(0.055)	0.1083	(0.056)
Kids11t16 ·*age*	-0.1778	(0.037)	0.1380	(0.042)	0.0398	(0.048)
Kids0t2 ·age^2	0.0056	(0.007)	0.0062	(0.010)	-0.0118	(0.011)
Kids3t5 ·age^2	0.0108	(0.005)	0.0067	(0.007)	-0.0175	(0.009)
Kids6t10 ·age^2	0.0233	(0.005)	-0.0157	(0.007)	-0.0076	(0.007)
Kids11t16 ·age^2	0.0184	(0.005)	-0.0193	(0.005)	0.0009	(0.006)
Kids6t16 · TwoAdults	-0.0574	(0.038)	0.0409	(0.039)	0.0164	(0.040)
Kids6t16 · ThreeAdults	-0.0147	(0.014)	0.0316	(0.016)	-0.0168	(0.014)
Number Kids $0-2$	-0.0600	(0.010)	-0.0148	(0.021)	0.0747	(0.021)
Number Kids $3-5$	-0.0204	(0.013)	-0.0411	(0.017)	0.0616	(0.023)
Number Kids $6-10$	-0.0197	(0.008)	-0.0364	(0.013)	0.0561	(0.013)
Number Kids $11-16$	-0.0133	(0.007)	-0.0255	(0.011)	0.0389	(0.011)
Kids0t2 · Kids3t5	0.1207	(0.033)	-0.0034	(0.037)	-0.1173	(0.040)
Kids0t5 · Kids6t16	0.0407	(0.021)	0.0302	(0.024)	-0.0709	(0.026)
Married · (Number Kids $0-2$)	0.0338	(0.012)	-0.0326	(0.023)	-0.0012	(0.024)
Married · (Number Kids $3-5$)	0.0093	(0.015)	-0.0053	(0.021)	-0.0040	(0.027)
Married · (Number Kids $6-10$)	-0.0029	(0.009)	-0.0029	(0.014)	0.0059	(0.014)
Married · (Number Kids $11-16$)	0.0041	(0.008)	0.0074	(0.012)	-0.0116	(0.012)
Married · Kids0t2 · Kids3t5	-0.0119	(0.034)	0.1042	(0.041)	-0.0922	(0.044)
Married · Kids0t5 · Kids6t16	0.0147	(0.021)	-0.0096	(0.028)	-0.0052	(0.030)
Born outside UK (Dummy)	0.0648	(0.005)	-0.1060	(0.005)	0.0412	(0.006)
Spouse employed (Dummy)	-0.0327	(0.009)	0.0245	(0.014)	0.0082	(0.014)
Spouse unemployed (Dummy)	-0.0275	(0.010)	-0.1187	(0.018)	0.1462	(0.018)
Spouse nonemployed (Dummy)	-0.0403	(0.013)	-0.0844	(0.017)	0.1247	(0.020)
Spouse earnings	0.0071	(0.002)	0.0104	(0.002)	-0.0175	(0.002)
(Spouse employed) · year	0.0029	(0.001)	0.0056	(0.001)	-0.0085	(0.001)

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	Full–Time		Part–Time		Nonemployment	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
(Spouse unemployed) · year	-0.0020	(0.001)	0.0010	(0.002)	0.0011	(0.002)
(Spouse nonemployed) · year	-0.0004	(0.001)	-0.0004	(0.002)	0.0008	(0.002)
(Spouse earnings) · year	-0.0002	(0.000)	-0.0002	(0.000)	0.0004	(0.000)
Doctor_2weeks	-0.0066	(0.003)	-0.0424	(0.004)	0.0490	(0.004)
Doctor> 1_2weeks	-0.0092	(0.007)	-0.0575	(0.008)	0.0667	(0.009)
Interest_not_92	0.0100	(0.006)	0.0328	(0.007)	-0.0429	(0.006)
Interest_in_92	0.0083	(0.017)	0.0819	(0.019)	-0.0902	(0.022)
Rent income	-0.0809	(0.017)	-0.0290	(0.032)	0.1099	(0.032)
House/Flat owner	0.0162	(0.003)	0.0149	(0.004)	-0.0311	(0.003)
Region 2	-0.0110	(0.007)	0.0336	(0.009)	-0.0226	(0.008)
Region 3	0.0183	(0.006)	0.0252	(0.009)	-0.0435	(0.007)
Region 4	0.0088	(0.007)	0.0296	(0.009)	-0.0384	(0.009)
Region 5	0.0271	(0.006)	0.0120	(0.008)	-0.0391	(0.008)
Region 6	-0.0300	(0.008)	0.0516	(0.012)	-0.0216	(0.010)
Region 7	0.0064	(0.007)	0.0585	(0.009)	-0.0649	(0.009)
Region 8	0.0001	(0.006)	0.0404	(0.009)	-0.0405	(0.008)
Region 9	-0.0100	(0.008)	0.0326	(0.010)	-0.0225	(0.008)
Region 10	0.0154	(0.008)	-0.0214	(0.009)	0.0061	(0.009)
Region 11	0.0330	(0.007)	-0.0066	(0.008)	-0.0264	(0.007)
YD76	-0.0284	(0.007)	-0.0028	(0.009)	0.0312	(0.008)
YD77	-0.0225	(0.008)	-0.0002	(0.009)	0.0227	(0.009)
YD78	-0.0488	(0.008)	0.0016	(0.010)	0.0472	(0.009)
YD79	-0.0501	(0.009)	0.0222	(0.010)	0.0278	(0.011)
YD80	-0.0634	(0.010)	0.0258	(0.010)	0.0376	(0.011)
YD81	-0.0844	(0.009)	0.0023	(0.011)	0.0821	(0.012)
YD82	-0.1035	(0.011)	0.0100	(0.012)	0.0934	(0.014)
YD83	-0.1117	(0.012)	-0.0143	(0.014)	0.1260	(0.015)
YD84	-0.1202	(0.013)	-0.0200	(0.015)	0.1402	(0.016)
YD85	-0.1372	(0.012)	0.0051	(0.015)	0.1320	(0.016)
YD86	-0.1402	(0.014)	-0.0003	(0.017)	0.1405	(0.017)
YD87	-0.1493	(0.016)	0.0297	(0.018)	0.1196	(0.018)
YD88	-0.1544	(0.017)	0.0206	(0.018)	0.1338	(0.020)
YD89	-0.1486	(0.017)	0.0186	(0.019)	0.1300	(0.021)
YD90	-0.1646	(0.019)	0.0473	(0.022)	0.1173	(0.024)
YD91	-0.1554	(0.019)	0.0109	(0.022)	0.1444	(0.023)
YD92	-0.1898	(0.022)	-0.0035	(0.024)	0.1933	(0.026)
YD93	-0.1997	(0.022)	0.0277	(0.023)	0.1719	(0.024)
YD94	-0.1793	(0.023)	0.0040	(0.026)	0.1753	(0.027)
YD95	-0.2027	(0.024)	0.0189	(0.025)	0.1838	(0.028)

Note: Estimated coefficients from SUR estimation of a linear probability model for Full–Time-, Part–Time- und Non–employment based on individual data from GHS (for definitions of variables, see table 18). The model ist estimated as a two–equation system for Full–Time– and Part–Time–employment (both dummy variables) as left–hand–side variables. The coefficients for non–employment are implied by the restrictions on three share equations. Standard errors are estimated by a bootstrap approach based on 700 **(I am planning for 1000)** resamples.

Table 4: Estimation of linear probability model 1975-1995 for women with medium skill level[a]

