More than meets the eye –
Gender differences in hierarchical positions and in earnings. Lessons from the Finnish metal industry[1]

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by

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Abstract

In this paper, we focus on two aspects of gender segregation which have so far received little attention in the literature. First, we examine the role of vertical gender segregation among white-collar workers in the Finnish metal industry in 2005 using a matched employee–employer dataset, in which all jobs are evaluated by the skills, efforts and responsibilities they require and are, based on this evaluation, given a hierarchical ranking which is independent of the job holder's occupational category. We also analyse the gender gap in earnings at each hierarchical position and explore the interplay between earnings and selection into a specific hierarchical position. Second, we broaden further the analysis of gender segregation and its impact on earnings by studying the gender wage gap in establishments located at different quintiles of the productivity distribution. Finally, we study how new forms of pay such as productivity and performance related bonuses and profit sharing systems are reflected in the gender wage gap. Our results show that also these dimensions are important and as a consequence deserve more attention in studies of gender segregation and wage gaps.

JEL J16, J31, J71

1. Introduction

In the international empirical literature it is widely established that gender segregation in the labour market accounts for a substantial proportion of the male–female wage gap.[1] Previous studies have provided ample evidence on the impact of gender segregation on wages (or earnings) using various levels of segregation: the occupation, industry, establishment and even job-cell level. There are, however, many questions concerning gender segregation that still remain unanswered. Do the rough categories that are typically used to describe gender segregation give an adequate picture about this phenomenon? Are there other dimensions of gender segregation that have been overlooked and should be accounted for?

In this paper, we focus on two aspects of gender segregation which have so far received little attention in the literature. First, we examine the role of vertical gender segregation among white-collar workers in the Finnish metal industry in 2005 by looking at the selection of males and females into different 'hierarchical positions', which involve increasingly higher levels of skill requirements and more demanding job responsibilities. We also analyse the gender gap in earnings at each hierarchical position and explore the possibility of an interplay between earnings and selection into a specific hierarchical position. The matched employee–employer dataset used in the empirical analysis is unique in several ways. In particular, in this dataset all jobs are evaluated – in a similar fashion across all establishments – by the skills, efforts and responsibilities they require and are, based on this evaluation, given a hierarchical ranking which is independent of the job holder's occupational category.

Second, studying gender segregation in the metal industry offers – despite its high male dominance – a possibility to broaden further the analysis of gender segregation and its impact on earnings. Establishments in the metal industry operate in a demanding global environment under hard international competition. The establishment's ability to pay competitive wages is directly related to the productivity of its employees. If men and women are increasingly working in establishments that belong to the same industry but nevertheless differ markedly in productivity, then traditional measures of gender segregation will not be able to capture the gender wage gap that may result from this kind of selection into

[1] Groschen (1991) and Bayard et al. (2003) are examples of studies on the US labour market. Asplund et al. (1996), Gupta & Rothstein (2005), Meyerson-Milgrom et al. (2001) and Korkeamäki & Kyyrä (2002) are examples of Nordic studies on this matter.

establishments. In this paper we provide new results on the gender wage gap in establishments located at different quintiles of the productivity distribution.[2]

Just as the way, in which gender segregation appears in the labour market, might change over time, so may also the pay compensation structure and, moreover, in a gender non-neutral way. New forms of pay such as productivity and performance related bonuses and profit sharing systems are growing in importance. One question that immediately arises from this is: Are these changes in pay schemes reflected in the gender wage gap? The highly competitive metal industry has in Finland been a forerunner in adopting new modes of pay schemes. Additionally, most of this change has occurred in the early 2000s and has concerned mainly white-collar workers. This implies that our white-collar worker data for 2005 provides an excellent basis for answering also this question.

Our analysis of the importance of various performance related pay schemes for the gender gap in earnings draws on comparing the outcomes from the use of two different earnings concepts. We start by using a more narrow and also more traditional concept of 'monthly earnings', which basically includes regular earnings that remain more or less fixed from one month to the other. We then turn to the use of a broader concept of 'total monthly earnings' which in addition to these regular monthly earnings also include fringe benefits, work effort related compensations, personal bonuses related to tenure as well as productivity and performance related bonuses and profit shares.

The paper proceeds as follows. In the next section the data set is described and in the third section the empirical model specifications are outlined. The fourth section reports the results from our empirical analysis of gender differences in the selection across the job hierarchy ladder. The fifth section discusses gender gaps in earnings. The last section gives a summary of our key results.

[2] The establishment's productivity is approximated by the average level of total monthly earnings of the male white-collar workers in the establishment.

2. The data

This study uses a matched employee–employer dataset on white-collar workers who were in December 2005 employed in the member firms of the Federation of Finnish Technology Industries. The Federation of Finnish Technology Industries represents a major part of all establishments in the metal industry and its member firms employ altogether 250,000 people.[3] Our data set to be used in subsequent empirical analyses is collected directly from the member firms by the Federation of Finnish Technology Industries in collaboration with the Confederation of Finnish Industries (EK) and also forms part of Statistics Finland's official statistics on employment and earnings in the metal industry. This original dataset includes 57,046 white-collar workers in 423 establishments. For our empirical analyses we have deleted from the dataset trainees, part-time workers and observations with missing information.[4] The final number of observations to be used in this study is 51,099.

A centrally negotiated wage agreement covers all white-collar workers in all member firms of the Federation of Finnish Technology Industries. Accordingly our dataset not only includes mutually agreed parts of the wage agreement but also reflects considerable establishment-level variation on aspects that are largely influenced by market forces. A particularly useful feature of the data is the mutually agreed principles on the evaluation of each job holder's position in the job hierarchy ladder. All jobs are evaluated by the skills, efforts and responsibilities which they require. When collecting the data the Federation of Finnish Technology Industries emphasises to its member firms that the reported hierarchical ranking should reflect actual duties and responsibilities in each job and should, in principle, be independent of the job holder's occupational category.

The *job hierarchy ladder* has four levels and each move upwards involves higher expertise and more responsibility: (1) The first level comprises '*mainly routine work*' which refers to jobs such as basic routine type of clerical, customer service or sales work. Job holders categorised into this level have some work experience and often

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[3] To be able to fully apply the contents of a centralised wage agreements in Finland the establishment or firm needs to be a member of an employer's federation/association that has signed the agreement. In practice, all large establishments in the metal industry are members of the Federation of Finnish Technology Industries. There are some smaller establishments which are not and, as a consequence, they are not included in the data.

