WP2: The Impact of Changes in the Supply of Qualifications on Wages – United Kingdom

Anna Vignoles and James Walker †

(June 2000)

We employ two different methodologies to examine the evolution of private rates of return to education in the UK during the 1990s. The first methodology uses linear regression techniques on a large pooled sample over the period in question. The second uses a combination of stochastic frontier and OLS estimation to look at the number of years UK residents are spending in education, and the effects this has on the returns to education. While the methodologies used differ significantly, both address the issue of what has happened to rates of return in the UK education system in a period of significant labour force expansion. Both methods suggest that rates of return have remained stable during the 1990s.

---

† Correspondence to a.f.vignoles@cep.ac.uk and j.t.walker@lse.ac.uk.

Introduction

In this report, we evaluate the impact of changes in the supply of qualifications in the UK on workers' wages. Specifically, we ask whether the large increase in the supply of qualifications in the UK has led to a fall in the wage returns to particular types of qualifications. In addition to investigating the wage returns to different types of qualifications, we also examine these changes over time, and take into account changes in occupational structure.

The analysis for this report is in two parts. Part I starts with a conventional wage equation analysis, using ordinary least squares regression, which investigates the impact of having a particular qualification on a person's wages, specifically focusing on changes in this "return" over time. Part II of the analysis models the average education "required" to carry out a particular occupation (based on a frontier estimation technique) and then evaluates the impact of this "required" education on workers' wages. Part III briefly concludes.

I. Standard Wage Equation Analysis: Using Ordinary Least Squares

For this analysis, we use the UK Labour Force Survey (LFS) to estimate the returns to particular educational qualifications in the 1990s. Our interest is in assessing the private wage returns to these qualifications, during a period of significant labour force expansion, as discussed in previous reports for this project *(Vignoles and Steedman (1999))*.

Using the LFS data set has four advantages. First, it is one of the most up to date data sources available for this type of analysis in the UK. Second, the LFS provides a large sample (a total of 79,815 individual observations were available over the sample period), enabling us to obtain highly precise estimates. Third, a consistent break down of both academic and vocational qualifications allows us to examine in great detail, and by type of qualification, the private returns to education. This level of detail is of great importance since, as Dearden, McIntosh, Myck, and Vignoles (2000) have shown, wage returns differ markedly between different types of qualifications. Finally, the comprehensive detail of the LFS data enables us to control for a number of other observable characteristics that are known to impact on wages, such as age, region etc.

We examine the impact of education on private financial returns between 1993 and 1999 in a general model being given by

$$\ln w_i = b_i^{'} S_i + b_i^{'} X_i + e_i$$

where w_i is the hourly wage earnings, S_i is a vector of academic or vocational qualifications, and X_i is a vector of background variables that are also believed to determine earnings. Equation (1) can be viewed as a form of regression based on linear matching, akin to a simplified version of the non-parametric estimator of Heckman *et al.* (1997, 1998). We pool seven individual cross-sections between 1993-1999, using year dummies to control for the impact of idiosyncratic labour market effects in any given year, and to simultaneously adjust for inflationary factors.[1]

Table 1 defines each of the qualifications used in the study by NVQ level equivalent and estimated years of education needed to obtain that particular qualification (see also Vignoles and Steedman (1999)). We avoid using years of education as an explanatory variable in our wage analysis, and instead use actual qualifications obtained. This is preferable since, in the UK system, estimating the precise number of years of education required to acquire a specific qualification (particularly a vocational qualification) is quite problematic.

In Table 2 we give descriptive statistics for qualifications obtained for the beginning and end years of our sample, as well as for the full pooled sample. There is a clearly discernable rise in the number of individuals obtaining qualifications, with 20% of individuals being unqualified in 1992 and only 12% in 1999. Also, in the main, at the end of the period there is a larger proportion of individual with higher level

[1] Our choice of years is determined by our interest in recent shifts in the labour market, and more pragmatically by data availability with wage data only being available in the LFS from 1992. The results of the copious cross-section analyses are available on request.

qualifications (in particular higher degrees), and with higher level vocational qualifications (e.g. HNC/HND BTEC National). This is consistent with the supply shift emphasised by Vignoles and Steedman (1999) and Dearden, McIntosh, Myck, and Vignoles (2000).[2]

Tables 3 through 5 give our results for the pooled regressions for the full sample (Table 3), and subdividing the sample by gender (Table 4 women, and Table 5 men). Specification 1, in each of the three tables, is a base-line regression including only the qualification type dummies. The base case is an individual with no qualifications at all. In our second specification, a typical set of background variables or demographic factors are used as controls, namely: age (also entered in a quadratic form); ethnicity, and the region where an individual works.[3] Finally, the third specification examines the impact of particular qualifications on wages, controlling for the occupation that the person is working in. Four occupational class dummies are included (managerial, professional, associate professional, and 'white-collar workers'), against the reference group of 'blue-collar workers'.[4] As the key interest of this study is to capture the impact of the changing supply of qualifications in the UK, on the evolution of wages, we incorporate interactions of each educational qualification variable with year (time) dummies.[5] These interaction variables will show any changes in the return to a particular qualification over the time period under consideration.

