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The impact of education and mismatch on wages: the USA, 1986 – 1996

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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 the USA, 1986 – 1996. 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, the returns to experience are the same in both countries, while the premiums on education and in particular required skills are much higher in the US.

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).

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. In this study we will reproduce their analysis for the USA 1986 – 1996, using CPS data and compare the results with those found for the Netherlands.

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 the USA for the period 1986 – 1996 from our data. During that decade the share of the working persons with grade 10 or less fell from 11,6 to 7,7 per cent. However, the share with college and full academic education (MA or PhD) increased from 43,8 to 55,1 per cent over that period. A similar development can be observed for the Netherlands.

Figure 2 shows that the share of jobs requiring high skills increased from 30,5 to 35,7 per cent over the observation period – this is much less than the increase 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. As one might expect, in both countries these shares are slightly decreasing.

Figure 1 Share of the workforce in the USA with respect to education, 1986 – 1996

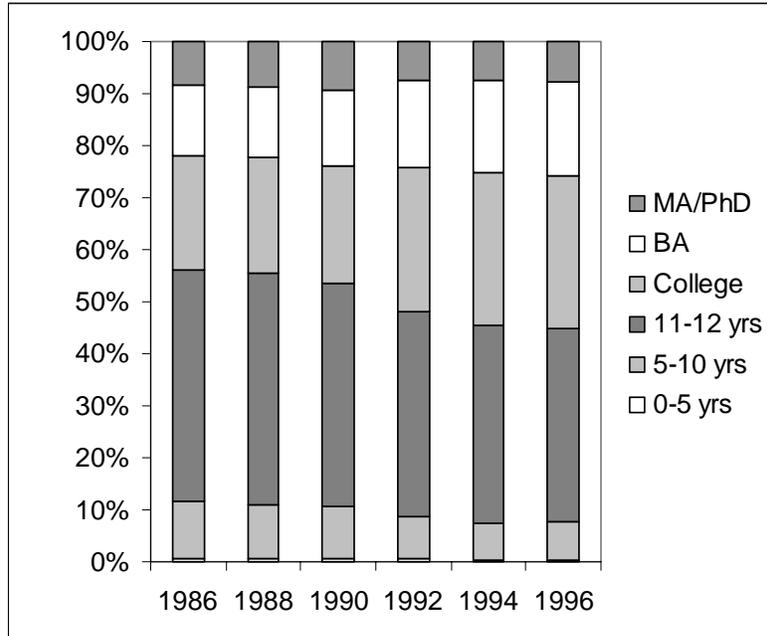
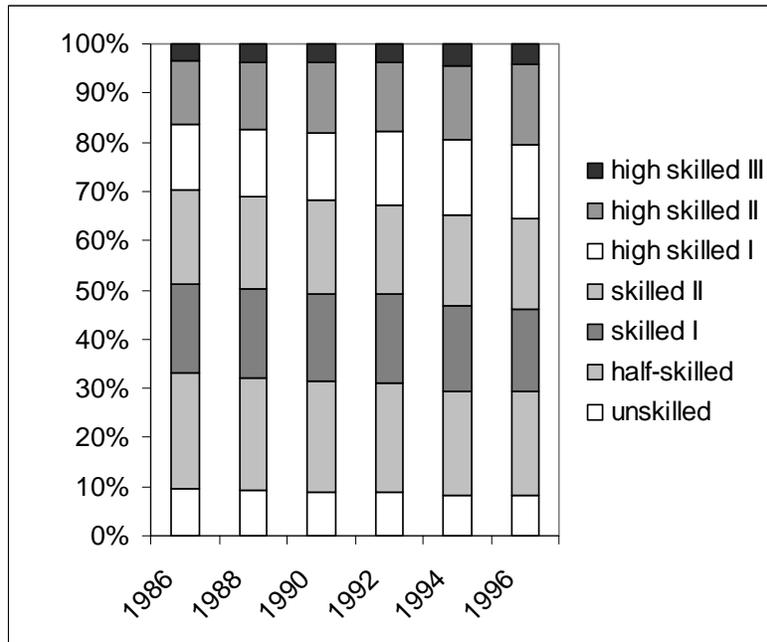


Figure 2 Share of the workforce in the USA with respect to required skills, 1986 – 1996



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 Auerbach and Skott (2000) and Wolff (2000).¹ Moreover, this phenomenon has been observed in many countries, cf. the survey by Groot and Maassen van den Brink (2000).²

Table 1 demonstrates that upskilling in the USA took place in all job categories. Acemoglu (2000) 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.

