Essays in Labour Economics and Economics of Education

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Szilvia Hámori

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Referent: Prof. Bernd Fitzenberger, Ph.D.
Korreferent: PD Dr. Friedhelm Pfeiffer
Abteilungssprecher: Prof. Dr. Hans Peter Grüner

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To Tilmann

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Introduction

Socialist wage policy in the Central and Eastern European (CEE) countries tried to diminish wage differentials, that is, workers were not rewarded according to skill or productivity and the returns to education were set centrally and were low. Not surprisingly, transition brought with itself an increase in earnings inequality attributed to (among other things) widening earnings differentials across education groups, which has been documented by numerous studies on the CEE countries (for example, Kertesi and Köllő (1999), Keane and Prasad (2001), Munich et al. (2002), Orazem and Vodopivec (1998) and Noorkôiv et al. (1997)). Despite the quantitative differences across the CEE countries, the cross-country consensus (based on ordinary least squares (OLS) estimates of Mincer earnings equations) indicates that relative to primary school or less, the average premium to high school and university education rose dramatically while the average (relative) return to vocational education remained constant or even declined during the 1990s.

The first two chapters of the dissertation investigate earnings differentials in Hungary from two perspectives. Whereas the emphasis of the first chapter lies on the cross-country comparison – between Germany and Hungary – of the returns to education (and other variables of interest), the second chapter focuses on the evolution of earnings in the Hungarian private and public sectors of employment during the decade of 1994 – 2003. Before describing the content of the first two chapters in more detail, one point in terms of the main goal of the first two chapters, which goes hand in hand with the estimation method, merits comment. The purpose of the first two chapters is purely descriptive. That is, the aim is to analyse both between- and within-group earnings differentials given the existing international evidence that aggregate earnings inequality arises from differences between as well as within groups (Fitzenberger et al. (2001)), coupled with the fact that within-group differentials have not been the center of attention in Hungary for the period under analysis. Accordingly, the first two chapters use quantile regression (Koenker and Basset (1978)), the usefulness of which in applied econometrics has been stressed by a collection of studies in Fitzenberger et al. (2001).

Chapter 1 focuses on the returns to education in Hungary and Germany in 2000. The data for the empirical analysis is drawn form the "Hungarian National Labour Center's Wage Survey" and from the "German Socio-economic Panel (GSOEP)" for Hungary and Germany respectively. The recent extensive educational information for the two countries – which are characterised by similar education systems – lends itself very well to a differentiated comparative analysis. The empirical analysis based on differentiated schooling categories is more informative than if only the years of schooling were used as a proxy for the formal component of human capital since both countries under analysis have multiple education streams at certain levels of education, and subsequently a year of schooling in itself does not necessarily convey the true value of education neither in the respective country nor in a cross-country comparison. Therefore, as a first step, the study develops a system for comparison of the German and Hungarian education systems, which can be used in the empirical analysis to compare the returns to education across the two countries in a meaningful way.

In the empirical analysis, Mincer earnings equations (1974) are estimated using OLS regression – in order to provide a benchmark for comparison with existing estimates for Hungary – and quantile regression. For each country, additional specifications are estimated which are augmented with interaction terms between gender and the other control variables in order to highlight the differences in the estimates between the two genders. Finally, the returns to different fields of study are estimated using the subgroup of Professionals of the university graduates for the two countries. For Hungary, the estimation results not only document the pattern of earnings premia to different fields of study but also offer some explanation for the observed earnings advantage of males at the university level.

It is the analysis of the private-public sector earnings gap in Hungary for the decade of 1994 – 2003 which Chapter 2 of the dissertation proceeds with. This time period is particularly interesting not only from the perspective of transition but also given the wage reforms in the early 2000s: (a) the level of the minimum wage was increased twice, first on 01.01.2001 from 25,500 Hungarian Forints (HUF) to 40,000 HUF and then on 01.01.2002 to 50,000 HUF and (b) between September 2002 and 2003, there was a 50 percent average increase in public sector nominal wages, affecting different groups of public sector employees in different magnitudes – as the public sector wages were lagging behind the wages of the private sector throughout the decade of transition. In Chapter 2 (as in Chapter 1) the data is drawn from the "Hungarian National Labour Center's Wage Survey" in order to examine (a) the evolution of the private-public earnings gap for full-time male employees, (b) the evolution of the private-public earnings gap for four groups of full-time male employees distinguished by education (unskilled, low-skilled, middle-skilled and high-skilled) and (c) the evolution of the returns to education in the private and public sectors separately – as the emphasis for the decade of transition has been placed on the private sector.

Chapter 3 departs from the descriptive analysis of earnings inequality in Germany and Hungary and focuses on the effect of school starting age and socio-economic factors on academic performance for Hungarian grade four students. This is an important empirical question since research in education provides mixed theories and evidence on the optimal age at which children should start school: whereas proponents of late school starting age argue that that starting school at an older age ensures that children have sufficient time to acquire the human capital necessary for educational success, opponents of delayed school entry argue that (a) the advantage of late school entry may be modest and transitory and (b) the emphasis should be placed on "making schools ready for children rather than making children ready for school" (Stipek (2000)).

The challenge in estimating the effect of school starting age on academic performance arises from the fact that given a choice regarding enrolment decision, despite the cut-off date regulation, the group of students with early / delayed entry does not represent a random sample. That is, late (early) entrants may come from the pool of lower (higher) ability children and potentially from wealthier families (for whom the burden of additional childcare costs may be irrelevant). Given this non-random selection, late starters may be, on average, lower ability children and thus regressing academic performance on actual school starting age by OLS may generate a downward biased estimate of the age effect on academic performance. There exists an extensive recent empirical literature which focuses on instrumental variable estimation (IV) in order to overcome the problem of non-random selection (Bedard and Dhuey (2005), Fertig and Kluve (2005), Frederikkson and Öckert (2005), Leuven et al. (2004), Puhani and Weber (2007) and Strøm (2004)). In these studies the "expected school starting age" generated by (1) the cut-off date for enrolment and (2) the children's month of birth is used as an instrument for "actual school starting age". The consensus of the majority of these studies using the IV estimation strategy is that (1) the OLS estimate of the association between age and schooling outcomes is negative, attributed to the non-random selection of early / late starters, and (2) the IV regression yields a positive age effect, which differs in magnitude and across countries. An exception is the study by Fertig and Kluve (2005) who provide evidence that there is no effect of age at school entry on educational outcomes in Germany.

The aim of this final chapter is to estimate the effect of school starting age on academic performance in Hungary – a country for which, despite the vast recent international evidence, such analysis has not been carried out to this date – based on data from the "Progress in International Reading and Literacy Study (PIRLS)" and the "Trends in Mathematics and Science Study (TIMSS)". In addition to the standard OLS regressions, the study uses an extension to the IV strategy, namely, the control function approach, proposed by Garen (1984) and Heckman and Robb (1985). The effect of the other explanatory variables for the three areas of academic performance, such as gender, parental education, family size, and proxies for economic wealth are also investigated.

1 A comparative analysis of the returns to human capital in Germany and Hungary (2000)

1.1 Introduction

Cross-country comparisons of the returns to education[1] are often conducted within the European Union. Although such studies shed light on the interplay between education and earnings inequality across countries, there is a danger that, unless the empirical analysis is based on differentiated schooling categories, the results may not be very informative. For instance, if only the years of schooling is used as a proxy for the formal component of human capital, cross-country comparisons can be misleading if one of the countries under analysis has multiple education streams at some level of education and subsequently a year of schooling in itself does not necessarily convey the true value of education neither in the respective country nor in a cross-country comparison.

Therefore, one of the objectives of this paper is to develop a system for comparison of the German and Hungarian education systems, which can be used to compare the returns to the education across the two countries in a meaningful way.[2] Given Hungary's recent EU accession this study has its relevance in analysing how the returns to education in a "new" EU member state compare to that of an "older" member state. Germany as an "older" EU member state is chosen because (a) Germany is a country with a stable wage structure in a cross-country comparison (despite the increase in wage inequality since 1993 / 94)[3] and (b) the two countries have similar education systems, which allows for a differentiated cross-country comparison.[4] In fact, from a historical perspective, the influence of the German education system on the Hungarian one has its roots in the 16th century. The high level of similarity is already apparent at the secondary level. That is, the traditional differentiation among the three types of lower secondary schools, according to "theoretical" (*Gymnasium*), "theoretical-practical" (*Realschule*) and "practical" (*Hauptschule*)" in Germany, which continue at the upper secondary level, also exists in Hungary. Namely, in Hungary the *gimnázim* is the

[1] Note that in this context (and in the rest of the paper), the term returns to education does not refer to an analysis of the causal effect of education on earnings, but to estimated earnings differentials between (and within) education groups.
[2] Note that "German" refers to the "West German" education system throughout the chapter.
[3] For descriptive evidence on wage inequality in Germany, among others, see Fitzenberger (1999), Fitzenberger et al. (2001), Abraham and Houseman (1995) in Freeman and Katz (Eds.), Krueger and Pischke (1995) in Freeman and Katz (Eds.) (with an emphasis on a East and West German comparison) and Pereira and Martins (2000) (with an emphasis on international comparison).
[4] Note also that there are strong economic ties between the two countries, i.e. by the mid-1990s Germany became Hungary's most important trading partner.

"theoretical", the *szakközépiskola* the "theoretical-practical" and the *szakmunkásképző* the "practical" form of upper secondary education.[5] The curricula of the academically most challenging institutions, the *Gymnasium* and the *gimnázim* in Germany and Hungary respectively have common traditions as the Hungarian model is based on the Austrian one.[6]

The model for vocational education is also similar in the two countries, that is, vocational training traditionally has both a practical and a general element. The German apprentice training (i.e. *Duales System*), which has its roots in the apprenticeship system for artisans in middle ages, was supplemented with part-time attendance in schools (the predecessors of the part-time schools, i.e. *Berufsschule*) at the end of the nineteenth century and between 1919 and 1938 part-time attendance at these schools became compulsory until the age of 18. In Hungary apprentice training schools were founded later than in Germany, namely in the 1870s, and the Education Act of 1949 established the *szakmunkásképző,* which is the vocational institution offering both practical and general education (similar to the German *Duales System*).

It is important to note, that the purpose of this chapter is purely descriptive. That is to say, the aim is not to deal with the problems of measuring the causal impact of education on earnings, namely, measurement error, omitted ability bias and self-selection bias. Instead, the purpose is to provide a comprehensive picture of earnings differentials in the two countries, that is, to analyse both "between- and within-educational-levels earnings differentials", given the existing evidence that aggregate earnings inequality arises from differences between as well as within educational groups, due to the heterogeneity of the labour force.[7] Moreover, it must be noted, that this study extends on the existing literature on the Hungarian labour market as, to the best of my knowledge, for Hungary "within-educational-levels earnings differentials" have not been estimated so far. Furthermore, in order to provide a more comprehensive

[5] It is important to note that the Hungarian education system always retained its traditional structure of differentiation (as opposed to East Germany). In particular, prior to 1945 the Hungarian education system was identical to the West German one in the sense that the differentiation (according to the different branches of education) started after the first four years of primary school. It was only after 1945 that the first stage of education was extended to last eight years and so the differentiation started after the completion of the eight years of primary school (i.e. at the upper secondary level). The beginning of transition marked the revival of differentiation at an earlier stage with the re-establishment of the six and eight year *gimnázium*, i.e. The 1990 Amendment to the 1985 Education Act authorised the six and eight year *gimnázium*.

[6] Phillips (1995), pp 243 – 247 offers an extensive discussion of the common traditions of the secondary education in Germany and Hungary (and other Central and Eastern European countries).

[7] See for example Pereira and Martins (2000).

picture to the returns to university education, the returns to specific fields of study at university are estimated.

Subsequently, in the empirical analysis standard Mincer earnings equations (regressions of the logarithm of monthly gross earnings on education, potential labour market experience and its square, gender, sector of employment) are estimated using both ordinary least squares estimation (OLS) and quantile regression (Koenker and Bassett (1978)). The advantage of quantile regression over OLS estimation is that quantile regressions allow for the full characterisation of the conditional earnings distribution, thereby providing a more comprehensive picture of the returns to education. In other words, whereas OLS estimation only reveals the differences in mean earnings associated with different education levels (i.e. "between-educational-levels earnings differentials"), quantile regression allows for the analysis of the differences in returns to education within educational groups ("within-educational-levels earnings differences"). That is, using quantile regression techniques, one can analyse, for instance, whether individuals at higher positions of the conditional earnings distribution enjoy higher returns to education than individuals at lower positions of the conditional earnings distribution.

The data for the empirical analysis is drawn form the "Hungarian National Labour Center's Wage Survey" and from the "German Socio-economic Panel (GSOEP)" for Hungary and Germany respectively. The analysis is restricted to the year 2000 in order to take advantage of the extensive educational information in the "Hungarian National Labour Center's Wage Survey" and of the newly surveyed educational information in the GSOEP which became available in 1996 and 2000 respectively. This recent educational information for the two countries lends itself very well to a differentiated comparative analysis.

There is a further reason for starting the analysis in 2000. Namely, at the outset of this study there were numerous studies focusing on the returns to human capital in Hungary for the transition period and for the years prior to transition (the years prior to transition being limited by the availability of the data). However, the studies did not go beyond the year 1999. Subsequently, this study aimed to augment the existing literature on the Hungarian labour market not only in terms of technique of estimation but also in terms of the time period in analysis. At this point, it is important provide a brief (and selective) review of the evolution of the returns to human capital in Hungary for the decade of 1989 – 1999. Socialist wage policy tried to diminish wage differentials, i.e. workers were not rewarded according to skill or productivity and the returns to education were set centrally and were low. Not surprisingly, transition brought with itself an increase in earnings inequality attributed to the widening earnings differentials across education groups. More specifically, studies on the Hungarian labour market for the time period of 1989 – 1999 find evidence for rising returns to education – in terms of increasing returns to general and vocational secondary school education and tertiary education relative to primary school education – and falling returns to (potential) labour market experience (i.e. a devaluation of labour market experience gained under socialism). As opposed to secondary and tertiary education, the (relative) return to vocational education did not increase during the decade. The "devaluation" of vocational training is partially due to the fact that prior to transition, the structure of vocational training was adjusted to the needs of the planned economy (especially concentrating on the heavy industry). Therefore, the skill composition of the skilled workers could not meet the demands of the economy during transition. Moreover, there is evidence for a widening wage gap between the public and private sectors and a narrowing gender wage gap (except for occupations requiring high education levels) during the years of transformation. Hungary is also characterised by striking regional differences in educational attainment and earnings.[8]

Despite the vast literature on the topic of returns to education and earnings inequality in Germany, this study extends the descriptive evidence in the sense that it draws conclusions based on (a) more differentiated schooling categories than most existing estimates are based on (for instance, it distinguishes between types of tertiary education institutions as well as between lower and higher level vocational degrees) and (b) quantile regression simultaneously.

The empirical findings provide evidence for the fact that the mean (relative) return[9] to education is not an accurate estimate of the (relative) return to education for the population (more specifically, for the selected samples). That is, (a) the estimated (relative) return to all five educational levels increases across the quantiles for both genders in Hungary and to high school and tertiary education for males in Germany and (b) the within-educational-levels dispersion is increasing with the increasing levels of education in Hungary, and is especially

[8] For an extensive discussion of the Hungarian labour market during transition see Köllő (2002) in Fazekas and Koltay (Eds.), pp. 70 – 77.

[9] The returns to education groups are relative to the group of individuals possessing "No formal vocational training and no high school degree" (when not stated otherwise).

high at the tertiary level. It is important to note that the within-educational-levels earnings dispersion is larger in Hungary than in Germany at all levels of education. Another finding worth noting is that the (relative) return to tertiary education is substantially larger in Hungary than in Germany, i.e. at the top decile the estimated additional return to university education is 164 and 78 percent in the two countries respectively. The high valuation of tertiary education can be in part attributed to (a) the fact that in Hungary the demand for highly qualified labour in 2000, as in the 1990s, is larger than the supply and (b) the earnings advantages of those in the occupational group of "Legislators, senior officials and managers". Moreover, the analysis of the subgroup of "Professionals" within the group of university graduates suggests that those individuals who have studied technical fields of study (such as Science and Computing) and Law enjoy an earnings premium relative to those with non-technical fields (Social sciences, Humanities and Arts) and relative to those in the teaching and medical professions. Finally, it must be emphasized that the effect of the other explanatory variables, namely, potential labour market experience, gender and sector, is not uniform across the quantiles. For instance, the gender earnings gap narrows and widens in Germany and Hungary respectively across the distribution and (b) the earnings gap in favour of the public sector (for the full samples) is only positive at the 10th quantile, becomes negative at the 25th quantile and increases across the quantiles in both countries reaching 18 and 48 percent at the top decile in Germany and Hungary respectively.

The remainder of this chapter is organised as follows: Section 1.2 describes briefly the framework for and (for completeness) the problems associated with measuring the returns to human capital, namely, that of measurement error, omitted ability bias and self-selection bias. Furthermore, Section 1.2 introduces quantile regression and summarises the advantage of using quantile regression over OLS when estimating the returns to education. In Section 1.3 the German and Hungarian education systems are described, and the system for comparing the two education systems is developed. Section 1.4 presents the data sets used in the empirical analysis for the two countries and some descriptive statistics. Section 1.5 presents the estimation results and Section 1.6 concludes. Tables and Figures are presented in Appendix 1.8.

1.2 Empirical framework for estimating the returns to human capital

1.2.1 Mincer earnings equation

Numerous studies on the returns to human capital are embedded in the framework of the Mincer earnings equation (1974):

$$\ln w_i = \alpha + \beta S_i + \gamma_1 EX_i + \gamma_2 EX_i^2 + X_i'\delta + \mu_i, \qquad i = 1,...,n \quad (1)$$

The dependent variable of the Mincer earnings equation is the logarithm of some measure of earnings $(\ln w_i)$ for individual i, which is explained by some measure of schooling (S_i), actual or potential labour market experience (EX_i), a vector of other explanatory variables (X_i), such as gender and region, and a random disturbance term (μ_i), which contains the unobserved determinants of earnings. The schooling variable represents the formal component of human capital and is either defined as the number of years spent in education or alternatively as the highest degree attained. The latter specification for schooling is preferable if one wants to relax the assumption that an additional year of schooling yields the same return at any degree level. Labour market experience is a proxy for the informal component of human capital i.e. learning on the job. The inclusion of the linear and quadratic forms of labour market experience is essential in order to capture the concavity of the wage-experience profiles, which is due to the depreciation of skills over a worker's life-cycle. If actual labour market experience is not available, Mincer proposed to include potential labour market experience in the regression, which is measured as the age of the individual minus years of schooling minus school starting age. Using potential labour market experience in the specification has a drawback however. Whereas it is a good proxy for male labour market experience it may well be an unsuitable proxy for female labour market experience, due to the fact that females interrupt their career for child-rearing reasons. In the semi-logarithmic specification, the estimated schooling coefficient β is interpreted as the percentage change in (monthly / weekly / daily / hourly) wages associated with an additional year of schooling / highest grade completed, that is, the private rate of return to schooling.

1.2.2 Problems with estimating the returns to human capital

1.2.2.1 Measurement error

One of the problems associated with estimating the returns to human capital is that of measurement error in the schooling variable, which is expected to lead to a downward bias of the OLS estimate of the schooling coefficient. Measurement error of the schooling variable may arise due to erroneous self-reporting. For instance, Ashenfelter and Krueger (1994) and Miller et al. (1995), using a sample of American and Australian twins respectively, find the level of self-reported schooling (measured as the years of schooling) to be higher than that reported by the co-twin. Furthermore, measurement error may arise if actual years of schooling is not available in a dataset, and hence the years of schooling are imputed from the average number of years required to complete a specific degree, i.e. different individuals may take different number of years to complete a degree. For example, Jaeger and Page (1996) using a sample of 18,699 individuals from the 1992 Current Population Sample find that among the individuals whose highest reported degree was a high school diploma 91 percent received exactly 12 years of education, 5 percent took longer than 12 years and the remaining 4 percent finished high school in less than 12 years. Therefore, degree attainment rather than years of schooling is often used as a proxy for the formal component of education in the Mincer earnings equation.

The use of an instrument for schooling (a valid instrument is one which is highly correlated with schooling but not with the disturbance term, and has no direct effect on earnings, apart form the effect through schooling) to fit the Mincer earnings function is a popular way to correct for measurement error.[10] However, valid instruments are difficult to find in practice. For instance, given the heterogeneity of the cost and benefit of schooling in the population, one must be cautions when a supply-side intervention (e.g. a change in compulsory schooling law) is used as an instrument. That is, if the intervention only affects one subsample of the population (due to the heterogeneity in the cost and benefit of schooling), the resulting IV estimate of the rate of return to schooling will equal the rate of return of that subgroup (i.e. may be higher or lower than the OLS estimate of β).[11]

[10] For an extensive discussion on instrumental variables estimation (IV) to correct for measurement error see Card (1999).

[11] See for example Harmon and Walker (1995).

In this study, the motivation for the use of dummies for degree attainment (i.e. the six categories are described in Section 1.3) as the measure of the formal component of human capital, rather than the years of schooling, is twofold. First, it serves to eliminate the potential bias caused by the computational error when the years of schooling is imputed form degree attainment (i.e. actual years of schooling is not reported in the Hungarian dataset). Second, as both the German and Hungarian education systems have multiple education streams starting from the secondary level, “type of schooling” is more suitable for a cross-country comparison of the returns to schooling than “year of schooling”. The schooling variable (used in the specifications) may nevertheless suffer from measurement error due to reporting error.

Furthermore, it must be noted that years of potential labour market experience is used as the proxy for the informal component of human capital for both countries (as actual labour market experience is not reported in the Hungarian dataset). Potential labour market experience, measured as age minus years of schooling minus school starting age, may suffer from measurement error (especially for Germany[12]) as years of schooling is imputed from the average number of years taken to complete a degree. Thus, the coefficient estimate needs to be interpreted with caution.

1.2.2.2 Omitted ability bias

If the Mincer earnings equation is estimated by OLS, a crucial assumption for unbiased coefficient estimate of β is that the schooling variable is uncorrelated with the components of the disturbance term. It has been argued however that the unobserved (innate) ability in the disturbance term is positively correlated with the schooling variable (and earnings). Therefore, if innate ability is not controlled for in the regression, the OLS estimate of the rate of return to schooling may potentially be biased upwards (“omitted ability bias”). Two approaches are commonly used to deal with the problem of omitted ability bias.

The first approach calls for the inclusion of an explicit measure (a proxy) for the unobserved ability in the regression equation, such as IQ scores. There are however various drawbacks of this technique, as described by Ashenfelter et al. (1999). For example, it is difficult to find a perfect proxy for unobserved ability which is not itself correlated with schooling. That is to say, the ability measured by most tests is affected by education prior to the test so that the

[12] That is, in Germany there is (potentially) more variability across individuals in the years taken to complete vocational degrees (e.g. *Lehre*) than in Hungary.

effect of innate ability on earnings cannot be distinguished from the effect of schooling. The consequence of using erroneous measures for ability (imperfect proxies) is a downward biased coefficient estimate.

The second method in order to correct for omitted ability bias is the twin approach which takes advantage of the fact that monozygotic twins, who have been reared together, are more alike than a randomly selected pair of individuals, since they share the same genes and same socio-economic background.[13]. Therefore, it is argued that the difference in their income is only associated with the difference in their educational levels. Consequently, when the difference in wages is regressed on the difference in the education level within a twin pair, the estimated coefficient for the rate of return to schooling should not suffer by omitted ability bias. Although a popular means to correct for ability bias, the twin approach has often been the centre of debate i.e. innate ability might not be perfectly correlated within a twin pair.

It is important to emphasize that the direction of the bias of the OLS estimate of the rate of return to schooling is not obvious as there are two opposing effects involved. The downward bias due to the measurement error in the schooling variable may be partially offset by the upward ability bias, as argued by Grilliches (1977). In fact, Ashenfelter and Zimmerman (1993) find evidence that the upward omitted ability bias is about the same size as the downward bias due to the measurement error in the schooling variable.[14]

Therefore, it is argued that the parameter estimates provided in the Appendix are reliable estimates of the return to education i.e. as discussed above, the use of proxies for unobserved ability (and instruments for schooling) is by no means universal due to the problems encountered when using invalid proxies (and invalid instruments for schooling such as parental background variables), coupled with the opposing effects of the two biases.

1.2.2.3 Self-selection bias

The third problem related to estimating the returns to human capital is that of self-selection bias. It is assumed that the higher earnings for individuals with higher educational levels are caused by their higher educational levels, in which case the estimate of β is not biased and reflects the causal effect of education on earnings. However, it may well be that the higher

[13] See Miller et al. (1995), pp. 587 – 588 for the analytical framework for the twin approach.
[14] See Ashenfelter and Krueger (1994) p. 1172.

earnings of workers with higher educational levels are caused by the fact that individuals with greater earnings capacity choose to acquire more schooling, in which case β suffers from self-selection bias.

In addition to self-selection into higher education, self-selection into employment poses a problem in this study.[15] That is, the German and Hungarian samples used for econometric analysis in this study include only individuals (males and females) who satisfy the following restrictions: (a) are wage and salary earners, (b) are full-time employees and (c) are aged 25 – 55 years. Therefore, the results must be interpreted conditional on the selected samples, rather than for the population as a whole.

1.2.3 Ordinary least squares vs. quantile regression

The OLS estimate of β in the benchmark Mincer earnings equation is an estimate of the mean return to schooling i.e. the mean earnings premium associated with an additional year of schooling (alternatively with an additional degree level). Whereas OLS estimation only reveals the differences in mean earnings associated with different education levels (i.e. “between-educational-levels earnings differentials”), quantile regression, introduced by Koenker and Bassett (1978), allows for the full characterisation of the conditional earnings distribution, thereby providing a more comprehensive picture of the returns to human capital. Subsequently, quantile regression allows for the analysis of the differences in returns to education not just between but also within educational groups (i.e. “within-educational-levels earnings differentials”).

The relevance of quantile regression in the returns to education literature can be best illustrated by an econometric example. Machado and Mata (2000) estimate Mincer earnings equations for Portugal by OLS and quantile regressions for the years 1982 and 1994 . Using OLS estimation, they find the coefficient estimate for the rate of return to an additional year of schooling to be approximately 8 percent in 1994. Using quantile regressions allows them to draw much more interesting conclusions about the rate of return to an additional year of schooling for 1994: the rate of return to an additional year of schooling at the 10th quantile is merely 4 percent, at the median it increases to around 7 percent and at the 90th qualtile it is as high as 11 percent. Moreover, they find that the mean return to education over the twelve-year

[15] The Heckman selectivity bias correction method (1979) is beyond the scope of this study as the dataset for Hungary only covers full-time employees i.e. excludes the self-employed, part-time employed, unemployed etc..

period increased by only 0.5 percent. Looking at the different quantiles gives another picture of the evolution of returns: the return to the low quantiles decreased by almost 2 percent, the median return stayed roughly constant and the return to the 90th quantile increased by 3 percent. The authors hence conclude that schooling is not only more valued for highly paid jobs but that this tendency has sharpened over time – a conclusion that could not be seen by just running OLS regressions.

The quantile regression model is formulated as:

$$y_i = x_i'\beta_\theta + \mu_{\theta_i}, \text{ with } Quant_\theta(y_i \mid x_i) = x_i'\beta_\theta, \qquad i = 1,...,n \qquad (2)$$

where y_i is the regression's dependent variable, x_i is a $K \times 1$ vector of regressors, μ_{θ_i} is a disturbance term and β_θ is the vector of parameters to be estimated. The subscript i indexes the individuals in the sample, $i = 1,...,n$. $Quant_\theta(y_i \mid x_i)$ denotes the θ^{th} conditional quantile of y_i, conditional of the regressor vector x_i. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x.

The θ^{th} regression quantile, $0 < \theta < 1$, is defined as a solution to the problem of minimizing a weighted sum of absolute residuals. The θ^{th} regression quantile can be computed by:

$$\min_{\beta \in R^k} \left\{ \sum_{i: y_i \geq x_i'\beta} \theta \mid y_i - x_i'\beta_\theta \mid + \sum_{i: y_i < x_i'\beta} (1-\theta) \mid y_i - x_i'\beta_\theta \mid \right\}, \qquad i = 1,...,n \qquad (3)$$

In the framework of the Mincer earnings equation (1), the resulting regression fit $x_i'\beta_\theta$ describes the θ^{th} quantile of the earnings of individual i given the characteristics (e.g. education level, potential labour market experience, gender etc.) of individual i.

As noted earlier, this study is purely descriptive in nature. I estimate Mincer earnings equations (1974) by OLS and quantile regression at five quantiles of the log earnings distribution, namely at the 10th quantile, at the 25th quantile, at the median, at the 75th quantile and at the 90th quantile. The dependent variable is the log of monthly gross earnings. The set of independent variables (see Section 1.4) includes: education, potential labour market and its square, sector of employment, gender and interaction terms between education and gender, potential labour market experience and gender and sector of employment and gender. For all specifications, weights are used in estimation. Standard errors are obtained by 1000 and 200 replications for the quantile regressions for Germany and Hungary respectively.

1.3 Description of the education systems in Germany and Hungary

1.3.1 The German education system

This section gives a brief description[16] of the (West) German education system, relying on the International Standard Classification of Education (ISCED-97) as a guidance. Figure 1.1 provides a depiction of the German education system.

In Germany, compulsory education starts at the age of six in the primary school, *Grundschule,* (ISCED-97 level 1). After the completion of the four-year-long *Grundschule*, children are screened according to academic ability, and can choose among the three tracks of lower secondary education (ISCED-97 level 2), namely, the *Hauptschule,* the *Realschule* or the *Gymnasium*. Admission to the different institutions is based on the teachers' recommendation combined with the parents' approval.

The academically least demanding type of school at the lower secondary level is the lower secondary school, *Hauptschule*, which is five years in duration and grants a general school leaving certificate, *Hauptschulabschluss*. The children are offered general education with a vocational orientation, as successful completion of the *Hauptschule* opens the door to vocational training, but not to further academic education (at the upper secondary level).

The six-year-long intermediate secondary school, *Realschule*, is positioned between the *Hauptschule* and the *Gymnasium*. Graduation from the *Realschule* provides the *Mittlerer Schulabschluss (Realschulabschluss),* which grants its holders access to institutions at the upper secondary level that provide vocational qualification or higher education entrance qualification.

The academically most demanding institution at the lower secondary level is the general secondary school, *Gymnasium,* which lasts six years and prepares its pupils for the upper level

[16] Extensive information on the structure of the German education system can be found, for example, in Secretariat for the Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany (2006).

of the general secondary school, *Gymnasiale Oberstufe*. After completing the *Gymnasium,* children are also free to continue their education at any other institution at the upper secondary level (i.e. vocational training).
The comprehensive school, *Gesamtschule*, combines all the three tracks described above in two possible ways. The first alternative is the cooperative comprehensive school which has the three different branches on its premises in order to facilitate transfer from one type of school to another. The other alternative is the integrated comprehensive school which combines the three different school types in one. That is, children are taught together until the beginning of grade seven, and from grade seven onwards certain subjects are taught at different levels and the qualifications are awarded accordingly. Therefore, graduates of the comprehensive school may either leave with the *Hauptschulabschluss,* the *Mittlerer Schulabschluss,* or the *Allgemeine Hochschulreife (Abitur)*.

The upper secondary level (ISCED-97 level 3) can be divided along three lines, (1) whether pupils obtain a vocational degree, which in itself does not enable them to pursue their studies at the tertiary level, (2) whether they obtain a degree, which enables them to continue their studies at the practically oriented tertiary institutions only or (3) whether they obtain a general higher education entrance qualification, which allows them to pursue further studies at any tertiary institution.

The two institutions belonging to the first subcategory at the upper secondary level are the dual system, *Duales System,* and the *Berufsfachschule*, which are both vocational in orientation. The *Duales System* lasts two to three years and offers an apprenticeship at an enterprise combined with general education at the part-time vocational school *Berufsschule*. Its graduates, at the age of 18, obtain the *Berufsqualifizierender Abschluss* which marks the completion of compulsory education and provides direct entry to the labour market or to further vocational education. The *Duales System* is the most common route after the completion of the *Hauptschule*, although graduates of the *Realschule* and *Gymnasium* may also choose this track. The second type of institution, the *Berufsfachschule*, is a two- to three-year-long full-time vocational school, which provides pupils with vocational training as well as general education, thereby preparing them for direct entry into the labour market or to further vocational education.

The institutions belonging to the second subcategory at the upper secondary level are those offering the *Fachhochschulreife*, which entitles its holders to further education at the practically oriented tertiary institutions. More specifically, the two-year-long upper secondary school, *Fachoberschule*, and the *Berufsoberschule*[17] belong to this subcategory. The entrance requirement for these institutions is the *Mittlerer Schulabschulss*.[18]

The route to university is through the third subcategory of upper secondary education, namely, the upper level of the general secondary school, *Gymnasiale Oberstufe.* The *Gymnasiale Oberstufe* is three years in duration, academically oriented, and grants its graduates the *Allgemeine Hochschulreife*, which is the prerequisite for university. The *Allgemeine Hochschulreife* can also be acquired at the *Fachgymnasium*[19], under certain conditions, at the *Berufsoberschule* and for adults at the *Abendgymnasium* or *Kolleg*.

Accordingly, there is room for further education for the graduates of the three subcategories of upper secondary education described above, namely, for those with the *Berufsqualifizierender Abschluss*, those with the *Fachhochschulreife* and those with the *Allgemeine Hochschulreife*.

The holders of the *Berufsqualifizierender Abschluss* may only pursue advanced vocational education offered at the *Fachschule* (ISCED-97 level 4). The *Fachschule* is a post-secondary non-tertiary institution of one to three years in duration, which, under certain conditions, grants the *Fachhochschulreife* in addition to a further vocational qualification (i.e. enables its graduates to become master craftsman in their field).

Those with a *Fachhochschulreife* aspire to *Fachhochschule* (ISCED-97 level 5). *Fachschulen* are more practically oriented tertiary institutions, offering subjects such as engineering, business and administration, and are shorter in duration than universities (i.e. three to four years).

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[17] The *Berufsoberschule* is attended by those who (in addition to the *Mittlerer Schulabschluss*) have completed vocational training or have five years of work experience (Secretariat of the Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany (2006)).

[18] Note that, under certain conditions, the *Fachhochschulreife* can be acquired at the *Berufsfachschlule* (Secretariat of the Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany (2006)).

[19] At the three-year-long *Fachgymnasium* career-oriented subjects such as business and economics are added to the general subjects offered at *Gymnasium*.

Finally, those individuals holding the A*llgemeine Hochschulreife* (or in some cases *Fachgebundene Hochschulreife*) fulfil the prerequisite for acceptance at university, *Universität* and *Technische Hochschule* (ISCED-97 level 5), which last at least eight semesters, depending on the field of study. Under certain conditions students can pursue further research at the second stage of tertiary education (ISCED-97 level 6).

1.3.2 The Hungarian education system

From the onset of transition there were significant changes in the structure of the Hungarian education system.[20] To mention one example, the 1993 Public Education Act and the 1996 Amendment to the Public Education Act extended the end of compulsory education from the age of 14 to the age of 16 and to the age of 18 (starting with those who enter primary school in the 1998 / 99 school year) respectively. It is important to note that even the youngest individuals of the 2000 sample completed their education before these reforms governing the structure of education[21] came into effect. Therefore, the purpose of this section is to provide a brief overview of the institutions as attended by the individuals under analysis, using the ISCED-97 framework as a guidance, rather than to describe in detail the continuous changes in the Hungarian education system which form the present education system. Figure 1.2 provides a depiction of the Hungarian education system.

Compulsory education in Hungary starts at the age of five in the kindergarten, *óvoda*, (ISCED-97 level 0). At the age of six[22] children are enrolled in primary school, *általános iskola*, which lasts eight years and consists of two levels, a lower level lasting 4 years, *alosó tagozat*, (ISCED-97 level 1) and an upper level lasting another 4 years, *felső tagozat* (ISCED-97 level 2).[23]

After the completion of primary and lower secondary education, children are screened according to ability in order to start one of the five types of upper secondary schools (ISCED-97 level 3). Admission to upper secondary institutions is based on a selection mechanism

[20] Lannert (2001) offers an extensive discussion on the changes in the structure of the education system after transition.
[21] The exception is the 1990 Amendment to the 1985 Education Act which authorised six and eight year general secondary schools. However, from the three alternatives, the dominant institution remained the four year general secondary school.
[22] The legal regulations allow children to start school at the age of five or seven.
[23] As the 1990 Amendment to the 1985 Education Act which authorised six and eight year general secondary schools, children who are to pursue their education in such institutions leave the primary school after six and four years respectively.

combining performance at the primary school and an entrance exam. There are two main categories of institutions at the upper secondary level, those offering a high school degree, *érettségi*, which entitles pupils to continue their education at the tertiary level, and those which do not.

The latter institutions have a vocational emphasis and their successful completion allows for direct entry to the labour market. The first type, the vocational school, *szakiskola*, offers two years of general and vocational education and grants its students a lower level vocational qualification. The apprentice school, *szakmunkásképző*, is the second, more advanced type of vocational institution which does not offer a high school degree. The three-year-long education in the apprentice schools takes place both at a firm and in school. Successful graduates of the *szakmunkásképző* obtain a skilled worker's qualification which allows them to work in various sectors including construction, agriculture and trade.

Institutions offering a high school degree, and thereby granting access to further education at the tertiary level, have three subdivisions. Vocational secondary schools, *szakközépiskola*, last four or five years and offer a vocational qualification as well as a high school degree. The vocational secondary schools have become the most popular institutions at the upper secondary level, especially the economic, commercial, catering and trade types. Technical schools, *technikum*, are a special form of secondary vocational schools which last five years and provide students with a technician's qualification in addition to a high school degree. General secondary schools, *gimnázium*, are four, six or eight years in duration (after the completion of eight, six or four years of primary school respectively) and offer only a high school degree. The various degrees at the upper secondary level can also be acquired via adult education.

Tertiary education (ISCED-97 level 5), like upper secondary education, is divided into two subdivisions depending on whether a more vocational or a more academic curriculum is offered. On the one hand, colleges, *főiskola*, offer education at a more practical level and last three to four years. Universities, *egyetem*, on the other hand, offer a more academic curriculum and last at least five years, depending on the field of study. After successful graduation from university, students can pursue further research leading to an advanced research qualification (ISCED-97 level 6). There is a tough mechanism in place for selection at the tertiary level based on performance at the upper secondary level and an entrance exam specific to the field of study.

1.3.3 System for comparison of the German and Hungarian education systems

The system for comparison of the German and Hungarian education systems, depicted in Table 1.1, has been constructed along the lines of the ISCED-97 framework. The six categories are based on the available educational information in the GSOEP and the "Hungarian National Labour Center's Wage Survey" for Germany and Hungary respectively. It is important to note that the level of differentiation of the schooling categories and the number of observations in each schooling category had to be traded off, especially at the upper secondary level (i.e. the resulting six categories are more aggregated than those reported in the datasets due to sample size considerations). For instance, optimally, one would want to differentiate between the all types of secondary degrees – with vs. without vocational qualification – for Germany, but the small number of cases motivate the aggregation of certain degrees. Consequently, the resulting six categories, on the one hand, are broad enough to assure the comparability of the degree levels between the two countries and, on the other hand, assure a sufficient number of observations for both countries for empirical analysis.

(1) No formal vocational degree and no high school degree: The general idea behind this educational group is to merge individuals from the datasets who (a) do not satisfy the compulsory (general) schooling requirement or (b) who only satisfy the compulsory (general) schooling requirement. These two groups have been merged as the number of observations in the former group is not sufficient for independent analysis. At most satisfying the compulsory (general) schooling requirement is, in fact, the equivalent of having no formal vocational degree and no high school degree in both countries.

In Germany, the compulsory (general) schooling requirement is nine years, that is, it ends with the completion of lower secondary education. Therefore, Group (1) consists of those individuals who (a) have less than a lower secondary school degree or (b) possess at most a lower secondary school degree, namely, *Hauptschulabschluss* or *Realschulabschluss* or *anderer Abschluss*.

In Hungary, when the individuals in the 2000 sample attended school, the compulsory schooling requirement was marked by the successful completion of the eight years of primary school. Subsequently, for these individuals their primary school degree is accepted as the minimum schooling requirement in the labour market. Hence, Group (1) consists of those individuals who (a) did not complete primary school or (b) at most possess a primary school degree.

(2) Lower level vocational degree and no high school degree: The general idea behind this educational group is to cover individuals who have completed a lower level of vocational training, which grants them direct access to the labour market but does not in itself enable them to continue their studies at the tertiary level.

For Germany, Group (2) is the largest group as it merges individuals with different schooling and vocational qualifications. As far as the schooling qualification is concerned, all those individuals who do not have a *Fachhochschulreife* or *Abitur* (i.e. have a *Hauptschulabschluss* or *Realschulabschluss* or *anderer Abschluss*) belong to Group (2). Although the *Hauptschulabschluss*, *Realschulabschluss* and *anderer Abschluss*, differ in terms of "quality", they are aggregated for two reasons. Namely, it would be difficult to differentiate between these subgroups in a way which (a) assures enough observations per category and (b) has a Hungarian equivalent (as in Hungary there is no such differentiation at the lower secondary level of education). As far as the vocational qualification is concerned, Group (2) merges all those individuals who possess a vocational qualification at the upper secondary level, that is, who have completed either the *Lehre* or *Berufsfachschule* or *Schule des Gesundheitswesens* or *Beamtensausbildung* or *sostige Ausbildung*. It is important to note however that in terms of vocational qualification Group (2) is not as heterogeneous as it may first seem. That is, approximately 76 percent of all individuals belonging to Group (2) completed the *Lehre* in the sample.

For Hungary, Group (2) merges (a) the graduates of the *szakiskola* and (b) the graduates of the *szakmunkásképző*. All these individuals posses a vocational qualification which grants them direct entry to the labour market but not to any tertiary institution. As for Germany, the aggregation of the two vocational qualifications cannot be considered a severe problem as in the sample approximately 91 percent of all individuals belonging to Group (2) obtained their vocational degree from the *szakmunkásképző.*

Moreover, the fact that most of the individuals in Group (2) undertook vocational training in the framework of the *Lehre* and in the *szakmunkásképző* in Germany and Hungary respectively has the advantage that, among all vocational institutions, the *Lehre* and *szakmunkásképző* are the most similar ones, and so Group (2) is well suited for the cross-country comparison.

(3) Higher level vocational degree and no high school degree / higher level vocational degree: The general idea behind Group (3) is to select those individuals who possess a qualification which is of a higher level than the qualifications held by the individuals belonging to Group (2).

For Germany, this amounts to subdividing the large group of individuals holding some kind of a “vocational degree and no high school degree” (i.e. they make up over half of the 2000 sample) according to the level of vocational degree held. The *Fachschule* graduates are selected into Group (3) as the *Fachschule* is the only post-secondary and non-tertiary vocational institution (ISCED-97 level 4), and thus education goes beyond that acquired at the institutions of vocational education in Group (2). That is, the *Fachschule* provides advanced vocational training for those pupils with initial (upper secondary level) vocational qualifications and employment.

For Hungary, the selection criterion for Group (3) is somewhat different than that for Germany. That is, the motivation is to subdivide the group of high school graduates[24], the largest group in the 2000 sample in a meaningful way. Subsequently, due to the differences in practical / academic curriculum (as well as differences in labour market opportunities), the graduates of the *technikum* are separated from the group of high school graduates i.e. belong to Group (3). Note also that the is *technikum* is an upper secondary institution which, in opposition to the four other tracks of upper secondary institutions in Hungary, is of five years in duration.[25]

Although the *technikum* is classified at the upper secondary level (ISCED-97 level 3), it is an institution which can be compared to the *Fachschule*[26] as graduation from the *technikum* grants a technician’s certificate; a vocational qualification which is more valuable on the

[24] Hence the name “Higher level vocational degree” rather than “Higher level vocational degree and no high school degree” for Group (3) for Hungary.
[25] With the exception of the bilingual general secondary schools and some vocational secondary schools which also last 5 years.
[26] In Hungary, ISCED-97 level 4 institutions for post-secondary vocational training have only been introduced in 1998 (i.e. the 2000 sample does not contain graduates from such vocational institutions).

labour market than that obtained at the other secondary vocational institutions. Moreover, the academic level the *technikum* is superior to the *szakiskola* and *szakmunmásképző* (the institutions belonging to Group (2)).

(4) High school degree and no tertiary degree: The general idea behind this educational category is to combine all those who could potentially pursue their studies at the tertiary level, but do not possess a degree at the tertiary level.

For Germany, Group (4) is the most heterogeneous one. First, it merges those who (a) have a *Fachhochschulreife*, hence can only enter the *Fachhoschschule* (approximately 42 percent), and (b) those who have an *Abitur*, which allows them to enter any tertiary institution (approximately 58 percent). Second, this group merges those with and without formal vocational training. The aggregation is due to the insufficient number of high school graduates (without tertiary degree) for a more differentiated analysis. The heterogeneity is mitigated by the fact that the majority of the individuals belonging to Group (4) do posses a vocational degree, i.e. approximately 86 percent of the individuals in Group (4) posses some kind of a vocational degree in the 2000 sample.

For Hungary, the graduates of (a) the *szakközépiskola* and (b) of the *gimnázium* have been merged. The aggregation is motivated by the fact that (unlike for the graduates of the *technikum*, who have been separated from Group (4)) the value of completing the *szakközépiskola* and the *gimnázium* in 2000 are roughly the same, which in turn implies that the aggregation of the two groups does not pose a qualitative problem for Hungary for the selected year.[27] Furthermore, the aggregation is in line with the aggregation of the various degrees in Group (4) for Germany, hence Group (4) is suitable for cross-country comparison.

It is important to note that there is a fundamental difference between the two countries as far as the subgroup "high school degree and vocational qualification" of Group (4) is concerned. On the one hand, in Germany, *Fachhochschulreife* and *Abitur* holders with a vocational qualification (*Lehre* etc.) are "educated" for over 12 and 13 years respectively. In Hungary, on the other hand, those with a "high school degree and vocational qualification", namely, the graduates of the *szakközépiskola*, do not have further "on-the-job vocational training", and subsequently only undertake a maximum of 13 years of schooling. Despite this difference in

[27] That is, the estimated return for the full sample differs by approximately 1 – 2 percentage points between the two groups at all of the estimated quantiles and at the mean.

the content and duration of vocational education, this subgroup remains comparable across the two countries in the sense that the individuals possess both a academic and an vocational qualification i.e. have similar labour market opportunities in both countries.

(5) College degree: The idea behind this educational group is to cover all those individuals who have a tertiary qualification which is (a) more applied in curriculum and (b) is shorter in duration than university education.

In Germany, *Fachhochschule* belongs to Group (5).[28]

In Hungary, *főskola* belongs to Group (5).

(6) University degree: This educational category merges all university graduates. That is, there is no distinction across the first (ISCED-97 level 5) and second stages of university education (ISCED-97 level 6), due to the fact that there is no differentiated reporting at the university level in neither datasets.

In Germany, *Universität* and *Technische Hochschule* belong to Group (6).

In Hungary, *egyetem* belongs to Group (6).

Note that whereas the six educational categories for Germany represent a ranking in terms of the level of education, this is not (always) true for Hungary where Group (3) is (potentially) of a higher level than Group (4). Note also that whereas Groups (1), (2), (5) and (6) are well suited for comparison across the two countries, Groups (3) and (4) are (somewhat) less suited for a cross-country comparison, due to the cross-country differences in the nature and duration of vocational training. Hence, the comparison of the estimated returns to the latter two groups across the two countries must be interpreted in light of these differences.

[28] Note that although the equivalent of the *Fachhochschule* is University of applied sciences (see Secretariat of the Standing of Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany (2006)), the term "college" for Group (5) was chosen for simplicity of the comparative analysis / discussion.

1.4 Data and descriptive statistics

1.4.1 Data for Germany

The data for Germany is drawn from the "German Socio-Economic Panel" (GSOEP), a micro-dataset, which was started in 1984 and since then data collection is carried out on an annual basis.[29] In 1984 around 12,000 individuals, aged over 16, who were either "West German Residents" (Sample A) or "Foreigners in West Germany" (Sample B) were interviewed. The GSOEP was extended to cover "German Residents in the GDR" (Sample C), and "Immigrants" (Sample D) in 1990 and in 1994 respectively. In 1998 a "Refreshment" sample (Sample E) and in 2000 an "Innovation" sample (Sample F) were added. Data is collected on a large number of socio-economic variables, covering eight main areas, including variables representing income, demography, educational attainment, level and sector of employment.

As far as educational attainment is concerned, information in the GSOEP is organised in three main (generated) categories, namely, secondary school degree, vocational degree and tertiary degree. The education level of foreigners and those who obtained their degree in East Germany prior to 1991 is integrated into these three main categories as well as reported separately. The subdivisions within these three categories are differentiated enough to construct variables for the highest degree attained, and to develop a system for comparison across the two countries.

In order to assure a sufficient number of observations Samples A through F are used in the empirical analysis. Subsequently, the analysis must start in 2000, which marks the first year when all of the six samples were available. Starting the analysis in 2000 has a further advantage: in 2000, instead of updating previous educational information, an explicit educational survey of all respondents was carried out, regardless of whether something has changed in the past years. Subsequently, this newly surveyed educational information is used in the empirical analysis. Only those individuals with a West German educational background are selected for the empirical analysis. This selection assures that the returns to the degrees of the Hungarian and West German education systems are compared – which is the aim of the study. An alternative to using all six samples would be to use Sample A only, since the (majority of the) individuals in Sample A have completed their education in West Germany.

[29] Haicksen-DeNew and Frick (Eds.) (2002) provide an extensive description of the GSOEP.

This alternative however has the disadvantage that after the working sample has been selected, the number of observations in Sample A is small.[30] Furthermore, excluding the individuals who have (a) completed schooling in West Germany but (b) come from a household where the household head is not West German would mean losing relevant information in terms of estimating the returns to degrees of the West German education system.

The samples are restricted to cover full-time employees (i.e. wage and salary earners, excluding the self-employed) of both genders who were (a) full-time employed for 12 months and (b) had a non-zero monthly wage for each month of the given year. In all specifications and for both countries, the logarithm of monthly gross earnings is used as the dependent variable, defined as monthly gross wages plus one twelfth of the sum of all bonuses paid over the year.[31] The logarithm of monthly gross earnings is used as the income measure, rather than the logarithm of hourly gross wages, because the only income variable available for Hungary is monthly gross earnings.[32] The choice of income measure subsequently implies that throughout the paper (monthly) earnings differentials rather than (hourly) wage differentials are estimated. The sample is restricted to consist of individuals aged 25 – 55 years.[33]

In addition to the standard explanatory variables i.e. (1) schooling, measured as the highest degree attained (the six schooling categories are described in detail in Section 1.3.3), (2) potential labour market experience (measured as age minus years of schooling minus six)[34] and (3) its square, and (4) gender, a dummy variable indicating the sector of employment, that is, "public vs. private" is included (as the level of earnings differs across the sectors of employment in both countries). An additional specification is fitted which is augmented with

[30] There are 1,520 individuals in Sample A who satisfy the selection criteria in 2000.

[31] Bonuses reported explicitly in the GSOEP include "13th month salary", "14th month salary", "additional Christmas bonus", "vacation bonus", "profit-sharing bonuses" and "other bonuses".

[32] In the Hungarian dataset, monthly gross wages and the amount / type of bonus paid is not reported separately. Furthermore, (actual) hours worked are not reported either, therefore, the hourly wage cannot be calculated.

[33] Note that the analysis is restricted to those aged at least 25 in both countries instead of 24 and 23 / 24 which marks the official end of the first stage of tertiary education in Germany and in Hungary respectively. This is due to the fact that (a) there is individual variation in school starting age (e.g. six or seven years old), (b) some fields of study (e.g. law and medicine) require longer to complete, (c) coupled with the fact that a fraction of university graduates take longer to complete their studies than set out officially.

[34] Note that although one of the advantages of the GSOEP is that actual labour market experience can be calculated using the *Biography Spell Data*, potential labour market experience is used in this study as a proxy for the informal component of human capital in order to assure comparability to the Hungarian specifications, for which only potential labour market experience can be calculated (as actual years of schooling is not available in the Hungarian dataset).

interaction terms between the explanatory variables and gender. Table 1.2 provides summary statistics for the full sample under analysis.

For completeness, the returns to three broad fields of university education are estimated. For this analysis the (occupational) group of "Professionals" is used because the field of study can only be inferred for this occupational group using occupational information (the *International Standard Classification of Occupations* (ISCO-88)) provided in the GSOEP.[35] The three categories are more general than the ISCED "Broad fields of university education" due to the small number of university graduates in the sample, and are as follows: (1) Education, (2) Social sciences, Humanities and Arts (3) Natural sciences. Section 1.8.5 of the Appendix describes the generation of the three categories for university education and Table 1.3 provides summary statistics for the sample of university graduates who belong to the (occupational) group of "Professionals" and are used in the analysis.

1.4.2 Data for Hungary

The data for Hungary is drawn from the "Hungarian National Labour Center's Wage Survey", a cross-section dataset, first carried out in May 1986. Until 1992 data was collected every three years and from 1992 and 1994 onwards on a yearly basis in the private and public sectors of employment respectively. In the private sector, data collection covers firms employing at least 20 employees, which provide information on a 10 percent random sample of their full-time employees. In the public sector, all institutions independent of size, provide information on their full-time employees.[36] One of the drawbacks of the lack of self-reporting specific to this analysis is that actual years of schooling and actual years of labour market experience are not available.

The Wage Survey has the advantage of having a large number of observations, ranging from 130,000 to 220,000, depending on the cross-section. Data is collected (in the month of May) on monthly gross earnings, defined as monthly gross wage plus one twelfth of the sum of all other payments and irregular incomes connected to the full-time job paid over the previous

[35] Self-reported fields of study would be preferable for the analysis to eliminate potential measurement error due to imputation. Due to the lack of such information, the use of the subgroup of university graduates who belong to the occupational group of "Professionals" for both the German and Hungarian samples, for whom the fields of study can be computed with a fair amount of precision, is considered the next best alternative.

[36] From 1995 and 2001 onwards, a 20 percent random sample of companies employing at least 10 and at least 5 employees respectively are included in the Wage Survey, which provide information on all of their full-time employees.

year, gender, age, educational attainment, occupation, firm size, location, ownership structure, sector of employment and industry classification. As for Germany, the analysis is restricted to full-time employees, of both genders, who are aged 25 – 55 years, given the evidence that the participation rate is the highest among the prime age workers.[37]

As for Germany, the dependent variable of the earnings equation is the logarithm of monthly gross earnings, which is explained by variables representing (1) schooling, measured as the highest degree attained (the six schooling categories are described in detail in Section 1.3.3), (2) potential labour market experience (measured in years) and (3) its square, (4) gender and (5) sector (public vs. private). An additional specification is estimated which is augmented with interaction terms between gender and the other explanatory variables of the earnings equation. Table 1.4 provides summary statistics for the full sample under analysis.

The large number of observations in 2000 has the advantage that the returns to the specific fields of study at university can be estimated in order to give a more comprehensive picture of the returns to university education. This amounts to replacing the schooling dummies with eight field of study dummies (i.e. the dependent variable and the other explanatory variables remain identical). As for Germany, for this specification the (occupational) group of "Professionals" is used from all occupational groups because (a) the field of study can only be inferred for this occupational group (using the *Foglaglkozások Egységes Osztályozasi Rendszere* (FEOR-93) classification[38]) and (b) the group of "Professionals" contains over half of the university graduates in the 2000 sample (see Table 1.16). The eight categories, based on the ISCED "Broad fields of university education", are as follows: (1) Training for secondary school teachers, (2) Training for primary school and other teachers, (3) Social sciences, Humanities and Arts, (4) Economics, Business and Law, (5) Science, Mathematics and Computing, (6) Engineering, (7) Medicine and Veterinary Medicine and (8) Other professionals. Section 1.8.6 of the Appendix provides detail on how the eight categories for university education have been generated, and Table 1.5 provides summary statistics for the sample of university graduates who belong to the (occupational) group of "Professionals" and are used in the analysis.

[37] For evidence see Laky (2002) in Fazekas and Koltay (Eds.).

[38] FEOR-93 is the system for the classification of occupations in Hungary since 1993 (four digit codes for 632 occupations) and is based on the *International Standard Classification of Occupations* (ISCO-88) to assure international comparability.

1.4.3 Cross-country comparison

As expected, the (sample) mean of monthly gross earnings is substantially higher in Germany than in Hungary in 2000. The German and Hungarian samples are similar in terms of (a) age composition (the mean age is around 40 years and 41 years in Germany and Hungary respectively), (b) years of potential labour market experience and (c) distribution across sector of employment. However, the gender composition of the sample of full-employees differs across the two countries. Whereas the Hungarian sample of full-time employees (who satisfy the selection criteria) consists of slightly more females than males, there are only approximately 31 percent female employees (who satisfy the selection criteria) in the German sample. This difference in gender composition across the two countries can partially be attributed to the differences in the proportion of part-timers within the group of employed women. That is, whereas in Hungary the fraction of part-timers within the group of employed women is not significant, in Germany female part-time employment has grown in the past two decades.[39] According to OECD figures for Hungary, female employment rate (women aged 15 – 64 years) was around 50 percent, and the share of part-timers within the group of employed women was merely around 5 percent in 2000. The respective figures for Germany were approximately 59 percent and approximately 34 percent. Note also that the share of part-timers within the group of employed women in Germany is not only high in comparison to Hungary but also in an international comparison – the share of part-time employment as a proportion of female employment in the OECD was around 21 percent in 2000[40].