I.1. The Impact of Qualifications on Wages

Table 3 provides a summary of the wage differentials between workers with particular qualifications, and those with no qualifications at all. The wage premium for a degree is around 75%, and 30% for A levels. Individuals with O levels still earn around 10% more than those with no qualifications at all, although there is no wage premium from

[2] There is considerable evidence that skill up grading is an international phenomena (see for example Machin and Van Reenen (1998).
[3] We experimented with specifications that included firm size, and cohort effects (via the inclusion of dummies that captured 5 yearly age groups). The inclusion of these factors had no discernible impact on our results, and are omitted in the specifications presented.
[4] The occupational classifications are: 1. Managers and administrators 2. Professionals 3. Associate Professionals 4. 'White Collar' (Clerical and Secretarial Occupations, personal and protective service operations, and sales) 5. 'Blue Collar' (Craft and related occupations, plant and machinery operatives and 'other' occupations).

having a lower grade CSE. Average returns to vocational qualifications are lower than the returns to academic qualifications. For example, a higher level vocational qualification (HNC/HND BTEC National) yields a wage premium of only 46%, compared to someone with no qualifications. However, these raw figures do not take any account of the difference in time taken by the student to acquire a particular qualification. Other work suggests that the ***annual*** return to some higher level vocational qualifications is similar to the return to academic qualifications (Dearden et al (2000)).

I.2. Gender Differences

There are a number of differences in the returns to specific qualifications by gender. In particular, the returns to nursing and to 'other' qualifications are much greater for females than for males. Conversely, some vocational qualifications (City and Guilds and apprenticeships) yield a much higher return for males, than for females. Overall however, comparing Tables 2 and 3, the wage returns to many types of qualification are broadly similar for men and women. Certainly there is no consistent pattern, i.e. wage returns are not always higher for women. The qualifications with the greatest return for both genders are degrees and higher degrees. Females with a higher degree earn just over 90% more than females with no qualifications at all, whilst the wage premium for a degree is just over 80% for women. For males, those with a higher degree earn just under 90% more than those with no qualifications at all, whilst the premium for a degree is just over 70% for males.

I.3. Additional Controls

Tables 3-5 show that in general, the effect of including demographic/background controls (Specification 2) is to lower the coefficients on the education variables, however these reductions made little quantitative and no qualitative difference to our

[5] The exclusion of time-qualification interactions had no significant effect on the robustness of our other results.

results. [6] The demographic controls (which are not reported) are in all cases significant, both individually and jointly, and are 'correctly' signed.[7]

The third specification, which includes the occupation dummy variables, suggests, unsurprisingly, that there is a positive wage for workers in professional, managerial and associate professional jobs, relative to 'blue-collar' workers with the exception of 'white-collar' males.[8] Including the occupational dummy variables in the specification reduces the return to most qualifications, since much of the labour market benefit from qualifications arises from the fact that they provide access to higher level occupations. Therefore taking into account occupation, the net return to some qualifications, particularly academic ones, is reduced. Including the occupational variables also tends to narrow the gap between the return to vocational and academic qualifications. Thus, within a given occupation group, such as white-collar workers, the return to most vocational qualifications is closer to the return to most academic qualifications. Obviously the occupational structure of the labour market changes over time, and there has been a well-documented decline in the number of blue-collar jobs. Specification 3 takes these changes in the occupational structure into account, providing estimates of the return to education, net of changes in occupational structure.

I.4 Changes Over Time

We turn now to the main focus of our report, namely changes in returns to education over time. In all specifications, we include education-year interactions, to measure whether the return to each particular qualification has increased over the time period under consideration (1993-1999). Specification 1 suggests that, on balance, there has been an increase in the return to most qualifications over time. Specifically there has

[6] In addition we undertake the following mis-specification tests: functional form using Ramsey's RESET statistic, and for normality of each variable by testing the kurtosis and skewness. In all cases the diagnostics support our specification.

[7] Our results are qualatively similar to those obtained by Dearden, McIntosh, Myck, and Vignoles (2000) who provide a more detailed analysis of each qualification.

[8] We consider that this may reflect the compositional make up of 'blue-collar' workers, which includes crafts and other occupations. In addition, the low return of female managers is likely to be affected by a larger proportion of female administrators, which are included in the occupation group.

been an increase in the return to degrees, higher level vocational qualifications, and mid-level academic and vocational qualifications (O levels/City and Guilds).

However, the introduction of background controls (Specification 2), and occupational groups (Specification 3) results in the majority of qualifications showing no change in returns over time. Specifically, there has been no increase in the wage return to a degree/higher degree, nor to A levels. However, HNC/HND, ONC/OND BTEC qualifications and apprenticeships show a small increase in the wage return over time. In no case does any qualification show a reduction in the wage return over time. Examining the split between the genders also indicates some differences, although again in no instance does any qualification show a significant reduction in the wage return over time – for males or females. Perhaps of most interest is the fact that the return for males to a degree has increased over time (although the change is only small in magnitude), but this has not been the case for women.

