FIEF Working Paper Series 1999, No. 149

Job assignment and the gender wage differential: theory and evidence on Finnish metalworkers[*]

Juhana Vartiainen[†]

April 28, 1999

Abstract

We study the determinants of the gender wage differential by using a data set on Finnish blue-collar metalworkers. The assignment of men and women into jobs of different complexity is a key factor that widens the final wage differential. Using the theory of optimal job assignment, we propose a model of individual productivity, ability and job complexity and formulate a hypothesis of asymmetric assignment according to which men and women of equal ability are allocated to different job levels. Using econometric panel data techniques, we find support for this hypothesis. The results are consistent with the Lazear-Rosen model of job ladders but can alternatively be interpreted as evidence for gender discrimination in job assignment. JEL J31, J50, J71.

1 Introduction

The gender wage differential is an important issue. It is often suspected that women's low earnings reflect differentiated treatment of the two sexes in the labour market. Firstly, there may be wage discrimination: women earn lower wages even when their productivity-related attributes as well as those of their tasks do not differ from those of men. Secondly, even the productivity-related attributes may differ in ways that to many do not seem warranted by purely economic considerations: women's career profiles and job assignments differ from those of men and women tend to be concentrated in firms and industries that are less generous wage-payers than male-dominated ones.

[*]Some of the results of this paper were presented at the Applied Econometrics Association Conference on Gender and the Labour Market, Perpignan, April 2-3, 1998. The author is indebted to Markus Jäntti, Reija Lilja, Pär Lundborg, Tuire Santamäki-Vuori, Ilpo Suoniemi and Johnny Zetterberg for useful suggestions and comments. Aila Mustonen has provided excellent research assistance.

[†]Labour Institute for Economic Research, Pitkänsillanranta 3A, FIN-00530 Helsinki. ph. +358-9-25357335, fax 25357332, juhana.vartiainen@labour.fi.

It is notoriously difficult to assess to what extent wage differentials and different job and employer attributes reflect discriminating treatment. As to outright wage discrimination, it is (in general) impossible to measure individual productivity independently of wages and thus to compare wages and productivity directly. Secondly, wages are affected by so many intervening factors that it is hard to obtain a conclusive statistical proof of wage discrimination. Lastly, to know whether women would be qualified to earn higher wages in more demanding jobs and male-dominated firms and industries would require counterfactual observations of women's performance in positions in which there are at present few women[1]. In general, empirical analyses of the wage differential have tended to show that the differential becomes very small and can even vanish if wages are conditioned on a large set of variables, including narrowly defined occupational dummies. This has tended to shift the main focus of attention into gender differences in careers and job assignment.

This paper sheds new light on these issues by analyzing the wages of Finnish metalworkers. The novel feature of the analysis is a thorough exploitation of observations on the complexity level of individual jobs. The metalworkers' collective agreement namely presupposes a fairly thorough evaluation of job attributes, the result of which is an observation on the complexity level of each job.

We first use an Oaxaca decomposition to show that job assignment is an important determinant of the wage differential. On average, men are allocated to more demanding jobs than women, and this factor can explain more than half of the gross wage differential. It is then natural to ask whether the assignment process treats men and women asymmetrically. Borrowing from the literature on optimal assignment (see Sattinger 1993), we suggest a model of ability, job complexity and earnings which permits an operational formulation of this asymmetry hypothesis. The hypothesis is tested by using panel data techniques proposed by Hausman and Taylor (1981). The results suggest that the job assignment process indeed treats men and women differently. However, discrimination in job assignment and careers is not the only possible interpretation of the results. The observed pattern can also be accommodated with models based on individual optimization like that of Lazear and Rosen (1990).

2 The metal and engineering industry's collective agreement

The wages of Finnish blue-collar metalworkers are legally based on the industry's collective agreement (henceforth CA) that was gradually introduced in the late 1980s[2]. That agreement encompasses practically all of the industry's firms

[1] As Heckman and Sedlacek (1985) point out, the study of comparative advantage is made difficult by the very principle of comparative advantage itself.

[2] This is the so-called PARAKE-agreement, the aim of which is to relate relative wage differentials to individual and job-specific attributes. It covers all workers whose pay is defined per hour. Salaried employees have separate arrangements.

and workers. According to the CA, the relative wages of metalworkers are determined by job complexity, personal achievement and eventual firm-specific and individual-specific arrangements, as follows:

1) All occupations within each firm have been evaluated according to their complexity. The criteria for evaluation include the time required to learn to do the job as well the responsibility and strain that is imposed on the worker. All occupations within an industry are thereby mapped into a scale of difficulty. The evaluation of occupations is carried out by a special expert group that assesses job attributes[3]. The collective agreement in turn includes a tabulated tariff wage for each level of complexity. Once a worker has been assigned to an occupation within the firm, the tariff wage of the corresponding complexity class becomes the starting point in the determination of his wage. This tariff wage is called his occupation-related wage. The occupation-related wage is based on job attributes alone is not supposed to change when the person filling the job slot changes.

In this paper, we treat the occupation-related wage as a continuous observation on job complexity, bearing in mind that the variable is measured in wage space. This choice differs from other analyses, since the job level information is most often treated as a classifying dummy variable. In our data, about 65 to 70 different complexity levels appear in the data in a typical year. This is not as much as one might hope, but perhaps enough to warrant an analysis in continuous space, in particular because the analysis reported in this paper would be cumbersome and difficult to carry out with a large set of occupational dummies.

2) In addition, the collective agreement stipulates that a worker's personal achievement in the task be reflected in his pay. The worker's performance is evaluated by a superior who assigns the worker a personal bonus of 2 to 17 percent on top of the occupation-related wage. The CA requires that the distribution of personal bonuses within each wage group within each firm obeys the normal distribution. The wage group is derived simply from a coarse partition of the job complexity axis into three subsets. The most complex jobs are carried out in wage group 1, the intermediate tasks in group 2 and the simple tasks in group 3. The point of this conditioning on the wage group and the requirement of a normal distribution within a group is to avoid a psychologically plausible outcome in which the highest bonuses would tend to accrue to the most skilled workers who anyway are located at the high end of the task complexity axis. Thus, the idea of the bonus is to evaluate the quality of the worker's input conditional job complexity.

The bonus-increased wage is called a person's basic wage. The basic wage is the person's fundamental reference wage. It is also the minimum wage that he can claim in time work.

3) The actual wage outcome is up to the firm's wage policy and any idiosyncratic bargains that the firm and the worker conduct. The employer is bound by

[3] Thus, the evaluation of job complexity is in principle seen as a genuine observation on the complexity of the job and not as a free instrument in the hands of the management.

the minimum requirement set by the basic wage, but nothing prevents the employer from paying more. Thus, actual pay depends on the methods of payment and the wage policy chosen by the firm. However, it is the spirit of the CA that final relative wages should reflect the relative differentials of the workers' basic wages. Indeed, it is the case that relative differentials in basic wages to a high extent determine relative differentials in actual wages and that basic wages also constitute a set of binding minimum wages – conditioned on job complexity – in the industry[4].

