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The impact of education and mismatch on wages: Germany, 1984 – 2000

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ABSTRACT

In analysing the impact of education on wage differentials and wage growth, we use next to personal characteristics (e.g. education and experience) also job characteristics (e.g. skills required) to explain wages. We estimate wage equations on individual data for Germany, 1984 – 2000. When discussing observed and previously unobserved heterogeneity it turns out that personal characteristics like education and experience explain about half of the variation in wages. At least 20 per cent is explained by variation in job characteristics. When comparing the results with similar research for the Netherlands an the USA, the returns to experience are the same in all countries, while the premiums on required skills and in particular education are much higher in the USA.

Keywords: wage inequality, overschooling, mismatch, unobserved heterogeneity

1. Introduction

There is a growing amount of literature that argues that wages are determined by both personal characteristics and job characteristics. A theoretical motivation for this notion is provided by the assignment or allocation literature stresses the interaction between demand and supply when explaining earnings differentials – cf. Hartog (1992) and Sattinger (1993). However, also imperfect-information search theoretical arguments and even human capital theory can provide a motivation to include job-related variables in the widely used Mincer (1974) earnings function (Hartog, 2000a), or the theory of career mobility (Sicherman and Galor, 1990; Büchel and Mertens, 2000).

Along these lines, Muysken and Ruholl (2001) show that for the Netherlands 1986 – 1998 indeed wage differentials should be explained by both personal and job characteristics. Roughly speaking half of the variation in wages can be explained by changes in personal characteristics, while the other half is explained by changes in job characteristics. Similar results were found by Muysken et al (2002) for the United States, 1986-1996. In this study we will reproduce their analysis for Germany, 1984 – 2000, using GSOEP data and compare the results with those found for the Netherlands and the USA.

To illustrate the relevance of different developments in these characteristics we look at education as a person-related variable and skills required as a job-related variable – these variables turn out to be important determinants of wage differentials as we show below. Figure 1 shows the increase in educational attainment in Germany for the period 1984 – 2000 from our data. During that decade the share of the working persons without further education than secondary school fell from 30,5 to 15,2 per cent. However, the share with college and full academic education (Fachhochschule or University) increased from 9,5 to 20,7 per cent over that period. A similar development can be observed for the Netherlands – and to a lesser extent in the USA.

Figure 2 shows that the share of jobs requiring high skills (high and medium white collar jobs) increased from 6,75 to 13,5 per cent over the observation period – this is much less than the increase in the corresponding share in educational attainment. Although popular belief might suggest that the USA has an abundance of low skilled jobs when compared to Europe, the share around 30 percent in the USA is hardly higher than the share around 28% in the Netherlands. However, the corresponding share of low skilled jobs in Germany is hard to identify. The share of "no collar"-jobs is much lower: it remained stable around 12 percent. The share of "blue collar"-jobs dropped from 47% to 37%. But, as Freeman and Schettkat (1999) argue, apparently low-skilled persons in Germany have much higher skills when compared to the USA. Therefore the skill classifications in Germany are very hard to compare with those in the USA. We elaborate on the classification of skills below.

Figure 1 Share of the workforce in Germany with respect to education, 1984 – 2000

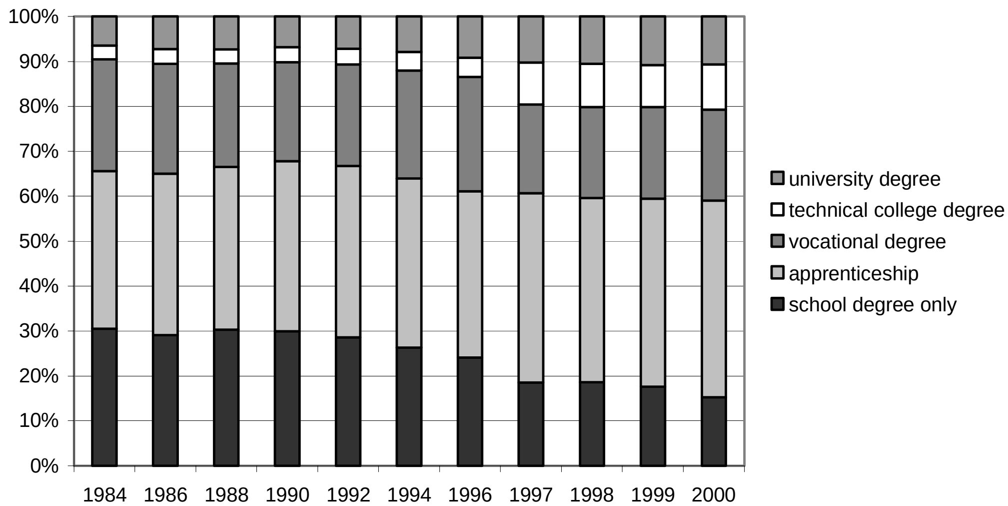
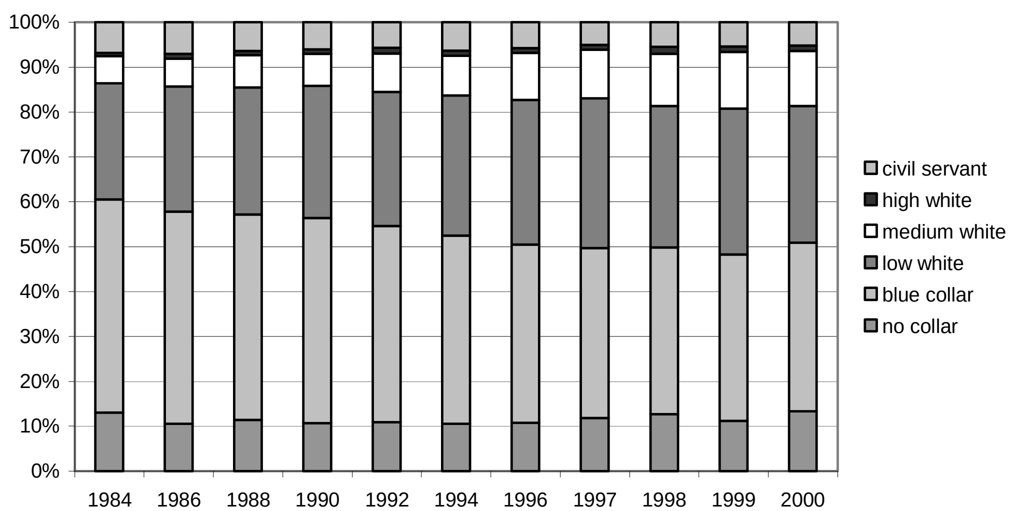


Figure 2 Share of the workforce in Germany with respect to required skills, 1984 – 2000



Comparison of Figures 1 and 2 suggests that the average level of education did increase stronger over time than the average level of skills required. This is consistent with the findings of Asselberghs cs. (1998) for the Netherlands and Auerbach and Skott (2000) and Wolff (2000) for the USA. Moreover, this phenomenon has been observed in many countries, cf. the survey by Groot and Maassen van den Brink (2000).[1]

The incidence of overeducation is also well documented for Germany. Table 1 summarises the findings from several studies for German males. One sees that the incidence of overeducation is about

[1] Auerbach and Skott (2000, n. 7) point out rightly that the conclusion of Groot and Maassen van den Brink that the incidence of overeducation has declined, is inconsistent with their own regression results.