The coefficients on the education-time variables, whilst small, are clearly of great material interest to policy makers. They indicate that, despite the massive increase in the supply of qualifications in the UK during the 1990s (Vignoles and Steedman (1999)) there has been no decrease in the return to education during this period. This in turn suggests that there is no aggregate "over supply" of qualifications, and that the demand for qualified workers has increased sufficiently to offset the increase in supply.

II. Efficiency, Education Decisions, and Wages in the UK (1993 and 1999): Using Stochastic Frontier and Ordinary Least Square

In Part I of this report, we showed that, despite the well-documented increase in the supply of qualifications in the UK during the 1980s and 1990s, there has been no significant fall in the return to these qualifications. In aggregate therefore, this suggests no over-supply problem. However, other evidence from the UK (Dolton and Vignoles (2000), and indeed the rest of Europe, has suggested that 'overeducated' workers are a significant phenomenon in the labour market. In other words, many workers appear to have more education than they actually require to perform their jobs. In this section of the report, we investigate the relationship between 'overeducation', or surplus education, and wages.

Following Ghignomi (2000) we apply a two step methodology to investigate: a) the degree of educational 'inefficiency', in the sense of education over and above what is 'required' in the UK labour market, and b) the effects of 'overeducation' on wage earnings.

II.1 Background

There is now a significant international literature on the phenomenon of overeducation. Much of this literature addresses the issue of why individuals may have more education than is required for their particular occupation, as well as the effect of this overeducation on the wages they receive in the labour market. Sicherman (1991) provides a summary of this literature, in which he identifies a number of potential explanations for the phenomenon. These explanations include[9]

- The potential trade-off between schooling and other components of human capital (e.g. on-the-job training). In other words, worker may invest in more education than is required for a particular job, to make up for their lack of work experience.

[9] See Sicherman (1991) for associated references.

- Career mobility, whereby workers may temporarily take jobs for which they are overeducated but that also provide them with the opportunity for greater earnings later in life.
- Co-ordination problems due to mismatch between firms and individuals may cause some workers to end up temporarily in jobs for which they are overeducated.
- Under-utilised workers may be a permanent phenomenon. In particular, if firms do not up-grade jobs in response to an increase in the supply of educated workers, many individuals may end up permanently in jobs for which they are overeducated.

Although we do not comment on the relative importance of these different explanations for overeducation, they do provide a framework within which to think about the results of our analysis. Hence we first attempt to quantify the extent of over-education in the UK labour market. We then assess the impact of this overeducation on wages. To do this we require a technique that measures the extent to which an individual has more education than is 'required' for their occupational level. We use a stochastic frontier technique to determine whether an individual is off the frontier, i.e. has more (or less) education than is generally associated with his or her occupational group.

There are a number of difficulties with this approach. Firstly, the "required" education for a particular occupation is determined by the observed education level of workers in that occupation. However, as workers become more educated on average, the "required" education for a particular occupation will also automatically rise, even if the actual job does not change at all. Thus separating out "credentialism" and genuine overeducation is impossible with this technique (Green et al. (2000)). It is also not immediately obvious why a stochastic frontier is appropriate, since it is by definition a disequilibrium model. Indeed, of the four explanations for 'over-education' listed above, only the fourth is consistent with a disequilibrium model of the labour market The first two explanations are consistent with the 'human capital' model, where individuals maximise their earning over their life cycle, and thus 'over-education' is an observed artefact of individuals' strategies to do so. The third suggests a short term matching problem. Only the fourth argument suggests that disequilibrium has a permanent role. Despite these problems, the justification for using this approach is that our interest is purely in measuring the extent of any 'over-education' (or inefficiency) and not in its causes.

Previously, the use of stochastic frontier estimation has generally been confined to modelling firm 'inefficiency', whereby the error term in the model is decomposed into random and strictly positive components. In their seminal paper, Aigner, Lovell and Schmidt (1977) argued that the random error component represented events outside the control of the firm (such as weather, or simply luck), while the 'inefficiency' component represented factors under the firm's control. We take an analogous interpretation that the 'inefficiency' component is controllable by the individual (who may be substituting between other types of human capital, because there is a higher probability of promotion etc.), while the random error component is not.

The data used for this analysis is the same data set as for Part I, namely the Labour Force Survey. We analyse two cross-sections in 1993 and 1999. We use these years since, analogous the OLS regression analysis in Part I, we are interested in examining the evolution of changes to the private rates of return to education. Since these two years provide the end points of the time span previously examined they are the logical choice of years, to identify shifts over time.

II.2. Frontier Estimations (STEP-ONE)

As noted above, the first methodological step is to estimate a frontier, modelling the number of years an individual requires to obtain a particular qualification, in our case the inverse of years of equivalent education $[(EQUIV)^{-1}]$. As was noted in Part 1, any proxy for equivalent years of education is likely to suffer from measurement error, since estimating the precise number of years required to acquire a specific qualification is problematic in the UK.[10] We posit that an individual's age $[AGE_i]$ is a key determinant of their number of years of education (cohort effects). We expect that older workers will tend to have less education; age will be negatively related to years of education, and thus positively related to its inverse. Also, we use dummy variables indicating the occupation or profession of workers $\left(\sum_{i=1}^{5} P_i\right)$. The occupational definitions mirror those used in Part 1, where the reference is ‘blue collar’ workers. Since other occupations generally require more education than do ‘blue collar’ jobs, the occupation dummies are positively related to years of education, and hence negatively to its inverse. Finally, we interact the individual’s age with their occupation $\left(\sum_{i=1}^{5} I_i\right)$, allowing for cohort driven changes in the occupational structure of the labour market. Formally

$$(EQUIV)^{-1} = b_0 + b_1 AGE + \sum_{i=1}^{5} P_i + \sum_{i=1}^{5} I_i + m + n \tag{1}$$

where the error term is decomposed into a normally distributed error component, $m \approx N(0, s_m^2)$, and a strictly positive half-normal component $n \approx +\frac{1}{2} N(0, s_u^2)$.[11]