Since the returns to human capital is the center of interest of this analysis, the distribution of educational attainment in the two countries merits comment. First, it must be noted that the distribution of educational attainment in the 2000 samples is representative for both countries. Namely, in Germany, the most common school degree is the *Hauptschulabschluss* (39 percent), followed by the *Realschulabschluss* (28 percent), the *Abitur* (23 percent) and, finally, the *Fachhochschulreife* (9 percent). Furthermore, around 49 percent of the individuals completed the *Lehre*, and around 22 percent of the individuals possess a tertiary degree. In Hungary, approximately 28 percent of the individuals have completed the apprentice school, about 31 percent posses a high school degree as the highest qualification and approximately 19 percent of the individuals have completed tertiary education. In both countries, the number of individuals without any kind of schooling degree is small, around 1 percent.

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[39] For evidence see Fitzenberger and Wunderlich (2004).
[40] See OECD Employment Outlook (2004) p. 296 and p. 310.

Moreover, a number of differences across the two countries in terms of the allocation across the six generated education groups merit comment. First of all, in Hungary, although decreasing, there is still a large number of individuals with only a primary school degree in the labour market in 2000.[41] Subsequently, it is not surprising that approximately 20 percent of the individuals belong to Group (1), which is twice as much as in Germany. Second of all, whereas in Germany about half of the individuals belong to Group (2), in Hungary, only around 30 percent of the individuals posses a lower level vocational degree – which reflects the importance / strength of the vocational education in the German education system as opposed to the Hungarian education system.[42] On the other hand, the fraction of individuals who posses a high school degree (and no tertiary degree) is substantially higher in Hungary than in Germany – approximately 31 percent in Hungary as opposed to 12 percent in Germany. Finally, although increasing during the 1990s, the rate of enrolment in university education in Hungary is still below the OECD level[43], which is reflected by the composition of Groups (5) and (6). That is, whereas in Germany approximately 9 percent and 13 percent of the individuals belong to Groups (5) and (6) respectively, in Hungary the respective figures are approximately 13 percent and 6 percent.

1.5 Results

1.5.1 Results for Germany

Tables 1.6 and 1.7 present the parameter estimates for the quantile regressions for five quantiles without and with interaction terms respectively. The OLS estimates are also provided in order to allow for the comparison with the mean effects.

The OLS estimates in Table 1.6 reveal some interesting aspects of the between-educational-levels earnings differentials. As expected, there is an earnings premium associated with the additional degree levels. The second result worth noting is that a higher level vocational degree (Group (3)) is worth more than a lower level vocational degree (Group (2)) in the labour market, i.e. the incremental (mean) return to having a higher level vocational degree rather than a lower level vocational degree is approximately 19 percent.

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[41] Note that transition brought with itself a decrease in demand for unskilled labour, and hence major changes in the composition of the workforce by qualification, namely, a reduction and an increase in the fraction of primary school graduates and college / university graduates respectively. For evidence see Labour Force Survey 1992 – 2001: Time Series (2002), p. 39.

[42] For an extensive discussion of the strength of vocational training in Germany see for example Kloss (1995) in Phillips, pp. 161 – 171.

[43] For evidence see Lannert (2001), pp. 21 – 23.

The parameter estimates of the selected quantiles shed light on the within-educational-levels earnings differentials in addition to the between-educational-levels differentials. First, the importance of differentiating between lower and higher level vocational training is supported by the fact that at all quantiles the return to higher level vocational training (Group (3)) is higher that that to lower level vocational training (Group (2)). However, it is interesting that a higher level vocational training is valued more at the lower quantiles than at the higher quantiles, i.e. the additional return to possessing a higher level vocational degree rather than a lower level vocational degree is 24, 19 and 16 percent at the 10^{th} quanitle, at the median and at the 90^{th} quantile respectively. Second, the estimated premium to a high school degree (relative to a higher vocational degree) is increasing across the earnings distribution (note also that at the 10^{th} quantile a higher level vocational degree is valued (slightly) more than a high school degree). The latter two findings suggest that at the lower quantiles vocational skills are valued more than academic skills, and the opposite is true at the upper quantiles. Moreover, in addition to high school education, the relative return to tertiary education, both college and university, is increasing across the distribution. Note also that a university degree (Group (6)) entails a higher monetary payoff than a college degree (Group (5)) at all estimated quantiles. Finally, as expected, the within-dispersion increases with the increasing levels of education, with the exception of higher level vocational training.

The effect of the other explanatory variables, namely, potential labour market experience, gender and sector, is not uniform across the quantiles. First, (a) as expected, at the mean and at all estimated quantiles, the experience profile is concave i.e. rapid initial earnings growth, which declines over the individual's career[44] (see Figure 1.3), (b) the return to the first year of potential labour market experience increases across the quantiles, (c) earnings growth declines more rapidly at the top of the distribution and (d) overall earnings growth is higher at the top of the distribution. Second, the coefficient estimate for the female-male earnings gap is approximately - 0.28, - 0.20 and - 0.15 at the 10^{th} quantile, at the median and at the 90^{th} quantile respectively, which indicates that earnings of female full-time employees are around 28, 20 and 15 percent lower than the earnings of their male counterparts at the respective quantiles – that is, the gender earnings gap in favour of males narrows over the earnings distribution. Finally, the public sector earnings premium decreases across the quantiles. That is, the earnings gap in favour of the public sector is only positive at the 10^{th} quantile (approximately 5 percent), and becomes negative at the 25^{th} quantile i.e. the private sector

[44] Note that the cross-section experience profiles reflect a combination of age, experience and cohort effects (Heckman and Robb (1985)).

earnings premium amounts to approximately 6 percent at the median and increases to approximately 18 percent at the top decile.

Table 1.7 reports the regression results with the gender interaction terms. A few points are worth noting about this specification. First, the OLS estimates reveal that the (mean) returns to education for males are lower at all education levels other than to college education than for females (which is in line with the findings of Krueger and Pischke (1995)). The results of the quantile regressions provide a more informative picture of the differences in returns to education across the genders and suggest the following: (a) whereas for males the return to high school and tertiary education increases across the quantiles (and no such pattern can be observed for vocational education), no such pattern is observed for females at any educational level and (b) whereas for males the within-dispersion increases with the level of education (i.e. the within-dispersion is largest at the university level), no such pattern is observed for females. In addition, it is important to note that (a) for both males and females an earnings premium exists to possessing a higher level vocational degree relative to possessing a lower level vocational degree and (b) this incremental return is higher for females than for males at all quantiles (other than at the top decile where the incremental return is of the same magnitude). Finally, the return of possessing a university degree is higher than that to possessing a college degree at all quantiles for both males (other than at the bottom decile) and females. The latter results give (continuous) support to the importance of subdividing the large group of individuals with a “vocational qualification and no high school degree” and the group of tertiary graduates when the center of analysis is the returns to education.

Turning to the informal component of human capital, the experience profiles for both males and females are concave (see Figures 1.4 and 1.5). The quantile regression results for males reveal that (a) the return to the first year of potential labour market experience increases across the quantiles, (b) earnings growth declines more rapidly at the top of the distribution and (c) overall earnings growth is higher at the top of the distribution. At the mean and all estimated quantiles the coefficient estimate of the interaction term between gender and the linear term for potential labour market experience is negative and the coefficient estimate of the interaction term between gender and squared term for potential labour market experience is positive (other than the 10^{th} quantile), which suggests that (a) the return to the first year of potential labour market experience is higher for males than for females and (b) earnings growth diminishes faster for males than for females (other than at the 10^{th} quantile) indicating that the difference in earnings growth declines at higher years of experience (other than at the 10^{th} quantile). Note also that visual inspection of Figures 1.4 and 1.5 suggests that overall earnings growth is higher for males than for females at the mean and at all estimated quantiles. Finally, the public-private sector earnings gap differs across the two genders. Namely, whereas the earnings of full-time public sector male employees are lower than that of their private sector counterparts (other than at the 10^{th} quantile), for females this is only applicable at the top of the distribution (at the 75^{th} and 90^{th} quantiles). However, for both males and females, the private sector earnings premium increases (from the 25^{th} and 75^{th} quantiles respectively) across the distribution, reaching around 18 and 16 percent at the 90^{th} quantile for males and females respectively. (Note that the quantile regression results contrast sharply with the OLS estimate of approximately 7 and 2 percent earnings gap in favour of the private sector for males and females respectively.)

Table 1.8 presents the regression results for the subgroup of university graduates who belong to the occupational group of "Professionals". Note that this specification is not augmented with gender interaction terms due to the small number of university graduates, especially females who have studied "Natural sciences" (for detail see Table 1.3). Note also that the three groups are heterogeneous in terms of both earnings prospects and educational background (in particular "Social sciences, Humanities and Arts" (Group 2)), and subsequently the coefficient estimates only provide a vague indication of the returns to university education for the selected sample. In summary, as expected, (a) the return to "Natural sciences" (relative to the other two groups) is the highest at all estimated quantiles (other than at the top decile) and (b) the return to both fields (relative to "Education") increases across the estimated quantiles. It is also worth noting that the earnings of the public sector full-time employed "professionals" are lower than that of their private sector counterparts at all estimated quantiles.

1.5.2 Results for Hungary

Tables 1.9 and 1.10 present the parameter estimates for the OLS estimation and the quantile regressions for five quantiles without and with interaction terms respectively.

The parameter estimates in Table 1.9 reveal some noteworthy features about the between- and within-educational-levels earnings differentials. First, it must be noted that, as expected, university education is valued the most in the labour market, followed by college education, technical school education, high school education, lower level vocational training and primary school or less at the mean and at all estimated quantiles.[45] Note also that the increasing educational levels, as expected, entail a larger within-dispersion (except for a high school degree, which has a larger within-dispersion than a college degree, which is in part attributed to the fact that the group of high school graduates includes individuals with and without vocational qualification). What is striking is the large within-dispersion at the university level. Namely, at the bottom decile the premium to a university degree (relative to "no vocational and no high school degree") is around 89 percent, it increases across the quanitles and at the top decile the relative return to university reaches 164 percent, which (a) supports further the standard finding that aggregate earnings inequality arises from differences between as well as within educational groups, and (b) is the first motivation for analysing the group of university graduates in more detail.

As far as the coefficient estimates of the other explanatory variables are concerned, the experience profiles are concave at the mean and at all the estimated quantiles (other than at the 90th quantile) i.e. earnings increase at a decreasing rate, and there is no evidence that earnings growth is higher at higher quantiles (see Figure 1.6). Furthermore, not surprisingly, the coefficient estimates for the female-male earnings gap indicate that the earnings of females are lower than that of males at all estimated quantiles, and the earnings premium for male full-time employees increases from approximately 3 percent at the 10th quantile to approximately 21 percent at the 90th quantile. Finally, note that the earnings of the public sector full-time employees are lower than that of their private sector counterparts (other than at the 10th quantile where the positive earnings premium of around 24 percent is in favour of the public sector), and this private sector earnings premium increases from around 3 percent at the 25th quantile to around 49 percent at the top decile.

The estimation results of the specification with the gender interaction terms (see Table 1.10) imply that (a) for both genders, university education is valued the most, followed by college, technical school, high school, lower level vocational and primary school education or less at the mean and at all estimated quantiles, (b) the estimated returns to the educational categories increase across the quantiles for both genders, (c) the within-educational-levels earnings differentials are smaller for females than for males at all educational categories and (d) as

[45] Note that, in Hungary, the relative return to a *szakiskola* degree is lower than that to a *szakmunkásképző* degree, so the aggregate return to Group (2) is an overestimate of the former and an underestimate of the latter type of vocational qualification.

expected, the within-educational-levels earnings differentials are the largest for university education for both genders, which in turn dictates a closer look at the university graduates. Accordingly, the estimated (relative) returns to the seven fields of study for the specifications without and with interaction terms for the group of "Professionals" are tabulated in Tables 1.11 and 1.12 respectively. Before commenting on the results, it is important to look at the gender composition of the different fields (see Table 1.5). As expected, there are over twice as many females as males in the teaching profession (approximately 39 percent vs. 17 percent), and approximately trice as many males as females who have studied "Science, Mathematics and Computing" and "Engineering" (approximately 12 percent vs. 4 percent and 25 percent vs. 8 percent for the respective fields of study). For the other fields of study, the proportion of males and females is approximately equal. Note that "Medicine and Veterinary Medicine" is selected as the reference category among the eight field of study groups due to (a) the large number of cases (i.e. the fraction of individuals belonging to "Medicine and Veterinary Medicine" is approximately 18 percent of the overall sample of professionals) and (b) the approximately equal fraction of males and females in this category (i.e. approximately 17 and 19 percent of all male and female professionals have studied "Medicine and Veterinary Medicine").

Because the results of the regression with the gender interaction terms (see Table 1.12) are more informative, they will be the center of analysis in this (sub)section. However, it must be noted that the between-field-of-study differentials are apparent from the specification without interaction terms (see Table 1.11). Not surprisingly, on average, relative to "Medicine and Veterinary Medicine" the group of "Economics, Business and Law" professionals enjoy the highest return, followed by "Other professionals" (who are mostly composed of administrative professionals, see Table 1.15), "Science, Mathematics and Computing" and "Engineering". Those who have studied "Training for secondary school teachers", "Training for primary school and other teachers" and "Social sciences, Humanities and Arts" reap negative returns relative to the omitted category (in increasing order). Therefore, one may conclude that, in addition to the group of university graduates who enjoy executive positions (i.e. the group "Legislators, senior officials and managers") and are not a part of this analysis, the high return to university education is driven by the high (relative) return to the fields of "Economics, Business and Law" and fields requiring technical skills such as "Science, Mathematics and Computing" and "Engineering". Finally, the estimation results of this specification and the gender composition of the group of Professionals (see Table 1.5) imply that the (average) earnings advantage of males at the university level (see Table 1.10) can be in part explained by the fact that most (approximately 63 percent) of the female professionals work in occupations which require the completion of lower-paying fields of study, i.e. “Training for secondary school teachers”, “Training for primary school and other teachers”, “Social Sciences, Humanities and Arts” and “Medicine and Veterinary Medicine” (in opposition to men for whom the corresponding figure is only around 37 percent).

The OLS estimates of the specification with the gender interaction terms (see Table 1.12) reveal that (a) the pattern of estimated (mean) relative returns to the fields of study is (qualitatively) identical for the two genders (i.e. same as described in the paragraph above), (b) (mean) relative return to the teaching profession and “Social Sciences, Humanities and Arts” is higher for females than for males and (c) the (mean) relative return to “Economics, Business and Law”, “Science, Mathematics and Computing”, “Engineering” and “Other professionals” is higher for males than for females, implying that (d) between-fields-of-study earnings dispersion is, on average, smaller for females than for males.

The quanitle regressions augment the OLS estimates in the following respects: (a) the between-fields-of-study earnings dispersion is smaller for females than for males at all quantiles other than at the 25th quanitle, (b) it increases across the quantiles for both genders and (c) whereas for males the high-paying fields i.e. “Other professionals”, “Science, Mathematics and Computing” and “Economics, Business and Law” experience the highest within-dispersion, for females the low-paying fields i.e. “Training for secondary school teachers” and “Training for primary school and other teachers” experience the highest within-dispersion. For instance, the OLS estimate of the return to “Economics, Business and Law” relative to “Medicine and Veterinary Medicine” is similar across the two genders, namely, approximately 57 and 52 percent for males and females respectively. However, whereas the mean earnings premium to “Economics, Business and Law” is a (relatively) good indicator for females, it is by no means a good indicator for males. That is, for males the earnings premium for “Economics, Business and Law” amounts to around 18, 54 and 110 percent at the bottom decile, at the median and at the top decile respectively. Subsequently, the higher within-dispersion for the group of male university graduates (relative to females) (see table 1.10), can be in part attributed to the higher (level and dispersion of) the earnings premium for the high-paying fields of study for male professionals (who make up around 63 percent of the group of male professionals).

1.5.3 Cross-country comparison

From the previous two sections various differences across the two countries in terms of the return to human capital become apparent. First, in terms of between-educational-levels earnings differentials the OLS estimates imply that, on average, relative to having “No high school degree and no vocational degree” (a) lower level vocational education enjoys a slightly higher additional return in Germany than in Hungary, namely, around 17 and 12 percent respectively, (b) “Higher vocational training” is valued more in Hungary than in Germany, (c) the return to “High school degree and no tertiary degree” is very similar in the two countries, namely, approximately 41 and 43 percent in Germany and Hungary respectively, (d) the return to college education is around 20 percentage points higher in Hungary than in Germany and (e) and return to university education is around 57 percentage points higher in Hungary than in Germany. The fact that the individuals who have completed “Higher vocational degree” enjoy a higher (relative) return in Hungary than in Germany is not surprising as the composition of academic skills (not only vocational skills) varies across the countries. That is, whereas in Hungary the individuals belonging to the group with “Higher vocational degree” possess a high school degree, in Germany they do not. The high relative return to tertiary education in Hungary is in fact characteristic for the 1990s (see, for example, Köllő (2002)), and is in part due to the increased demand for highly skilled labour.

Furthermore, a few points are worth noting in terms of the within-educational-levels earnings differentials: (a) in Hungary, the returns to all educational categories are increasing across the quantiles for both genders (as opposed to Germany, where an increase across quantiles is only observed for males with high school or tertiary degrees), (b) as expected, the within-educational-levels earnings dispersion is substantially lower for a vocational degree than for a university degree for both genders in Hungary and for males in Germany and (c) the within-educational-level earnings dispersion is larger in Hungary than in Germany at all educational levels. Thus, Hungary is no exception (see Pereira and Martins (2000)) to the fact that aggregate earnings inequality is attributed to both between and within-educational-levels earnings differentials. It is important to add that the quantile regression estimates of the specification using the subsample of professionals within the sample of university graduates reveal an expected similarity across the two countries in terms of university education, namely, the high valuation of technical skills (i.e. high relative returns to “Natural sciences” in Germany and to “Science, Mathematics and Computing” and “Engineering” in Hungary.)

Although the center of the empirical analysis is the comprehensive comparison of the returns to education in the two countries, a few points about the remaining explanatory variables merit comment. In terms of the informal component of human capital, it is worth noting that the pattern of higher earnings growth at the top of the distribution characterizes the pooled sample, the female sample and male sample in Germany only (see figures 1.3 – 1.8). Second, in both countries, the earnings of female full-time employees are lower than that of their male counterparts, on average, by approximately 23 and 15 percent in Germany and Hungary respectively. However, whereas in Germany the earnings disadvantage of women declines across the estimated quantiles, the opposite is true in Hungary – the estimated earnings premium for males at the bottom and top deciles amounts to approximately 28 and 15 percent in Germany and to around 4 and 21 percent Hungary. It is important to note, that in both countries the estimated earnings gap in favour of men could be in part attributed to the differences in working hours between the men and women. That is to say, although only full-time employees are selected for the empirical analysis, it is possible that male full-time employees work longer hours, especially in the private sector of employment, than their female counterparts, which (in part) generates their estimated "earnings advantage". Subsequently, hourly wage as an income measure would be an asset in estimating the "wage disadvantage" of females.[46] Furthermore, in both countries, on average, the earnings of full-time public sector employees is lower than the earnings of their private sector counterparts – by approximately 5 and 21 percent in Germany and Hungary respectively. The earnings disadvantage of public sector employees is in fact characteristic of the entire distribution (other than at the 10th quantile) in both countries, and it increases in magnitude in both countries – the earnings gap in favour of the private sector reaches around 18 percent and as high as 48 percent at the 90th quantile in Germany and Hungary respectively. Finally, the following similarities across the two counties merit comment: (a) females experience lower returns to tertiary education than males at the top of the earnings distribution, (b) the within-educational-levels earnings differentials are smaller at the tertiary level for females than for males and (c) the estimated private sector earnings premium is smaller for females than for males at all estimated quantiles.

1.6 Conclusion

In this study standard Mincer earnings equations were estimated using both OLS and quantile regression in order to give a comprehensive picture of the returns to education in Germany

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[46] I would like to thank PD Dr. Pfeiffer for pointing this out.

and Hungary for the year 2000. To make the cross-country comparison of the returns to education informative, six differentiated categories for formal education, rather than years of education, were generated and used in the empirical analysis.

In summary, the regression results document several differences between the returns to formal education in Germany and Hungary. Namely, (a) whereas the (relative) returns to lower vocational training and high school education are similar in the two countries across the estimated quantiles, (b) the (relative) return to tertiary education is substantially higher in Hungary than in Germany, especially at the top quantiles and (c) the returns to all educational categories are increasing in Hungary across the estimated quantiles, for both genders, as opposed to Germany, where an increase across qunatiles is only observed for males with high school and tertiary degrees. It is important to note that the quantile regression estimates for Germany augment those of Pereira and Martins (2000) who find evidence (using the GSOEP for the period of 1984 – 1995 and years of schooling as a proxy for the formal component of human capital) for a negative relationship between the returns to education and the earnings distribution. The (substantially) higher returns to university education in Hungary can be in part attributed to the fact that, although the composition of the workforce has changed by qualification over the past decade, the demand for qualified labour was still larger than its supply for the year under analysis. Note also that such high relative returns to tertiary degrees, despite the increase in the number of individuals holding tertiary degrees, has also been observed for Portugal (see Machado and Mata (2000)), and is in line with the literature for Hungary (see, for example, Köllő (2002)) and for other Central and Eastern European countries (see, for example, Orazem and Vodopvec (1997)). It is also important to note that (a) the within-dispersion is substantially larger at the university level than at the lower vocational level for both genders in Hungary and for males in Germany and (b) the within-educational-levels earnings dispersion is larger in Hungary than in Germany at all educational levels and is especially high at the tertiary level. Concerning tertiary education, two similarities across the two countries are worth pointing out: (a) females experience lower returns to tertiary education than males at the top of the earnings distribution and (b) the within-educational-levels earnings differentials are smaller at the tertiary level for females than for males.

For Hungary, the additional specifications for the subgroup of professionals within the group of university graduates shed light on the valuation of the fields of study at university in general and across the two genders, thereby offering some explanation for the high within-dispersion at the tertiary level. Relative to medical professionals, the group of “Economics, Business and Law” professionals enjoy the highest return, followed by “Other professionals” (who are mostly composed of administrative professionals), “Science, Mathematics and Computing” and “Engineering”. Pre-tertiary level teachers and those who completed degrees in “Social sciences, Humanities and Arts” reap negative returns relative to medical professionals. This pattern of relative returns characterizes both the pooled sample of professionals as well as the separate samples of female and male professionals. Note that the low return to medicine and (pre-tertiary level) teaching is not surprising given that wages in medical and teaching professions were low (prior to and) in 2000 relative to the private sector jobs requiring the same level of education, and was one of the motivating factors behind the wage reforms between September 2002 and 2003, whereby there was a 50 percent average increase in public sector (nominal) wages, affecting the various groups of public sector employees in different magnitudes.[47] Furthermore, apart from the fact that more male than female university graduates belong to the occupational group of “Legislators, senior officials and managers” (for whom, on average, earnings are higher than for other university graduates), the lower average return to university education for females can be attributed to the fact that (a) the majority (around 63 percent) of female professionals work in occupations requiring low-paying fields of study and (b) female professionals reap lower returns to the high-paying fields than their male counterparts.

A few points concerning the other variables of interest merit comment. First, in terms of potential labour market experience, the pattern of higher earnings growth at the top of the distribution characterizes the Germany samples under analysis only. Second, the estimated earnings premium for males relative to females declines and increases across the quantiles in Germany and Hungary respectively. Third, the earnings advantage of private sector full-time employees relative to their private sector counterparts is (a) larger at every estimated quantile in Hungary than in Germany and (b) is smaller in magnitude for females than for males at all estimated quantiles in both countries. Note that the large private-public sector earnings gap in Hungary, which characterised the transition period, generated the public sector wage increases in 2002.

[47] For detail on the wage increases for various groups in the public sector see Employment and Earnings 1998 – 2003 (2005), pp. 127 – 132, Labour Report: January – December 2003 (2004), pp. 10 – 20 and Közalkalmazotti Bértábla: Béremelés 2002 szeptember.

Overall, the estimates of the quantile regressions provide evidence for the fact that in Hungary, like in other EU countries (see Pereira and Martins (2000)), aggregate earnings inequality is attributed to both between- and within-educational-levels earnings differentials, and subsequently emphasize the relevance of using quantile regression when analysing the returns to education.

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1.8 Appendix

1.8.1 Education systems

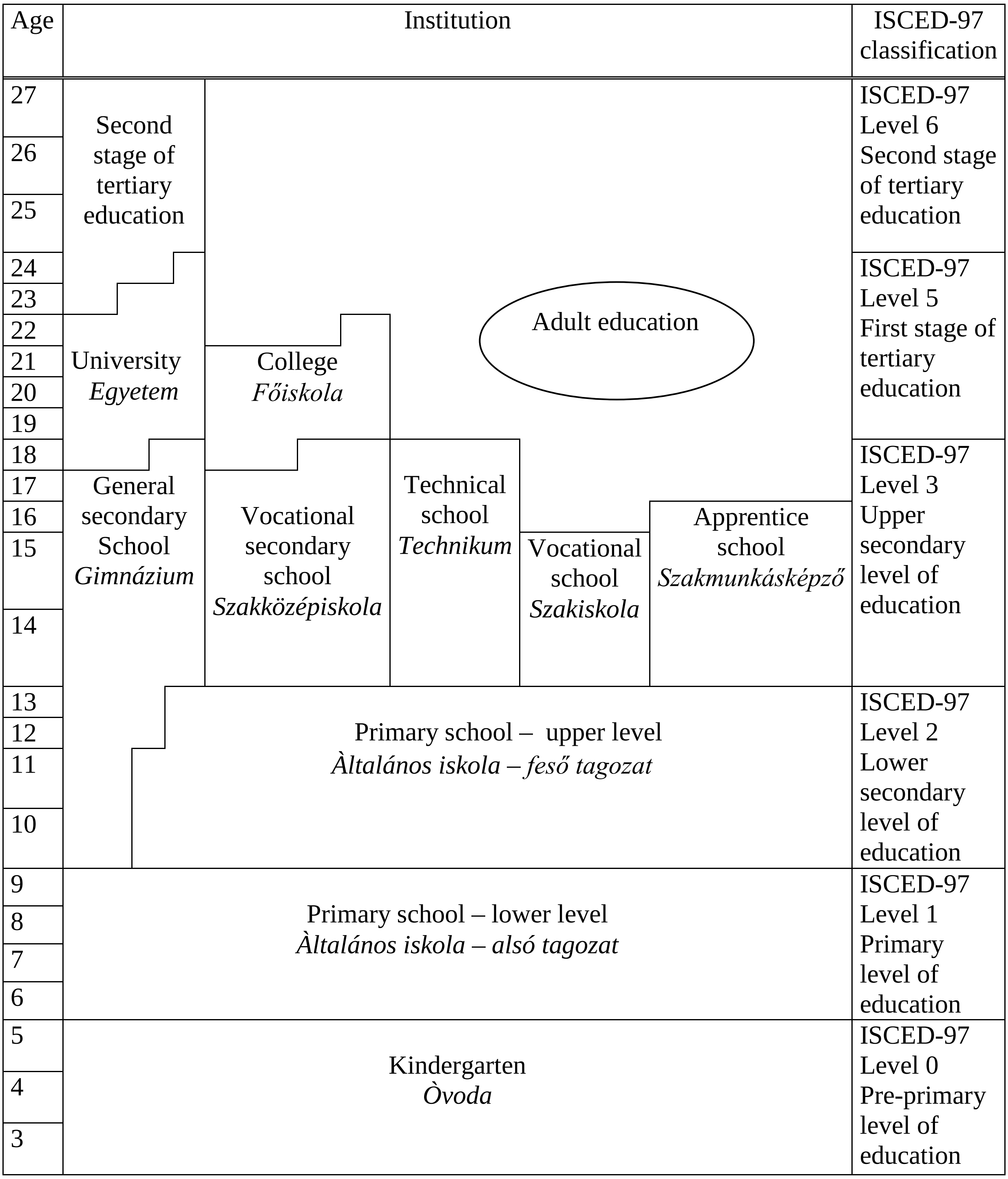
Figure 1.1 The German education system

Age	Institution				ISCED-97 classification
27 26 25	Adult education *Abendgymnasium / Kolleg*			Second stage of tertiary education	ISCED-97 Level 6 Second stage of tertiary education
24 23 22 21 20 19		School for higher level vocational education *Fachschule* (ISCED 4)	University of applied sciences *Fachhochschule* (ISCED 5)	University / *Universiät / Technische Hochschule* (ISCED 5)	ISCED-97 Level 5 First stage of tertiary education ISCED-97 Level 4 Post-secondary non-tertiary
18 17 16	Apprenticeship with part-time vocational school *Duales System – Berufsschule*	Full-time vocational school *Berufsfachschule*	Upper secondary schools leading to *Fachhochschule* entrance qualification *Fachoberschule / Berufsoberschule*	General secondary school – upper level *Gymnasiale Oberstufe / Fachgymnasium*	ISCED-97 Level 3 Upper secondary level of education
15 14 13 12 11 10	Lower secondary school *Hauptschule*[1)]	Intermediate secondary school *Realschule*[1)]		General secondary school – lower level *Gymnasium*[1)]	ISCED-97 Level 2 Lower secondary level of education
9 8 7 6	Primary school *Grundschule*				ISCED-97 Level 1 Primary level of education
5 4 3	Kindergarten *Kindergarten*				ISCED-97 Level 0 Pre-primary level of education

Sources: 1) OECD (1999) Classifying Educational Programmes – Manual for ISCED-97 Implementation in OECD Countries. 2) Cortina et al. (Eds.) (2003).

Note on Figure 1.1: 1) The comprehensive school, *Gesamtschule*, combines the *Hauptschule*, *Realschule* and *Gymnasium*, lasting 9 to 13 years, depending on the degree pursued.

Figure 1.2 The Hungarian education system



Sources: 1) OECD (1999) Classifying Educational Programmes – Manual for ISCED-97 Implementation in OECD Countries. 2) Lannert (Ed.) (2001).

Table 1.1 Six schooling categories for Germany and Hungary

	Six schooling categories	
	(1) No formal vocational degree and no high school degree	
Germany	*Ohne Abschluss verlassen /* *Hauptschulabschluss /* *Realschulabschluss /* *Anderer Abschluss*	
Hungary	*Less than általános iskola /* *Àltalános iskola*	
	(2) Lower level vocational degree and no high school degree	
Germany	School degree	Plus one of the vocational qualifications
	Hauptschulabschluss / *Realschulabschluss /* *Anderer Abschluss*	*Lehre /* *Berufsfachschule /* *Schule des Gesundheitswesens /* *Beamtenausbildung /* *Sonstige Ausbildung*
Hungary	*Szakiskola /* *Szakmunkásképző*	
	(3) Higher level vocational degree and no high school degree / higher level vocational degree	
Germany	School degree	Plus vocational qualification
	Hauptschulabschluss / *Realschulabschluss /* *Anderer Abschluss*	*Fachschule*
Hungary	*Technikum*	
	(4) High school degree and no tertiary degree	
Germany	School degree	Plus one / none of the vocational qualifications
	Fachhochschulreife / *Abitur*	*Lehre /* *Berufsfachschule /* *Schule des Gesundheitswesens /* *Fachschule /* *Beamtenausbildung /* *Sonstige Ausbildung*
Hungary	*Szakközépiskola /* *Gimnázium*	
	(5) College degree	
Germany	*Fachhochschule*	
Hungary	*Főiskola*	
	(6) University degree	
Germany	*Universität /* *Technische Hochschule*	
Hungary	*Egyetem*	

Note: The six schooling categories are based on the educational information provided by the "German Socio-Economic Panel" (GSOEP) and on the educational information provided by the "Hungarian National Labour Center's Wage Survey".

1.8.2 Descriptive statistics

Table 1.2 Descriptive statistics for Germany, full sample, 2000

Variable	
Mean monthly gross earnings	3, 086.88
Secondary school degree (%)	
Hauptschulabschluss	38.61
Realschulabschluss	28.15
Fachhochschulreife	8.67
Abitur	23.17
Anderer Schulabschluss	0.28
Ohne Abschluss verlassen	1.13
Vocational degree (%)	
Lehre	48.35
Berufsfachschule	9.16
Schule des Gesundheitswesens	1.89
Fachschule	7.82
Beamtenausbildung	5.89
Sonstige Ausbildung	1.59
Tertiary degree (%)	
Fachhochschule	8.71
Universität / Technische Hochschule	12.86
Six categories for the highest level of education completed (%)	
(1) No formal vocational degree and no high school degree	9.09
(2) Lower level vocational degree and no high school degree	52.26
(3) Higher level vocational degree and no high school degree	5.37
(4) High school degree and no tertiary degree	11.71
(5) College degree	8.71
(6) University degree	12.86
Gender (%)	
Male	68.98
Female	31.02
Sector (%)	
Private sector	71.93
Public sector	28.07
Mean years of potential labour market experience	19.94
Mean age	39.62
Observations	3,440

Table 1.3 Descriptive statistics for Germany, subgroup of university graduates belonging to the occupational group of “Professionals”, 2000

	Full sample	**Male**	**Female**
Mean monthly gross earnings	4,177.94	4, 574.47	3, 461.00
Field of Study (%)			
Education	30.26	20.25	48.38
Social sciences, Humanities and Arts	35.03	31.96	40.58
Natural sciences	34.72	47.79	11.04
Gender (%)			
Male	64.41		
Female	35.59		
Sector (%)			
Private	49.57	55.97	37.98
Public	50.43	44.03	62.02
Mean years of potential labour market experience	16.78	17.18	16.05
Mean age	41.20	41.63	40.42
Observations	263	187	76

Table 1.4 Descriptive statistics for Hungary, full sample, 2000

Variable	
Mean monthly gross earnings	352.18
Highest level of education completed (%)	
Less than primary school (less than általános iskola)	0.75
Primary school (általános iskola)	19.27
Vocational school (szakiskola)	2.34
Apprentice school (szakmunkásképző)	27.96
Vocational secondary school (szakközépiskola)	17.22
General secondary school (gimnázium)	10.02
Technical school (technikum)	3.45
College (főiskola)	12.84
University (egyetem)	6.14
Six categories for the highest level of education completed (%)	
(1) No formal vocational degree and no high school degree	20.02
(2) Lower level vocational degree and no high school degree	30.30
(3) Higher level vocational degree	3.45
(4) High school degree and no tertiary degree	27.24
(5) College degree	12.84
(6) University degree	6.14
Gender (%)	
Male	49.00
Female	51.00
Sector (%)	
Private sector	71.02
Public sector	28.98
Mean years of potential labour market experience	22.94
Mean age	40.66
Observations	150,775

Table 1.5 Descriptive statistics for Hungary, subgroup of university graduates belonging to the occupational group of “Professionals”, 2000

	Full sample	**Male**	**Female**
Mean monthly gross earnings	659.35	760.23	554.25
Field of Study (%)			
Training for secondary school teachers	19.91	12.60	27.52
Training for primary school and other teachers	7.72	4.01	11.60
Social sciences, Humanities and Arts	4.08	3.39	4.70
Economics, Business and Law	14.65	14.30	15.01
Science, Mathematics and Computing	7.81	11.71	3.73
Engineering	16.22	24.78	7.92
Medicine and Veterinary Medicine	18.34	17.43	19.30
Other professionals	11.27	11.68	10.86
Gender (%)			
Male	51.02		
Female	48.98		
Sector (%			
Private	41.60	54.67	27.98
Public	58.40	45.33	72.02
Mean years of potential labour market experience	17.28	16.71	17.89
Mean age	40.28	39.71	40.89
Observations	6,243	3,194	3,049

Notes on Tables 1.2 – 1.5: 1) Earnings are denoted in Euro. 2) Years of potential labour market experience is measured as age minus years of schooling minus six.

1.8.3 Estimation results for Germany

Table 1.6 Estimation results for Germany, full sample, 2000

	Germany, full sample, 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Education group						
(2)	0.165	0.115	0.161	0.169	0.124	0.140
	(0.023)	(0.041)	(0.029)	(0.035)	(0.052)	(0.050)
(3)	0.353	0.355	0.316	0.357	0.260	0.295
	(0.034)	(0.046)	(0.040)	(0.044)	(0.065)	(0.073)
(4)	0.411	0.344	0.348	0.397	0.408	0.468
	(0.029)	(0.062)	(0.047)	(0.042)	(0.067)	(0.067)
(5)	0.660	0.549	0.571	0.608	0.635	0.679
	(0.031)	(0.058)	(0.044)	(0.043)	(0.066)	(0.105)
(6)	0.670	0.622	0.674	0.712	0.700	0.777
	(0.028)	(0.117)	(0.046)	(0.039)	(0.061)	(0.070)
Experience	0.029	0.021	0.027	0.034	0.037	0.048
	(0.003)	(0.008)	(0.005)	(0.004)	(0.006)	(0.006)
Experience^2(/100)	-0.049	-0.034	-0.047	-0.059	-0.063	-0.085
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.231	-0.278	-0.229	-0.202	-0.174	-0.145
	(0.014)	(0.036)	(0.024)	(0.018)	(0.025)	(0.029)
Public sector	-0.054	0.052	-0.007	-0.059	-0.127	-0.179
	(0.014)	(0.033)	(0.018)	(0.017)	(0.022)	(0.030)
Constant	8.063	7.817	7.919	8.017	8.193	8.245
	(0.039)	(0.082)	(0.054)	(0.045)	(0.073)	(0.073)
Observations	3,440	3,440	3,440	3,440	3,440	3,440

Table 1.7 Estimation results for Germany, full sample, 2000

	Germany, full sample, 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Education group						
(2)	0.138	0.124	0.124	0.128	0.122	0.168
	(0.028)	(0.045)	(0.033)	(0.039)	(0.050)	(0.040)
(3)	0.300	0.355	0.269	0.278	0.246	0.317
	(0.039)	(0.052)	(0.043)	(0.049)	(0.058)	(0.066)
(4)	0.365	0.262	0.308	0.356	0.366	0.502
	(0.036)	(0.072)	(0.054)	(0.046)	(0.055)	(0.058)
(5)	0.669	0.563	0.564	0.584	0.667	0.790
	(0.036)	(0.064)	(0.047)	(0.052)	(0.081)	(0.139)
(6)	0.636	0.503	0.638	0.679	0.734	0.845
	(0.034)	(0.261)	(0.049)	(0.046)	(0.061)	(0.063)
Experience	0.039	0.023	0.032	0.042	0.047	0.048
	(0.004)	(0.010)	(0.005)	(0.005)	(0.007)	(0.009)
Experience^2(/100)	-0.069	-0.036	-0.056	-0.078	-0.082	-0.084
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.078	-0.197	-0.039	-0.133	0.027	0.055
	(0.079)	(0.222)	(0.119)	(0.106)	(0.172)	(0.168)
Public sector	-0.072	0.036	-0.004	-0.084	-0.142	-0.181
	(0.017)	(0.036)	(0.021)	(0.020)	(0.025)	(0.043)
Interaction terms						
(2) * female	0.070	-0.121	0.048	0.137	0.018	-0.088
	(0.048)	(0.165)	(0.075)	(0.081)	(0.158)	(0.124)
(3) * female	0.203	-0.114	0.241	0.209	0.049	-0.093
	(0.087)	(0.208)	(0.190)	(0.106)	(0.195)	(0.330
(4) * female	0.116	0.139	0.071	0.128	0.024	-0.059
	(0.060)	(0.182)	(0.105)	(0.103)	(0.192)	(0.156)
(5) * female	-0.070	-0.100	0.011	0.021	-0.157	-0.346
	(0.069)	(0.185)	(0.107)	(0.095)	(0.181)	(0.191)
(6) * female	0.078	0.054	0.021	0.040	-0.152	-0.303
	(0.061)	(0.313)	(0.112)	(0.097)	(0.166)	(0.153)
Experience *	-0.023	-0.002	-0.023	-0.021	-0.019	-0.009
female	(0.007)	(0.017)	(0.011)	(0.009)	(0.012)	(0.013)
Experience^2 *	0.049	-0.004	0.044	0.044	0.033	0.017
female (/100)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector * female	0.050	0.079	0.033	0.088	0.081	0.021
	(0.030)	(0.071)	(0.054)	(0.037)	(0.047)	(0.061)
Constant	7.993	7.800	7.890	7.976	8.094	8.210
	(0.048)	(0.109)	(0. 060)	(0.056)	(0.079)	(0.098)
Observations	3,440	3,440	3,440	3,440	3,440	3,440

Notes on Tables 1.6 – 1.7: 1) The reference group among the education categories is Group (1) “No formal vocational training and no high school degree”. 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus six). 5) Standard errors are in parenthesis. 6) Standard errors are computed by 1000 bootstrap replications for the quantile regressions.

Table 1.8 Estimation results for Germany, subgroup of university graduates belonging to the occupational group of "Professionals"

	Germany, university graduates (Professionals), 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Field of Study						
Social sciences, Humanities	0.031	-0.152	-0.174	0.020	0.067	0.311
and Arts	(0.091)	(0.158)	(0.127)	(0.116)	(0.096)	(0.133)
Natural sciences	0.008	0.005	0.004	0.089	0.138	0.308
	(0.107)	(0.975)	(0.178)	(0.116)	(0.103)	(0.097)
Experience	0.046	0.087	0.051	0.053	0.052	0.064
	(0.018)	(0.035)	(0.028)	(0.019)	(0.018)	(0.015)
Experience^2(/100)	-0.082	-0.165	-0.095	-0.106	-0.108	-0.147
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.118	-0.150	-0.240	-0.164	-0.165	-0.094
	(0.075)	(0.140)	(0.106)	(0.081)	(0.063)	(0.063)
Public sector	-0.215	-0.160	-0.252	-0.160	-0.265	-0.200
	(0.081)	(0.165)	(0.099)	(0.093)	(0.099)	(0.099)
Constant	8.555	7.861	8.512	8.590	8.764	8.685
	(0.179)	(0.309)	(0.255)	(0.201)	(0.171)	(0.133)
Observations	263	263	263	263	263	263

Notes on Table 6: 1) The reference group among the "Field of Study" categories is "Education". 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus school six). 3) Standard errors are in parenthesis. 5) Standard errors are computed by 1000 bootstrap replications for the quantile regressions.

Figure 1.3 Experience profiles for Germany, full sample

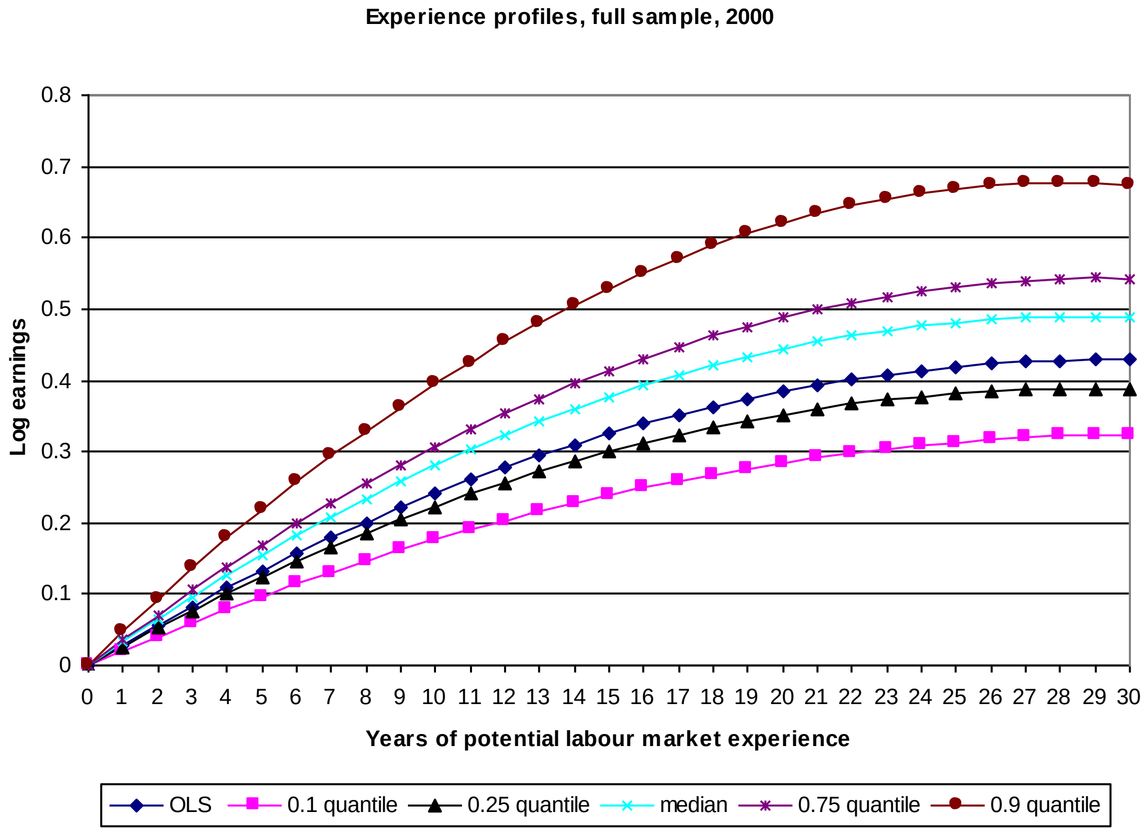


Figure 1.4 Experience profiles for Germany, males

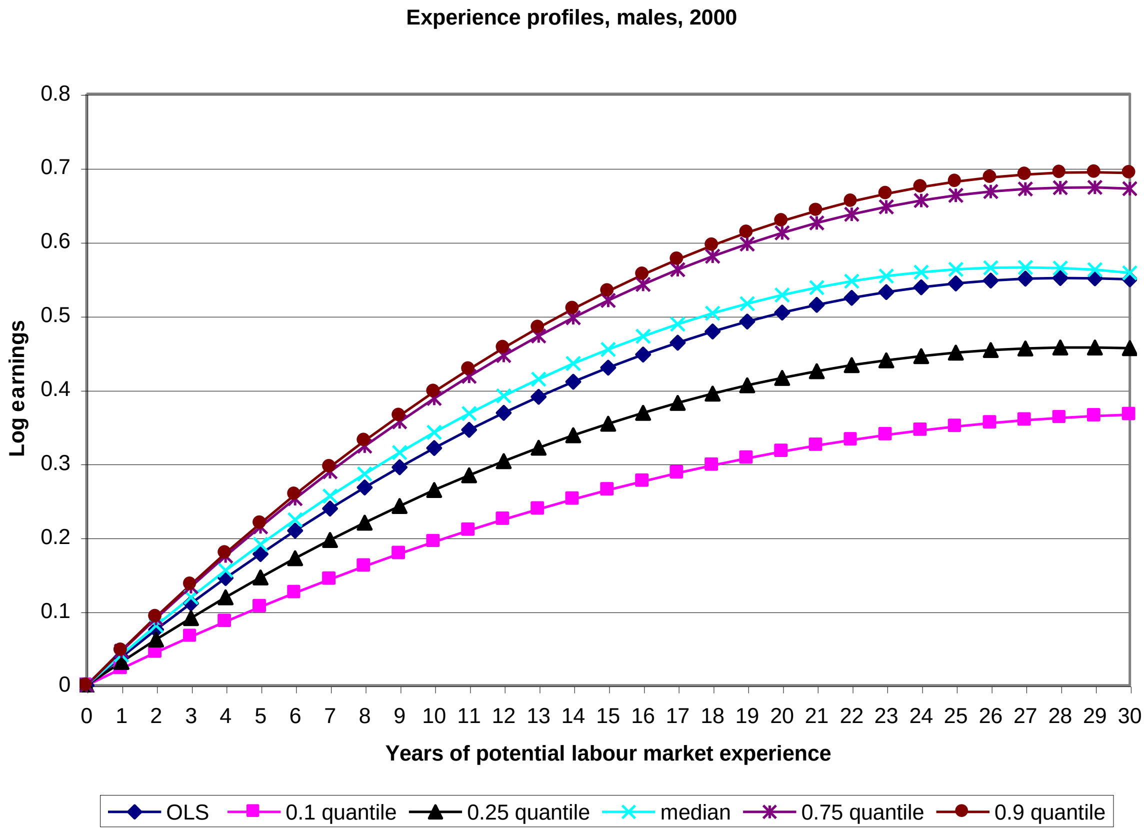
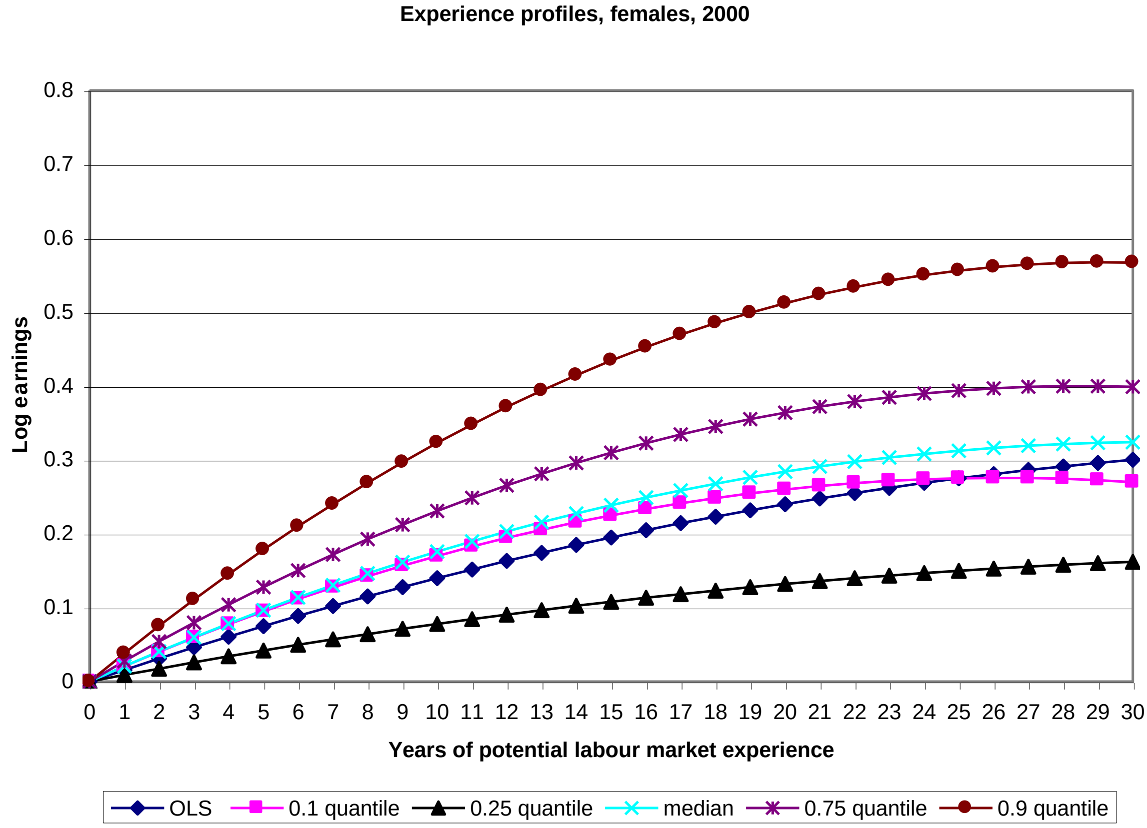


Figure 1.5 Experience profiles for Germany, females



1.8.4 Estimation results for Hungary

Table 1.9 Estimation results for Hungary, full sample, 2000

	Hungary, full sample, 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Education group						
(2)	0.124	0.107	0.122	0.133	0.150	0.176
	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)
(3)	0.565	0.400	0.570	0.562	0.633	0.721
	(0.008)	(0.033)	(0.015)	(0.012)	(0.012)	(0.016)
(4)	0.430	0.241	0.391	0.451	0.502	0.595
	(0.004)	(0.007)	(0.006)	(0.007)	(0.005)	(0.009)
(5)	0.864	0.706	0.816	0.832	0.894	1.028
	(0.005)	(0.007)	(0.005)	(0.006)	(0.006)	(0.011)
(6)	1.227	0.885	1.057	1.163	1.377	1.640
	(0.007)	(0.013)	(0.007)	(0.010)	(0.011)	(0.014)
Experience	0.014	0.018	0.024	0.019	0.009	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Experience^2(/100)	-0.012	-0.021	-0.027	-0.022	-0.003	0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.150	-0.036	-0.120	-0.166	-0.184	-0.209
	(0.003)	(0.005)	(0.006)	(0.006)	(0.005)	(0.007)
Public sector	-0.213	0.238	-0.033	-0.267	-0.395	-0.480
	(0.003)	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)
Constant	10.674	9.873	10.145	10.633	11.067	11.395
	(0.008)	(0.012)	(0.011)	(0.013)	(0.013)	(0.020)
Observations	150,775	150,775	150,775	150,775	150,775	150,775

Table 1.10 Estimation results for Hungary, full sample, 2000

	Hungary, full sample, 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Education group						
(2)	0.141	0.056	0.121	0.137	0.157	0.193
	(0.006)	(0.008)	(0.013)	(0.011)	(0.010)	(0.011)
(3)	0.551	0.332	0.553	0.539	0.619	0.698
	(0.010)	(0.039)	(0.019)	(0.016)	(0.015)	(0.019)
(4)	0.397	0.132	0.353	0.401	0.466	0.567
	(0.007)	(0.013)	(0.018)	(0.013)	(0.011)	(0.016)
(5)	0.926	0.593	0.812	0.894	1.050	1.216
	(0.009)	(0.016)	(0.015)	(0.011)	(0.017)	(0.018)
(6)	1.251	0.762	1.041	1.201	1.447	1.711
	(0.009)	(0.017)	(0.015)	(0.016)	(0.018)	(0.022)
Experience	0.014	0.009	0.020	0.017	0.011	0.011
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Experience^2(/100)	-0.015	-0.004	-0.021	-0.022	-0.011	-0.013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.196	-0.230	-0.230	-0.295	-0.255	-0.146
	(0.017)	(0.023)	(0.036)	(0.034)	(0.032)	(0.035)
Public sector	-0.230	0.297	-0.057	-0.322	-0.426	-0.474
	(0.040)	(0.008)	(0.009)	(0.008)	(0.008)	(0.012)
Interaction terms						
(2) * female	-0.040	0.067	0.002	-0.006	-0.008	-0.024
	(0.008)	(0.010)	(0.016)	(0.013)	(0.013)	(0.014)
(3) * female	0.060	0.140	0.033	0.071	0.053	0.104
	(0.017)	(0.049)	(0.032)	(0.027)	(0.028)	(0.034)
(4) * female	0.054	0.168	0.053	0.077	0.050	0.038
	(0.008)	(0.015)	(0.019)	(0.015)	(0.012)	(0.019)
(5) * female	-0.087	0.178	0.012	-0.069	-0.205	-0.283
	(0.011)	(0.017)	(0.016)	(0.013)	(0.018)	(0.022)
(6) * female	-0.046	0.187	0.034	-0.056	-0.149	-0.174
	(0.013)	(0.020)	(0.018)	(0.018)	(0.024)	(0.038)
Experience *	0.001	0.016	0.006	0.004	0.002	-0.008
female	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Experience^2 *	0.005	-0.028	-0.008	0.002	0.006	0.026
female (/100)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector * female	0.028	-0.077	0.035	0.083	0.045	-0.008
	(0.007)	(0.010)	(0.012)	(0.010)	(0.011)	(0.016)
Constant	10.690	10.015	10.214	10.696	11.078	11.338
	(0.012)	(0.019)	(0.032)	(0.030)	(0.028)	(0.027)
Observations	150,775	150,775	150,775	150,775	150,775	150,775

Notes on Tables 1.9 – 1.10: 1) The reference group among the education categories is Group (1) “No formal vocational training and no high school degree”. 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus six). 3) Standard errors are in parenthesis. 5) Standard errors are computed by 200 bootstrap replications for the quantile regressions.