The methods of payment fall into two categories: time pay and performance pay. The latter category is further subdivided into two: piece rates and "premium" rates. Premium pay is a mixture of time and piece, so that there is a fixed hour rate on top of which comes remuneration according to number of units produced. Many workers share their working hours between two or three pay schemes. The final mean wage per hour can be computed as a weighted average of pay per hour within each of the three pay schemes. In this study, we pay most attention to time wages, since most workers have time hours whereas piece and premium pay are less prevalent. Furthermore, regressions of wages earned within the different pay schemes suggest that linear models that best describe earnings differ across schemes, so that different pay forms are best treated separately.

3 The Data

The data were collected by systematic sampling from the Finnish Employers Association's wage records. Notwithstanding errors in the recording process, these records are completely comprehensive: they contain the quarterly observations of all wage variables of all workers within all member firms (practically all firms) in the metal and engineering industry. The 1990 data was ordered by firm and within each firm the workers were ordered according to their mean pay. A subset of workers was then sampled from this set of workers, by picking each 15th worker of the set. By using personal codes to identify each worker, the sample was then continued to years 1991 through 1995 and backwards, to years 1989 through 1980. For each year, attrition was compensated for by adding new observations[5]. In this paper, however, we only use the panel of the years 1990 through 1995, since it is for these years only that the job complexity variable is available. As in most countries, the metal industry's labour force is predominantly male, so that women amount to about 25% of it in a typical

[4] For example, a cross section reduction of variance (carried out by the author) indicates that about 70 per cent of the variation in average hour pay is explained by the job complexity variable, age and gender variables and the composition of pay schemes (shares of performance pay and time pay) variables. Adding firm means raises the adjusted R-square to about 80 per cent.

[5] This supplementing was carried out in the following way. For year 1991, say, the worker population was partitioned into "newcomers" and "old" according to whether that year is the first one when the worker in question appears in the industry's records. The supplementary workers of the panel were then sampled from among the newcomers.

year.

From the 5182 sampled workers of year 1990, about half (2517) were observed in all the subsequent years from 1991 through 1995. Of these 2517 individuals, 1396 performed time work in each of these six years, and most of our analyses focuses on that subsample of the data.

As to the variables, they include the following:

- Age and sex of worker;
- Money earned and time worked within all pay schemes (time work, piece work, premium work);
- The level of job complexity and the personal bonus of the worker;
- An employer code that partitions the set of workers into subsets according to employer identity;
- An area code that partitions the country in two classes (dense metropolitan vs. sparsely populated area).

By using the information of the sample, other variables can be formed. We have used variables such as

- "Total experience" = Total number of years in which the workers appears in the data in years 1980 through 1995. This can be interpreted as a crude measure of how professionally the individual is engaged in the metal industry. In a panel estimation, it is invariant and contains information on future years if used with 1980-1994 data;
- Share of performance work hours (piece plus premium hours) in total hours of the worker;
- Indicator variables for worker who is either new in his firm or is just going to leave the firm.

4 The wage differential

This section presents the stylized facts of the gender wage differential. Figure 1 depicts two variables: the ratio of female earnings per hour in time work to male hour earnings; and the ratio of female average earnings per hour to male earnings. Both ratios stay around 82 percent, approximately. Thus, women earn about four fifths of male earnings.

Next, we report an Oaxaca decomposition of the log wage differential, using the data for year 1990 as an example[6]. The decomposed variable is the log of the average wage per hour earned in time work, computed over all workers who carried out time work in year 1990. We use the male wage structure (i.e. the

[6] See the papers by Oaxaca (1973) and Oaxaca and Ransom (1994) for the basic idea of the decomposition.

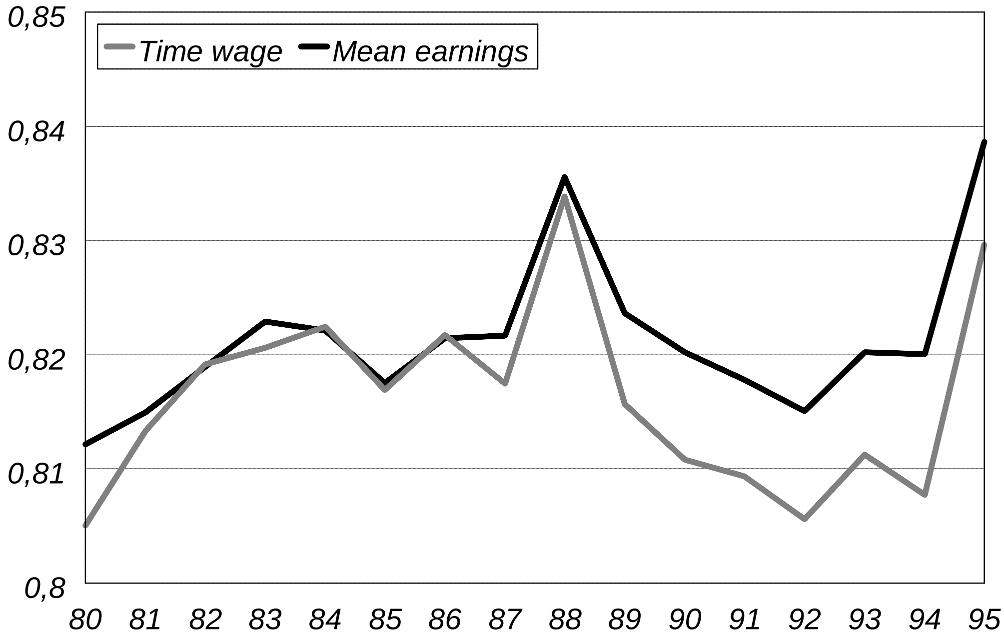

Figure 1: Ratio of female to male earnings per hour, measured by time wages and mean hour earnings, for Finnish metalworkers in years 1980-1995.