Table 1 Average educational level of the workforce in the USA for each level of required skills, 1986 – 1996

Skills Year	unskilled	half- skilled	skilled I	skilled II	high skilled I	high skilled II	high skilled III	all
1986	3,84	4,04	4,25	4,57	5,03	5,42	6,24	4,55
1988	3,85	4,06	4,27	4,58	5,04	5,42	6,25	4,58
1990	3,86	4,07	4,30	4,62	5,12	5,47	6,22	4,62
1992	3,97	4,18	4,40	4,69	5,08	5,50	6,21	4,69
1994	4,01	4,23	4,45	4,76	5,14	5,53	6,26	4,77
1996	4,03	4,23	4,44	4,76	5,16	5,51	6,27	4,78

The development of wages is well documented in Acemoglu (2000, section 2) who summarises several empirical trends for the US, which are relevant for our analysis. The returns to college education fell sharply during the 1970s – cf. Freeman’s (1976)

¹ Although there are several studies discussing over- and undereducation in the US, most of them use data prior to 1990. Cf. the overview in Auerbach and Skott (2000).

² 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.

overeducated American – but during the 1980s returns rose sharply again. On the other hand overall wage inequality started to increase from the early 1970s onwards, after a period of relative stability. These developments are well documented and induced a strong debate on the causes of inequality, starting with Bound and Johnson (1992) and Katz and Murphy (1992). Acemoglu points at two additional developments, which got less attention in that debate. First, the decline in real terms of the wages of low-skill workers to levels below those in the early 1960s. Second, residual inequality increased sharply from the 1970s onwards. Residual or within-group inequality is inequality among observationally equivalent workers. Hence, from the early 1970s both overall and residual inequality increased steadily.

The result that both overall and residual inequality increased, while during the 1970s returns to schooling fell, is quite puzzling. Acemoglu (2000, section 7) shows that from a simple skill model of wage inequality, this phenomenon can only be explained by changes in the distribution of unobserved skills – i.e. composition effects. However, reproducing the studies by Blackburn, Bloom and Freeman (1992) and Juhn, Murphy and Pierce (1993), Acemoglu (2000, section 9) argues that such effects do not explain the changes in the wage structure. That is, changes in the distribution of *unobserved* skills did not play an important role in this respect – changes in the composition of the explanatory variables in the Mincerian wage equation of course do matter.³

Acemoglu therefore concludes that one should use multi-dimensional skill models instead of single-index skill models to explain wage developments. He illustrates this for a model in which he distinguishes between two types of education and two types of skills. Actually Acemoglu’s “two-index skill” model is very close to our approach, once one assumes that unskilled means working in an unskilled job and skilled means working in a skilled job. Then Acemoglu’s explanation that skill-biased technical progress will benefit skilled workers in both educational groups, means in our explanation that skill biased technical progress benefits workers working in skilled jobs. The main difference between both interpretations is that in Acemoglu’s approach skills are unobserved, whereas in our

³ To derive this result Acemoglu assumes that for a specific age cohort the unobserved characteristics do not change over time. However, Table 1 shows that job characteristics do.

approach skills are observed by job characteristics. This also enables to test Acemoglu's conclusion that the increase in residual inequality implies that the price of unobserved skills has increased (we reject this).

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 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, 1986 – 1996, 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 Muysken and Ruhoff (2001) have made a similar analysis for the Netherlands, we can compare the results for both countries. Section 6 shows that the returns to experience are the same in both countries, while the premiums on education and in particular required skills are much higher in the US. Moreover, a “good” match has a higher reward in the US, which suggests that its labour market is more efficient in that respect, when compared to 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:

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

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 to 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:

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

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:

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

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 the USA 1986–1996. 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 (2000) 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. However, section 5 takes a different approach to determine the impact of job characteristics on wage differentials, since Acemoglu’s approach leaves several questions open which we cannot solve in the present analysis. We explain this in section 5.