Table 1.11 Estimation results for Hungary, subgroup of university graduates belonging to the occupational group of "Professionals"

	Hungary, university graduates (Professionals), 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Field of Study						
Training for secondary	-0.068	0.091	0.046	-0.022	-0.143	-0.295
school teachers	(0.023)	(0.016)	(0.014)	(0.015)	(0.019)	(0.030)
Training for primary school	-0.148	-0.028	-0.056	-0.106	-0.222	-0.343
and other teachers	(0.031)	(0.023)	(0.020)	(0.017)	(0.021)	(0.037)
Social sciences, Humanities	-0.220	-0.133	-0.153	-0.217	-0.262	-0.268
and Arts	(0.040)	(0.069)	(0.032)	(0.029)	(0.034)	(0.076)
Economics, Business and	0.538	0.359	0.447	0.530	0.624	0.628
Law	(0.030)	(0.078)	(0.050)	(0.050)	(0.057)	(0.053)
Science, Mathematics and	0.309	0.024	0.082	0.271	0.485	0.460
Computing	(0.035)	(0.079)	(0.070)	(0.062)	(0.072)	(0.089)
Engineering	0.162	0.109	0.105	0.085	0.198	0.129
	(0.031)	(0.056)	(0.043)	(0.040)	(0.060)	(0.059)
Other professionals	0.404	0.167	0.206	0.320	0.416	0.651
	(0.028)	(0.029)	(0.030)	(0.030)	(0.052)	(0.093)
Experience	0.027	0.022	0.023	0.029	0.031	0.036
	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)
Experience^2(/100)	-0.050	-0.019	-0.025	-0.044	-0.049	-0.070
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.082	-0.004	-0.035	-0.055	-0.077	-0.124
	(0.015)	(0.017)	(0.014)	(0.012)	(0.014)	(0.023)
Public sector	-0.164	0.383	-0.103	-0.361	-0.422	-0.509
	(0.023)	(0.059)	(0.043)	(0.036)	(0.052)	(0.049)
Constant	11.488	10.479	11.138	11.547	11.838	12.225
	(0.039)	(0.080)	(0.053)	(0.045)	(0.060)	(0.061)
Observations	6,243	6,243	6,243	6,243	6,243	6,243

Table 1.12 Estimation results for Hungary, subgroup of university graduates belonging to the occupational group of “Professionals”, 2000

	Hungary, university graduates (Professionals), 2000					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Field of Study						
Training for secondary school teachers	-0.084	0.054	0.008	-0.046	-0.137	-0.277
	(0.037)	(0.024)	(0.019)	(0.024)	(0.029)	(0.043)
Training for primary school and other teachers	-0.186	-0.108	-0.120	-0.157	-0.222	-0.311
	(0.055)	(0.051)	(0.029)	(0.033)	(0.043)	(0.078)
Social sciences, Humanities and Arts	-0.251	-0.410	-0.239	-0.269	-0.270	-0.072
	(0.060)	(0.129)	(0.084)	(0.051)	(0.065)	(0.203)
Economics, Business and Law	0.578	0.180	0.341	0.541	0.731	1.104
	(0.044)	(0.187)	(0.094)	(0.083)	(0.084)	(0.243)
Science, Mathematics and Computing	0.435	-0.042	0.068	0.342	0.683	0.994
	(0.046)	(0.115)	(0.130)	(0.100)	(0.090)	(0.232)
Engineering	0.266	0.054	0.085	0.115	0.359	0.549
	(0.042)	(0.077)	(0.067)	(0.066)	(0.078)	(0.204)
Other professionals	0.521	0.121	0.196	0.356	0.623	1.382
	(0.039)	(0.047)	(0.044)	(0.050)	(0.117)	(0.250)
Experience	0.023	0.001	0.015	0.028	0.034	0.042
	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.008)
Experience^2(/100)	-0.046	0.031	-0.002	-0.046	-0.063	-0.089
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.041	-0.325	-0.283	-0.088	0.062	0.438
	(0.077)	(0.156)	(0.112)	(0.102)	(0.113)	(0.230)
Public sector	-0.084	0.335	-0.103	-0.337	-0.320	-0.154
	(0.033)	(0.090)	(0.064)	(0.057)	(0.074)	(0. 205)
Interaction terms						
Training for secondary school teachers * female	0.016	0.068	0.067	0.040	-0.017	-0.065
	(0.048)	(0.030)	(0.026)	(0.032)	(0.039)	(0.061)
Training for primary school and other teachers * female	0.042	0.113	0.111	0.078	-0.014	-0.064
	(0.067)	(0.055)	(0.037)	(0.041)	(0.050)	(0.094)
Social science, Humanities and Arts * female	0.058	0.418	0.141	0.092	0.023	-0.226
	(0.080)	(0.146)	(0.088)	(0.066)	(0.076)	(0. 221)
Economics, Business and Law * female	-0.061	0.224	0.223	-0.005	-0.131	-0.566
	(0.061)	(0.208)	(0.112)	(0.107)	(0.113)	(0.354)
Science, Mathematics and Computing * female	-0.346	0.067	-0.032	-0.235	-0.499	-0.905
	(0.077)	(0.184)	(0.155)	(0.139)	(0.125)	(0.249)
Engineering * female	-0.242	0.035	-0.009	-0.069	-0.373	-0.653
	(0.065)	(0.111)	(0.094)	(0.089)	(0.106)	(0.240)
Other professionals* female	-0.227	0.046	0.034	-0.033	-0.298	-1.013
	(0.055)	(0.060)	(0.062)	(0.062)	(0.129)	(0.260)
Experience * female	0.011	0.031	0.017	0.001	-0.004	-0.010
	(0.007)	(0.010)	(0.008)	(0.007)	(0.007)	(0.010)

Table 1.12 continues on next page

Table 1.12 continued

Experience^2 * female	-0.013	-0.072	-0.034	0.006	0.022	0.036
(/100)	(0.000)	(0. 000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector * female	-0.154	-0. 004	0.019	-0.029	-0.108	-0.427
	(0.046)	(0. 128)	(0.088)	(0.074)	(0.098)	(0.215)
Constant	11.451	10.740	11.252	11.567	11.718	11.788
	(0.054)	(0.118)	(0.084)	(0.084)	(0.089)	(0.216)
Observations	6,243	6,243	6,243	6,243	6,243	6,243

Notes on Tables 1.11 – 1.12: 1) The reference group among the "Field of Study" categories is "Medicine and Veterinary Medicine". 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus six). 3) Standard errors are in parenthesis. 5) Standard errors are computed by 1000 bootstrap replications for the quantile regressions.

Figure 1.6 Experience profiles for Hungary, full sample

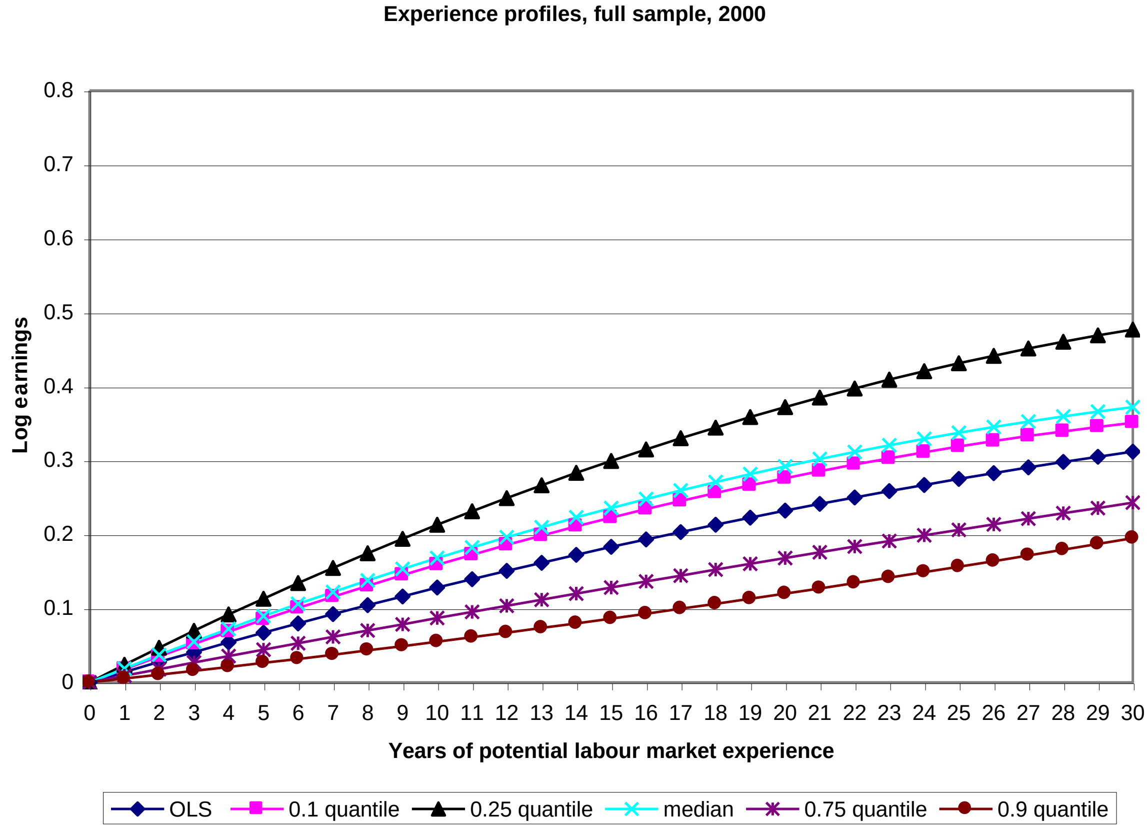


Figure 1.7 Experience profiles for Hungary, males

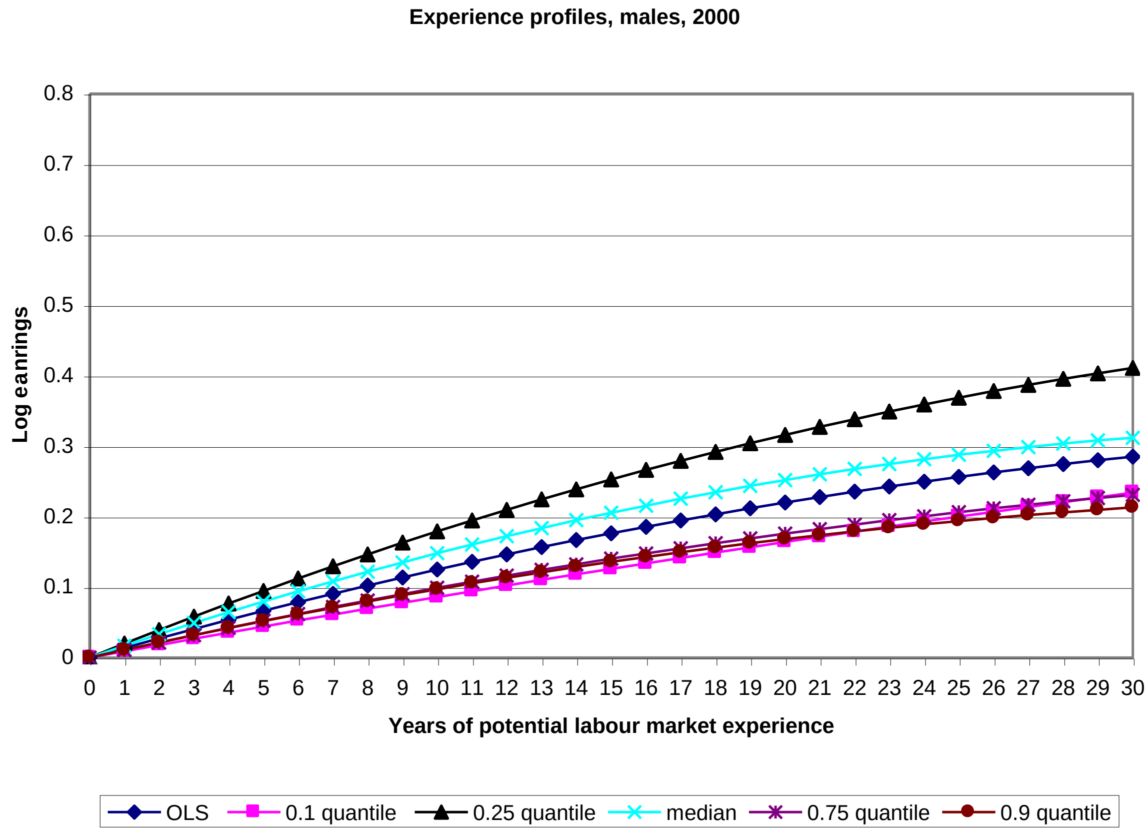
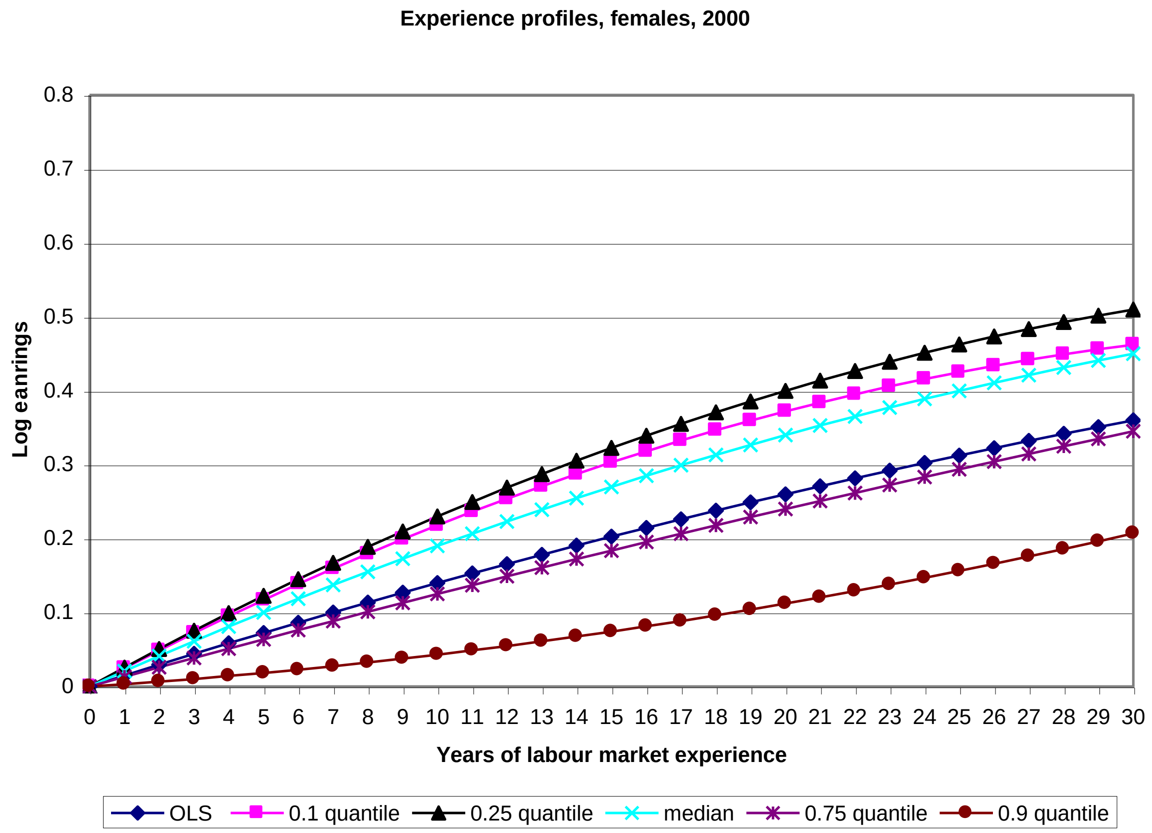


Figure 1.8 Experience profiles for Hungary, females



1.8.5 Generation of field of study groups in Germany

The three broad field of study groups have been generated using the occupational information (ISCO-88) provided in the GSOEP. To make cross-country comparison possible, the occupational composition of the field of study groups is identical across the two countries. That is, in a first step, the university graduates belonging the main occupational group of "Professionals" have been allocated to eight field of study groups in both countries according to their occupational background (see Table 1.14 in Section 1.8.6 for detail) and, in a second step, these eight categories have been merged into three broad categories for the German subsample in order to assure a sufficient number of observations for econometric analysis. Table 1.13 presents the field of study groups for the two countries. Group (2) is the most heterogeneous one in Germany in terms of both educational background and earnings prospects.

Table 1.13 Field of study groups in Germany and Hungary

Field of study	
Hungary	**Germany**
(1) Training for secondary school teachers (2) Training for primary school and other teachers	(1) Education
(3) Social sciences, Humanities and Arts (4) Economics, Business and Law	(2) Social sciences, Humanities and Arts
(5) Science, Mathematics and Computing (6) Engineering (7) Medicine and Veterinary Medicine	(3) Natural sciences
(8) Other professionals	

Note: For Germany, those who would otherwise belong to the Group of "Other professionals" (because the field of study cannot be inferred from the occupation), namely, "Administrative professionals" and "Tertiary education teaching professionals" are omitted form the analysis. Furthermore, the subgroup of "Pharmacists" and "Social workers" have been allocated to the Group of "Natural sciences" and "Social sciences, Humanities and Arts" respectively. This allocation procedure is preferred to generating a fourth group of "Other professionals" with a small number of observations.

1.8.6 Generation of field of study groups in Hungary

The eight field of study groups have been generated using the occupational information in the "Hungarian National Labour Center's Wage Survey". The eight groups reflect the ISCED classification of university education and are tailored to the dataset due to considerations about (a) sample size and (b) characteristics of the Hungarian education system (as well as earnings prospects), which allow the subdivision of some broad fields of study alternatively the merging of some narrow fields of study. For example, "Education" has been subdivided into "Training for secondary school teachers" and "Training for primary school and other teachers" as these two subgroups of "Education" are large enough to support meaningful econometric analysis. Note also that the subdivision makes sense in terms of both educational qualification and earnings prospects. Moreover, "Social sciences" and "Humanities and Arts" have been group together for sample size considerations. Table 1.14 presents the occupation composition of the eight field of study groups, with Group (3) being the most heterogeneous one.

Table 1.14 Occupational composition of the eight field of study groups

Occupation	**Field of study**
All secondary education teaching professionals (general and vocational)	(1) Training for secondary school teachers
Primary education teaching professionals, Pre-primary education teaching professionals, Special education teaching professionals	(2) Training for primary school and other teachers
Historians, Sociologists, Anthropologists and related professions, Philologists, Translators, Interpreters, Psychologists, Librarians and related information professionals, Authors, Journalists, Sculptors, Painters, Composers, Musicians, Singers, Actors, Directors	(3) Social sciences, Humanities and Arts
Economists, Accountants, Other business professionals, Lawyers, Judges, Legal professionals not elsewhere classified	(4) Economics, Business and Law
Biologists, Biochemists, Zoologists, Pharmacologists, Physicists, Meteorologists, Chemists, Other scientists not elsewhere classified, Mathematicians, Computing professionals	(5) Science, Mathematics and Computing
All engineering professionals, Architects	(6) Engineering
Medical doctors, Dentists, Veterinarians	(7) Medicine and Veterinary Medicine
Health and welfare professionals (nursing and midwifery professionals, pharmacists, social work and counselling professionals), Other technical professionals, Tertiary education teaching professionals, Administrative professionals	(8) Other professionals

The final group of “Other professionals” consists of (a) those fields of study which account for approximately one percent of the selected sample (namely occupations belonging to the “Health and Welfare” category) and (b) those occupations for which the exact field of study cannot be determined (namely “Other technical professionals”, “Tertiary education teaching professionals” and “Administrative professionals”). Table 1.15 provides information of the exact occupational composition of the “Other professionals” category.

Table 1.15 Occupational composition (%) of “Other professionals”

“Other professionals”	
Health and Welfare	11.00
Other technical professionals	14.53
Tertiary education teaching professionals	14.98
Administrative professionals	59.49
Observations	622

Note that only the individuals belonging to the (major occupational) group of “Professionals” are used in estimation, who represent approximately 57 percent of all university graduates in the 2000 sample. This is due to the fact that the field of study can only be imputed for the “Professionals” using the FEOR classification code. For completeness, Table 1.16 provides information on the (major) occupational composition of all university graduates (i.e. individuals who belong to Education group (6) “University degree”), males and females separately.

Table 1.16 Major occupational composition of all university graduates

	Full sample	**Male**	**Female**
Major occupation group (%)			
(1) Legislators, senior officials and managers	32.86	40.51	22.29
(2) Professionals	57.26	50.35	66.79
(3) Technicians and associate professionals	7.86	7.50	8.34
(4) Clerks	0.95	0.37	1.76
(5) Service workers	0.24	0.22	0.26
(6) Skilled agricultural and fishery workers	0.06	0.10	0.00
(7) Craft and related trades	0.50	0.61	0.35
(8) Plant and machine operators and assemblers	0.17	0.25	0.05
(9) Elementary occupations	0.11	0.07	0.15
Observations	11,001	6,454	4,547

2 An analysis of the earnings structures in the public and private sectors in Hungary

2.1 Introduction

Socialist wage policy in the Central and Eastern European (CEE) countries tried to diminish wage differentials, that is, workers were not rewarded according to skill or productivity and the returns to education were set centrally and were low. Furthermore, the socialist education system was adjusted to the needs of the planned economy, and thus put a strong emphasis on technical skills as opposed to business related skills (see, for example, Kertesi and Köllő (1999) and Flanagan (1995)). Not surprisingly, transition brought with itself an increase in earnings inequality attributed to the widening earnings differentials across education groups, which has been documented by an ample of studies on the CEE countries. Despite the quantitative differences across the CEE countries, the cross-country estimates (based on ordinary least squares (OLS) estimates of Mincer earnings equations), document an increasing mean return to an additional year of schooling during the period of transition. For example, for the Czech Republic Munich et al. (2002) find that men's average rate of return to an additional year of schooling increased from around 3 percent in 1989 to 6 percent in 1996.[48] Similarly, Chase (1997) finds that the average return to education increased from around approximately 2 and 3 percent in 1984 to around 5 percent in 1993 for Czech and Slovak men respectively. Moreover, Rutkowski (1997) finds that the average rate of return to an additional year of schooling rose form 5 percent in 1987 to 7 percent in 1992 in Poland. Furthermore, Andrén et al. (2005), using cross-sections from 1950 – 2000, estimate the mean return to schooling to be 3 – 4 percent during the socialist period, rising during the 1990s and reaching around 9 percent by 2000. Kézdi (2005) estimates the mean return to an additional year of schooling to rise from 7 percent in 1989 to 12 percent in 2002. On the other hand, Krueger and Pischke (1995) find evidence that in East Germany the mean rate of return to a year of schooling declined from around 8 percent in 1988 to 6 percent in 1991, thus concluding that education attained under the Communist system became less valuable during the transition period.

Using categorical variables for educational attainment, in order to shed light on how different degrees are valued in the transition process, the cross-country consensus is that relative to primary school or less, the average premium to high school and university education rose

[48] Log percentage points throughout the chapter.

dramatically while the average return to vocational education remained constant or even declined during the transition period, partially due to the inefficient training in vocational institutions, on the one hand, and due to the increasing demand for high-skilled labour on the other. For example, for the Czech Republic Munich et al. (2002) find evidence that the mean return to university education relative to junior high school increased from around 28 percent in 1989 to 72 percent in 1996. Moreover, Orazem and Vodopivec (1998) find that relative to less than primary school the average return to high school and 4 years of university increased from approximately 32 and 72 percent in 1987 to 41 and 94 percent respectively in 1991 for Slovene men. Keane and Prasad (2001) find that whereas the average wage premium for a college degree relative to primary school rose substantially between 1986 and 1996 in Poland (i.e. around 37, 53 and 68 percent in 1986, 1992 and 1996 respectively), the average return to vocational training remained in the range of 11 and 17 percent throughout the decade of 1986 – 1996. In addition, Noorkôiv et al. (1997) find evidence that the average premium to university education relative to less than primary school rose from around 19 percent in 1989 to 54 and 66 percent in 1993 and 1995 respectively for Estonian men. Finally, Kertesi and Köllő (2002) find that the mean rate of return relative to primary school or less to vocational training school, high school and college increased from approximately 12 to 13 percent, from 14 to 22 percent and from 36 to 60 percent respectively between 1986 and 1994 for Hungarian full-time employees in the private sector. By 1999 the corresponding figures are 12, 21 and 63 percent, hence indicating an approximately constant average relative return to vocational education and increasing premium to high school and university education. It is important to note that the earnings advantage for tertiary graduates in Hungary has not only increased after 1990, but is higher than in any other OECD country under analysis in 2005 (Education at a Glance 2007 (2007)).

Moreover, there is evidence for a widening wage gap between the private and public sectors of employment during the transition period in Hungary and other CEE countries (Kertesi and Köllő (2002) and Keane and Prasad (2001)). Note that in Hungary the share of the public sector employment over total employment remained high during the transition period – around 20 percent. Wage setting in the public sector is subject to political pressure and pursues the goals of equity, whereby the public sector wage scale[49] is characterised by the

[49] The public sector wage scale (*Közalkalmazotti bértábla*) assures equal wages for public sector employees for a given job with the same qualification and seniority. The wage scale is such that wages increase mechanically both horizontally and vertically: wages increase along the 10 educational categories (A – J) and for each qualification category wages increase with seniority along 14 brackets in different magnitudes. A separate wage

principle of not paying too low wages for low-skilled employees and not too high for their high-skilled counterparts. Subsequently, the wage distribution is more compressed in the public sector of employment than in the private sector – where competitive goals are pursued. The goal of equity and fairness of wages in the public sector, coupled with the more compressed distribution of public sector wages, characterises also Western economies (Melly (2005), Dustmann and van Soest (1997), Lucifora and Meurs (2004)). Moreover, Hungary is no exception to the fact that the education level is higher in the public sector than in the private sector, due to the professional composition of the public sector. However, there are major differences in the unconditional level of mean wages between Hungary and the Western economies. Whereas unconditional mean wages are higher in the public sector of employment, for instance, in Germany (Dustmann and van Soest (1997) and Melly (2005)), France, Great Britain and Italy (Lucifora and Meurs (2004)), in Hungary the transition period has been characterised by higher unconditional mean wages in the private sector of employment (as Figure 2.1 in the Appendix illustrates). The low level of public sector wages in Hungary has been a problem – for fairness as well as migration reasons –, and has generated public sector wage reforms in the early 2000s, which will be discussed below.

The goal of this study is to examine the evolution of earnings in the public and private sectors of employment in Hungary for full-time male employees for the time period of 1994 – 2003. The analysis is restricted to the time period of 1994 – 2003 (a) because of data availability considerations – 1994 marks the first year when data is available for both the private and public sectors on an annual basis – and (b) because this particular time period witnessed numerous reforms which had a potential effect not only on relative wages but also on the distribution of the wages in the two sectors of employment.

At this point a brief description of the evolution of wages and the wage reforms during the period of observation is of order. The time period of 1994 – 1997 is characterised by the "transformational recession" and the stabilization package (the *Bokros Csomag* which was carried out in 1995).[50] Real wages were decreasing throughout this period. During the second

scale exists for (a) tertiary education and research institutes and (b) civil servants (*Köztisztviselői előmeneteli és illetmény rendszer*). For detail see Közalkalmazotti Bértábla: Béremelés 2002 szeptember.

[50] Transformational recession was characterised by declining GDP growth, double digit inflation and an instable currency. In 1995, the government adopted a stabilization programme (*Bokros Csomag*) in order to restore macroeconomic stability. The stabilisation measures of the *Bokors Comag* (among other things) constrained the growth of public sector nominal wages. During the second half of the 1990s, real GDP increased by 4 – 5 percent per year, inflation dropped from around 28 percent in 1995 to less than 10 percent by 2000 and the Forint was stabilised (Kovács and Moulin (2004)).

period of 1998 – 2000, characterised as the “boom of the Hungarian economy”, real wages started to rise (Horváth and Hudomiet (2005)). In the early 2000s, significant wage reforms were implemented, which meant large increases in (a) the minimum wage and (b) the public sector wages respectively, and subsequent increases in the government deficit. More specifically, the minimum wage was increased twice, first on 01.01.2001 from 25,500 Hungarian Forints (HUF) to 40,000 HUF (57 percent increase in nominal wages) and then on 01.01.2002 to 50,000 HUF (25 percent increase in nominal wages). It is important to note that when the statutory minimum wage[51] was introduced (set by the government) in Hungary in 1989, it amounted to around 35 percent of the average earnings (Kertesi and Köllő (2003)) – below the European average (Dolado et al. (1996)). In the 1990s, the ratio of the minimum wage to average earnings was falling, and it amounted to approximately 29 percent in 2000 (Hungarian Central Statistical Office (2007)). Following the two increases, the minimum wage reached approximately 41 percent of average earnings in 2002 (Hungarian Central Statistical Office (2007)), which, according to 2002 Eurostat figures, (from 17 countries) is higher than in Romania (31 percent), Slovakia (32 percent), Poland (33 percent), the Czech Republic (34 percent), the UK (34 percent), the US (34 percent), Latvia (35 percent), Spain (37 percent), Bulgaria (37 percent), and Lithuania (38 percent), and lower than in Portugal (43 percent), Slovenia (45 percent), Luxembourg (49 percent), the Netherlands (49 percent), Ireland (50 percent), Malta (54 percent) (Paternoster (2004)).

The political motivation behind the minimum wage increases in the early 2000s merits comment. The motivation of the government (in office between 1998 and 2002) can be outlined as follows: to “restore the prestige of work”, to combat “living on benefits” and to “whiten the black economy” (Kertesi and Köllő (2003)). Despite the mixed theoretical and international empirical research on the effect of increases in minimum wage on employment level[52], the government then in office argued that the increase in the minimum wage would increase the employment level – which is low in international comparison. According to OECD statistics, (total) employment rate in Hungary in 2000 was 56 percent, which is 7.5 percent lower than the average of the former 15 EU member states. In fact, during the 1990s employment rate lagged behind that of the EU average: between 1992 and 2000 the average (total) employment rate in the former 15 EU member states was approximately 61 percent, the

[51] The statutory minimum wage relates to gross monthly earnings net of overtime pay, shift pay and bonuses. The minimum wage is legally binding and covers all employment contracts. Compliance with the minimum wage regulations is high. For instance, in 2001, less than 2 percent of the full-time employees were paid less than the minimum wage (Kertesi and Köllő (2003)).
[52] For a summary see, for instance, Dolado et al. (1996) and Kertesi and Köllő (2003).

corresponding figure for Hungary was 54 percent (OECD Factbook 2007 (2007)). It was argued that increasing the minimum wage would lead to incentive effects on the supply side, that is, higher wages would increase the incentives for job search by widening the gap between benefits and wages, especially in the depressed regions of Hungary. However, Kertesi and Köllő (2003) find no evidence for the expected positive employment effect.

Moreover, in Hungary where (especially in small firms) employers may report workers at the officially declared minimum wage but pay them above that level, an increase in the minimum wage should lead to increased revenue from social security contributions (given that the employees do not lose their jobs), as discussed in detail in Tonin (2007).[53] Tonin (2007) finds that the increase in the minimum wage in 2001 was effective for the purposes of increasing tax revenues from the affected households – those who are officially earning between the old and new minimum wage before the reform – at the same time inducing a fall in income for these households.

The increases in the minimum wage compressed the public sector wage scale. As mentioned earlier, the public sector wages, for each education group, were lagging behind the wages of the private sector throughout the decade of transition (as Figures 2.1 – 2.3 in the Appendix demonstrate) – which was one of the motivating factors behind the Socialist-led government's promise of large increases in the wages of public servants in 2002.[54] In addition to fairness reasons, the increase in public sector wages also aimed at avoiding (a) a negative selection in the public sector in terms of entering and leaving public sector jobs and (b) the migration of the highly qualified workforce abroad, which in the long-run has potential negative effects on the quality of the public sector employment (Telegdy (2006)). Subsequently, the government in office carried out a 50 percent average increase in public sector (nominal) wages, affecting the various groups of public service employees (approximately 800,000 employees which represents around 20 percent of the labour force) in different magnitudes between September 2002 and 2003. The government revised the existing wage scale, thereby altering relative

[53] Note that the possible problem of underreporting wages in this study is mitigated by the fact that firms employing more than 20 employees are used for the empirical analysis (in order to maintain the comparability of the data collection in the private sector throughout the period under analysis, which will be discussed in Section 2.1).

[54] To address the issue of the private-public sector wage gap previous governments have increased the wages of relatively small groups, such as judges, public prosecutors, armed forces personnel (The New Government increases public sector pay and low earners' income). For example, between July 2001 and January 2002 the wages of civil servants, public order officers and army officers were increased (Labour Report: January – December 2003 (2004), p. 10).

wages. According to the revised wage scale, the wages in the lowest qualification and seniority category (A1) are equal to the statuary minimum wage and those in (the lowest seniority bracket) of the highest qualification category (J1) earn 2.65 times more than the minimum wage. Moreover, the government introduced a minimum monthly wage for tertiary graduates, whereby the wages of the (lowest education and seniority bracket of) tertiary graduates (F1) were set to 100,000 HUF (which is twice the statutory minimum wage).[55]

In light of the evolution of wages and the wage reforms, the analysis of the evolution of the wage structures in the Hungarian private and public sectors is particularly interesting. However, it must be pointed out that the purpose of this chapter is to analyse the evolution of earnings in the private and public sectors for the decade of 1994 – 2003 rather than to concentrate explicitly on the effects of the wage reforms. In particular, this chapter examines (a) the evolution of the private-public earnings gap for full-time male employees, (b) the evolution of the private-public earnings gap for groups of full-time male employees distinguished by education and (c) the evolution of the returns to education in the private and public sectors separately – as the emphasis for the decade of transition has been placed on the private sector. Therefore, this study augments the existing literature as it analyses earnings differentials by education groups for both sectors of employment for a long period of time. Moreover, whereas existing studies use OLS regression to analyse (a) the mean private-public earnings gap (for instance, Telegdy (2006)) and (b) the evolution of the mean returns to education (for instance, Kézdi (2005) and Kertesi and Köllő (2002)), the second contribution of the study is that it is concerned with distributional aspects. The focus on distributional issues in turn motivates the use of quantile regression (Koeneker and Bassett (1978)), which allows the analysis of the effect of each covariate along the entire distribution of earnings. Quantile regression is particularly applicable for the analysis of the development of the private and public sector wages as the wage setting in the public sector (as discussed above) implies that distribution of wages is more compressed in the public sector of employment than in the private sector, which in turn implies that focusing on the mean private-public sector wage gap may not be appropriate. For instance, Lucifora and Meurs (2004) – estimating the public-private wage gap by quantile regression using standard wage equations – conclude that for France, Italy and Great Britain, that the public sector pay gap declines along the wage distribution in all three countries. Similarly, Poterba and Rueben (1994) and Mueller (1998)

[55] For detail on the wage increases for various groups in the public sector see Employment and Earnings 1998 – 2003 (2005), pp. 127 – 132, Labour Report: January – December 2003 (2004), pp. 10 – 20 and Közalkalmazotti Bértábla: Béremelés 2002 szeptember.

find declining public sector wage premium as quantiles increase for the US and Canada respectively. Telegdy (2006), using standard OLS regression, concludes that following the public sector wage reforms in Hungary, “the government has not only levelled the wages in the public and corporate sector but also pays a premium to the majority of its employees”. Given the different distributions of wages in the two sectors, it is therefore important to ask (a) whether the statement above applies to just the average wage gap, and (b) how the private-public wage gap (for different education groups) varies along the conditional wage distribution in Hungary over the period under analysis. Although the importance of quantile regression technique, which has been stressed by the studies in Fitzenberger et al. (Eds.) (2001), has been applied to the analysis of the wage structure in the private and public sectors, among others, by Budria (2006), Lucifora and Meurs (2004), Melly (2005), Mueller (1998) Poterba and Rueben (1994) and Nielsen and Rosholm (2001), it has not been previously applied in Hungary, to the best of my knowledge.

The data for the empirical analysis is drawn from the “Hungarian National Labour Center’s Wage Survey”, which is a cross-section dataset. The analysis is restricted to full-time prime age male employees (aged 25 – 55). The educational information in the dataset allows for the differentiation of four education groups for the period under analysis, namely, primary school or less (unskilled), vocational degree (low-skilled), high school degree (middle-skilled) and tertiary degree (high-skilled). It is important to note that the study is purely descriptive in nature, it aims to provide a comprehensive picture of the evolution of earnings structures in the two sectors for the selected sample. Another issue that needs to taken into consideration is that the estimated cross-section experience profiles reflect age, experience and cohort effects (as pointed out by Heckman and Robb (1985) and analysed by several studies such as Fitzenberger (1999), Fitzenberger et al. (2001) and MaCurdy and Mroz (1985)).

The empirical evidence for the estimated private-public sector earnings gap for both the entire sample of full-time male employees and the subsamples distinguished by educational attainment indicates that there is a private sector earnings premium (other than at the 10^{th} quantile in some cross-sections) which increases across the distribution between 1994 and 2002. The fact that in Hungary for the period under analysis there is a private sector earnings premium, as opposed to a public sector earnings premium, is not surprising given that in Hungary the earnings of public sector employees have been lagging behind those of their private sector counterparts between 1994 and 2002 – which was one of the motivating factors behind the average 50 percent increase in (nominal) wages in 2003. Following the public sector wage reforms, in 2003, the private-public sector gap declined at all estimated quantiles and the magnitude of the decline in the private-public earnings gap between 2002 and 2003 is uniform across the distribution other than at the 10^{th} quantile, where the decline is more pronounced. In 2003, there is a public sector earnings premium at the bottom of the distribution. In fact, for the unskilled in 2003 the public sector earnings premium is characteristic of the entire distribution, other than the top of the distribution. Thus, the mean as well as the quantile regression results indicate that the unskilled – the only education group – are better off in the public sector of employment in 2003 – as opposed to the other years under analysis. Similarly to the middle-skilled, for the high-skilled, the private-public sector earnings gap declined at all estimated quantiles between 2002 and 2003, with a sharper decline at the bottom of the distribution, whereby in 2003 at the 10^{th} quantile the sector earnings gap is around 27 percent in favour of the public sector – for the first time for the decade under analysis. Despite the public sector wage reforms, at the top of the earnings distribution, the private sector earnings premium is still high relative (a) to the other education groups and (b) the pre-reform level.

The estimated earnings differentials in the two sectors separately reflect the different wage policy / wage structure in the private and public sectors: (a) earnings differentials especially between the high-skilled and unskilled are lower in the public sector, (b) within-education-group-earnings differentials are lower in the public sector and (c) the private-public sector difference in high-skilled earnings premium at the top of the distribution is especially high. Specific to the period under observation, two phases in terms of the evolution of earnings differentials can be distinguished: 1994 – 2000 and 2000 – 2003. Starting with the private sector, the first period is characterised by increasing tertiary premium: not only do tertiary graduates experience high and increasing relative returns at the estimated quantiles, the within-dispersion is the highest from all education groups, and the increase in the high-skilled premium (relative to the unskilled) is more pronounced at the top of the distribution between 1994 and 2000. Therefore, this period is characterised by an increase in aggregate earnings inequality due to an increase in both between- and within-dispersion in the private sector. Second, in the early 2000s, in the private sector, as a result of the minimum wage hikes, which affected the private employees at the bottom of the education and earnings distribution, the returns to each education group relative to the group of unskilled decreased, and the decline is more pronounced at the bottom of the earnings distribution. Nevertheless, the final year of observation is still characterised by high tertiary premium, especially at the top of the distribution. Turning to the public sector of employment, (a) the tertiary premium also increased between 1994 and 2000 and (b) within-dispersion is increasing in education level. Between 2000 and 2002, as expected, the relative return to all education levels declined relative to the unskilled, with sharper decline at the bottom of the distribution. After the public sector wage reforms – which aimed at increasing the tertiary premium – the average relative return to high-skilled relative to middle-skilled increased substantially, from around 55 percent in 2002 to 65 percent in 2003 – which is the highest high-skilled premium (relative to middle-skilled) over the decade under observation. The increase in high-skilled premium was most pronounced at the bottom of the distribution, and in 2003, the earnings differentials are roughly uniform across the distribution – contrary to the private sector of employment. Although in 2003 the difference in tertiary premium between the private and public sectors is the lowest for the period under analysis, at the top of the distribution the private sector high-skilled employees still enjoy a substantially higher earnings premium (relative to their unskilled counterparts) than their public sector counterparts.

The mean estimates for the returns to formal education are in line with the cross-country consensus for CEE countries in terms of increasing between-education-group inequality, which manifests itself especially in the increasing incremental return to university education – despite the slight decline in earnings differentials in the early 2000s due to the minimum wage hikes. The separate analysis for the two sectors, coupled with the quantile regression estimates, "disentangle" the high tertiary premium in Hungary. More precisely, the quantile regression estimates demonstrate that there is high dispersion in the tertiary premium in the private sector, and a substantial gap in tertiary premium across the two sectors of employment (even in 2003). This in turn indicates that, although in general tertiary degree is valuable in Hungary in terms of earnings advantages, its "value" is not uniform, neither across the sectors nor within the private sector of employment.

The remainder of this chapter is organised as follows: Section 2.2 presents the data used in the empirical analysis and a brief descriptive analysis of the skill composition and the evolution of earnings of the sample for the time period of 1994 – 2003 in the private and public sectors. Section 2.3 proceeds with a description of the empirical framework. Section 2.4 describes the estimation results for the years under analysis and finally Section 2.5 concludes. Tables and Figures are presented in the Appendix.

2.2 Data and descriptive evidence

2.2.1 Data

The data for the empirical analysis is drawn from the "Hungarian National Labour Center's Wage Survey". The Wage Survey was first carried out in May 1986. Initially data was collected every three years and from 1994 onwards data is collected on a yearly basis in both the private and public sectors of employment. In the private sector, data collection covers firms employing at least 20 employees, which provide information on a 10 percent random sample of their full-time employees.[56] In the public sector, all institutions independent of size, provide information on their full-time employees.[57] The Wage Survey has the advantage of having a large number of observations, ranging from 130,000 to 220,000, depending on the year. Data is collected on monthly gross earnings, defined as monthly gross wage plus one twelfth of the sum of all other payments and irregular incomes connected to the full-time job paid over the previous year[58], gender, age, educational attainment, occupation, firm size, location and ownership structure, sector of employment and industry classification. Weights are included in the dataset.

The period under analysis in the study is restricted to the period of 1994 – 2003, given that for this time period data is available on both sectors of employment on an annual basis. In the private sector, the analysis is restricted to firms employing more than 20 employees, as the selection procedure has changed twice over the observation period, in 1995 and 2001. This amounts to dropping all observations that come from (a) firms employing 10 – 20 employees between the years 1995 and 2000, (b) firms employing 5 – 20 employees from the year 2001 onwards and (c) firms with missing observations on firm size (only applicable in 1997, 1999 and 2003).[59] The analysis focuses on full-time male employees with permanent attachment to

[56] From 1995 and 2001 onwards, a 20 percent random sample of companies employing at least 10 and at least 5 employees respectively are included in the Wage Survey, which provide information on all of their full-time employees.

[57] Information on the size of the public sector institutions is not provided in the dataset.

[58] Note that neither hourly wages nor the number of hours worked are reported in the cross-sections (other than from 2002 onwards), hence hourly wages cannot be used for the decade under analysis in the estimation.

[59] Apart from sample comparability purposes, using firms employing more than 20 employees implies that the reported earnings information is reliable as (a) the general practice of underreporting wages is more common in smaller companies and (b) the compliance rate to the minimum wage regulation (which is high in general) is lower in smaller firms (Kertesi and Köllő (2003)). However, it must be noted that not including firms employing less than 20 employees has a (potential) disadvantage. Namely, the estimated earnings gap between the private and public sectors could potentially be (somewhat) larger when the analysis is restricted to firms employing more than 20 individuals than if firms employing less than 20 individuals were also included in the estimation procedure, given the evidence that smaller firms tend to pay lower wages than larger firms. Subsequently, the results must be interpreted with caution, taking into account the selection procedure for the empirical analysis.

the labour market, i.e. aged 25 – 55 years. From 2002 onwards, part-timers are also included in the Wage Survey. Subsequently, in the years 2002 and 2003, all workers working part-time i.e. less than 36 hours per week are dropped from the sample. The analysis is restricted to male employees given the problems in estimation, namely, the problem of potential self-selection of females into employment coupled with the problem associated with estimating experience profiles for females due to their more unstable labour market attachment for family reasons. Furthermore, the full sample cannot be treated as a homogeneous group due to (a) the gender gap in the level and distribution of earnings, (b) the differences in gender composition across sectors, (c) the differences in educational attainment and finally (d) the differences in returns to both formal and informal education across genders. More specifically, looking at the first and last years under analysis, there are more males working in the private sector: the Wage Survey provides evidence that around 91 and 83 percent of all males and around 71 and 49 percent of all females work in the private sector in 1994 and 2003 respectively. Moreover, the Wage Survey provides evidence that in both 1994 and 2003 the educational attainment differs across the genders in a similar manner in both sectors, i.e. the fraction of females who (1) left or finished at most primary school is higher, (2) possess a vocational degree is lower, (3) have a high school degree is higher and (4) graduated from college is lower.

Throughout the analysis four education groups are used, namely, unskilled (U), low-skilled (L), middle-skilled (M) and high-skilled (H), which is motivated by (a) the structure of the Hungarian education system, (b) the fact that the four education groups can be generated for the entire observation period[60] and (c) the fact that it is comparable to the existing literature estimating (a) the average sector gap in earnings and (b) the average returns to schooling in Hungary. The education groups U, L, M and H stand for “No vocational degree and no high school degree”, “Vocational degree and no high school degree”, “High school degree and no tertiary degree” and “Tertiary degree” respectively, thereby representing a ranking in terms of educational level. Table 2.1 describes how the degree levels reported in the Wage Survey have been aggregated for 1994 – 1995 and for 1996 – 2003 respectively. Earnings are monthly gross earnings, defined as monthly gross wage plus one twelfth of the sum of all other payments and irregular incomes connected to the full-time job paid over the previous year, denoted in HUF and converted to 2003 earnings by the annual consumer price index.

[60] Note that the reporting system for educational attainment in the Wage Survey has changed in 1996, from five categories to nine categories (which is described in Table 2.1).

Table 2.2 presents some descriptive statistics for the first and last years of the period under analysis.

2.2.2 Differences in educational attainment across sectors

First of all, Table 2.2 documents the differences across sectors in the educational attainment of the sample of male full-time employees for the first and last cross-sections of the observation period. The educational composition of the sample suggests that the average skill level is higher in the public sector, which also characterises Western European economies (Dustmann and van Soest (1997) and Lucifora and Meurs (2004)) and the US (Poterba and Rueben (1994)). In particular, in the private sector in both years (and indeed in each cross-section of the dataset), (a) the fraction of unskilled workers is higher, (b) the fraction of low-skilled workers is substantially higher and (c) the fraction of high-skilled workers is substantially lower. Whereas in the public sector the tertiary graduates make up almost half of the sample (approximately 44 and 49 percent in 1994 and 2003 respectively), in the private sector in both years only around 14 percent possess a tertiary degree, and the category which most individuals belong to is that of low-skilled (approximately 39 and 45 percent in 1994 and 2003 respectively). Between 1994 and 2003 the most notable change in the distribution of skills of the sample is the reduction of the fraction of unskilled workers (primary school or less) and a corresponding rise in the fraction of low-skilled (vocational degree) workers in both sectors.

2.2.3 Evolution of earnings 1994 – 2003

Figure 2.1 depicts the evolution of the unconditional average real monthly gross earnings for the period of 1994 – 2003 for the private and public sectors respectively for the sample of full-time employed males. The evolution of average real monthly earnings for the selected sample reflects the three phases of the Hungarian economy described in the Introduction. During the early years of transition, characterised by the “transformational recession” and the stabilization package (*Bokros Csomag*, carried out in 1995), average real monthly earnings of the selected sample declined (more in the public sector than in the private sector). From 1997 and 1996, average real monthly earnings of the selected sample started rising in the public and private sector respectively. Between 2000 and 2003, wage growth was especially high in the public sector which reflects the increases in the minimum wage and in public sector wages: (a) the (nominal) minimum wage was increased twice, first on 01.01.2001 from 25,500 HUF to 40,000 HUF and then on 01.01.2002 to 50,000 HUF and (b) between September 2002 and

2003, there was a 50 percent average increase in public sector nominal wages.[61] Between 2000 and 2003, the growth in real monthly gross earnings for the selected sample amounted to approximately 19 and 48 percent in the private and public sectors respectively.

As discussed in the Introduction, public sector wages were lagging behind the wages of the private sector throughout the decade of transition – which was one of the motivating factors behind the increase the wages of public servants. Accordingly, Figure 2.1 documents that unconditional average real monthly earnings for the selected sample are higher in the private sector between 1994 and 2002. Following the public sector wage reforms, in 2003, unconditional average real monthly earnings were higher in the public sector – unconditional average monthly gross earnings in the public sector were 11 percent higher than earnings in the private sector. Note that, contrary to Hungary, international evidence indicates that unconditional average wages are higher in the public sector of employment – for example, in Germany (Dustmann and van Soest (1999) and Melly (2005)), Great Britain, Italy and France (Lucifora and Meurs (2004)) and Zambia (Nielsen and Rsoholm (2001) – attributed partly to the observed higher educational level in the public sector, which is also characteristic for Hungary.

Finally, Figure 2.1 presents the evolution of the real monthly minimum wage for the time period under analysis. The statutory monthly minimum wage was falling between 1994 and 1997 and increasing slightly until 2000 – the year before the first hike in minimum wages. As a result of the minimum wage hikes in 2001 and 2002, real monthly minimum wage increased between 2000 and 2002 (by 44 and 19 percent in 2001 and 2002 respectively) and fell by 2003 (as the nominal level of the minimum wage remained at its 2002 level). The evolution of the statutory minimum wage relative to average earnings for the selected sample in the private and public sectors respectively merits comment. Between 1994 and 2000 the monthly minimum wage as a proportion of average monthly gross earnings in the private sector for the selected sample[62] was falling, from 27 percent in 1994 to 24 percent in 2000. After the first and second increases, the monthly minimum wage amounted to 33 percent and 36 percent of

[61] For a detailed description of the wage increases for various groups in the public sector see Employment and Earnings 1998 – 2003 (2005), pp. 127 – 132 and Labour Report: January – December 2003 (2004), pp. 10 – 20 and Közalkalmazotti Bértábla: Béremelés 2002 szeptember.

[62] Note the minimum wage / average earnings ratio is somewhat lower than the figures presented in the Introduction because of the sample selection in this study. Namely, three groups who are likely to be paid lower wages or wages close to the minimum wage – females, individuals aged less than 25 and employees in small firms – are not a part of this analysis. Nevertheless, the general trend is in accordance with the trends presented in existing studies (Kertesi and Köllő (2003)) and the figures of the Hungarian Central Statistical Office (2007).

the average monthly gross earnings in the private sector (for the selected sample), and the ratio declined to 33 percent in 2003. The evolution of the monthly minimum wage as a proportion of average monthly gross earnings in the public sector for the selected sample shows a similar pattern: the ratio of monthly minimum wage to average monthly gross earnings in the public sector was falling (although not monotonically) between 1994 and 2000, from 30 percent in 1994 to 27 percent in 2000 and it increased to 36 and 40 percent in the years of the minimum wage increases (in 2001 and 2002 respectively). Given the increases in public sector wages the following year, in 2003, the proportion of minimum wage to average monthly gross earnings for the selected sample amounted to 30 percent – which for the first time for the period under analysis was lower than the corresponding ratio in the private sector.

2.2.4 Evolution of earnings by education groups 1994 – 2003

Figures 2.2 and 2.3 show the evolution of real average monthly gross earnings for the four education groups in the private and public sectors respectively. First of all, note that in the public sector, the proportion of unskilled to high-skilled average earnings between 1994 and 1997 is higher than in the latter part of the observation period: unskilled male full-time employees in the public sector earned approximately 55 and 44 percent of their high-skilled counterparts in the 1994 and 2003 cross-sections of the Wage Survey. It is notable that following the minimum wage increases, between 2000 and 2002, (a) the proportion of unskilled to low-skilled, to middle-skilled and to high-skilled average earnings and (b) the proportion of low-skilled to the middle-skilled average earnings increased, implying a compression in earnings at the bottom of the education scale between 2000 and 2002. On the other hand, the proportion of middle-skilled to high-skilled earnings did not increase: the middle-skilled – who were (a) on average not likely to be affected by the minimum wage hikes and (b) did not, on average, enjoy as much of a pay rise as their high-skilled counterparts in 2003 – earned around 60, 59 and 56 percent of their high-skilled counterparts in 2000, 2002 and 2003. In fact, visual inspection of Figure 2.3 suggests an increased earnings dispersion between the middle-skilled full-time public sector male employees and their high-skilled counterparts throughout the sample period.

Unlike in the public sector, in the private sector for the selected sample the ratio of unskilled to low-skilled, middle-skilled and high-skilled average earnings declined between first and last years of the observation period, and the decline was most pronounced for the unskilled to high-skilled earnings ratio: unskilled male full-time employees in the private sector earned around 91, 64 and 35 percent of the their low-skilled, middle-skilled and high-skilled counterparts respectively in the 1994 cross-section of the Wage Survey; the corresponding figures are 87, 61 and 26 percent in 2003. However, the decline in the earnings ratio of the unskilled to the other skill groups was not monotone over the period under observation: following the first minimum wage hike in 2001 – which affected mostly the unskilled private sector employees from the skill groups – the ratio of unskilled average earnings to the other skill groups did not decline any further. Moreover, unlike in the public sector, the proportion of low-skilled to middle-skilled earnings remained roughly constant over the period of observation: low-skilled full-time private sector male employees earned around 70 percent of their middle-skilled counterparts throughout the observation period. As in the public sector, the proportion of middle-skilled to high-skilled earnings declined (almost year by year) over the observation period: middle-skilled full-time private sector employees earned around 55 percent and 43 percent of their high-skilled counterparts in 1994 and in 2003 respectively. In fact, a common feature in both sectors is that from all education groups average monthly earnings increased the most for the high-skilled employees by 2003.

For the selected sample, as expected, the earnings distribution is more compressed – in the sense that the proportion of unskilled to high-skilled earnings is higher – in the public sector of employment than in the private sector for the selected sample for the time period under observation as wage setting in the public sector is subject to political pressure and pursues the goals of equity, whereby the public sector wage scale is characterised by the principle of not paying too low wages for low-skilled employees and not too high for their high-skilled counterparts.

It is also worth noting that the proportion of public to private sector average earnings differs across education groups. Visual inspection of Figures 2.2 and 2.3 indicates that for the selected sample (a) earnings for all education groups are higher in the private sector, other than in 2003 for the unskilled group and (b) the differences in average earnings levels are higher the higher the education level – which reflects the principles behind the wage setting in the public sector. In particular, in 1994, the unskilled, low-skilled, middle-skilled and high-skilled full-time male employees in the public sector earn roughly 86, 83, 82 and 55 percent of their private sector counterparts respectively. The corresponding figures are 82, 73, 73 and 53 percent in 2002 and 105, 94, 82 and 63 percent in 2003. In 2003, (a) the higher public sector average earnings for the unskilled workers relative to their private sector counterparts and (b) the higher (average) public / private sector earnings ratio for the other education groups relative to 2002 reflect the increase in public sector wages in 2003.

Furthermore, the public / private sector earnings ratio for the different education groups across the distribution merits comment, given that the distribution of earnings is more compressed in the public sector of employment than in the private one (in general and for each education group). Table 2.2 presents, in addition to the mean monthly gross earnings, monthly gross earnings for the different education groups at the 25th quantile, at the median and at the 75th quantile for the first and final years of the observation period. The public / private sector earnings ratio is lower at the top of the earnings distribution for all education groups in both 1994 and 2003. For example, the group of high-skilled full-time employees earn approximately 71, 65 and 57 percent at the bottom quartile, at the median and at the top quartile respectively of their private sector counterparts in 1994. The corresponding figures are 96, 74 and 60 percent in 2003.

In light of the descriptive evidence and the wage reforms, a number of hypotheses about the evolution of the private-public sector earnings gap and the earnings differentials by education in the two sectors can be drawn. First of all, given the public sector wage increases, the private-public sector earnings gap is expected to be lower in 2003 than in the rest of the decade under analysis. Moreover, given that the public sector pursues egalitarian goals, the private-public sector earnings gap is expected to be higher for those with tertiary degrees relative to those who are less skilled. Moreover, given the more compressed public sector wage structure, it is expected that the private-public sector earnings gap is smaller at the bottom of the distribution for all education groups. Following the public sector wage increases, a lower private-public sector earnings gap for each education group is expected than prior to the reform, however, it is expected that this decline is more pronounced at the bottom of the distribution. In terms of the earnings differentials between and within education groups in the private and public sectors, it is expected that the returns to all skill groups relative to the unskilled have risen over the decade by 2000, especially in the private sector of employment, and that within-dispersion for the high-skilled also increased. In the early 2000s, as the minimum wage hikes affected the unskilled, (a) lower earnings differentials between the unskilled and the other education groups are expected, especially at the bottom of the distribution and (b) after the public sector wage reforms, a higher high-skilled earnings premium is expected in the public sector at the bottom of the distribution than in the pre-reform period.

2.3 Empirical framework

The private-public earnings differential is estimated using the standard wage equation (Mincer (1974)), pooling data for both sectors and including a dummy variable for the private sector of employment:

$$\ln(w_{i,t}) = \alpha_t + \beta_{1,t} S_{i,t} + \beta_{2,t} EX_{i,t} + \beta_{3,t} EX^2_{i,t} + \beta_{4,t} P_{i,t} + \beta_{5,t} R_{i,t} + \mu_{i,t}, \qquad i = 1,...,n \qquad (4)$$

where $i = 1,...,n$ indexes individuals in the selected sample and $t = 1994,..., 2003$ stands for calendar year. The dependent variable $\ln(w_{i,t})$ for individual i in year t is the logarithm of monthly gross earnings, defined as monthly gross wages plus one twelfth of the sum of all bonuses paid over the year denoted in HUF and converted to 2003 earnings by the annual CPI. The explanatory variables include a set of education dummies (S), potential labour market experience – age minus years of schooling minus school starting age – (EX) and its square (EX^2), a dummy variable for private sector (P) (equals 1 if private sector and 0 otherwise), a dummy variable for region (R) (equals 1 if Budapest and 0 otherwise) and a random disturbance term (μ), which contains the unobserved determinants of earnings. Equation (1) is first estimated for the entire economy and then Equation (1) is estimated for the four groups distinguished by education in order to focus on the private-public sector earnings gap within the particular education groups. Finally, Equation (1) is estimated for the private and public sectors separately in order to analyze the evolution of the earnings differentials by education in the two sectors seperately. In light of the empirical evidence that experience / age profiles differ by education groups (Fitzenberger (1999), Fitzenberger et al. (2001), Köllő (1999) and MaCurdy and Mroz (1995)), experience profiles are also estimated for each education group separately.