[4] By doing this we assume that there are no systematic variation in the missing information and, hence, also not across the deleted observations. In fact, according to our descriptive statistics the restricted data set appears to have very similar features as the larger, original data set.

secondary education. (2) The second level '*expert work*' requires, among other things, practical expertise and good knowledge in procedures and production processes. Typically these job holders have earlier work experience and often also (lower-level) higher education. (3) The third level '*specialised expert work*' demands comprehensive expertise and good knowledge about procedures, production processes and theories. Occasionally job holders at this level have managerial duties. Usually they have versatile work experience in their field of expertise and a higher education. (4) The highest level '*management*' mostly involves managerial duties at the production line, department, organisation or establishment level. These job holders often have extensive earlier work experience and normally a university-level degree.

Table 1 reports the distribution of the white-collar job holders in the data across the four job hierarchy levels described above. It shows that the group under study is highly male dominated; only 26.6 per cent are women. The by far largest number of job holders is experts with 44.3 per cent of the males and 41.5 per cent the females being categorised as experts. Women are in majority (57.3 per cent) at the lowest job hierarchy level but in clear minority at the highest – management – level (14.2 per cent). The concentration of women is highest at mainly routine work level.[5]

Table 1. Share of white-collar workers by hierarchical position in 2005

	Job hierarchy level				
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**	**Total**
Total number of employees	7,318	22,247	17,168	4,366	51,099
- Number of men	3,126	16,609	14,035	3,746	37,516
- Number of women	4,192	5,638	3,133	620	13,583
Share of women, %	57.3	25.3	18.2	14.2	26.6
Within gender shares					
%-share among men	8.3	44.3	37.4	10.0	100.0
%-share among women	30.9	41.5	23.1	4.6	100.0
Concentration of women	2.15	0.95	0.68	0.53	1.00

[5] The concentration indicator is calculated by dividing the within %-share of women at each level by the overall share of women in the data. Hence it provides a measure of women's under- or overrepresentation at each level.

As discussed above our dataset on white-collar workers is rich in detail when it comes to describing the earnings of each job holder. The data being based on employers' registers, the earnings information is highly reliable and reports the actual earnings that each individual worker has received at the point of observation (December 2005). The two earnings concepts used in the subsequent earnings equations are: (1) 'monthly earnings' which refer to basic (regular) monthly earnings (including shift work compensations but not overtime) and (2) 'total monthly earnings' which in addition include fringe benefits, other work effort related compensations, personal bonuses related to tenure as well as productivity and performance related bonuses and profit shares.

Table 2 gives a first glimpse at the distribution of our two earnings concepts by job hierarchy level and gender. The female white-collar employees earned on average 81-82 per cent of the average monthly earnings of their male colleagues. This overall difference in male and female pay exceeds the within female/male earnings ratios given for each job hierarchy level, which reflects the uneven distribution of women and men across these hierarchy levels. The gender earnings gap is lowest, about 5 per cent, at the specialised expert level and highest, about 15 per cent, at routine work.

Table 2. Average earnings by job hierarchy level and gender in 2005

	Job hierarchy level				
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**	**All**
Monthly earnings					
All employees, €	2,406	2,837	3,820	5,353	3,321
Male employees, €	2,628	2,899	3,860	5,403	3,486
Female employees, €	2,240	2,654	3,643	5,049	2,864
Female/male earnings, %	85.2	91.6	94.4	93.5	82.2
Total monthly earnings					
All employees, €	2,537	2,837	4,288	6,565	3,690
Male employees, €	2,766	3,107	4,325	6,629	3,886
Female employees, €	2,365	2,851	4,123	6,178	3,146
Female/male earnings **%**	85.5	91.7	95.3	93.2	81. 0

Table 2 shows that in terms of earnings creation the overall differences between the four job hierarchy levels are much more important than the gender differentials at each level. Managers earn more than twice as much as employees at the lower end of the hierarchical ladder. This is true irrespective of the sex of the employee.

Furthermore, it can be calculated from Table 2 that, in addition to the regular monthly earnings, the white-collar workers receive on average 11 per cent more due to new payment schemes (which are included into the 'total monthly earnings'). The importance of new, individual payment schemes grows the further up hierarchical ladders one climes. At the management level regular earnings increase by 22.6 per cent, while at the mainly routine work level only by 5.5 per cent due to these schemes. This is the case for both male and female employees.

3. Empirical model specifications

3.1. Ordered probit models

As a first step in our empirical analysis we analyse the selection into the different job hierarchy levels and evaluate whether or not there appear to be gender differences in this respect.[6]

Our choice of empirical probability model reflects the fact that the different job levels are clearly hierarchical involving increasing amounts of skills and responsibility. This kind of hierarchical rankings can be captured by *ordered probability models.*

The basic ordered choice model is based on the following specification in which there is a latent regression

(1) $$y_i^* = \boldsymbol{\beta}'\boldsymbol{x}_i + \varepsilon_i,$$ for each observation i=1,...,N

where the latent variable y_i^* which determines the selection into a specific hierarchical job level j is not observed. $\boldsymbol{\beta}$ is a vector of unknown parameters and $\boldsymbol{x}_i$ is the corresponding vector of explanatory variables. ε_i is the error term, ε_i ~ N(0,1). Thus, we assume that the latent variable y_i^* is normally distributed and, hence, use the *ordered probit model* as our empirical specification.

[6] Later, as a second step, we estimate log(earnings)- equations conditional on this selection process that is described here.