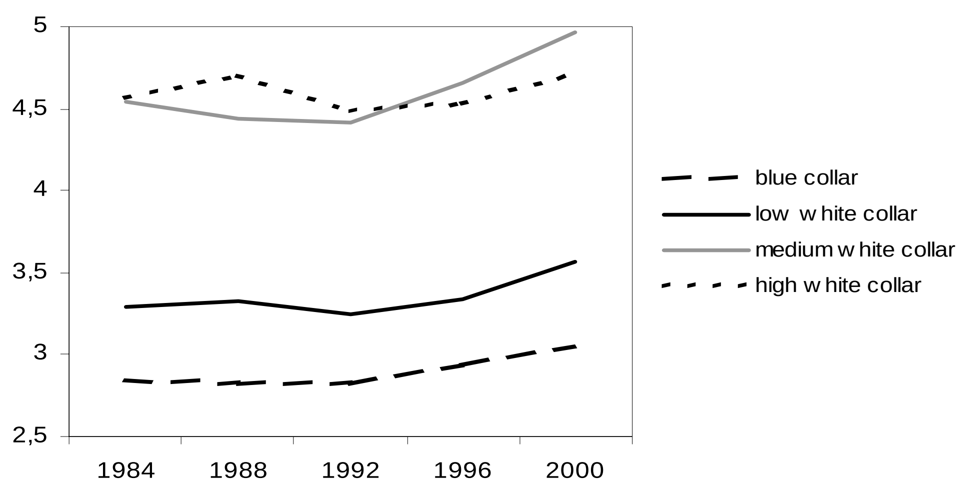
15 per cent, whereas that of undereducation is much lower.[2] We elaborated on the methods used to determine job requirements below.

Table 1 *Over- and undereducation for German males (shares)*

Period	*Overeducation*	*Undereducation*	*Source*	*Method*
1984	14	6.9	Daly et. al. (2000)	Subjective
1984 – 1998	12	10	Bauer (2002)	Mean
1984 – 1998	30	20	Bauer (2002)	Mode
1984 – 1997	12-14	2	Büchel & Mertens (2000)	Combined subjective

Figure 3, which uses our classification, demonstrates that upskilling and overeducation in the Germany took place in all job categories.[3] Acemoglu (2002) explains this finding by skill-biased technological change, which accelerated since the early 1970s. Thus the average education of workers on jobs with a certain level of skills required has increased over time. This can be observed for each level, but the increase is higher the lower the required skill is. The latter phenomenon indicates that next to general upskilling, also bumping down has occurred.[4]

Figure 3 *Average educational level of the workforce in Germany for each level of required skills, 1984 – 2000*



The above findings suggest that in explaining the development of wages, we should also take into account the job characteristics of the workforce, next to personal characteristics. Section 2 shows that this notion is already well established in the literature and presents a wage equation which takes this

[2] The shares found for female workers are consistently higher for both over- and undereducation.
[3] The data for high skilled jobs from 1992 onwards are affected by the impact of the reunification. We ignore the data for 1994 because definition problems clearly show up here.
[4] The exception is high level white collar workers. However, their share in total employment is very low.

feature into account. Section 3 describes the data for which this equation will be estimated. The new element in our results compared to earlier studies is that we track the development of wages over a longer period, 1984 – 2000, and show that returns to education, experience and required skills are rather stable over time – cf. section 4.

An interesting aspect of our approach is that we are able to analyse the impact of including job characteristics in the wage equation on unobserved heterogeneity. Section 5 takes a first step in that direction and shows how personal characteristics and job characteristics each influence the mean wage and the variation in the wage in a different way. It turns out that personal characteristics like education and experience explain about half of the variation in wages. At least 20 per cent is explained by variation in job characteristics.

Finally, since there exist similar analyses for the Netherlands and the USA, we can compare the results for all three countries. Section 6 shows that the returns to experience are very close to each other in all countries, while the premiums on education are much higher in the USA compared to in Germany and the Netherlands. However, the premium on required skills in Germany is similar to that in the USA, and much higher than in the Netherlands. Section 7 concludes our analysis.

2. The wage equation used

Our approach suggests that in explaining the development of wages, we should take job characteristics into account, next to personal characteristics of the workforce. A specification of the wage equation which neatly allows for both types of characteristics, since it explicitly allows for both overeducation (O) and undereducation (U) next to required education (R), is what Hartog (2000a) calls the ORU-specification:

$$w_i = \alpha r_i + \beta . max\{0,(a_i - r_i)\} - \gamma . max\{0,(r_i - a_i)\} + \delta z_i + \varepsilon_i \qquad (1)$$

where w_i is the log of wage of individual i, a_i her actual years of schooling and r_i the years of schooling required for the job on which she is working – z_i represents the other relevant characteristics. In this equation α represents the premium on required education, β the premium for overeducation and γ the premium for undereducation.

Hartog (2000a and b) surveys various studies in which this relationship has been estimated. He consistently finds with respect to the premiums $\alpha > \beta > \gamma > 0$. That is, when a person is working on a job where the required education equals her actual education, she earns more than when she is undereducated for that job. And when she is overeducated for that job, she would earn more when she would find a job that required her actual level of education. A consequence of Hartog's finding also is that the ORU- specification performs better than the Mincerian wage equation ($\alpha = \beta = \gamma$) or the Thurow (1975) model of job competition ($\beta = \gamma = 0$).