Descriptive statistics are given in Tables 6.1 and 6.2 for the 1993 and 1999 cross-sections respectively. The years of education observed ranges between two and twelve years, with the relationship between a particular qualification and years of education given in Table 1. We assumed that the equivalent years of education for individuals with no education is zero. While this reduces our sample sizes somewhat, they remain adequate and in any case computational constraints forced us to make this assumption. We appreciate that this leads to some difficulties interpreting the results. We are excluding the least educated workers, so the observed (and required) years of education will be higher in our data, than is actually the case. Also the proportion of

---

[10] This caveat is important because stochastic frontiers (being based on relative measurement) are highly sensitive to outliers hence mis-measurement poses a potentially more serious problem then in the OLS estimation (being based on averaging measurement) in Part 1.

[11] As Schmidt (1985-86) points out, while the half normal distribution has been the most commonly assumption for the (inefficiency) errors, there is no reason apparent for this to be the case. We experimented with the exponential, and Stevensons (1980) more general truncated error terms and found our results differed only marginally. In addition, a number of alternative algorithms were employed to namely Joreskog and Gruvaeus (1970), Berndt, Gakk, Hall and Hausman (1974), and

workers with no qualifications has fallen over the period, potentially biasing our results. [NOTE FOR BARCELONA MEETING: WE WOULD BE GRATEFUL FOR GUIDANCE ON THIS POINT – IN PARTICULAR HOW TO ESTIMATE THE MODEL WHILE STILL INCLUDING WORKERS WITH NO QUALIFCATIONS].

Comparing actual observed mean education levels with those predicted by the model, the predicted value is an underestimate in both years. The residual decomposition indicates that about 30% of the sample exhibits negative residual for both years.

The results of the two frontiers and OLS equations are given in Tables 7.1 and 7.2. The results for the OLS and half-rounded stochastic frontiers are similar for each year. While we cannot compare the resulting goodness of fit estimates of the OLS and MLE models we note that OLS model has an acceptable level of predictive power, and that the coefficients are in all cases well determined and intuitively signed.[12]

II.2.B. Estimating Private Rates of Return to Education (STEP TWO)

We now turn to wage estimation. Unlike the OLS regression in Part I, we have additional information from the first-step frontier regression on the extent of 'over-education' in the UK labour. Specifically, for each individual we have their actual years of schooling, plus an estimate of the required years of education for their occupation/age group, and hence the sign and magnitude of their residual value from the frontier estimation. We begin by estimating a wage equation similar to the third specification used in Part 1, as below,

$$\ln(w) = b_0 + b_1 AGE + b_2 AGE^2 + b_3 ACT\_EDUC + \sum_{i=1}^{5} P_i \qquad (2.1)$$

where $[ACT\_EDUC]$ is the actual number of years of education, and age is entered in both raw and quadratic forms. It is important to note that while the above

Newton's method (see Limdep 7.0 for details), to enhance the efficiency of the non-linear esimation. The resulting impacts did not enhance the computation of the estimators significantly.

specification is similar to Specification 3 in Part 1, it is not equivalent. There are two reasons for this. In Part 1 our base case or comparison group is unqualified workers, while this group is excluded from the analysis here. Furthermore, for the analysis in this section we use years of education, rather than the set of qualification dummy variables used in Part I. It is therefore not possible to directly compare the coefficients between the two methods. That said, reassuringly both the 1993 and 1999 results (contained in Tables 8.1 and 8.2) are qualitatively similar to those found in Part I, and the coefficients on the actual level of education are well determined. The OLS results from Tables 8.1 and 8.2 indicate a return of around 5% per additional year of education in both 1993 and 1999, compared to those with just very low-level qualifications (2 years of schooling). This confirms our main result from Part I, namely that the return to education has not fallen significantly during the 1990s. In addition, and consistent with the results from Part I, the wage premium from being in a higher level occupation, with the exception of 'white collar' workers, has increased relative to 'blue collar' workers.[13]

Next we examine the effect of including the 'over-education' residual obtained from the frontier regression as an explanatory variable. We first include the level of education predicted in the first step frontier estimation $[EST\_EDUC]$ as well as the strictly positive residual term $[RESID^{+}]$. In essence, the predicted level of education is a measure of the education "required" for that occupation/age group. The residual measures the extent, if any, of the individual's overeducation.

$$\ln(w) = b_0 + b_1 AGE + b_2 AGE^2 + b_3 EST\_EDUC + b_4 RESID^{+} + \sum_{i=1}^{5} P_i \qquad (2.2)$$

The results of this estimation are labelled specification 1 in Table 8.1 and 8.2. The coefficients on both the predicted or required years of education and the surplus education or 'inefficiency' component are found to be positive and well defined. Specifically the return to required years of education is just over 3% in both 1993 and

[12] We note that this is in contrast to Ghignoni (2000), although this may be partcially reflect differing dependent variable in that 'uneducated workers' included in that paper.