Equation (1) is estimated by OLS and by quantile regression at five quantiles of the log earnings distribution, at the 10th quantile, at the 25th quantile, at the median, at the 75th quantile and at the 90th quantile. For all specifications weights are used in estimation. Standard errors are obtained by 200 bootstrap replications for the quantile regressions. As noted earlier, the study is purely descriptive in nature, that is, its objective is to shed light on the public-private earnings gap and the evolution of the returns to the formal and informal components of education in the private and public sectors separately over the entire conditional earnings distribution for the time period of 1994 – 2003.

The quantile regression model is formulated as:

$$y_i = x_i'\beta_\theta + \mu_{\theta_i}, \text{ with } Quant_\theta(y_i \mid x_i) = x_i'\beta_\theta, \qquad i = 1,...,n \qquad (5)$$

where y_i is the regression's dependent variable, x_i is a $K \times 1$ vector of regressors, μ_{θ_i} is a disturbance term and β_θ is the vector of parameters to be estimated. The subscript i indexes the individuals in the sample, $i = 1,...,n$. $Quant_\theta(y_i \mid x_i)$ denotes the θ^{th} conditional quantile of y_i, conditional of the regressor vector x_i. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x.

The θ^{th} regression quantile, $0 < \theta < 1$, is defined as a solution to the problem of minimizing a weighted sum of absolute residuals. The θ^{th} regression quantile can be computed by:

$$\min_{\beta \in R^k} \left\{ \sum_{i: y_i \geq x_i'\beta} \theta \mid y_i - x_i'\beta_\theta \mid + \sum_{i: y_i < x_i'\beta} (1-\theta) \mid y_i - x_i'\beta_\theta \mid \right\}, \qquad i = 1,...,n \quad (6)$$

In the framework of the Mincer earnings equation (1), the resulting regression fit $x_i'\beta_\theta$ describes the θ^{th} quantile of the earnings of individual i given the characteristics (for example, education level, potential labour market experience etc.) of individual i.

2.4 Results

2.4.1 Estimated private-public sector earnings gap

Figures 2.4 – 2.6 illustrate the estimated private-public sector earnings gap conditional on education, potential labour market experience and region at the mean and at five quantiles for three time periods, namely, 1994 – 1997, 1997 – 2000 and 2000 – 2003 respectively. Note that the three periods correspond to the three phases of the Hungarian economy: the first period corresponds to the (final years of the) period of the "transformational recession" and the stabilization package when (unconditional) real earnings were falling, 1997 – 2000 is the period when real earnings growth was positive and the final period of 2000 – 2003 represents the year prior to the wage reforms and the years of the wage reforms – characterised by especially high earnings growth in the public sector.

Starting with Figure 2.4, in 1994, the estimated mean private-public sector earnings gap is around 23 percent, that is, earnings of private sector male employees are on average around 23 percent higher than the earnings of their public sector counterparts.[63] The quantile regression estimates reveal that (a) the positive earnings gap is in favour of the private sector at all estimated quantiles and (b) it increases across the estimated quantiles from approximately 13 percent at the bottom quartile to approximately 40 percent at the 90th quantile. In 1995, 1996 and 1997, the average earnings gap amounts to 21, 31 and 38 percent respectively – the increase in the average sector earnings gap is due to freeze of nominal wages in the public sector (as the income measure of the stabilization package), which in turn lead to a higher decline in real monthly earnings in the public sector than in the private sector. Similarly to 1994, in the other three years, (a) the positive earnings gap is in favour or the private sector at all estimated quantiles and (b) it increases across the estimated quantiles. Note that between 1994 and 1997, the increase in the private-public sector earnings gap is higher at the top of the distribution: the earnings gap in favour of the public sector is 25 percent at the bottom quartile and 62 percent at the top quantile in 1997.

During the period of 1997 to 2000, a period of positive earnings growth, (a) the average private-public sector earnings gap ranges between approximately 30 and 38 percent – it is lower in 1998 and 1999 when public sector earings growth picked up – and (b) increases across the estimated quantiles. In the year prior to the wage reforms, the average private-public sector earnings gap amounts to around 37 percent, and private-public sector earnings gap increases across the distribution: it amounts to around 3 percent and 55 percent at the 10th and 90th quantiles respectively.

[63] At this point it must be noted that the estimated private-public sector earnings gap could in part be attributed to differences in working hours in the two sectors. That is, although the analysis is restricted to full-time male employees, differences in working hours may exist. For instance, it may well be that (some) full-time employees in the private sector work longer hours than their public sector counterparts, which in turn generates higher earnings. Subsequently, information on the actual hours worked or alternatively on hourly wages would be necessary to estimate the (hourly) wage gap between the two sectors for the decade under analysis.

Figure 2.6 illustrates that the magnitude of the mean private-public sector earnings gap is similar in the three years prior to the public sector wage reforms: the mean private-public sector gap amounts to approximately 37, 36 and 32 percent in 2000, 2001 and 2002 respectively. In 2003, given the average 50 percent increase in (nominal) wages of the public sector employees, the estimated average private-public sector earnings gap amounts to around 14 percent – which is not only substantially lower than in 2002 (by 18 percentage points) but is the lowest estimated average earnings premium in favour of the private sector for the observation period. In fact, the magnitude of the decline in the private-public earnings gap between 2002 and 2003 is uniform across the distribution other than at the 10th quantile, where the decline (21 percentage points) is the largest. The coefficient estimate for the private-public sector earnings gap at the 10th quantile amounts to approximately - 0.24, which indicates that earnings of private sector male employees are around 24 percent lower than the earnings of their public sector counterparts. Note that at the 25th quantile in 2003 there is also a public sector earnings premium: earnings of private sector male employees are around 4 percent lower than the earnings of their public sector counterparts.

Given that the decline in the private-public sector earnings gap between 2002 and 2003 is higher at the 10th quantile than at the other estimated quantiles, one may conclude that the public sector employees at the bottom of the earnings distribution benefited more from the public sector wage reforms, which aimed at reducing the earnings gap between the two sectors of employment. These individuals are more likely to be at the bottom of the education distribution. In order to investigate to what extend each education group “benefited from the wage reforms” (i.e. the magnitude of the reduction in the private-public sector earnings gap), the private-public sector earnings gap is estimated for each education group separately. In fact, the analysis of the private-public sector earnings gap for each education group is important for each year under observation as the educational composition of the two sectors is different: whereas approximately half of the public sector employees are professionals with college / university education, the private sector is dominated by low-skilled employment (as Section 2.2.2 discusses). Finally, the private-public sector earnings gap is expected to vary for each education group given (a) the egalitarian wage policy in the public sector (manifested in high ceilings to the unskilled and low floors for the high-skilled) and (b) given the different evolution of earnings for each education group (see Figures 2.2 and 2.3).

2.4.2 Estimated private-public sector earnings gap by education groups

The private-public sector earnings gap at the mean and at the estimated quantiles (conditional on potential labour market experience and region) for the different education groups are depicted in Figures 2.7 – 2.18. Figures 2.7 – 2.9 document the estimated private-public sector earnings gap for the unskilled full-time male prime age employees for the time periods of 1994 – 1997, 1997 – 2000 and 2000 – 2003 respectively. Figures 2.10 – 2.12, Figures 2.13 – 2.15 and Figures 2.16 – 2.18 illustrate the estimated private-public sector earnings gap for the low-skilled, middle-skilled and high-skilled for the three time periods respectively.
Before turning to each education group in more detail, it must be noted that, as expected (see discussion in Section 2.2.4), the estimated average private-public sector earnings gap is increasing in education level for most of the cross-sections under analysis.

2.4.2.1 Estimated private-public sector earnings gap, Unskilled

Turning specifically to the group of unskilled, between 1994 and 1997, the estimated average earnings premium in favour of the private sector increases each year in the first time period, from around 8 percent in 1994 to 26 percent in 1997 – as earnings growth picked up for the unskilled in 1996 and 1997 in the private and public sectors respectively. The quantile regression estimates reveal that each year the private-public sector earnings gap increases across the distribution, for instance, it amounts to approximately 10 percent in favour of the public sector at the 10th quantile and 26 percent in favour of the private sector at the 90th quantile in 1994. Visual inspection of Figure 2.7 indicates that the increase in the private sector earnings premium is roughly constant across the distribution between 1994 and 1997. Coming to the next period, Figure 2.8 demonstrates (a) that between 1997 and 1998, the average private-public sector earnings gap decreases to around 17 percent, remains at its 1998 level in 1999 and increases to 24 percent by 2000 and (b) the private-public sector earnings gap increases across the distribution.

The most interesting time period for the unskilled group is between 2000 and 2003, as both the minimum wage reforms and public sector wage reforms affected the earnings of this education group, thereby altering the distribution of earnings and the private-public sector earnings gap for this time period. In 2000, prior to the reforms, (a) the mean private-public earnings gap amounts to around 24 percent, (b) the private-public sector earnings gap increases across the estimated quantiles: the coefficient estimate at the 10th quantile is around - 0.06 indicating that the earnings of private sector employees are around 6 percent lower than that of their public sector counterparts, and the private-public sector earnings gap amounts to around 44 percent at the 90th quantile. After the first and second minimum wage increases, the average private-public sector earnings gap dropped to around 21 and to 15 percent in 2001 and 2002 respectively. The magnitude of the decline is (approximately) uniform across the distribution in both years apart from the bottom quntile, where the magnitude of the private-public sector earnings gap remained around the same. After the increase in public sector wages, in 2003, as expected, the mean private-public sector earnings gap declined further. For the first time for the period under analysis the average earnings gap is in favour of the public sector and amounts to around 6 percent. In fact, in 2003, the public sector earnings premium is characteristic of the entire distribution, other than at the top of the distribution. The public sector earnings premium amounts to 20 and 5 percent at the 10th quantile and at the median respectively, and the private sector premium amounts to around 10 percent at the 90th quantile. Thus, the mean as well as the quantile regression results indicate that the unskilled are better off in the public sector of employment in 2003 – as opposed to the other years under analysis.

2.4.2.2 Estimated private-public sector earnings gap, Low-skilled

Figures 2.10 – 2.12 present the private-public sector earnings gap for the low-skilled group for the three time periods respectively. Before turning to some noteworthy changes over time, it is important to note that for all cross-sections there is a general pattern of negative earnings gap in favour of the private sector at the bottom of the distribution which turns positive at the 25th quantile and increases across the distribution – which is similar to the observed earnings gap for the unskilled. For instance, in 2000, at the 10th quantile the public-private sector earnings gap amounts to around 1 percent, at the 25th quantile the private-public sector earnings gap amounts to around 22 percent and it increases across the qunatiles, reaching 57 percent at the top quantile. The average private-public sector earnings gap for the low-skilled is increasing in the last years of the “transformational recession” and the stabilization package, from around 11 percent in 1994 to around 31 percent in 1997, decreases to 26 percent by 1998, increases to around 31 percent by 2000, and after the wage reforms it decreases year by year from 30 percent in 2001 to 4 percent in 2003. Note also that (a) the evolution of the average private-public sector earnings gap is similar for the two education groups and (b) in all cross-sections the average private-public sector earnings gap for the low-skilled is slightly higher than that for the unskilled. In 2003, the decline in private-public sector earnings gap amounts to around 22 percentage points at the mean, and this decline is uniform at the estimated quantiles, resulting in a public sector earnings premium at the bottom of the earnings distribution. The public sector earnings premium amounts to 28 and 11 percent at the 10^{th} and 25^{th} quantiles, the private sector earnings premium amounts to 5 percent at the median and increases to 30 percent at the 90^{th} quantile.

2.4.2.3 Estimated private-public sector earnings gap, Middle-skilled

Figures 2.13 – 2.15 illustrate the private-public sector earnings gap for the middle-skilled. First of all, note that the mean private-public sector earnings gap for the middle-skilled evolves in a similar way over the decade as that of the unskilled and low-skilled. More specifically, the private-public sector earnings gap amounts to around 14 percent in 1994 and increases to around 41 percent by 1997 – the high private-public sector earnings gap by 1997 is not surprising because, whereas in the public sector real earnings of the middle-skilled fell constantly until 1997, with a marked decline between 1996 and 1997, in the private sector real earnings started to grow steadily from 1995 onwards. The private-public sector earnings gap declines to around 28 percent by 1998 – as public sector earnings growth for the middle-skilled picked up in 1997 –, remains approximately the same in magnitude until 2001 and decreases to around 14 percent by 2003 (as a result of the public sector wage reforms) – which is equivalent to the 1994 level, in opposition to the other two education groups for whom the estimated private-public sector earnings gap is lower in 2003 than in 1994. The quantile regression estimates reveal that, as for the other two education groups, the private-public sector earnings gap is sensitive to the quantile estimated, and increases across the distribution for most cross-sections. Furthermore, the quantile regression estimates reveal a difference to the other two education groups analysed so far, namely, whereas for the unskilled and low-skilled groups the changes in the magnitude of the private-public sector earnings gap over time are (more or less) uniform across the distribution, for the middle-skilled the changes are more pronounced at the top of the distribution for the time periods of 1994 – 1997 and 1997 – 2000, and the changes more pronounced at the bottom of the distribution for the 2000 – 2003 period. For example, whereas the private-public sector earnings gap remained about the same in magnitude between 1997 and 2000 at the bottom of the distribution, at the 90^{th} quantile the estimated private-public sector earnings gap declined gradually, from around 63 percent in 1997 to around 32 percent by 2000. Moreover, between 2002 and 2003 the private-public sector gap declined at each estimated quantile (and at the mean), with a sharper decline at the bottom of the distribution: at the 10^{th} quantile the earnings premium is in favour of the public sector and amounts to around 26 percent and at the 90th quantile the private-public sector earnings gap amounts to 41 percent.

2.4.2.4 Estimated private-public sector earnings gap, High-skilled

Figures 2.16 – 2.18 document the estimated private-public sector earnings gap for the high-skilled group. Starting with the mean estimates, the private-public sector earnings gap is increasing over the ten year period, or remains roughly constant, with the exception of 1995, 1998 and 2003 – the three years of high public sector high-skilled earnings growth (see Figure 2.3)). Between 2002 and 2003, the average private-public sector earnings gap declined by 21 percentage points from 45 to 23 percent. As expected, due to the higher earnings dispersion in the private sector, in all cross-sections, the private-public sector earnings gap increases across the distribution: for example, in 1994, from around 21 percent at the 10th quantile to 69 percent at the 90th quantile. The private-public sector earnings gap declined at all estimated quantiles between 2002 and 2003, with a sharper decline at the bottom of the distribution, whereby in 2003, at the 10th quantile the sector earnings gap is around 27 percent in favour of the public sector – for the first time for the decade under analysis – and around 62 percent in favour of the private sector at the 90th quantile. Despite the public sector wage reforms, at the top of the earnings distribution, the private sector premium is still high relative (a) to the other education groups and (b) the pre-reform level.

2.4.3 Results for the private sector

Tables 2.3 – 2.12 present the parameter estimates for the OLS and quantile regressions from 1994 to 2003 respectively. The first six columns of each table present the parameter estimates for the private sector.

First of all, in terms of the between-educational-levels earnings differentials, as expected, there is an earnings premium associated with the additional degree levels at the mean and at all estimated quantiles for all cross-sections. Starting with 1994, the mean returns to low-skilled, middle-skilled and high-skilled employees are around 14, 43 and 94 percent respectively relative to their unskilled counterparts. In light of the existing empirical evidence (for example, Köllő (2002)) for the private sector and the evolution of real monthly gross earnings for each education group (see Figure 2.2), an increasing average relative return to university / college education between 1994 and 2000 is expected. However, in the early 2000s, the average return to the high-skilled labour relative to unskilled labour is not expected to increase further, as the minimum wage reforms raised (mostly) the wages of the unskilled employees in the private sector. In fact, the OLS estimates indicate that the mean return to the low-skilled employees relative to their unskilled counterparts increased slightly to approximately 18 percent by 2000, and after the minimum wage hikes there was a slight gradual decline in the average relative return, reaching 14 percent in 2003. The relative return to the middle-skilled group increased slightly to 48 percent by 2000 and declined to 42 percent by 2003. The relative return to the high-skilled group increased to 118 percent between 1994 and 2000 and declined slightly in the early 2000s to 114 percent by 2003. Therefore, the mean estimates reveal that whereas the relative return to vocational degrees and high school degrees increased slightly until 2000 and declined in the early 2000s (whereby the relative returns are the same in 2003 as in 1994), the return to college / university degree, despite the slight decline in the early 2000s, increased significantly over the decade under observation – and remains high in international comparison (see, for instance, Education at a Glance 2007 (2007)).

Given the evidence above concerning the evolution of average earnings differentials by education, the quantile regression estimates will be discussed for two phases: 1994 – 2000 and 2000 – 2003, whereby the first period is characterised by increasing average relative returns, especially for the high-skilled, and the second period is characterised by a slight decline in relative returns. First of all, for the cross-sections of 1994 – 2000, (a) the returns to all additional educational levels are increasing across the quantiles, (b) the within-dispersion is higher the higher the education level and (c) high-skilled workers experience the highest within-group dispersion. This is in line with the international evidence, despite the differences in magnitude (for example, Machado and Mata (2001)). Between 1994 and 2000, the increase in the high-skilled premium (relative to the unskilled) is more pronounced at the top of the distribution: the return to high-skilled relative to unskilled amounts to around 77, 90 and 119 at the 10^{th} quantile, at the median and at the 90^{th} quantile respectively in 1994 and the corresponding figures are around 94, 115 and 151 percent in 2000.

The increase in minimum wage in the early 2000s should effect the bottom of the earnings distribution and the bottom of the education scale in the private sector of employment, which in turn compresses the distribution of earnings for the unskilled. The expected effects of the increases in minimum wage are (a) declining earnings differentials by education groups, especially at the bottom of the earnings distribution, and (b) given the more compressed wage structure of the unskilled, an increase in the relative within-dispersion for the other education groups. Investigating the estimates for 2000 and 2001, (a) the returns to each education group relative to the group of unskilled decreased, and the decline is more pronounced at the bottom of the earnings distribution, and (b) at each education level the within-dispersion increased. The declining relative returns also characterises the bottom of the distribution in 2002, as well as the increase in within-dispersion for each education group, relative to the unskilled. The final year of the observation period is still characterised by high-within dispersion, especially for the group of high-skilled: the returns relative to the unskilled at the 10^{th} quantile, at the median and at the 90^{th} quantiles are around 6, 15 and 20 percent for the low-skilled, 24, 43 and 57 percent for the middle-skilled and 81, 117 and 148 percent for the high-skilled. Finally, (keeping in mind the distinct evolution of earnings differentials by education in the early 2000s as a result of the increases in the minimum wage) the relative return to the high-skilled workers increased at all estimated quantiles between 1994 and 2003, by a higher amount at the top of the distribution i.e. the return at the 10^{th} and 90^{th} quantiles increased by approximately 4 and 29 percent respectively between 1994 and 2003.

The experience profiles for the private sector at the mean and at the estimated quantiles are illustrated in Figures 2.19 – 2.28 for each year under analysis. All experience profiles have the expected concave shape i.e. earnings increase at a decreasing rate until the end of the individual's career.[64] Between 1994 and 1998 and in 2003, earnings growth is higher at the top of the distribution. In 1994, earnings growth reaches around 27, 39 and 55 percent at the 10^{th} quantile at the median and at the 90^{th} quantile respectively by the end of the career, in 1998 the corresponding figures are around 23, 29 and 33 percent, and in 2003 the corresponding figures are around 21, 33 and 46 percent. Between 1999 and 2002, the experience profiles are (roughly) uniform across the distribution (other than the 10^{th} quantile in 2002). Visual inspection of the mean experience profiles suggests that the experience profiles flattened between 1994 and 2003, although this was not uniform during the period.

Given the (international) evidence that experience / age profiles are not the same across education groups (for example, Fitzenberger (1999), Fitzenberger et al. (2001), Köllő (2002), MaCurdy and Mroz (1995)), the experience profiles are estimated for each skill group separately. The experience profiles at the mean and at four quantiles for the low-skilled,

[64] Note that in what is to follow the individual's career is defined by the sample selection of this study – that is, the beginning of the career corresponds to the mid 20s and the end of the career to the mid 50s respectively – and not the official retirement age set by law.

middle-skilled and high-skilled are presented for 2003 in Figures 2.39 – 2.41 respectively in order to investigate the differences in experience profiles across education groups.[65] As expected, (a) for all education groups, earnings growth declines over the career, (b) at the beginning of the career earnings growth increases in education level and (c) as opposed to the low- and middle-skilled, at 22 years of experience, earnings growth reaches slightly negative for the high-skilled private sector male employees. The quantile regressions point to further differences between the education groups: (a) for the low-skilled, earnings growth is uniform across the estimated quantiles i.e. the experience profiles are indistinguishable, (b) for the middle-skilled, overall life-cycle earnings growth increases across the distribution and (c) for the high-skilled, earnings growth is higher at the beginning of the career at the top of the distribution and it declines at a faster rate at the top of the distribution. Within-group dispersion in earnings growth is higher the higher the education level.

Figures 2.42 – 2.50 present the experience profiles at the mean and at four quntiles in the private sector for the high-skilled for 1994 – 2003 respectively.[66] The most remarkable change over the time period of observation for the high-skilled full-time private sector male employees is the shape of the cross-section experience profiles. Starting with the mean experience profiles, whereas between 1994 and 1998 average earnings growth is positive and declines over the career, from 1998 onwards, average earnings growth declines and reaches slightly negative after around 22 – 25 years of experience. More precisely, earnings growth becomes negative at 25 years of experience in 1999 and in 2000, at 23 years of experience in 2001 and in 2002 and finally at 22 years of experience in 2003. This constant change in shape characterizes the experience profiles at all the estimated quantiles. Furthermore, in all cross-sections the top of the distribution is characterised by higher earnings growth (when positive).

Finally, the parameter estimates for the Budapest dummy merit brief discussion. As expected, in all cross-sections, those private sector employees working in the capital have higher average earnings. This average premium, relative to rest of the country, ranges between approximately 13 percent in 2000 and 21 percent in 2003. The quantile regression estimates

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[65] The experience profiles for each education group for 2003 are presented as in 2003, unlike in the other years under analysis, the quantile regression and OLS regression parameter estimates were significant for each education group, other than for the unskilled and at the 10^{th} quantile for each education group. Therefore, the experience profiles (a) at the 10^{th} quantile and (b) for the unskilled are not presented.

[66] The high-skilled experience profiles are presented because, unlike for the other three education groups, the returns to experience to this group were significant in all years. Note also that at the 10^{th} quantile the experience profiles are not presented given that the parameter estimates were not significant.

reveal that the Budapest premium increases across the quantiles under the period under analysis.

2.4.4 Results for the public sector

The final six columns of Tables 2.3 – 2.12 present the parameter estimates for the OLS and quantile regressions for the public sector for 1994 to 2003 respectively.

Summarising briefly the OLS results in the public sector, there is an earnings premium associated with the additional degree levels – as in the private sector. In 1994, the mean returns to low-skilled, middle-skilled and high-skilled full-time employed males are approximately 11, 41 and 63 percent respectively relative to their unskilled counterparts. Given the evolution of real monthly gross earnings in Figure 2.3, the earnings differentials by education groups will be discussed for the time period of 1994 – 2000 and of 2000 – 2003, with an emphasis on five years: 1995, 1998, 2001, 2002 and 2003. The OLS parameter estimates indicate that over the period of 1994 – 2000, relative to the unskilled full-time public sector male employees, (a) the return to their low-skilled counterparts ranged between 8 and 14 percent, (b) the return to their middle-skilled counterparts ranged between 33 and 36 percent and (c) the return to their high-skilled counterparts increased from 63 percent in 1994 to 99 percent in 2000. The average incremental return to high-skilled public sector employment (relative to middle-skilled) merits comment, as this is expected to increase between 1994 and 2000: in 1994, the incremental return amounted to approximately 22 percent, increased to 40 percent by 1995, to 52 percent in 1998, and remained at this level until 2000. Following the minimum wage increases, as expected, the relative return to all education levels relative to the unskilled declined compared to their pre-reform level: to around 4, 33 and 88 percent for the respective education groups by 2002. Given that the wage scale was revised in 2003 – aiming at increasing the tertiary degree premium – the average relative return to high-skilled employment relative to middle-skilled employment increased substantially, from around 55 percent in 2002 to 65 percent in 2003 – which is the highest high-skilled premium (relative to middle-skilled) over the decade under observation.

In terms of within-dispersion, in 1994, (a) the relative return to the middle- and high-skilled groups is increasing over the distribution and (b) the within-dispersion is increasing in education level. For instance, the return to middle-skilled full-time employed males relative to their unskilled counterparts is approximately 33 and 48 percent at the 10th quantile and 90th

quantile respectively, and the corresponding figures for high-skilled individuals are approximately 47 and 77 percent respectively. This pattern is characteristic for the period of 1994 – 2000. Between 2000 and 2001, the earnings differential between the unskilled and the other skill groups declined at all quantiles, with a sharper decline at the bottom of the distribution, which is expected as the increases in minimum wage affected especially those at the bottom of the earnings and skill distribution. Note that the decline in earnings differentials continue in 2002, and the earnings differential between the low-skilled and unskilled at the top of the distribution diminishes. After the revision of the public sector wage scale, which introduced a statutory minimum wage for college graduates (see Introduction for detail) and aimed at a higher skill premia for the higher educated in general, the incremental return to high-skill public sector employment increased at all quantiles, with sharper increases at the bottom of the distribution. The tertiary degree premium (relative to high-school degree) is around 66, 65 and 69 percent at the 10th quantile, at the median and at the 90th quantile respectively in 2003. Note also that in 2003, unlike in the other years under observation, the earnings differentials are roughly uniform across the distribution.

The cross-section experience profiles for the public sector for the time period of 1994 – 2003 are depicted in Figures 2.29 – 2.38. There is evidence that (a) earnings grow over the career, (b) earnings growth declines over the career at the mean and at all estimated quantiles and (c) in most cross-sections, earnings growth is higher at the top of the distribution.

Figures 2.51 – 2.60 illustrate the cross-section experience profiles for high-skilled public sector employees separately for 1994 – 2003 respectively.[67] Note for the time period under analysis, the high-skilled group makes up around half of the selected sample (in the public sector), due to the professional composition of public sector employment (health, education and public administration). In 1994, mean earnings growth for the high-skilled males declines and turns negative at the end of the career. In the other years under analysis, mean earnings growth declines and remains positive over the career. In all cross-sections, earnings growth in the early years in labour market is higher at the top of the distribution, and this difference in growth rates declines over the career. Overall earnings growth is higher at the top of the distribution, however, the magnitude varies over the time period. Finally, visual inspection of the experience profiles suggests a change in the general shape of the experience profiles: the experience profiles become less concave over the time period under analysis.

[67] The cross-section experience profiles for the high-skilled are presented because, unlike for the other education groups, the returns to experience were significant at the mean and the estimated quantiles for the high-skilled.

Finally, the Budapest dummy indicates that, as in the private sector, (a) those public sector employees working in the capital have higher average earnings for the observation period and (b) the Budapest earnings premium increases across the quantiles for the period under analysis.

2.4.5 Cross-sector comparison

As the wage policy in the private and public sector differs – competitive versus egalitarian goals – the wage structure in the public sector is more compressed relative to the private sector, and the wage differentials are expected to reflect this: in comparison to the private sector, (a) lower earnings differentials between the high-skilled and unskilled, (b) lower within-education-group-earnings differentials and (c) an especially high private-public sector difference in high-skill earnings premium at the top of the distribution are expected. Specific to the period under observation, the difference in high-skill premium between the private and public sectors is expected to decline when the wages of high-skilled public sector employees are increased.

Starting with the first year under observation, as expected, (a) the average relative return to all educational levels is lower in the public sector than in the private sector and (b) this difference is the highest for the high-skilled employees. The quantile regression estimates show that (a) the relative return to all educational levels is lower in the public sector than in the private sector at all estimated quantiles, other than at the 10th quantile for the group of low-skilled individuals and (b) the gap in high-skilled earnings premium is the highest at the top of the distribution. The latter observations characterise all the cross-sections. In 2003, the difference in the average private-public sector high-skill earnings premium is lower than prior to the public sector wage reform. This is in accordance with the revised public sector wage scale which aimed at increasing the public sector high-skill premium. As the quantile regression estimates indicate, this decline in the private-public sector high-skill earnings premium is more pronounced at the bottom of the distribution. That is, at the top of the distribution the private sector high-skilled employees still enjoy a substantially higher earnings premium (relative to their unskilled counterparts) than their public sector counterparts.

In terms of the estimated experience profiles several points are worth noting. First, in all cross-sections, the overall life-cycle earnings growth is higher in the public sector at the mean and at all estimated quantiles. For the group of high-skilled male employees, whereas the overall life-cycle earnings growth is higher in the public sector at the mean and at the bottom of the distribution, in some cross-sections the overall life-cycle earnings growth is higher in the private sector the top of the distribution, which in turn implies higher within-dispersion in the private sector in terms of overall earnings growth for the high-skilled. In other words, experience is more valued at high paid jobs in the private sector.

2.5 Conclusion

The study examined the evolution of earnings in the private and public sectors of employment in Hungary for the decade of 1994 – 2003. More specifically, the study examined (a) the evolution of the private-public earnings gap for full-time prime aged male employees, (b) the evolution of the private-public earnings gap for groups of full-time male employees distinguished by education and (c) the evolution of the returns to education in the private and public sectors separately based “Hungarian National Labour Center’s Wage Survey” using OLS and quantile regression. The use of quantile regression is motivated by the fact that the earnings distribution in the two sectors of employment differs, whereby wages are more compressed in the public sector due to the egalitarian wage policy pursued. Moreover, the particular time period under analysis witnessed numerous reforms – the increases in minimum wages in 2001 and 2002 and the increases in public sector wages in 2003 – which had an effect on the distribution of the wages in the two sectors of employment. Whereas quantile regression has been applied in other countries to address the wage structures in the private and public sectors of employment (for example, Budria (2006), Lucifora and Meurs (2004), Melly (2005), Poterba and Rueben (1994) and Mueller (1998)), and Nielsen and Rosholm (2001)), it has not been applied in Hungary so far.

The first set of results describes the evolution of the private-public sector earnings gap for the decade under analysis. First of all, in 2003, given the average 50 percent increase in (nominal) wages of the public sector employees, the estimated average private-public sector earnings gap amounts to around 14 percent – which is not only lower than in 2002, but is the lowest estimated average earnings premium in favour of the private sector for the observation period. The decline in the mean private-public sector earnings gap is in line with the finding of Telegdy (2006) who estimates the mean sector earnings gap at around 27 percent in favour of the private sector in 2000 and at around 7 percent in favour of the public sector in 2004, based on the same dataset for the pooled sample of males and females.

In light of the different wage policies in the two sectors, resulting in different wage distributions, it is expected that the private-public sector earnings gap is sensitive to the quantile estimated. In fact, existing evidence from Lucifora and Meurs (2004) suggests that in France, Italy and Great Britain in 1998 the estimated positive gap in favour of the public sector is decreasing along the wage distribution and it only turns negative at the top of the distribution, indicating that males are better off in the public sector at the lowest quantiles and the opposite is true for the highest quantiles. Poterba and Rueben (1994) and Mueller (1998) find declining public sector wage premium as quantiles increase in the US and in Canada respectively. For Hungary, between 1994 and 2002, at all estimated quantiles, there is a private sector earnings premium (other than at the 10^{th} quantile in some cross-sections) which increases across the distribution. The fact that in Hungary for the period under analysis there is a private sector earnings premium, as opposed to a public sector earnings premium, is not surprising given that in Hungary the earnings of public sector employees have been lagging behind those of their private sector counterparts between 1994 and 2002 – which was one of the motivating factors behind the average 50 percent increase in (nominal) wages in 2003. Following the public sector wage reforms, in 2003, the private-public sector earnings gap declined at all estimated quantiles and the magnitude of the decline in the private-public earnings gap between 2002 and 2003 is uniform across the distribution other than at the 10^{th} quantile, where the decline is more pronounced. In 2003, there is a public sector earnings premium at the bottom of the distribution.

Before turning to a brief summary of the findings for each education group, three points merit comment. First, as expected, the estimated average private-public sector earnings gap is increasing in education level in (almost) all cross-sections. Second, the evolution of the average private-public sector earnings gap mirrors the phases of the Hungarian economy and is similar for all education groups (despite the differences in magnitude): the average private-public sector earnings gap is increasing in last years of the "transformational recession" and the stabilization package (1994 – 1997), decreases by 1999, increases by 2000, and after the wage reforms the average private-public sector earnings gap declines substantially by 2003. Moreover, whereas the average private-public sector earnings gap for the unskilled, low-skilled and high-skilled is lower in the last year under observation than in the first year under observation (and in fact in all cross-sections), this is not true for the middle-skilled, for whom after the wage reforms, though lower than in 2002, the average private-public sector earnings gap is the same in magnitude as in 1994.

The quantile regression estimates demonstrate that, in line with the existing international evidence, the private-public sector earnings gap is sensitive to the quantile estimated for each education group. Since the private-public sector earnings gap after the public sector wage reform has been the center of attention in the literature, the time period of 2000 – 2003 will be the focus for each education group in order to augment the results to the existing evidence, which only consider the average earnings gap.

First, in 2003, for the first time for the period under analysis, the average earnings gap for the unskilled employees is in favour of the public sector, which is in line with the findings of Telegdy (2006). In fact, in 2003 the public sector earnings premium is characteristic of the entire distribution, other than at the top of the distribution. Thus, the mean as well as the quantile results indicate that the unskilled – the only education group – are better off in the public sector of employment in 2003 – as opposed to the other years under analysis. The quantile regression estimates for the middle-skilled male employees reveal a difference to their unskilled and low-skilled counterparts: whereas for the unskilled and low-skilled employees the magnitude of the decline of the private-public sector earnings gap in the early 2000s is (roughly) uniform across the distribution, for the middle-skilled the decline is more pronounced at the bottom of the distribution for the 2000 – 2003 period. In 2003, the middle-skilled public sector employees at the 10^{th} quantile of the earnings distribution face an earnings premium relative to their private sector counterparts (like the unskilled and low-skilled public sector employees). Similarly to the middle-skilled, for the high-skilled, the private-public sector earnings gap declined at all estimated quantiles between 2002 and 2003, with a sharper decline at the bottom of the distribution, whereby in 2003 at the 10^{th} quantile the sector earnings gap is around 27 percent in favour of the public sector – for the first time for the decade under analysis. Despite the public sector wage reforms, at the top of the earnings distribution, the private sector premium is still high relative (a) to the other education groups and (b) the pre-reform level.

The set of results concerning the earnings differentials by education confirm the expectations in light of the wage policies / wage distributions in the two sectors: (a) earnings differentials especially between the high-skilled and unskilled are lower in the public sector, (b) within-education-group-earnings differentials are lower in the public sector and (c) the private-public sector difference in high-skill earnings premium at the top of the distribution is especially high. Two distinct phases in terms of the evolution of earnings differentials can be distinguished for the decade under observation: 1994 – 2000 and 2000 – 2003. Starting with the private sector, the first period is characterised by increasing tertiary premium: not only do tertiary graduates experience high and increasing relative returns at the estimated quantiles, the within-dispersion is the highest from all education groups, and the increase in the high-skilled premium (relative to the unskilled) is more pronounced at the top of the distribution between 1994 and 2000. Therefore, this period is characterised by an increase in aggregate earnings inequality due to an increase in both between- and within-dispersion in the private sector. Second, in the early 2000s, in the private sector as a result of the minimum wage hikes, which affected the private employees at the bottom of the education and earnings distribution, the returns to each education group relative to the group of unskilled decreased, and the decline was more pronounced at the bottom of the earnings distribution. Nevertheless, the final year of observation is still characterised by high tertiary premium, especially at the top of the distribution. Turning to the public sector of employment, (a) the tertiary premium also increased between 1994 and 2000 and (b) within-dispersion is increasing in education level. Between 2000 and 2002, as expected, the relative return to all education levels declined relative to the unskilled, with sharper decline at the bottom of the distribution. After the public sector wage reforms – which aimed at increasing the tertiary premium – the average relative return to high-skilled relative to middle-skilled increased substantially, from around 55 percent in 2002 to 65 percent in 2003 – which is the highest high-skilled premium (relative to middle-skilled) over the decade under observation. The increase in high-skilled premium was most pronounced at the bottom of the distribution, and in 2003, the earnings differentials are roughly uniform across the distribution – contrary to the private sector of employment. Although in 2003 the difference in tertiary premium between the private and public sectors is the lowest for the period under analysis, at the top of the distribution the private sector high-skilled employees still enjoy a substantially higher earnings premium (relative to their unskilled counterparts) than their public sector counterparts. Note that the estimates of this study confirm the international consensus that the returns to education, especially at the tertiary level, are higher in the private sector than in the public sector (for example, Dustmann and van Soest (1997), Psacharopoulos (1994) and Nielsen and Rosholm (2001)). Moreover, for samples of full-time employed men in a number of EU countries (the year under analysis ranging from 2000 to 2003), Budria (2006) concludes that "the impact of schooling on within-groups dispersion is found to be substantially larger in the private than in the public sector" – which is in line with the evidence for Hungary.

In terms of the estimated experience profiles two points merit comment. First, in all cross-sections, the overall life-cycle earnings growth is higher in the public sector at the mean and at all estimated quantiles. Second, for the group of high-skilled male employees, whereas the overall life-cycle earnings growth is higher in the public sector at the mean and at the bottom of the distribution, in some cross-sections the overall life-cycle earnings growth is higher in the private sector the top of the distribution, which in turn implies higher within-dispersion in the private sector in terms of overall earings growth for the high-skilled. Experience is more valued at high paid jobs in the private sector.

Finally, note that the mean estimates for the returns to formal education are in line with the cross-country consensus for CEE countries and with the existing evidence on Hungary in terms of increasing between-education-group inequality, which manifests itself especially in the increasing incremental return to university education (for example, Kertesi and Köllő (1999), Keane and Prasad (2001), Kézdi (2005), Munich et al. (2002), Orazem and Vodopivec (1998) and Noorkôiv et al. (1997)) – despite the slight decline in earnings differentials in the early 2000s due to the minimum wage hikes. For instance, the OLS estimates based also on the "Hungarian National Labour Center's Wages Survey" for full-time male and female private sector employees by Kézdi (2005) indicate that the mean return relative to primary school or less (a) to vocational education ranged between 10 and 14 percent, (b) to high school increased from 30 to 40 percent and (c) to university education increased from 80 to 150 percent between 1989 and 2002. The estimation results for Portugal are also worth noting, since Portugal is also a country where despite the increasing level of education, the incremental return to college education has been increasing and remains high in international comparison. For instance, Machado and Mata (2001) document that between 1982 and 1994, whereas the mean return to all education categories relative to less than 4 years of elementary schooling have decreased, the mean return to college education increased from 102 percent to 109 percent. Furthermore, Machado and Mata (2001) also document a sharper rise in the incremental return to college education at higher quantiles between 1982 and 1994.

It is important to note that the earnings advantage of university graduates has been found not only increasing during the 1990s in Hungary but also higher than in any other OECD country under analysis by 2005 (Education at a Glance 2007 (2007)). As mentioned above, the mean estimates of this study confirm the general picture of the increasing tertiary premium. However, the separate analysis for the two sectors, coupled with the quantile regression estimates, “disentangle” the high tertiary premium. More precisely, the quantile regression estimates demonstrate that there is large dispersion in the tertiary premium in the private sector, and a substatnial gap in tertiary premium across the two sectors of employment (even in 2003). This in turn indicates that, although in general a tertiary degree is valuable in Hungary in terms of earnings advantages, its “value” is not uniform, neither across the sectors nor within the private sector of employment.

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2.7 Appendix

2.7.1 Descriptive statistics

Table 2.1 Education groups used in the empirical analysis

Education groups used in the empirical analysis		Five categories for highest degree attained 1994 – 1995	Nine categories for highest degree attained 1996 – 2003
Unskilled (U)	No vocational degree and no high school degree	(1) Less than 8 years of primary school (2) 8 years of primary school	(1) Less than 8 years of primary school (2) 8 years of primary school
Low-skilled (L)	Vocational degree and no high school degree	(3) Vocational degree	(3) *Szakiskola* (vocational school) (4) *Szakmunkásképző* (apprentice school)
Middle-skilled (M)	High school degree and no tertiary degree	(4) High school degree	(5) *Gimnázium* (general secondary school) (6) *Szakközépiskola* (vocational secondary school) (7) *Technikum* (technical school)
High-skilled (H)	Tertiary degree	(5) Tertiary degree	(8) *Főiskola* (college) (9) *Egyetem* (university)

Table 2.2 Descriptive statistics for 1994 and 2003

	Private sector		Public sector	
	1994	2003	1994	2003
Educational composition (%)				
Unskilled (U)	21.67	15.71	15.39	11.54
Low-skilled (L)	39.37	45.13	12.70	18.29
Middle-skilled (M)	25.38	25.97	28.08	21.44
High-skilled (H)	13.58	13.19	43.83	48.73
Mean monthly gross earnings	122,122.70	152,092.40	109,937.10	168,698.80
Monthly gross earnings for education group U				
Mean	85,040.96	94,851.91	73,173.08	99,776.24
25^{th} quantile	57,581.72	64,306.00	57,887.08	76,733.00
Median	76,878.45	85,442.00	68,808.29	93,175.00
75^{th} quantile	101,970.70	112,145.00	83,216.18	118,614.00
Monthly gross earnings for education group L				
Mean	93,852.98	109,279.80	78,366.44	102,634.20
25^{th} quantile	64,324.52	72,146.00	62,841.35	82,817.00
Median	84,730.50	97,670.00	73,391.77	97,120.00
75^{th} quantile	112,714.30	132,088.00	85,768.09	116,512.00
Monthly gross earnings for education group M				
Mean	133,642.80	155,430.60	109,814.90	128,143.80

Table 2.2 continues on next page

Table 2.2 continued

25th quantile	84,873.84	91,255.00	76,336.28	92,817.00
Median	116,422.30	130,142.00	98,200.52	113,504.00
75th quantile	158,611.50	186,153.00	141,558.2	140,506.00
Monthly gross earnings for education group H				
Mean	241,730.60	360,113.10	132,077.10	227,658.70
25th quantile	124,635.8	170,310.00	89,074.06	162,800.00
Median	186,230.8	273,265.00	120,120.80	203,225.00
75th quantile	284,325.3	430,500.00	162,338.10	260,400.00
Mean age	40.24	40.03	40.21	41.46
Budapest (%)	24.80	23.55	9.79	25.83
Observations	54,138	50,700	7,903	8,659

Note: Earnings are denoted in HUF and converted to 2003 earnings by the annual CPI

Figure 2.1 Evolution of unconditional average monthly gross earnings in the private and public sectors and evolution of minimum wage, 1994 – 2003

Figure 2.2 Evolution of conditional average monthly gross earnings in the private sector and evolution of minimum wage, 1994 – 2003

Figure 2.3 Evolution of conditional average monthly gross earnings in the public sector and evolution of minimum wage, 1994 – 2003