	Full–Time		Part–Time		Nonemployment	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
Intercept	-0.1709	(0.112)	0.4584	(0.110)	0.7124	(0.106)
age	0.5649	(0.092)	-0.2752	(0.094)	-0.2897	(0.091)
age^2	-0.1032	(0.026)	0.0945	(0.026)	0.0087	(0.025)
age^3	0.0042	(0.002)	-0.0096	(0.002)	0.0054	(0.002)
$age \cdot year$	-0.0012	(0.000)	-0.0004	(0.000)	0.0016	(0.000)
Married (Dummy)	0.1397	(0.082)	0.1069	(0.087)	-0.2466	(0.082)
Married · TwoAdults	0.1677	(0.030)	-0.1426	(0.032)	-0.0251	(0.029)
Married · ThreeAdults	0.0761	(0.031)	-0.0443	(0.032)	-0.0317	(0.030)
Married · HHKidslt5	0.0045	(0.054)	-0.0251	(0.054)	0.0206	(0.055)
Married · HHKids5t15	0.0302	(0.043)	0.0023	(0.048)	-0.0325	(0.040)
Married · Kids0t2	0.0918	(0.056)	-0.1357	(0.062)	0.0439	(0.069)
Married · Kids3t5	0.0614	(0.050)	-0.0729	(0.060)	0.0115	(0.064)
Married · Kids6t16	0.0046	(0.024)	0.0091	(0.031)	-0.0138	(0.031)
Married ·*age*	-0.2345	(0.046)	-0.0307	(0.045)	0.2652	(0.043)
Married ·age^2	0.0278	(0.006)	0.0038	(0.006)	-0.0317	(0.006)
Married ·*year*	0.0066	(0.002)	0.0043	(0.002)	-0.0108	(0.002)
Widowed/Divorced (Dummy)	0.0005	(0.118)	0.0239	(0.131)	-0.0245	(0.124)
Widowed/Divorced · HHKidslt5	-0.1190	(0.038)	-0.0019	(0.047)	0.1209	(0.051)
Widowed/Divorced · HHKids5t15	-0.0998	(0.036)	0.0341	(0.038)	0.0657	(0.037)
Widowed/Divorced · Kids0t2	0.0473	(0.030)	0.0153	(0.040)	-0.0627	(0.048)
Widowed/Divorced · Kids3t5	0.0316	(0.027)	-0.0124	(0.036)	-0.0192	(0.040)
Widowed/Divorced · Kids6t16	-0.0139	(0.023)	-0.0099	(0.027)	0.0238	(0.027)
Widowed/Divorced ·*age*	-0.0282	(0.063)	-0.0333	(0.068)	0.0614	(0.067)
Widowed/Divorced ·age^2	0.0020	(0.008)	0.0077	(0.008)	-0.0097	(0.009)
Widowed/Divorced ·*year*	0.0049	(0.002)	-0.0003	(0.001)	-0.0046	(0.002)
TwoAdults (Dummy)	0.1795	(0.032)	-0.0588	(0.030)	-0.1207	(0.030)
TwoAdults ·*age*	-0.0507	(0.009)	0.0293	(0.009)	0.0213	(0.009)
ThreeAdults (Dummy)	0.0830	(0.033)	-0.0508	(0.029)	-0.0322	(0.026)
ThreeAdults ·*age*	-0.0270	(0.010)	0.0239	(0.009)	0.0031	(0.008)
OneAdult>60	-0.1121	(0.037)	-0.0432	(0.044)	0.1554	(0.048)
TwoAdults>60	0.0128	(0.018)	-0.0131	(0.020)	0.0004	(0.017)
HHKidslt5 (Dummy)	0.2234	(0.149)	-0.2513	(0.249)	0.0279	(0.253)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
HHKids5t15 (Dummy)	0.3994	(0.134)	-0.4764	(0.162)	0.0770	(0.121)
Kids0t2 (Dummy)	-0.0725	(0.161)	0.1864	(0.251)	-0.1140	(0.250)
Kids3t5 (Dummy)	-0.1021	(0.112)	0.2898	(0.182)	-0.1877	(0.182)
Kids6t10 (Dummy)	0.5096	(0.105)	-0.0941	(0.148)	-0.4156	(0.137)
Kids11t16 (Dummy)	0.5200	(0.115)	-0.0648	(0.123)	-0.4552	(0.115)
HHKidslt5 $\cdot age$	-0.2564	(0.093)	0.1420	(0.157)	0.1144	(0.161)
HHKids5t15 $\cdot age$	-0.2917	(0.075)	0.2951	(0.093)	-0.0034	(0.074)
HHKidslt5 $\cdot age^2$	0.0452	(0.014)	-0.0192	(0.025)	-0.0261	(0.025)
HHKids5t15 $\cdot age^2$	0.0398	(0.010)	-0.0380	(0.013)	-0.0018	(0.010)
Kids0t2 $\cdot age$	-0.1031	(0.104)	-0.0777	(0.160)	0.1808	(0.160)
Kids3t5 $\cdot age$	-0.0416	(0.066)	-0.0945	(0.115)	0.1361	(0.115)
Kids6t10 $\cdot age$	-0.3487	(0.059)	0.1229	(0.092)	0.2258	(0.083)
Kids11t16 $\cdot age$	-0.2264	(0.064)	0.0273	(0.070)	0.1990	(0.069)
Kids0t2 $\cdot age^2$	0.0201	(0.016)	0.0106	(0.025)	-0.0307	(0.025)
Kids3t5 $\cdot age^2$	0.0050	(0.010)	0.0058	(0.018)	-0.0108	(0.018)
Kids6t10 $\cdot age^2$	0.0490	(0.008)	-0.0223	(0.013)	-0.0267	(0.012)
Kids11t16 $\cdot age^2$	0.0241	(0.009)	-0.0026	(0.010)	-0.0215	(0.010)
Kids6t16 · TwoAdults	-0.0984	(0.060)	0.0019	(0.067)	0.0965	(0.066)
Kids6t16 · ThreeAdults	-0.0611	(0.019)	0.0403	(0.024)	0.0208	(0.022)
Number Kids $0-2$	-0.0499	(0.020)	-0.0751	(0.028)	0.1250	(0.030)
Number Kids $3-5$	-0.0589	(0.017)	-0.0281	(0.034)	0.0871	(0.036)
Number Kids $6-10$	-0.0558	(0.013)	-0.0037	(0.017)	0.0595	(0.015)
Number Kids $11-16$	-0.0417	(0.013)	0.0199	(0.014)	0.0218	(0.014)
Kids0t2 · Kids3t5	0.1720	(0.038)	-0.0955	(0.042)	-0.0766	(0.044)
Kids0t5 · Kids6t16	0.0788	(0.022)	-0.0327	(0.030)	-0.0461	(0.029)
Married · (Number Kids $0-2$)	0.0041	(0.021)	-0.0039	(0.030)	-0.0002	(0.032)
Married · (Number Kids $3-5$)	0.0278	(0.020)	0.0082	(0.037)	-0.0360	(0.039)
Married · (Number Kids $6-10$)	0.0247	(0.013)	-0.0244	(0.016)	-0.0003	(0.015)
Married · (Number Kids $11-16$)	0.0250	(0.013)	-0.0137	(0.015)	-0.0113	(0.014)
Married · Kids0t2 · Kids3t5	-0.0718	(0.042)	0.1243	(0.048)	-0.0525	(0.050)
Married · Kids0t5 · Kids6t16	-0.0103	(0.023)	0.0355	(0.032)	-0.0252	(0.031)
Born outside UK (Dummy)	0.0127	(0.008)	-0.0688	(0.007)	0.0561	(0.007)
Spouse employed (Dummy)	-0.0591	(0.019)	0.0602	(0.020)	-0.0011	(0.022)
Spouse unemployed (Dummy)	-0.0300	(0.031)	-0.0229	(0.035)	0.0530	(0.038)
Spouse nonemployed (Dummy)	-0.1132	(0.036)	0.0097	(0.038)	0.1035	(0.041)
Spouse earnings	0.0050	(0.003)	-0.0011	(0.003)	-0.0039	(0.003)
(Spouse employed) · year	0.0046	(0.002)	0.0018	(0.002)	-0.0064	(0.002)
(Spouse unemployed) · year	0.0005	(0.002)	-0.0040	(0.003)	0.0035	(0.003)
(Spouse nonemployed) · year	0.0062	(0.003)	-0.0045	(0.003)	-0.0018	(0.003)
(Spouse earnings) · year	-0.0003	(0.000)	0.0003	(0.000)	0.0000	(0.000)
Doctor_2weeks	-0.0078	(0.005)	-0.0230	(0.005)	0.0307	(0.005)
Doctor> 1_2weeks	-0.0154	(0.009)	-0.0553	(0.010)	0.0707	(0.011)
Interest_not_92	-0.0273	(0.006)	0.0205	(0.007)	0.0068	(0.006)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
Interest_in_92	0.0479	(0.014)	0.0318	(0.018)	-0.0797	(0.018)
Rent income	-0.0326	(0.019)	-0.0380	(0.021)	0.0707	(0.020)
House/Flat owner	0.0413	(0.005)	0.0422	(0.005)	-0.0835	(0.004)
Region 2	-0.0296	(0.009)	0.0402	(0.010)	-0.0105	(0.010)
Region 3	-0.0110	(0.008)	0.0297	(0.009)	-0.0187	(0.009)
Region 4	-0.0111	(0.009)	0.0320	(0.012)	-0.0210	(0.010)
Region 5	0.0047	(0.009)	0.0106	(0.010)	-0.0153	(0.010)
Region 6	-0.0227	(0.011)	0.0265	(0.013)	-0.0038	(0.011)
Region 7	-0.0671	(0.009)	0.0873	(0.010)	-0.0202	(0.009)
Region 8	-0.0287	(0.007)	0.0346	(0.009)	-0.0059	(0.009)
Region 9	-0.0321	(0.008)	0.0254	(0.011)	0.0067	(0.011)
Region 10	-0.0022	(0.010)	-0.0042	(0.011)	0.0064	(0.011)
Region 11	-0.0154	(0.010)	0.0195	(0.011)	-0.0041	(0.010)
YD76	-0.0047	(0.011)	0.0006	(0.013)	0.0041	(0.011)
YD77	-0.0175	(0.011)	-0.0029	(0.014)	0.0204	(0.013)
YD78	-0.0088	(0.012)	-0.0047	(0.012)	0.0135	(0.012)
YD79	-0.0141	(0.014)	-0.0041	(0.015)	0.0182	(0.013)
YD80	-0.0129	(0.014)	-0.0172	(0.014)	0.0301	(0.014)
YD81	-0.0280	(0.014)	-0.0149	(0.014)	0.0429	(0.013)
YD82	-0.0326	(0.014)	-0.0180	(0.015)	0.0506	(0.014)
YD83	-0.0497	(0.015)	-0.0401	(0.018)	0.0897	(0.015)
YD84	-0.0604	(0.015)	-0.0362	(0.017)	0.0966	(0.014)
YD85	-0.0678	(0.017)	-0.0169	(0.018)	0.0847	(0.016)
YD86	-0.0673	(0.017)	-0.0059	(0.019)	0.0733	(0.019)
YD87	-0.0588	(0.017)	-0.0040	(0.019)	0.0628	(0.018)
YD88	-0.0417	(0.019)	-0.0269	(0.020)	0.0686	(0.020)
YD89	-0.0482	(0.021)	0.0052	(0.021)	0.0430	(0.021)
YD90	-0.0389	(0.022)	-0.0042	(0.023)	0.0431	(0.022)
YD91	-0.0551	(0.022)	-0.0053	(0.022)	0.0604	(0.021)
YD92	-0.1086	(0.026)	-0.0034	(0.024)	0.1120	(0.025)
YD93	-0.0774	(0.025)	0.0217	(0.024)	0.0557	(0.024)
YD94	-0.0761	(0.024)	0.0128	(0.024)	0.0633	(0.025)
YD95	-0.0767	(0.026)	0.0115	(0.024)	0.0653	(0.025)

Note: see table 3

Table 5: Estimation of linear probability model 1975-1995 for high–skilled women[a]

Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
Intercept	-0.1161	(0.196)	1.1523	(0.219)	-0.0362	(0.164)
age	0.3073	(0.161)	-0.6433	(0.178)	0.3360	(0.134)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
age^2	-0.0263	(0.044)	0.1877	(0.047)	-0.1613	(0.036)
age^3	-0.0021	(0.004)	-0.0174	(0.004)	0.0195	(0.003)
$age \cdot year$	-0.0030	(0.001)	-0.0002	(0.001)	0.0032	(0.001)
Married (Dummy)	0.5464	(0.145)	-0.2568	(0.143)	-0.2897	(0.123)
Married · TwoAdults	-0.0027	(0.048)	0.0147	(0.050)	-0.0120	(0.043)
Married · ThreeAdults	0.0038	(0.054)	0.0315	(0.053)	-0.0352	(0.044)
Married · HHKidslt5	-0.1156	(0.131)	0.0292	(0.152)	0.0864	(0.143)
Married · HHKids5t15	-0.1053	(0.091)	0.0897	(0.095)	0.0156	(0.097)
Married · Kids0t2	-0.0688	(0.150)	0.1405	(0.202)	-0.0716	(0.212)
Married · Kids3t5	0.2196	(0.129)	-0.0658	(0.169)	-0.1538	(0.174)
Married · Kids6t16	0.0594	(0.065)	-0.0246	(0.081)	-0.0348	(0.076)
Married $\cdot age$	-0.3020	(0.077)	0.0704	(0.075)	0.2316	(0.062)
Married $\cdot age^2$	0.0311	(0.010)	-0.0060	(0.010)	-0.0251	(0.008)
Married $\cdot year$	-0.0002	(0.003)	0.0086	(0.003)	-0.0085	(0.003)
Widowed/Divorced (Dummy)	-0.0576	(0.300)	0.4299	(0.273)	-0.3722	(0.238)
Widowed/Divorced · HHKidslt5	-0.0360	(0.137)	-0.0633	(0.168)	0.0993	(0.159)
Widowed/Divorced · HHKids5t15	-0.0930	(0.076)	0.0313	(0.094)	0.0617	(0.084)
Widowed/Divorced · Kids0t2	-0.0642	(0.126)	-0.0308	(0.169)	0.0950	(0.152)
Widowed/Divorced · Kids3t5	0.0996	(0.103)	0.0131	(0.131)	-0.1127	(0.121)
Widowed/Divorced · Kids6t16	0.0011	(0.053)	0.0014	(0.072)	-0.0025	(0.067)
Widowed/Divorced $\cdot age$	0.0309	(0.151)	-0.2487	(0.134)	0.2178	(0.120)
Widowed/Divorced $\cdot age^2$	-0.0052	(0.018)	0.0328	(0.016)	-0.0276	(0.014)
Widowed/Divorced $\cdot year$	-0.0009	(0.003)	0.0019	(0.003)	-0.0010	(0.002)
TwoAdults (Dummy)	0.1027	(0.055)	-0.0964	(0.052)	-0.0063	(0.041)
TwoAdults $\cdot age$	-0.0238	(0.015)	0.0240	(0.014)	-0.0002	(0.013)
ThreeAdults (Dummy)	-0.0131	(0.059)	-0.1161	(0.049)	0.1293	(0.042)
ThreeAdults $\cdot age$	-0.0078	(0.018)	0.0330	(0.015)	-0.0253	(0.013)
OneAdult>60	-0.0817	(0.069)	-0.1589	(0.050)	0.2407	(0.063)
TwoAdults>60	-0.0809	(0.033)	0.0201	(0.033)	0.0608	(0.025)
HHKidslt5 (Dummy)	-0.8561	(0.385)	0.4124	(0.588)	0.4437	(0.594)
HHKids5t15 (Dummy)	0.2848	(0.341)	-0.7530	(0.371)	0.4682	(0.337)
Kids0t2 (Dummy)	0.6056	(0.406)	-0.9358	(0.599)	0.3303	(0.617)
Kids3t5 (Dummy)	0.6078	(0.349)	0.1023	(0.382)	-0.7100	(0.434)
Kids6t10 (Dummy)	0.1899	(0.309)	0.8160	(0.379)	-1.0059	(0.320)
Kids11t16 (Dummy)	-0.0231	(0.325)	0.0009	(0.321)	0.0222	(0.316)
HHKidslt5 $\cdot age$	0.4337	(0.210)	-0.2241	(0.326)	-0.2096	(0.334)
HHKids5t15 $\cdot age$	-0.1775	(0.186)	0.4277	(0.207)	-0.2501	(0.188)
HHKidslt5 $\cdot age^2$	-0.0580	(0.029)	0.0376	(0.044)	0.0204	(0.045)
HHKids5t15 $\cdot age^2$	0.0249	(0.023)	-0.0549	(0.026)	0.0300	(0.024)
Kids0t2 $\cdot age$	-0.4187	(0.227)	0.4510	(0.319)	-0.0322	(0.327)
Kids3t5 $\cdot age$	-0.5111	(0.191)	0.0937	(0.215)	0.4175	(0.245)
Kids6t10 $\cdot age$	-0.1832	(0.159)	-0.3673	(0.207)	0.5505	(0.174)
Kids11t16 $\cdot age$	-0.0026	(0.170)	-0.0266	(0.182)	0.0292	(0.174)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
Kids0t2 $\cdot age^2$	0.0688	(0.032)	-0.0656	(0.044)	-0.0032	(0.045)
Kids3t5 $\cdot age^2$	0.0699	(0.027)	-0.0226	(0.029)	-0.0473	(0.034)
Kids6t10 $\cdot age^2$	0.0266	(0.020)	0.0450	(0.027)	-0.0716	(0.023)
Kids11t16 $\cdot age^2$	-0.0023	(0.021)	0.0064	(0.023)	-0.0041	(0.022)
Kids6t16 · TwoAdults	-0.0759	(0.108)	-0.0459	(0.106)	0.1218	(0.109)
Kids6t16 · ThreeAdults	-0.0019	(0.035)	0.0382	(0.040)	-0.0363	(0.035)
Number Kids $0-2$	-0.2122	(0.059)	0.1696	(0.137)	0.0426	(0.159)
Number Kids $3-5$	-0.0589	(0.084)	-0.0850	(0.123)	0.1439	(0.130)
Number Kids $6-10$	-0.0595	(0.036)	-0.0374	(0.038)	0.0969	(0.031)
Number Kids $11-16$	-0.0034	(0.031)	-0.0005	(0.032)	0.0039	(0.021)
Kids0t2 · Kids3t5	0.2677	(0.102)	-0.0433	(0.100)	-0.2244	(0.119)
Kids0t5 · Kids6t16	0.0765	(0.065)	-0.0255	(0.071)	-0.0509	(0.074)
Married · (Number Kids $0-2$)	0.1211	(0.060)	-0.2560	(0.138)	0.1348	(0.159)
Married · (Number Kids $3-5$)	-0.0312	(0.086)	0.0085	(0.133)	0.0227	(0.136)
Married · (Number Kids $6-10$)	-0.0011	(0.037)	0.0259	(0.037)	-0.0248	(0.028)
Married · (Number Kids $11-16$)	-0.0189	(0.031)	0.0148	(0.030)	0.0042	(0.022)
Married · Kids0t2 · Kids3t5	-0.1736	(0.113)	0.0079	(0.116)	0.1657	(0.126)
Married · Kids0t5 · Kids6t16	0.0045	(0.063)	-0.0373	(0.079)	0.0327	(0.082)
Born outside UK (Dummy)	0.0627	(0.012)	-0.0654	(0.014)	0.0027	(0.013)
Spouse employed (Dummy)	-0.0647	(0.033)	0.0581	(0.039)	0.0066	(0.034)
Spouse unemployed (Dummy)	-0.0428	(0.071)	-0.0009	(0.069)	0.0437	(0.082)
Spouse nonemployed (Dummy)	-0.0136	(0.064)	-0.0579	(0.071)	0.0716	(0.069)
Spouse earnings	-0.0022	(0.004)	0.0051	(0.006)	-0.0030	(0.005)
(Spouse employed) · year	0.0059	(0.003)	0.0007	(0.003)	-0.0065	(0.003)
(Spouse unemployed) · year	0.0033	(0.005)	-0.0037	(0.005)	0.0004	(0.006)
(Spouse nonemployed) · year	0.0027	(0.004)	-0.0003	(0.005)	-0.0024	(0.006)
(Spouse earnings) · year	0.0005	(0.000)	-0.0007	(0.001)	0.0002	(0.000)
Doctor_2weeks	-0.0339	(0.009)	0.0064	(0.011)	0.0274	(0.008)
Doctor> 1_2weeks	-0.0146	(0.019)	-0.0209	(0.020)	0.0356	(0.018)
Interest_not_92	-0.0302	(0.008)	0.0034	(0.010)	0.0268	(0.008)
Interest_in_92	-0.0404	(0.035)	0.1156	(0.036)	-0.0752	(0.030)
Rent income	-0.0528	(0.022)	0.0306	(0.025)	0.0222	(0.025)
House/Flat owner	0.0220	(0.008)	0.0437	(0.011)	-0.0658	(0.009)
Region 2	0.0039	(0.019)	-0.0011	(0.021)	-0.0028	(0.017)
Region 3	0.0431	(0.018)	-0.0130	(0.020)	-0.0301	(0.014)
Region 4	0.0553	(0.016)	-0.0530	(0.018)	-0.0024	(0.014)
Region 5	0.0584	(0.018)	-0.0428	(0.021)	-0.0157	(0.015)
Region 6	0.0378	(0.023)	-0.0498	(0.029)	0.0120	(0.021)
Region 7	0.0139	(0.017)	0.0173	(0.020)	-0.0312	(0.014)
Region 8	0.0255	(0.014)	-0.0252	(0.017)	-0.0004	(0.012)
Region 9	0.0140	(0.018)	-0.0224	(0.022)	0.0083	(0.016)
Region 10	0.0245	(0.020)	-0.0350	(0.023)	0.0105	(0.018)
Region 11	-0.0094	(0.018)	-0.0008	(0.021)	0.0102	(0.014)

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Variable	Full–Time Coeff.	(s.e.)	Part–Time Coeff.	(s.e.)	Nonemployment Coeff.	(s.e.)
YD76	0.0296	(0.024)	-0.0617	(0.027)	0.0321	(0.024)
YD77	0.0370	(0.025)	-0.0373	(0.028)	0.0004	(0.020)
YD78	0.0798	(0.026)	-0.0542	(0.030)	-0.0255	(0.025)
YD79	0.0540	(0.023)	-0.0929	(0.026)	0.0389	(0.022)
YD80	0.0847	(0.027)	-0.0750	(0.027)	-0.0097	(0.022)
YD81	0.0745	(0.025)	-0.0757	(0.031)	0.0012	(0.024)
YD82	0.0591	(0.031)	-0.0460	(0.035)	-0.0131	(0.024)
YD83	0.0920	(0.029)	-0.0958	(0.035)	0.0037	(0.028)
YD84	0.1347	(0.030)	-0.1362	(0.032)	0.0015	(0.027)
YD85	0.1730	(0.031)	-0.1642	(0.035)	-0.0088	(0.029)
YD86	0.1425	(0.032)	-0.1265	(0.034)	-0.0160	(0.029)
YD87	0.2002	(0.033)	-0.1500	(0.039)	-0.0501	(0.030)
YD88	0.2131	(0.034)	-0.1554	(0.037)	-0.0577	(0.030)
YD89	0.2305	(0.038)	-0.1327	(0.043)	-0.0978	(0.034)
YD90	0.2221	(0.038)	-0.1308	(0.044)	-0.0913	(0.034)
YD91	0.2660	(0.040)	-0.1974	(0.043)	-0.0686	(0.035)
YD92	0.3046	(0.051)	-0.2860	(0.051)	-0.0186	(0.046)
YD93	0.2712	(0.042)	-0.1803	(0.050)	-0.0909	(0.042)
YD94	0.2798	(0.046)	-0.1789	(0.052)	-0.1009	(0.042)
YD95	0.3155	(0.044)	-0.2180	(0.050)	-0.0975	(0.043)

Note: see table 3

Table 6: Quantile regressions of full–time earnings for low–skilled women (U)