1999. The results also indicate a small positive labour market return to years of 'over-education'.

Finally, we then replace the required or predicted years of education variable with actual years of education, but including the residual variable (Specification 2 in Tables 8.1 and 8.2). This specification yields the return to education, and measures the separate effect of having surplus years of education.

$$\ln(w) = b_0 + b_1 AGE + b_2 AGE^2 + b_3 ACT\_EDUC + b_4 RESID^{+} + \sum_{i=1}^{5} P_i \qquad (2.3)$$

The results are similar to Specification 1, although the 1993 results suggest no return to surplus years of education, since the coefficient on the residual term is insignificantly different from zero. These finding conflict with the Ghignoni (2000) study of the Italian labour market in 1993, where the coefficient on the years of surplus education variable (the 'inefficiency' term) was found to be always positive and significant. In particular, Ghignoni found very large effects from estimating the equivalent of Specification 2 in Tables 8.1 and 8.2. In contrast we find that there is discernable but very modest impact from years of surplus education. Overall our results suggest that additional years of 'over-education' will yield a positive return, but that the effect is extremely small.

Note that all three specifications in Tables 8.1 and 8.2 suggest a positive and stable return to actual and required years of education. Hence our main proposition, that the increase in the supply of qualified labour has not led to a fall in the return to education, holds.

III. Conclusions

We have employed two radically different methodologies to assess the returns to education in the UK during the 1990s. While the two approaches are not strictly

---

[13] We note however that the sign of the 'white collar' workers dummy is negative. This result likely reflects the rather crude categorisation of workers and was found to be the case in a number of cross-sections examined (but unreported) in Section 1.

comparable, they both point to the same conclusion: there is no aggregate "over supply" of qualifications, and that the demand for qualified workers has increased sufficiently to maintain education related wage differentials.

References

Aigner, D., Lovell, K.A., and Schmidt, P. (1977), 'Formulation and Estimation of Stochastic Frontier Production Functions', Journal of Econometrics 6, 21-37

Dearden, L., McIntosh, S., Myck, M., and A. Vignoles (2000), 'The Returns to Academic, Vocational and Basic Skills in Britain', Report for the Department of Education and Employment

Dolton, P., and Vignoles, A. (2000)

Ghignoni, E. (2000), 'Frontier de Competence et Foncition de Gain', EDEX, Work Package 2.3

Green, W.H. (1995), *LIMDEP: Version 7.0 User's Manual*, Econometric Software Inc.

Green, F., McIntosh, S., and Vignoles, A. (2000)

Heckman, J.J., Ichimura, H., and Todd, P. (1997), 'Matching as an Econometric Evaluation Estimator', *Review of Economics and Statistics* 64, 605-54

Heckman, J.J., Ichimura, H., Smith, J. and Todd, P. (1998), 'Characterising Selection Bias Using Experimental Data', *Econometrica* 66, 1017-98

Machin and Van Reenen, J. (1998), 'Technology changes and Changes in Skill Structure: Evidence from the Seven OECD Countries', *Quarterly Journal of Economics* 113, 1215-44

Schmidt, P. (1985-86), 'Frontier Production Functions', *Econometric Reviews* 4(2), 289-328

Sicherman, N. (1991), '"Overeducation" in the Labour Market', *Journal of Labour Economics* 9(2), 102-22

Stevenson, R.E. (1980)., 'Likelihood Functions for Generalised Stochastic Frontier Estimation', *Journal of Econometrics* 13, 57-66

Vignoles, A., and H. Steedman, *Schooling and the Supply of Qualifications in the UK 1930-1997*, Report for the European Union TSER Programme (EDEX)

Table 1

Qualification	**NVQ Equivalent**	**Years of Education Equivalent**
Higher Degree	NVQ5	12
First Degree	NVQ5	11
BTEC, HNC, HND	NVQ4	9
Teaching	NVQ4	9
Nursing	NVQ4	9
BTEC, ONC, OND	NVQ3	7
A Level & equivalent	NVQ3	7
City & Guilds	NVQ3	5
Apprenticeship	NVQ3	5
O Level/ GCSE A-C	NVQ2	4
CSE below Grade 1 or GCSE below Grade	NVQ1	4
Other qualifications	NVQ1	2

Table 2: Descriptive Statistics, LFS (1993, 1999, Pooled 1993-1999)