	Constant	Age	Total experience	Job complexity	Total
β_m	0,481	0,011	0,004	0,857	
β_f	0,473	0,004	0,005	0,879	
$\bar{X}_m$	1,000	37,320	9,340	3,556	
$\bar{X}_f$	1,000	40,130	8,420	3,411	
$\beta_m(\bar{X}_m - \bar{X}_f)$	0,000	-0,005	0,003	0,124	0,123
%	0,000	-2,550	1,590	61,110	60,150
$\bar{X}_f(\beta_m - \beta_f)$	0,009	0,159	-0,009	-0,077	0,081
%	4,170	77,970	-4,620	-37,680	39,850
SUM	0,009	0,153	-0,006	0,048	0,204
%	4,170	75,420	-3,020	23,430	100,000

Table 1: Oaxaca decomposition of time wages for 1990 data. The effect of age squared is incorporated into the age contribution entries.

coefficients of the linear model estimated from the male subsample) as the reference structure. This is not an uncontroversial choice, but is perhaps warranted by the fact that male workers constitute about three quarters of the industry's workforce[7]. The main point of this exercise is to show that the difference in average job complexity is one of the main factors that contributes to the overall wage differential. Table 1 reports the results of this decomposition in which we have used age (plus age squared), total experience and log of job complexity as explanatory factors. The first two rows display the coefficients, β^m for men and β^f for women, of each variable in a linear model estimated for the 1990 cross-section. The next two rows, $\bar{X}^m$ and $\bar{X}^f$, display the means of the variables for the male and female subsample, respectively. The next row, $\beta_m(\bar{X}_m - \bar{X}_f)$ shows the contribution, to the overall wage differential, of the difference in male and female average of the variable in question. The next row displays the relative share of that contribution within the overall wage differential. The row $\bar{X}_f(\beta_m - \beta_f)$ in turn displays the contribution of differential treatment associated with each variable and the next row in turn shows the relative share of that contribution. The last row sums both factors for each variable whereas the last column sums, over all variables, the contributions of different means and those of differential treatment. Thus, the last entry of the SUM row is the overall wage differential of 20.4 per cent. A negative entry in a cell means that the contribution in question diminishes the wage differential.

We see that age and job complexity are the important factors that contribute to the wage differential. The difference in average job complexity accounts for 61 per cent of the total wage differential of 20 per cent. Yet there is an intriguing pattern: the coefficient of complexity is higher for women, and this generates a negative contribution to the wage differential. The differential treatment of age

[7] See Oaxaca and Ransom (1994) and Neumark (1988) for a thorough discussion on the choice of the reference structure.

Figure 2: Empirical density function of job complexity for male and female workers, 1990 data.

can explain almost four-fifths of the overall differential.

Thus, broadly, women are in less complex jobs, although being in a more complex job brings greater rewards to women than for men. Moreover, men's wages increase with age, in contrast to women's. We emphasize that the above decomposition is presented as a crude empirical characterization that motivates the subsequent sections. By itself, it would warrant a more careful analysis of the role of the different variables. In particular, interpreting the coefficients and contributions of a variable like job complexity is hazardous, since that variable is extremely likely to be strongly endogenous[8].

Whatever the best decomposition, the differential in average job complexity clearly is an important factor that increases the wage differential. Figure 2 depicts the empirical density function of job complexity for men and women. As we see, women tend to be concentrated in occupations deemed less valuable and less demanding than those of men.

[8] In his original paper (Oaxaca 1973), Oaxaca discusses the use of occupational variables in the decomposition and points out that conditioning on occupation effectively eliminates one potential source of discrimination. A more satisfactory decomposition would require more information on individual ability. Then the role of complexity as an intermediate variable could be clarified, as well as the role of firm selection effects.

5 A theoretical model of ability, complexity and productivity

The results of the previous section suggest that it is important to study the process of job assignment in order to evaluate the fairness of women's pay. This raises the obvious question: could it be the case that a woman's expected job complexity level, conditional on her productive abilities, is lower than that of her male colleagues? We call this the asymmetric assignment hypothesis. The rest of the paper is devoted to a theoretical formulation as well as statistical tests of this hypothesis.

As there is no direct observation of productive ability, and the occupation-related wage is strongly correlated with the actual wage, there is no direct way to test the asymmetry hypothesis. However, plausible economic models predict that the marginal relationship between job complexity and productivity may be informative on job assignment. This section borrows from the theoretical and empirical literature on wages, job complexity and job assignment and argues that the elasticity of an individual's wage with respect to the complexity level can reveal something on the relationship between his ability and the complexity of his job[9]. By and large, straightforward empirical applications of assignment models have been relatively few, since the theory operates with variables like job characteristics and worker ability that are rarely directly observable. Studies by van Ophem & al. (1993) and Teulings (1995) are important exceptions. The study by van Ophem & al. in particular elaborates ideas similar to this paper, especially the notion of a concave relationship between job complexity and productivity for an individual of given ability.

To begin with, note that the Ricardian model of differential rents and job assignment, as elaborated by Michael Sattinger (1979), implies that earnings are a concave function of job complexity for any given individual at the neighbourhood of the optimum assignment point. The differential rents model presupposes that output y is a function $y = f(c; a)$ of the job level c and individual ability a (assume throughout this section that the price of the product is normalized to unity). It is generally assumed that there is comparative advantage, so that, in equilibrium, there is a positive relationship between worker ability and machine complexity. Comparative advantage entails that the function f is not multiplicatively separable into factor functions of c and a, respectively[10].

In the assignment literature, the complexity of the job is traditionally referred to as the "size" of the machine that the worker operates. We will use the terms "sophistication and "complexity" as equivalent concepts. Suppose that

---

[9] Michael Sattinger (1993) provides an analytic survey of this literature: among the pioneering papers are those of Tinbergen (1951), Roy (1951) and Sattinger (1975). One conclusion of this literature is that there is no reason to expect a robust statistical relationship between worker characteristics and earnings, since the distribution of earnings is mediated by the assignment of workers into different jobs. The papers have also investigated the conditions under which the distribution of earnings is of a different shape than the distribution of abilities.

[10] See Sattinger (1975). As pointed out by Teulings (1995), the function $f(c;a)$ is consistent with comparative advantage provided the condition $f_{ac}f \geq f_a f_c$ holds.

each firm owns one machine and employs one worker. Equilibrium assignment can be characterized in two equivalent ways: either firms choose the appropriate ability a of their worker to maximize profits $f(c;a) - w$, taking as given a wage schedule $w = w(a)$ according to which the wage is a function of ability; or the workers maximize their earnings, $f(c;a) - r$ taking as given a machine rent schedule according to which the cost of operating a machine is an increasing function $r = r(c)$ of the size of the machine. Sattinger (1979) shows that, provided there are no discontinuities in the distributions of machine complexity and worker ability and that the cross derivative f_{ca} is positive everywhere, there is an equilibrium assignment in which both of the necessary first order conditions are met and the wage and rent functions are both increasing. Furthermore, the second order condition for the worker's maximization problem is met[11]. This implies that, around equilibrium, earnings are a concave function of machine complexity for any given individual. The immediate conclusion of the model is that the marginal effect of increasing complexity is higher than average (i.e. positive) for any worker whose complexity-ability ratio in the current occupation is below average.