3. The data used

We have used survey data obtained by the CPS for the years 1986 – 1996 (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). However, the remaining size of the survey data remained too large to handle comfortably. Therefore we used only about half of the survey, drawn in a random way – this amounts to approximately 30,000 cases for each year. 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 race, 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 that the youth minimum wage is highly increasing in age below 20 years in the early years of the sample. 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, large or small, whether the firm is under union coverage or not, and the kind of sector in which the firm is operating. Second the level of skills required on the job can be derived from the data.⁴

Information on these characteristics is summarised for each year in the Annex, together with the natural log of the hourly net wage, which is the dependent variable.

⁴ The data are transformed with the so-called ARBI scale, which starts from the detailed occupational classification and divides occupations into 7 skill levels, from low to high (*Skill lev* in our notation). The classification uses the complexity of occupations as a criterion and takes into account, amongst others, the

The data show a surprisingly equal and stable distribution between men and women in the workforce (cf. the gender dummy).⁵ Moreover, the share of persons working full-time increases somewhat, which corresponds to a slight increase in the number of hours worked (Mhours). Also the share of workers of young age, below 20 years, has decreased, while the average experience of the workers increased somewhat over time. The share of lower educational levels decreases modestly over time, i.e. till grade 12, 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 skill levels (5-7) increases too, whereas that with the lower skill levels (1-4) decreases, cf. also Figure 2 above. 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,⁶ 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 2 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 3–5 below, we feel quite confident that our estimation results do not suffer strongly from a specification bias.⁷

job content, the required knowledge and mental ability. More details are provided in Hartog (1992), pp.154-155 and Annex 5.2.

⁵ 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.

⁶ This was obvious from visual inspection of the estimated residuals and confirmed by White's general test.

⁷ 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.

The estimation results indicate that almost all variables attributed to personal characteristics are highly significant for all years. As might be expected, being female, young or black all have 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.

Most of the variables attributed to job characteristics are significant too for all years. Both belonging to a unionised firm and working in a larger firm pay a higher wage.⁸ And when the job requires a higher level of skills, this generally also yields a higher wage.

We did not test for interaction effects between personal and job characteristics – in particular between educational and functional levels. According to the assignment approach such interaction would indicate comparative advantage for certain job-education combinations. None of these effects turned out to be significant for the Netherlands.⁹

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, race, gender and hours worked

From the estimation results it can easily be inferred that being female implies that one would earn about 16 per cent less of the mean wage, when compared to otherwise similar males, although this percentage fluctuates over the years. A black person earns about 9 per cent less. It can also be inferred that when working part-time, decreasing returns to

⁸ Actually the impact of firm size turned out to be insignificant, once we took union coverage into account. The reason is that union coverage is in particular strong in large firms.

⁹ This is a question for further research, however. Some results for the Netherlands show interaction effects between education and experience.

hours worked prevail.¹⁰ However, working full time instead of part-time (150 in stead of 75 hours per month) yields a premium of approximately 12 per cent on the mean hourly wage, because working full time as such yields a premium too. Finally, the impact of the low level of the youth minimum wage shows up in the premium of being 20 years or older, which varies in the range of 3.5 to 7 per cent till 1994, from 1994 onwards this premium disappears.

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 3 shows the estimated premium to total experience after 17 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 to experience is obtained after around 30 years.