	1993		1999		Pooled (1993-1999)	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Higher degree	250	3%	775	5%	3132	4%
Degree	978	12%	1947	12%	9468	12%
HNC/HND BTEC National	442	5%	1095	7%	5197	7%
Teaching	149	2%	227	1%	1233	2%
Nursing	257	3%	427	3%	2393	3%
ONC/OND BTEC National	259	3%	513	3%	2560	3%
City and Guilds	802	10%	1813	12%	8937	11%
A levels	530	6%	1209	8%	5687	7%
O levels	1484	18%	3095	20%	15480	19%
Apprenticeship	436	5%	644	4%	3695	5%
CSE	342	4%	489	3%	2775	3%
Other qualifications	656	8%	1623	10%	7930	10%
No qualifications	1655	20%	1856	12%	11328	14%
TOTAL	8240	100%	15713	100%	79815	100%

Table 3: Returns to Detailed Qualifications (LFS)
[Depend variable Is ln(wages)]
Pooled regressions (1993-99), N=79,815

	Specification 1		Specification 2		Specification 3	
	Coeff.	(S.E.)	Coeff.	(S.E.)	Coeff.	(S.E.)
Higher degree	0.927	(0.024)	0.936	(0.023)	0.603	(0.023)
Degree	0.744	(0.014)	0.802	(0.015)	0.512	(0.015)
HNC/HND BTEC National	0.461	(0.018)	0.566	(0.018)	0.370	(0.018)
Teaching	0.723	(0.033)	0.736	(0.033)	0.442	(0.030)
Nursing	0.437	(0.021)	0.520	(0.022)	0.311	(0.021)
ONC/OND BTEC National	0.206	(0.023)	0.398	(0.022)	0.284	(0.021)
City and Guilds	0.193	(0.013)	0.326	(0.015)	0.259	(0.014)
A levels	0.287	(.0195)	0.453	(0.018)	0.342	(0.018)
O levels	0.091	(0.011)	0.277	(0.013)	0.219	(0.013)
Apprenticeship	0.164	(0.018)	0.228	(0.019)	0.186	(0.018)
CSE	-0.027	(0.019)	0.165	(0.020)	0.134	(0.019)
Other qualifications	0.080	(0.014)	0.138	(0.016)	0.112	(0.015)
Education and year interations:						
Higher degree*year	0.008	(0.004)	-0.005	(0.004)	-0.004	(0.004)
Degree*year	0.018	(0.003)	0.002	(0.003)	0.005	(0.003)
NC/HND BTEC National*year	0.030	(0.004)	0.010	(0.004)	0.011	(0.003)
Teaching*year	0.021	(0.007)	0.000	(0.007)	0.001	(0.006)
Nursing*year	0.016	(0.004)	-0.005	(0.004)	-0.004	(0.004)
ONC/OND BTEC National*year	0.041	(0.005)	0.015	(0.004)	0.015	(0.004)
City and Guilds*year	0.030	(0.002)	0.005	(0.003)	0.007	(0.003)
A levels*year	0.019	(0.004)	0.001	(0.004)	0.001	(0.004)
O levels*year	0.021	(0.002)	-0.002	(0.003)	0.010	(0.004)
Apprenticeship*year	0.028	(0.004)	0.011	(0.004)	0.001	(0.002)
CSE*year	0.023	(0.004)	-0.001	(0.004)	0.002	(0.004)
Other qualifications*year	0.019	(0.003)	0.001	(0.003)	0.001	(0.003)
Occupations:						
Managers					0.370	(0.006)
Professional					0.366	(0.007)
Associate Professional					0.253	(0.006)
White Collar					0.065	(0.004)
R^2		0.267		0.382		0.458
P-value age				0.000		0.000
P-value white				0.000		0.000
P-value region effects				0.000		0.000
P-value year effects		0.000		0.000		0.000
P-value education-year interactions		0.000		0.000		0.000

*Uneducated workers provide the reference group for each education group;
London the reference group for regions; Blue Collar workers are the occupational reference group

Table 4: Female Returns to Detailed Qualifications (LFS):
[Depend variable Is ln(wages)]
Pooled regressions (1993-99), N=40,082