Such a model, however, implies that the effect, on earnings, of changes in complexity must always be zero if the economy operates near its optimum. This is unduly restrictive and we would prefer a richer model that can accommodate a positive relationship between complexity changes and changes in earnings. One way to do this is to incorporate worker preferences into the model. Suppose as above that output is a function $f(c;a)$ of complexity (of the machine operated by the individual) and ability, with $f_{ac} > 0$[12], and that there is a cost of capital (rent) $r = r(c)$ associated with the machine. For simplicity, assume that this function is linear, so that $r(c) = rc$. Furthermore let us make the assumption that operating complex machines is a stressful activity for the worker. Thus, increasing machine complexity c decreases the well-being of the

[11] Sattinger's argument is as follows. One starts by assuming tentatively that there is an equlibrium assignment according to which more sophisticated machines are associated with individuals of higher ability, so that ability a, in equilibrium, is an increasing function $a(c)$ of machine complexity (throughout, one assumes comparative advantage for able individuals in complex tasks). From the point of view of the individual worker with ability a^*, maximization of earnings $f(c;a^*) - r(c)$ with respect to c leads to the first order condition $\frac{\partial f(a^*;c)}{\partial c} = r'(c)$. Thus, the derivative of the rent function $r(c)$ is $r'(c) = \left.\frac{\partial f(a^*;c)}{\partial c}\right|_{a^*=a(c)}$, the derivative of the production function with respect to complexity, evaluated at the value of a corresponding to c in equilibrium. Differentiation of the last expression with respect to c yields

$$r''(c) = \left[\frac{\partial^2 f(a^*;c)}{\partial c^2}\right]_{a^*=a(c)} + \left[\frac{\partial^2 f(a^*;c)}{\partial a^* \partial c}\right]_{a^*=a(c)} \frac{da^*}{dc}.$$

Suppose now that the second order condition for the individual maximization problem above were not met, i.e. $\frac{\partial^2 f(a^*;c)}{\partial c^2} - r''(c) \geq 0$. Assuming that $\frac{\partial^2 f(a^*;c)}{\partial a \partial c}$ is always positive, the previous formula would then imply that $\partial a^*/\partial c$ is negative, contradicting the tentative assumption. Thus, there is a consistent equilibrium assignment in which more complex machines are associated with higher ability and each individual optimizes his job level to maximize earnings.

[12] We make the usual assumptions about f: $f_c > 0$, $f_a > 0$, $f_{cc} < 0$, $f_{aa} < 0$.

worker, but the amount of disutility associated with each unit of complexity is a function of the individual's ability: for gifted workers, it is less stressful to operate a sophisticated machine than for less gifted workers. Suppose that the disutility, measured in pecuniary terms, associated with a unit of complexity is an increasing function $G(c/a)$ of the ratio of complexity to ability. The disutility associated with working with a machine of complexity c is then $cG(c/a)$. The worker maximizes the sum of his wage earnings $R(c;a) = f(c;a) - rc$ less the disutility term $cG(c/a)$. Consequently, the worker chooses c to maximize utility

$$U = f(c;a) - rc - cG(c/a): \tag{1}$$

Assume that the function $f(c;a)$ is linear homogeneous. This is perhaps not a large loss in generality, since we anyhow have no observations on and thus no scale for ability. The first order condition is

$$f_c(c/a) = r + G(c/a) + (c/a)G'(c/a); \tag{2}$$

so that optimal complexity is a multiple of ability (multiple that depends on the machine rent factor r):

$$c/a = \phi(r) = \phi: \tag{3}$$

Such a model entails, inter alia, that earnings are a linear function of complexity, when measured over the worker population[13].

Suppose now that, for whatever reason, some subset of workers (like women) operates below the optimal c/a-ratio, and, furthermore, that the ability-complexity differential is proportionally constant. For example, we might assume that women's ability is perceived to be lower than their true ability, either because of prejudiced superiors or because of women's unduly low self-esteem. Thus, we assume that perceived ability c^* is $c^* = (1-\delta)c$. Therefore, if (3) holds for men,

$$c = (1-\delta)\phi a; \; 0 < \delta < 1; \tag{4}$$

holds for women[14].

Suppose also that job complexity is subject to shocks. This is a plausible assumption: as the firm has to meet the wishes of its different customers, it must continuously adjust the exact composition of its production line. Furthermore, some workers will be absent some of the days and other workers must carry out the tasks left by the absentees. Workers therefore jump around their optimum

[13] Since f is neoclassical, earnings are $f(c;a) - rc = c[f(1;1/\phi) - r]$ and the cross section elasticity of earnings with respect to job complexity is unity.

[14] An alternative assumption would be that the stress function $cG(c/a)$ is more steeply increasing for women. This would also lead to lower c/a-ratio for women, although in general not to a constant proportional disadvantage, because of the form of the utility function (1).

c/a ratio. Finally, the workers of our subsample who all stay in the industry, probably advance gradually at least slowly towards more demanding jobs, on the average[15]. Consequently, workers shift between different complexity levels, although such variation is probably of low magnitude compared to the variation of job complexity between individuals. Consider ε_{Rc}, the elasticity of earnings with respect to job complexity, evaluated for a worker of given ability who is at his equilibrium point. For an individual male worker with given ability a,

$$\varepsilon_{Rc;man} = \left[\frac{c}{R(c;a)}\frac{\partial R(c;a)}{\partial c}\right]_{a\ \text{given};\ c=\phi a} = \frac{cf_c(\phi) - rc}{f(c;c/\phi) - rc} = \frac{f_c(\phi) - r}{f(1;1/\phi) - r}; \tag{5}$$

whereas, for a woman operating at $c = (1-\delta)\phi a$,

$$\varepsilon_{Rc;woman} = \left[\frac{c}{R(c;a)}\frac{\partial R(c;a)}{\partial c}\right]_{a\ \text{given};\ c=(1-\delta)\phi a} \tag{6}$$

$$= \frac{cf_c(\phi(1-\delta)) - rc}{f(c;c/\phi(1-\delta)) - rc} = \frac{f_c(\phi(1-\delta)) - r}{f(1;1/\phi(1-\delta)) - r}$$

so that $\varepsilon_{Rc;woman} > \varepsilon_{Rc;man}$ holds because of the neoclassical assumptions about f that we have made ($f_c(c/a)$ is a decreasing function). Note that since f is neoclassical, $cf_c < f$ and the formula after the second equality sign in (5) implies that $\varepsilon_{Rc;man}$ is below unity. Thus, if the above model is an adequate description of production conditions, we have a well-defined prediction associated with the hypothesis of asymmetric assignment: the elasticity of women's earnings with respect to job complexity should exceed that of men, for each individual[16].

6 Statistical specification

On the basis of the previous section, we propose that the asymmetric assignment hypothesis be tested by comparing the coefficients of job complexity for men and women in an earnings equation. If the asymmetric assignment hypothesis is correct, the marginal effect of job complexity on earnings should be higher for women than for men. Figure 3 illustrates this: if earnings are a concave function of job complexity and women operate below the c/a ratio of men, the slope of the earnings function (for each individual) should exceed that of men. In Figure 3, we have drawn the concave earnings function plus some fictive data points for complexity and earnings for three individuals (or, equivalently, groups

[15] See the next section on the stationarization of the data.

[16] As an example of this model, assume that output is just a multiple of machine size c, multiplied by a factor that indicated how well the skill of the worker matches the sophistication of the machine: $f = c(1 + b\log\frac{a}{c})$. Suppose the worker stress function is $G(c/a) = \mu b\log(c/a)$; where μ is a parameter. The optimal a/c ratio is then $e^{\frac{r+\mu}{1+\mu}}$, and the elasticity of earnings with respect to complexity for a male individual becomes $\varepsilon_{Rc;men} = \frac{\mu(1-r)}{\mu(2-r)+1}$, which is below unity.