The observed counterpart is y_i which obtains values from 0 to 3,[7] the value of 0 referring to the lowest job hierarchy level and the value of 3 to the highest (management) level:

$$(2) \qquad y_i \qquad \begin{aligned} &= 0 \text{ if } y_i^* \leq \mu_0 \\ &= 1 \text{ if } \mu_0 < y_i^* \leq \mu_1 \\ &= 2 \text{ if } \mu_1 < y_i^* \leq \mu_2 \\ &= 3 \text{ if } \mu_2 < y_i^* \leq \mu_3 \end{aligned}$$

The probabilities which enter the likelihood function are

$$(3) \qquad \text{Prob}[\ y_i = j\ ] = \text{Prob}[\ y_i^* \text{ is in the } j^{\text{th}} \text{ range }]\text{, where } j = 0, 1, 2, 3.$$

The ordered probit models to be estimated include different categories of explanatory variables. We have chosen these variables in line with the instructions of the Federation of Finnish Technology Industries, which emphasise that all jobs should be evaluated by the skills and responsibilities which they require, independent of the job holder's occupational category.

Thus, in addition to the constant term and female dummy indicator, which is of our primary interest, the model includes *eight* age dummy indicators and *five* tenure dummy indicators (to approximate work experience). Skills are measured by *three* 'level of education' dummy indicators and *nine* 'filed of education' dummy indicators. The latter indicators are used for identification in the two stage estimation process, in which the ordered probability model represents the first stage (i.e. they are not present in the second stage). Furthermore, *four* establishment level variables are included to allow for differences in establishments' specialisation, production processes and productivity; size of the establishment, share of female employees, share of employees with technical degree, and share of employees with doctoral degree. The ordered probability model to be estimated with this variable set is called the 'basic' model.

It is worth noting, that our 'basic' model does not include occupation dummy indicators. We exclude them for two (quite opposite) reasons. First, they should not have any information value, if one is to believe the instructions of the Federation of Finnish Technology Industries on how employees' position at different hierarchical

[7] This definition comes from the LIMDEP programme, which we use in our estimations. See Greene (2007), Vol. 1, E22, 1-20.

ladders should be determined. Second, despite these instructions occupation and hierarchical position may be determined simultaneously, which may cause problems in our econometric setting, in which hierarchical position is determined endogenously with earnings.

In order to check the potential role of occupation in this setting, we estimate separate ordered probability models with female and occupation dummy indicators only, as well as the 'basic' model into which occupation dummy indicators are added.

3.2. Conditional earnings equations

When studying gender earnings differentials our focus is on the different hierarchical job levels. We ask whether we can still observe gender gaps in earnings after having controlled for the selection process into the separate job hierarchy levels as well as for the effects of other background factors. We are interested especially in the interaction between the selection process and the subsequent earnings levels.

Hence, the log of earnings equation is estimated *conditional* on selection into a specific hierarchical position. More specifically, the earnings equation is estimated as a *sample selection model* in which the appropriate asymptotic covariance matrix for the model is based on the ordered probit model specified above.[8]

(4) $$\ln(earnings_i) = \boldsymbol{\alpha}'\boldsymbol{x_i} + u_i,$$

where $\boldsymbol{\alpha}$ is the vector of parameters to be estimated and $\boldsymbol{x}_i$ is the corresponding vector of explanatory variables, u_i is the normally distributed error term with mean zero, standard deviation σ and correlation ρ with ε (the error term in the ordered probit equation (1)).

In the estimations, $\ln(earnings_i)$ is observed only when $y_i = j$ for some j in (0,1,2,3). Thus, the earnings equations are estimated separately for each hierarchical level j=0,1,2,3. Each equation is estimated using a two-step procedure following Heckman (1979) and Greene (1981). From the first step the ordered probability model produces an "extra" variable, the so-called sample selection term λ. The coefficient of λ shows whether or not the unobserved factors that affect the selection

[8] See Greene (2007), Vol. 2, E31, 61-63.

into different job hierarchy levels, are correlated with the unobserved factors affecting earnings. If the coefficient is statistically different from zero, this means that there are indeed unobserved factors that we have not been able to capture with our observable variables but which make the selection into the different job hierarchy levels and the observed earnings levels interrelated. We return to this point when interpreting the results.

As already noted, the subsequent empirical estimations are based on two alternative earnings concepts: the log of monthly earnings and the log of total monthly earnings. As explanatory variables we use the same variables as in the 'basic' ordered probit model with the exception of the 'field of education' dummy indicators, which are excluded for the identification purposes.

In reporting the estimation results for the earnings equations we focus on the coefficient of the female dummy indicator and the coefficient of λ, which – as described above – indicates the interaction between the selection and earnings determination processes.

4. Gender differences in hierarchical positions

4.1. Overall differences

In the estimation of the ordered probit models, which explain the selection of male and female white-collar workers into the four job hierarchy levels, the following procedure is chosen. We start with (1) the 'basic' model, then estimate (2) the model with female and occupation dummy indicators only and finally estimate (3) the 'basic' model which includes also occupation indicators. As a reference point we use the gender difference in the basic data set. The full estimation results are reported in Appendix Table A1.

Table 3 reports how, based on our estimations, the *probability* to be located at a certain hierarchical job level is affected by the fact of being a woman as compared to being a man. This effect for the female dummy indicator is calculated at the mean values of the included variables and, therefore, it tells how a female employee's propensity of being at a certain job hierarchy level differs from an otherwise similar male employee's propensity (i.e. both have the same average background factors). Since all reported effects are marginal, this implies that when the likelihood of being located at a certain level rises, it must decline at the other levels; i.e., the sum of marginal effects is zero.

Table 3 shows that, even after controlling for many observable differences, white-collar women in the Finnish metal industry have a lower propensity to climb up the hierarchical ladder than their male colleagues. According to our 'basic' model, a woman's propensity to belong to the group of routine workers is (11.4 percentage points) higher than for a similar man with average white-collar worker properties in this particular industry. The contrary holds true in specialised expert and management positions where women are less likely to appear than men (model 1).

Table 3. Female-male difference[1] in the probability of appearing in a particular job hierarchy level, percentage points

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**
Gender difference in the basic data set	**22.5**	**-2.8**	**-14.3**	**-5.4**
Gender difference in the probability of appearing in a particular job hierarchy level according to various model specifications				
(1) Basic model with female, age, education, tenure and establishment indicators	11.4	10.0	-17.0	-4.4
(2) Model with female and occupation indicators only	12.1	8.2	-14.7	-5.5
(3) Model with female, education, age, tenure, establishment and occupation indicators	8.3	9.5	-14.5	-3.2
Basic model (1):				
%, right predictions	17.6	71.6	60.0	4.1
No. of observations	7,318	22,247	17,168	4,366

[1] These effects are calculated separately as the difference between the estimated female and male probabilities evaluated at the mean values of the variables from the whole data set. Note that in all model specifications the negative female coefficient is highly significantly different from zero (P[|Z| > z] is 0.0000).