	Specification 1		Specification 2		Specification 3	
	Coeff.	(S.E.)	Coeff.	(S.E.)	Coeff.	(S.E.)
Higher degree	0.985	(0.038)	0.922	(0.036)	0.494	(0.035)
Degree	0.806	(0.021)	0.793	(0.203)	0.426	(0.020)
HNC/HND BTEC National	0.424	(0.031)	0.460	(0.028)	0.256	(0.026)
Teaching	0.874	(0.037)	0.846	(0.037)	0.425	(0.032)
Nursing	0.600	(0.023)	0.615	(0.023)	0.350	(0.023)
ONC/OND BTEC National	0.219	(0.030)	0.326	(0.028)	0.201	(0.028)
City and Guilds	0.026	(0.026)	0.112	(0.025)	0.050	(0.025)
A levels	0.307	(0.024)	0.390	(0.022)	0.260	(0.021)
O levels	0.169	(0.015)	0.248	(0.015)	0.163	(0.032)
Apprenticeship	0.070	(0.034)	0.075	(0.033)	0.040	(0.015)
CSE	0.072	(0.023)	0.142	(0.022)	0.096	(0.022)
Other qualifications	0.173	(.0186)	0.166	(0.018)	0.094	(0.017)
Education and year interations:						
Higher degree*year	-0.008	(0.007)	-0.003	(0.007)	-0.002	(0.006)
Degree*year	-0.003	(0.004)	-0.001	(0.004)	0.004	(0.004)
HNC/HND BTEC National*year	0.019	(0.006)	0.018	(0.006)	0.017	(0.005)
Teaching*year	0.007	(0.008)	0.003	(0.008)	0.007	(0.006)
Nursing*year	0.000	(0.005)	-0.003	(0.005)	0.006	(0.004)
ONC/OND BTEC National*year	0.024	(0.006)	0.016	(0.006)	0.016	(0.006)
City and Guilds*year	0.024	(0.005)	0.014	(0.005)	0.012	(0.005)
A levels*year	0.005	(0.005)	0.003	(0.004)	0.003	(0.004)
O levels*year	0.008	(0.003)	0.003	(0.003)	0.005	(0.003)
Apprenticeship*year	0.009	(0.007)	0.006	(0.007)	0.003	(0.006)
CSE*year	0.000	(0.005)	-0.005	(0.005)	-0.001	(0.004)
Other qualifications*year	-0.003	(0.004)	-0.004	(0.004)	0.000	(0.003)
Occupations:						
Managers					0.439	(0.009)
Professional					0.579	(0.011)
Associate Professional					0.392	(0.009)
White Collar					0.103	(0.005)
R^2		0.311		0.393		0.470
P-value age				0.000		0.000
P-value white				0.000		0.000
P-value regional effects				0.000		0.000
P-value year effects		0.000		0.000		0.000
P-value education-year interactions		0.000		0.000		0.000

*Uneducated workers provide the reference group for each education group;
London the reference group for regions; Blue Collar workers are the occupational reference group

Table 5: Male Returns to Detailed Qualifications (LFS):
[Depend variable Is ln(wages)]
Pooled regressions (1993-99), N=39,733

	Specification 1		Specification 2		Specification 3	
	Coeff.	(S.E.)	Coeff.	(S.E.)	Coeff.	(S.E.)
Higher degree	0.863	(0.032)	0.770	(0.030)	0.518	(0.030)
Degree	0.706	(0.023)	0.659	(0.021)	0.430	(0.021)
HNC/HND BTEC National	0.450	(0.026)	0.459	(0.023)	0.286	(0.023)
Teaching	0.728	(0.079)	0.610	(0.074)	0.428	(0.072)
Nursing	0.392	(0.066)	0.371	(0.064)	0.161	(0.058)
ONC/OND BTEC National	0.223	(0.035)	0.332	(0.029)	0.217	(0.028)
City and Guilds	0.178	(0.020)	0.207	(0.018)	0.169	(0.018)
A levels	0.359	(0.034)	0.441	(0.028)	0.308	(0.027)
O levels	0.151	(0.024)	0.301	(0.024)	0.215	(0.020)
Apprenticeship	0.147	(0.024)	0.107	(0.021)	0.117	(0.022)
CSE	-0.027	(0.034)	0.146	(0.030)	0.117	(0.029)
Other qualifications	0.098	(0.026)	0.064	(0.025)	0.060	(0.024)
Education and year interations:						
Higher degree*year	0.004	(0.006)	0.002	(0.005)	0.018	(0.006)
Degree*year	0.013	(0.004)	0.011	(0.004)	0.010	(0.004)
NC/HND BTEC National*year	0.021	(0.005)	0.012	(0.005)	0.011	(0.004)
Teaching*year	-0.004	(0.015)	-0.009	(0.015)	-0.018	(0.014)
Nursing*year	0.017	(0.014)	0.009	(0.013)	0.015	(0.018)
ONC/OND BTEC National*year	0.029	(0.007)	0.015	(0.006)	0.015	(0.006)
City and Guilds*year	0.017	(0.004)	0.006	(0.001)	0.006	(0.004)
A levels*year	0.004	(0.007)	0.001	(0.006)	0.000	(0.005)
O levels*year	0.005	(0.005)	0.013	(0.005)	-0.003	(0.004)
Apprenticeship*year	0.015	(0.005)	-0.004	(0.004)	0.012	(0.004)
CSE*year	0.017	(0.007)	0.004	(0.006)	0.005	(0.006)
Other qualifications*year	0.009	(0.005)	0.006	(0.005)	0.003	(0.005)
Occupations:						
Managers					0.364	(0.007)
Professional					0.312	(0.009)
Associate Professional					0.262	(0.008)
White Collar					0.008	(0.006)
R^2		0.236		0.420		0.470
P-value age				0.000		0.000
P-value non-white				0.000		0.000
P-value regional effects				0.000		0.000
P-value year effects		0.000		0.000		0.000
P-value education-year interactions		0.000		0.004		0.003

*Uneducated workers provide the reference group for each education group;
London the reference group for regions; Blue Collar workers are the occupational reference group

Table 6.1: Descriptive Statistics, LFS 1993

Variables	Mean	Std Dev	Minimum	Maximum	N
Act_Educ (Level of Education Observed)	6.69	2.684	2	12	5700
Est_Educ (Level of Education Predicted)	5.54	1.287	2.165	7.994	5700
RESID (Residual)	1.150	2.194	-3.981	7.370	5700
$RESID^+$ (Positive Residual)	2.280	1.760	0.012	7.370	3819
$RESID^-$ (Negative Residual)	-0.786	0.709	-3.981	-0.010	1881