Groot and Maassen van den Brink (2000) find in their survey that $\alpha > \gamma > \beta > 0$ prevails. The only difference with respect to Hartog's conclusion is the ranking of the premiums for over- and undereducation. We use the ambiguity with respect to this ranking to motivate the restriction $\beta = \gamma$. In that case we can separate the required skills and actual schooling in the wage equation, which leads to the following specification:

$$w_i = \theta r_i + \beta a_i + \delta z_i + \varepsilon_i \qquad (2)$$

Compared to equation (1) this implies that we assume $\beta = \gamma$, and $\theta = \alpha - \beta$ should be positive. The advantage of equation (2) is that the specification does not require a direct comparison of actual and required education in terms of years of schooling. Our data do not allow such a comparison: Both actual and required skills are not defined in years of schooling, but in discrete educational and skills levels, respectively. We therefore prefer to impose the restriction that the premiums on under- and overeducation are equal. Moreover, the discrete nature of our measures implies that we estimate the equation in the following form:

$$w_i = \Sigma_{j=1..E}\ \theta_j r_{ij} + \Sigma_{j=1..S}\ \beta_j a_{ij} + \delta z_i + \varepsilon_i \qquad (3)$$

where E is the number of educational levels we distinguish and S is the number of skill levels. The parameters θ_j and β_j are the premiums for educational level and skill level j, respectively, and both should be increasing in j, since we expect a higher level to earn a higher premium.

We will estimate equation (3) using data for Germany 1984 – 2000. The difference with the studies reviewed in Hartog (2000a,b) and Groot and Maassen van den Brink (2000) is that our study systematically covers a longer period. Moreover we differentiate between different levels of education and different skill levels, although we then have to impose equal returns to under- and overeducation. Section 4 presents the estimation results.

By explicitly observing job characteristics, our analysis also allows us to observe part of the otherwise "unobserved skills". Thus we can further analyse the question of unobserved heterogeneity. This is measured by Acemoglu (2002) from the properties of the estimated values of ε in equation (3), when this equation is estimated ignoring job characteristics, i.e. under the restriction $\theta = 0$. We can compare these with the properties of the residual when equation (3) is estimated without this restriction.

Bauer (2002) tackles the problem of unobserved heterogeneity by using the panel structure of the data. He does not discuss the variance of residuals, but shows that a fixed effects model explains the data better than a random effects model, which in turn is superior to the pooled OLS model. He suggests that this shows that "the probability of educational mismatch is correlated with innate ability" (p. 222). However, he emphasises that his results should be interpreted with some care because of the low within-sample variation of the schooling variables. In terms of equation (1) above, his finding is that the differences in return to education for over- and undereducation become smaller or disappear altogether when compared to those of adequate education.

Bauer's finding can be partly explained by the way he measures job characteristics, or more precisely required schooling: He uses the mean or modal values of observed schooling within occupational groups. To the extent that over- and under education occurs systematically, these observed values do not reflect required education well. Moreover, this method also explains Bauer's finding of low within schooling variance. On the other hand his pooled OLS results show much larger differences in returns to over- and under education than his fixed-effect estimates. The interpretation that the latter result is due to unobserved innate abilities should be qualified, however. For, the fixed effects are also due to large tenure effects in jobs. Muysken (2002) elaborates this point by showing that for many firm or job related variables one should realise that average tenure in Germany is in the range 6 – 9 years of current employment. Thus not only unobserved personal characteristics are incorporated in the fixed effects, but also unobserved job characteristics. The fixed effects method then ignores any tendency for systematic mismatch over the period under study. Amongst others for those reasons, section 5 takes a different approach to determine the impact of job characteristics on wage differentials.

3. The data used

We have used survey data obtained by the GSOEP for the years 1984 – 2000 (even years only). These data are a representative sample of the workforce. We eliminated those cases from the survey data for which either some observations were missing (in most cases) or some reported data seemed totally unreliable (in some cases only). We used these data to estimate wage equations with explanatory variables which can be attributed either to the personal characteristics of the worker, or the job (s)he performs.

Personal characteristics of the worker are first of course, gender and age. However, since age correlates strongly with total experience, we only allow for an age dummy, which indicates whether the worker is younger than 20 years of age, or not. The motivation is to allow for the impact of the low wages of trainees and apprentices. The second personal characteristic then is working experience. Moreover, in order to allow for decreasing returns to learning-on-the-job, total experience squared is added. The third personal characteristic is education received. Here we distinguish between educational level on the one hand and the type of educational instruction on the other. Finally we have included number of hours worked as a personal characteristic, although this is already on the borderline with job characteristics.

The characteristics of the job occupied by the worker are first the size of the firm in which this job is located and, secondly, the level of skills required on the job. The latter will be explained in the intermezzo.

Intermezzo: The measurement of required skills

We actually use three measures of required skills next to each other. The first measure is somewhat similar to that used in Daly cs. (2000) and asks whether the person is working in the occupation he or she trained for.[5] If the respondent answers yes, our dummy variable *trocc* equals unity.

The question used in Daly cs (2000) is also used in Büchel and Mertens (2000). However, they complement that question with another question, relating to the occupational position of the job holder. The latter question is also used by us to construct the variable *collar*, which we use in Figure 2. While Büchel and Mertens (2000) combine both variable in a complex scheme to indicate mismatch status, we use both variables separately.

Finally we also use a measure which is derived using the Ganzeboom scale, leading to a division into high, medium and low skilled jobs – see Gangl (2001). This constitutes our variable *funlev*.

We use all three variables independently as indicators of required skills. One of the advantages of using the specification of equation (3), is that we don't have to combine them a priori in one indicator.

Actually we used in the case of the Netherlands a different measure of required skills, which was based on a very detailed classification of various jobs according to required skills – cf Muysken and Ruholl (2001). The data are transformed with the so-called ARBI scale, which starts from the detailed occupational classification and divides occupations into 7 required skill levels, coded 1 to 7 from low to high. The classification uses the complexity of occupations as a criterion and takes into account, amongst others, the job content, the required knowledge and mental ability.[6] We have used the same transformation for the USA data in Muysken et al (2002).

An alternative method, which we did not use, can be found in Bauer (2002) for Germany. He employs realised job matches to infer required education either by the mean level of schooling within a certain occupation (Verdugo and Verdugo, 1998), or the modal value (Kiker et al 1997). In both cases a one-standard-deviation range around mean or mode is taken.

The outcomes of the three German studies are summarised in Table 1 above.

[5] Daly cs. (2000) use the question "What sort of training is usually necessary to perform this job?", but the corresponding variable was not significant in our estimations.
[6] Some more details are provided in Hartog (1992), pp. 154-155 and Annex 5.2.

Turning back to the data we use in this study, information on the means characteristics is summarised for each year in the Annex, together with the natural log of the hourly net wage, which is the dependent variable.