2.7.2 Estimated private-public sector earnings gap, 1994 – 2003

Figure 2.4 Private-public sector earnings gap, 1994 – 1997

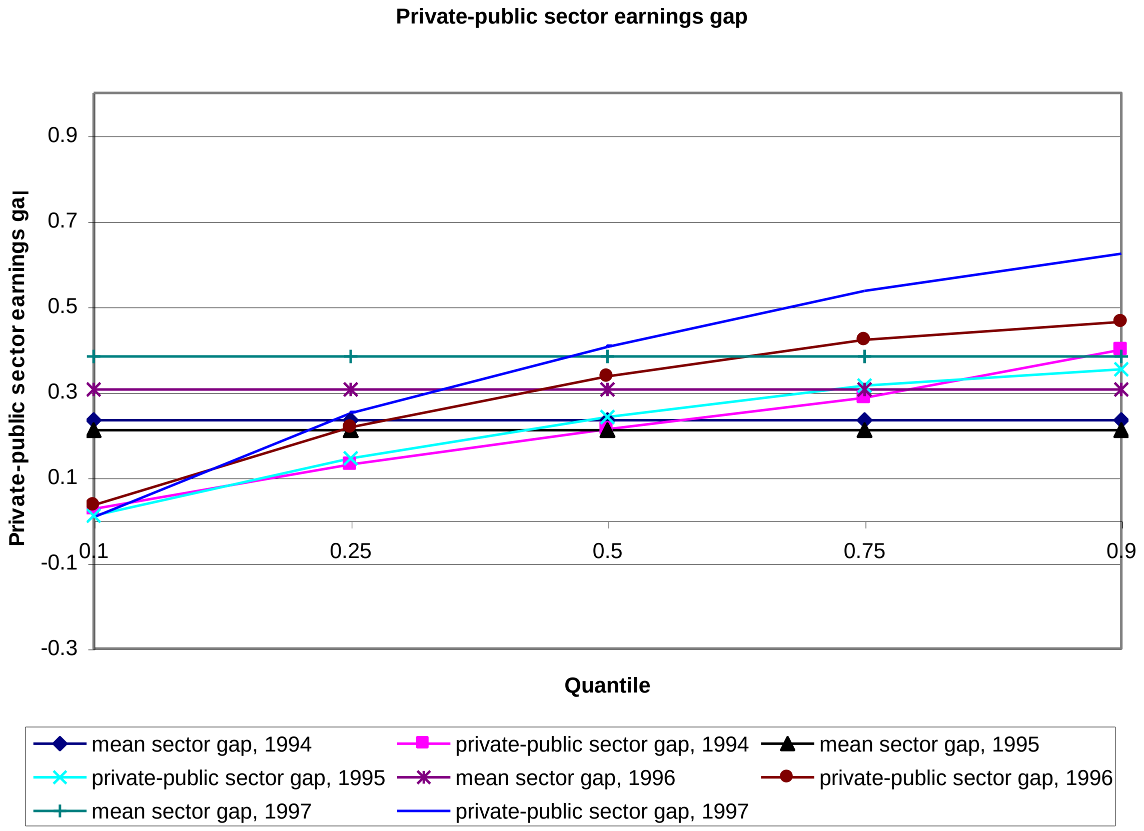


Figure 2.5 Private-public sector earnings gap, 1997 – 2000

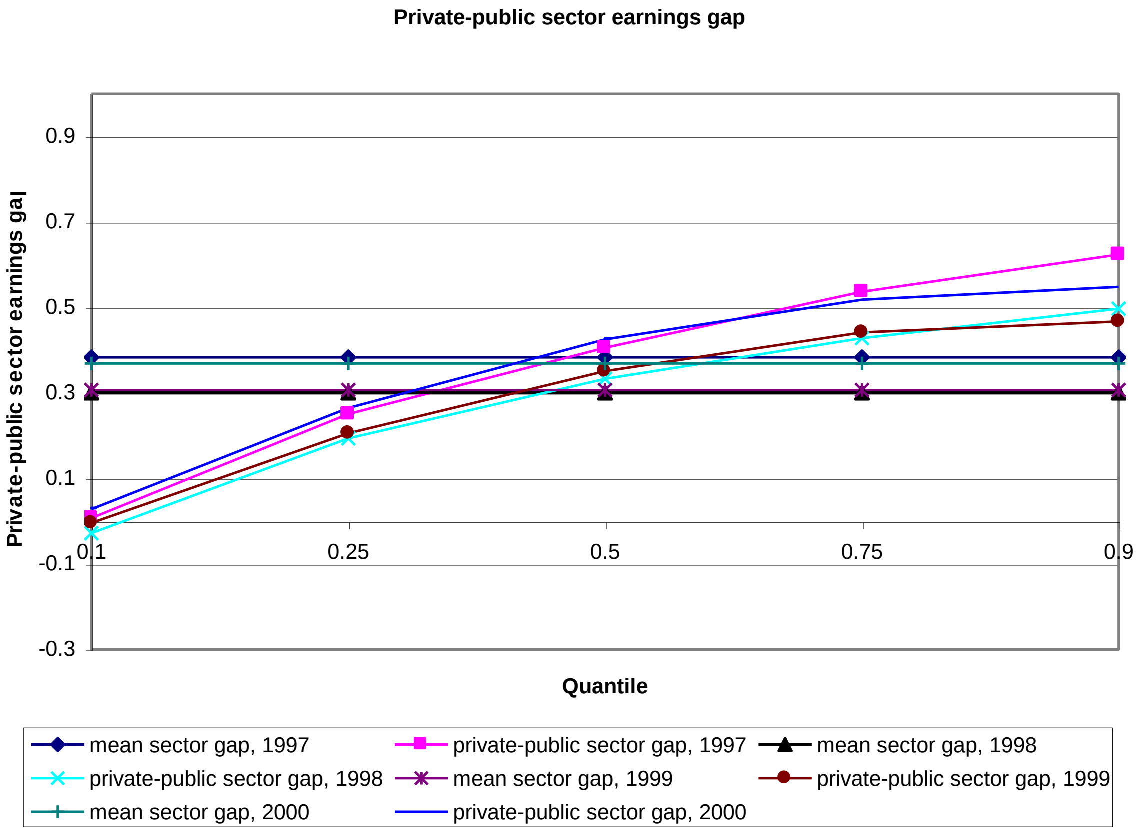


Figure 2.6 Private-public sector earnings gap, 2000 – 2003

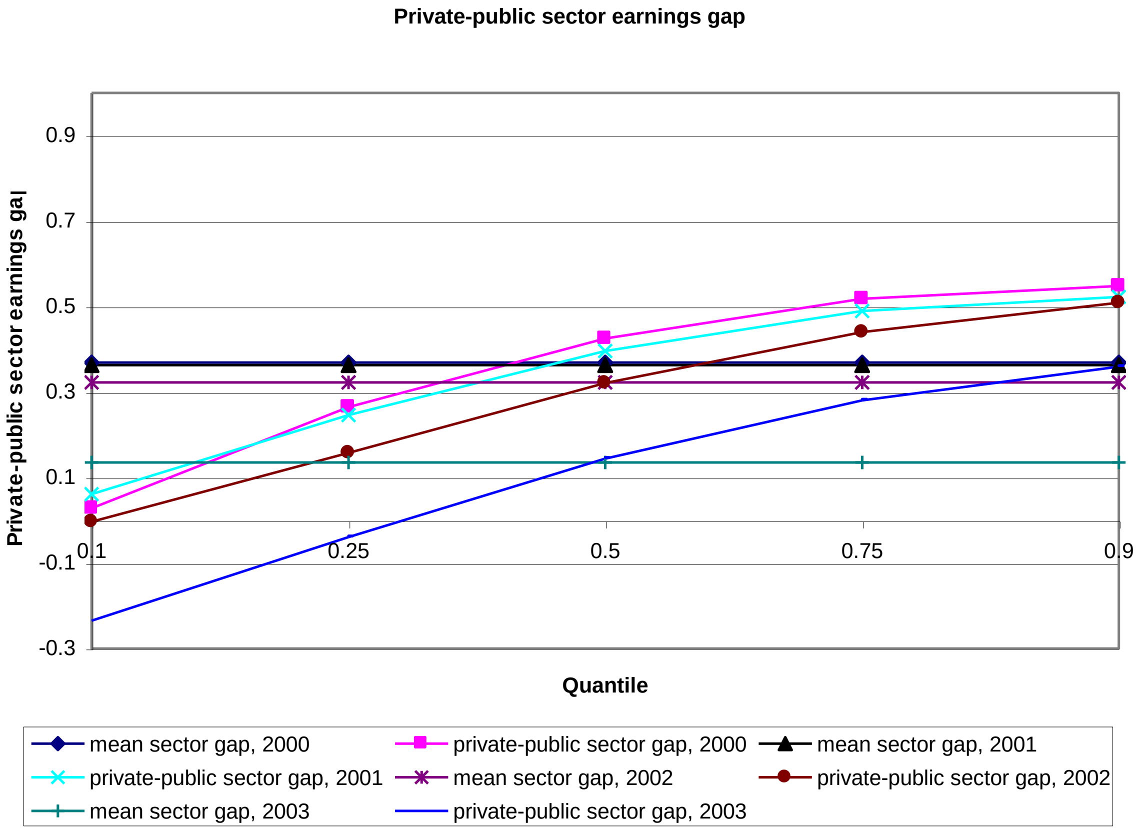


Figure 2.7 Private-public sector earnings gap, 1994 – 1997, Unskilled

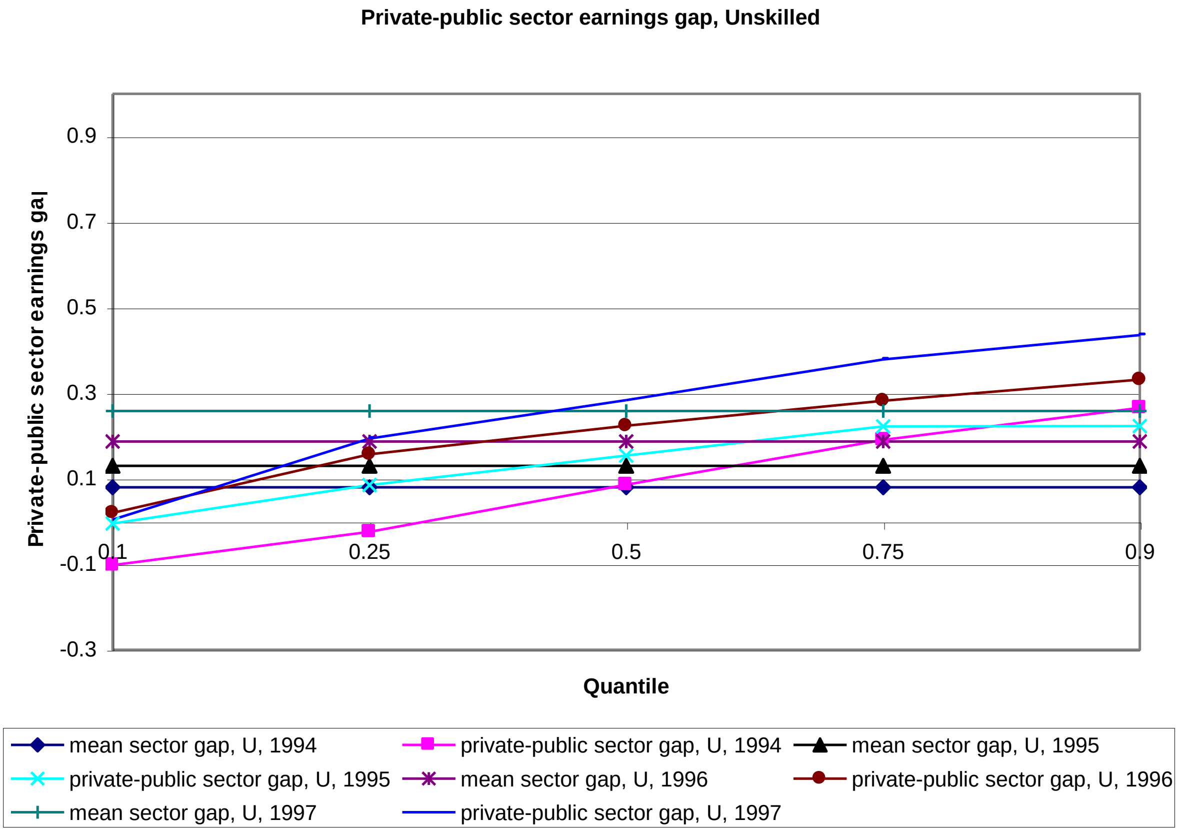


Figure 2.8 Private-public sector earnings gap, 1997 – 2000, Unskilled

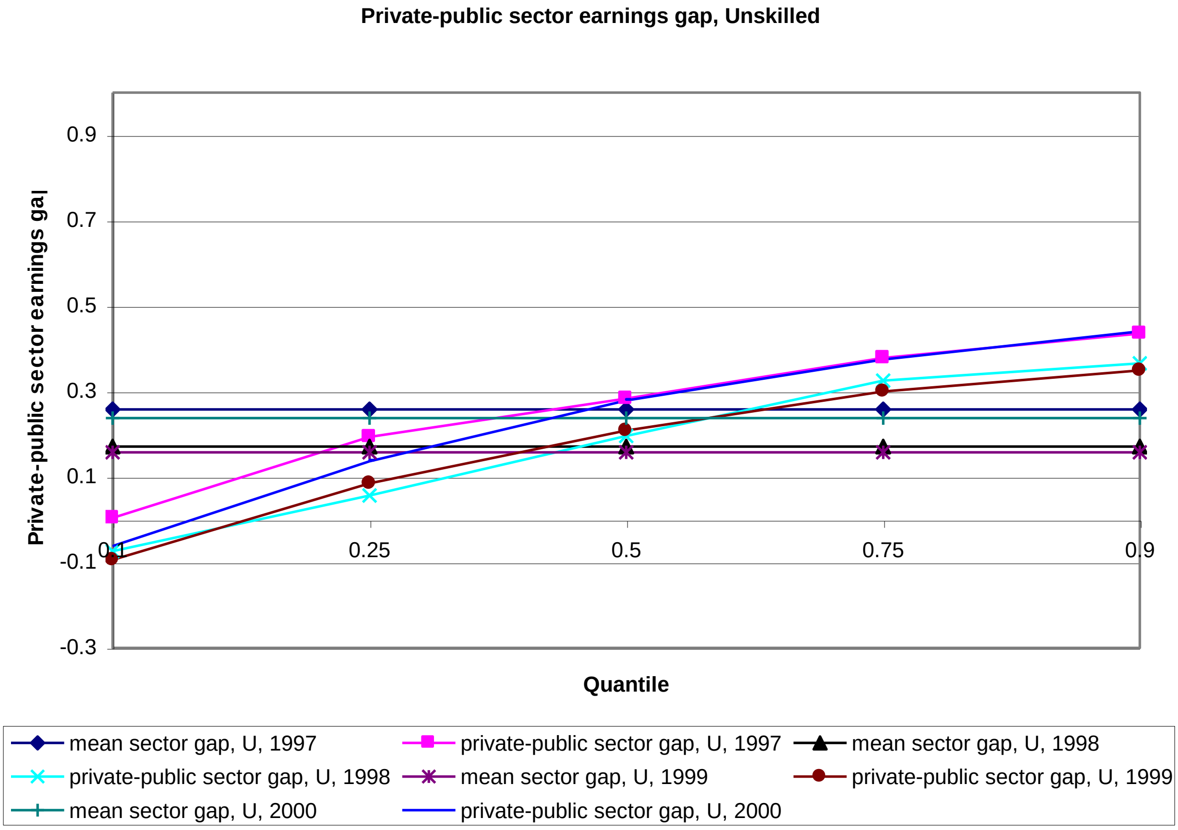


Figure 2.9 Private-public sector earnings gap, 2000 – 2003, Unskilled

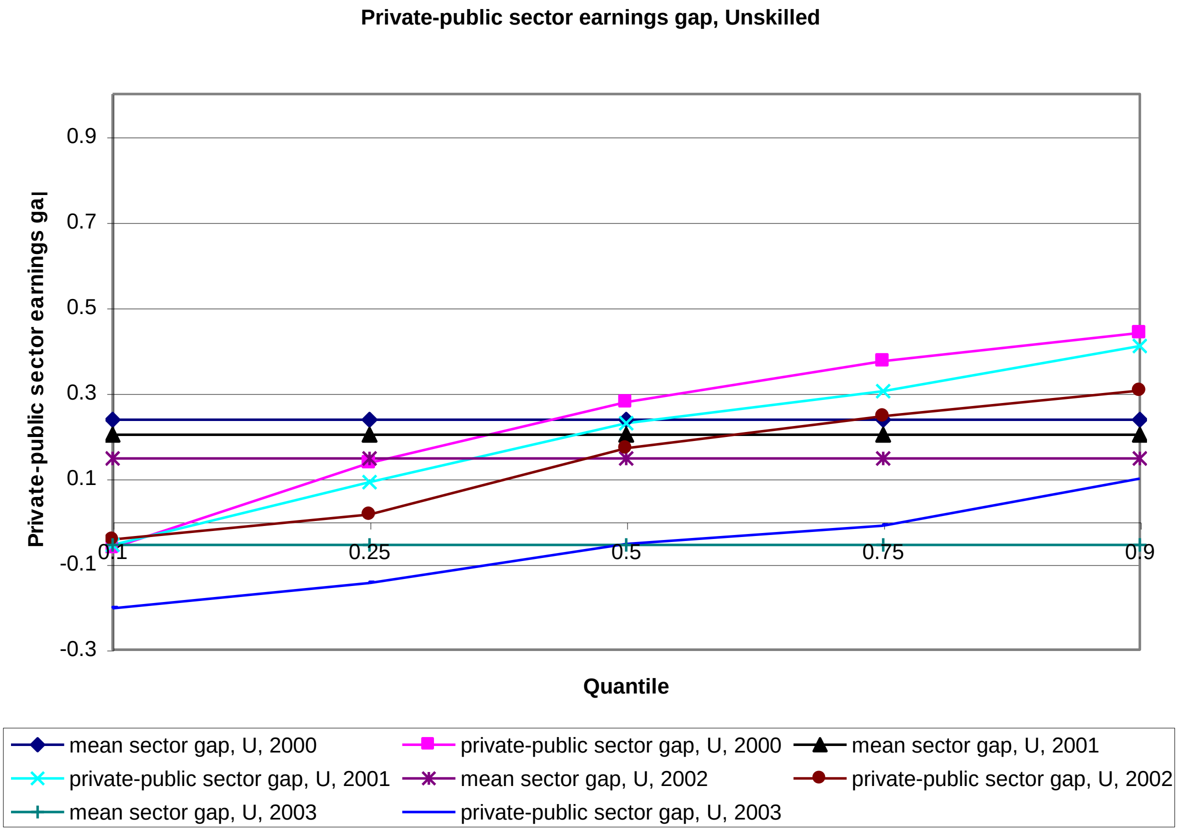


Figure 2.10 Private-public sector earnings gap, 1994 – 1997, Low-skilled

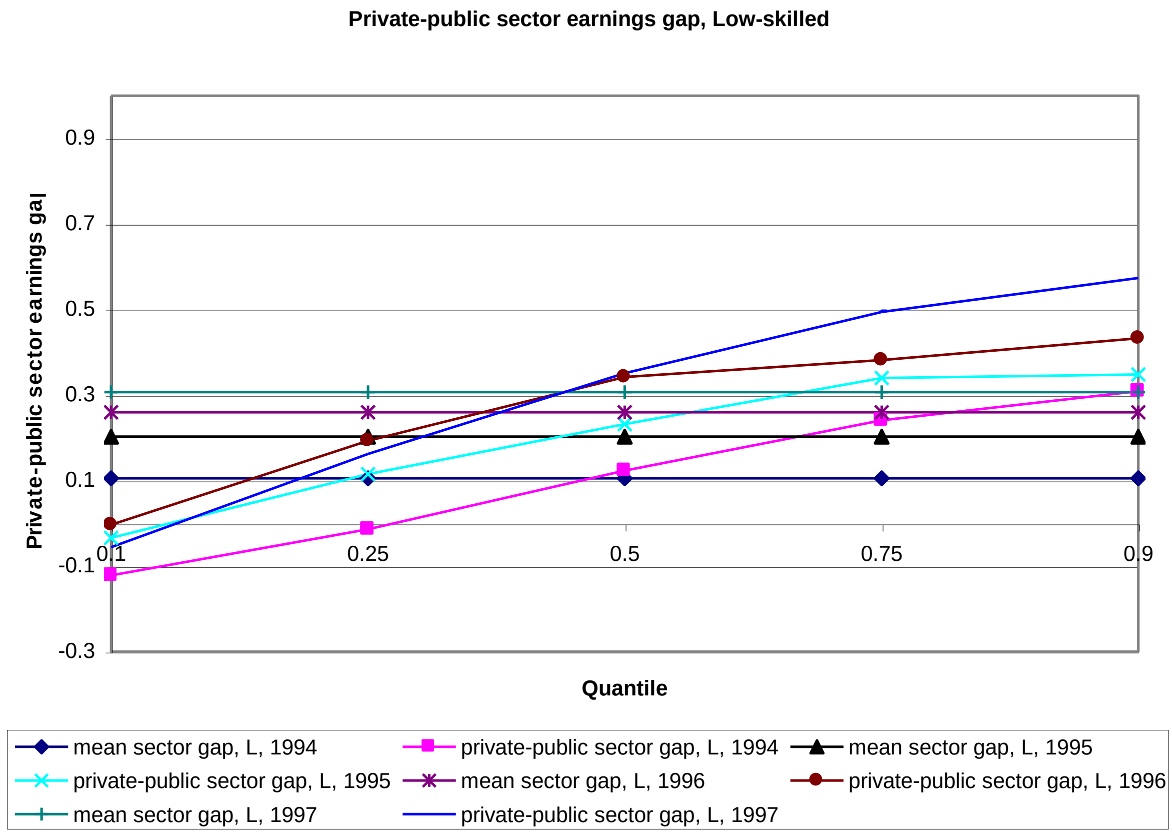


Figure 2.11 Private-public sector earnings gap, 1997 – 2000, Low-skilled

Figure 2.12 Private-public sector earnings gap, 2000 – 2003, Low-skilled

Figure 2.13 Private-public sector earnings gap, 1994 – 1997, Middle-skilled

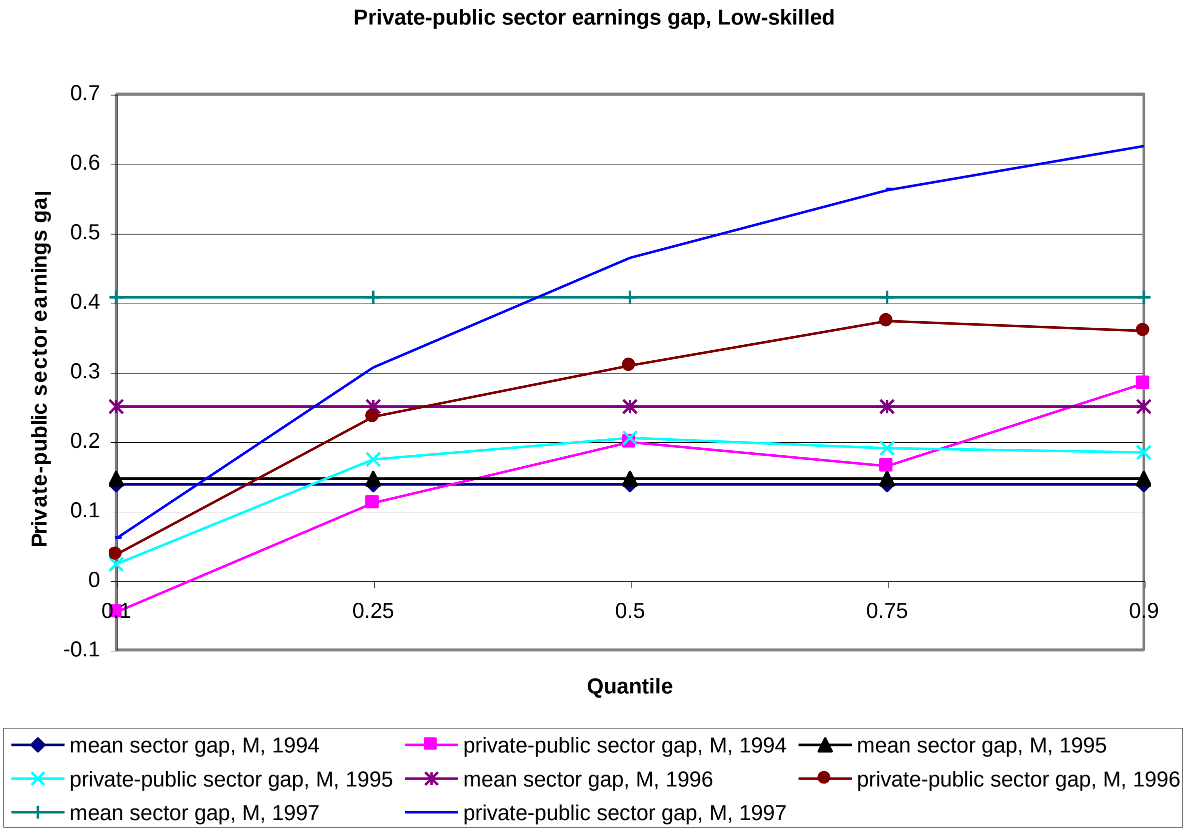


Figure 2.14 Private-public sector earnings gap, 1997 – 2000, Middle-skilled

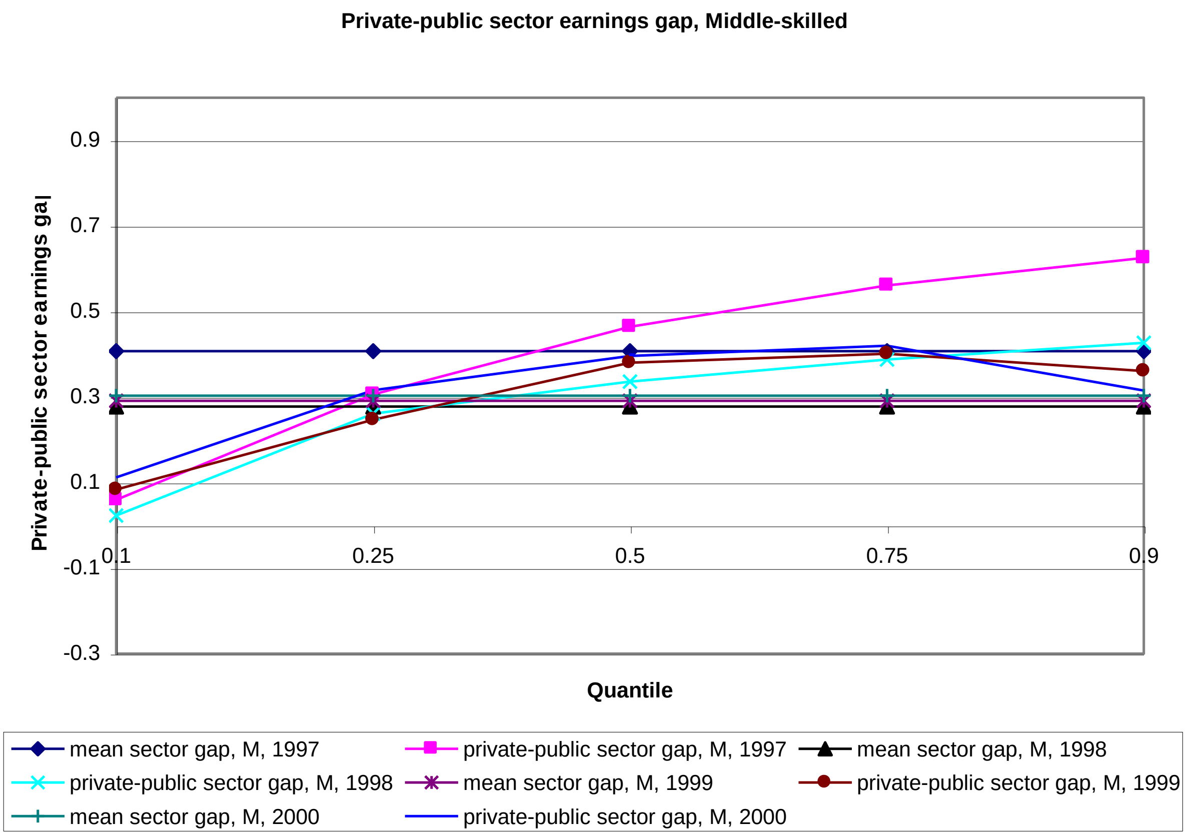


Figure 2.15 Private-public sector earnings gap, 2000 – 2003, Middle-skilled

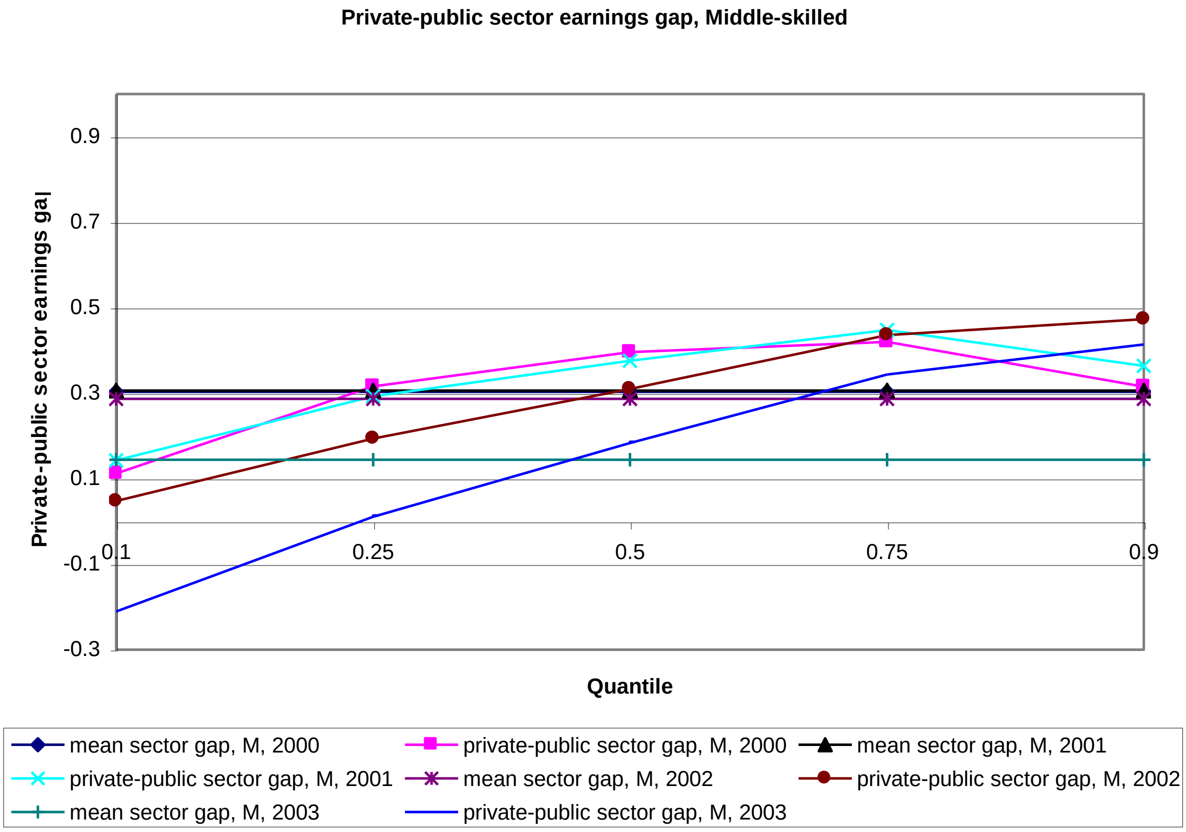


Figure 2.16 Private-public sector earnings gap, 1994 – 1997, High-skilled

Figure 2.17 Private-public sector earnings gap, 1997 – 2000, High-skilled

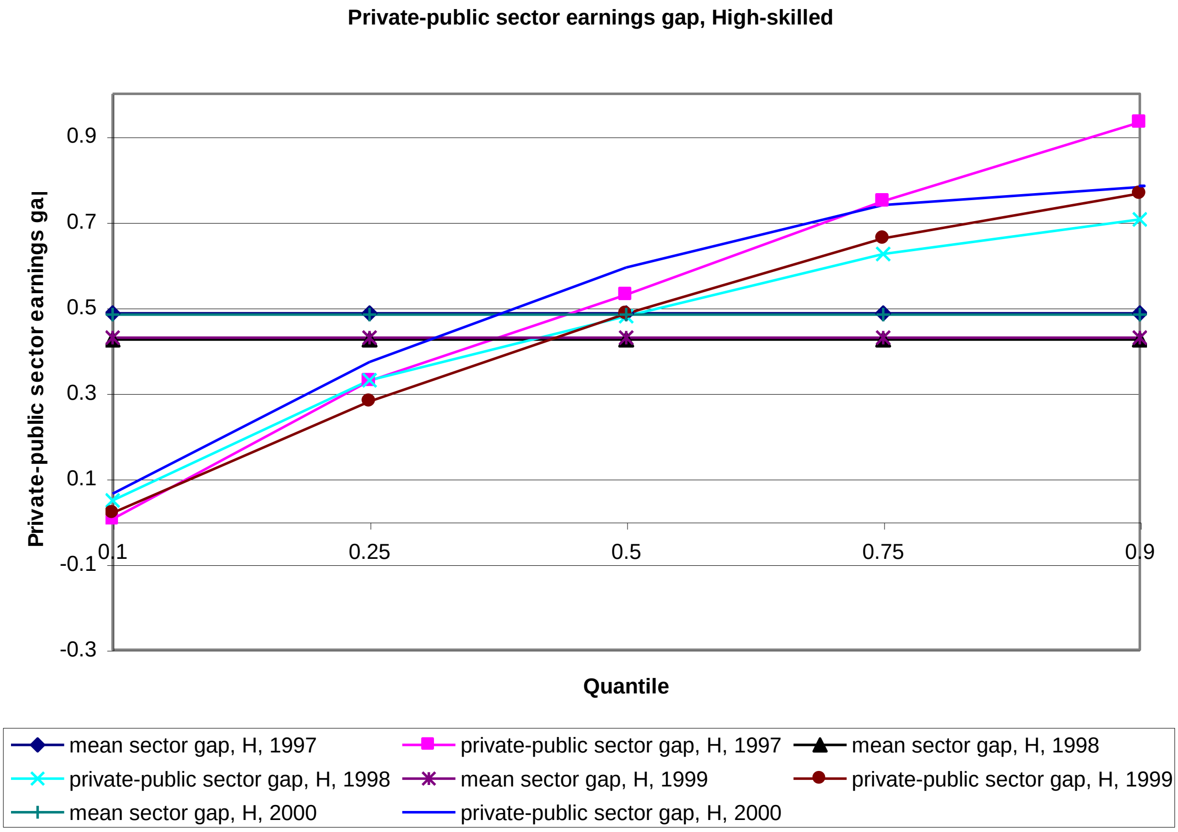
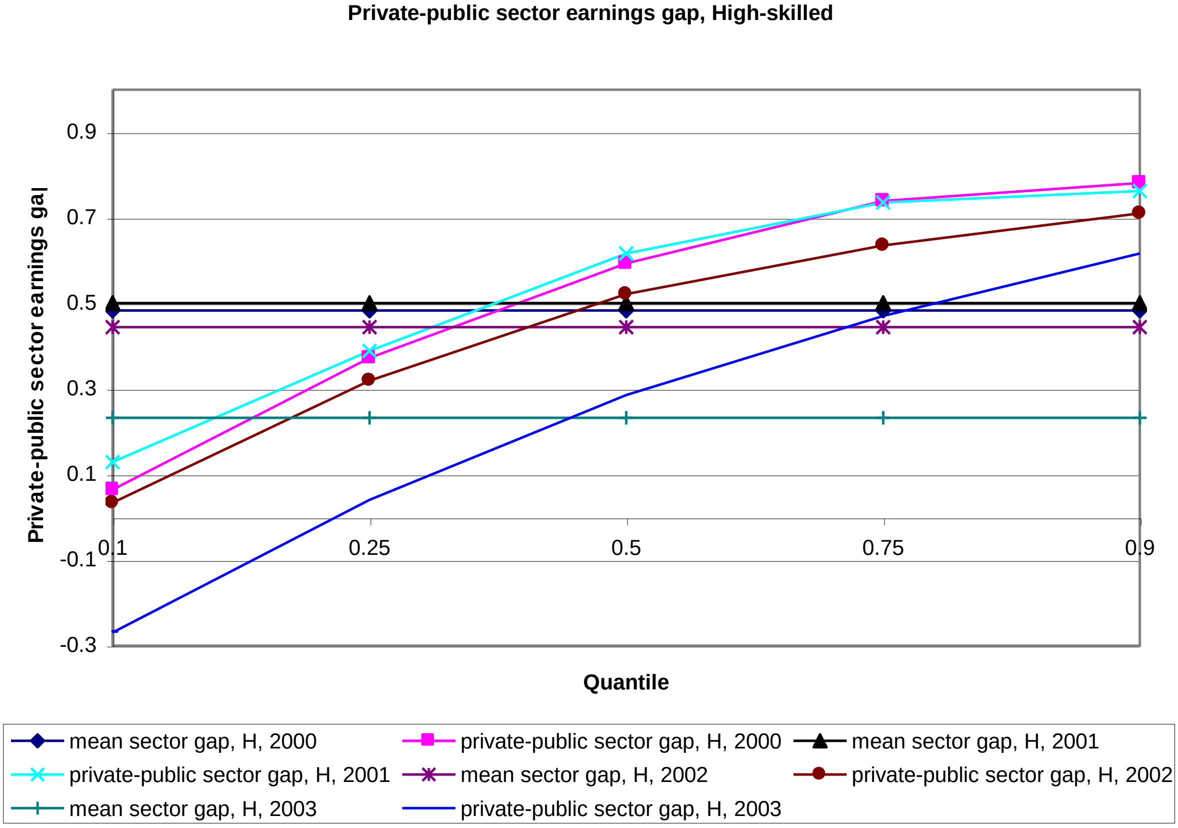


Figure 2.18 Private-public sector earnings gap, 2000 – 2003, High-skilled



2.7.2 Estimation results for the private and public sectors, 1994 – 2003

Table 2.3 Estimation results, 1994

	1994 Private sector						**1994 Public sector**					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.135	0.167	0.139	0.126	0.129	0.138	0.109	0.178	0.120	0.090	0.091	0.094
	(0.006)	(0.012)	(0.009)	(0.008)	(0.009)	(0.011)	(0.016)	(0.024)	(0.014)	(0.011)	(0.016)	(0.025)
M	0.432	0.402	0.408	0.424	0.442	0.502	0.405	0.331	0.310	0.357	0.469	0.478
	(0.006)	(0.015)	(0.010)	(0.008)	(0.009)	(0.012)	(0.014)	(0.020)	(0.026)	(0.028)	(0.022)	(0.033)
H	0.937	0.769	0.828	0.899	1.038	1.187	0.630	0.466	0.554	0.658	0.761	0.768
	(0.008)	(0.019)	(0.013)	(0.010)	(0.014)	(0.017)	(0.013)	(0.039)	(0.030)	(0.016)	(0.019)	(0.020)
Exp	0.025	0.013	0.017	0.025	0.029	0.034	0.035	0.014	0.030	0.037	0.048	0.049
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)
Exp^2(/100)	-0.037	-0.012	-0.022	-0.039	-0.045	-0.054	-0.053	-0.009	-0.042	-0.054	-0.076	-0.082
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.170	0.119	0.158	0.185	0.200	0.195	0.076	-0.079	0.035	0.104	0.216	0.185
	(0.005)	(0.012)	(0.008)	(0.006)	(0.009)	(0.010)	(0.011)	(0.058)	(0.045)	(0.045)	(0.033)	(0.040)
Constant	9.700	9.277	9.527	9.721	9.941	10.123	9.482	9.344	9.373	9.436	9.476	9.675
	(0.014)	(0.030)	(0.020)	(0.017)	(0.021)	(0.025)	(0.023)	(0.069)	(0.055)	(0.035)	(0.050)	(0.059)
Obs	54,138	54,138	54,138	54,138	54,138	54,138	7,903	7,903	7,903	7,903	7,903	7,903

Notes on Tables 2.3 – 2.12: 1) The reference group among the education groups is Unskilled (U) "No formal vocational training and no high school degree". 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus six). 3) Standard errors are in parentheses. 4) Standard errors are computed by 200 bootstrap replications for the quantile regressions.

Table 2.4 Estimation results, 1995

	1995 Private sector						**1995 Public sector**					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.133	0.158	0.135	0.124	0.134	0.149	0.082	0.169	0.112	0.047	0.028	0.065
	(0.006)	(0.014)	(0.009)	(0.007)	(0.008)	(0.010)	(0.014)	(0.028)	(0.018)	(0.022)	(0.038)	(0.053)
M	0.401	0.364	0.381	0.403	0.427	0.467	0.415	0.326	0.298	0.396	0.492	0.533
	(0.006)	(0.015)	(0.009)	(0.008)	(0.009)	(0.012)	(0.014)	(0.025)	(0.022)	(0.027)	(0.043)	(0.057)
H	0.911	0.731	0.801	0.888	1.022	1.181	0.816	0.740	0.756	0.816	0.843	0.868
	(0.008)	(0.024)	(0.015)	(0.010)	(0.016)	(0.018)	(0.013)	(0.02$)	(0.023)	(0.023)	(0.030)	(0.059)
Exp	0.023	0.010	0.019	0.024	0.027	0.030	0.049	0.035	0.047	0.050	0.048	0.057
	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.010)
Exp^2(/100)	-0.034	-0.008	-0.029	-0.038	-0.043	-0.048	-0.073	-0.049	-0.071	-0.073	-0.073	-0.088
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.162	0.076	0.143	0.178	0.202	0.212	0.199	0.177	0.194	0.190	0.192	0.277
	(0.005)	(0.017)	(0.009)	(0.007)	(0.007)	(0.010)	(0.009)	(0.02/)	(0.022)	(0.017)	(0.030)	(0.049)
Constant	9.900	9.507	9.696	9.891	10.115	10.326	9.368	9.172	9.215	9.319	9.576	9.654
	(0.014)	(0.036)	(0.023)	(0.017)	(0.020)	(0.030)	(0.023)	(0.047)	(0.043)	(0.040)	(0.071)	(0.099)
Obs	48,239	48,239	48,239	48,239	48,239	48,239	8,273	8,273	8,273	8,273	8,273	8,273

Table 2.5 Estimation results, 1996

	1996 Private sector						1996 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.163	0.168	0.157	0.155	0.174	0.188	0.106	0.227	0.109	0.072	0.075	0.096
	(0.006)	(0.016)	(0.011)	(0.008)	(0.009)	(0.010)	(0.013)	(0.026)	(0.020)	(0.026)	(0.048)	(0.056)
M	0.439	0.373	0.394	0.432	0.481	0.538	0.384	0.360	0.307	0.345	0.385	0.533
	(0.007)	(0.020)	(0.013)	(0.009)	(0.010)	(0.012)	(0.013)	(0.029)	(0.027)	(0.033)	(0.042)	(0.090)
H	1.016	0.783	0.862	0.968	1.167	1.371	0.778	0.733	0.736	0.773	0.800	0.905
	(0.009)	(0.028)	(0.017)	(0.017)	(0.015)	(0.019)	(0.012)	(0.039)	(0.028)	(0.030)	(0.039)	(0.051)
Exp	0.021	0.011	0.020	0.019	0.025	0.027	0.036	0.029	0.036	0.042	0.042	0.028
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)	(0.004)	(0.006)	(0.008)	(0.015)
Exp^2(/100)	-0.032	-0.009	-0.031	-0.028	-0.038	-0.044	-0.052	-0.038	-0.050	-0.064	-0.061	-0.034
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.157	0.047	0.131	0.162	0.199	0.229	0.231	0.171	0.214	0.234	0.252	0.327
	(0.006)	(0.020)	(0.012)	(0.008)	(0.009)	(0.012)	(0.008)	(0.027)	(0.026)	(0.033)	(0.053)	(0.065)
Constant	10.097	9.632	9.857	10.138	10.327	10.544	9.641	9.317	9.431	9.545	9.752	10.087
	(0.015)	(0.044)	(0.025)	(0.022)	(0.021)	(0.029)	(0.022)	(0.067)	(0.047)	(0.066)	(0.091)	(0.164)
Obs	44,422	44,422	44,422	44,422	44,422	44,422	10,426	10,426	10,426	10,426	10,426	10,426

Table 2.6 Estimation results, 1997

	1997 Private sector						1997 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.162	0.142	0.140	0.155	0.184	0.193	0.131	0.242	0.171	0.121	0.077	0.052
	(0.007)	(0.018)	(0.014)	(0.011)	(0.011)	(0.015)	(0.009)	(0.018)	(0.015)	(0.016)	(0.020)	(0.036)
M	0.441	0.365	0.411	0.443	0.477	0.516	0.326	0.332	0.312	0.312	0.326	0.346
	(0.008)	(0.022)	(0.017)	(0.012)	(0.011)	(0.016)	(0.010)	(0.019)	(0.019)	(0.017)	(0.031)	(0.044)
H	1.042	0.785	0.902	1.008	1.200	1.394	0.871	0.847	0.841	0.854	0.866	0.918
	(0.010)	(0.035)	(0.018)	(0.014)	(0.016)	(0.020)	(0.009)	(0.019)	(0.016)	(0.016)	(0.024)	(0.038)
Exp	0.020	0.015	0.015	0.018	0.024	0.026	0.036	0.028	0.031	0.036	0.044	0.045
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.007)
Exp^2(/100)	-0.029	-0.020	-0.019	-0.026	-0.038	-0.040	-0.047	-0.031	-0.035	-0.046	-0.066	-0.070
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.138	0.035	0.135	0.156	0.177	0.177	0.108	0.095	0.118	0.140	0.120	0.118
	(0.006)	(0.023)	(0.013)	(0.009)	(0.009)	(0.012)	(0.007)	(0.012)	(0.012)	(0.017)	(0.017)	(0.036)
Constant	10.297	9.765	10.081	10.328	10.535	10.773	9.754	9.479	9.584	9.716	9.862	10.077
	(0.017)	(0.051)	(0.028)	(0.024)	(0.021)	(0.033)	(0.017)	(0.030)	(0.026)	(0.030)	(0.044)	(0.082)
Obs	38,653	38,653	38,653	38,653	38,653	38,653	11,025	11,025	11,025	11,025	11,025	11,025

Table 2.7 Estimation results, 1998

	1998 Private sector						1998 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.181	0.159	0.173	0.175	0.195	0.231	0.118	0.164	0.105	0.061	0.111	0.118
	(0.007)	(0.018)	(0.014)	(0.011)	(0.009)	(0.012)	(0.013)	(0.019)	(0.017)	(0.023)	(0.032)	(0.026)
M	0.482	0.403	0.458	0.486	0.516	0.597	0.408	0.328	0.275	0.388	0.468	0.544
	(0.008)	(0.022)	(0.017)	(0.011)	(0.011)	(0.014)	(0.013)	(0.019)	(0.030)	(0.031)	(0.038)	(0.036)
H	1.110	0.860	0.994	1.091	1.249	1.447	0.926	0.797	0.794	0.875	0.989	1.195
	(0.010)	(0.035)	(0.018)	(0.016)	(0.019)	(0.023)	(0.012)	(0.021)	(0.017)	(0.021)	(0.028)	(0.045)
Exp	0.017	0.010	0.015	0.017	0.019	0.021	0.038	0.034	0.034	0.040	0.043	0.037
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.010)
Exp^2(/100)	-0.024	-0.008	-0.020	-0.025	-0.029	-0.034	-0.051	-0.045	-0.045	-0.057	-0.062	-0.047
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.158	0.042	0.137	0.175	0.211	0.203	0.155	0.102	0.139	0.161	0.179	0.228
	(0.006)	(0.023)	(0.013)	(0.009)	(0.010)	(0.011)	(0.008)	(0.020)	(0.019)	(0.021)	(0.033)	(0.033)
Constant	10.456	9.935	10.191	10.468	10.735	10.963	9.937	9.642	9.796	9.902	10.055	10.257
	(0.016)	(0.051)	(0.028)	(0.021)	(0.025)	(0.033)	(0.022)	(0.040)	(0.033)	(0.046)	(0.066)	(0.112)
Obs	42,713	42,713	42,713	42,713	42,713	42,713	10,713	10,713	10,713	10,713	10,713	10,713

Table 2.8 Estimation results, 1999

	1999 Private sector						1999 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.176	0.159	0.150	0.159	0.197	0.230	0.099	0.142	0.082	0.079	0.110	0.198
	(0.007)	(0.019)	(0.016)	(0.009)	(0.010)	(0.013)	(0.013)	(0.023)	(0.019)	(0.021)	(0.021)	(0.074)
M	0.484	0.440	0.441	0.473	0.528	0.589	0.394	0.318	0.327	0.363	0.462	0.564
	(0.008)	(0.022)	(0.014)	(0.010)	(0.011)	(0.015)	(0.015)	(0.025)	(0.024)	(0.024)	(0.024)	(0.061)
H	1.115	0.865	0.946	1.081	1.271	1.467	0.933	0.842	0.847	0.918	1.015	1.109
	(0.010)	(0.027)	(0.017)	(0.015)	(0.017)	(0.020)	(0.020)	(0.025)	(0.021)	(0.019)	(0.019)	(0.058)
Exp	0.017	0.013	0.015	0.018	0.019	0.017	0.045	0.033	0.036	0.043	0.054	0.070
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.012)
Exp^2(/100)	-0.026	-0.016	-0.025	-0.029	-0.031	-0.026	-0.065	-0.040	-0.049	-0.063	-0.085	-0.116
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.163	0.038	0.147	0.182	0.191	0.210	0.179	0.123	0.152	0.185	0.204	0.277
	(0.006)	(0.027)	(0.017)	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)	(0.017)	(0.019)	(0.019)	(0.051)
Constant	10.628	10.076	10.390	10.643	10.886	11.156	10.006	9.776	9.921	9.998	10.053	10.109
	(0.016)	(0.043)	(0.029)	(0.023)	(0.023)	(0.035)	(0.035)	(0.035)	(0.043)	(0.047)	(0.047)	(0.125)
Obs	42,042	42,042	42,042	42,042	42,042	42,042	9,710	9,710	9,710	9,710	9,710	9,710

Table 2.9 Estimation results, 2000

	2000 Private sector						2000 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.184	0.167	0.182	0.189	0.193	0.213	0.139	0.176	0.134	0.110	0.099	0.069
	(0.007)	(0.017)	(0.013)	(0.015)	(0.012)	(0.013)	(0.014)	(0.013)	(0.011)	(0.014)	(0.016)	(0.032)
M	0.473	0.423	0.458	0.469	0.510	0.577	0.462	0.305	0.328	0.419	0.516	0.682
	(0.008)	(0.022)	(0.015)	(0.015)	(0.012)	(0.016)	(0.015)	(0.018)	(0.017)	(0.015)	(0.026)	(0.047)
H	1.182	0.940	1.033	1.154	1.328	1.506	0.988	0.855	0.871	0.919	1.012	1.144
	(0.010)	(0.028)	(0.018)	(0.016)	(0.017)	(0.021)	(0.014)	(0.015)	(0.014)	(0.013)	(0.019)	(0.038)
Exp	0.018	0.018	0.017	0.018	0.017	0.016	0.034	0.026	0.029	0.035	0.032	0.042
	(0.001)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.007)
Exp^2(/100)	-0.027	-0.023	-0.025	-0.029	-0.025	-0.022	-0.043	-0.028	-0.031	-0.046	-0.042	-0.066
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.134	-0.097	0.082	0.144	0.199	0.224	0.280	0.143	0.172	0.226	0.294	0.447
	(0.006)	(0.026)	(0.014)	(0.011)	(0.011)	(0.014)	(0.010)	(0.013)	(0.013)	(0.010)	(0.017)	(0.048)
Constant	10.718	10.092	10.446	10.742	11.021	11.286	10.112	9.901	10.002	10.093	10.314	10.448
	(0.016)	(0.047)	(0.035)	(0.039)	(0.033)	(0.033)	(0.028)	(0.024)	(0.032)	(0.027)	(0.048)	(0.077)
Obs	44,027	44,027	44,027	44,027	44,027	44,027	9,143	9,143	9,143	9,143	9,143	9,143

Table 2.10 Estimation results, 2001

	2001 Private sector						2001 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.156	0.084	0.141	0.162	0.186	0.202	0.079	0.052	0.064	0.053	0.042	0.055
	(0.007)	(0.009)	(0.012)	(0.009)	(0.009)	(0.012)	(0.015)	(0.010)	(0.009)	(0.014)	(0.015)	(0.023)
M	0.450	0.287	0.404	0.463	0.538	0.588	0.389	0.162	0.246	0.350	0.429	0.611
	(0.008)	(0.015)	(0.013)	(0.011)	(0.011)	(0.016)	(0.016)	(0.014)	(0.016)	(0.019)	(0.023)	(0.047)
H	1.155	0.841	1.031	1.176	1.325	1.460	0.905	0.712	0.767	0.834	0.944	1.090
	(0.010)	(0.024)	(0.017)	(0.016)	(0.016)	(0.020)	(0.014)	(0.011)	(0.012)	(0.016)	(0.019)	(0.027)
Exp	0.013	0.011	0.012	0.012	0.012	0.010	0.035	0.032	0.027	0.029	0.030	0.046
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Exp^2(/100)	-0.018	-0.015	-0.016	-0.017	-0.019	-0.016	-0.050	-0.048	-0.038	-0.040	-0.042	-0.076
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.128	-0.037	0.095	0.148	0.182	0.186	0.319	0.175	0.221	0.263	0.299	0.498
	(0.006)	(0.011)	(0.013)	(0.011)	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)	(0.014)	(0.020)	(0.050)
Constant	10.963	10.459	10.659	10.948	11.230	11.534	10.350	10.139	10.285	10.406	10.589	10.621
	(0.015)	(0.026)	(0.024)	(0.025)	(0.025)	(0.033)	(0.030)	(0.027)	(0.025)	(0.031)	(0.045)	(0.062)
Obs	42,048	42,048	42,048	42,048	42,048	42,048	8,501	8,501	8,501	8,501	8,501	8,501

Table 2.11 Estimation results, 2002

	2002 Private sector						2002 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.152	0.039	0.131	0.174	0.180	0.220	0.043	0.051	0.038	0.061	0.007	-0.008
	(0.006)	(0.006)	(0.010)	(0.009)	(0.010)	(0.014)	(0.015)	(0.010)	(0.009)	(0.011)	(0.020)	(0.028)
M	0.438	0.207	0.398	0.469	0.523	0.608	0.325	0.152	0.236	0.339	0.347	0.433
	(0.007)	(0.009)	(0.012)	(0.010)	(0.011)	(0.018)	(0.015)	(0.015)	(0.016)	(0.014)	(0.022)	(0.037)
H	1.143	0.699	1.012	1.177	1.336	1.506	0.883	0.681	0.755	0.852	0.970	1.086
	(0.009)	(0.015)	(0.017)	(0.014)	(0.017)	(0.021)	(0.014)	(0.015)	(0.012)	(0.013)	(0.021)	(0.027)
Exp	0.016	0.006	0.013	0.014	0.015	0.015	0.035	0.031	0.032	0.034	0.037	0.036
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.007)
Exp^2(/100)	-0.026	-0.009	-0.019	-0.022	-0.025	-0.025	-0.055	-0.052	-0.054	-0.057	-0.060	-0.056
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.155	0.000	0.111	0.178	0.199	0.196	0.129	0.063	0.113	0.149	0.179	0.197
	(0.005)	(0.004)	(0.012)	(0.009)	(0.008)	(0.014)	(0.010)	(0.012)	(0.013)	(0.014)	(0.016)	(0.031)
Constant	11.041	10.736	10.758	11.004	11.294	11.555	10.620	10.434	10.496	10.597	10.754	10.965
	(0.013)	(0.013)	(0.024)	(0.023)	(0.027)	(0.032)	(0.023)	(0.025)	(0.021)	(0.032)	(0.040)	(0.062)
Obs	51,551	51,551	51,551	51,551	51,551	51,551	8,429	8,429	8,429	8,429	8,429	8,429

Table 2.12 Estimation results, 2003

	2003 Private sector						2003 Public sector					
	OLS	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**OLS**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
L	0.142	0.055	0.135	0.154	0.171	0.198	0.066	0.169	0.108	0.076	0.007	-0.016
	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)	(0.014)	(0.012)	(0.015)	(0.023)	(0.026)	(0.030)	(0.032)
M	0.415	0.236	0.368	0.426	0.489	0.570	0.269	0.270	0.241	0.252	0.191	0.313
	(0.007)	(0.013)	(0.010)	(0.009)	(0.010)	(0.015)	(0.012)	(0.016)	(0.024)	(0.025)	(0.031)	(0.044)
H	1.142	0.807	1.014	1.167	1.307	1.480	0.922	0.933	0.898	0.901	0.885	0.999
	(0.009)	(0.016)	(0.015)	(0.014)	(0.016)	(0.023)	(0.011)	(0.015)	(0.023)	(0.026)	(0.032)	(0.032)
Exp	0.023	0.012	0.018	0.021	0.024	0.033	0.035	0.030	0.029	0.032	0.038	0.049
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
Exp^2(/100)	-0.037	-0.015	-0.026	-0.034	-0.041	-0.058	-0.047	-0.039	-0.038	-0.042	-0.053	-0.076
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Budapest	0.208	0.027	0.166	0.225	0.242	0.263	0.167	0.133	0.144	0.164	0.179	0.176
	(0.005)	(0.011)	(0.010)	(0.008)	(0.010)	(0.013)	(0.007)	(0.014)	(0.012)	(0.019)	(0.019)	(0.024)
Constant	11.032	10.683	10.771	11.024	11.260	11.416	10.837	10.560	10.719	10.841	11.006	11.050
	(0.014)	(0.017)	(0.022)	(0.023)	(0.023)	(0.030)	(0.019)	(0.030)	(0.033)	(0.035)	(0.057)	(0.081)
Obs	50,700	50,700	50,700	50,700	50,700	50,700	8,659	8,659	8,659	8,659	8,659	8,659

Notes on Tables 2.3 – 2.12: 1) The reference group among the education groups is Unskilled (U) "No formal vocational training and no high school degree". 2) Experience is measured as years of potential labour market experience (measured as age minus years of schooling minus six). 3) Standard errors are in parentheses. 4) Standard errors are computed by 200 bootstrap replications for the quantile regressions.