Table 6.2: Descriptive Statistics, LFS 1999

Variables	Mean	Std Dev	Minimum	Maximum	N
Act_Educ (Level of Education Observed)	6.74	2.89	2	12	12492
Est_Educ (Level of Education Predicted)	5.22	1.26	1.86	7.91	12492
RESID (Residual)	1.52	2.29	-2.77	7.88	12492
$RESID^+$ (Positive Residual)	2.78	1.90	0.00	7.88	8720
$RESID^-$ (Negative Residual)	-0.46	0.53	-2.77	0.00	3772

Table 7.1: OLS & Stochastic Frontier Estimations, LFS 1993 (N=5,700)
[Depend variable is the Inverse of Equivalent Years of Education]

Variable	OLS Coefficient	(S.E.)	Frontier Coefficient	(S.E.)
Constant	0.192	0.004	0.203	0.010
Age	0.001	0.000	0.001	0.000
Managers & Admin (P1)	-0.043	0.008	-0.043	0.007
Prof (P2)	-0.067	0.008	-0.067	0.012
Associate Prof (P3)	-0.054	0.009	-0.054	0.010
White collar (P4)	-0.024	0.005	-0.024	0.010
Interactions				
P1*Age	-0.001	0.000	-0.001	0.000
P2*Age	-0.001	0.000	-0.001	0.000
P3*Age	-0.001	0.000	-0.001	0.000
P4*Age	0.000	0.000	0.000	0.000
$\mathrm{var}[m]/\mathrm{var}[u]$			0.781	0.283
$\sqrt{\mathrm{var}^* m + \mathrm{var}^*}$			0.050	0.007
Adj-R^2		0.382		
Log Likelihood				8956

*"Blue collar" workers provide the reference group

* Errors are assumed half normally distributed

Table 7.2: OLS & Stochastic Frontier Estimations, LFS 1999 (N=12,493)

Variable	OLS Coefficient	Std. Error	Frontier Coefficient	Std. Error
Constant	0.225	0.004	0.261	0.006
Age	0.000	0.000	0.000	0.000
Managers & Admin (P1)	-0.119	0.006	-0.115	0.007
Prof (P2)	-0.134	0.006	-0.137	0.012
Associate Prof (P3)	-0.132	0.007	-0.136	0.009
White collar (P4)	-0.055	-0.055	-0.050	0.006
Interactions				
P1*Age	-0.002	0.000	-0.002	0.000
P2*Age	-0.001	0.000	0.000	0.000
P3*Age	-0.001	0.000	-0.001	0.000
P4*Age	0.001	0.000	-0.001	0.000
$\mathrm{var}[m]/\mathrm{var}[u]$			0.981	0.103
$\sqrt{\mathrm{var}^* m + \mathrm{var}^*}$			0.080	0.002
Adj-R^2		0.407		
Log Likelihood				16690

*"Blue collar" workers provide the reference group

* Errors are assumed half normally distributed

Table 8.1: Wage Equations, LFS 1993
[Depend variable Is ln(wages)]

Variable	OLS Coefficient	(S.E.)	Specification 1 Coefficient	(S.E.)	Specification 2 Coefficient	(S.E.)
Constant	0.254	0.065	0.045	0.436	0.045	0.436
Age	0.060	0.003	0.081	0.005	0.081	0.005
Age^2	-0.001	0.000	-0.001	0.000	-0.001	0.000
Managers & Admin (P1)	0.362	0.017	0.277	0.112	0.277	0.112
Prof (P2)	0.339	0.021	0.404	0.298	0.404	0.298
Associate Prof (P3)	0.219	0.017	0.029	0.195	0.094	0.029
White collar (P4)	0.002	0.014	-0.010	0.028	-0.010	0.028
Act_Educ	0.047	0.003			0.034	0.017
Est_Educ			0.035	0.018		
RESID[+]			0.008	0.001	-0.039	0.084
Adj-R^2		0.435		0.437		0.443
N		5700		3819		3819

*"Blue collar" workers provide the reference group

Table 8.2: Wage Equations, LFS 1999
[Depend variable Is ln(wages)]

Variable	OLS Coefficient	Std. Error	Specification 1 Coefficient	Std. Error	Specification 2 Coefficient	Std. Error
Constant	0.262	0.044	0.148	0.137	0.148	0.137
Age	0.065	0.002	0.076	0.003	0.076	0.003
Age^2	-0.001	0.000	-0.001	0.000	-0.001	0.000
Managers & Admin (P1)	0.406	0.014	0.373	0.037	0.373	0.037
Prof (P2)	0.365	0.017	0.361	0.109	0.361	0.109
Associate Prof (P3)	0.206	0.016	0.168	0.065	0.168	0.065
White collar (P4)	-0.075	0.011	-0.134	0.015	-0.134	0.015
Act_Educ	0.046	0.002			0.033	0.003
Est_Educ			0.033	0.017		
RESID[+]			0.018	0.008	0.015	0.009
Adj-R^2		0.434		0.440		0.440
N		12493		8720		8720

*"Blue collar" workers provide the reference group