It appears from Table 3 that gender differences in occupational positions explain, at the lower ladders of job hierarchy, part of the observed differences in hierarchical positions (model 2). At two upper ladders of the job hierarchy, occupation has no effect whatsoever on the gender difference. Hierarchical positions should be evaluated independently (in the member firms) from the occupations in which the job holders are. Table 3 suggests that this seems to be true more at the upper than at the lower part of the job hierarchy. At the lower part there seems to be some 'female' specific occupations of which inclusion into the estimated model lowers the gender difference. Furthermore, it appears that including occupation indicators to the basic model (model 3) improves the model performance only slightly.

In our 'basic' model specification the McFadden Pseudo R-squared is 0.1562, which can be regarded as quite a satisfactory figure for these kinds of models. Also the predictive power of the model is as a whole quite satisfactory. Using the information from the observed variables, the model could in 54 per cent of the cases give a correct prediction about the employee's hierarchical position.

However, Table 3 also reveals an interesting pattern in the predictive power of the 'basic' model regarding the four hierarchical job levels. The model can best predict the level of expert work, which forms the largest group in the data. The predictive power declines towards the two tails of the hierarchical distribution and is particularly poor at the management level; only about *four* per cent of the observations are predicted correctly at this particular level. It seems that the further up the hierarchical ladder a white-collar worker in the Finnish metal industry climbs, the more difficult it becomes to measure and predict this success with the use of traditional, easily measurable career enhancing variables.

In Table 4 the probabilities of appearing in a particular job hierarchy level for male and female employees with the same average characteristics are reported. The figures are based on the estimation of our 'basic' model. Table 4 confirms the earlier results by showing that women have 2.7 times as high propensity to appear in routine work as similar men, the corresponding figure for the management level being only 0.27.

Table 4 can be used as a basis when we evaluate how vertical segregation, in the Finnish metal industry, influences earnings differentials between men and women. If we assume that men and women get the *same* average pay at each job hierarchy level (according to Table 2) but differ only from each other in their *propensities* to appear in these levels (as presented in Table 4), we can calculate how much these differences in propensities can account for the overall gender differences in earnings.

Table 4. Probability of appearing in a particular job hierarchy level by gender evaluated for men and women at the same mean values of observable variables

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**
- Male propensity, %	6.7	47.4	39.9	6.0
- Female propensity, %	18.0	57.4	22.9	1.6
- Female/male propensity	2.70	1.21	0.57	0.27

According to our calculations the fact, that women have a smaller propensity to climb up the hierarchical ladders, explains 52 per cent of the gender earnings gap when using 'monthly earnings', and as much as 60 per cent when using 'total monthly earnings' as a basis point for calculations. These results suggest that *vertical gender segregation* is an important factor affecting gender pay gap. New payment schemes seems to add to the importance of this type of gender segregation.

4.2. Differences by type of establishment

It is likely that establishments, which are highly productive, use their workforce as efficiently as possible. In this sub-section we study whether men's and women's propensity to be situated at different job hierarchy levels differs in metal industry establishments located at different quintiles of the *productivity distribution* characterising the industry. As we do not have a direct measure of each establishment's productivity, we have approximated the productivity differences between establishments by the average level of total monthly earnings of the establishment's male white-collar workers. Some basic characteristics of the quintile distribution are reported in Appendix Tables A2-A3.

In Table 5 the results from ordered probability model estimations ('basic' model) for two sub-samples of establishments are reported: (a) the first four quintiles (Q1–Q4) of the productivity distribution and (b) the highest quintile (Q5).[9] Male and female

[9] The estimation results will be provided by the authors upon request.

employees' probabilities of appearing in a particular job hierarchy level are evaluated at sample means of variables.

Table 5. Probability of appearing in a particular job hierarchy level by for two subsamples of establishments located at different quintiles of the productivity distribution (Q1 lowest – Q5 highest quintile)

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**
Quintiles Q1-Q4				
- Male propensity, %	9.3	55.8	30.6	4.3
- Female propensity, %	25.2	59.9	14.0	0.9
- Female/male propensity	2.71	1.07	0.46	0.21
Quintile Q5				
- Male propensity, %	4.9	40.2	47.2	7.6
- Female propensity, %	13.6	53.1	31.0	2.4
- Female/male propensity	2.76	1.32	0.66	0.31

It appears from Table 5 that segregation into different types of establishments is not irrelevant when it comes to the propensity to work at more demanding jobs. The most productive establishments (Q5) are larger in size and use more highly skilled experts than smaller, less productive establishments (Q1-Q4). Table 5 shows that white-collar workers in these (Q5) establishments are also more likely to be found at more demanding, higher job hierarchy levels. In most productive establishments women have a higher probability - compared to their similar male colleagues - to have at least an expert level job than in less productive establishments. Women's probability of getting a management job is one fifth of that of men's in less productive establishment and one third in more productive ones.

5. Gender gaps in earnings

5.1. Overall earnings differentials

In this section we report results from conditioning the log of earnings on a set of explanatory variables as outlined in sub-section 3.2 above. In particular, we concentrate on interpreting the coefficients estimated for the female dummy and the selection term in order to gain a better understanding about the mechanisms underlying the gender wage gap. Tables A4 (using monthly earnings) and A5 (using total monthly earnings) in the Appendix provides full estimation results for the log of earnings equations at different job hierarchy levels.

Table 6 reports estimates for the female dummy indicator as obtained from estimations of earnings equations for each hierarchical job level using (a) log(monthly earnings) and (b) log(total monthly earnings) as the dependent variable. Note that the earnings effects of a large bulk of background factors have been controlled for and basically the comparisons concern male and female white-collar workers in the Finnish metal industry having very similar characteristics.