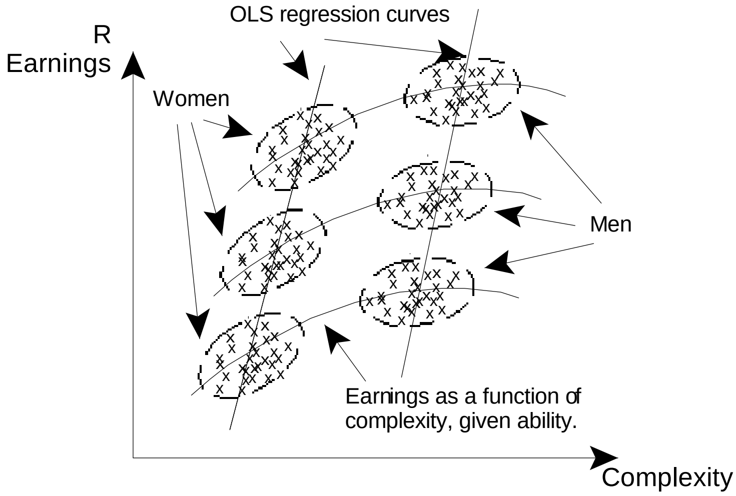

Figure 3: True (as conjectured) and observed pattern of job complexity and earnings.

of individuals), one with low ability, one with intermediate ability and one with high ability. Women find themselves on a steeper part of their earnings curve than men.

The same figure also suggests why a simple OLS regression on a cross section can not deliver a reliable estimate of the individual slope coefficient, since job complexity is correlated with individual ability. The OLS regression coefficient will then only reflect the steepness of the earnings schedule, as a function of complexity, when workers' abilities change in pace with machine complexity.

The endogeneity problem can be tackled with instrumental variable methods, and exploiting both the time and the cross section dimension of the present data makes estimation more efficient. Thus, we will be working with a familiar random effects model

$$w_{it} = X_{it}\beta + Z_i\gamma + \alpha_i + \epsilon_{it} \tag{7}$$

in which i indexes individuals and t indexes time. Let $T = 6$ be the number of time periods and $N = 1396$ be the number of individuals. Then w_{it} is an $NT \times 1$ vector of observations on individual wages, X_{it} is an $(NT \times k_1)$ matrix of observations on time-variant variables, Z_i is an $(NT \times k_2)$ matrix of observations on time-invariant variables, α_i is an $(NT \times 1)$ matrix of stochastic individual intercept terms that capture individual differences in ability, and ϵ_{it} is an $(NT \times 1)$ disturbance matrix. Observations are indexed first over individuals and then over time so that the vector α, for example, is a sequence of sequences of T identical entries for each individual. Following Hausman and Taylor, we partition the X_{it} matrix into two parts, so that $X_{it} = [X_1\ X_2]$; where the submatrix X_1 contains those variables that are asymptotically uncorrelated with the individual α_i-effects and X_2 in turn consists of "endogenous" variables correlated with α_i. Thus, the statistical assumptions are[17]:

$$\begin{aligned} \operatorname*{plim}_{N\to\infty}(1/N)X_1'\alpha_i &= 0;\ \operatorname*{plim}_{N\to\infty}(1/N)Z'\alpha_i = 0 \\ \operatorname*{plim}_{N\to\infty}(1/N)X_2'\alpha_i &\neq 0. \end{aligned} \tag{8}$$

Since α_i is correlated with the endogenous variables of the X_{it} matrix, OLS and GLS estimates of model (7) are biased and inconsistent. There are several ways of arriving at consistent estimates of β and γ. One can transform the equation by the familiar orthogonal projections operator $Q_V = I_{NT} - (I_N \otimes \frac{1}{T}\iota\iota')$, which transforms each variable into deviations from individual means (ι is a T vector of ones). Estimation of the resulting equation delivers the fixed effect estimate of β, while γ is not identified. A more efficient way suggested by Hausman and Taylor (1981) is to use the exogenous variables as instruments. The Hausman-Taylor (HT) estimator is the IV estimator of the equation obtained by multiplying (7) by the familiar matrix[18] $\Omega^{-1/2} = Q_V + \theta P_V$, where $P_V = I_N \otimes \frac{1}{T}\iota\iota'$ transforms the variables into vectors of individual means over time and $\theta = (\sigma_\nu^2/(\sigma_\nu^2 + T\sigma_\alpha^2))^{-1/2}$. In the IV estimation, X_1 and Z_1 as well as the deviations from means of entire X are used as instruments[19].

We report the GLS, fixed effects ("within), "between" as well as the HT estimates of equation (7). The dependent variable was the log of time wage from year 1990 through year 1995. The wage and complexity variables were first stationarized by projecting them on time dummies and taking the residual, in order to eliminate any general effects of inflation and productivity growth[20]. The variables of the regressor matrices were:

X_1: (exogenous, time-variant variables):

- Age and age squared

[17] In the Hausman-Taylor model, even the Z matrix is partioned in the same way, but in this analysis we assume no endogenous time-invariant variables.

[18] The $\Omega^{-1/2}$ matrix converts the covariance matrix of the disturbance term into a diagonal matrix.

[19] Subsequently, Amemiya and MaCurdy (1986) and Breusch, Mizon and Schmidt (1989) have suggested estimators that are even more efficient, provided stronger exogeneity conditions are met.

[20] Note that our balanced panel is a subset of a larger data set that also includes individuals that leave or enter the industry between years 1990 and 1995. The stationarization was carried out within the entire sample that also included those workers who were not part of the balanced sample. This probably leaves a slight upward trend in complexity, since the workers who are not newcomers nor leave the sample within the period of investigation are likely to be serious professionals who advance to better occupations. However, stationarizing the sample within the balanced panel does not change our main estimates and qualitative conclusions in any significant way.

- Age and age squared × woman dummy
- Total hours worked
- Firm dummies
- Regional dummy
- Newcomer (was not in the current firm one year ago)
- Leaver (leaves the current firm between this observation and the next)

X_2: (endogenous time-varying variables):

- Job complexity
- Job complexity × woman dummy
- Personal bonus
- Time share of performance pay

Z_1: (exogenous time-invariant variables):

- Total experience
- Gender (woman dummy)
- Firm dummies.

Most of these variables are self-evident. "Total hours worked" is the sum of hours worked within all three pay schemes. The regional dummy is a partition of the data into two classes, metropolitan and rural[21]. "Newcomer" denotes a worker who was not in the current firm one year ago, and "leaver" denotes a worker whose firm affiliation changes from this year to the next. "Time share of performance pay" denotes the share of piece and premium hours in total hours[22]. Firm dummies appear both as time-invariant and time-variant variables, depending on whether change occurs in the firm's workforce during our period of investigation.