Figure 3 Premium to 17 years of experience, 1986 – 1996

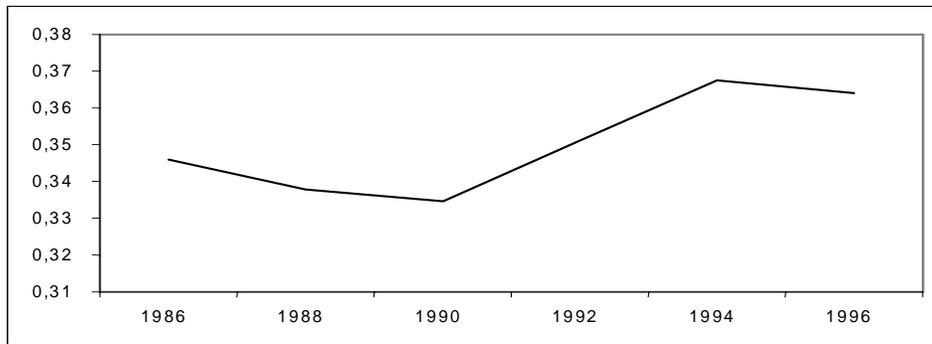
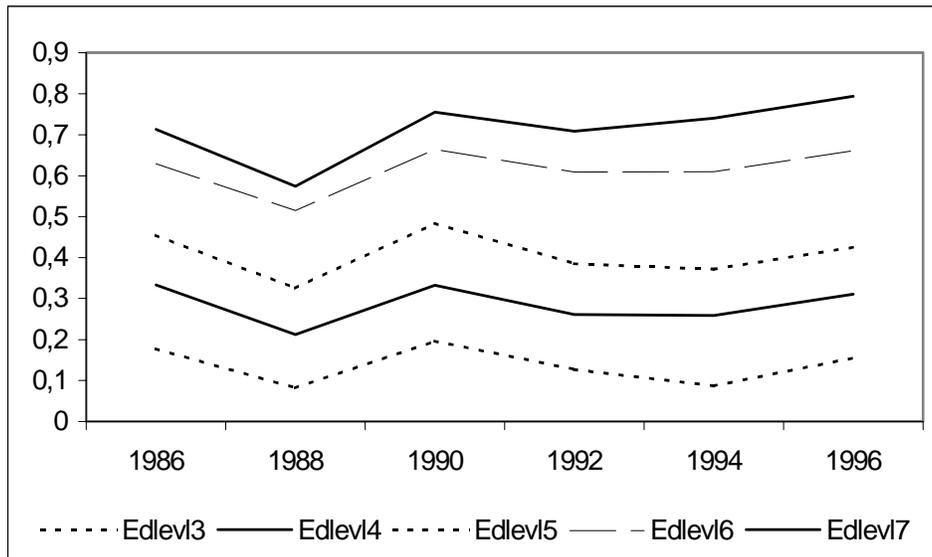


Figure 4 depicts the estimated premium on the various forms of education. As one might expect, this premium increases with the level of education. Moreover, the estimated premium for each level of education is quite stable over the sample period, although there is a dip in 1988.

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.

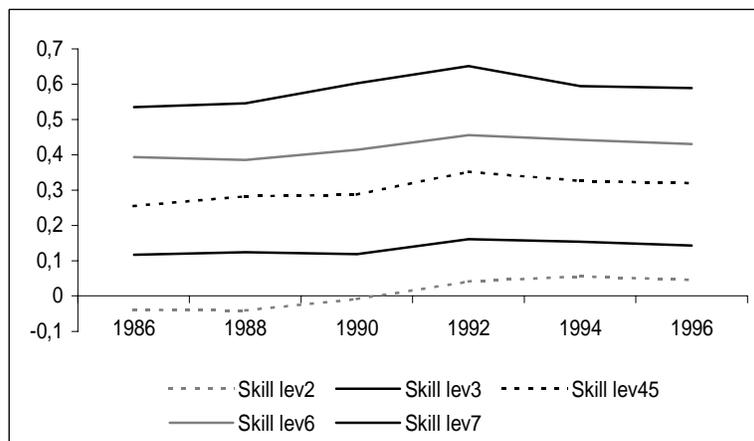
Figure 4 Premium to education, 1986 – 1996



Job skills required

An interesting variable for our analysis is the level of skills required for the job. Figure 5 presents the impact of various levels of required skills, compared to no skills required. One sees that the impact generally increases with higher requirements, although levels 4 and 5 are comparable, and levels 1 and 2 too.¹¹

Figure 5 Premium on required skills, 1986 – 1998



¹¹ An increase of the premium with higher job requirements is also found in Hartog (1992).

Finally, an interesting observation follows from comparing Figure 5 with Figure 4. The impact of a higher skill level is lower on average than the impact of a higher level of education. We will use this observation later on to explain the relationship between overeducation and wage development.