The data show, not surprisingly, an increasing share of women in the workforce (cf. the gender dummy).[7] Moreover, there has been to a slight increase in the number of hours worked (Mhours). Also the share of workers of young age, below 20 years, has almost halved, which fits the picture of an increase in higher education. The average experience of the workers stayed constant over time. The share of lower educational levels decreases modestly over time, i.e. persons who only possess a high school degree, which is compensated by an increase of the share above that level. Thus the average educational level of the workforce increases over time, cf. also Figure 1 above. The share of persons occupying jobs with higher required skill levels (funlevhi) increases too, whereas that with medium skill levels (funlevme) decreases. The share of low skilled stayed constant over time. However, the share of blue collar workers and civil servants clearly fell, while the overall share of white collar workers rose. The share of people working in management tripled over the time period, while the share of workers in production dropped by almost a third. The share of scientists also rose. The shares or means of the other variables show no clear development over time.

4. The estimation results

We used the data presented above to estimate the wage equation in the ORU-specification – cf equation (3) above. Since the ordinary least squares estimation results suffer from heteroskedasticity,[8] we re-estimated the equations with the HCCM (Heteroskedasticity Consistent Covariance Matrix) method offered by EViews (White, 1980). This method automatically computes the heteroskedasticity-robust standard errors, hence the t-statistics are also meaningful.

Table A2 in the Annex shows that the estimated parameter values for most variables are remarkably constant over time – i.e. the parameter values lie within a relatively narrow range. Since this definitely is the case for those variables which have a large impact, compare Figures 4–7 below, we feel quite confident that our estimation results do not suffer strongly from a specification bias.[9]

The estimation results indicate that almost all variables attributed to personal characteristics are highly significant for all years. As might be expected, being female or young has a negative impact on hourly wages, as does working more hours. Both current and previous experiences have a positive impact, although with decreasing returns. The returns to education are positive too.

[7] In most European countries the share of men is larger, although it is decreasing over time. For instance, in the Netherlands the share of men decreased from 64 percent in 1986 to 56 percent in 1998.
[8] This was obvious from visual inspection of the estimated residuals and confirmed by White’s general test.
[9] In the spirit of the assignment approach we should estimate the job match simultaneously with our wage equation. However, Hartog (1992, Ch. 7) also finds that the specification bias does not have a significant impact. Moreover, in most instances the ORU-specification is estimated without any further discussion.

Most of the variables attributed to job characteristics are significant too for all years. And when the job requires a higher level of skills, this generally also yields a higher wage.

Since both the direction of educational instruction and the sector in which the person is working are very broad aggregates and the pattern in the estimation results is not very clear, we will not elaborate the results for these two variables. All other results are discussed below.

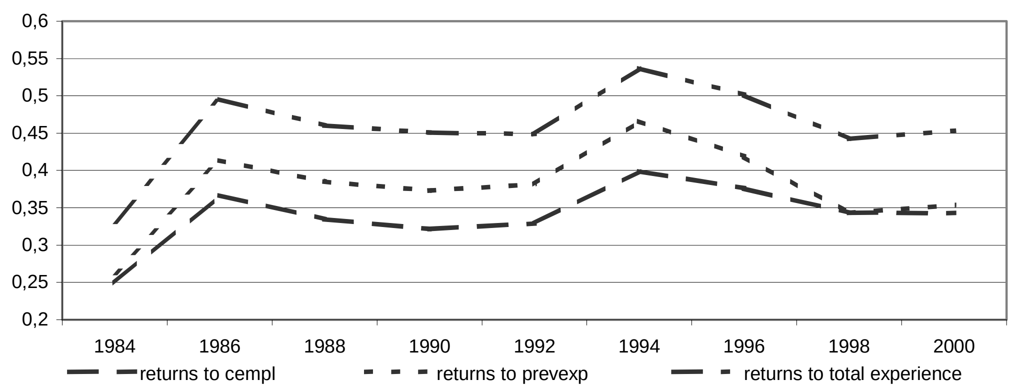
Age, gender and hours worked

From the estimation results it can easily be inferred that being female implies that one would earn about 25 per cent less of the mean wage, when compared to otherwise similar males, although this percentage fluctuates over the years. It can also be inferred that when working part-time, decreasing returns to hours worked prevail.[10] The large negative impact of the agedummy is due to the impact of the low wages of trainees and apprentices.

Experience and education

We look at the returns to experience and education in more detail since they are crucial elements of a skill variable. Figure 4 shows the estimated premium on total experience after 21 years as well as the returns to current employment (9 years) and previous employment (12 years) for each year in our sample. One sees that this estimated premium is quite stable over the sample period. Moreover, due to the property of diminishing returns, the maximum premium on experience is obtained after around 30 years.

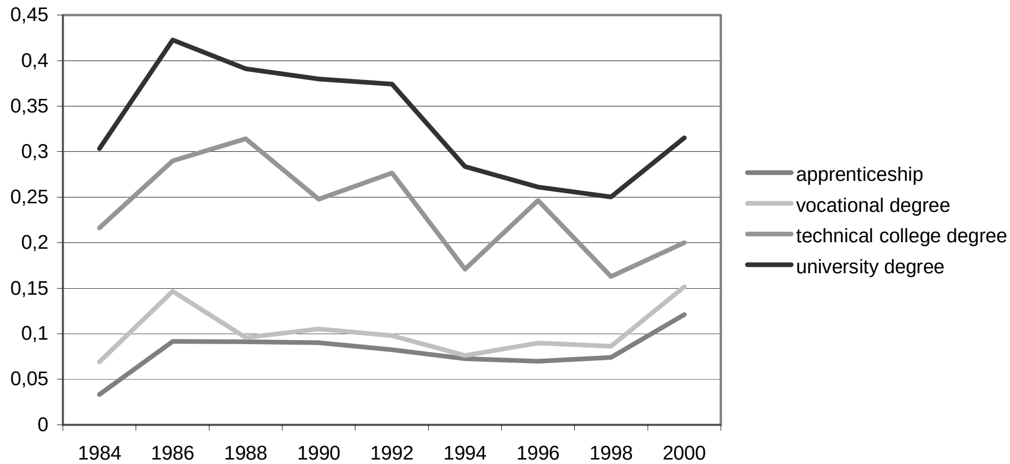
Figure 4 Premium on 21 years of experience, 1984 – 2000



[10] This can be explained since we analyse the impact on net wages, i.e. after deduction of taxes and social security premiums. Because these premiums are relatively lower for low incomes, the net hourly wages may be higher when less hours are worked.