Table 6. Estimates of the female dummy indicator in log of earnings equations for different job hierarchy levels

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**
Log(monthly earnings) equation	-0.05370*** (0.0120)	-0.0132* (0.0079)	0.0247** (0.0125)	0.0110 (0.0325)
Log(total monthly earnings) equation	-0.0668*** (0.0114)	-0.0303*** (0.0077)	-0.0122 (0.0128)	-0.0052 (0.0366)

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level.

Two things are quite apparent when looking at Table 6. First, the negative earnings effect of being a woman declines when moving up the hierarchical ladder. It is largest at the routine work level (about 5-7 per cent) whereas at the specialised expert and management levels gender seems to play no significant role in earnings formation when other factors affecting earnings are accounted for.

Second, broadening the earnings concept to include productivity and performance related bonuses and profit sharing increases slightly the estimates of the gender pay gap. The increase is about 1-2 percentage points at lower hierarchical levels while at management level the result of no gender difference remains.

Another interesting feature in the earnings determination process is revealed in Table 7 which reports the estimates for the sample selection term λ.[10] The obtained estimates of λ imply that those unobserved characteristics which influence the likelihood of being in a particular job hierarchy level are *highly negatively correlated*

[10] The separate estimation results for male and female employees will be provided by the authors upon request.

with the unobserved characteristics, which affect the earnings of employees at this particular job hierarchy level. More precisely, the negative sign of λ suggests that the typical *unobserved* features which make it more likely for a person to be a in a particular hierarchical ladder tend to *reduce* his or her earnings capacity when selected to this ladder. This outcome may have several explanations. It is an indication of some kind of *inefficiency* related to the selection process; employees, who would be most productive (measured by their earnings capacity) at a particular hierarchical level, are not selected to this level.

Table 7 suggests that the influence of unobserved factors on the selection process into different hierarchical job levels and, hence, on earnings levels strengthens when *moving up the hierarchical ladder*. Furthermore, our separate estimations for male and female employees show that for men the negative coefficient of the sample selection term λ rises sharply at the managerial level while that for women becomes statistically insignificant. Thus, potential inefficiencies in the selection process do not seem to apply when female managers are selected among women. The opposite seem to hold for male managers of which selection seems to be highly inefficient (among men!).

Table 7. Estimates for the sample selection term (λ) measuring the interrelationship between unobserved factors affecting (a) the selection into a specific job hierarchy level and (b) the monthly earnings at a given job hierarchy level

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**
Log(monthly earnings) equation, all employees	-0.1851*** (0.0204)	-0.1610*** (0.0125)	-0.1797*** (0.0199)	-0.2187*** (0.0554)
- Separate estimation for males	-0.1529*** (0.0256)	-0.1520*** (0.0139)	-0.1923*** (0.0228)	-0.3215*** (0.0783)
- Separate estimation for females	-0.1568*** (0.0255)	-0.1614*** (0.0192)	-0.1579*** (0.0293)	-0.0460 (0.0644)
Log(total monthly earnings) equation, all employees	-0.1651*** (0.0193)	-0.1438*** (0.0121)	-0.1714*** (0.0203)	-0.2345*** (0.0624)
- Separate estimation for males	-0.1332*** (0.0243)	-0.1449*** (0.0141)	-0.1944*** (0.0241)	-0.3361*** (0.0847)
- Separate estimation for females	-0.1461*** (0.0251)	-0.1535*** (0.0194)	-0.1463*** (0.0297)	-0.0593 (0.0788)

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level.

When one looks in a more detailed fashion the estimation results of the ordered probability and earnings equations, one possible explanation to the detected inefficiency in the selection process appears. The ordered probability model estimations show that employees are most likely to be found at higher hierarchical levels when their tenure has lasted 1-3 years (or 10-15 years). They have the lowest propensities to be found at higher hierarchical levels with tenures of 3-10 years and when they have been employed with the same employer for 15 years or more. These results suggest that the establishments do not apply straightforward tenure tracks for promotions. This may lead to inefficiencies if information on employees, which longer tenures make possible to obtain, are not fully utilised in the recruitment processes.

Furthermore, when looking at the estimation results from earnings equations, a similar pattern seems to appear. Tenure plays a minor role in determining the earnings levels. Age, which is used to approximate employees' general work experience, has a stronger and stronger influence on earnings the higher up hierarchical ladders one climes. This suggests that technology industries are rewarding more *general* competences than *'firm' specific* competences. The negative coefficients for λ suggest that this may not be the best strategy available.

5.2. Differences by type of establishment

As noted earlier, an establishment's ability to pay competitive wages is directly related to the productivity of its employees. In this sub-section we present results concerning the gender wage gap in metal industry establishments located at different quintiles of the productivity distribution characterising the industry.

As in the previous sub-section, we concentrate on interpreting the estimates obtained for the female dummy indicator.[11] Table 8 reports estimates for the female dummy indicator when the dependent variable is a) the narrow concept of log monthly earnings and when it is b) the broader concept of log total monthly earnings. This is done for two subsamples of establishments: the first four quintiles (Q1–Q4) of the productivity distribution and the highest quintile (Q5).

[11] The full estimation results for the two establishment types will be provided by the authors upon request.

Table 8. Estimates for the female dummy indicator in two log(earnings) equations at different job hierarchy levels by establishment quintiles

	Job hierarchy level			
	Mainly routine work	**Expert work**	**Specialised expert work**	**Management**
Log(monthly earnings)				
Coefficient for quintiles Q1–Q4	-0.0787***	-0.0556***	0.0118	-0.0406
	(0.0141)	(0.0113)	(0.0242)	(0.0545)
Coefficient for quintile Q5	-0.0536***	0.0003	0.0260*	-0.0417
	(0.0161)	(0.0097)	(0.0141)	(0.0256)
Log(total monthly earnings)				
Coefficient for quintiles Q1–Q4	-0.0920***	-0.0795***	0.0094	-0.0310
	(0.0135)	(0.0109)	(0.0289)	(0.0680)
Coefficient for quintile Q5	-0.0644***	-0.0156*	0.0083	-0.0752***
	(0.0155)	(0.0091)	(0.0139)	(0.0284)

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level

It appears from Table 8 that the gender gap is affected by the productivity level of the establishment. The gender gaps in the establishments located at the top of the productivity distribution (Q5) are – at the lower end of job hierarchy levels – 2-6 percentage points smaller than the gaps in the less productive establishments (Q1-Q4). At the specialised expert level there is no negative gender gap in either of the establishment types reflecting highly competitive specialist labour markets in the technology industry.