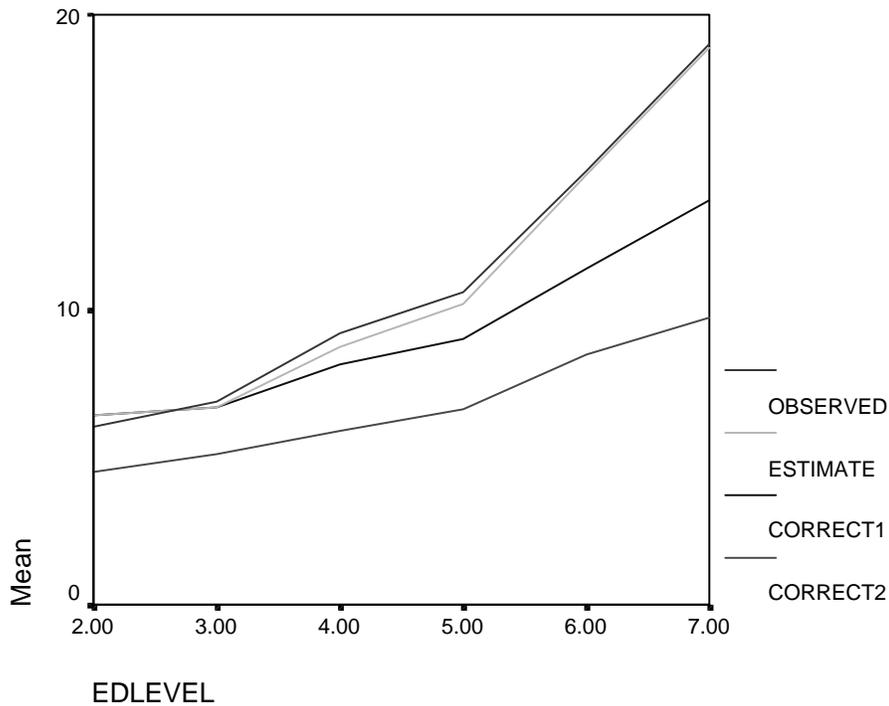
5. Wage differences due to personal and job characteristics

Acemoglu (2000) found a strong increase in unobserved heterogeneity since the early 1970s. 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 thusfar unobserved component on wage heterogeneity. Moreover, Figure 5 shows that the premium on these skills has remained constant over time, whereas Figure 2, and even more Table 1, show that their composition changed. We therefore do not agree with Acemoglu's conclusion that the composition of unobserved skills has not changed, whereas their price has increased: It is the other way around, at least for the job characteristics.

We do not reproduce Acemoglu's analysis for our data, because at this stage of our analysis too many questions remain. We found strong heteroskedasticity in our estimated wage equations. This implies directly that increased overall inequality and unobserved heterogeneity will be observed simultaneously. 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 6 presents various manipulations with the wage equation of 1996 – 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.

Figure 6 The mean hourly wage rate for 1996



The estimated hourly wage I indicates the correction for job characteristics. That is, the firm is non-unionised, there are no skills required for the job and the firm sector is the manufacturing sector. It is interesting to observe that this hardly affects the mean wage of workers with educational levels 1-3, and only substantially affects the mean wage of workers with educational levels 6-7, which constitute less than 20 per cent of our sample. However, as Figure 7 shows, the distribution of the wages is definitely affected by the correction.¹² 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.

Moreover, since in particular the higher educated persons will occupy higher skill levels, it is not surprising to see that the mean income for the educational levels 6 and 7 clearly is lower due to the correction for job characteristics. These characteristics account for 15-20 per cent of the mean hourly wage.

As a final point it is interesting to observe that whereas, after the correction, the mean hourly wage differs from 6 at educational level 1-3 to 13 at educational level 7 – cf. Figure 6 – the dispersion of the wage for educational level 3 ranges from below 3 to above 9 – cf. Figure 7. This indicates that wage dispersion within educational groups is considerable, even after correction for job characteristics.

Next the estimated hourly wage II shows the correction for the personal characteristic of experience. That is, in the estimated wages both current and previous experience, and total experience squared are set equal to zero. From Figure 6 one sees that this leads to a more or less equal reduction in the hourly wage for all educational levels. This is not surprising as long as experience is more or less equally distributed over all educational levels. Experience accounts for roughly an additional 20-30 per cent of the hourly wage. However, when comparing corrections I and II, one sees from the figure that education can partly compensate for a lack of experience.

Figure 7 shows the quite interesting result that correction for experience leads to an enormous reduction in wage dispersion. While the initial dispersion was in the range 3.5 – 13.5, although quite skewed, the correction for job characteristics reduced the range to 3.5 to 9.0 with a less skewed distribution. Finally correction for experience reduces the range to 3.5 to 6.0 with a hardly skewed distribution. Thus most of the dispersion per educational level observed after correction I (for job characteristics) is due to 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 the lower educational levels experience fills most of the gap, for higher educational levels both education and skills requirements for jobs also start to pay off. However, the latter applies only to about 20 per cent of the work force.