Figure 5 depicts the estimated premium on the various forms of education. As one might expect, this premium increases with the level of education.[11] Moreover, the estimated premium for higher levels of education is slightly falling over time.

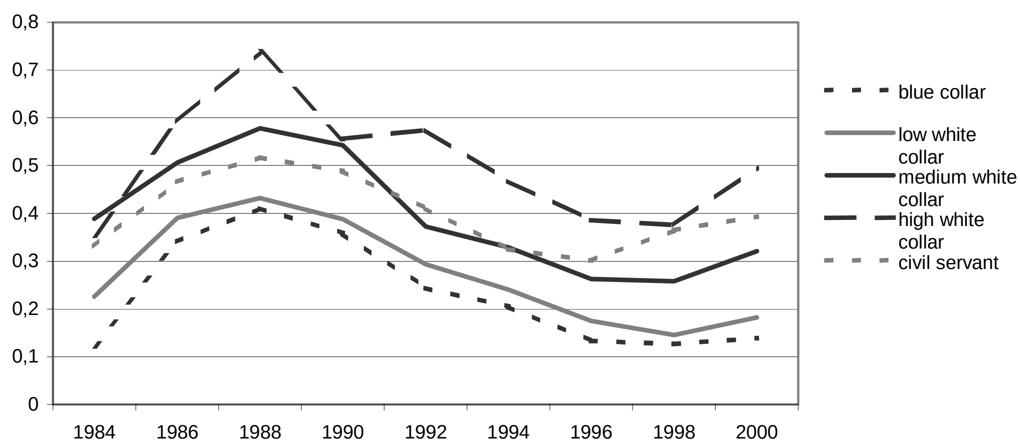
Figure 5 Premium on education, 1986 – 1996



Job skills required

An interesting set of variables for our analysis are the skills indicators for the job. Figures 6 and 7 present the impact of various levels of required skills, one in the form of the collar variable, and one in the form of the required skill level. One sees that the impact generally increases with higher requirements.[12]

Figure 6 Premium on job levels, 1984 – 2000



[11] The strong fluctuations for technical college degree (edlev 5) over time are due to changes in definition.
[12] An increase of the premium with higher job requirements is also found in Hartog (1992).

Interestingly, the premiums to the collar variable seems to be weakly negatively correlated to the premiums to the functional level variable, i.e. the impact of the collar variables has weakened over time and the impact of the functional level has increased, with a dip in 1998.

Figure 7 *Premium on functional levels, 1984 – 2000*

Intermezzo: interaction effects

We did also test for interaction effects between personal and job characteristics – in particular between education obtained and job requirements measured by the variable *collar*. According to the assignment approach such interaction would indicate comparative advantage for certain job-education combinations. Surprisingly, almost all combinations turned out to be significant for Germany.

Figure 8 *Interaction effects between education and skills, 1984 – 2000*

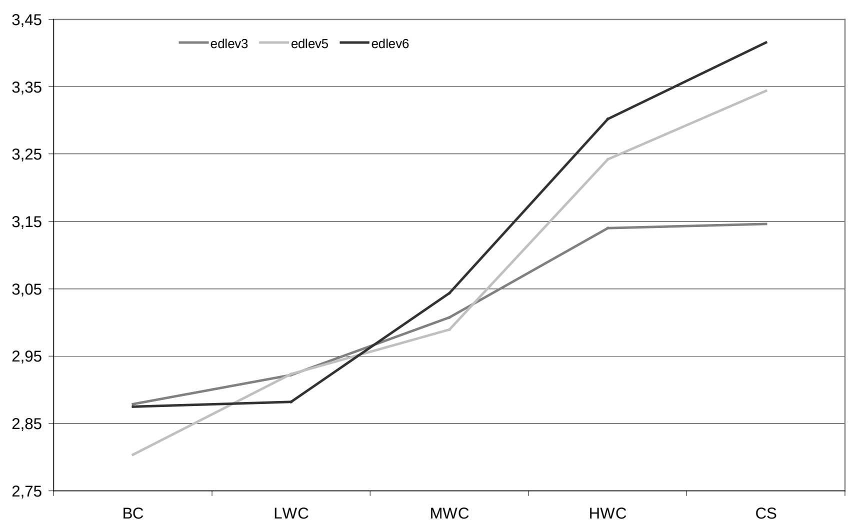


Figure 8 illustrates that all educational levels have a "comparative advantage" with respect to the equivalent collar level. Being a blue collar worker, the wage is highest with educational level 3, while the same educational level in a high skilled white collar position (collar4) pays a lot less than a higher educational level. These findings suggests that comparative advantages are present in these matches – for a further elaboration see Rieder (2002).

5. Wage differences due to personal and job characteristics

We found strong heteroskedasticity in our estimated wage equations. This implies directly that increased overall inequality and unobserved heterogeneity will be observed simultaneously. Acemoglu (2002) found a strong increase in unobserved heterogeneity since the early 1970s for the USA. He attributes this to an increased return to unobserved skills, assuming no change in the composition of unobserved skills. We have included job levels as an additional characteristic in the wage equation, which enables us to analyse the impact of this thus far unobserved component on wage heterogeneity. Table 2 shows that indeed unobserved heterogeneity measured by the variance of residuals declines somewhat, due to the inclusion of job characteristics.

Table 2 Variance of residuals before and after including job characteristics as an additional variable in the wage equation, Germany and USA.

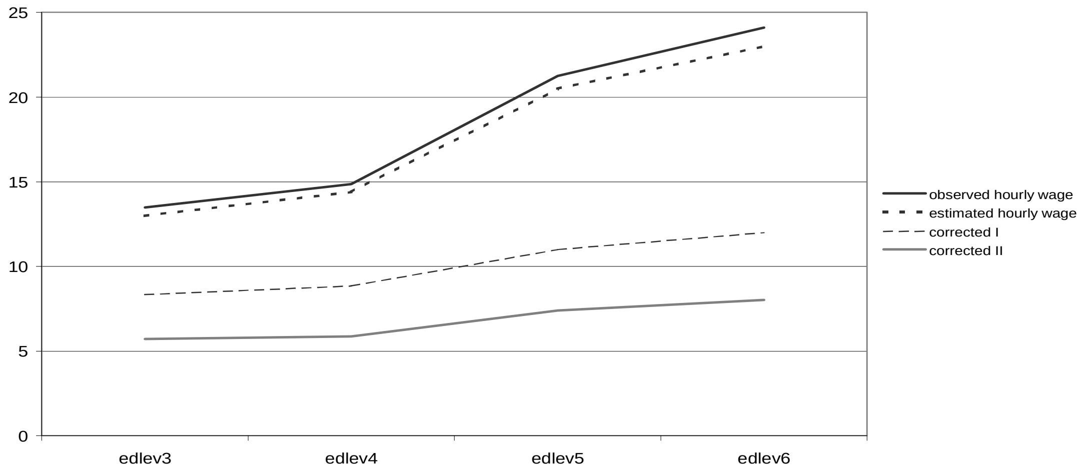
	Germany		*US*	
	1984	2000	1986	1996
After	0.373	0.345	0.404	0.432
Before	0.379	0.357	0.428	0.452