The crucial variable of the analysis is of course the cross variable complexity × gender. In the estimation, this variable was formulated by multiplying the instrumented complexity variable by the female dummy[23]. We first fitted the model into the pooled sample of men and women and then separately to the gender subsamples.

[21] The collective agreement stipulates slightly higher pay in metropolitan areas where the cost of living is presumably higher.

[22] See the paper by Brown (1990) who shows that individuals with higher ability are more likely to work in performance-related pay schemes.

[23] The commonplace way to use an instrumented cross variable is to instrument the cross variable in question directly. In our estimation, it is more sensible to instrument only the job complexity part of the cross variable, since the cross variable is identically zero for men. Choosing the other method, however, does not change the results.

7 Estimation results

Table 2 reports the results from fitting the model into the pooled sample of men and women. On theoretical considerations (cf. figure 3), we expect the coefficient of job complexity to drop when we move from the inconsistent GLS estimates to the consistent FE and HT estimates. Furthermore, we expect the coefficient of the cross term complexity $\times$ gender to be positive if the asymmetric assignment hypothesis is true. Both of these predictions are borne out by the estimation results. The coefficient of complexity drops from .64 to .37 as one moves from GLS to HT. The between coefficient is 0.82, i.e. not quite unity as predicted in footnote 13 but not very far from it.

The last line of the table reports Hausman tests of the overidentifying restrictions used in the instrumental variable estimations. These χ^2-tests are computed against the fixed effect estimator that is by assumption consistent but inefficient. We see that the null hypothesis of uncorrelated X_{it} and α_i is strongly rejected but that the exogeneity assumptions (overidentifying restrictions) necessary for the validity of the instruments used in HT estimation are not, even at a .001 probability level. By and large, the HT estimates are very similar to the FE (within) estimates, and there appears to be a small increase in estimation precision for most coefficients.

	GLS	Between	Within	HT
Constant	-0.1747	-0.1091	-0.2675	-0.0202
	(-5.097)	(-2.261)	(-3.857)	(-3.191)
AGE	0.0138	0.0075	0.0170	0.0171
	(8.173)	(3.177)	(7.131)	(7.996)
AGE^2	-0.00016	-0.000088	-0.00020	-0.00020
	(-7.612)	(-2.982)	(-6.982)	(-7.735)
WOMAN	0.1957	0.0939		0.1079
	(2.467)	(0.908)		(0.959)
AGE×WOMAN	-0.0139	-0.0065	-0.0145	-0.0149
	(-3.701)	(-1.298)	(-2.522)	(-2.940)
(AGE×WOMAN)^2	0.00018	0.000075	0.00024	0.00023
	(3.989)	(1.268)	(3.644)	(3.958)
REGIONAL DUMMY	-0.0297	-0.0139	-0.0057	-0.0276
	(-4.335)	(-1.736)	(-0.201)	(-1.652)
HOURS	0.000013	-0.000035	0.000013	0.000013
	(1.288)	(-0.682)	(1.283)	(1.409)
NEWCOMER	-0.0114	-0.1791	-0.0080	-0.0084
	(-3.315)	(-2.460)	(-2.289)	(-2.602)
LEAVER	-0.0071	0.2173	0.00033	-0.0015
	(-1.581)	(2.062)	(0.073)	(-0.349)
TOTAL EXPERIENCE	0.00078	0.0010		-0.00015
	(1.028)	(1.180)		(-0.066)
<u>COMPLEXITY</u>	0.6403	0.8244	0.3678	0.3822
	(24.859)	(23.256)	(9.655)	(10.864)
<u>COMPLEXITY×WOMAN</u>	0.0316	0.0206	0.2460	0.2047
	(0.606)	(0.296)	(3.070)	(2.822)
<u>PERSONAL BONUS</u>	0.3831	0.7871	0.2392	0.2377
	(10.428)	(11.072)	(5.603)	(5.980)
<u>PERFORMANCE SHARE</u>	0.0184	0.0947	-0.0118	-0.0110
	(3.906)	(10.281)	(-2.163)	(-2.168)
χ^2 (Hausman) (235 firm dummies)	$\chi^2_{120} = 2890.0$			$\chi^2_{117} = 0.149$

Table 2: Estimation results for the pooled sample. Dependent variable: log of time wage. Endogenous variables underlined. t-values in parentheses below each estimate. Number of individuals $N = 1396$. 235 firm dummies were included in the estimation. The Hausman test statistic of GLS is based on comparing Within and GLS estimates, and the test statistic of HT is based on comparing Within and HT estimates. The COMPLEXITY×WOMAN variable was computed by multiplying the instrumented COMPLEXITY variable by WOMAN. The estimated variance components were: $\hat{\sigma}^2_\varepsilon = 0.00439$; $\hat{\sigma}^2_\alpha = 0.064$; $\hat{\mu} = 0.893$.

Tables 3 and 4 report the results from fitting the model separately to the male and female subsamples. Again, the ordering of the complexity coefficients is as we expected and, furthermore, the complexity coefficient is clearly higher for women than for men. Interestingly, the difference between the GLS com-

	GLS	Between	Within	HT
Constant	-0.1988	-0.0975	-0.2448	-0.0247
	(-5.493)	(-1.710)	(-3.809)	(-4.647)
AGE	0.0124	0.0049	0.0170	0.0166
	(6.946)	(1.778)	(7.359)	(8.028)
AGE^2	-0.00015	-0.000051	-0.0002	-0.00020
	(-6.566)	(-1.509)	(-7.302)	(-7.881)
HOURS	0.0000062	-0.000072	0.000011	0.000011
	(0.586)	(-1.173)	(0.993)	(1.040)
REGIONAL DUMMY	-0.0520	-0.0419	-0.0283	-0.0512
	(-7.675)	(-5.583)	(-1.132)	(-3.495)
NEWCOMER	-0.0091	-0.2659	-0.0066	-0.0070
	(-2.381)	(-3.282)	(-1.798)	(-1.966)
LEAVER	0.0021	0.1628	0.0072	0.0058
	(0.463)	(1.682)	(1.556)	(1.366)
TOTAL EXPERIENCE	0.0043	0.0036		0.0049
	(5.120)	(4.047)		(2.177)
<u>COMPLEXITY</u>	0.6120	0.8018	0.3647	0.3783
	(23.138)	(20.841)	(9.936)	(11.191)
<u>PERSONAL BONUS</u>	0.2938	0.7154	0.1654	0.1613
	(6.992)	(8.121)	(3.498)	(3.687)
<u>PERFORMANCE SHARE</u>	0.0054	0.0817	-0.0195	-0.0192
	(1.017)	(7.539)	(-3.208)	(-3.425)
χ^2 (Hausman) (50 firm dummies)	$\chi^2_{33} = 365.55$			$\chi^2_{30} = 0.088$

Table 3: Estimation results for the male subsample. Dependent variable: log of time wage. Endogenous variables underlined. Number of male individuals $N = 1071$. 50 firm dummies were included in the estimation. The estimated variance components were: $\hat{\sigma}^2_{\varepsilon} = 0.0042$; $\hat{\sigma}^2_{\alpha} = 0.0171$; $\hat{\theta} = 0.900$.

plexity coefficient and the HT complexity coefficient is lower for women than men[24]. We conclude that these estimators corroborate the asymmetric assignment hypothesis, provided that the theoretical model of section 5 is an adequate description of productivity, complexity and ability.