With respect to the variation in wages, job characteristics play an important role. Together with experience they explain an important part of the wage differences amongst workers per educational category. The remaining part of the wage differences is

¹² The figure shows the results for educational level 3, but the results for the levels 2 and 4 are similar.

explained by educational level. Figure 6 shows that even after correction for job characteristics and experience, education causes a wage differential of almost 50 per cent.¹³ This is also reflected in the high premium to education of Figure 4.

6. Comparison with results for the Netherlands

It is interesting to compare the results presented above with those found in Muysken and Ruholl (2001) for the Netherlands. The composition of the labour force with respect to skills and required education is quite similar.¹⁴ As a consequence the process of upgrading observed for the Netherlands is quite similar to that in Table 1 for the US. However, Table 3 shows that the wage differentials are much larger in the US. The observed wage differentials between highest and lowest education is a factor 2.85 – compare Figure 4 above. The corresponding factor for the Netherlands is 1.79.

Table 3 Wage differentials highest and lowest education for the Netherlands and the USA, 1994

	Observed	Corrected for job characteristics	Also corrected for experience
USA	2.85	2.25	2.11
NL	1.79	1.62	1.35

Table 4 The impact of personal characteristics, the Netherlands 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

¹³ 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.

¹⁴ When we compare Figures 1 and 2 above with the corresponding Figures 1 and 2 in Muysken and Ruholl (2001), we identify the US educational categories 0-10 yrs with “lower” education, 11-12 yrs and college with “extended and medium” education (subdivisions are quite different for both countries), Ba with “higher” education and MA/PhD with “university” education. Similarly, we identify the required skills un- and half-skilled with “lower”, skilled I and II with “extended” high skilled I with “medium” and high skilled II and III with “higher and university”.

Table 4 summarises the estimated impact of some personal characteristics for the Netherlands and the US, averaged over 1994 and 1996. Remarkable features are that the impact of gender on wages is quite similar for both countries. The impact of the age dummy and racial dummy 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 both countries.

On the other hand, pronounced differences occur with respect to the impact of the other two variables that affect wage differentials: education and required skills. Figure 8 shows that the premium on education is much higher in the US than it is in the Netherlands.¹⁵ Since the distribution of education in the US is similar to that in the Netherlands, this implies that the difference in premium is an important source of difference in inequality. The same conclusion holds for differences in the premium on required skills: As Figure 9 shows, again premiums are higher in the US.

The conclusion therefore is that the wage differentials between the USA and the Netherlands are mainly caused by differences in the premium for education and for required skills. Table 3 confirms this notion, since correction for job characteristics leads to a stronger reduction of the wage differential in the US than in the Netherlands, but the final wage differential, which is mainly due to education, remains as large as the original differential.

These observations suggest that the premium on a good match between education and skill requirements is much higher in the US than in the Netherlands. In that respect the US labour market then is more efficient.

¹⁵ For the sake of comparison we took the Dutch level 4 to be equivalent to the American levels 4 and 5.

Figure 8 *The impact of education on wages in the Netherlands and the USA, 1994-96*

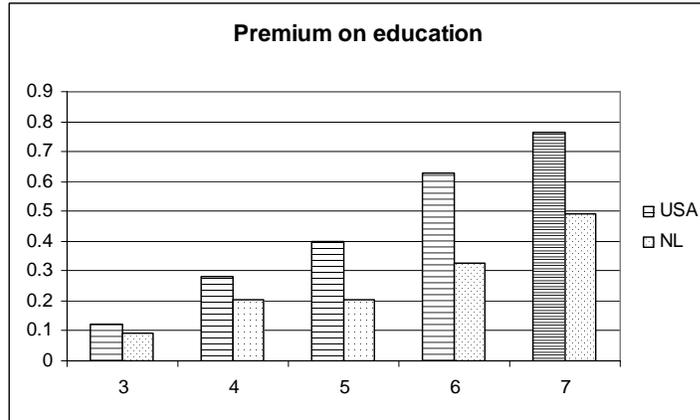
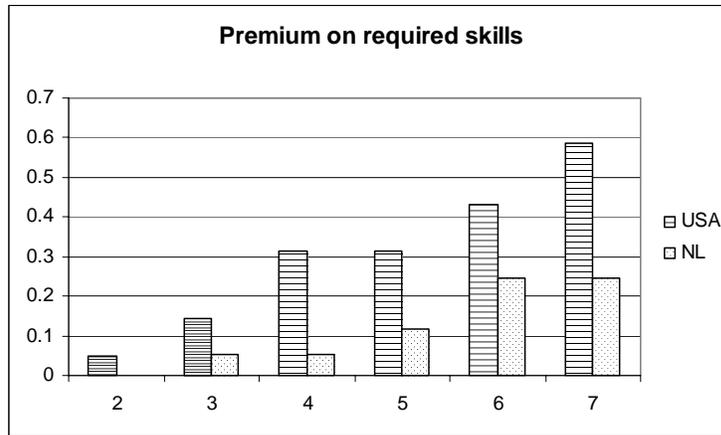