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	1.5246	(0.883)	1.8408	(0.804)	2.4390	(1.119)
age	1.1074	(0.719)	0.9878	(0.664)	0.8288	(0.919)
age^2	-0.2553	(0.189)	-0.1957	(0.176)	-0.1851	(0.246)
age^3	0.0189	(0.016)	0.0129	(0.015)	0.0152	(0.021)
t	0.6985	(0.153)	0.3883	(0.132)	0.2813	(0.123)
t^2	-0.9789	(0.356)	-0.3668	(0.334)	-0.0757	(0.303)
t^3	0.6545	(0.289)	0.2397	(0.279)	0.0351	(0.250)
t^4	-0.1486	(0.074)	-0.0559	(0.072)	-0.0086	(0.065)
$1 - PFT$	0.3087	(0.287)	-0.0175	(0.284)	-0.5342	(0.328)
PPT	0.5541	(0.264)	0.7577	(0.289)	0.9513	(0.314)
$(1 - PFT)^2$	-0.0600	(0.220)	0.2855	(0.231)	0.6333	(0.258)
PPT^2	0.3259	(0.249)	0.1382	(0.243)	0.3135	(0.263)
$(1 - PFT) \cdot PPT$	-1.0260	(0.353)	-1.1445	(0.358)	-1.4116	(0.354)
$(age - 2) \cdot (1 - PFT)$	-0.4178	(0.308)	-0.4883	(0.233)	-0.0783	(0.283)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
$(age-2) \cdot PPT$	0.2257	(0.371)	0.3185	(0.311)	-0.0687	(0.361)
$(age-2)^2 \cdot (1-PFT)$	0.2107	(0.167)	0.1979	(0.134)	0.0127	(0.169)
$(age-2)^2 \cdot PPT$	-0.1546	(0.203)	-0.2125	(0.163)	-0.0025	(0.185)
$(age-2)^3 \cdot (1-PFT)$	-0.0317	(0.027)	-0.0277	(0.022)	-0.0089	(0.029)
$(age-2)^3 \cdot PPT$	0.0334	(0.033)	0.0425	(0.026)	0.0126	(0.030)
Model without selection correction						
Intercept	2.8636	(0.189)	3.0344	(0.187)	2.9271	(0.272)
age	0.1078	(0.162)	0.1329	(0.148)	0.3993	(0.207)
age^2	-0.0117	(0.043)	-0.0060	(0.038)	-0.0738	(0.051)
age^3	0.0000	(0.004)	-0.0012	(0.003)	0.0043	(0.004)
t	0.7485	(0.142)	0.4229	(0.118)	0.2401	(0.122)
t^2	-1.1568	(0.344)	-0.5189	(0.304)	-0.0651	(0.294)
t^3	0.8163	(0.282)	0.3768	(0.257)	0.0614	(0.239)
t^4	-0.1912	(0.072)	-0.0912	(0.066)	-0.0201	(0.062)
Orthogonalized year dummies included in both models						

Note: Coefficients of linear quantile regressions of log real earnings based on individual data from GHS (for definitions of variables, see table 18). For the model accounting for selection correction, a second order power series expansion in PFT and PPT is used. Both models also includes year dummies (omitted above to save space) orthogonalized with respect to the fourth order polynomial in time t, t^2, t^3, t^4. Standard errors are estimated by a bootstrap approach based on 700 **(I am planning for 1000)** resamples taking into account the estimation error in the selection correction terms from the estimation of the linear probability model.

Table 7: Quantile regressions of full–time earnings for women (M) with medium skill level accounting for selection correction

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	-1.1603	(0.872)	-0.8043	(0.902)	-0.4293	(1.284)
age	3.3513	(0.757)	3.0392	(0.759)	2.6404	(1.106)
age^2	-0.7976	(0.213)	-0.6658	(0.209)	-0.4954	(0.305)
age^3	0.0613	(0.019)	0.0466	(0.019)	0.0290	(0.027)
t	0.3117	(0.159)	0.1352	(0.179)	0.0610	(0.228)
t^2	-0.2326	(0.325)	0.0660	(0.360)	0.1725	(0.509)
t^3	0.1530	(0.248)	-0.0133	(0.268)	-0.0335	(0.389)
t^4	-0.0384	(0.061)	-0.0068	(0.065)	-0.0098	(0.095)
$1-PFT$	0.0492	(0.264)	0.1019	(0.328)	0.2279	(0.490)
PPT	1.2002	(0.281)	1.3818	(0.317)	1.3814	(0.408)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
$(1-PFT)^2$	-0.0204	(0.228)	0.0155	(0.292)	-0.0267	(0.436)
PPT^2	-0.0986	(0.358)	-0.1782	(0.383)	0.6112	(0.434)
$(1-PFT)\cdot PPT$	-0.6094	(0.392)	-0.7051	(0.470)	-1.0655	(0.533)
$(age-2)\cdot(1-PFT)$	-0.1880	(0.240)	-0.0561	(0.256)	0.0457	(0.367)
$(age-2)\cdot PPT$	-1.2858	(0.381)	-1.4466	(0.412)	-1.5601	(0.574)
$(age-2)^2\cdot(1-PFT)$	0.0581	(0.159)	-0.0501	(0.163)	-0.1465	(0.231)
$(age-2)^2\cdot PPT$	0.6376	(0.222)	0.6606	(0.232)	0.5530	(0.320)
$(age-2)^3\cdot(1-PFT)$	-0.0061	(0.030)	0.0147	(0.029)	0.0334	(0.042)
$(age-2)^3\cdot PPT$	-0.0843	(0.039)	-0.0812	(0.040)	-0.0546	(0.054)
Model without selection correction						
Intercept	1.0071	(0.230)	0.7380	(0.225)	0.3062	(0.275)
age	1.7947	(0.197)	2.1832	(0.188)	2.6518	(0.226)
age^2	-0.4470	(0.054)	-0.5370	(0.051)	-0.6349	(0.060)
age^3	0.0360	(0.005)	0.0427	(0.004)	0.0490	(0.005)
t	0.3619	(0.162)	0.1081	(0.156)	0.0905	(0.213)
t^2	-0.4218	(0.283)	0.0420	(0.314)	0.0451	(0.468)
t^3	0.3248	(0.202)	0.0437	(0.228)	0.0937	(0.351)
t^4	-0.0826	(0.049)	-0.0253	(0.055)	-0.0450	(0.086)
Orthogonalized year dummies included in both models						

Note: see table 6.

Table 8: Quantile regressions of full–time earnings for high–skilled women (H) accounting for selection correction

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	-4.7853	(1.730)	-5.2692	(1.026)	-4.0131	(1.381)
age	6.8604	(1.441)	7.1485	(0.879)	6.3819	(1.157)
age^2	-1.8629	(0.400)	-1.8328	(0.246)	-1.6137	(0.317)
age^3	0.1644	(0.036)	0.1532	(0.022)	0.1359	(0.028)
t	0.8200	(2.152)	0.3228	(0.939)	0.4197	(0.866)
t^2	-1.1777	(3.666)	-0.4745	(1.614)	-0.6781	(1.495)
t^3	0.9109	(2.386)	0.5628	(1.054)	0.6587	(0.982)
t^4	-0.2296	(0.525)	-0.1733	(0.232)	-0.1825	(0.218)
$1-PFT$	-1.2010	(0.491)	-0.3149	(0.309)	-1.0217	(0.407)
PPT	3.0347	(0.477)	2.2211	(0.339)	1.8651	(0.446)
$(1-PFT)^2$	0.8922	(0.472)	0.5389	(0.339)	1.1671	(0.422)
PPT^2	-2.1211	(0.775)	-1.6604	(0.480)	-0.0891	(0.681)
$(1-PFT)\cdot PPT$	-0.8957	(0.944)	-0.7009	(0.611)	-1.4379	(0.859)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
$(age-2)\cdot(1-PFT)$	0.2191	(0.698)	-0.6087	(0.430)	-0.3181	(0.568)
$(age-2)\cdot PPT$	-1.9213	(0.838)	-1.4080	(0.516)	-1.5051	(0.704)
$(age-2)^2\cdot(1-PFT)$	-0.0304	(0.414)	0.3779	(0.257)	0.2538	(0.331)
$(age-2)^2\cdot PPT$	1.3880	(0.503)	0.9933	(0.305)	0.8076	(0.392)
$(age-2)^3\cdot(1-PFT)$	-0.0264	(0.071)	-0.0730	(0.044)	-0.0652	(0.057)
$(age-2)^3\cdot PPT$	-0.2450	(0.088)	-0.1780	(0.052)	-0.1257	(0.066)
Model without selection correction						
Intercept	-0.2133	(0.705)	-0.0077	(0.384)	-0.5440	(0.507)
age	2.6507	(0.469)	2.7021	(0.297)	3.3181	(0.321)
age^2	-0.6018	(0.124)	-0.5974	(0.081)	-0.7593	(0.087)
age^3	0.0442	(0.011)	0.0432	(0.007)	0.0569	(0.008)
t	0.9437	(1.783)	0.2956	(1.074)	0.4240	(1.202)
t^2	-1.3740	(2.749)	-0.4275	(1.876)	-0.7353	(1.703)
t^3	1.0583	(1.715)	0.5331	(1.244)	0.7435	(1.049)
t^4	-0.2684	(0.369)	-0.1668	(0.277)	-0.2099	(0.228)
Orthogonalized year dummies included in both models						

Note: see table 6.

Table 9: Quantile regressions of part–time earnings for low–skilled women (U) accounting for selection correction

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	-1.5795	(3.122)	1.1400	(2.204)	2.6906	(2.643)
age	3.1523	(2.332)	1.5172	(1.620)	0.6759	(1.892)
age^2	-0.8373	(0.575)	-0.4482	(0.394)	-0.2573	(0.448)
age^3	0.0711	(0.047)	0.0418	(0.031)	0.0272	(0.035)
t	0.0221	(0.439)	0.1863	(0.712)	0.1216	(1.326)
t^2	-0.2211	(0.855)	-0.5381	(1.250)	-0.2520	(2.283)
t^3	0.3600	(0.638)	0.5055	(0.843)	0.3103	(1.505)
t^4	-0.1257	(0.159)	-0.1336	(0.192)	-0.0915	(0.335)
$1-PFT$	2.4514	(0.570)	1.9719	(0.459)	1.3796	(0.500)
PPT	-0.8539	(0.809)	-1.5261	(0.646)	-1.5184	(0.652)
$(1-PFT)^2$	0.5737	(0.510)	-0.3051	(0.429)	-0.1889	(0.497)
PPT^2	0.7064	(0.405)	1.1915	(0.345)	1.1147	(0.301)
$(1-PFT)\cdot PPT$	-1.2281	(0.628)	-0.5158	(0.538)	-0.3102	(0.514)
$(age-2)\cdot(1-PFT)$	-0.1965	(0.707)	0.7959	(0.434)	1.2727	(0.510)
$(age-2)\cdot PPT$	-1.0527	(0.857)	-0.4630	(0.586)	-0.1680	(0.671)
$(age-2)^2\cdot(1-PFT)$	0.1875	(0.402)	-0.5257	(0.257)	-0.7532	(0.290)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
$(age-2)^2 \cdot PPT$	0.6149	(0.444)	0.3904	(0.296)	0.2911	(0.313)
$(age-2)^3 \cdot (1-PFT)$	-0.0346	(0.068)	0.0826	(0.043)	0.1120	(0.049)
$(age-2)^3 \cdot PPT$	-0.0986	(0.070)	-0.0734	(0.046)	-0.0615	(0.046)
Model without selection correction						
Intercept	5.1754	(0.554)	5.1438	(0.759)	5.5880	(0.685)
age	-2.7797	(0.415)	-2.1094	(0.552)	-2.0024	(0.479)
age^2	0.7630	(0.101)	0.5465	(0.131)	0.4950	(0.113)
age^3	-0.0651	(0.008)	-0.0443	(0.010)	-0.0388	(0.009)
t	-0.0490	(0.320)	0.1368	(0.529)	0.1475	(1.227)
t^2	-0.3951	(0.685)	-0.7131	(0.940)	-0.4186	(2.101)
t^3	0.6349	(0.553)	0.7509	(0.646)	0.4860	(1.384)
t^4	-0.2134	(0.146)	-0.2079	(0.151)	-0.1419	(0.309)
Orthogonalized year dummies included in both models						

Note: see table 6.