However, the measures used by Acemoglu are inequality measures on the residuals. Hence the inequality in the residuals measured in this way is not related to the overall inequality, although this relationship is a prominent feature of Acemoglu’s analysis. To develop such a relationship falls outside the scope of the present analysis. We therefore leave a full analysis of unobserved heterogeneity for further research and proceed in a different way here.

Figure 9 presents various manipulations with the wage equation of 1992 – the results are very similar for the other years. First we compare the fit of the equation to the observed data for various educational levels. One sees that the wage is slightly under estimated for all levels.

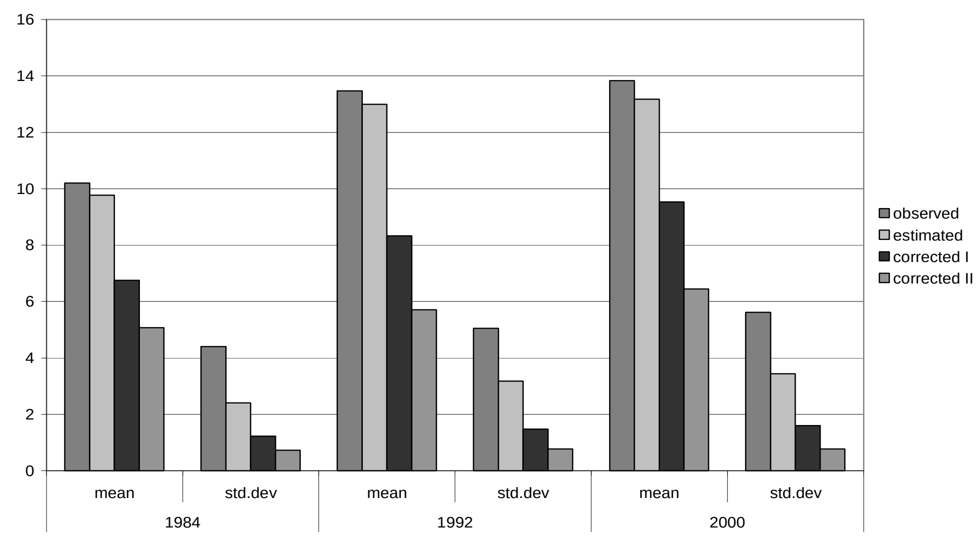
The estimated hourly wage I indicates the correction for job characteristics. It is interesting to observe that this affects the mean wage of all workers, in particular the mean wage of workers with educational levels 5 and 6. In the latter case these characteristics account for almost 50 per cent of the mean hourly wage. Figure 10 shows that the distribution of the wages also is affected by the

Figure 9 The mean hourly wage rate for 1992



correction.[13] Whereas the estimated distribution is skewed to the right, although mean and mode more or less coincide, the corrected distribution is skewed to the left and the mode exceeds the mean. Thus wage differences become smaller when corrected for job characteristics. The latter is in particular due to the differences in skill levels occupied by workers.

Figure 10 The mean hourly wage rate for educational level 3 in various years



The estimated hourly wage II in Figure 9 is corrected for the impact of experience. One sees that this correction uniformly lowers the mean wage for all educational levels. Figure 10 shows that correction for experience also leads to a further reduction in wage dispersion. It shows that most of the dispersion

[13] The figure shows the results for educational level 3, but the results for the other levels are similar.

per educational level observed is due to job characteristics and experience. The remaining factors – gender, hours worked, youth and direction of education – only contribute very little to wage dispersion per educational level.

From these results we conclude that one third to one half of the total mean wage is independent of additional educational attainment, experience and job characteristics. For all educational levels job characteristics fill most of the gap. With respect to the variation in wages, job characteristics also play an important role. Together with experience they explain an important part of the wage differences amongst workers per educational category. [14] The remaining part of the wage differences is explained by educational level.

6. Comparison with results for the Netherlands and the USA

It is interesting to compare the results presented above with those found in Muysken and Ruholl (2001) for the Netherlands and in Muysken et al (2002) for the United States. The composition of the labour force with respect to skills and required education in the three countries is quite similar. As a consequence the process of upgrading observed in Figure 3 for Germany is quite similar to that for the Netherlands and the USA. However, Table 3 shows that the wage differentials are much larger in the USA. The observed wage differentials between highest and lowest education is a factor 2.85. The corresponding factor for Germany is 2.21 – compare Figure 9 above – and for the Netherlands it is 1.79.

Table 3 *Wage differentials highest and lowest education for the Netherlands and the USA, 1994, and 1992 for Germany*[15]

	Observed	*Corrected for job characteristics*	*Also corrected for experience*
USA	2.85	2.25	2.11
NL	1.79	1.62	1.35
GER	2.21	1.73	1.64

Table 4 summarises the estimated impact of some personal characteristics for Germany, the Netherlands and the USA, averaged over 1994 and 1996. The impact of the gender, age and racial dummies is different, whereas part-time working also has a different impact on hourly wages – all this reflects institutional differences. However, we saw above that experience has a very strong impact on wage differentials. In that light it is remarkable that the return to experience is very similar in all three countries.

[14] These findings are also consistent with Sels cs. (2000) who find for Belgian white-collar workers in 1998 that wage differences are explained for about 56 per cent by personal characteristics and the remaining part by job and organisation characteristics.

[15] The 1994 results for Germany are too much influenced by the reunification.