Figure 9 *The impact of required skills on wages in the Netherlands and the USA, 1994-96*



Finally, an interesting observation follows from comparing Figures 8 and 9. Both in the Netherlands and in the US, 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 US. However, that is outside the scope of the present paper.

7. Concluding remarks

In this contribution we estimate wage equations on yearly individual data for the USA, 1986 – 1996. 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, 1986 – 1996. 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 to 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 20 per cent is explained by variation in job characteristics.

Finally, since Muysken and Ruhoff (2001) have made a similar analysis for the Netherlands, we compare the results for both countries. It turns out that the returns to experience are the same in both countries, while the premiums on education and in particular required skills are much higher in the US. Moreover, a “good” match has a higher reward in the US, which suggests that its labour market is more efficient in that respect, when compared to the Netherlands.

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Annex The data used

a) **Dependent Variable**

LN HW: Natural logarithm of hourly wage, where

$$\text{Hourly wage} = (\text{number of yearly periods net income is paid} * \text{net income per period}) / (12 * \text{hours worked per month})$$

b) **Personal characteristics**

Gender:	Gender Dummy: female 1, male 0
Agedum:	Age dummy: 1 for persons below 20, 0 otherwise
Black:	Dummy Variable: 1 if black, 0 if non-black
Texp:	Total experience in years
Texpsq:	Total experience squared
Mhours:	Hours worked per month
Fulltime:	Fulltime work dummy: 1 for ≥ 40 hrs worked per week, 0 otherwise
Edlevl3:	Dummy for educational attainment (note that the years of schooling measure refers to 1986-1990, while the credentials oriented measure applies to 1992-1996): 1 for 5-10 years of schooling or grades 5 through 10, 0 otherwise
Edlevl4:	Dummy for educational attainment: 1 for 11-12 years of schooling or 11 th grade to High school graduate, diploma or GED, 0 otherwise
Edlevl5:	Dummy for educational attainment: 1 for 13-15 years of schooling, or some college, but no degree, to associate degree in college – academic program, 0 otherwise
Edlevl6:	Dummy for educational attainment: 1 for 16 years of schooling, or Bachelor's degree, 0 otherwise

Edlev17: Dummy for educational attainment: 1 for 17-18 years of schooling, or Master's degree to Doctorate Degree, 0 otherwise

Control Group: Edlev12: years of schooling 1-4 or up to and including 4th grade (including less than 1st grade)

c) **Firm characteristics**

Unioncov: Dummy for coverage of job through union contract: 1 if yes, 0 if not

Funlev2: Function level dummy: 1 for half-skilled, 0 otherwise

Funlev3: Function level dummy: 1 for skilled I, 0 otherwise

Funlev45: Function level dummy: 1 for skilled II or specialized higher skilled I, 0 otherwise

Funlev5: Function level dummy: 1 for specialized higher skilled I, 0 otherwise

Funlev6: Function level dummy: 1 for specialized higher skilled II, 0 otherwise

Funlev7: Function level dummy: 1 for specialized higher skilled III, 0 otherwise

Control Group: Function level 1: unskilled

Fsect234: Firm sector dummy: 1 for trade, transport, and communication; banking, business and personal services; construction and agriculture, 0 otherwise

Fsect3: Firm sector dummy: 1 for banking, business and personal services, 0 otherwise

Fsect4: Firm sector dummy: 1 for non-profit services (incl. public sector), 0 otherwise