On the other hand, at the management level, when using a more narrow earnings concept, no statistically significant gender gap can be detected. However, when using the broader concept of total monthly earnings, a negative gender gap in the more productive establishments and no gap in the less productive establishments appears. This somewhat surprising result may be due to the fact that the more productive establishments are large in size and may have more varied managerial positions (which is not controlled for in our estimations) than the smaller, less productive establishments.

The obtained estimates of the sample selection term λ for the two subsamples are somewhat lower (and weaker) than for the whole sample but remain negative. Thus, also in the case of these subsamples those unobserved characteristics which influence the likelihood of being in a particular job hierarchy level are *negatively* *correlated* with the unobserved characteristics, which affect the earnings of employees at this particular job hierarchy level.

All in all, our results suggest that for gender equality, it is not irrelevant in which type of establishment a women selects to work.

6. Summary

Our estimation results show that white-collar women in the Finnish metal industry face a notable disadvantage when it comes to climbing up the hierarchical ladder. This result remains even when a large set of measurable background factors are accounted for when predicting the probability of a white-collar worker to be posited at a specific hierarchical level. Our results show that the *vertical gender segregation* is an important factor affecting gender pay gap. The fact that women have a smaller propensity to climb up the hierarchical ladders explains about *50-60 per cent* of the observed gender pay gap in the metal industry. New payment schemes adds to the importance of this type of gender segregation.

The predictive power of the ordered probability model for hierarchical ladders declines notably towards the two tails of the hierarchical distribution. It is particularly poor at the management level; about 4 per cent of the observations are predicted correctly at this particular hierarchical level. It seems that the further up the hierarchical ladder a white-collar worker in the Finnish metal industry climbs the more difficult it becomes to measure and predict this success with the use of traditional, easily measurable career enhancing variables.

Moreover, women have a clear disadvantage compared to men also when it comes to earnings in the different hierarchical positions. However, the negative effect of being a woman declines when moving up the hierarchical ladder. It is largest at the lowest (routine work) level, whereas at the specialised expert and management level gender seems to play no significant role in explaining the observed earnings differentials.

Our results also suggest that the unobserved factors related to the selection process into the different hierarchical job levels and to the level of earnings are interrelated. It appears that those unobserved characteristics which influence the likelihood of being in a particular job hierarchy level are highly negatively correlated with the unobserved characteristics which affect the earnings of employees at this particular job hierarchy level. More precisely, the typical *unobserved* features, which make it more likely for a person to be a in a particular hierarchical ladder, tend to *reduce* his or her earnings capacity when selected to this ladder. This result can be an indication of some kind of *inefficiency* related to the selection or recruitment processes; employees, who would be most productive (measured by their earnings capacity) at a particular hierarchical level, are not selected to this level. According to our analyses the technology industries appears to reward more *general* competences than *'firm' specific* competences. Our results suggest that this strategy may not be the best one available.

Broadening the earnings concept to include productivity and performance related bonuses and profit sharing increases slightly the negative female effect on earnings. Our results also show that it is not irrelevant for the size of the gender wage gap in which type of establishment a woman selects or is selected to work. With the exception of the category of managers, the gender gap in earnings tends to be smaller in high-productivity establishments than it is in less productive ones.

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Appendix

Table A1. Estimation results from the ordered probability models

Variables	**Model (1)**	**Model (2)**	**Model (3)**
Constant	2.4223***	1.5358***	2.2855***
	(0.0659)	(0.0093)	(0.0679)
Female	-0.5862***	-0.5519***	-0.4888***
	(0.0140)	(0.0131)	(0.0148)
Age group (Reference: 30 ≤ Age < 35)			
Age < 25	-0.6734***	--	-0.6558***
	(0.0598)		(0.0612)
25 ≤ Age < 30	-0.4637***	--	-0.4557***
	(0.0183)		(0.0186)
35 ≤ Age < 40	0.3860***	--	0.3922***
	(0.0158)		(0.0160)
40 ≤ Age < 45	0.5703***	--	0.5733***
	(0.0173)		(0.0175)
45 ≤ Age < 50	0.5999***	--	0.6025***
	(0.0194)		(0.0197)
50 ≤ Age < 55	0.5716***	--	0.5849***
	(0.0216)		(0.0219)
55 ≤ Age < 60	0.5988***	--	0.6172***
	(0.0240)		(0.0245)
Age ≥ 60	0.6780***	--	0.6883***
	(0.0381)		(0.0387)
Level of education (Reference: higher university or doctoral level)			
Vocational education	-1.6126***	--	-1.5083***
	(0.0188)		(0.0198)
Polytechnic education	-1.2138***	--	-1.0893***
	(0.0159)		(0.0166)
Lower university level	-0.5804***	--	-0.5097***
	(0.0133)		(0.0137)
Field of education (Reference: technology)			
General programmes	0.7807***	--	0.7476***
	(0.0263)		(0.0271)
Teacher education and educational science	-0.0306	--	-0.3271***
	(0.1041)		(0.1083)
Humanities and art	-0.4320***	--	-0.3942***
	(0.0379)		(0.0391)
Social sciences and business	-0.1128***	--	-0.0944***
	(0.0162)		(0.0183)
Natural sciences	-0.0274	--	-0.0350
	(0.0253)		(0.0257)
Agriculture and forestry	-0.3006***	--	-0.3005***
	(0.0688)		(0.0700)
Health and welfare	-0.1331**	--	-0.2293***
	(0.0665)		(0.0794)
Services	-0.2063***	--	-0.1090*
	(0.0549)		(0.0572)