Table 10: Quantile regressions of part–time earnings for women (M) with medium skill level accounting for selection correction

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	16.7019	(4.574)	9.5655	(3.158)	11.1105	(3.338)
age	-10.7963	(3.429)	-5.5040	(2.313)	-6.5990	(2.560)
age^2	2.6237	(0.854)	1.3762	(0.572)	1.6256	(0.660)
age^3	-0.2048	(0.069)	-0.1102	(0.046)	-0.1274	(0.055)
t	-0.0846	(0.932)	0.0240	(0.881)	-0.1236	(0.790)
t^2	0.1233	(1.733)	-0.0690	(1.594)	0.3268	(1.424)
t^3	0.0148	(1.138)	0.1767	(1.016)	-0.0313	(0.905)
t^4	-0.0245	(0.250)	-0.0605	(0.218)	-0.0322	(0.194)
$1-PFT$	1.8664	(0.787)	1.6759	(0.542)	2.0785	(0.582)
PPT	-3.9416	(1.491)	-1.3669	(1.169)	-0.6628	(1.182)
$(1-PFT)^2$	1.0889	(0.622)	0.0342	(0.408)	-0.4855	(0.426)
PPT^2	1.3319	(0.894)	0.2592	(0.646)	-0.2594	(0.676)
$(1-PFT) \cdot PPT$	-0.7807	(1.018)	-0.0232	(0.679)	-0.6375	(0.692)
$(age-2) \cdot (1-PFT)$	1.5057	(0.763)	1.6223	(0.487)	1.2739	(0.543)
$(age-2) \cdot PPT$	3.4682	(1.269)	1.5229	(0.812)	2.2912	(0.803)
$(age-2)^2 \cdot (1-PFT)$	-1.0983	(0.469)	-1.0624	(0.312)	-0.8558	(0.338)
$(age-2)^2 \cdot PPT$	-1.6984	(0.670)	-0.7550	(0.424)	-1.0678	(0.476)
$(age-2)^3 \cdot (1-PFT)$	0.1886	(0.084)	0.1665	(0.057)	0.1348	(0.060)
$(age-2)^3 \cdot PPT$	0.2537	(0.108)	0.1197	(0.069)	0.1494	(0.083)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model without selection correction						
Intercept	8.1120	(1.084)	7.9685	(0.762)	3.7095	(0.938)
age	-4.7213	(0.829)	-3.8112	(0.612)	0.1347	(0.784)
age^2	1.1857	(0.208)	0.8977	(0.157)	-0.1036	(0.208)
age^3	-0.0942	(0.017)	-0.0677	(0.013)	0.0125	(0.018)
t	0.2003	(0.581)	0.2584	(0.503)	-0.2077	(1.433)
t^2	-0.5899	(1.081)	-0.6020	(0.959)	0.5248	(2.595)
t^3	0.6437	(0.761)	0.5920	(0.682)	-0.1438	(1.646)
t^4	-0.1895	(0.181)	-0.1610	(0.162)	-0.0169	(0.349)
Orthogonalized year dummies included in both models						

Note: see table 6.

Table 11: Quantile regressions of part–time earnings for high–skilled women (H) accounting for selection correction

Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
Model accounting for selection correction						
Intercept	13.7211	(7.461)	14.8953	(3.430)	9.2929	(2.534)
age	-9.2694	(5.641)	-10.4805	(2.777)	-4.3705	(1.787)
age^2	2.3745	(1.451)	2.7852	(0.740)	1.1107	(0.469)
age^3	-0.1953	(0.121)	-0.2332	(0.063)	-0.0862	(0.040)
t	0.2223	(5.605)	0.2142	(2.291)	0.0787	(3.987)
t^2	-0.8013	(6.549)	-0.4630	(2.746)	-0.3387	(4.678)
t^3	0.5099	(3.340)	0.4132	(1.443)	0.4966	(2.377)
t^4	-0.0882	(0.628)	-0.1141	(0.279)	-0.1623	(0.442)
$1 - PFT$	2.2773	(1.301)	0.0510	(0.724)	1.2831	(0.487)
PPT	-0.3093	(2.005)	1.7208	(0.980)	-2.3835	(0.695)
$(1 - PFT)^2$	-0.6334	(0.936)	-1.3769	(0.580)	-0.4144	(0.401)
PPT^2	-1.2519	(1.634)	-3.0188	(0.939)	1.0951	(0.611)
$(1 - PFT) \cdot PPT$	-0.5167	(1.810)	2.2546	(1.080)	-0.3203	(0.685)
$(age - 2) \cdot (1 - PFT)$	2.7460	(1.715)	2.3427	(0.903)	0.5565	(0.654)
$(age - 2) \cdot PPT$	2.8193	(2.070)	2.8534	(1.190)	2.3286	(0.830)
$(age - 2)^2 \cdot (1 - PFT)$	-1.5494	(1.013)	-1.1037	(0.527)	-0.3956	(0.375)
$(age - 2)^2 \cdot PPT$	-1.6896	(1.220)	-1.9519	(0.725)	-1.1288	(0.496)
$(age - 2)^3 \cdot (1 - PFT)$	0.2539	(0.172)	0.1640	(0.092)	0.0617	(0.063)
$(age - 2)^3 \cdot PPT$	0.2774	(0.206)	0.3367	(0.124)	0.1540	(0.083)
Model without selection correction						
Intercept	8.9889	(2.477)	4.4968	(1.771)	1.9206	(1.772)
age	-4.6318	(1.638)	-0.6542	(1.229)	1.4301	(0.406)

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Variable	20%-quantile Coeff.	(s.e.)	50%-quantile Coeff.	(s.e.)	80%-quantile Coeff.	(s.e.)
age^2	1.1384	(0.424)	0.1552	(0.327)	-0.3122	(0.105)
age^3	-0.0907	(0.035)	-0.0118	(0.028)	0.0232	(0.009)
t	0.3891	(4.739)	0.7602	(2.863)	0.0997	(5.231)
t^2	-1.1559	(5.549)	-1.7808	(3.413)	-0.2180	(6.028)
t^3	0.8975	(2.859)	1.4852	(1.815)	0.3948	(3.006)
t^4	-0.1933	(0.548)	-0.3821	(0.359)	-0.1377	(0.549)
Orthogonalized year dummies included in both models						

Note: see table 6.

Table 12: Wald tests for joint significance of sample selection terms for 20%–, 50%– and 80%–quantile for specification in tables 6–11

Skill level: U $\chi^2(15)$–stat	P–Value	M $\chi^2(15)$–stat	P–Value	H $\chi^2(15)$–stat	P–Value
Full–time earnings					
111.5	.00	133.7	.00	163.9	.00
Part–time earnings					
1154.4	.00	2125.3	.00	910.2	.00

Note: For full–time earnings χ^2–test for joint significance of selection terms $(1-PFT)$, PPT, $(1-PFT)^2$, PPT^2, $(1-PFT)\cdot PPT$, $age^j(1-PFT)$, and $age^j PPT$ (j=1,...,3) in tables 6–8. For part–time earnings χ^2–test for joint significance of selection terms PFT, $1-PPT$, PFT^2, $(1-PPT)^2$, $PFT\cdot(1-PPT)$, $age^j PFT$, and $age^j(1-PPT)$ (j=1,...,3) in tables 9–11. It is tested jointly whether the coefficients are significant for all three quantiles considered. Standard errors are estimated by a bootstrap approach based on 700 **(I am planning for 1000)** resamples taking into account the estimation error in the selection correction terms from the estimation of the linear probability model.

Table 13: Wald tests for significance of interaction terms of sample selection terms with polynomial time trend

Skill	20%-quantile $\chi^2(8)$–stat	P–Value	50%-quantile $\chi^2(8)$–stat	P–Value	80%-quantile $\chi^2(8)$–stat	P–Value	all quantiles $\chi^2(24)$–stat	P–Value
Full–time earnings								
U	4.1	.84	4.0	.85	2.5	.96	9.2	.99
M	4.8	.78	10.3	.23	4.9	.76	21.5	.60
H	4.2	.83	3.0	.93	3.4	.90	10.5	.99
Part–time earnings								

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	20%-quantile		50%-quantile		80%-quantile		all quantiles	
Skill	$\chi^2(8)$–stat	P–Value	$\chi^2(8)$–stat	P–Value	$\chi^2(8)$–stat	P–Value	$\chi^2(24)$–stat	P–Value
U	3.6	.88	5.7	.67	6.0	.64	14.8	.92
M	11.3	.18	8.0	.42	7.6	.46	20.1	.69
H	6.2	.62	3.8	.86	2.4	.96	12.6	.97

Note: χ^2–test for significance of interaction terms $t^j \cdot PFT$ and $t^j \cdot PPT$ for $j = 1, ..., 4$ in quantile regressions with selection correction. Specifications the same as in tables 6–11 plus the eight interaction terms. Standard errors are estimated by a bootstrap approach based on 700 **(I am planning for 1000)** resamples taking into account the estimation error in the selection correction terms from the estimation of the linear probability model.