2.7.4 Estimated cross-section experience profiles, 1994 – 2003

Figure 2.19 Experience profiles, private sector, 1994

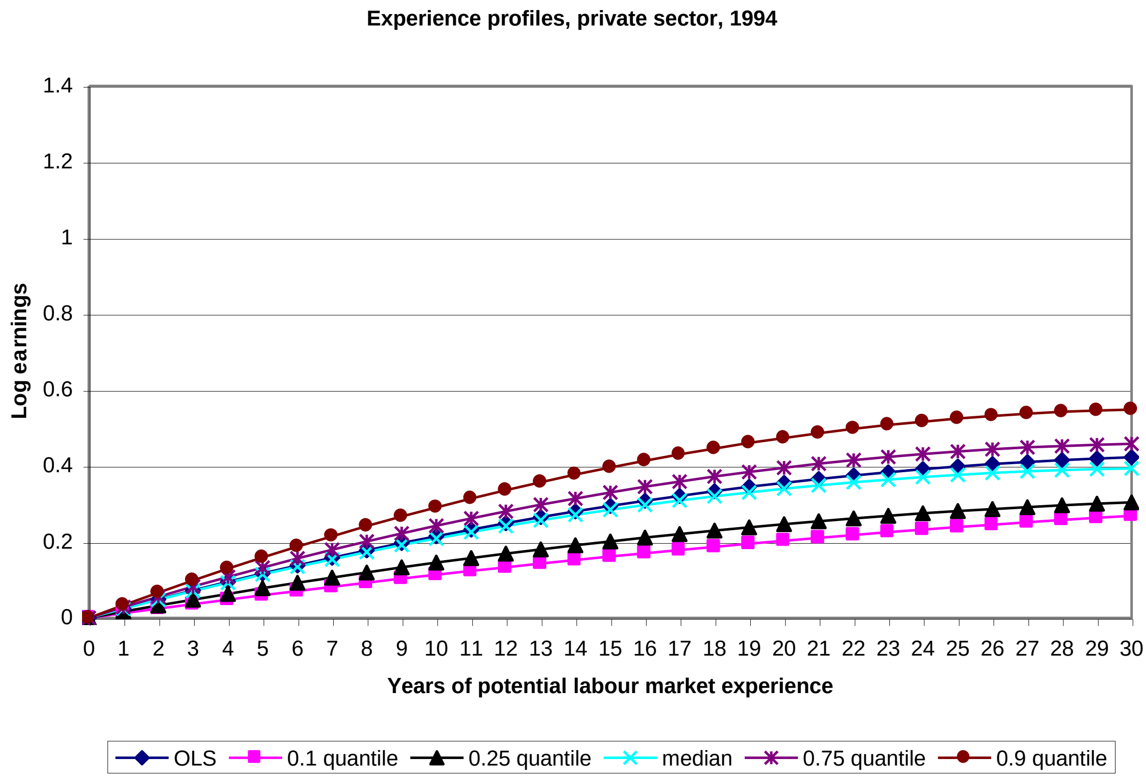


Figure 2.20 Experience profiles, private sector, 1995

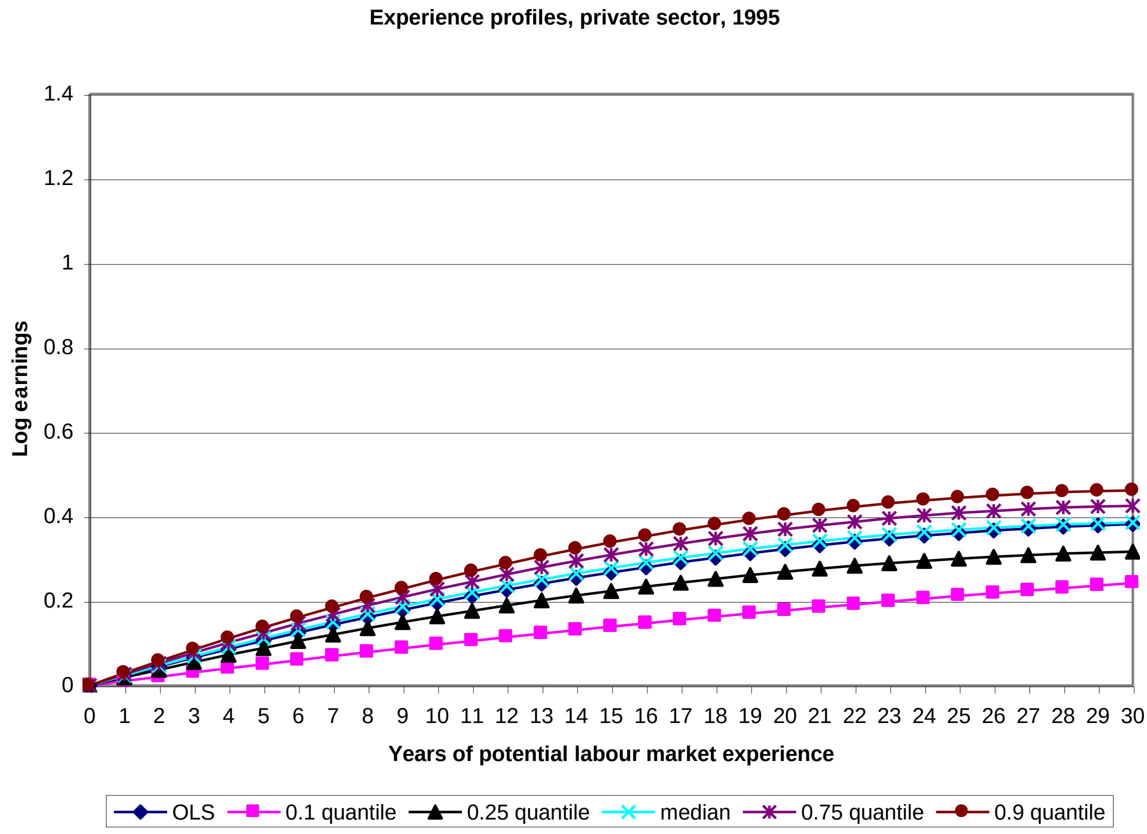


Figure 2.21 Experience profiles, private sector, 1996

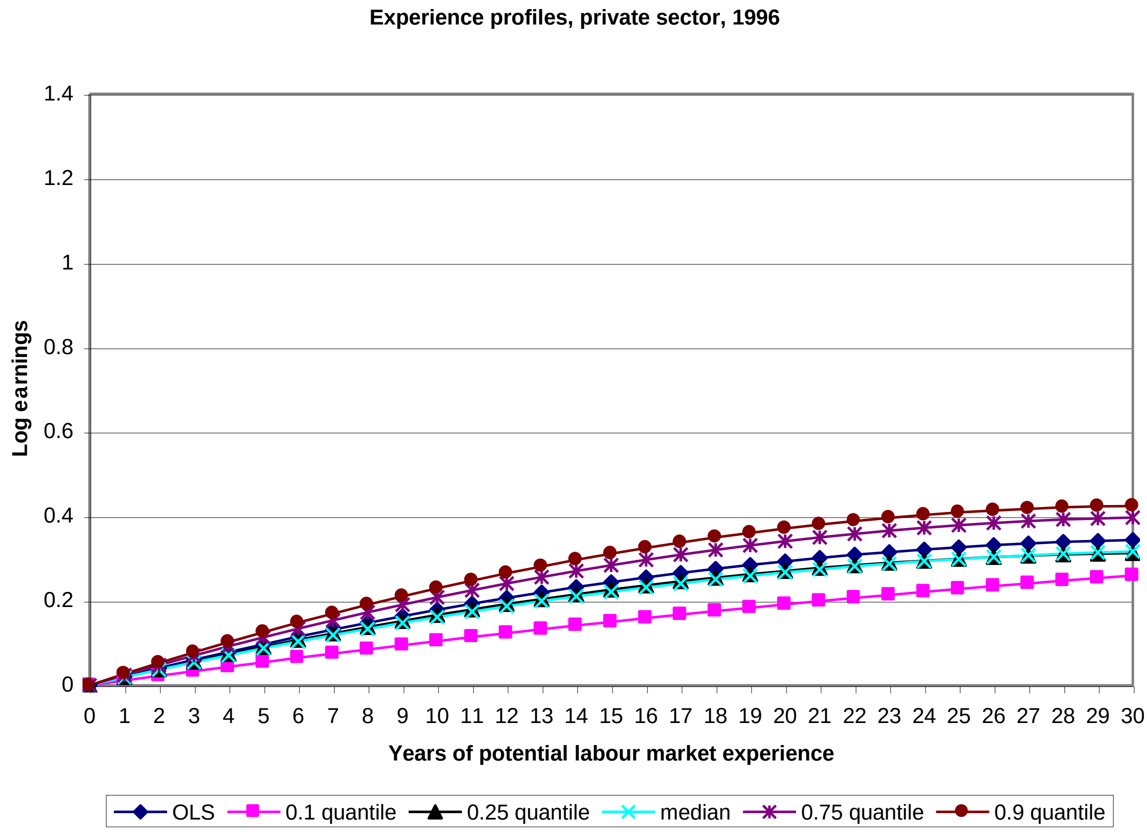


Figure 2.22 Experience profiles, private sector, 1997

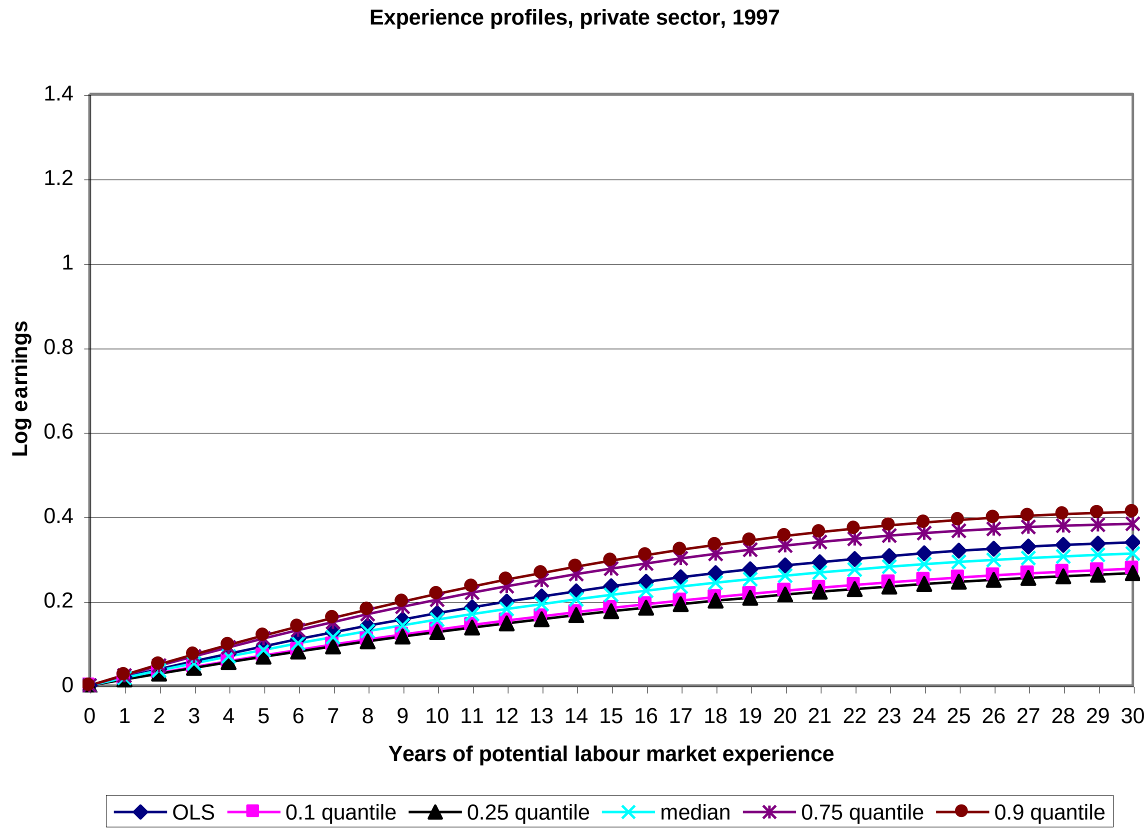


Figure 2.23 Experience profiles, private sector, 1998

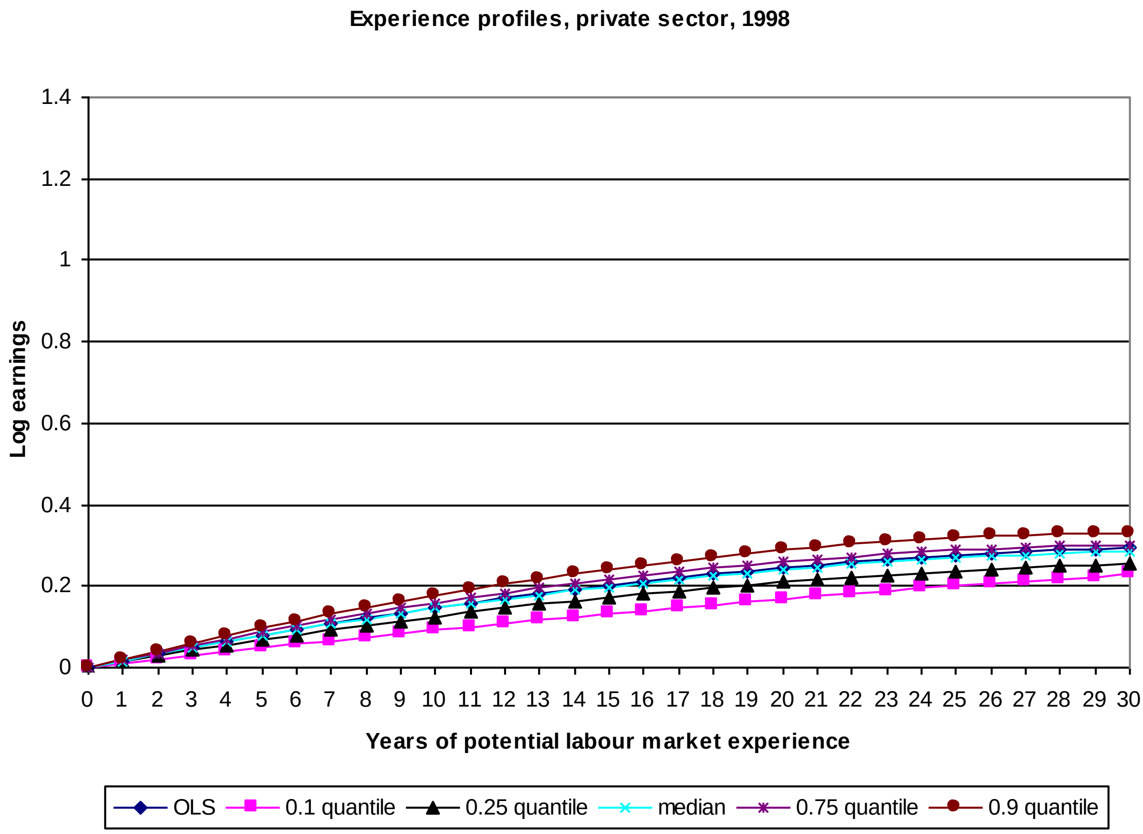


Figure 2.24 Experience profiles, private sector, 1999

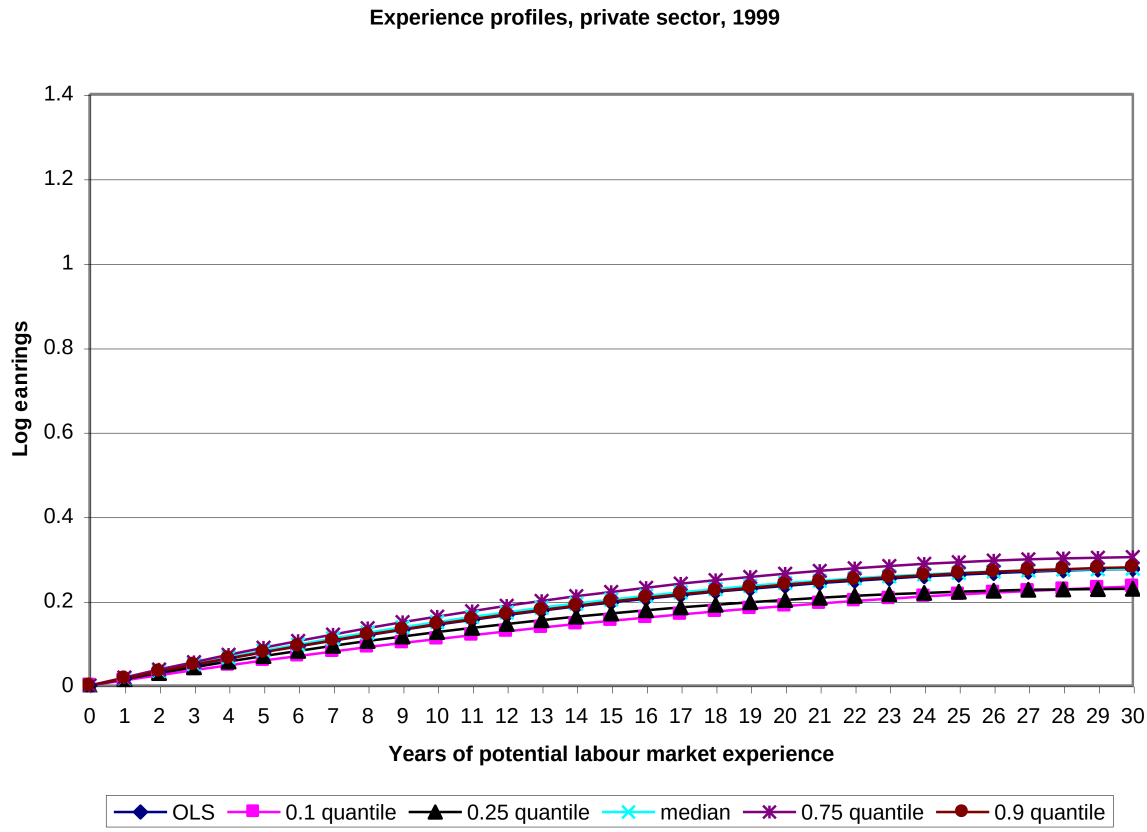


Figure 2.25 Experience profiles, private sector, 2000

Figure 2.26 Experience profiles, private sector, 2001

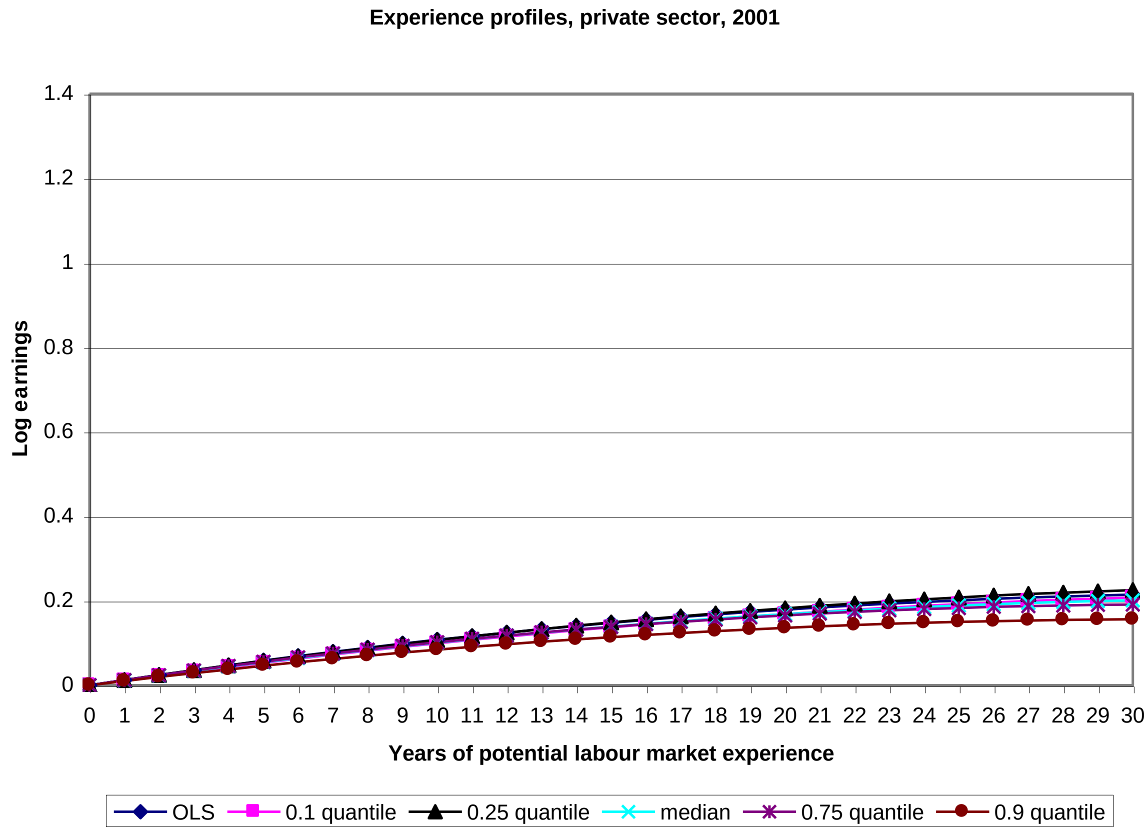


Figure 2.27 Experience profiles, private sector, 2002

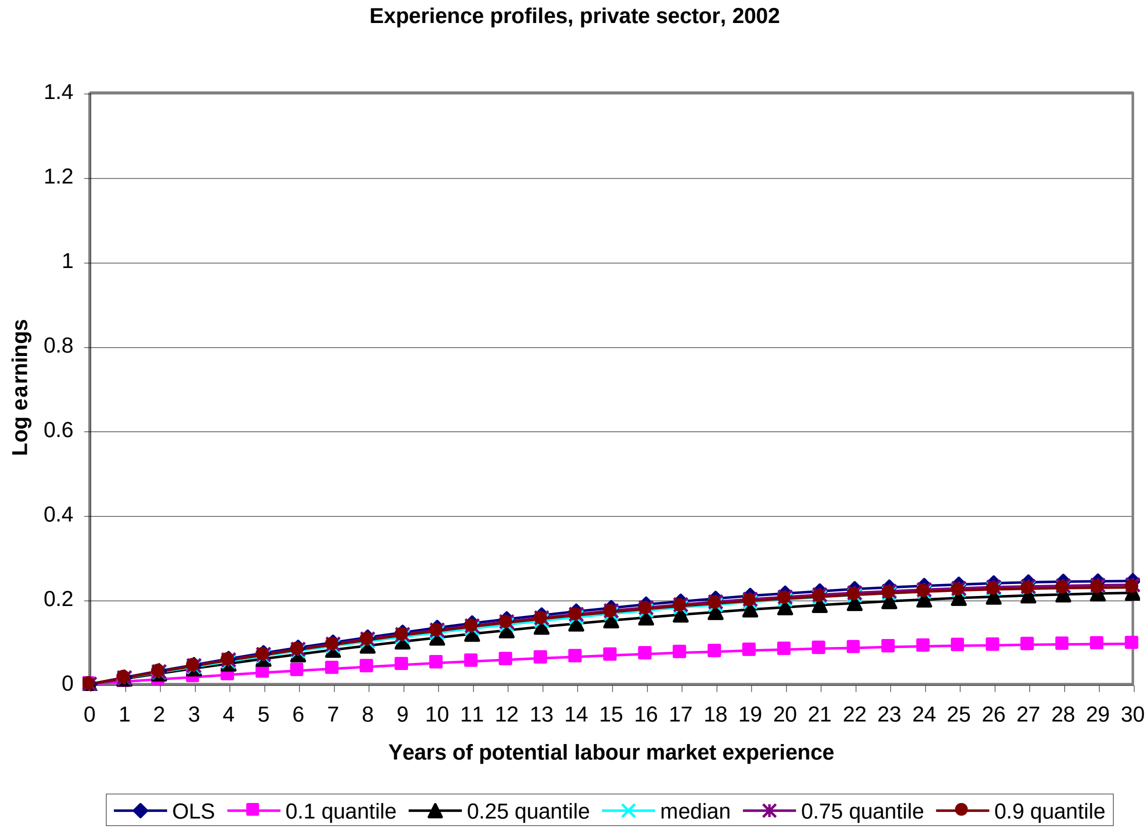


Figure 2.28 Experience profiles, private sector, 2003

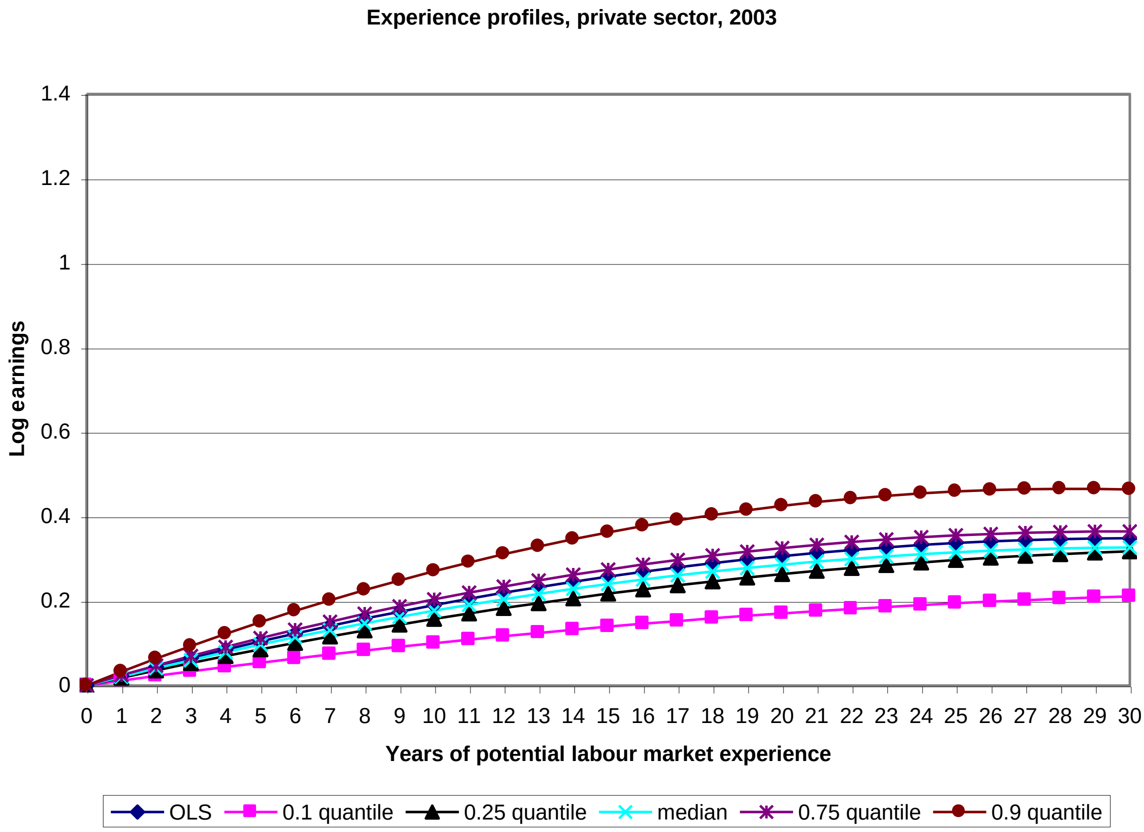


Figure 2.29 Experience profiles, public sector, 1994

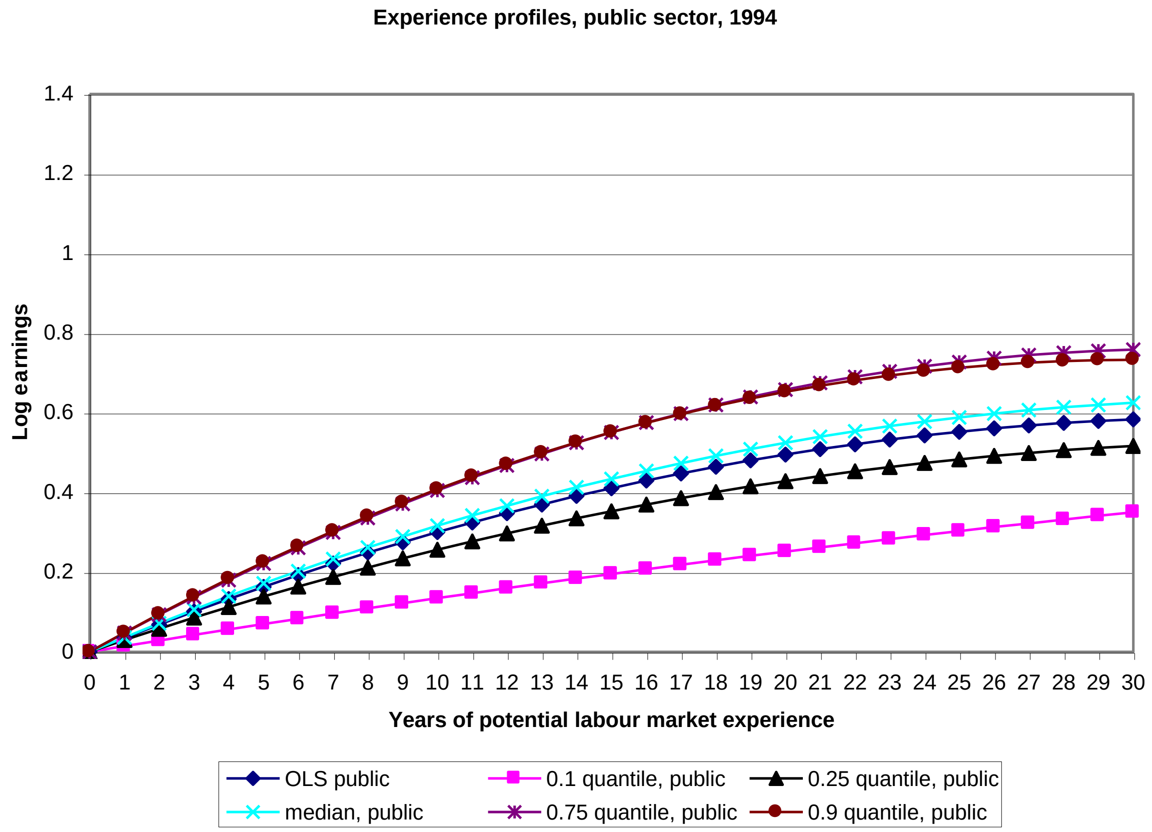


Figure 2.30 Experience profiles, public sector, 1995

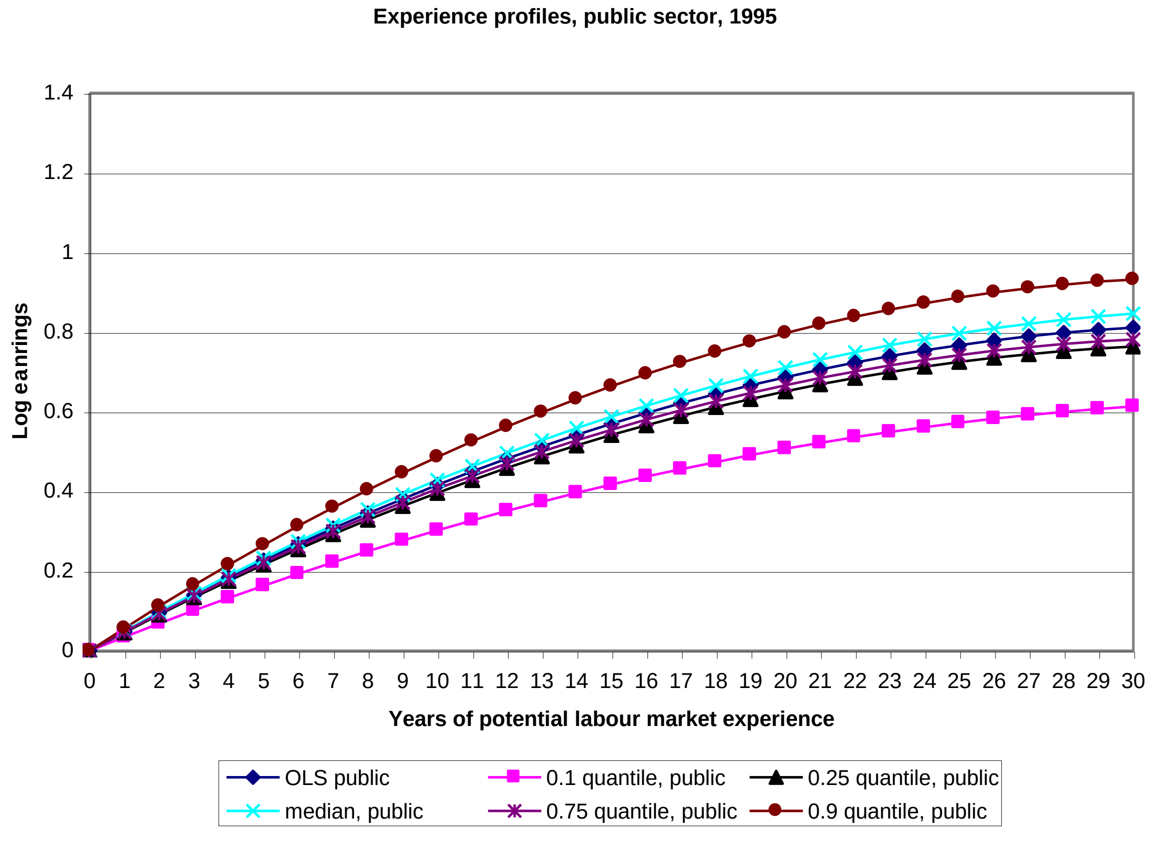


Figure 2.31 Experience profiles, public sector, 1996

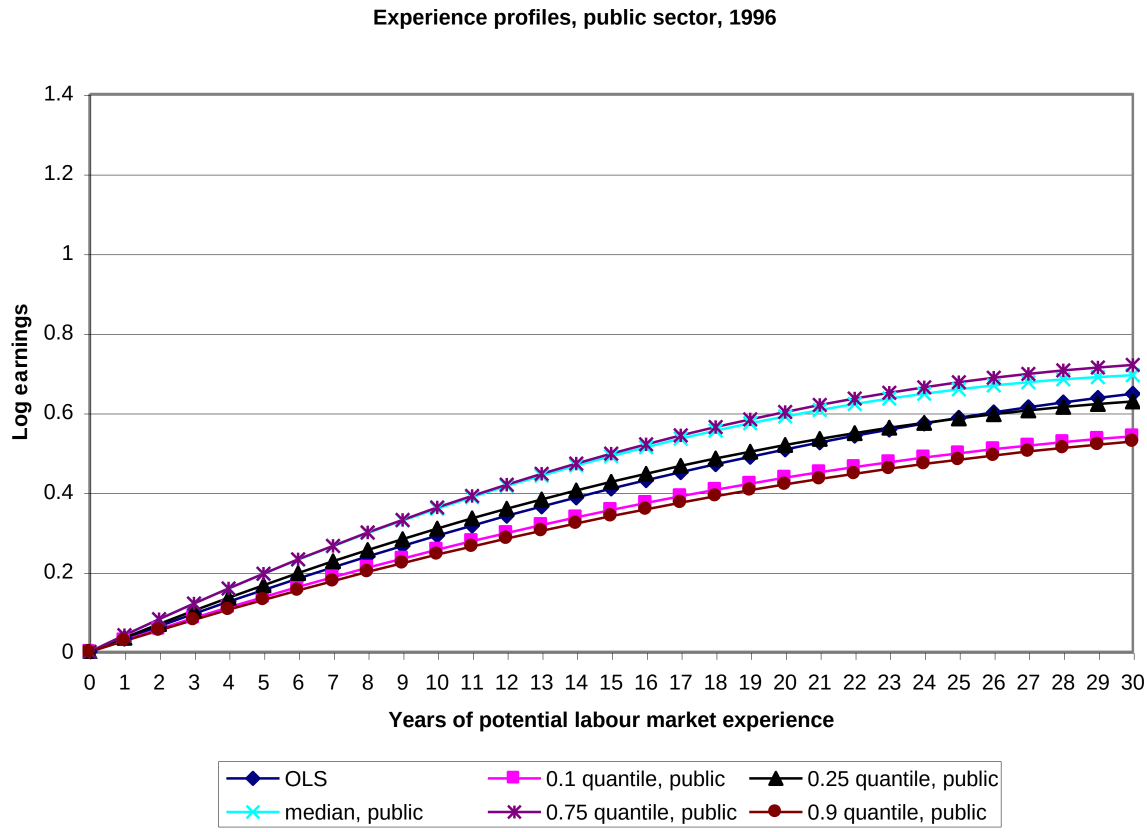


Figure 2.32 Experience profiles, public sector, 1997

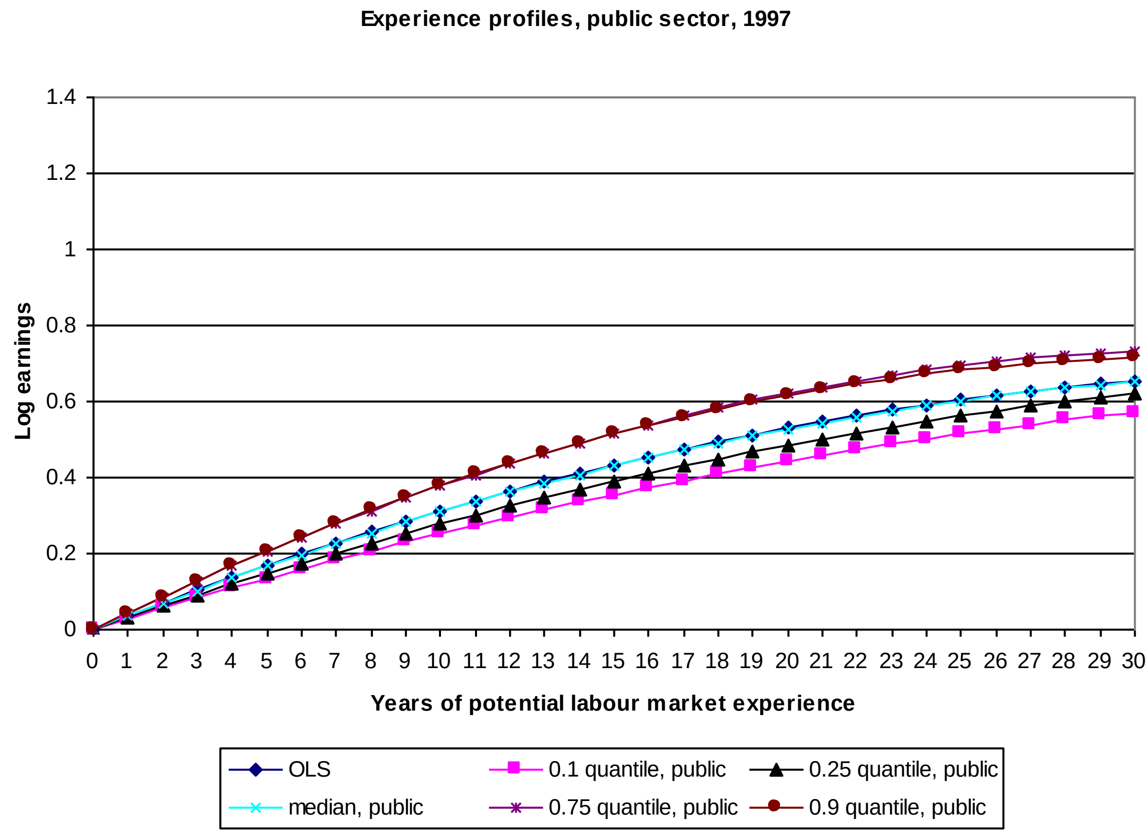


Figure 2.33 Experience profiles, public sector, 1998

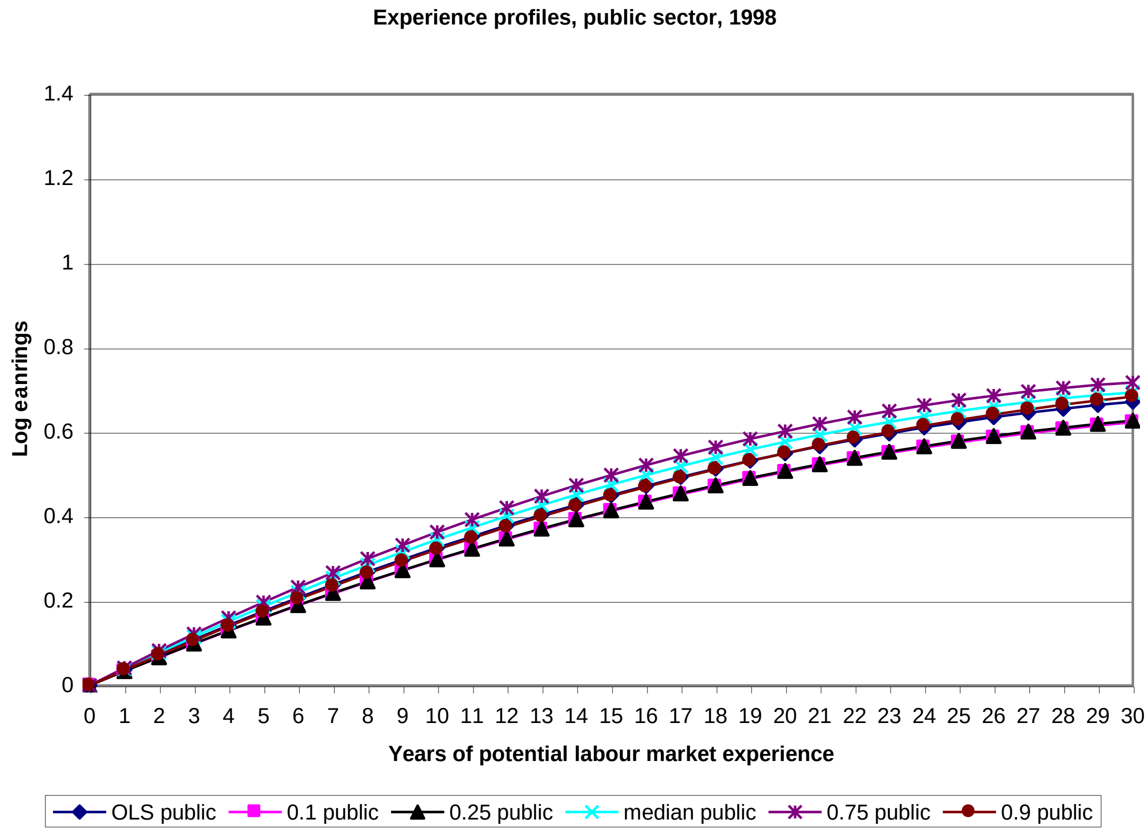


Figure 2.34 Experience profiles, public sector, 1999

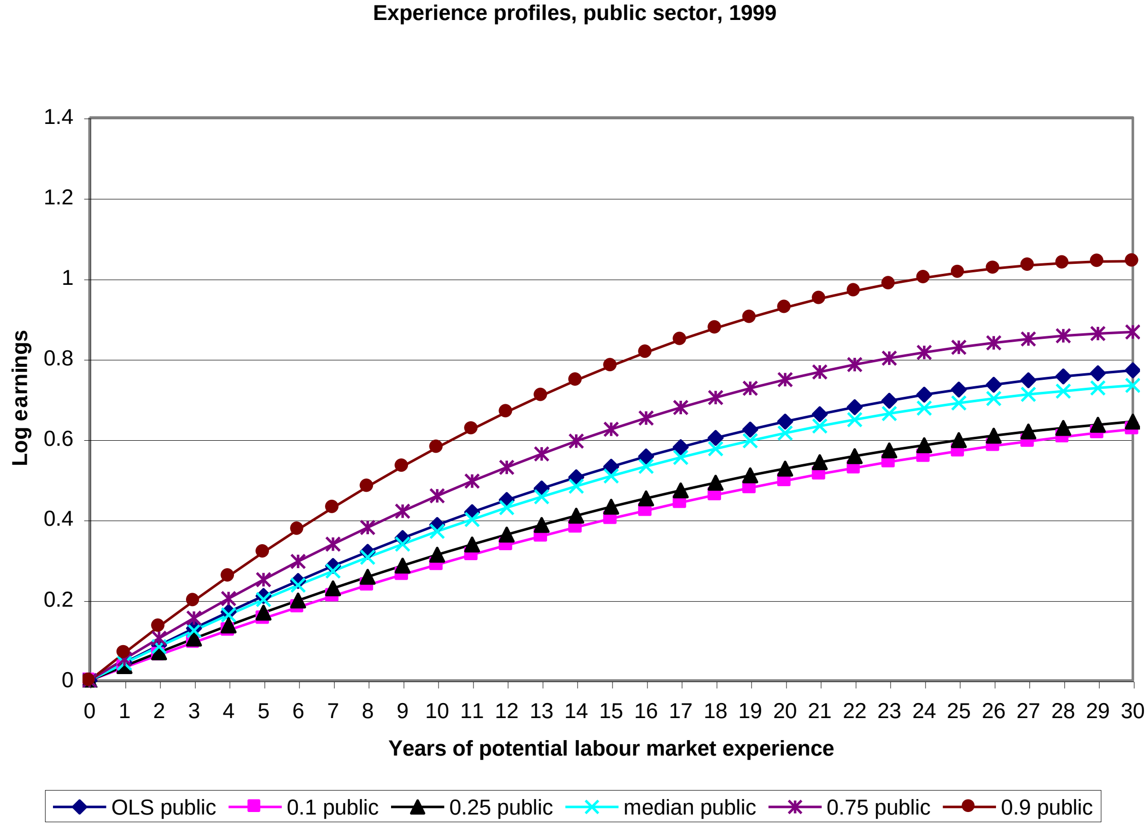


Figure 2.35 Experience profiles, public sector, 2000

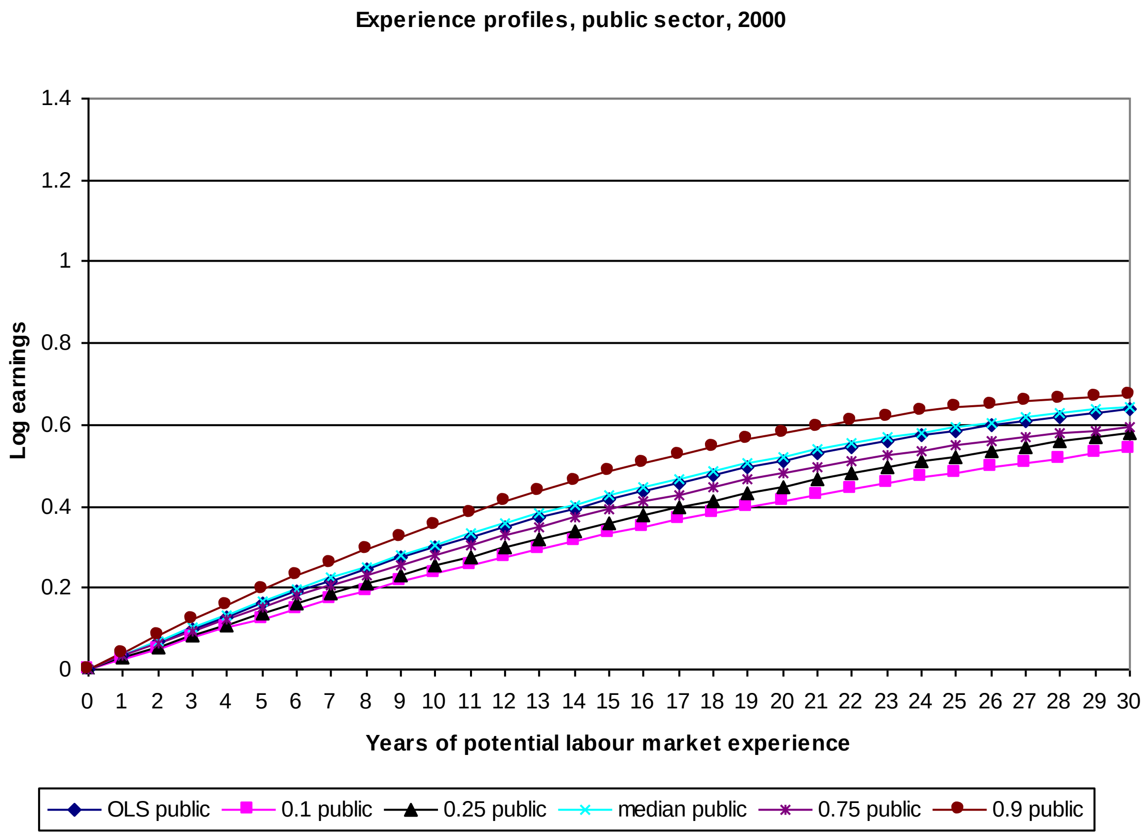


Figure 2.36 Experience profiles, public sector, 2001

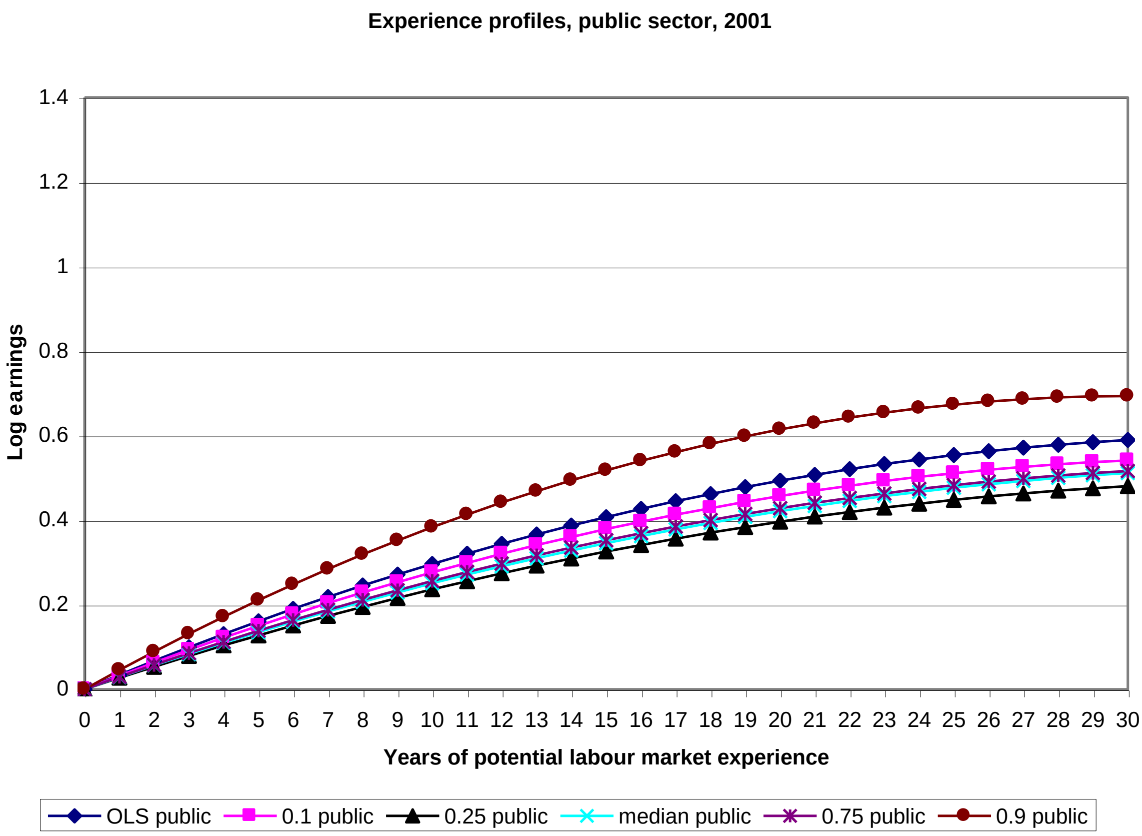


Figure 2.37 Experience profiles, public sector, 2002

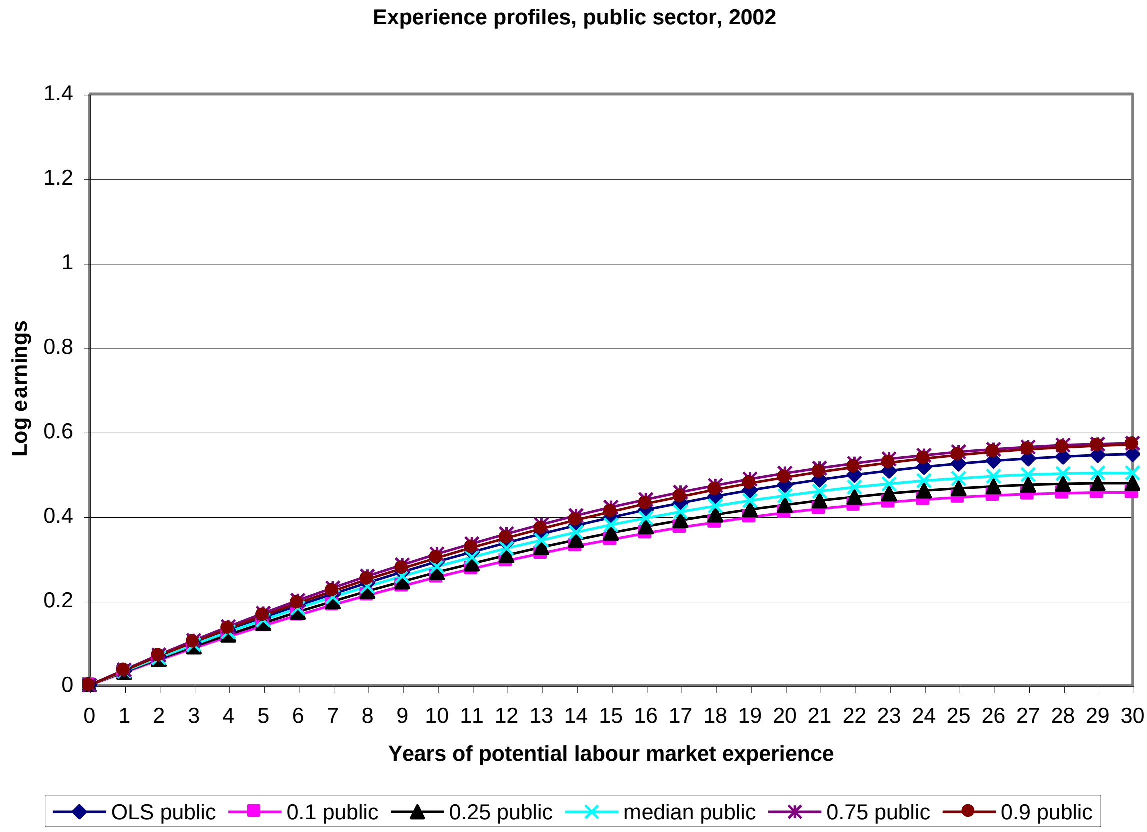


Figure 2.38 Experience profiles, public sector, 2003

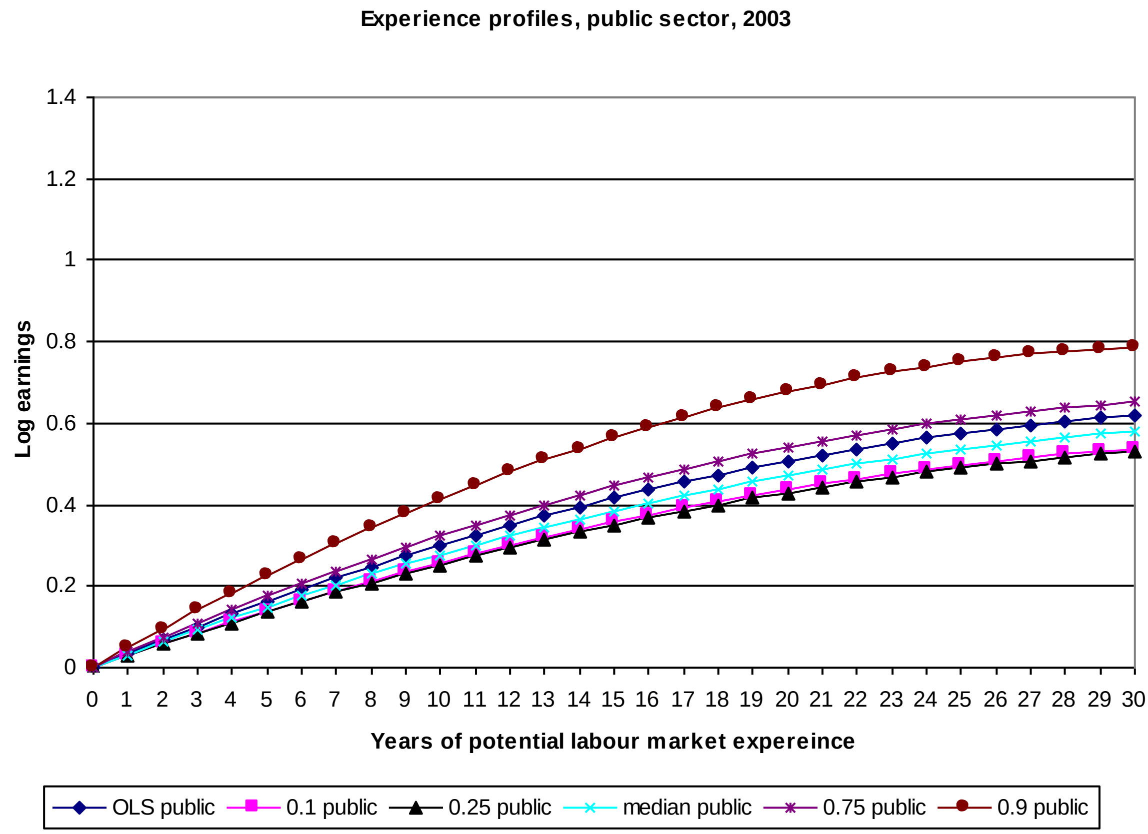


Figure 2.39 Experience profiles, private sector, 2003, Low-skilled

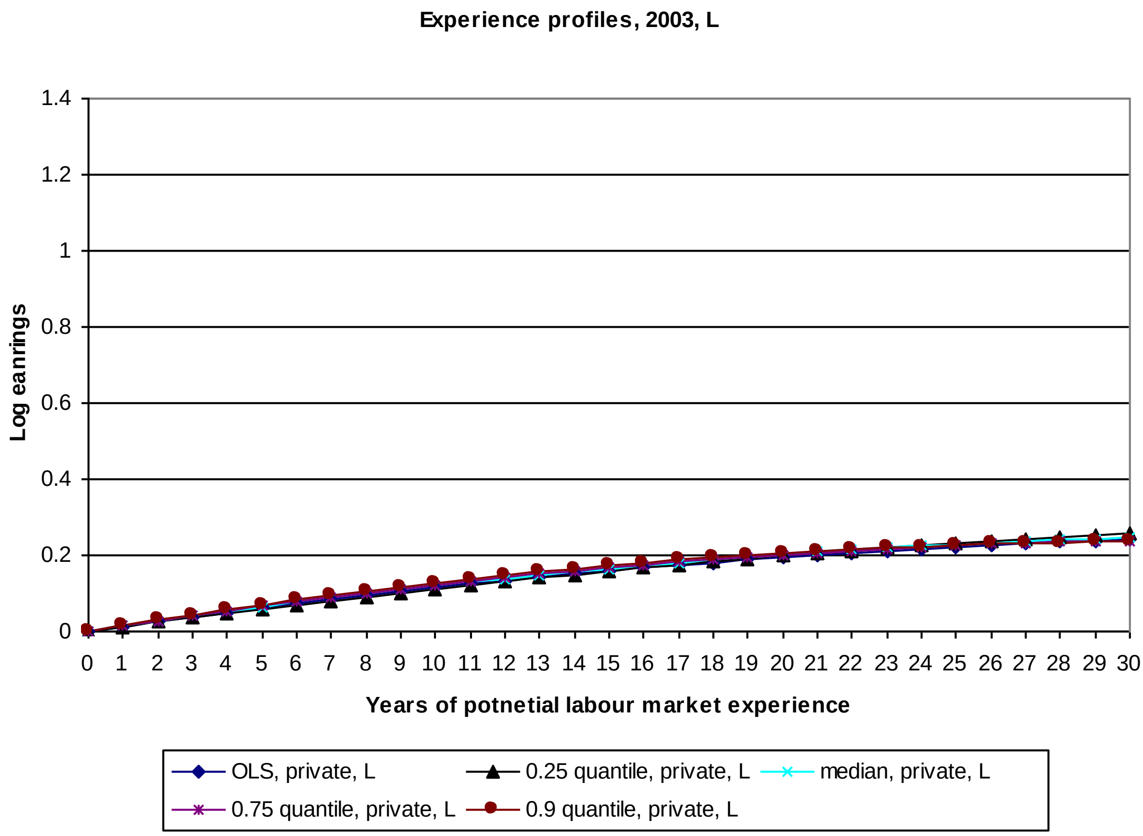


Figure 2.40 Experience profiles, private sector, 2003, Middle-skilled

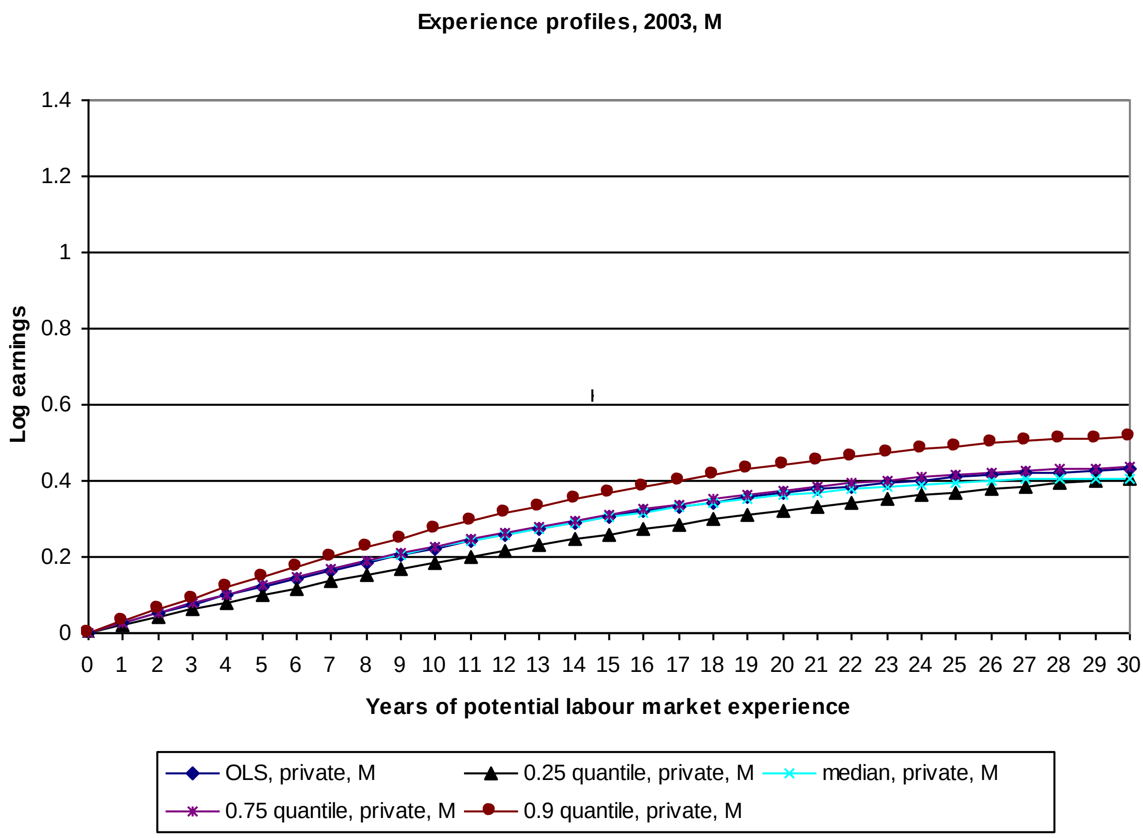


Figure 2.41 Experience profiles, public sector, 2003, High-skilled

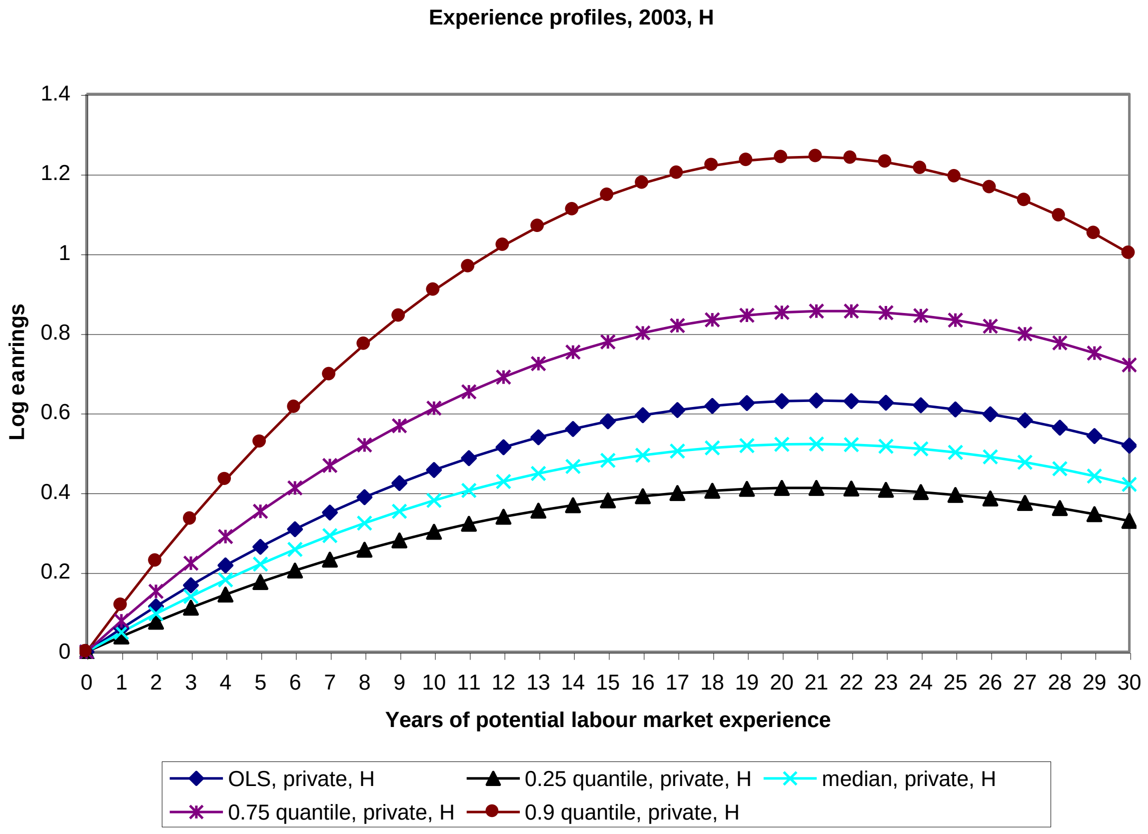


Figure 2.42 Experience profiles, private sector, 1994, High-skilled

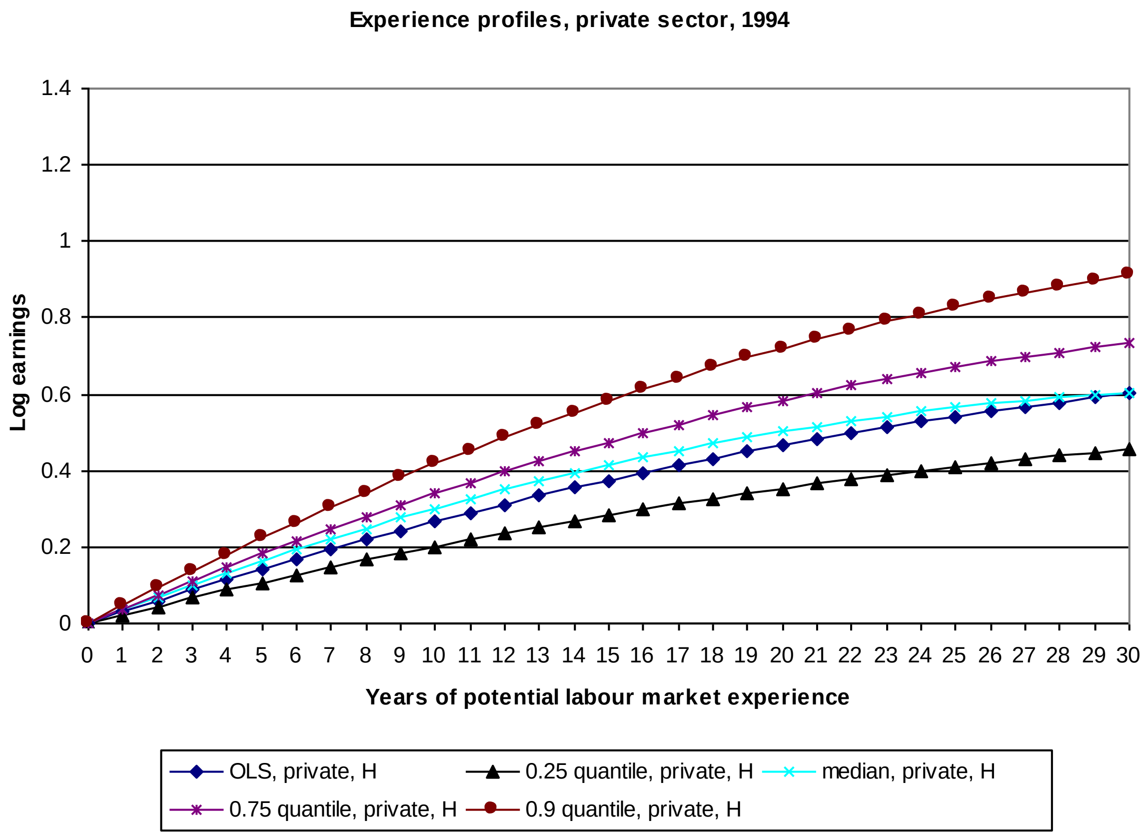


Figure 2.43 Experience profiles, private sector, 1995, High-skilled

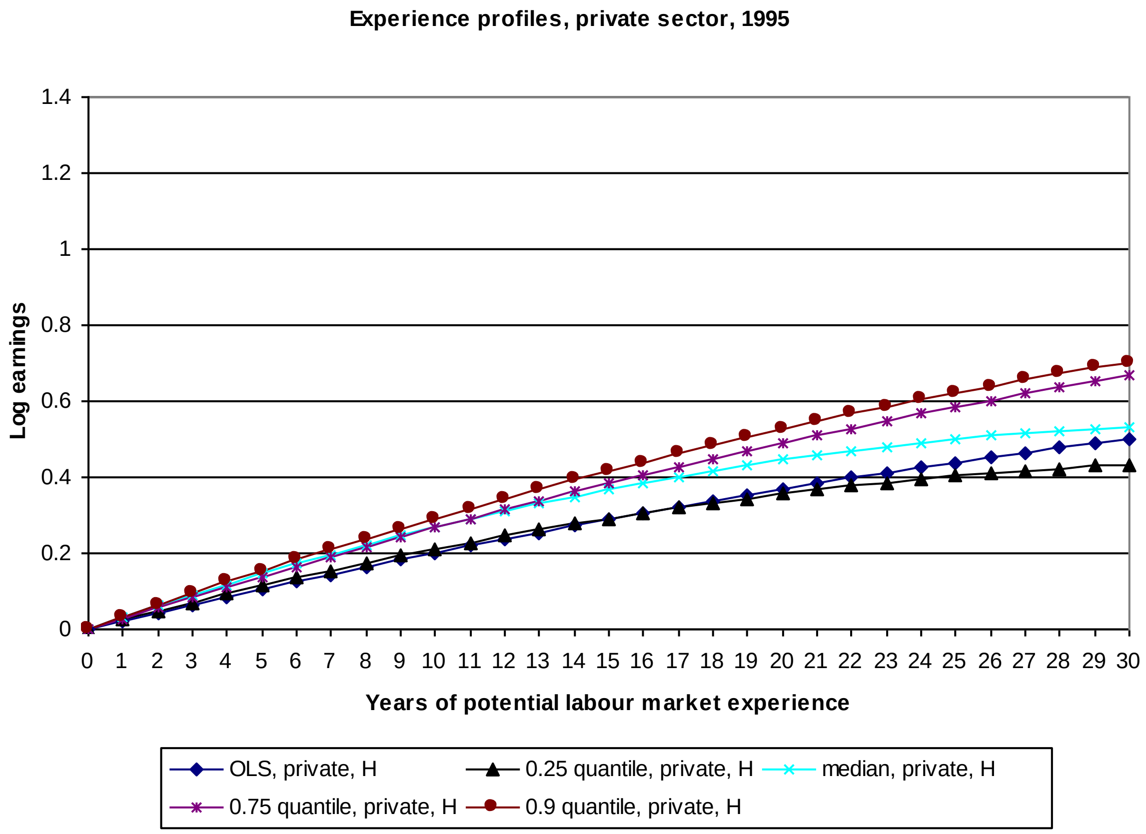


Figure 2.44 Experience profiles, private sector, 1996, High-skilled

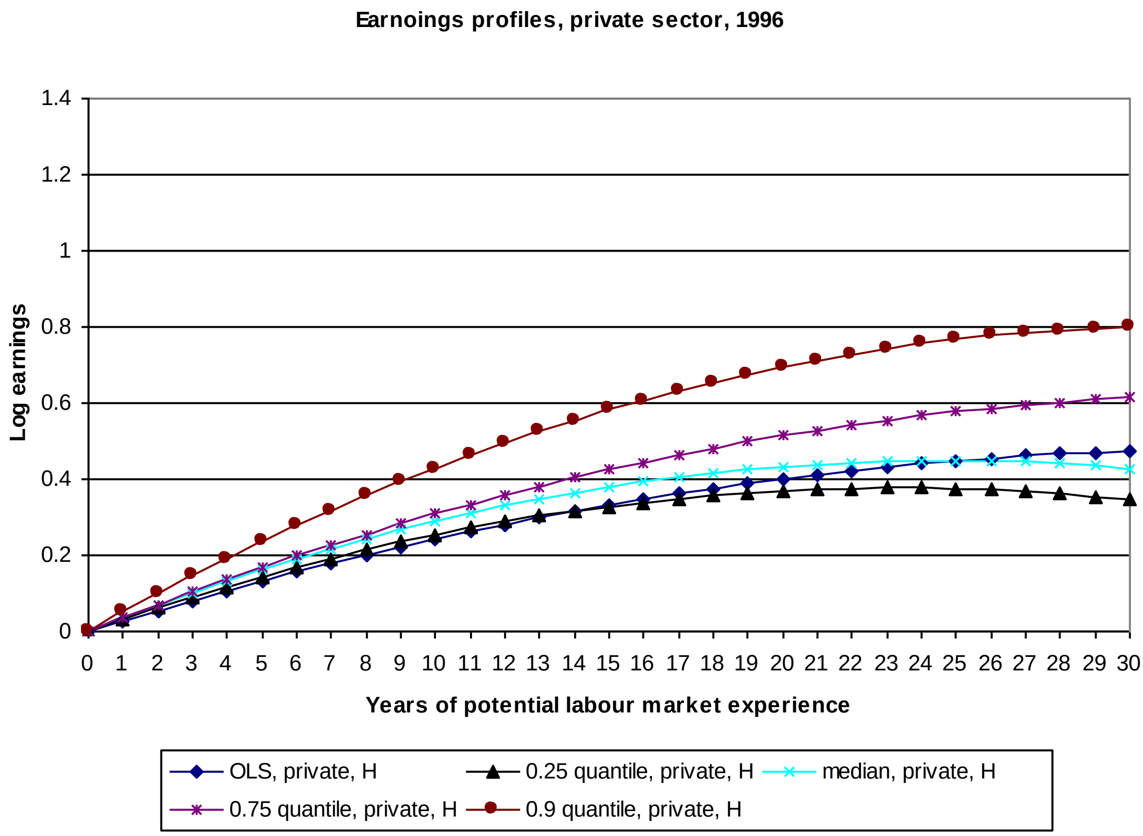


Figure 2.45 Experience profiles, private sector, 1997, High-skilled

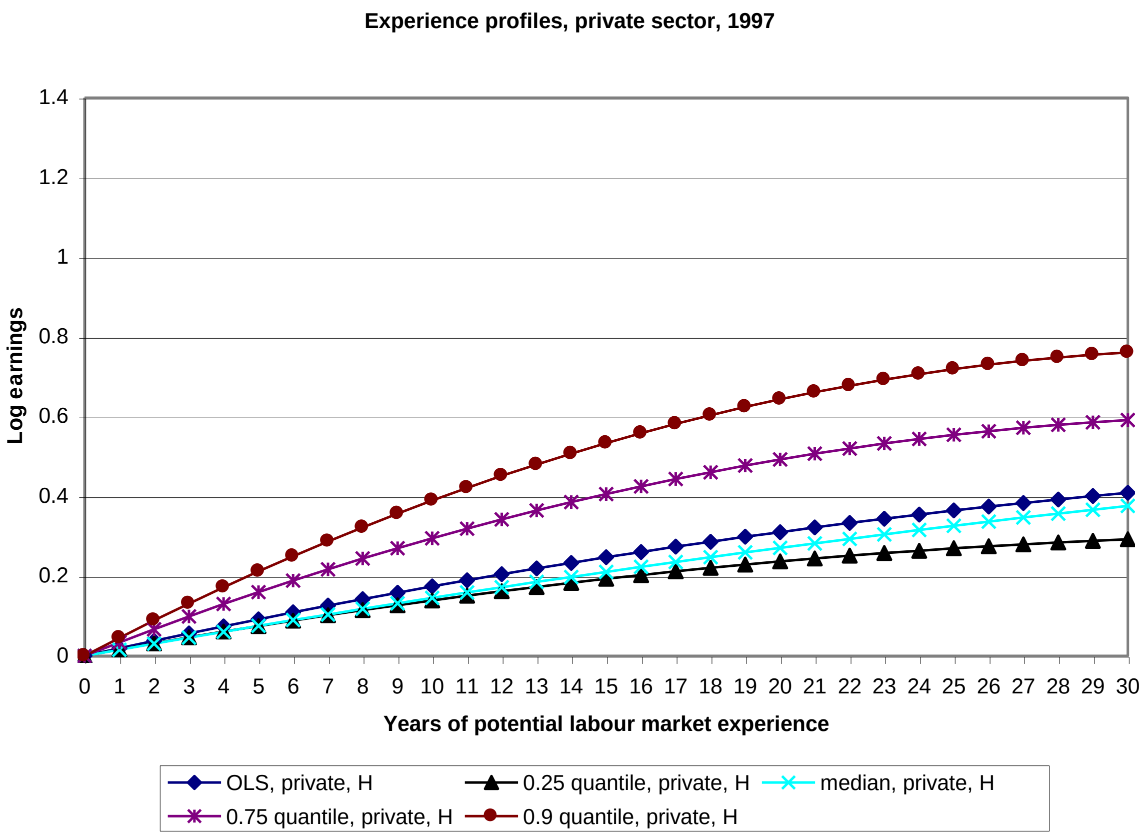


Figure 2.46 Experience profiles, private sector, 1998, High-skilled

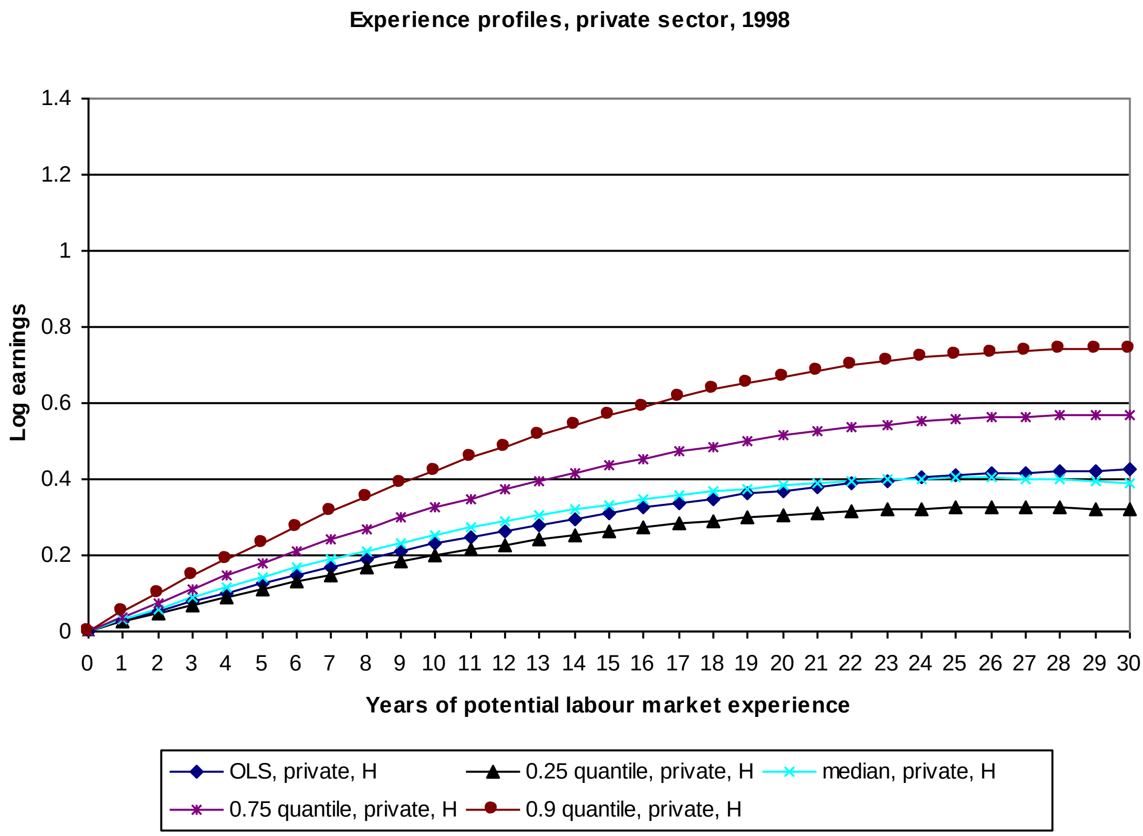


Figure 2.47 Experience profiles, private sector, 1999, High-skilled

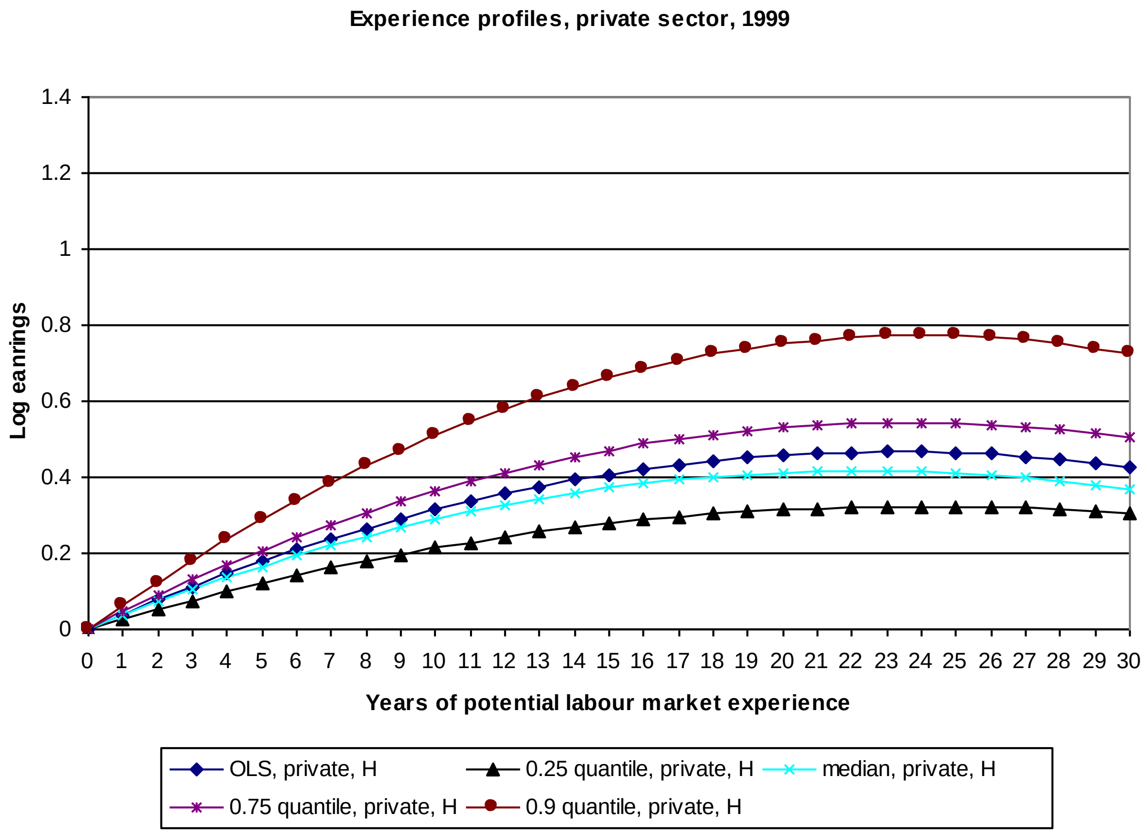


Figure 2.48 Experience profiles, private sector, 2000, High-skilled

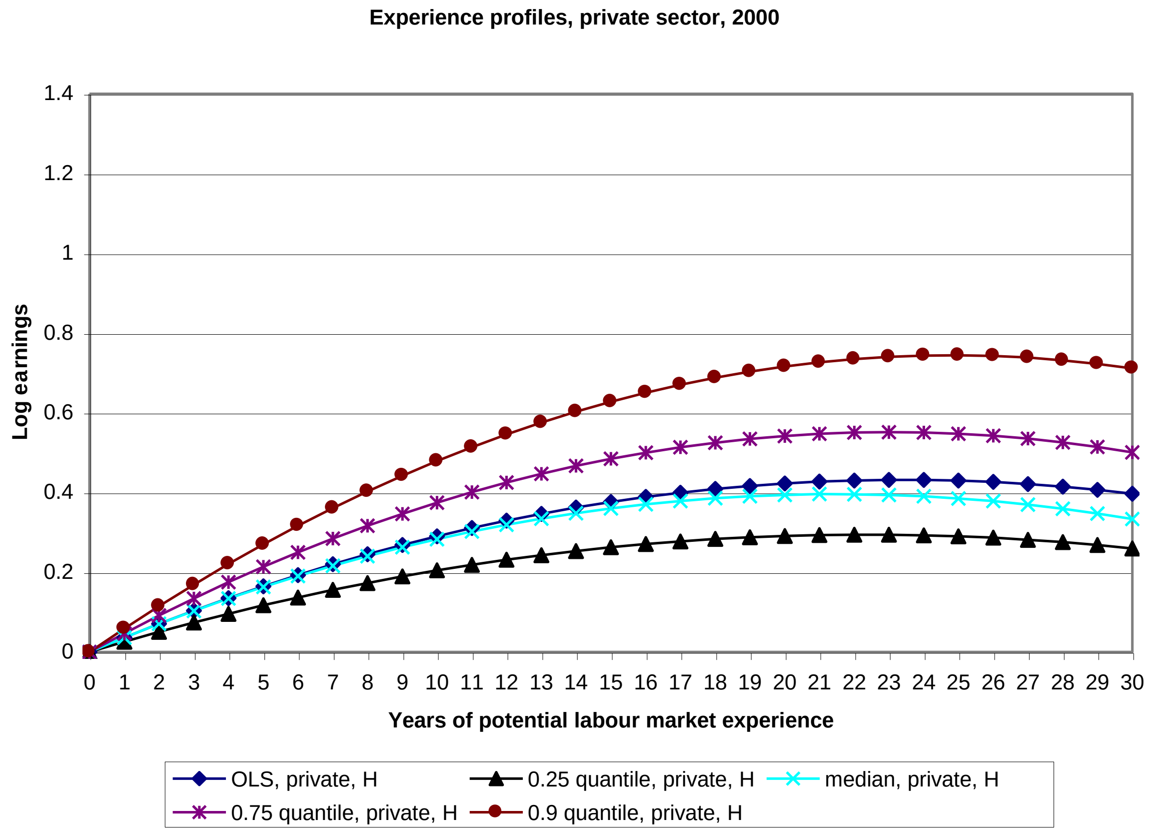


Figure 2.49 Experience profiles, private sector, 2001, High-skilled

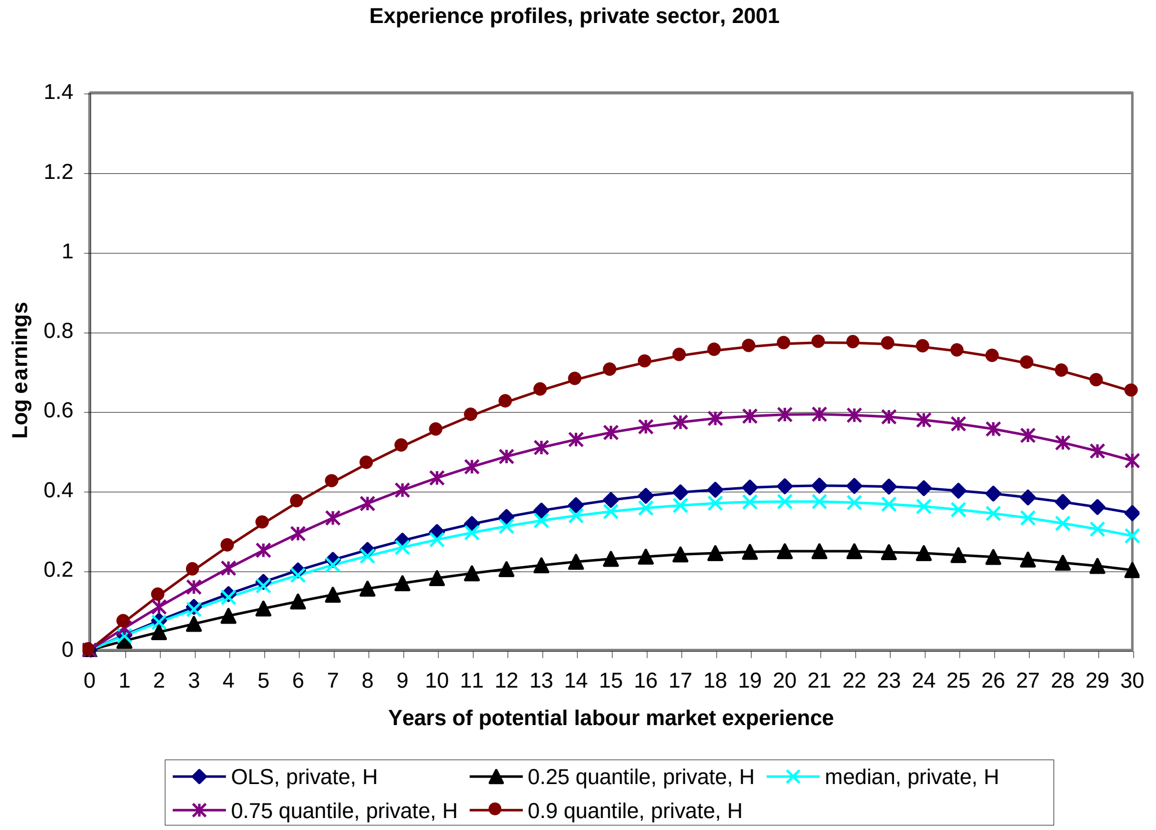


Figure 2.50 Experience profiles, private sector, 2002, High-skilled

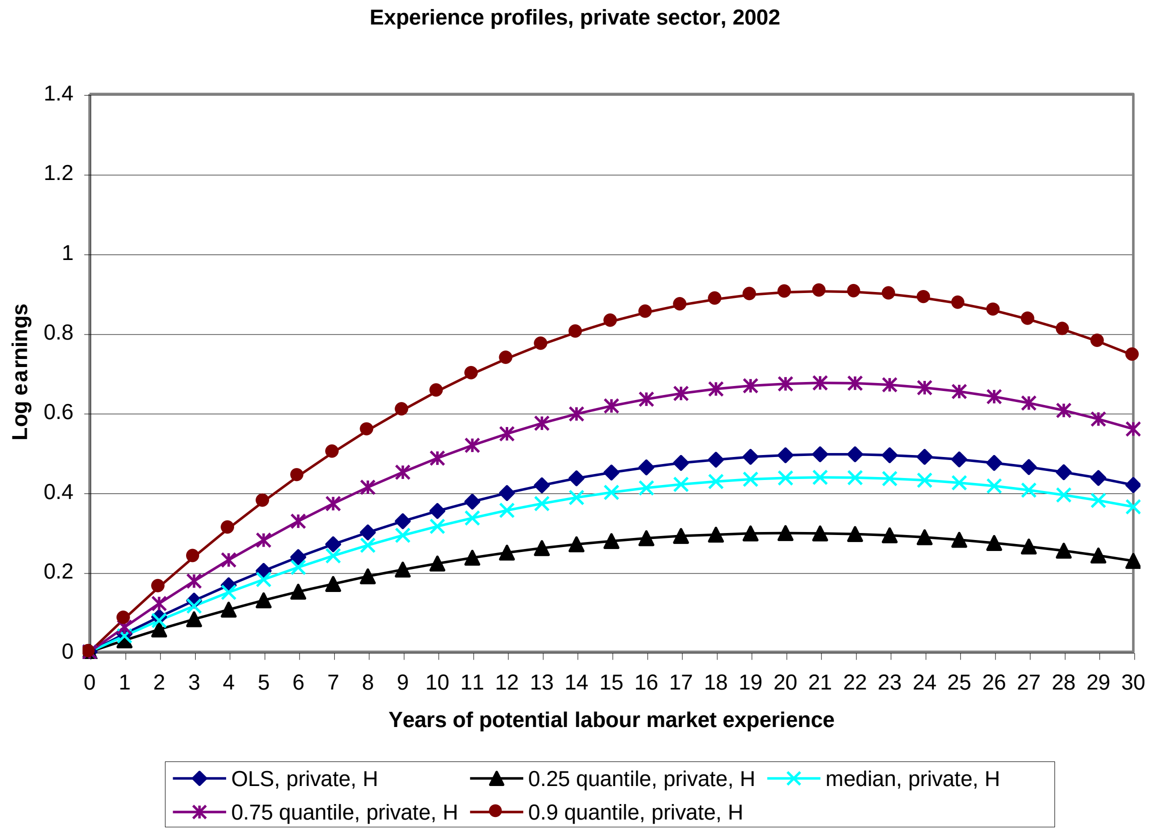


Figure 2.51 Experience profiles, public sector, 1994, High-skilled

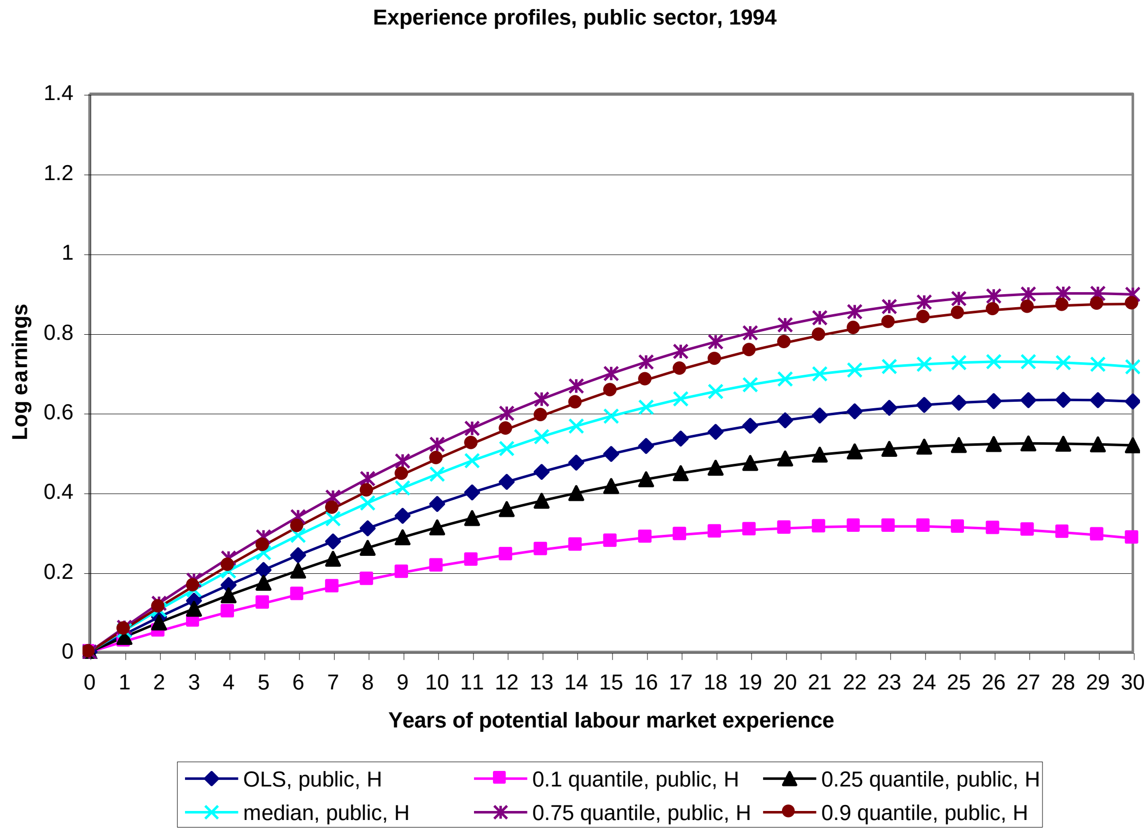


Figure 2.52 Experience profiles, public sector, 1995, High-skilled

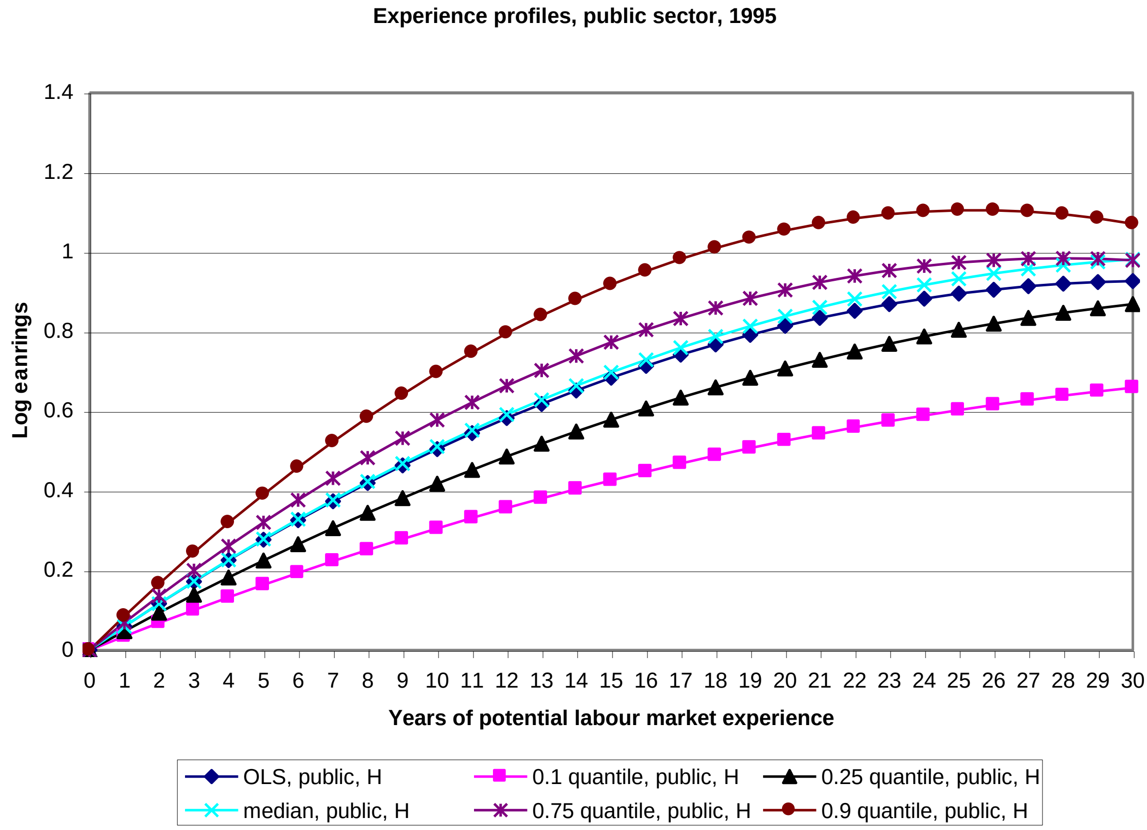


Figure 2.53 Experience profiles, public sector, 1996, High-skilled

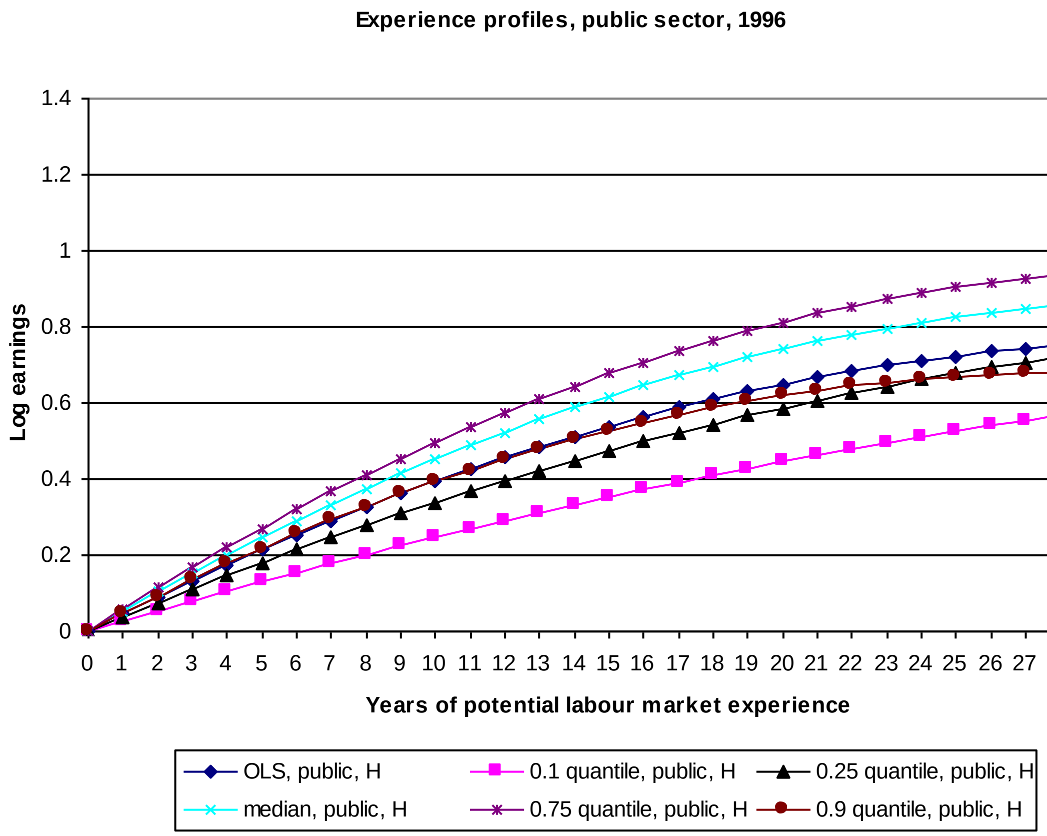


Figure 2.54 Experience profiles, public sector, 1997, High-skilled

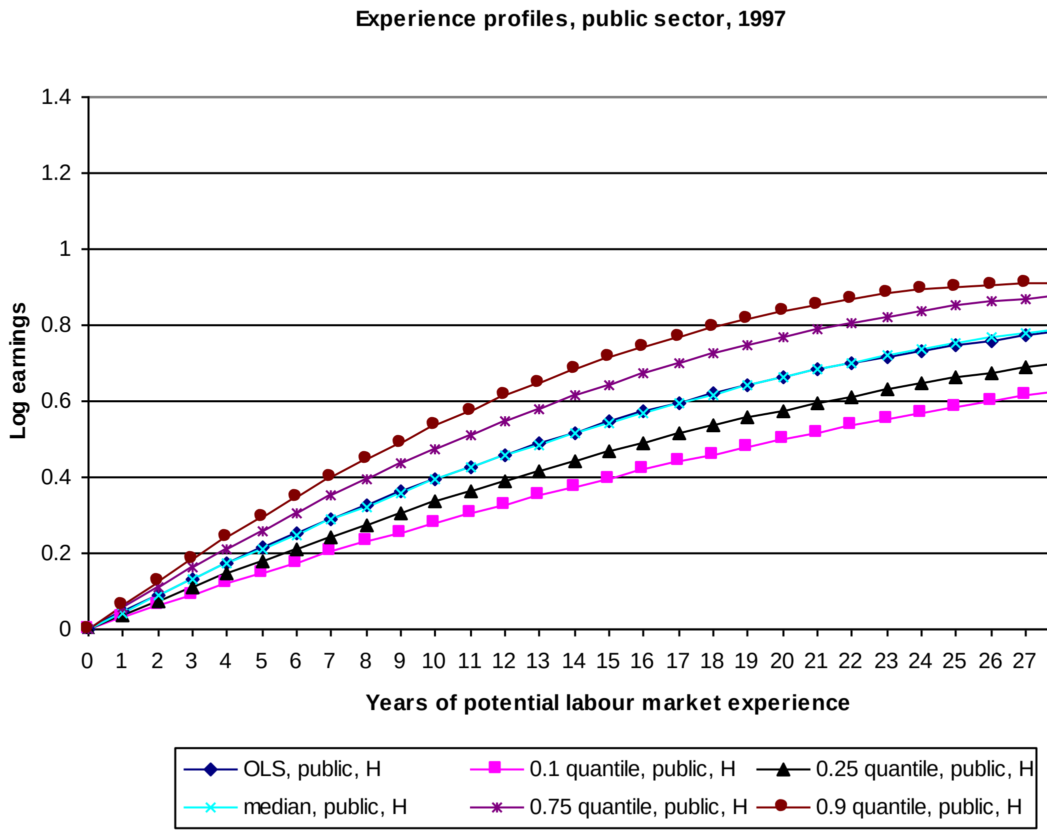


Figure 2.55 Experience profiles, public sector, 1998, High-skilled

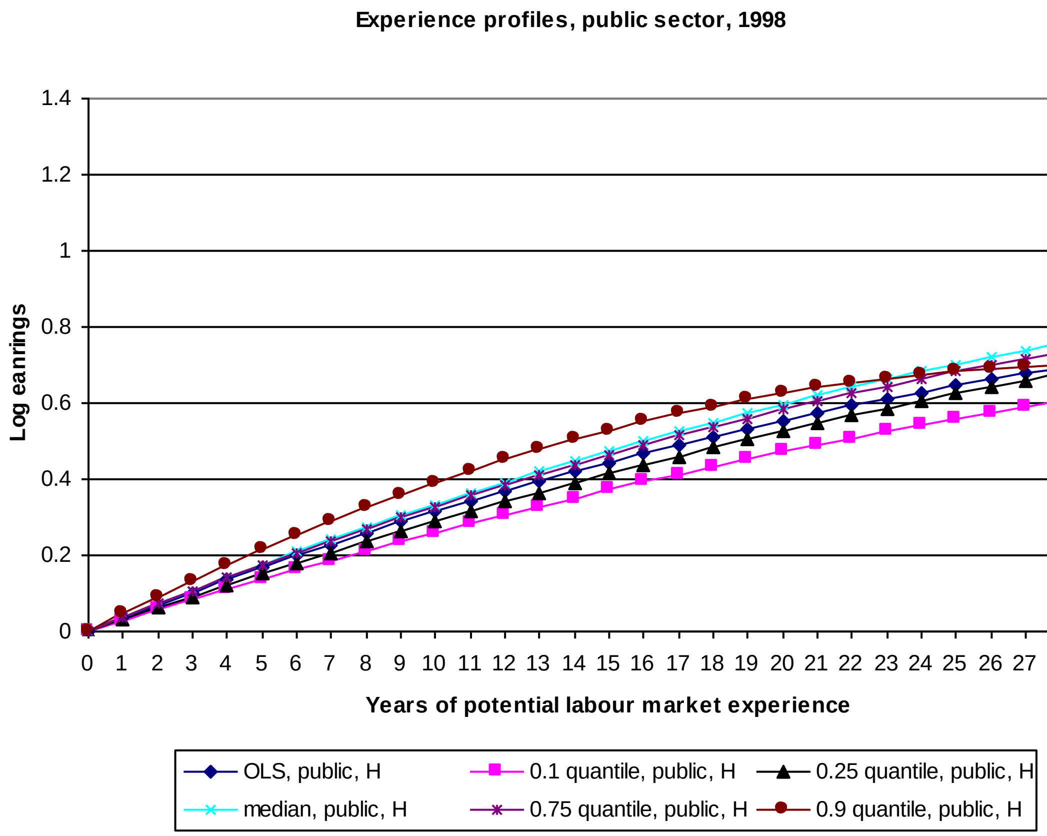


Figure 2.56 Experience profiles, public sector, 1999, High-skilled

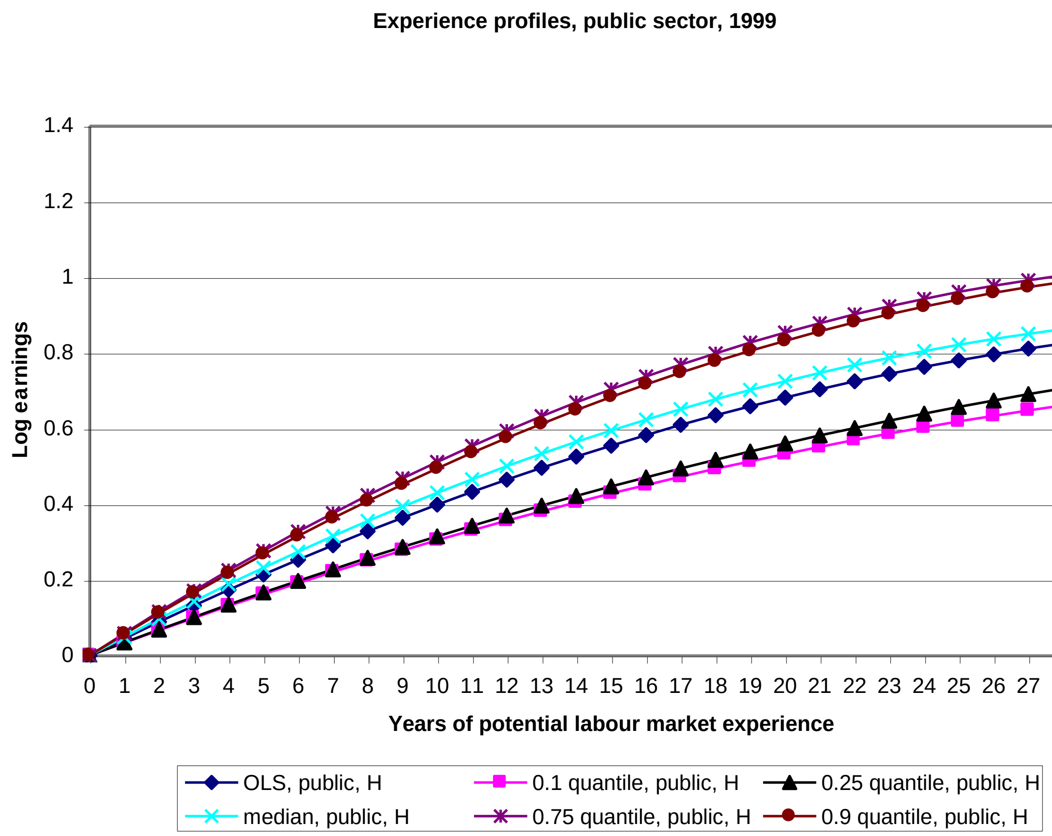


Figure 2.57 Experience profiles, public sector, 2000, High-skilled

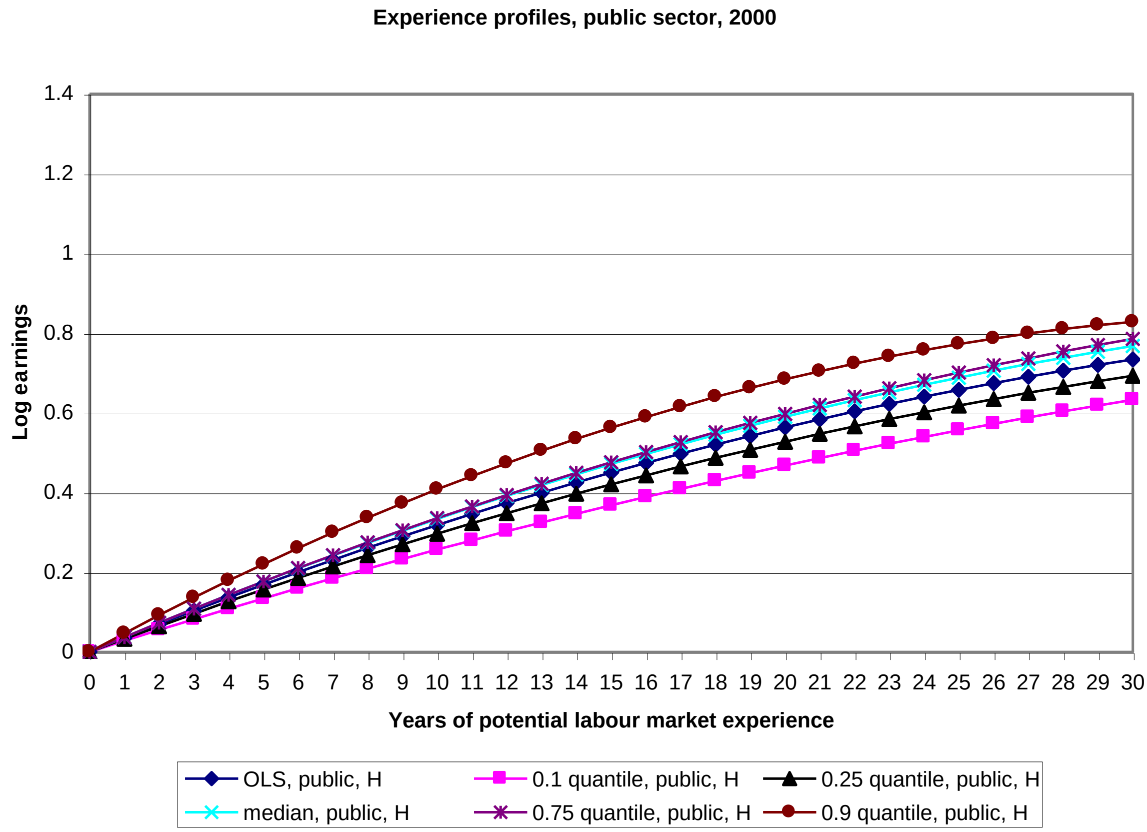


Figure 2.58 Experience profiles, public sector, 2001, High-skilled

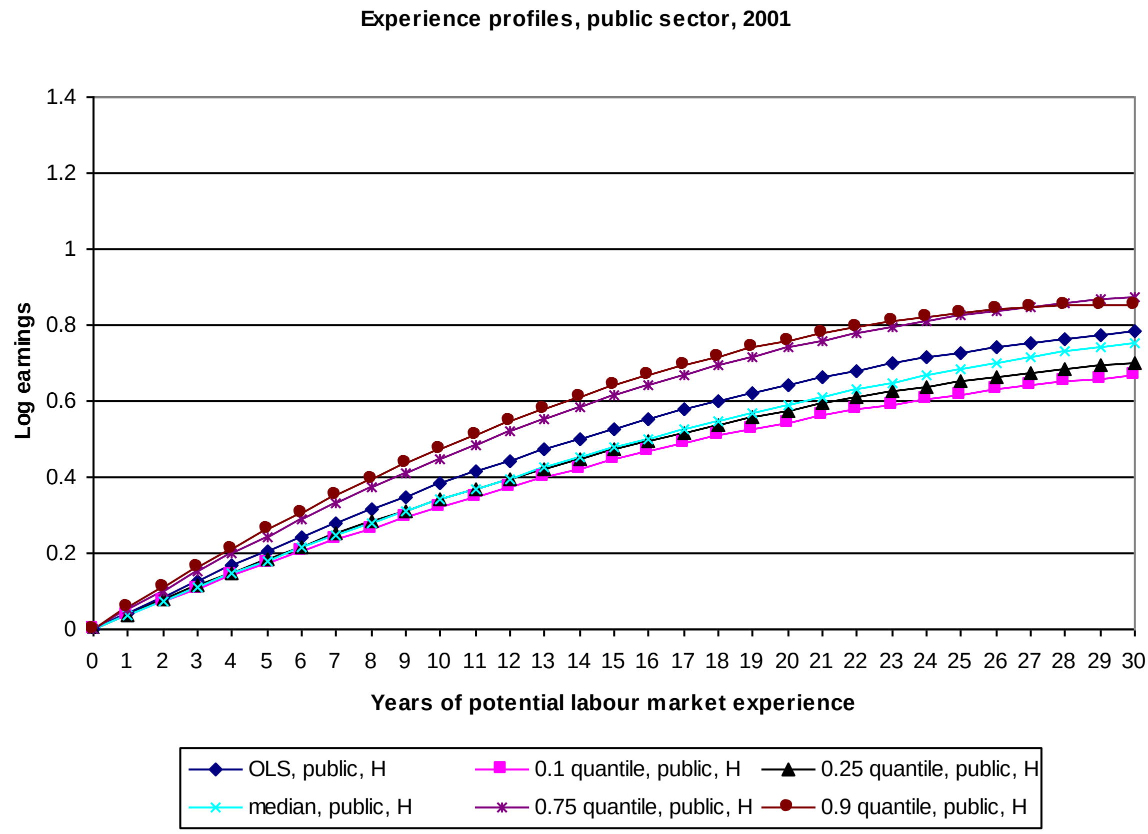


Figure 2.59 Experience profiles, public sector, 2002, High-skilled

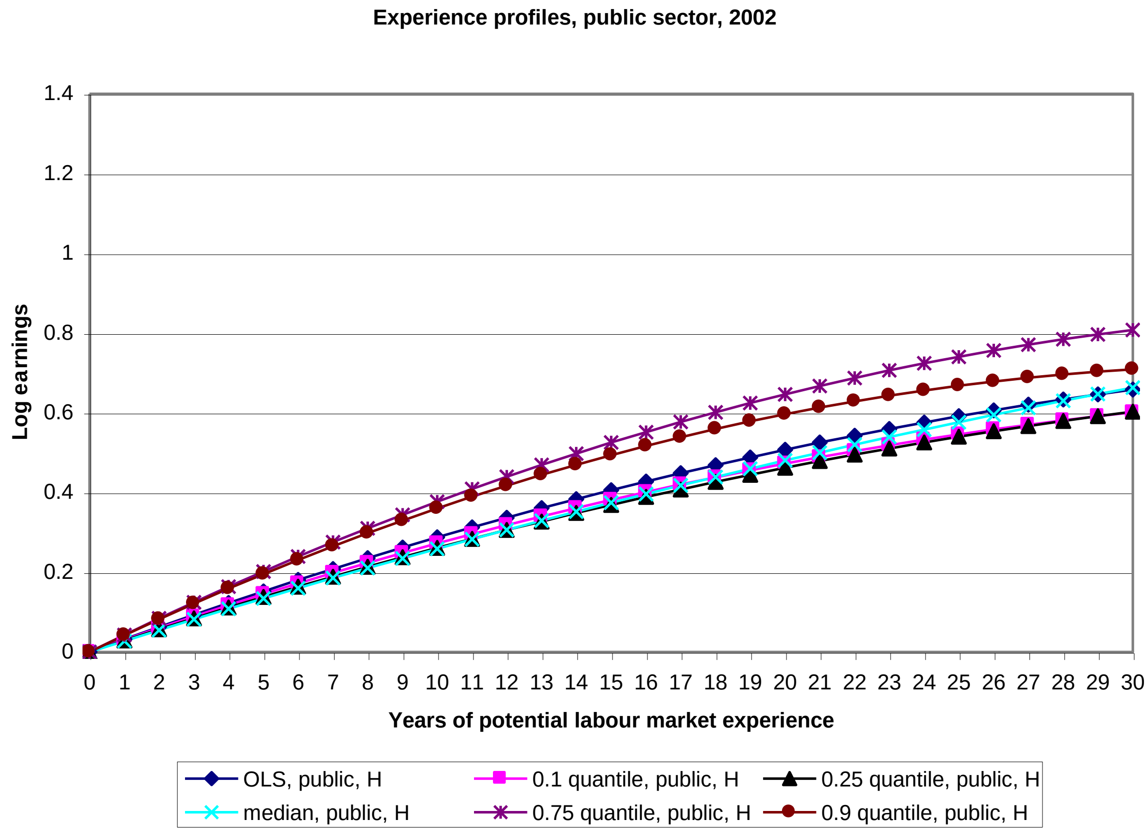
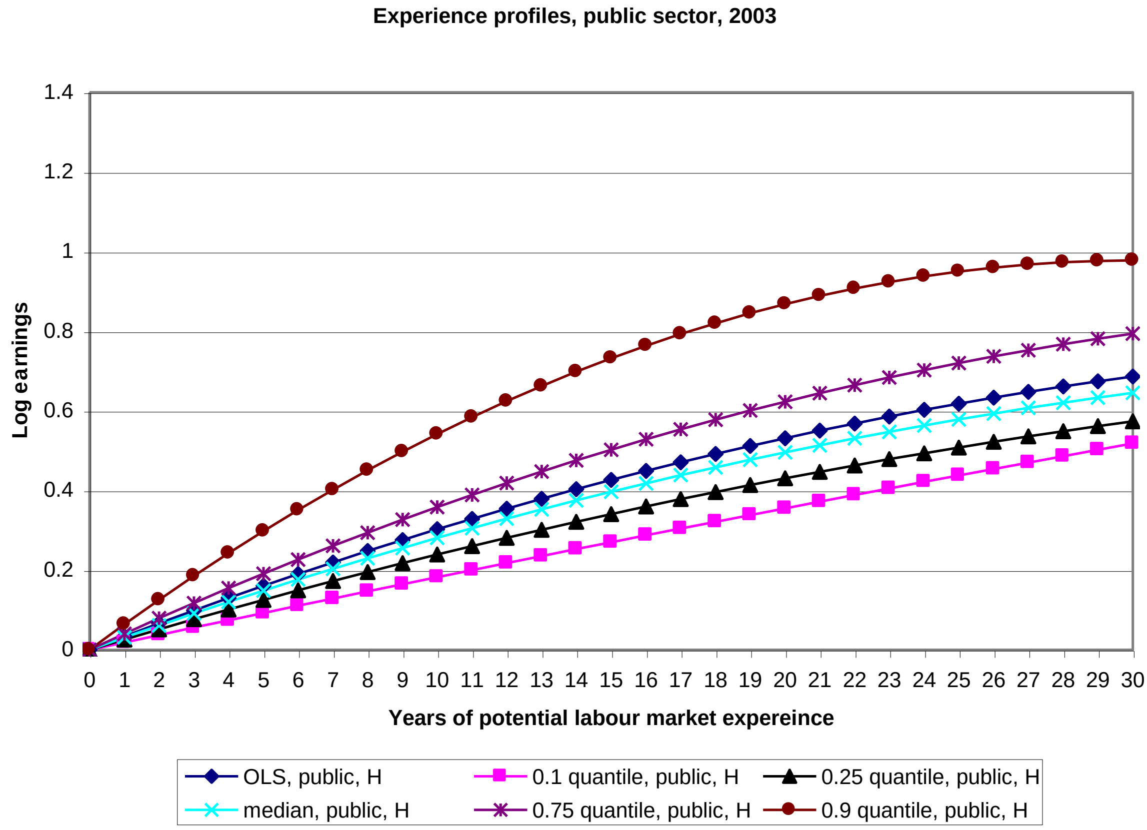


Figure 2.60 Experience profiles, public sector, 2003, High-skilled



3 The effect of school starting age on academic performance in Hungary

3.1 Introduction