Table A1. Estimation results from the ordered probability models, continues

Variables... continues	**Model (1)**	**Model (2)**	**Model (3)**
Tenure, years (Reference: 1 ≤ Tenure < 3)			
Tenure < 1	-0.1077***	--	-0.1058***
	(0.0215)		(0.0219)
3 ≤ Tenure < 5	-0.0833***	--	-0.0939***
	(0.0192)		(0.0197)
5 ≤ Tenure < 10	-0.0916***	--	-0.0799***
	(0.0145)		(0.0149)
10 ≤ Tenure < 15	0.0045	--	0.0255
	(0.0191)		(0.0195)
Tenure ≥ 15	-0.0726***	--	-0.0466***
	(0.0174)		(0.0178)
Establishment characteristics			
Establishment size/1,000	0.0859***	--	0.0751***
	(0.0028)		(0.0031)
Share of female employees	-0.5438***	--	-0.4622***
	(0.0854)		(0.0875)
Share of employees with technical degree	-0.6399***	--	-0.4240***
	(0.0663)		(0.0682)
Share of employees with doctoral education	-3.6743***	--	-3.2181***
	(0.3357)		(0.3507)
Threshold parameters			
μ(1)	1.6029***	1.4866***	1.7165***
	(0.0070)	(0.0066)	(0.0074)
μ(2)	3.0566***	2.7743***	3.2197***
	(0.0097)	(0.0086)	(0.0100)
Occupational indicators	No	Yes	Yes
Number of observations	51.099	51.099	51.099
Number of parameters	32	55	83
Log likelihood function	-52472.83	-56066.14	-50113.09
Chi squared	19428.57	12241.94	24148.04
Degrees of freedom	29	52	80
Prob [Chi squared > value]	0.0000	0.0000	0.0000
McFadden Pseudo R-squared	0.1562	0.0984	0.1942
Share of right predictions	0.5419	0.4901	0.5663

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level.

Table A2. Average size of the establishments and total monthly earnings (in 2005) of white-collar workers in establishments located at different quintiles of the productivity distribution (Q1 lowest – Q5 highest quintile)

	Q1	**Q2**	**Q3**	**Q4**	**Q5**
Average size of the establishment (number of white collar workers)	25	45	100	129	374
Average male monthly earnings per establishment. €	3,265	3,732	4,057	4,269	5,051
Average female monthly earnings per establishment. €	3,028	3,074	3,421	3,461	4,241
Female/male earnings ratio	92.7	82.4	84.3	81.1	84.0

Table A3. Number of employees and share of women by job hierarchy level in metal industry establishments located at different quintiles of the productivity distribution (Q1 lowest – Q5 highest quintile)

	Mostly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**	**Total**
Quintiles Q1-Q4					
Number of employees	3,944	11,124	6,123	1,416	22,607
- Men	1,766	8,748	5,298	1,262	17,074
- Women	2,178	2,376	825	154	5,533
% of women	55.2	21.4	13.5	10.9	24.5
Quintile Q5					
Number of employees	3,374	11,123	11,045	2,950	28,492
- Men	1,360	7,861	8,737	2,484	20,442
- Women	2,014	3,262	2,308	466	8,050
% of women	59.7	29.3	20.9	15.8	28.3

Table A4. Results from the conditional OLS regression model estimations, dependent variable log(monthly earnings)

	Job hierarchy level			
Variables	**Mostly routine work**	**Expert work**	**Specialised expert work**	**Manage-ment**
Constant	7.5983***	7.8481***	8.3633***	8.6891***
	(0.06524)	(0.0277)	(0.0323)	(0.1051)
Female	-0.0537***	-0.0132*	0.0247**	0.0110
	(0.0120)	(0.0079)	(0.0125)	(0.0325)
Age group				
(Reference: 30 ≤ Age < 35)				
Age < 25	-0.0516***	-0.0612***	-0.1478**	--
	(0.0215)	(0.0205)	(0.0735)	
25 ≤ Age < 30	-0.0024	-0.0209***	-0.0679***	-0.1297**
	(0.1249)	(0.0072)	(0.0129)	(0.0549)
35 ≤ Age < 40	0.0013	0.0094	0.0192**	0.0419
	(0.0126)	(0.0071)	(0.0095)	(0.0262)
40 ≤ Age < 45	-0.0005	0.0206**	0.0367**	0.0868***
	(0.0147)	(0.0086)	(0.0120)	(0.0321)
45 ≤ Age < 50	0.0017	0.0296***	0.0683***	0.1188***
	(0.0158)	(0.0094)	(0.0131)	(0.0339)
50 ≤ Age < 55	-0.0035	0.0357***	0.0718***	0.1363***
	(0.0162)	(0.0097)	(0.0136)	(0.0340)
55 ≤ Age < 60	0.0029	0.0309***	0.0843***	0.1283***
	(0.0175)	(0.0104)	(0.0148)	(0.0370)
Age ≥ 60	0.0188	0.0454***	0.1071***	0.1725***
	(0.0274)	(0.0159)	(0.0204)	(0.0484)
Level of education				
(Reference: higher university or doctoral level)				
Vocational education	-0.1318***	-0.0138**	0.0323	0.0548
	(0.0257)	(0.0145)	(0.0219)	(0.0567)
Polytechnic education	-0.1065***	-0.0360***	0.0339	0.0505
	(0.0233)	(0.0131)	(0.0216)	(0.0585)
Lower university level	-0.1005***	-0.0208***	0.0021	0.0177
	(0.0175)	(0.0077)	(0.0109)	(0.0274)
Tenure, years				
(Reference: 1 ≤ Tenure < 3)				
Tenure < 1	-0.0239*	0.0005	0.0290**	0.0676**
	(0.0125)	(0.0075)	(0.0113)	(0.0287)
3 ≤ Tenure < 5	0.0330***	0.0171**	0.0016	0.0168
	(0.0120)	(0.0069)	(0.0096)	(0.0226)
5 ≤ Tenure < 10	0.0201*	0.0143***	-0.0136**	-0.0019
	(0.0103)	(0.0054)	(0.0068)	(0.0168)
10 ≤ Tenure < 15	0.0193	0.0052	0.0022	-0.0099
	(0.0138)	(0.0076)	(0.0083)	(0.0171)
Tenure ≥ 15	0.0272**	0.0052	0.0051	-0.0182
	(0.0117)	(0.0068)	(0.0081)	(0.0166)

Table A4. Results from the conditional OLS regression model estimations. dependent variable log(monthly earnings), continues