Table 14: Descriptive Statistics on Estimated Probabilities PFT and PPT based on results for linear probability model in table 3–5

	Mean	Std Dev	Minimum	Maximum
Full–time Low Skilled Women (U)				
PFT	0.29656	0.16425	0.00000	0.83419
PPT	0.35245	0.14494	0.00000	0.70411
Full–time Medium Skilled Women (M)				
PFT	0.45299	0.18607	0.00000	0.75151
PPT	0.33223	0.11490	0.00000	0.71847
Full–time High Skilled Women (H)				
PFT	0.47181	0.17121	0.00000	0.81401
PPT	0.37400	0.11526	0.00000	0.72586
Part–time Low Skilled Women (U)				
PFT	0.18048	0.11348	0.00000	0.77164
PPT	0.42356	0.13085	0.00000	0.71490
Part–time Medium Skilled Women (M)				
PFT	0.45299	0.18607	0.00000	0.75151
PPT	0.33223	0.11490	0.00000	0.71847
Part–time High Skilled Women (H)				
PFT	0.47181	0.17121	0.00000	0.81401
PPT	0.37400	0.11526	0.00000	0.72586

Table 15: Quantile regressions of full–time earnings for low-skilled male workers without selection correction

	20%-quantile		50%-quantile		80%-quantile	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
Intercept	3.3700	(0.042)	3.6177	(0.038)	3.8394	(0.052)

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	20%-quantile		50%-quantile		80%-quantile	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
age	0.3855	(0.027)	0.3856	(0.028)	0.3484	(0.037)
age^2	-0.1123	(0.017)	-0.1116	(0.017)	-0.0816	(0.022)
age^3	0.0119	(0.003)	0.0116	(0.003)	0.0061	(0.003)
t	0.1627	(0.238)	-0.0063	(0.210)	0.1021	(0.299)
t^2	-0.3124	(0.445)	0.0771	(0.416)	-0.0614	(0.590)
t^3	0.2820	(0.328)	0.0096	(0.329)	0.1301	(0.453)
t^4	-0.0834	(0.083)	-0.0191	(0.089)	-0.0539	(0.118)
c_b^2	-0.0467	(0.012)	-0.0452	(0.011)	-0.0535	(0.013)
c_b^3	-0.0063	(0.003)	-0.0060	(0.003)	-0.0085	(0.003)
Orthogonalized year dummies included						

Note: Coefficients of linear quantile regressions of log real earnings based on individual data from GHS (for definitions of variables, see table 18). The estimates are exactly the same as in tables 2–4 in Fitzenberger/Wunderlich (2001) except that here a fourth order polynomial in time is estimated instead of a fifth order polynomial and the orthogonalized year dummies are adjusted accordingly. Standard errors are estimated by a bootstrap approach based on 700 resamples.

Table 16: Quantile regressions of full–time earnings for male workers with medium skill level without selection correction

	20%-quantile		50%-quantile		80%-quantile	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
Intercept	3.3779	(0.047)	3.6293	(0.039)	3.8832	(0.039)
age	0.5833	(0.042)	0.5714	(0.030)	0.5416	(0.040)
age^2	-0.2000	(0.028)	-0.1762	(0.021)	-0.1250	(0.027)
age^3	0.0232	(0.005)	0.0188	(0.004)	0.0076	(0.005)
t	0.1500	(0.243)	0.0086	(0.212)	-0.1033	(0.166)
t^2	-0.2437	(0.434)	0.0227	(0.389)	0.2260	(0.296)
t^3	0.2379	(0.301)	0.0967	(0.280)	0.0125	(0.212)
t^4	-0.0725	(0.071)	-0.0480	(0.069)	-0.0395	(0.053)
c_b^2	-0.0424	(0.019)	-0.0622	(0.016)	-0.0860	(0.019)
c_b^3	-0.0052	(0.005)	-0.0093	(0.004)	-0.0170	(0.005)
Orthogonalized year dummies included						

Note: see table 15.

Table 17: Quantile regressions of full–time earnings for high–skilled male workers without selection correction

	20%-quantile		50%-quantile		80%-quantile	
Variable	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
Intercept	3.4240	(0.061)	3.6582	(0.063)	3.8435	(0.063)
age	0.6754	(0.051)	0.6883	(0.036)	0.7816	(0.053)
age^2	-0.2079	(0.029)	-0.2002	(0.021)	-0.2176	(0.032)
age^3	0.0192	(0.005)	0.0187	(0.004)	0.0199	(0.006)
t	0.0828	(0.347)	-0.1112	(0.365)	-0.2437	(0.331)
t^2	-0.0167	(0.675)	0.3085	(0.682)	0.6288	(0.628)
t^3	0.1295	(0.508)	-0.0472	(0.497)	-0.2825	(0.478)
t^4	-0.0535	(0.130)	-0.0208	(0.124)	0.0347	(0.125)
Orthogonalized year dummies included						

Note: see table 15.

Table 18: Variable definitions

Variable	Description
YDj, j=76,...,95	dummy variable for year j (1975 is omitted category)
year	*year*=(calendar year-1975)
t	t=year/10
age	*age*=(age in years)/10
c_b	$c = t - (age - 20)$ (cohort ≡ "year of age 20") and $c_b = c$ if $c < 0$ and $c_b = 0$ if $c \geq 0$, i.e. c_b denotes older birth cohorts of age above 20 in 1975 ("cohorts before 1975", see tables 15–16 and Fitzenberger/Wunderlich, 2001)
Skill U, M, H	individuals with low, medium, high skill level, respectively
qmiss	dummy variable for missing skill information
FT, *PT*, *NE*	dummy variables for employment status (full–time, part–time, nonemployed)
RD1	dummy variable region "North"
RD2	dummy variable region "Yorks, Humberside"
RD3	dummy variable region "North West"
RD4	dummy variable region "East Midlands"
RD5	dummy variable region "West Midlands"
RD6	dummy variable region "East Anglia"
RD7	dummy variable region "London/Greater London"
RD8	dummy variable region "South East"
RD9	dummy variable region "South West"
RD10	dummy variable region "Wales"
RD11	dummy variable region "Scotland"
Married	dummy variable for marital status "married"
Widowed/Divorced	dummy variable for marital status "widowed", "divorced" or "separated"

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Variable	Description
TwoAdults	dummy variable for household type "2 adults under age 60"
HHKidslt5	dummy variable for household type "children under age 5 in household"
HHKids5t15	dummy variable for household type "all children age 5-15"
ThreeAdults	dummy variable for household type "3 or more adults"
OneAdult>60	dummy variable for household type "1 adult age 60 or over"
TwoAdults>60	dummy variable for household type "2 adults, 1 or 2 age 60 or over"
Kids0t2	dummy variable for "child(ren) age 0-2 years in household"
Kids3t5	dummy variable for "child(ren) age 3-5 years in household"
Kids6t10	dummy variable for "child(ren) age 6-10 years in household"
Kids11t16	dummy variable for "child(ren) age 11-16 years in household"
Born outside UK	dummy variable for "born outside UK"
Spouse employed	dummy variable for "spouse employed"
Spouse unemployed	dummy variable for "spouse unemployed"
Spouse nonemployed	dummy variable for "spouse nonemployed"
Spouse earnings	log real weekly wage, when employed (otherwise zero)
Doctor_2weeks	dummy variable for "talked to a doctor in the last two weeks"
Doctor> 1_2weeks	dummy variable for "talked more than once to a doctor in the last two weeks"
Interest_not_92	dummy variable for "interest income etc. (except for 1992)"
Interest_in_92	dummy variable for "interest income in year 1992"
Rent income	dummy variable for "any rent from property or subletting at present"
House/Flat owner	dummy variable for "owner/co–owner of the house or flat, where household is living"
PFT	estimated probabilities for full–time employment from the linear probability model censored to lie in the interval $[0,1]$
PPT	estimated probabilities for part–time employment from the linear probability model censored to lie in the interval $[0,1]$
PNE	estimated probabilities for part–time employment from the linear probability model censored to lie in the interval $[0,1]$

Note: The selection correction terms in the estimated quantile regressions involve a series expansion of the estimated probabilities for full–time employment and for part–time employment, PFT and PPT.

Figure 1: Estimated Selection Effect $g(\hat{P}(FT_i = 1), \hat{P}(PT_i = 1))$ for women as a function of propensity score for employment state (full–time or part–time) assuming that one minus employment probability is equally distributed among other employment state and non–employment