Table 4 *The impact of personal characteristics, the Netherlands, Germany and the USA 1994-96*

	Gender	*Age dummy*	*Black*	*Man hours*	*Full-time*	*Total experience*	*Total exp. squared*
USA	-0.165		-0.096	-0.00076	0.175	0.030	-0.0005
NL	-0.146	-0.435		-0.00125		0.033	-0.0005
GER	-0.296	-0.556		-0.00097		0.040	-0.0007

Figure 11 shows that the returns to education in the USA are consistently higher when compared to those in Germany and the Netherlands. The latter two are close for most levels - except for university education. The returns to required skills are rather close for the USA and Germany, however.[16] Figure 12 reveals that the latter returns are much higher than those for the Netherlands. We therefore conclude that the main determinant of the higher wage differentials for the USA observed in Table 3 is the much higher returns to education. The differences between Germany and the Netherlands are caused by higher returns to skills in Germany.

Figure 11 *The impact of education on wages in Germany, the Netherlands and the USA, 1994-96*

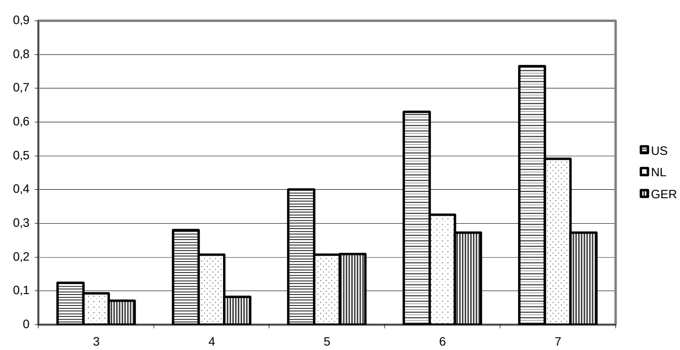
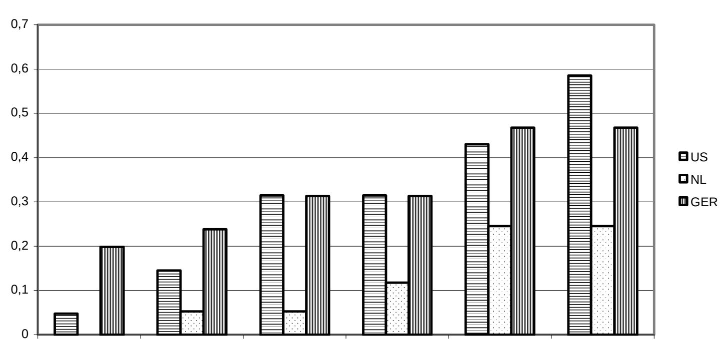


Figure 12 *The impact of required skills on wages in Germany, the Netherlands and the USA, 1994-96*



[16] We ignore here the skill variables “trocc” and “functional levels”. These will add at most 0.2 to the values in Figure 12 for Germany.

Finally, an interesting observation follows from comparing Figures 11 and 12. Both in the Netherlands and in the USA, the impact of a higher required skill level is lower on average than the impact of a higher level of education. Muysken and Ruholl (2001) use this notion to explain the divergence between educational attainment and wage-productivity growth in the Netherlands. Essentially they argue that part of the increase in educational attainment is absorbed by increased skill requirements, which have a lower wage premium. A similar analysis might be relevant to the discussion of the productivity slow-down in the USA. However, a further elaboration of this notion for the case of Germany is outside the scope of the present paper.

7. Concluding remarks

In this contribution we estimate wage equations on yearly individual data for Germany, 1984 – 2000. In the tradition of Hartog's (2000a) ORU-specification, we use job characteristics (e.g. skills required) next to personal characteristics (e.g. schooling and experience) also to explain wages. A new element in our study is that we track the development of wages over a longer period, 1984 – 2000. We find that returns to education, experience and required skills are rather stable over time – cf. section 4.

An interesting aspect of our approach is that we are able analyse the impact of including job characteristics in the wage equation on unobserved heterogeneity. When analysing the impact of both observed and previously unobserved heterogeneity, we find that personal characteristics like education and experience explain about half of the variation in wages. At least 30 per cent is explained by variation in job characteristics.

Finally, since Muysken and Ruholl (2001) and Muysken et al (2002) have made a similar analysis for the Netherlands and the USA, respectively, we compare the results for these countries. It turns out that the returns to experience are the same in all countries, while the premiums on education are much higher in the USA. The premiums on required skills in Germany are in the same range as those in the USA, but much higher when compared to the Netherlands. These differences explain the wage differentials between the three countries. This also casts some doubt on the "universalistic" view on the labour market as expressed in Daly et al (2000).

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ANNEX: THE DATA USED

diwlnhw: Natural logarithm of hourly net wage, calculated by using the maximum of either actual or agreed upon hours worked per week

gender: Gender dummy is equal to one if person is female

agedummy: Age dummy is equal to one if person is younger than 20

cempl: Years a person has worked in the current job

prevexp: Years of experience a person had previously to current job

texpsq: Total years of experience squared

mhours: Number of hours actually worked by a person

edlev2: Education base level - a person has finished secondary school, but has received no other education

edlev3: Person has done apprenticeship

edlev4: Person has done vocational training other than apprenticeship

edlev5: Person has finished technical college (Fachhochschule)

edlev6: Person has finished university

collar1: Person has blue collar job

collar2: Person has low- or semiskilled white collar job or is industrial foreman

collar3: Person is semi-skilled professional

collar4: Person has professional or managerial job

collar5: Person is civil servant

persons with no information given on collar standing serve as base level

occa: Person is working in business according to one digit isco code (=4)

occb: Person is working in management according to one digit isco code (=2)

occc: Person is working in production according to one digit isco code (=7)

occd: Person is working as office worker according to one digit isco code (=3)

occe: Person is working as scientist according to one digit isco code (=1)

service sector, farming, forestry and fishing serve as base level

funlevlo:	Person is working in low skilled job according to the classification by Ganzeboom **-** serves as base level
funlevme:	Person is working in medium skilled job according to the classification by Ganzeboom
funlevhi:	Person is working in high skilled job according to the classification by Ganzeboom
trocc:	Dummy variable equal to one if person is working in occupation trained for
fsize3:	Size of the firm the person is working in is between 200 and 2000 employees
fsize4:	Size of the firm the person is working is larger than 2000 employees
all other firm sizes serve as a base level	
ost:	Dummy variable equal to one if person is working in the former east of Germany