[24] This might suggest that the endogeneity phenomenon is less pronounced for women, so that womens' job assignment depends less on individual ability than that of men. Without other analyses, such a conclusion is tentative, of course.

	GLS	Between	Within	HT
Constant	-0.1298	-0.0995	-0.4562	-0.0222
	(-1.718)	(-0.988)	(-2.220)	(-1.512)
AGE	0.0031	0.0066	0.00083	0.0015
	(0.911)	(1.485)	(0.144)	(0.303)
AGE^2	-0.000023	-0.000075	0.000051	0.000033
	(-0.576)	(-1.460)	(0.793)	(0.588)
HOURS	0.000032	-0.00016	0.000033	0.000034
	(1.435)	(-1.561)	(1.413)	(1.561)
REGIONAL DUMMY	-0.0542	-0.0659	0.0943	-0.0303
	(-4.986)	(-5.458)	(0.973)	(-0.907)
NEWCOMER	-0.0166	0.0653	-0.0100	-0.0111
	(-2.339)	(0.750)	(-1.328)	(-1.614)
LEAVER	-0.0162	-0.0960	-0.0104	-0.0121
	(-1.756)	(-0.871)	(-1.023)	(-1.311)
TOTAL EXPERIENCE	0.00034	0.00052		-0.0030
	(0.265)	(0.362)		(-0.709)
<u>COMPLEXITY</u>	0.7112	0.7782	0.6049	0.5975
	(14.378)	(11.150)	(7.852)	(8.543)
<u>PERSONAL BONUS</u>	0.4978	0.6663	0.4916	0.4887
	(6.296)	(4.463)	(5.185)	(5.581)
<u>PERFORMANCE SHARE</u>	0.0173	0.0398	0.0066	0.0068
	(1.868)	(2.567)	(0.560)	(0.626)
χ^2 (Hausman)	$\chi^2_{27} = 75.96$			$\chi^2_{24} = 0.060$
(50 firm dummies)				

Table 4: Estimation results for the female subsample. Dependent variable: log of time wage. Endogenous variables underlined. Number of female individuals $N = 325$. 50 firm dummies were included in the estimation. The estimated variance components were: $\hat{\sigma}^2 = 0.0052$; $\hat{\sigma}^2_{\alpha} = 0.0671$; $\hat{\theta} = 0.889$.

We conducted a number of additional statistical investigations to examine the robustness of these results. Firstly, with a smaller set of firm dummies, we computed the Amemiya-MaCurdy and Breusch-Mizon-Schmidt estimates in addition to the HT estimates. The results were very similar to those of tables 2 through 4 and are therefore not reported. We also deleted individuals the observation on whom were exceptionally influential, as measured by the statistical leverage. This did not change the results either.

Another possible extension has to do with age. Inasmuch as the phenomenon of asymmetric assignment has to do with women's childbearing, one might conjecture that the asymmetry would weaken with age, as older women who are unlikely to get children can concentrate on their careers better than those in childbearing age. Re-estimation of the model on the basis of samples splitted into younger and older workers, however, does not confirm this conjecture[25].

[25] In fact, the gender differential between the complexity coefficients seems to be a bit lower for younger workers.

8 Earnings and pay schemes

We have concentrated on time wage earnings, since time wages are the benchmark remuneration scheme. If piece rate earnings were available for all workers and one could assume a more or less uniform level of effort, piece rates could in principle deliver another reliable observation of individual productivity. By the same token, women should at each complexity level earn more than men. Selection into piece work is not random, however. The choice between time pay and performance pay has been explored by Lazear (1986) and Brown (1990), who show that the more productive workers choose piece work while the least productive part of the workforce choose time pay. This is due to a cost of measuring the output ("counting the pieces") of the worker. Suppose that a worker's output per time unit is q and the cost of measuring output is μ. If the firm offers a fixed time wage w, the worker chooses between w and $q - \mu$, so that piece work is preferred if $q > w + \mu$. Suppose that individual productivities q are unknown to the firms who only know their distribution. Lazear (1986) shows that both piece rate establishments and time rate establishments (or sections within a firm) will coexist, so that the more productive workers will seek employment in piece work and others will prefer time pay. Consequently, regressions of piece rates should take into account this selection process and would therefore better be analysed within a more elaborate theoretical model in which both the assignment and pay scheme selection process are analysed.

There is one prediction, however, implied by the Lazear-Brown framework, that can be tested fairly easily. If the more productive workers at each complexity level seek pay according to performance, we should observe more willingness among women to choose piece work or premium work. If one looks at the share of performance pay hours in workers' total hours, it turns out the distribution of this share is starkly bimodal. About a third of the workers are in time pay only, about a third use predominantly performance pay and the rest are scattered somewhere in between. If one partitions the worker data, correspondingly, into three groups and fits an ordered probability model to explain the choice of the group, female gender gets a statistically significant positive coefficient so that women indeed are more likely to seek more performance work. This is shown in Table 5, which reports the results from fitting an ordered logit model with three alternatives.

9 The earnings gap and personal bonuses

Our last piece of evidence concerns the distribution of personal bonuses. As indicated in section 2 above, the performance of each worker is evaluated and a personal bonus is assigned to each worker on top of the task-related wage. If women are of higher ability than men at all levels of job complexity, their personal bonuses should on average exceed those of men. A look at the bonuses indeed reveals that to be the case just in those tasks of wage group 3 that include

	Coefficient	t-value
AGE	0.0387	4.354
AGE^2	-0.00055	-4.905
WOMAN	0.1348	4.042
JOB COMPLEXITY	-0.8285	-6.984
SIZE OF FIRM	0.00070	22.323
NEWCOMER	-0.3126	-8.349
LEAVER	-0.2060	-5.535
TOTAL HOURS	0.00072	6.114

Table 5: Estimation results for an ordered logit model on the choice of performance pay. Denoting the share of performance pay hours by x, the grouping was based on the following partition of the performance hours share axis: Group 1: $x = 0$; Group 2: $0 < x < 0.7$; Group 3: $0.7 < x < 1$. Number of observations 25961, loglikelihood -25401.9, cut points -2.2 and -1.69, respective standard errors 0.433 and 0.433.

	Wage group 1	Wage group 2	Wage group 3
Women	9.6%	10.2%	11.1%
Men	10.3%	9.8%	9.2%

Table 6: Average personal bonus in each wage group. Wage group 1 contains the most complex jobs and wage group 3 the least complex jobs.

most female workers[26]. Table 6 lists the average personal bonuses of men and women in each wage group.