Propensity Score: $\hat{P}(FT_i = 1)$ Propensity Score: $\hat{P}(PT_i = 1)$

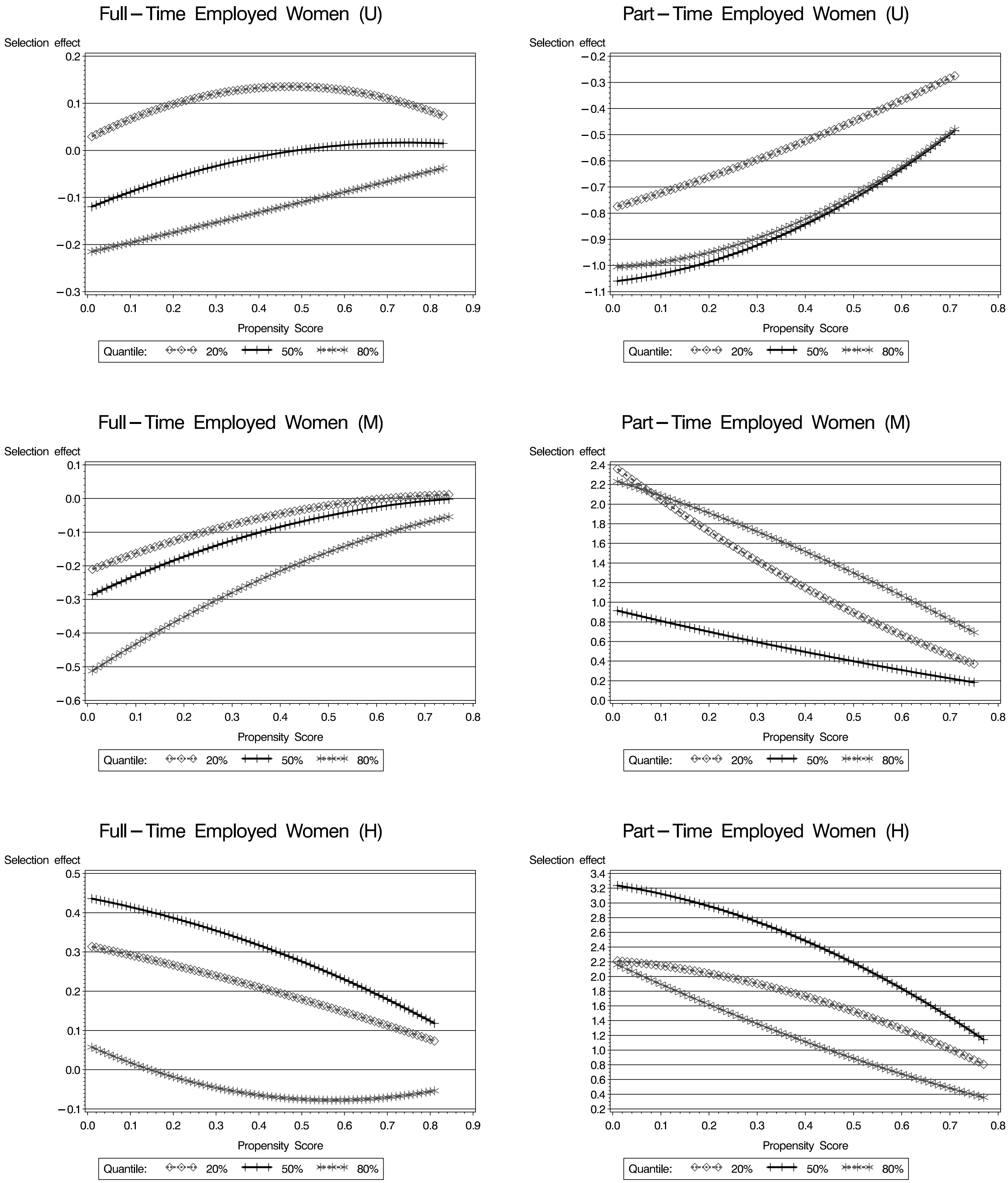


Figure 2: Estimated time trends for full–time employed women across quantiles

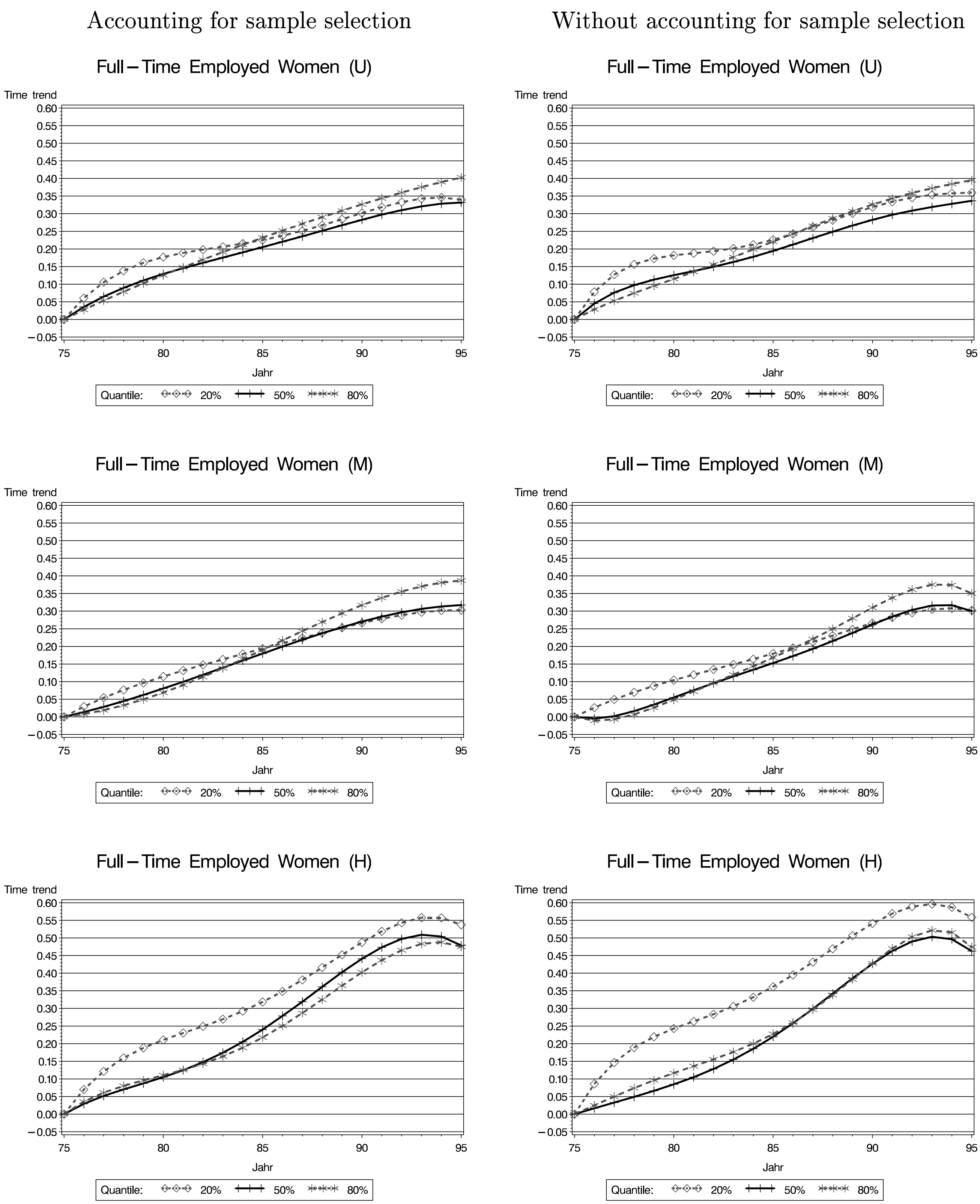


Figure 3: Estimated time trends for part–time employed women across quantiles

Accounting for sample selection | Without accounting for sample selection

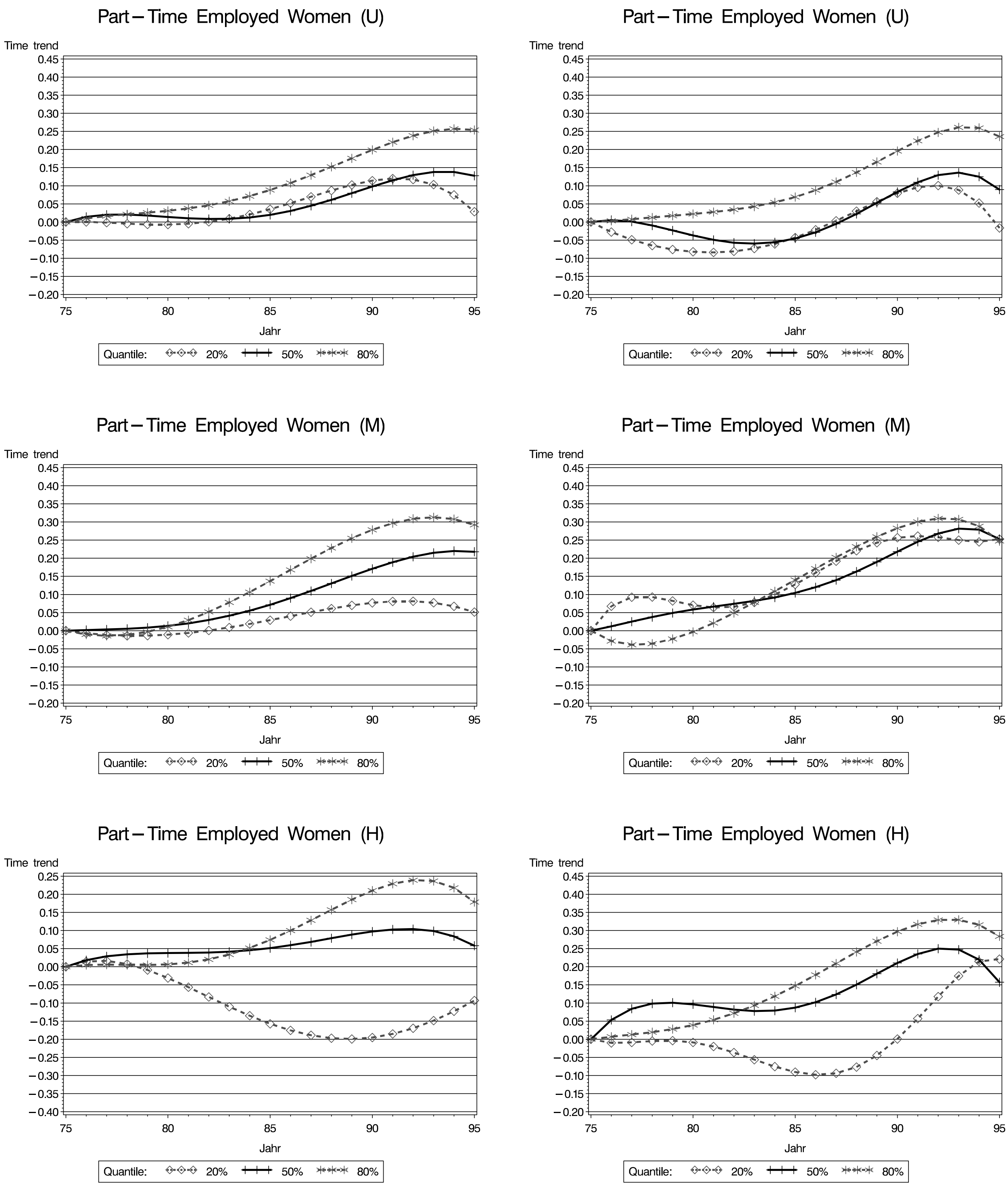


Figure 4: Differences in estimated time trends for full–time employed women relative to full–time employed men across quantiles