Table A1 Mean values of the data used

	1984	**1986**	**1988**	**1990**	**1992**	**1994**	**1996**	**1997**	**1998**	**1999**	**2000**
GENDER	0.37	0.36	0.38	0.40	0.41	0.41	0.42	0.43	0.44	0.44	0.43
AGEDUMMY	0.06	0.04	0.05	0.04	0.03	0.0272	0.03	0.03	0.04	0.03	0.03
CEMPL	8.94	9.47	9.48	9.44	9.67	9.74	8.89	8.12	8.11	8.55	8.05
PREVEXP	12.07	11.64	11.49	11.41	11.75	11.66	11.98	12.92	13.06	13.22	13.26
TEXPSQ	585.36	588.92	587.10	582.46	602.68	600.7	567.95	567.99	574.94	597.39	583.26
MHOURS	168.25	170.09	166.75	166.64	165.76	164.6	163.50	169.89	169.19	168.45	171.53
EDLEV3	0.36	0.36	0.36	0.38	0.38	0.38	0.37	0.42	0.41	0.42	0.44
EDLEV4	0.26	0.24	0.23	0.22	0.23	0.24	0.26	0.20	0.20	0.20	0.20
EDLEV5	0.03	0.03	0.03	0.03	0.04	0.041	0.04	0.09	0.10	0.09	0.10
EDLEV6	0.07	0.07	0.07	0.07	0.07	0.079	0.09	0.10	0.10	0.11	0.11
OCCB	0.01	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.04	0.04	0.04
OCCC	0.45	0.44	0.44	0.43	0.41	0.39	0.37	0.35	0.33	0.34	0.34
OCCD	0.18	0.19	0.18	0.17	0.18	0.19	0.19	0.18	0.17	0.17	0.16
OCCE	0.15	0.15	0.16	0.16	0.17	0.17	0.19	0.20	0.21	0.22	0.22
COLLAR1	0.48	0.47	0.46	0.46	0.44	0.42	0.40	0.38	0.37	0.37	0.38
COLLAR2	0.26	0.28	0.28	0.29	0.30	0.31	0.32	0.33	0.31	0.32	0.30
COLLAR3	0.06	0.06	0.07	0.07	0.09	0.089	0.11	0.11	0.12	0.13	0.12
COLLAR4	0.01	0.01	0.01	0.01	0.01	0.011	0.01	0.01	0.02	0.01	0.01
COLLAR5	0.07	0.07	0.06	0.06	0.06	0.063	0.06	0.05	0.05	0.05	0.05
FUNLEVME	0.60	0.59	0.59	0.60	0.60	0.59	0.58	0.55	0.54	0.53	0.53
FUNLEVHI	0.14	0.15	0.16	0.16	0.17	0.18	0.19	0.21	0.22	0.23	0.23
TROCC	0.42	0.42	0.42	0.44	0.49	0.50	0.51	0.53	0.54	0.54	0.52
FSIZE3	0.21	0.03	0.23	0.23	0.25	0.23	0.22	0.21	0.21	0.21	0.20
FSIZE4	0.25	0.04	0.25	0.25	0.25	0.24	0.23	0.20	0.19	0.19	0.19
OST						0.009	0.02	0.26	0.25	0.20	0.12

Table A2 *Estimation results for Germany, 1989-2000*

	1984	**1986**	**1988**	**1990**	**1992**	**1994**	**1996**	**1997**	**1998**	**1999**	**2000**
C	1872	1515	1277	1646	1975	1952	2040	2024	2147	2273	2091
GENDER	-0.35	-0.30	0.32	-0.28	-0.32	-0.31	-0.29	-0.25	-0.23	-0.28	-0.25
AGEDUMMY	-0.20	-0.44	-0.42	-0.47	-0.46	-0.47	-0.64	-0.44	-0.60	-0.67	-0.53
CEMPL	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
PREVEXP	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.03
TEXPSQ	-0.0004	-0.0006	-0.0006	-0.0006	-0.0006	-0.0007	-0.0007	-0.0006	-0.0006	-0.0006	-0.0006
MHOURS	-0.001	-0.0008	-0.001	-0.0008	-0.001	-0.0009	-0.001	-0.001	-0.001	-0.002	-0.002
EDLEV3	0.03	0.09	0.09	0.09	0.08	0.07	0.07	0.08	0.07	**0.03**	0.12
EDLEV4	0.07	0.15	0.10	0.11	0.10	0.08	0.09	0.09	0.09	0.09	0.15
EDLEV5	0.22	0.29	0.31	0.25	0.28	0.17	0.25	0.19	0.16	0.07	0.20
EDLEV6	0.30	0.42	0.39	0.38	0.37	0.28	0.26	0.28	0.25	0.22	0.32
OCCB	0.29	0.25	0.27	0.24	0.25	0.23	0.25	0.32	0.28	0.24	0.24
OCCC	0.10	0.06	***0.03***	0.06	0.08	***0.03***	0.08	0.09	0.09	0.09	0.08
OCCD	0.11	0.13	0.11	0.10	0.07	0.10	0.09	0.10	0.11	0.09	0.08
OCCE	0.08	0.12	0.09	0.12	0.11	0.14	0.11	0.18	0.16	0.15	0.13
COLLAR1	0.12	0.34	0.41	0.36	0.24	0.20	0.13	0.20	0.13	**0.06**	0.14
COLLAR2	0.23	0.39	0.43	0.39	0.29	0.24	0.17	0.21	0.15	0.13	0.18
COLLAR3	0.39	0.51	0.58	0.54	0.37	0.33	0.26	0.32	0.26	0.24	0.32
COLLAR4	0.35	0.59	0.74	0.56	0.57	0.47	0.39	0.43	0.38	0.39	0.50
COLLAR5	0.33	0.47	0.52	0.49	0.41	0.33	0.30	0.37	0.36	0.33	0.39
FUNLEVME	0.09	0.05	0.05	0.08	0.09	0.07	0.09	0.05	0.05	0.04	0.09
FUNLEVHI	0.16	0.12	0.11	0.11	0.15	0.12	0.19	0.07	0.08	0.09	0.11
TROCC	0.06	0.08	0.08	0.09	0.07	0.08	0.07	0.10	0.09	0.09	0.08
FSIZE3	0.06	***0.01***	0.06	0.07	0.06	0.09	0.07	0.12	0.10	0.13	0.13
FSIZE4	0.08	0.10	0.11	0.12	0.12	0.14	0.12	0.16	0.14	0.18	0.17
OST						0.16	***-0.04***	-0.26	-0.2	***-0.01***	-0.20
R-squared	0.49	0.60	0.63	0.61	0.59	0.57	0.56	0.57	0.56	0.52	0.53
Adj. R-squared	0.49	0.60	0.63	0.61	0.59	0.57	0.56	0.56	0.55	0.52	0.52
n	3484	3214	3413	3425	3281	3235	3419	4857	4630	4831	5267

not sign at 5%
not sign at 10%