Variables ...continues	**Job hierarchy level**			
	Mostly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**
Establishment characteristics				
Establishment size/1,000	0.0001	-0.0020	0.0000	0.0225***
	(0.0023)	(0.0014)	(0.0019)	(0.0048)
Share of female employees	-0.0087	0.1010***	-0.0234	0.0446
	(0.0488)	(0.0316)	(0.0436)	(0.1025)
Share of employees with technical degree	0.0617	0.0198	-0.1607***	0.0140
	(0.0401)	(0.0241)	(0.0336)	(0.0817)
Share of employees with doctoral education	1.7094***	1.1456***	1.1687***	1.5531***
	(0.1809)	(0.1341)	(0.1687)	(0.3878)
Sample selection term lambda	-0.1851***	-0.1610***	-0.1797***	-0.2187***
	(0.0204)	(0.0124)	(0.0199)	(0.0554)
Dependent variable				
Mean	7.7648	7.9341	8.2290	8.5563
Standard deviation	0.1971	0.1778	0.1947	0.2455
Number of observations	7.318	22.247	17.168	4.344
Number of parameters	23	23	23	22
Degrees of freedom	7295	22224	17145	4344
Log likelihood function	3644.06	11065.24	6883.55	956.87
Chi squared (b=0)	4287.81	8424.41	6302.75	2040.51
Prob [Chi squared > value]	0.0000	0.0000	0.0000	0.000
Adjusted R-squared	0.4417	0.3146	0.3064	0.3703

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level.

Table A5. Results from the conditional OLS regression model estimations, dependent variable log(total monthly earnings)

Variables	**Job hierarchy level**			
	Mostly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**
Constant	7.7457***	8.0750***	8.6146***	8.9028***
	(0.0618)	(0.0269)	(0.0331)	(0.1183)
Female	-0.0668***	-0.0303***	0.0122	-0.0052
	(0.0114)	(0.0079)	(0.0127)	(0.0366)
Age group				
(Reference: 30 ≤ Age < 35)				
Age < 25	-0.0592***	-0.0841***	-0.1779**	--
	(0.0204)	(0.0199)	(0.0753)	
25 ≤ Age < 30	-0.0074	-0.0359***	-0.0815***	-0.1604***
	(0.0119)	(0.0070)	(0.0132)	(0.0618)
35 ≤ Age < 40	0.0125	0.0154**	0.0313***	0.0568*
	(0.0120)	(0.0069)	(0.0097)	(0.0296)
40 ≤ Age < 45	0.0174	0.0310***	0.0529***	0.1109***
	(0.0139)	(0.0084)	(0.0123)	(0.0362)
45 ≤ Age < 50	0.0196	0.0411***	0.0845***	0.1501***
	(0.0149)	(0.0091)	(0.0134)	(0.0381)
50 ≤ Age < 55	0.0143	0.0452***	0.0874***	0.1688***
	(0.0153)	(0.0095)	(0.0139)	(0.0383)
55 ≤ Age < 60	0.0260	0.0434***	0.0977***	0.1410***
	(0.0166)	(0.0101)	(0.0151)	(0.0417)
Age ≥ 60	0.0291	0.0623***	0.1298***	0.1770***
	(0.0259)	(0.0154)	(0.0209)	(0.0545)
Level of education				
(Reference: higher university or doctoral level)				
Vocational education	-0.1391***	-0.0525***	0.0259	0.0567
	(0.0243)	(0.0141)	(0.0225)	(0.0639)
Polytechnic education	-0.1179***	-0.0485***	0.0337	0.0603
	(0.0221)	(0.0127)	(0.0221)	(0.0659)
Lower university level	-0.1046***	-0.0353***	-0.0041	0.0172
	(0.0165)	(0.0075)	(0.0111)	(0.0309)
Tenure, years				
(Reference: 1 ≤ Tenure < 3)				
Tenure < 1	-0.0624***	-0.0364***	-0.0126	-0.0197
	(0.0118)	(0.0072)	(0.0116)	(0.0323)
3 ≤ Tenure < 5	0.0289**	0.0253***	0.0095	0.0136
	(0.0113)	(0.0069)	(0.0098)	(0.0256)
5 ≤ Tenure < 10	0.0110	0.0176***	-0.0078	-0.0084
	(0.0098)	(0.0052)	(0.0069)	(0.0189)
10 ≤ Tenure < 15	0.0174	0.0107	0.0148*	-0.0181
	(0.0130)	(0.0074)	(0.0084)	(0.0192)
Tenure ≥ 15	0.0232**	0.0063	0.0050	-0.0307*
	(0.0111)	(0.0066)	(0.0082)	(0.0186)

Table A5. Results from the conditional OLS regression model estimations. dependent variable log(total monthly earnings), continues

Variables ...continues	Job hierarchy level			
	Mostly routine work	**Expert work**	**Specialised expert work**	**Manage-ment**
Establishment characteristics				
Establishment size/1.000	0.0110***	0.0078***	0.0181***	0.0474***
	(0.0022)	(0.0014)	(0.0020)	(0.0054)
Share of female employees	-0.0949**	-0.0438	-0.2396***	-0.0916
	(0.0462)	(0.0307)	(0.0446)	(0.1154)
Share of employees with technical degree	-0.0138	-0.1649***	-0.3899***	-0.0833
	(0.0380)	(0.0235)	(0.0343)	(0.0921)
Share of employees with doctoral education	1.6364***	0.7522***	1.2753***	2.0122***
	(0.1717)	(0.1304)	(0.1723)	(0.4368)
Sample selection term lambda	-0.1651***	-0.1438***	-0.1714***	-0.2345***
	(0.0193)	(0.0121)	(0.0203)	(0.0624)
Dependent variable				
Mean	7.8156	7.999	8.336	8.7389
Standard deviation	0.2077	0.2005	0.2351	0.3236
Number of observations	7.318	22.247	17.168	4.366
Number of parameters	23	23	23	22
Degrees of freedom	7295	22224	17145	4344
Log likelihood function	3125.04	8214.64	4231.21	44.66
Chi squared (b=0)	4013.91	8054.98	7469.45	2627.34
Prob [Chi squared > value]	0.0000	0.0000	0.0000	0.000
Adjusted R-squared	0.4204	0.3031	0.3520	0.4495

Standard errors of coefficients are in parentheses. *** = significant at the 1% level. ** = significant at the 5% level. *=significant at the 10% level.