Research in education provides mixed theories and evidence on the optimal age at which children should start school.[68] According to the proponents of late school starting age, starting school at an older age ensures that children have sufficient time to acquire the human capital necessary for educational success. In addition to the intellectual competencies of concentration and the ability to follow instructions, which children gain as they age, emotional aspects, such as being able to be apart from the parents, and social ones, such as being able to share with other children, play a significant role in success in school. Opponents of delayed school entry argue that (a) the advantage of late school entry may be modest and transitory (given that the school system is efficient in equalising early inequalities by promoting academic competencies accordingly) and (b) the emphasis should be placed on "making schools ready for children rather than making children ready for school"[69], in the sense that teaching and learning opportunities should be tailored to the intellectual, emotional and social skills of children. From an economic perspective, the potential academic gains of starting school later need to be weighted against (a) the additional childcare costs imposed on the parents in case of delayed school entry, (b) the extra economic loss in labour market (which entails monetary and productivity losses) if the mother only returns to work once the child has started school and, most importantly, (c) the economic loss associated with entering the labour market later, given that eventual schooling attainment and retirement age are unaffected.

There is an extensive recent empirical economic literature concentrating on the relationship between academic outcomes and school starting age.[70] The difficulty in estimating the effect of school starting age on academic performance arises from the fact that there is a choice regarding enrolment decision despite the cut-off date regulation. Given a certain degree of discretion regarding enrolment decisions, based on teacher's recommendation, boards of specialists giving school readiness tests assessing emotional and intellectual readiness and,

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[68] For an extensive review of the theories and findings in educationalist literature see Stipek (2002).

[69] Stipek (2002), p. 14.

[70] For evidence on the effect of school starting age on academic performance see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2007) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

most importantly, parental choice, the group of students with early / delayed entry does not represent a non-random sample. That is, whereas early entrants may well be higher ability children and children of ambitious parents who want an early start (regardless of the child's ability), the late starters come from the pool of lower ability children and potentially from wealthier families (for whom the burden of additional childcare costs may be irrelevant). Given this non-random selection, late starters may be, on average, lower ability children. Subsequently, regressing academic performance on actual school starting age by ordinary least squares (OLS) may generate a downward biased estimate of the age effect on academic performance.

In order to overcome the problem of non-random selection in countries where the cut-off date regulation for enrolment is not exogenous, the empirical literature has concentrated on instrumental variable estimation (IV), that is, finding a valid instrument for actual school starting age which is (1) correlated with actual school starting age and (2) uncorrelated with the unobserved determinants of academic performance i.e. ability. Numerous studies have hence exploited the exogenous variation in school starting age driven by (1) the cut-off date for enrolment and (2) the children's month of birth, which generates the "expected school starting age".[71] Accordingly, the empirical strategy is to use the "expected school starting age" as an instrument for "actual school starting age". It is important to note that the IV approach identifies the local average treatment effect (LATE), that is, the average causal effect of school starting age on academic performance for the group of "compliers", who are defined as those individuals whose school entry age is affected by the instrument used (introduced by Imbens and Angrist (1994)). At this point is important to clarify that the group of "LATE-compliers" is not equivalent to the group of students who enrol on time. The latter group, using the definitions of Angrist et al. (1996), is composed of the "LATE-compilers" as well as "always-takers" who are unaffected by the particular instrumental variable, that is, those who always enrol on time regardless of the value of the instrument to which they might be exposed.[72] Subsequently, throughout the study the group of "LATE-compliers" /

[71] For empirical evidence using IV estimation in order to estimate the causal effect of school starting age on academic performance see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2007) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

[72] Note that Angrist et al. (1996) in the LATE framework differentiates between three important groups: (a) the *compliers*, who comply with the assignment mechanism of the instrument, and two other groups who are not affected by the instrument, namely, (b) the *never-takers*, who in this particular setting never enrol on time regardless of the value of the instrument to which they might be exposed, and (c) the *always-takers*, who always enrol on time regardless of the value of the instrument to which they might be exposed.