There is a statistically significant gap in the bonuses in favour of women in the lowest wage group where most women tend to work. Interestingly, there is a reverse gap in the group of complex tasks, but whatever the two sexes' relative abilities are in that group, they are of no great significance since few women work in those tasks.

The model and the results imply that the expected ability of women exceeds that of men at each complexity level. Can that prediction be accommodated with the fact that women tend to earn less in general? Not quite. If we estimate an ANOVA model for time pay earnings in which we condition pay on categorized job complexity variables and firm dummies, we can "squeeze" the female pay disadvantage to little under 3 per cent. This is not much but still of the wrong sign. Thus, the model cannot be literally true without extra assumptions. The easiest way out is simply to assume, on top of the model exposed in section 5, that some wage discrimination occurs: although the marginal conditions of the model hold, some men in some firms get a positive wage increment on top of their productivity while some women in some firms fet a negative increment.

[26] Recall that the wage grouping partitions the complexity axis in three parts, with the simplest jobs in group 3 and the demanding tasks in group 1.

Such an assumption is ad hoc but not unplausible[27]. A general lesson of these estimations is that is that the woman dummy coefficient is anyway not a very reliable indicator of women's wage position, since the final wage outcome is mediated by many complicated and interacting mechanisms like job assignment, selection into firms and differential treatment of age.

10 Conclusion: Interpreting the results

To my knowledge, job complexity and earnings have so far not been analysed with continuous random effects models. Our results, however, do not contradict other findings. By and large, the fact that women tend to be selected into less demanding occupations has been observed in many labour markets and has attracted the attention of labour economists. Furthermore, some recent studies have shown, at least tentatively, that women need to perform better than men in order to be promoted. (see in Winter-Ebmer and Zweimüller 1997 in particular)[28]. Our results are in accordance with those results. Taken literally, they imply that a female promotion leads to a larger increase in productivity than a male promotion, on average. A related finding is reported in a study of van Ophem & al. (1993), who show that females face a steeper wage profile across job complexity levels[29].

Whether womens' poorer careers are a result of occupational discrimination or an expression of different preferences is hard to assess definitively, of course. Sophisticated theoretical explanations for the observed pattern have been developed by Lazear and Rosen (1990). In their model, women's alternative occupation (at home) is more attractive than that of men, which implies that women are more likely than men to leave the firm in the post-training situation in which their productivity in the more complex job has been revealed. An earlier contribution of Becker (1985) builds on the assumption that married women spend less effort on market work than married men. Interpreted as an outcome of equilibrium behaviour, our results indicate that the marginal cost of putting women into more demanding tasks is higher than that for men, which is a result perfectly compatible with the Lazear-Rosen model. Such models notwithstanding, similar results are often interpreted as evidence for discriminatory mechanisms within the job assignment process. Our model and the empirical results suggest that there is an unexploited ability potential in women, and many commentators would probably regard this as a "problem" to be mended regardless of

[27] Thus, to generate the empirical result, it is sufficient that some large firms practice wage discrimination. Indeed, it turns out that the negative female coefficient depends a lot on which firms are selected into the estimation.

[28] Not all empirical results fall into the same pattern, however; Hersch and Viscusi, for example, in their investigation of a public utility, find that promotions increase wages more for men than for women (Hersch and Viscusi 1996). That result may be due the different character of a public utility which needs to be less concerned about individual productivity.

[29] van Ophem & al. suggest that this may indicate that the earnings disadvantage of women diminishes with job complexity. In the light of our results, this is not the only possible explanation, of course.

whether it reflects optimizing behaviour or discrimination.

References

[1] Amemiya, Takeshi & MaCurdy, Thomas E. (1986): Instrumental-variable estimation of an error-components model. Econometrica 54(4), p. 869-880.

[2] Becker, Gary (1985): Human Capital, Effort, and the Sexual Division of Labor. Journal of Labor Economics 1985, 3:1., p. S33-S58.

[3] Breusch, T.S., Mizon, G.E. & Schmidt, P. (1989): Efficient estimation using panel data. Econometrica 57, p. 695-700.

[4] Brown, Charles (1990): Firms' choice of method of pay. Industrial and Labour Relations Review 43, February 1990, p. 165S-182S..

[5] Hausman, Jerry A. & Taylor, William E. (1981): Panel data and unobservable individual effects. Econometrica 49 (6), p. 1377-1398.

[6] Heckman, J. & Sedlacek, G. (1985): Heterogeneity, Aggregation and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market. Journal of Political Economy 93, p. 1077-1125.

[7] Hersch, Joni & Viscusi, W.Kip (1996): Gender Differences in Promotions and Wages. Industrial Relations 35:4, October 1996, p. 461-472..

[8] Lazear, Edward (1986): Salaries and Piece Rates. Journal of Business 59:3, 1986, p. 405-431.

[9] Lazear, Edward P. & Rosen, Sherwin (1990): Male-Female Wage Differentials in Job Ladders. Journal of Labor Economics 8, 1990, supplement, p.106-123, 1990.

[10] Neumark, David (1988): Employers' discriminatory behavior and the estimation of wage discrimination. Journal of Human Resources 12, 1988, p. 279-295.

[11] Oaxaca, Ronald (1973): Male-Female Wage Differentials in Urban Labor Markets. International Economic Review 14(3), p. 693-709.

[12] Oaxaca, Ronald & Ransom, Michael (1994): On Discrimination and the Decomposition of Wage Differentials. Journal of Econometrics 61, p. 5-21.

[13] van Ophem, Hans & Joop Hartog & Wim Vijverberg (1993): Job Complexity and Wages. International Economic Review 34:4, November 1993, p. 853-872.

[14] Roy, Andrew D. (1951): Some Thoughts on the Distribution of Earnings. Oxford Economic Papers 3, June 1951, p. 135-146.

[15] Sattinger, Michael (1975): Comparative Advantage and the Distributions of Earnings and Abilities. Econometrica 43(3), May 1975, p. 455-468.

[16] Sattinger, Michael (1979): Differential Rents and the Distribution of Earnings. Oxford Economic Papers 31:1, 1979, p. 60-71.

[17] Sattinger, Michael (1993): Assignment Models of the Distribution of Earnings. Journal of Economic Literature 31, june 1993, p. 831-880.

[18] Teulings, Coen N. (1995): The Wage Distribution in a Model of the Assignment of Skills to Jobs. Journal of Political Economy 103:2, p. 280-315.

[19] Tinbergen, Jan (1951): Some Remarks on the Distribution of Labour Incomes. International Economic Papers n. 1, Translations prepared for the International Economic Association, Edited by Alan Peacock & al.,. London, Macmillan 1951.

[20] Winter-Ebmer, Rudolf.& Zweimüller, Josef (1997): Unequal Assignment and Unequal Promotion in Job Ladders. Journal of Labor Economics 1997, 15:1, p. 43-71.