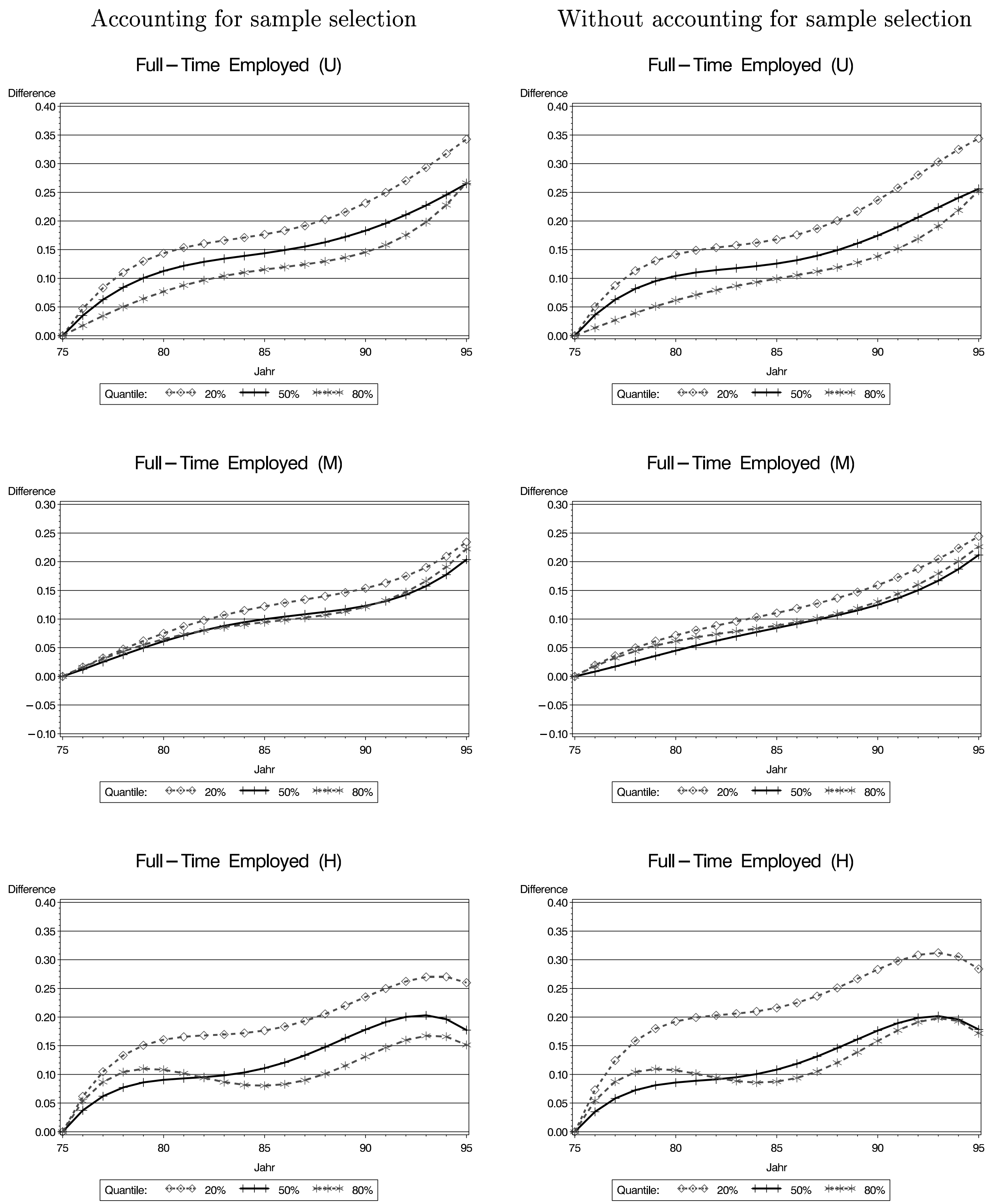
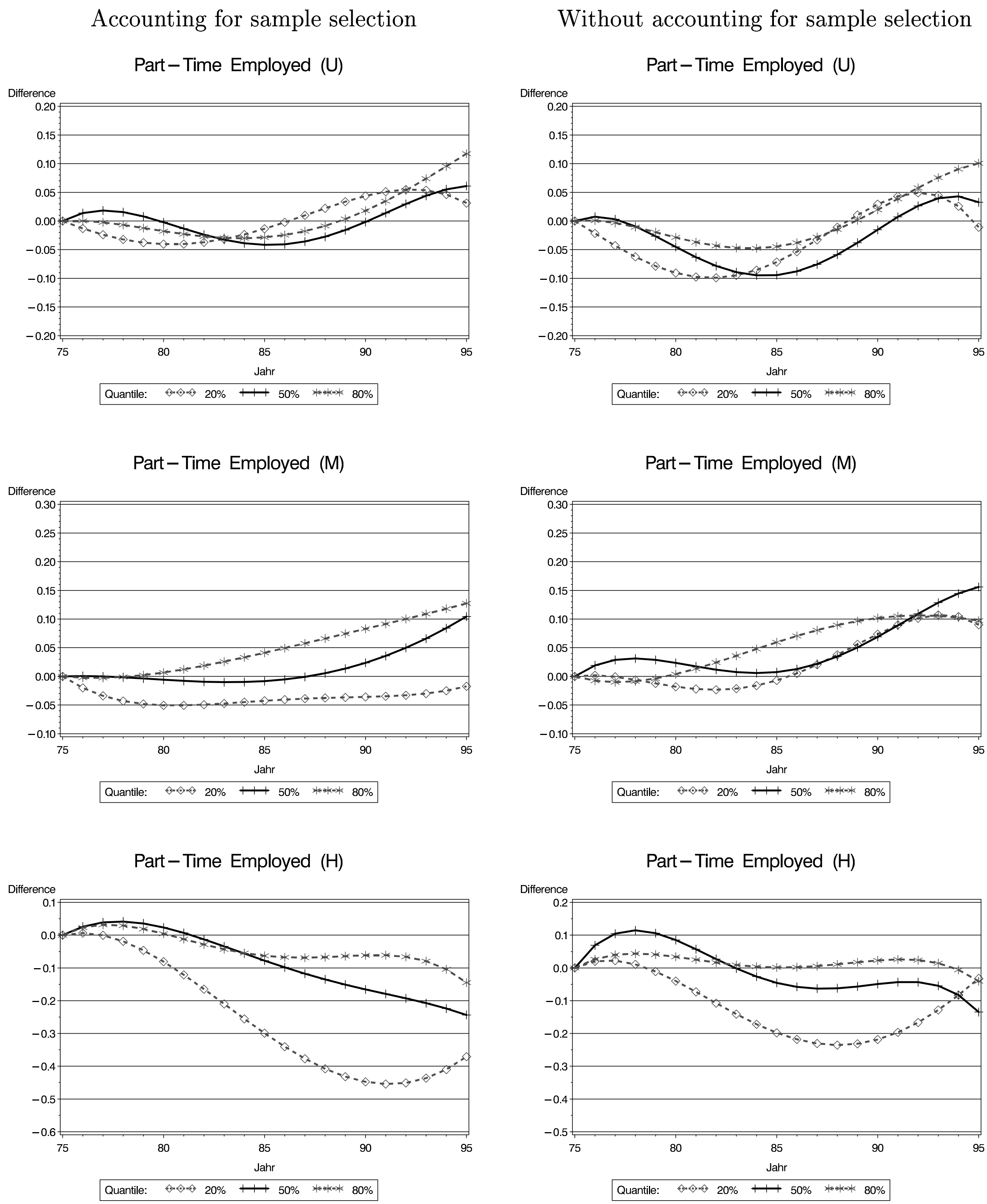


Figure 5: Differences in estimated time trends for part–time employed women relative to full–time employed men across quantiles



References

Altonji, J. and Blank, R. (1999) Race and Gender in the Labor Market. In: Ashenfelter, O. and Card, D. (Hrsg.), Handbook of Labor Economics, Vol. III, 3144-3259.

Andrews, D. and M. Schafgans (1998) Semiparametric Estimation of a Sample Selection Model. Review of Economic Studies, 65, 449-517.

Bell, D. and Ritchie, F. (1998) Female Earnings and Gender Differentials in Great Britain 1977-1994. Labour Economics, 5, 331-357.

Blackaby, D.H., Clark, K., Leslie, D.G., and Murphy, P.D. (1997) The Distribution of Male and Female Earnings 1973-91. Evidence for Britain. Oxford Economic Papers, 49, 256–272.

Blau, F. and L. Kahn (1996) Wage Structure and Gender Earnings Differentials: An International Comparison. Economica, 63, S29–S62.

Blau, F. and L. Kahn (1997) Swimming Upstream: Trends in the Gender Wage Differential in the 1980s. Journal of Labor Economics, 15, 1–42.

Blinder, A.S. (1973) Wage Discrimination: Reduced Form and Structural Variables. The Journal of Human Resources, 8, 436–456.

Buchinsky, M. (1998), The Dynamics of Changes in the Female Wage Distribution in the USA: A Quantile Regression Approach. Journal of Applied Econometrics, 13, 1–30.

Buchinsky, M. (2001), Quantile Regression with Sample Selection: Estimating women's return to education in the U.S. . Empirical Economics, 26, 87–113.

Desai, T., Gregg, P., Steer, J., and Wadsworth, J. (1999) Gender and the Labour Market. In: Gregg, P. and Wadsworth, J. (eds.), 168–184.

Ermish, J.F. and Wright, R.E. (1991) Wage Offers and Full-time and Part-time Employment by British Women. The Journal of Human Resources, 111–133.

Fitzenberger, B., Hujer, R., MaCurdy, T., and Schnabel, R., (2001) Testing for Uniform Wage Trends in West Germany: A Cohort Analysis Using Quantile regressions for Censored Data. Empirical Economics, 26, 41–86.

Fitzenberger, B. and Wunderlich, G. (2001) The Changing Gender Gap Across the Wage Distribution in the U.K. . Discussion Paper No. 01-56, Centre for European Economic Research (ZEW), Mannheim.

Fitzenberger, B. and Wunderlich, G. (2002) Gender Wage Differences in West Germany: A Cohort Analysis. German Economic Review, 3(4), 379–414.

García, J., Hernández, P.J., and A. López-Nicolás (2001) How wide is the gap? An investigation of gender wage differences using quantile regression. Empirical Economics, 26, 149–168.

Gosling, A., Machin, S., and Meghir, C. (2000) The Changing Distribution of Male Wages in the U.K. Review of Economic Studies, 67, 635-666.

Gregg, P. and Wadsworth, J. (eds.) (1999a) The State of Working Britain. Manchester University Press, Manchester and New York.

Gregg, P. and Wadsworth, J. (1999b) Job Tenure. In: Gregg, P. and Wadsworth, J. (eds.), 109–126..

Gregg, P. and Wadsworth, J. (2000) Mind the Gap, Please: The Changing Nature of Entry Jobs in Britain. Economica, 67, 499–524.

Harkness, S. (1996) The Gender Earnings Gap: Evidence from the UK. Fiscal Studies, 17, 1-36.

Heckman, J. J. and Robb, R. (1985) Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations. In: Mason, W. and Fienberg, S., (eds.), Cohort Analysis in Social Research. New York.

Joshi, H. and Paci, P. (1998) Unequal Pay for Women and Men: Evidence from the British Birth Cohort Studies. MIT Press, Cambridge.

Juhn, C., Murphy, K. and Pierce, B. (1993) Wage Inequality and the Rise in Returns to Skill. Journal of Political Economy, 101, 410–442.

Koenker, R. and Bassett, G. (1978) Regression Quantiles. Econometrica, 46, 33–50.

Machin, S. (1999) Wage Inequality in the 1970s, 1980s and 1990s. In: Gregg, P. and Wadsworth, J. (eds.), 185– 205.

MaCurdy, T.E. and Mroz, T. (1995) Measuring Macroeconomic Shifts in Wages from Cohort Specifications. Unpublished Manuscript, Stanford University and University of North Carolina.

Makepeace, G., Paci, P., Joshi, H., and Dolton, P. (1998) How Unequally Has Equal Pay Progressed Since the 1970s? A Study of Two British Cohorts. The Journal of Human Ressources, 534–556.

Manning, A. (2000) Movin' on up: Interpreting the Earnings-Experience Profile. Bulletin of Economic Research, 52, 261-295.

Manning, A. and Robinson, H. (1998) Something in the Way She Moves: A Fresh Look at an Old Gap. CEPR Discussion Paper No. 389.

Newey, W.K. (1999) Two–Step Series Estimation of Sample Selection Models. MIT Department of Economics, Discussion Paper, Nr. 99-04.

Oaxaca, R. (1973) Male-female Wage Differentials in Urban Labour Markets. International Economic Review, 14, 693–709.

OECD (1996) Economic Outlook – Earnings Inequality, Low Paid Employment and Earnings Mobility. Chapter 3. Paris.

Wright, R.E. and Ermish, J.F. (1991) Gender Discrimination in the British Labor Market: A Reassessment. The Economic Journal, 101, 508-522.