”compliers” and those “enrolling on time” / ”complying with the cut-off date regulation” will not refer to the same student population.

The studies using the IV estimation strategy described above analyse the effect of school starting age on academic performance in various countries, using different age groups (for example, second, fourth and eighth graders), different subsamples (such as minority students or students with lower educated parents) and different outcomes of interest, ranging from which track a student chooses (for example, academic versus vocational) to test scores in different subjects. A number of studies, namely, Leuven et al. (2004) for the Netherlands (for some subsamples of students), Strøm (2004) for Norway, Frederikkson and Öckert (2005) for Sweden, Puhani and Weber (for full samples of students and some subsamples) (2007) for Germany and Bedard and Dhuey (2005) for a number of OECD countries find evidence that (1) the OLS estimate of the association between age and schooling outcomes is negative, attributing this to the non-random selection of early / late starters and (2) the IV regression, described above, yields a positive LATE estimate, which differs in magnitude across countries. An exception is the study by Fertig and Kluve (2005) who provide evidence that there is no effect of age at school entry on educational outcomes in Germany.

The aim of this chapter is to estimate the effect of school starting age on academic performance in Hungary – a country for which, despite the vast recent international evidence, to the best of my knowledge, such analysis has not been carried out to this date. It is important to extend the international evidence because, as outlined above, the effect of age on schooling performance is not clear from the outset, and the cross-country differences may be caused by, among other factors, the different educational structures, which may equalise opportunities among students to different degrees.

In Hungary, the school starting age regulation requires children who turn six years old by the 31st of May to start school on the 1st of September in the corresponding year.[73] Children born after that date need to wait an additional year in order to enrol. In Hungary, as in some other countries such as Germany and the US, the school cut-off date regulation is not exogenous, given that there is teacher, specialist and parental discretion regarding the school starting age.

[73] Note that the cut-off date for enrolment prior to 1986 was August 31st rather than May 31st. All the samples under analysis have started school according the May cut-off date regulation, hence the change in regulation does not cause a problem for the purposes of this study. See Vágó (2005) for further detail on the cut-off date regulation in Hungary.

For example, for the samples under analysis, children who are born in the summer months may start school at the age of six instead of waiting another year, and those who are born just before the cut-off date may wait another year to enrol instead of starting at the age of six. Given the degree of discretion regarding enrolment, i.e. non-random selection of early / delayed school starters in Hungary, an OLS regression of academic achievement on school starting age may yield a downward biased estimate of the (mean) age effect, as described above.

Therefore, in addition to the standard OLS regressions, the study uses an extension to the IV strategy of the existing literature, using “expected school starting age” as an instrument for “actual school starting age”, namely, the control function approach, proposed by Garen (1984) and Heckman and Robb (1985). The advantage of the control function approach over the IV estimation strategy is that in addition to the bias due to non-random selection of early / late entrants outlined above, it also accounts for the individual heterogeneity in the age effect. Whereas the IV-LATE estimate captures the average causal effect for the group of “compliers”, as defined above, which may not be representative of the entire population, the control function approach estimates the average treatment effect (ATE), which reflects the age effect on academic performance for a random individual.

The data for the analysis is drawn from the 2001 “Progress in International Reading and Literacy Study (PIRLS)” and the 2003 “Trends in Mathematics and Science Study (TIMSS)” at the grade four level. Therefore, the effect of age on different areas of schooling performance, namely, Reading, Mathematics and Science is analysed. Although the key parameter of interest of the study is the effect of age on test scores, the effect of numerous other determinants of academic performance, such as gender, family size, parental education, home possessions (depending on the availability of data) are analysed.

The OLS results suggest that the relationship between the actual school starting age and Reading, Mathematics and Science test scores at the fourth grade level is negative, for the samples as a whole as well as for the subsamples split by gender and parental education. This negative association, as discussed above, cannot be interpreted as the causal effect of age on academic performance. The ATE estimates of the age effect of the control function approach exceed the corresponding OLS estimates for the samples as a whole as well as for the subsamples split by gender and parental education. The other explanatory variables, namely, gender, parental education, family size, and proxies for economic wealth play a significant role in academic performance, their effects are as expected and are robust across subjects and subsamples of students. For instance, the gender achievement gap is in favour of girls for Reading and in favour of boys for Mathematics and Science, and amounts to around 22, 10 and 13 percent of the standard deviation of the Reading, Mathematics and Science test scores respectively. Moreover, the incremental (mean) Reading score for children whose parents (at least one parent) hold (s) a high school degree relative to those whose parents at most finished primary school is around 89 percent of the standard deviation of the Reading scores, and those students who have more than two siblings score around 46 percent of the standard deviation of the Reading tests lower than only children.

The remainder of this chapter is organised as follows: Section 3.2 proceeds with a presentation of the data used in the empirical analysis and some descriptive statistics. Sections 3.3 and 3.4 present the empirical strategy and the estimation results respectively and finally Section 3.5 concludes. Tables for the descriptive statistics and the estimation results are presented in Appendix 3.7.

3.2 Data and descriptive evidence

3.2.1 Progress in International Reading Literacy Study (PIRLS), 2001

The data for reading literacy is drawn from the 2001 "Progress in International Reading Literacy Study" (PIRLS), which is available for 35 countries. The sample of students assessed consists of fourth graders who were tested at the end of the academic year. Fourth graders were chosen because grade four represents an important stage in a child's development as a reader because by the end of fourth grade children are expected to have learned to read efficiently and are therefore reading in order to learn. The children are tested on four areas (via multiple choice and constructed response), namely, (1) retrieving explicitly stated information, (2) making straightforward inferences, (3) interpreting and integrating ideas and information and (4) examining and evaluating content and language, based on the booklet they are given which consists of two blocks of either literary text or informational text.[74]

[74] For an extensive description of the PIRLS dataset, testing procedure, scoring guide see Gonzalez and Kennedy (Eds.) (2003).

For the empirical analysis, data from the Student Questionnaire (which contains the Reading test scores and basic student background information) and the Home Survey (which contains demographic and socio-economic indicators) are merged. The outcome variable of interest is the Reading score, which is standardized so that the mean is equal to 500 and the standard deviation equals 100 when all countries are weighted equally. The control variables included in the regression are the standard variables that are likely to be significant determinants of student achievement, namely, gender, parental education, family size[75] and some indicator for household income. Accordingly, five categories for parental education[76] and for the number of siblings[77] respectively are generated, and dummy variables indicating gender and whether the family owns a car, as an indicator of family income, are included in the regression equation.[78] The number of observations in the sample is 4,508.

Table 3.1 provides summary statistics of the variables used in the analysis. Note that the mean Reading score in the Hungarian sample is around 45 points above the international mean of 500 points. Not surprisingly, mean Reading scores differ by gender and parental background, namely, girls and students with academic parents attain a higher score in the sample. In terms of the control variables included in the regression analysis, it is interesting to note that approximately 43 percent of the sample have parents with vocational degrees, and around half of the sample come from families with two children. Note also that mean actual school starting age, measured in yearly units (varying by month of birth) is slightly higher than mean expected school starting age (i.e. six years and eleven months versus six years and ten

[75] Note that in addition to family size, birth order also has a significant effect on academic performance (Behrman and Taubman (1986) and Strøm (2004)). That is, there is evidence that older siblings attain a higher tests score than younger ones. (Birth order is not available in the TIMMS and PIRLS datasets for Hungary.)

[76] The categories for parental education (which are more aggregated than those reported in the dataset due to sample size considerations) have been generated using the seven highest schooling degrees completed reported for each parent separately in the dataset, namely, "did not go to school", "ISCED level 2" (eight years of primary school), "ISCED level 3a, b" (high school degree), "ISCED level 3c" (lower level vocational degree), "ISCED level 4a" (higher level vocational degree), "ISCED level 5a" (college degree) and "ISCED level 5b" (university degree). These seven schooling degrees are coded into four possible "parental educational groups" (see Table 3.1 for detail), whereby (a) at least one parent has the corresponding degree and (b) the groups represent a ranking in terms of the level of education. Those observations with missing educational information for both parents are in the Missing category. Including a category with missing educational information is preferred to dropping these observations because (a) dropping the observations with missing values on educational information would reduce the sample size and (b) would possibly result in a non-random sample if the missing values were not missing randomly, which ultimately may lead to biased coefficient estimates.

[77] There is a variable in the dataset indicating the number of children living at home, ranging from one to more than ten (i.e. eleven categories), which have been aggregated into five groups (see Table 3.1 for detail). Those observations with missing information on the number of children living at home have been allocated to the Missing category for reasons outlined in the previous footnote (and this also applies to the TIMMS dataset).

[78] Among others, Behrman and Taubman (1986) provide extensive theoretical background and econometric evidence on the effects of birth order, family size, parental education and family earnings on the years of schooling.

months), which reflects (a) that the majority of the students do enrol on time and (b) for those who do not enrol on time, a tendency (on average) towards later enrolment.

3.2.2 Trends in Mathematics and Science Study (TIMSS), 2003

The data for Mathematics and Science scores is drawn from the 2003 “Trends in Mathematics and Science Study” (TIMSS), which has been conducted in 48 countries. Like in PIRLS, the sample of students assessed consists of fourth graders who were tested at the end of the academic year. Similarly to PIRLS, the fourth grade students were tested in various areas, namely, (1) knowing facts and procedures, (2) using concepts, (3) solving routine problems and (4) reasoning for Mathematics and (1) factual knowledge, (2) conceptual understanding and (3) reasoning and analysis for Science (whereby the broad field of Science is composed of three content domains, namely, Life Science, Physical Science and Earth Science).[79]

The outcome variables of interest are the Mathematics score and Science score respectively. As for the PIRLS, the TIMMS mean score for Mathematics and Science for the participating countries is set at 500 and the standard deviation at 100. The control variables include five categories for the number of persons living at home[80], dummy variables indicating gender and whether the family owns a VCR. Unfortunately, a drawback of the TIMSS at the fourth grade level is that information on parental education background is not available.[81] The number of observations in the sample is 3,222.

Table 3.2 provides summary statistics of the variables used in the analysis. Note that the mean Mathematics and the mean Science scores in the Hungarian sample are approximately 30 and 32 points above the international mean of 500 points respectively. Boys attain higher scores in both Mathematics and Science than girls, in opposition to Reading. Approximately 42 percent

[79] For an extensive discussion of the TIMSS dataset, the content and cognitive domains tested for Mathematics and Science respectively, the test design and scoring guide see Martin (Eds.) (2005)

[80] There is a variable in the dataset indicating the number of persons living at home, ranging from two to eight or more (i.e. seven categories), which have been merged into five groups (see Table 3.2) in an identical way as categories for number of siblings in the PIRLS dataset.

[81] Note that the unavailability of information on parental education in the TIMMS dataset potentially affects the OLS estimates of the age effect on mathematics and science test score, which can be deduced from running regressions with the PIRLS dataset with and without information on parental education. The parameter estimate for the age effect when parental education is included as a control variable in the OLS regression of test score on school starting age and other determinants of test score is less negative than when parental education is not included. This is in accordance with the estimation results based on the PIRLS dataset for Germany (Puhani and Weber (2007)). Subsequently, it is possible that the estimated age effect using the TIMMS dataset (reported in Tables 3.5 and 3.7) are more negative than if parental education was included as a control variable in the regression.

of the sample comes from families with four persons living at home. As in the PIRLS 2001 data, in the TIMMS data the mean actual school starting age measured in years (varying by month) is slightly higher than mean expected school starting age (i.e. seven years versus six years and ten months), which reaffirms (a) that the majority of the students do enrol on time and (b) for those who do not enrol on time a tendency (on average) towards later enrolment.

3.3 Estimation strategy

3.3.1 Ordinary least squares

The study first estimates the effect of school starting age on scholastic achievement using a simple specification:

$$Y_i = \beta_1 + \beta_2 A_i^s + X_i'\beta_3 + \varepsilon_i, \qquad i = 1,...,n \quad (1)$$

where Y_i is test score for individual i, A_i^s is actual school starting age, X_i represents a vector of student and family background variables that may influence student performance, such as gender and number of siblings, and ε_i is a random disturbance term which contains the unobserved determinants of student performance such as ability. The key parameter of interest is β_2, the age effect.

The problem with estimating equation (1) by ordinary least squares (OLS) is that, since the cut-off date regulation for enrolment is not exogenous, i.e. there is teacher and parental discretion, the early / late school entrants represent a non-random sample. That is, it is possible that (a) ambitious parents may prefer an early enrolment, (b) wealthier parents may prefer a later start irrespective of the additional childcare costs and (c) children with lower and higher abilities may start school a year later and earlier than proposed by the cut-off date regulation respectively i.e. $Cov\left(A_i^S, \varepsilon_i\right) \neq 0$. If the non-random pattern of enrolment is such that, on average, less able children enter school a year later, the OLS estimate for the effect of school starting age on test score β_2 may be downward biased.

3.3.2 Instrumental variables estimation

In order to overcome the problem of non-random selection of early / late school entrants, the recent empirical literature has proposed instrumental variable estimation (IV), using an instrument for actual school starting age A_i^S which is (1) correlated with actual school starting age and (2) uncorrelated with the unobserved determinants of academic performance ε_i (most importantly ability). The IV approach in the existing literature exploits the exogenous variation in school starting age driven by the children's month of birth and the cut-off date regulation for enrolment. Accordingly, expected school starting age A_i^E, defined as the age when the child is supposed to start school according to the cut-off date regulation and his / her month of birth, is used as the instrument for actual school starting age A_i^S.[82] As discussed in the Introduction, the IV approach identifies the local average treatment effect (LATE), that is, the average causal effect of school starting age on academic performance for the group of "LATE-compliers": the individuals who alter their school entry age in response to the instrument (discussed by Imbens and Angrist (1994), Angrist and Imbens (1995) and Angrist et al. (1996)), which may not be representative for the entire student population. Therefore, the studies using the IV strategy characterize how school starting age influences academic outcomes for the group of "LATE-compliers", and hence the estimates must be interpreted accordingly.

Formally, in the IV approach, the first-stage regression (to be estimated by OLS) involves a regression of A_i^S for individual i on the instrument A_i^E and the vector of control variables X_i, such as student and family background variables, to obtain the fitted values $\hat{A}_i^S$:

$$A_i^S = \alpha_1 + \alpha_2 A_i^E + X_i'\alpha_3 + \mu_i, \qquad i = 1,...,n \qquad (2)$$

where μ_i is a random disturbance term which contains the unobserved determinants of children's actual school entry age such as intellectual, mental and social maturity.

[82] For examples see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2007) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

The second stage involves a regression (to be estimated by OLS) of test score Y_i for individual i on $\hat{A}_i^S$ and X_i:

$$Y_i = \beta_1 + \beta_2 \hat{A}_i^S + X_i'\beta_3 + \varepsilon_i, \qquad i = 1,...,n \qquad (3)$$

where ε_i is a random disturbance term which contains the unobserved determinants of student performance such as ability. The IV estimation approach yields the LATE estimate of age effect $\hat{\beta}_2$.

3.3.3 Control function approach

Unlike the existing studies which use the IV estimation approach, this study uses the control function approach, discussed by Garen (1984) and Heckman and Robb (1985). The control function approach is an extension to the IV approach. The advantage of the control function approach over the IV estimation strategy is that, in addition to the bias due to the correlation between the unobserved determinants (i.e. ability level) and actual school starting age (for reasons outlined above), in this context called the "absolute advantage bias", it also accounts for the individual heterogeneity in the age effect.

More precisely, if individuals differ in their academic ability at different ages, they have a comparative advantage at certain ages. That is, the age effect is not constant for all ages for an individual. If the parents of the children or the teachers know the comparative advantage of the particular child and act accordingly, they will enrol the child at the age which yields the highest return (i.e. age effect). In this case, the age effect and the actual age at school entry will be correlated, causing a bias in the estimated age effect. This is the additional source of bias, the so-called "comparative advantage bias", which the control function approach controls for.

Formally, the model consists of two equations. The first equation (as in the IV estimation approach described above), keeping to the notation in the previous subsection, involves the relationship between actual school entry age A_i^S for individual i and the instrument A_i^E and a vector of other control variables X_i:

$$A_i^S = \alpha_1 + \alpha_2 A_i^E + X_i' \alpha_3 + \varepsilon_{Si}, \qquad i = 1,...,n \qquad (4)$$

where ε_{Si} is a random disturbance term which contains the unobserved determinants of children's actual school entry age such as intellectual, mental and social maturity.

For simplicity of notation, Equation (4) can be rewritten as:

$$A_i^s = Z_i' \alpha + \varepsilon_{Si}, \qquad i = 1,...,n \qquad (5)$$

where Z_i represents the vector of explanatory variables from Equation (4).

The second equation of the model, the "test equation", involves the relationship between test score Y_i for individual i and A_i^S and a vector of exogenous regressors X_i which affect test score such as student and family background variables:

$$Y_i = \gamma_1 + \gamma_{2i} A_i^S + X_i' \gamma_3 + \varepsilon_i, \qquad i = 1,...,n \qquad (6)$$

where ε_i is a random disturbance term which contains the unobserved determinants of student performance such as innate ability. Taking into account the two sources of unobserved heterogeneity outlined above, the "test equation" can be rewritten as follows:

$$Y_i = \gamma_1 + \overline{\gamma_2} A_i^S + X_i' \gamma_3 + \varepsilon_i + \left(\gamma_{2i} - \overline{\gamma_2}\right) A_i^S, \qquad i = 1,...,n \qquad (7)$$

where $\overline{\gamma}_2$ is the average age effect and $\varepsilon_i + \left(\gamma_{2i} - \overline{\gamma_2}\right) A_i^S$ is a composite disturbance term, which represents the two sources of unobserved heterogeneity: the first component of the disturbance term, ε_i, represents unobserved individual characteristics which affect the test score (regardless the school starting age of the individual) and $\left(\gamma_{2i} - \overline{\gamma}_2\right)$ represents the unobserved individual heterogeneity in the age effect. As outlined above, there are two potential sources of bias in Equation (7): the "absolute advantage bias" due to the correlation between A_i^S and ε_i (which the standard IV estimation strategy of the recent literature controls for) and the "comparative advantage bias" due to the correlation between $\left(\gamma_{2i} - \overline{\gamma_2}\right)$ and A_i^S.

For simplicity of notation denoting the term $\left(\gamma_{2i}-\overline{\gamma_2}\right)\equiv\eta_i$ and the exogenous variables Z_i and X_i in equations (5) and (7) respectively by r_i, the conditional expectation of the composite error term $\varepsilon_i+\left(\gamma_{2i}-\overline{\gamma_2}\right)A_i^S$ is:

$$\begin{aligned} E\left(\varepsilon_i+\eta_i A_i^S \mid A_i^S, r_i\right) &= E\left(\varepsilon_i+\eta_i A_i^S \mid A_i^S=Z_i^{'}\alpha+\varepsilon_{Si}, r_i\right) \\ &= E\left(\varepsilon_i \mid \varepsilon_{Si}=A_i^S-Z_i^{'}\alpha, r_i\right)+E\left(\eta_i \mid \varepsilon_{Si}=A_i^S-Z_i^{'}\alpha, r_i\right)\cdot A_i^S, \end{aligned} \qquad i=1,\ldots,n \quad (8)$$

$$E\left(\varepsilon_i \mid \varepsilon_{Si}=A_i^S-Z_i^{'}\alpha, r_i\right)=\frac{Cov\left(\varepsilon_i,\varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)}\cdot\varepsilon_{Si}, \qquad i=1,\ldots,n \quad (9)$$

$$E\left(\eta_i \mid \varepsilon_{Si}=A_i^S-Z_i^{'}\alpha, r_i\right)=\frac{Cov\left(\eta_i,\varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)}\cdot\varepsilon_{Si}, \qquad i=1,\ldots,n \quad (10)$$

Therefore, the conditional expectation of the "test equation" (7) is:

$$E\left(Y_i \mid A_i^S, X_i, Z_i\right)=\gamma_1+\overline{\gamma_2}A_i^S+X_i^{'}\gamma_3+\frac{Cov\left(\varepsilon_i,\varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)}\cdot\varepsilon_{Si}+\frac{Cov\left(\eta_i,\varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)}\cdot\varepsilon_{Si}\cdot A_i^S, \quad i=1,\ldots,n \quad (11)$$

As the last two terms in (11) are nonzero, OLS estimation of the "test equation" will yield inconsistent estimates of the effect of age on test score.

Obtaining a consistent estimate of ε_{Si}, $\hat{\varepsilon}_{Si}$, and including $\hat{\varepsilon}_{Si}$ and the interaction of $\hat{\varepsilon}_{Si}$ and A_i^S as regressors in the "test equation" corrects for the bias caused by the unobserved factors. Consistent estimate of the error term, $\hat{\varepsilon}_{Si}$, can be obtained from the OLS estimation of equation (5).

Accordingly, the implementation of the control function regression consists of a two-stage procedure. The first stage involves OLS estimation of Equation (5):

$$A_i^S=Z_i^{'}\alpha+\varepsilon_{Si}, \qquad i=1,\ldots,n \quad (12)$$

to obtain the fitted values $\hat{\varepsilon}_{Si} = A_i^S - Z_i^{'}\hat{\alpha}$.

The second stage involves the OLS estimation of the regression of test score Y_i for individual i on A_i^S, X_i and the two additional regressors: the estimated residual from the first-stage regression $\hat{\varepsilon}_{Si}$ and the interaction of A_i^S and $\hat{\varepsilon}_{Si}$:

$$Y_i = \gamma_1 + \overline{\gamma_2} A_i^s + X_i'\gamma_3 + \gamma_4\hat{\varepsilon}_{Si} + \gamma_5 A_i^s \hat{\varepsilon}_{Si} + \tilde{\varepsilon}_i, \qquad i = 1,...,n \quad (13)$$

where $\tilde{\varepsilon}_i$ is the random disturbance term. The inclusion of $\hat{\varepsilon}_{Si}$ and the interaction of A_i^S and $\hat{\varepsilon}_{Si}$ as additional regressors purges the relationship between test score and actual school starting age of the "absolute advantage bias" and of the "comparative advantage bias" respectively. The control function approach yields consistent estimates for the effect of age on test score for a random individual $\overline{\gamma}_2$ which is equivalent of the average treatment effect (ATE).

It is important to note that the control function approach is valid under the assumption that the conditional expectations of the two unobserved heterogeneity components ε_i and η_{i} are linear in A_i^S and A_i^E. This assumption in combination with the assumption that the two unobserved heterogeneity components are mean independent (uncorrelated) of the instrument A_i^E:

$$E\left[\varepsilon_i \mid A_i^E\right] = E\left[\eta_i \mid A_i^E\right] = 0, \qquad i = 1,...,n \quad (14)$$

implies:

$$E\left[\varepsilon_i \mid A_i^S, A_i^E\right] = \gamma_4 \varepsilon_{Si}, \qquad i = 1,...,n \quad (15)$$

and

$$E\left[\eta_i \mid A_i^S, A_i^E\right] = \gamma_5 \varepsilon_{Si}, \qquad i = 1,...,n \quad (16)$$

where ε_{Si} is defined in Equation (5).

Furthermore, note that estimating the test equation (13) with the additional regressor $\hat{\varepsilon}_{Si}$ but without the interaction of A_i^S and $\hat{\varepsilon}_{Si}$:

$$Y_i = \gamma_1 + \overline{\gamma_2} A_i^s + X_i'\gamma_3 + \gamma_4 \hat{\varepsilon}_{Si} + \tilde{\varepsilon}_i, \qquad i = 1,...,n \quad (17)$$

controls for ”absolute advantage bias” only (and not for heterogeneity in the age effect) and is numerically equivalent to the standard IV estimation described in Section 3.3.2. Therefore, the control function approach is an extension to the IV approach.

The difference between the LATE and the ATE estimates of the age effect on test score of the IV estimation approach of the control function approach respectively must be pointed out. Whereas the ATE estimate is the age effect for a random individual, the LATE estimate is the age effect for the “compliers”, that is, those individuals whose school entry age is changed by the instrument, which may not be representative for the student population (implying that the two estimates may well differ from one another).

At this point, the choice and the generation of the instrument merit comment. This study also builds on the use of “expected school starting age” as an exogenous determinant of “actual school starting age”, as discussed above, given the institutional features of the Hungarian education system.

In Hungary, the school starting age regulation requires children who turn six years old (72 months old) by the 31st of May to start school on the 1st of September in the corresponding year. Children born after that date need to wait an additional in order to enrol. Therefore, the “expected school starting age” A_i^E, in yearly units (varying by the month of birth), is generated using to the cut-off regulation c and birth month b_i for individual i is as follows:

$$A_i^E = \begin{cases} \dfrac{72+9-b_i}{12} & if \;\; 1 \le b_i \le c \\ \dfrac{84+9-b_i}{12} & if \;\; c < b_i \le 12 \end{cases} \qquad i = 1,...,n \quad (18)$$

Given that the cut-off date is May $c = 5$, A_i^E is between 6.33 years for the youngest children born in May, which corresponds to 6 years and 4 months, and 7.25 years for the oldest children born in June, which corresponds to 7 years and 3 months. More precisely, for children born between September, who start school at age seven, and those born in May, there is a month-for-month decrease A_i^E. Children born after the cut-off date, May, are required to wait until the following September to enrol in school, and thus A_i^E jumps up by 11 months between May and June children and falls again by month between June and August.

Figures 3.1 and 3.2 provide graphical illustrations of A_i^S and A_i^E for the PIRLS and the TIMSS datasets respectively. Before proceeding with a description of the Figures it important to recall the distinction discussed in detail in the Introduction between the group of students who comply with the cut-off-date regulation i.e. enrol on time and the group of "LATE-compliers", who alter their school entry age in response to the particular instrument. The proceeding discussion of the Figures refers to the former group. First of all, note that the figures reaffirm the pattern which emerges from the summary statistics from Tables 3.1 and 3.2, namely, (a) that the majority of students enrol on time and (b) for those not enrolling on time, there is a tendency (on average) towards late enrolment. The particular pattern of compliance to the cut-off date regulation merits comment: (a) compliance in both years under analysis is weaker in the first six months of the year than in the latter six months and (b) June and July (the months just after the cut-off date) are the only months characterized, on average, by early entry. Finally, note that the broad pattern of the (average) tendency towards late entry, with the exception of the months just after the cut-off date, is in line with other countries, such as Germany.[83]

Finally, it is important to comment on the similarity between the estimation approach in this study and the regression-discontinuity design (applied, for example, by van Klauuw (1996) and Angrist and Levy (1999)[84]) as both make explicit use of a discontinuity induced by an assignment rule to identify a treatment effect. The similarities between the two approaches

[83] For a comparison to (a) Germany as a whole using the 2003 PIRLS data and "Pupil-Level Data of the Statistics of General Schools for the State of *Hessen* 2004/2005" see Puhani and Weber (2007) and to (b) the former West and to (c) the former East Germany using the "Young Adult Longitudinal Survey 1991 – 1995/1996" see Fertig and Kluve (2005).

[84] The papers provide examples of how fuzzy regression-discontinuity (where assignment is not deterministic i.e. misassignment relative to the cut-off value is possible) can be analyised in an instrumental variables framework.

can be highlighted from (a) the study by Angrist and Levy (1999), which aims to estimate the causal effects of class size on scholastic achievement, and (b) briefly recalling the formula for the generation of the expected school starting age in the context of this study.

Starting with the study of Angrist and Levy (1999), note that the endogeneity problem in the regression of class size on test score arises from the correlation of class size with the unobserved determinants of test score and, thus warrants instrumental variables estimation. To construct instrumental variables estimates of the effect of class size on scholastic achievement Angrist and Levy (1999) use the discontinuity in Maimonides' rule, which is used (as one of the factors) to determine the class size as a function of total school enrolment in Israeli public schools. More specifically, the Maimonides' rule induces a discontinuity in the relationship between enrolment and class size at enrolment multiples of 40. That is, the rule requires that one class be added in a school whenever the class size exceeds the predetermined threshold of 40[85]. Thus, the authors use the discontinuities in the relationship between total school enrolment and class size according to Maimonides' rule to identify the causal effect of class size on scholastic achievement.

Coming to the identification strategy of the study, recall that in Equation (18), the formula for the generation of expected school starting age, the discontinuity is induced by the cut-off date regulation for enrolment. That is, when the student's month of birth exceeds the predetermined threshold c, A_i^E jumps up by 11 months (see Figures 3.1 and 3.2).

3.4 Estimation results

3.4.1 PIRLS – OLS results

Table 3.3 reports the parameter estimates for the OLS regressions for the entire sample and the subsamples split by gender and parental educational background respectively for the PIRLS.

The OLS coefficient estimates are negative and significantly different from zero (other than for the subsample with the academic parental background). Therefore, the OLS estimation results indicate a negative relationship between Reading test scores and actual school starting age for the full sample and for all of the subsamples.

[85] The class size function derived from Maimonides' rule captures that if total enrolment equals 40, one class will be formed, and if total enrolment equals 41 – 80 two classes will be formed etc..

Although the key parameter of interest is the age effect on Reading performance, the effect of the other control variables is worth commenting on. First, boys, on average, attain a lower score in Reading than girls at the fourth grade level, by approximately 14 points, which corresponds to around 22 percent of the standard deviations in the PIRLS scores for the full sample. Moreover, parental education plays a significant role in educational success, that is, there is a “score premium” associated with the additional degree levels of the parents. For instance, the incremental (mean) Reading score for children whose parents (at least one parent) hold (s) a high school degree relative to those whose parents at most finished primary school is around 54 points for the entire sample, which corresponds to 89 percent of the standard deviation. Those children whose parents do not own a car score lower on the Reading test, by around 15 points for the full sample, which corresponds to 25 percent of the standard deviation. Finally, as expected, the number of siblings is a significant determinant of Reading scores. For example, for the full sample of students, those who have more than two siblings score around 28 lower relative to only children, which corresponds to 46 percent of the standard deviation. Note that the effect of these latter two variables remains stable in sign and magnitude across the subsamples.

3.4.2 PIRLS – Control function approach results

Table 3.4 reports the parameter estimates for the control function approach for the full sample and the subsamples split by gender and parental educational background respectively for the PIRLS. The coefficient estimates for the other covariates not reported, as they are similar in sign and magnitude to the OLS coefficient estimates.

First, note that the first-stage coefficient estimates are significant for the full sample and all the subsamples under analysis. Second, the control function approach, which estimates the ATE, switches the sign of the estimated age effect from negative to positive for the full sample and for all of the subsamples considered. Hence, the control function approach indicates that the estimated age effect of the simple OLS regression of Reading scores on actual school starting age is downward biased. For the full sample, the ATE estimate for the age effect is around 6 points, which corresponds to 10 percent of the standard deviation in the Reading scores for the full sample. The subsample analysis reveals that the ATE estimate for the age effect is the highest for boys, around 13 points, which corresponds 21 percent of the standard deviation in the Reading test scores for the sample of boys. (Note however that the point estimates for the age effect are not significant.)

3.4.3 TIMMS, Mathematics – OLS results

Table 3.5 reports the parameter estimates for the OLS regressions for the entire sample and for the separate samples of boys and girls respectively for the TIMMS, where the outcome of interest is the Mathematics score for the fourth graders.

The OLS coefficient estimates are negative and significantly different from zero, thereby indicating a negative relationship between Mathematics test scores and actual school starting age for the full sample and for the subsamples of boys and girls.

In terms of the other explanatory variables it is worth noting that, the (average) gender achievement gap is in favor of boys, unlike for Reading, which amounts to approximately 7 points, corresponding to 10 percent of the standard deviation in the TIMMS Mathematics scores for the full sample of fourth graders. Turning to the variable which serves as a proxy for household income, those children whose parents do not own a VCR, score lower on the Mathematics test, by 26 points for the full sample, which corresponds to 36 percent of the standard deviation. Moreover, family size is a significant determinant of Mathematics performance. For example, for the full sample of students those students from households with more than five people score around 35 points lower relative to only children (or two children with single parents), which corresponds to 47 percent of the standard deviation, which reaffirms the notion that children in larger families possibly receive less educational resources / attention than single children. Finally, note that the effect of these latter two variables remains similar in sign and magnitude across the subsamples of boys and girls.

3.4.4 TIMMS, Mathematics – Control function approach results

Table 3.6 reports the parameter estimates for the control function approach for the full sample and for boys and girls respectively for the TIMMS, where the outcome of interest is the Mathematics score. The coefficient estimates for the other covariates not reported, they are similar in sign and magnitude to the OLS coefficient estimates.

First of all, the first-stage coefficient estimates are significant for the full sample and for the subsamples of boys and girls. Second of all, the ATE estimates of age effect are above the corresponding OLS estimates for the full sample and for the subsamples of boys and girls.

3.4.5 TIMMS, Science – OLS results

Table 3.7 reports the parameter estimates for the OLS regressions for the entire sample and for boys and girls respectively for the TIMMS, where the outcome of interest is the Science score for the fourth graders.

The OLS coefficient estimates are negative and significantly different from zero, indicating (as for Reading and Mathematics achievement) a negative relationship between Science test scores and actual school starting age for the full sample and boys and girls separately.

The (average) gender achievement gap in favor of boys is similar to that in Mathematics: approximately 10 points, which corresponds to 13 percent of the standard deviation in the TIMMS Science scores for the full sample of fourth graders. Not surprisingly, the effects of the other covariates on Science performance are similar in sign and magnitude as for the Mathematics performance. Namely, those children whose parents do not own a VCR are found to have a lower score on the Mathematics test by around 26 points for the full sample, which corresponds to 35 percent of the standard deviation. For the full sample of students, those students from households with more than five people score around 33 points lower relative to only children (or two children with single parents), which corresponds to 45 percent of the standard deviation. Finally, note that the effect of these latter two variables is robust across the subsamples of boys and girls.

3.4.6 TIMMS, Science – Control function approach results

Table 3.8 reports the parameter estimates for the control function approach for the full sample and for girls and boys respectively for the TIMMS, where the outcome of interest is the Science score. The coefficient estimates for the other covariates not reported, as they are similar in sign and magnitude to the OLS coefficient estimates.

The coefficient estimates confirm the same picture for Science performance as for Mathematics and Reading performance: (1) the first-stage coefficient estimates are significant for the full sample and for the subsamples of boys and girls and (2) the ATE estimates of the age effect of the control function approach exceed the corresponding OLS estimates for the full sample and the subsamples of boys and girls. For the full sample, the point estimate of the age effect is around 17 points, which corresponds to 19 percent of the standard deviation in the Science scores for the full sample. (Note however that the point estimates for the age effect are not significant.)

Note that for all datasets and all subsamples an additional specification is estimated which includes interactions between the month of birth and the instrument in order to control for the fact that, as demonstrated in Figures 3.1 and 3.2, the compliance rate for children born in the first six months of the year differs (i.e. is somewhat lower) from that of those born in the latter half of the year. Table 3.9 reports the estimated age effects based on the control function approach for the full sample and the subsamples separately for the PIRLS and TIMMS, where the outcome of interest is the Reading score, the Mathematics score and the Science score respectively. Comparing the parameter estimates to the corresponding OLS estimates indicates again that the ATE estimates exceed the corresponding OLS estimates for the full samples and for all of the subsamples considered.

3.5 Conclusion

This study examined the relationship between school starting age and academic performance for grade four students in Reading, Mathematics and Science in Hungary. The challenge in estimating the effect of school starting age on academic performance arises due to the fact that there is choice regarding enrolment decisions, and subsequently it is a non-random sample of students who start school earlier / later than dictated by the cut-off date regulation for enrolment. That is, whereas early entrants may well be higher ability children and children of ambitious parents who want an early start (regardless of the child's ability), the late starters come from the pool of lower ability children and potentially from wealthier families (for whom the burden of additional childcare costs may be irrelevant). Given this non-random selection, late starters may be, on average, lower ability children. Subsequently, regressing academic performance on actual school starting age by OLS may generate a downward biased estimate of the age effect on academic performance. In order to overcome the problem of non-random selection in countries where the cut-off date regulation is not exogenous, the empirical literature has concentrated on instrumental variable estimation, exploiting the exogenous variation in school starting age driven by (1) the cut-off date for enrolment and (2) the children's month of birth, which generates the "expected school starting age" as an instrument for “actual school starting age”. It is important to note that the IV approach identifies the local average treatment effect (LATE), that is, the average causal effect of school starting age on academic performance for the group of “compliers”, who are defined as those individuals whose school entry age is affected by the instrument used (introduced by Imbens and Angrist (1994)).

Similarly to the existing literature investigating the effect of school starting age on schooling outcomes, this study uses “expected school starting age”, defined as the age when the child is supposed to start school according to the cut-off date regulation and his / her month of birth as an instrument for actual school starting age. However, unlike the existing studies, this study uses the control function approach, motivated by Garen (1984) and Heckman and Robb (1985), to estimate the effect of school starting age on early academic achievement. The advantage of the control function approach is that it extends the standard IV approach to estimate the effect of age on scholastic achievement to incorporate the individual heterogeneity of the age effects. Whereas the IV approach estimates the LATE: the age effect for the “compliers” (those individuals whose school entry age is changed by the instrument), the control function approach estimates the average treatment effect (ATE): the effect of age on test score for a random individual.

Turning to the results, the OLS coefficient estimates suggest a negative relationship between school starting age and academic performance, for all three subjects and for all the subsamples under analysis, split by gender and parental education. The ATE estimates of the age effect of the control function approach exceed the corresponding OLS estimates for all the samples and subsamples considered, thereby suggesting a downward bias of the OLS estimate. Put differently, (the ATE estimates indicate that) there is no significant negative effect of (later) school starting age on academic performance for fourth graders.

It is important to note that the OLS estimates are in line with of the international evidence. Among others, Frederikkson and Öckert (2005) for Sweden, Puhani and Weber (2007) for Germany and Bedard and Dhuey (2005) for a number of OECD countries (for example, for Austria, for the Czech Republic and for Portugal) find evidence from OLS regressions for a negative association between academic achievement and actual school starting age, attributing this to the non-random selection of early / late school starters who differ in unobserved academic ability.

Furthermore, the majority of the international literature finds evidence for a positive age effect using the IV strategy, with differences in the magnitude across countries and as well as age groups under analysis. One point must be reemphasized, namely, that the IV approach of these studies yields the LATE estimate, which is equivalent of the age effect for the group of "compliers" and is not directly comparable to the estimates of this study, which yield the ATE estimates. Nevertheless, the estimated age effects from the papers which analyse the same age group, namely, grade four students, and the same datasets (but differ somewhat in the covariates included) merit comment. For example, Puhani and Weber (2007) find the estimated age effect (for the group of "compliers") based on the PIRLS data for German grade four students to be around 40 percent of the standard deviations of the Reading test score in the full German sample. The authors further conclude that German males benefit more than females from later school entry at the grade four level as far as Reading performance is concerned. Moreover, the evidence by Bedard and Dhuey (2005) based on the TIMMS data for a number of OECD countries also suggests a positive age effect for fourth graders in Science (for the group of "compliers"), differing in magnitude across the countries, ranging from around 18 percent to 37 percent of the international standard deviations for the Science test score for Canada and New Zealand respectively.

Although the center of interest is the effect of school starting age on academic performance, the effect of the other explanatory variables (which remain similar in sign and magnitude across the subjects and subsamples considered), especially gender, parental education and family size also merit comment. First, as expected, the (average) gender achievement gap at the fourth grade level is in favour of girls for Reading and in favour of boys in Mathematics and Science. Whereas, on average, boys attain a lower score in Reading than girls, by approximately 23 percent of the standard deviations in the Reading scores for the full PIRLS sample, they attain a higher score in Mathematics and Science by around 10 and 13 percent of the standard deviation in the Mathematics and Science scores respectively. This is in line with the international evidence explicitly focusing on the effect of gender on academic performance. For instance, Strøm (2004) finds evidence for a gender achievement gap in favour of girls in Reading in Norway using the PISA 2000 data covering 15 – 16 year old students (approximately 33 percent of the standard deviation of the international PISA Reading scores), which is robust across specifications.

Moreover, parental education plays a significant role in educational success in Hungary. For instance, the incremental (mean) Reading score for children whose parents (at least one parent) hold (s) a high school degree relative to those whose parents at most finished primary school is around 89 percent of the standard deviation of the Reading scores. In addition to other factors, this may be driven by the fact that children from highly educated families are more likely to be engaged in activities that promote academic success. Although the direct impact of such parental input on test scores is difficult to pin down, there are numerous variables in the PIRLS dataset that indicate a positive association between parental education and home activities which promote academic success. For example, whereas approximately 58 percent of the students with parents having at most primary school degree reported that they are often told stories at home, the corresponding figure for students with parents who possess a college or university degree is 83 percent. Among others, Elder and Lubotsky (2006) for the US and Fertig and Kluve (2005) for Germany find evidence for the importance of parental education for schooling success. The latter two authors, based on the "Young Adult Longitudinal Survey" covering 18 – 29 year old individuals, find that in both former East and West Germany, children from low educated families (whose parents at most completed the *Hauptschule*) are less likely to attain a high school degree (*Abitur*) and the opposite is true for their counterparts from high educated families (whose parents completed more than *Hauptschule*). Another piece of evidence which shows the importance of socio-economic background for academic success in Hungary from another perspective merits comment: the comparative analysis of OECD countries implies that the relationship between (15 year old) students' socio-economic background and their expectations to complete tertiary education is the strongest in Hungary among OECD countries (Education at a Glance 2007 (2007)).

Finally, as expected, the number of siblings is a significant determinant of test scores, irrespective of the subject and subsample considered. For example, those students who have more than two siblings score around 46 percent of the standard deviation of the Reading tests lower relative to single children. This finding (a) is supportive of the notion that, on average, families with fewer children have greater endowments in their children's human capital and (b) confirms the international evidence. For instance, Strøm (2004) finds evidence that the number of siblings has a negative effect on the Reading test score using the PISA 2000 data.

3.6 References

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3.7 Appendix

3.7.1 Descriptive statistics

Table 3.1 Descriptive statistics, PIRLS, 2001

	PIRLS (2001)
Variable	
Average reading score	
Overall	544.97
Boys	537.79
Girls	551.80
Academic parents	579.30
Non-academic parents	529.03
Parental education (%)	
Primary school or less	7.95
Vocational degree	42.59
High school degree	12.83
College or university degree	28.11
Missing	8.53
Number of sibling (%)	
Zero	14.84
One	50.74
Two	20.66
More than two	8.85
Missing	4.90
Gender (%)	
Male	48.71
Female	51.29
Car (%)	
Yes	67.73
No	32.27
Mean observed school starting age	6.97
Mean expected school starting age	6.80
Number of observations	4,508

Table 3.2 Descriptive statistics, TIMSS, 2003

	TIMSS (2003)
Variable	
Average mathematics score	
Overall	530.42
Boys	532.45
Girls	528.37
Average science score	
Overall	531.49
Boys	535.04
Girls	527.90
Number of people at home (%)	
Two or three	18.81
Four	42.23
Five	21.66
More than five	14.27
Missing	3.02
Gender (%)	
Male	50.23
Female	49.77
VCR (%)	
Yes	71.03
No	28.97
Mean observed school starting age	7.02
Mean expected school starting age	6.80
Number of observations	3,222

Notes on Tables 3.1 – 3.2: School starting age is measured in years.

Figure 3.1 Actual school starting age vs. expected school starting age (PIRLS 2001)

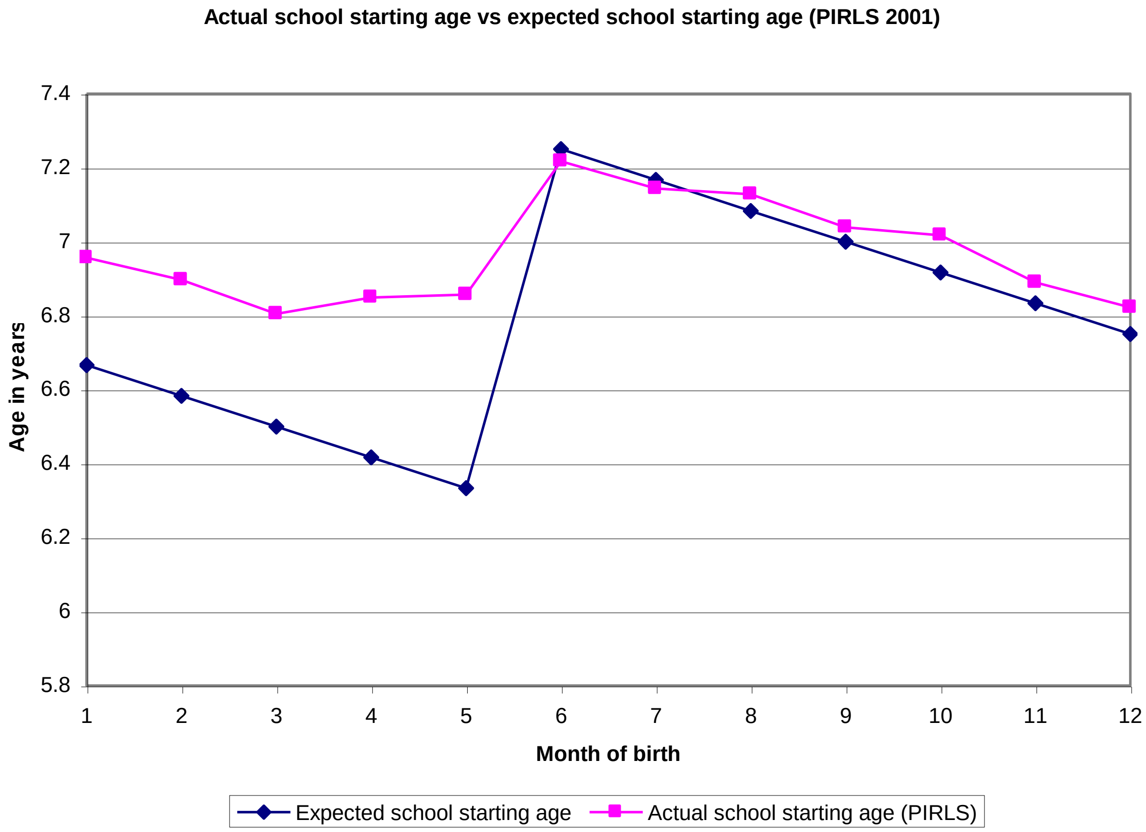
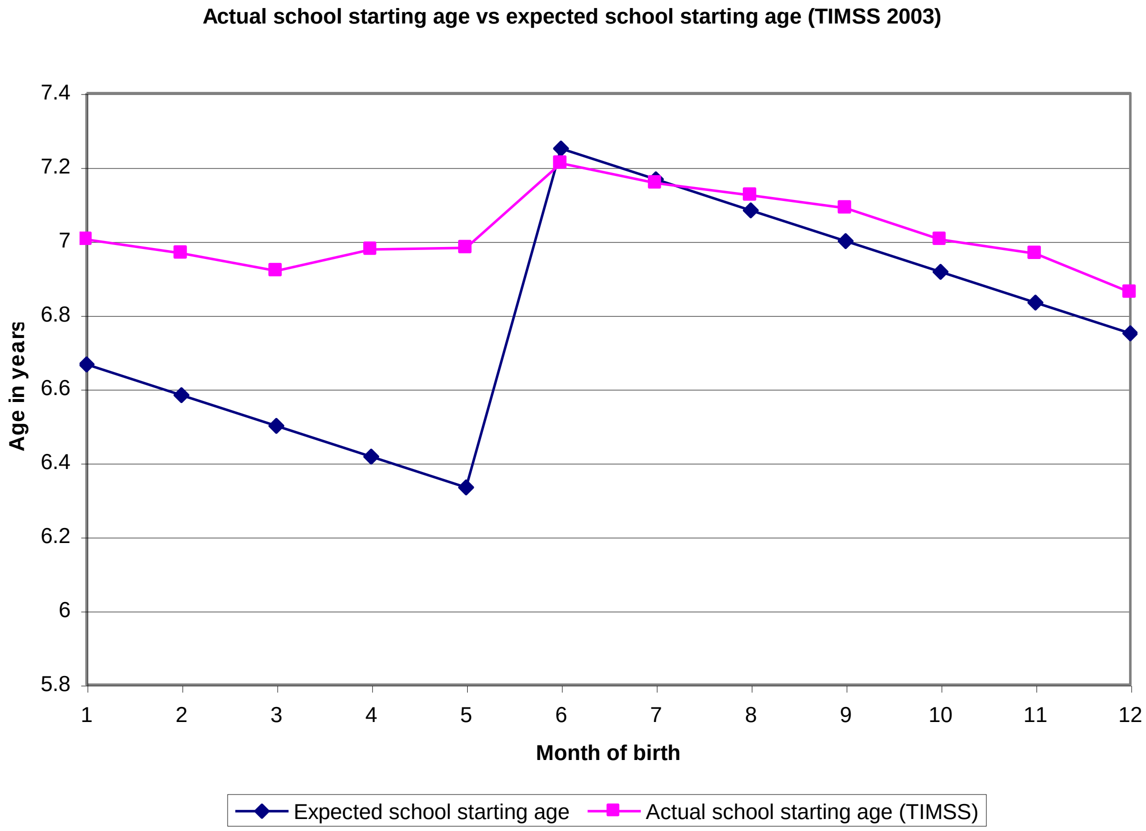


Figure 3.2 Actual school starting age vs. expected school starting age (TIMSS 2003)



3.7.2 Estimation results, PIRLS

Table 3.3 OLS regression results, PIRLS, 2001

OLS estimates, PIRLS (2001)					
	Entire sample	**Boys**	**Girls**	**Academic**	**Non-Academic**
School starting age	-16.35	-19.30	-13.64	-5.75	-22.12
	(2.61)	(3.13)	(3.91)	(6.26)	(2.94)
Male	-13.69			-10.57	-15.10
	(1.85)			(3.88)	(2.09)
No car	-15.22	-9.95	-20.10	-12.31	-19.27
	(2.16)	(3.07)	(2.88)	(4.78)	(2.59)
Number of siblings					
One	-3.18	-5.27	-0.77	1.28	-5.80
	(2.33)	(3.49)	(3.66)	(4.70)	(3.17)
Two	-10.19	-13.65	-6.35	2.20	-17.76
	(3.18)	(4.21)	(4.31)	(5.21)	(4.23)
More than two	-27.85	-30.33	-24.84	-13.60	-36.36
	(4.98)	(7.44)	(5.49)	(8.60)	(5.67)
Missing	-25.58	-28.81	-21.21	-16.04	-32.92
	(4.45)	(6.48)	(6.37)	(8.37)	(5.99)
Parental education					
Vocational degree	30.56	30.70	30.96		
	(3.85)	(6.49)	(4.28)		
High school degree	54.10	54.94	53.85		
	(4.68)	(7.36)	(5.21)		
Tertiary degree	76.17	80.70	72.30		
	(4.56)	(6.40)	(5.65)		
Missing	18.07	23.32	13.10		
	(4.90)	(6.50)	(6.18)		
Constant	650.32	650.56	636.82	642.12	732.32
	(19.25)	(23.34)	(28.49)	(40.69)	(20.65)
Observations	4,508	2,232	2,276	1,142	3,003

Notes: 1) School starting age is measured in years. 2) The reference group among the parental education categories is "Primary school or less". 3) The reference group for number of siblings is "Zero". 4) Standard errors are in parentheses. 5) Standard errors are adjusted for clustering at school level.

Table 3.4 First-stage and second-stage regression results, PIRLS, 2001

Control function approach, PIRLS (2001)		
	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.42	6.25
(N = 4,508)	(0.03)	(7.79)
Boys	0.36	13.29
(N = 2,232)	(0.04)	(13.35)
Girls	0.47	1.62
(N = 2,276)	(0.04)	(9.12)
Academic	0.43	10.31
(N = 1,142)	(0.03)	(15.15)
Non-academic	0.44	4.15
(N = 3,003)	(0.05)	(9.38)

Notes: 1) School starting age is measured in years. 2) Control variables included in the regressions are reported in Table 3.1. 3) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level. 5) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

3.7.3 Estimation results, TIMMS, Mathematics

Table 3.5 OLS regression results, TIMSS, Mathematics, 2003

OLS estimates, TIMSS, Mathematics (2003)			
	Entire sample	**Boys**	**Girls**
School starting age	-23.73	-22.97	-24.07
	(3.75)	(3.86)	(5.87)
Male	7.01		
	(2.82)		
No VCR	-26.00	-21.26	-30.91
	(3.71)	(4.14)	(5.26)
Number of people at home			
Four	-2.63	3.83	-9.87
	(4.36)	(6.14)	(4.82)
Five	-14.10	-6.21	-22.85
	(4.49)	(5.99)	(5.35)
More than five	-34.51	-20.71	-48.82
	(6.24)	(7.62)	(7.99)
Missing	-82.01	-83.32	-76.34
	(8.66)	(11.58)	(9.62)
Constant	738.63	727.94	754.33
	(25.54)	(27.95)	(40.78)
Observations	3,222	1,609	1,613

Notes: 1) School starting age is measured in years. 2) The reference group for number of people at home is “Two or three”. 3) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level.

Table 3.6 First-stage and second-stage regression results, TIMSS, Mathematics, 2003

Control function approach, TIMSS, Mathematics (2001)		
	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.27	-2.61
(N = 3,222)	(0.03)	(17.09)
Boys	0.16	12.32
(N = 1,609)	(0.05)	(39.34)
Girls	0.38	-9.78
(N = 1,613)	(0.04)	(16.00)

Notes: 1) Variables included in the regressions are reported in Table 3.2. 2) Standard errors are in parentheses. 3) Standard errors are adjusted for clustering at school level. 4) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

3.7.4 Estimation results, TIMMS, Science

Table 3.7 OLS regression results, TIMSS, Science, 2003

	OLS estimates, TIMSS, Science (2003)		
	Entire sample	**Boys**	**Girls**
School starting age	-21.49	-18.94	-23.98
	(4.08)	(3.93)	(6.15)
Male	10.02		
	(2.87)		
No VCR	-25.97	-22.58	-29.18
	(3.22)	(4.13)	(4.50)
Number of people at home			
Four	-7.69	-1.57	-14.21
	(3.76)	(4.98)	(4.75)
Five	-14.30	-13.21	-16.59
	(4.28)	(5.76)	(5.37)
More than five	-32.50	-22.90	-42.13
	(5.27)	(6.63)	(7.09)
Missing	-91.24	-93.71	-84.83
	(9.13)	(10.77)	(13.72)
Constant	724.62	708.15	750.63
	(28.02)	(27.59)	(42.54)
Observations	3,222	1,609	1,613

Notes: 1) School starting age is measured in years. 2) The reference group for number of people at home is “Two or three”. 3) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level.

Table 3.8 First-stage and second-stage regression results, TIMMS, Science, 2003

Control function approach, TIMSS, Science (2001)		
	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.27	17.18
(N = 3,222)	(0.03)	(17.28)
Boys	0.16	16.77
(N = 1,609)	(0.05)	(40.22)
Girls	0.38	17.24
(N = 1,613)	(0.04)	(16.98)

Notes: 1) Variables included in the regressions are reported in Table 3.2. 2) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level. 5) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

Table 3.9 Control function approach regression results with interaction terms between expected school starting age and month of birth for PIRLS (2001), TIMSS, Mathematics (2003) and TIMSS, Science (2003)

Control function approach, PIRSL (2003), TIMSS, Mathematics (2001), TIMSS, Science (2001)			
	PIRLS	**TIMMS Mathematics**	**TIMSS Science**
	γ_2	γ_2	γ_2
Entire sample	8.12	7.98	13.68
	(6.84)	(12.58)	(13.10)
Boys	9.59	-12.85	-12.21
	(9.12)	(17.10)	(17.39)
Girls	2.98	11.42	22.52
	(8.00)	(14.68)	(14.21)
Academic	6.89		
	(11.00)		
Nonacademic	7.78		
	(8.28)		

Notes: 1) Variables included in the regressions are those reported in Tables 3.1 and 3.2 for the PIRLS and TIMSS datasets respectively plus the interaction terms between expected school starting age and month of birth. 2) Standard errors are in parentheses. 3) Standard errors are computed by 1000 bootstrap replications.

Hiermit erkläre ich, dass ich diese Dissertationsschrift selbständig angefertigt habe und mich anderer als der in ihr angegebenen Hilfsmittel nicht bedient habe. Entlehnungen aus anderen Schriften sind ausdrücklich als solche gekennzeichnet und mit Quellenangaben versehen.

Szilvia Hámori

Curriculum Vitae

2007 –	Junior research fellow Labour Research Department Hungarian Academy of Sciences – Institute of Economics, Budapest
2005 – 2006	Economics Doctoral Support Program Central European University (CEU), Budapest
2001 – 2008	Doctoral student Center for Doctoral Studies in Economics (CDSE), University of Mannheim
2001	M.Sc. in Economics The London School of Economics and Political Science (LSE)
2000	Diploma in Economics The London School of Economics and Political Science (LSE)
1999	B.A. in German with French, European Studies Queen Mary College, London
1997 – 1998	ERASMUS student Ruprecht-Karls-University, Heidelberg
1995	International Baccalaureate American International School of Budapest
1976	Born in Budapest, Hungary