Fsect5: Firm sector dummy: 1 for construction and agriculture, 0 otherwise

Control Group: Firm sector 1: manufacturing

Table A Summary of data used 1986-1998

Variables \ Year	1986	1988	1990	1992	1994	1996
LNHW	1,98	2,034	2,17	2,23	2,29	2,34
Gender	0,50	0,51	0,51	0,51	0,51	0,51
Agedum	0,078	0,079	0,071	0,058	0,056	0,062
Texp	16,58	16,78	17,35	17,87	18,01	18,35
Texpsq	452,90	455,25	472,36	482,62	483,00	495,28
Black	0,086	0,091	0,091	0,085	0,087	0,099
Mhours	150,042	150,89	151,39	151,51	153,29	154,41
Fulltime	0,71	0,71	0,72	0,72	0,73	0,74
Edlev13	0,11	0,10	0,10	0,081	0,071	0,073
Edlev14	0,45	0,45	0,43	0,39	0,38	0,37
Edlev15	0,22	0,22	0,22	0,28	0,29	0,29
Edlev16	0,14	0,13	0,15	0,17	0,18	0,18
Edlev17	0,083	0,088	0,092	0,074	0,076	0,076
Unioncov	0,038	0,035	0,038	0,032	0,024	0,021
Funlev2	0,21	0,22	0,21	0,21	0,21	0,20
Funlev3	0,18	0,18	0,17	0,18	0,18	0,17
Funlev4	0,20	0,20	0,20	0,19	0,19	0,19
Funlev5	0,13	0,13	0,13	0,15	0,15	0,14
Funlev6	0,14	0,14	0,15	0,15	0,15	0,17
Funlev7	0,039	0,041	0,043	0,041	0,049	0,048
Fsect2	0,28	0,29	0,29	0,29	0,28	0,29
Fsect3	0,18	0,19	0,19	0,18	0,19	0,18
Fsect4	0,26	0,27	0,28	0,29	0,29	0,29
Fsect5	0,080	0,080	0,074	0,068	0,064	0,068
OBS used	31960	30678	33110	32088	29034	25928
OBS total	73833	70050	74521	70000	69722	60602

Table 2 The estimation results (dependent variable LN hourly wages)

Variables \ Year	1986	1988	1990	1992	1994	1996
Constant	1.32	1.49	1.42	1.48	1.54	1.53
Gender	-0.21	-0.20	-0.19	-0.16	-0.17	-0.16
Agedum	-0.077	-0.053	-0.035	-0.035	0.00050*	-0.013*
Black	-0.068	-0.086	-0.095	-0.093	-0.088	-0.103
Texp	0.028	0.027	0.027	0.028	0.030	0.030
Texp ^{sq}	-0.00047	-0.00047	-0.00046	-0.00048	-0.00050	-0.00050
Mhours	-0.00088	-0.00082	-0.00039	-0.00076	-0.00085	-0.00067
Fulltime	0.21	0.21	0.16	0.18	0.17	0.18
Edlev13	0.17	0.081	0.19	0.12	0.086	0.16
Edlev14	0.33	0.21	0.33	0.26	0.25	0.31
Edlev15	0.45	0.32	0.48	0.38	0.37	0.43
Edlev16	0.62	0.51	0.66	0.60	0.60	0.66
Edlev17	0.71	0.57	0.75	0.70	0.74	0.79
Unioncov	0.12	0.13	0.15	0.11	0.13	0.100
Funlev2	-0.038	-0.040	-0.0090*	0.040	0.054	0.042
Funlev3	0.11	0.12	0.12	0.16	0.15	0.14
Funlev45	0.25	0.28	0.29	0.35	0.32	0.31
Funlev5	0.048	0.033	0.015*	0.0085*	0.021**	0.0029*
Funlev6	0.39	0.38	0.41	0.45	0.44	0.42
Funlev7	0.53	0.54	0.60	0.65	0.59	0.58
Fsect234	-0.14	-0.13	-0.13	-0.11	-0.10	-0.11
Fsect3	0.0099*	0.016**	0.019	0.013*	0.0027*	-0.0040*
Fsect4	-0.0089*	-0.018**	-0.027	-0.010*	-0.017**	-0.008*
Fsect5	-0.073	-0.074	-0.073	-0.050	-0.036	-0.038
Adjusted R ²	0.47	0.46	0.47	0.45	0.42	0.43

* insignificant

** significant at 5%

all others: significant at 1%

Figure 7 *Estimated and corrected hourly wages (educational level 3, 1996)*

