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Population Aging and Continued Education

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ABSTRACT

Population Aging and Continued Education*

This study investigates whether the incidence of continued vocational education has changed as the German workforce commenced an aging process which is expected to intensify. As the lifespan in productive employment, lengthens human capital investments for older workers become increasingly worthwhile. Using the data of a German population survey we describe recent trends in the development of human capital investments and apply decomposition procedures to the probability of continued education. Holding everything else constant the shift in the population age distribution by itself would have led to a decline in training participation over the considered period, 1996-2004. However, the decomposition analyses yield that behavioral changes caused an increase in training particularly among older workers.

JEL Classification: J24, J10, M53

Keywords: specific human capital investment, training, population aging, demographic change

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1. Introduction

Are human capital investments really determined by their expected returns? This study offers an answer to this important question. If expected returns affect human capital investment we should see investments go up after increases in returns. The returns to investments in human capital rise when workers stay in the labor force longer – a development currently occurring in many demographically aging European societies, where institutional and policy changes cause workers to stay active longer. In West Germany the average retirement age rose from 59.2 to 61.1 years between 1980 and 2004 (DRV 2005). As the generosity of the unemployment insurance for older workers declines, the minimum legal retirement age increases, and early labor force exit options are abolished, these developments will gain momentum. When workers are in the labor force longer, it pays more to train, also at older ages.

We know from existing studies that the participation of workers in continued education programs is described by a concave age profile, with rapid declines in training probabilities at older ages (cf. Pischke 2001, OECD 1999). We hypothesize that the negative age gradient of the training incidence flattens as workers become more likely to work at older ages, just as predicted by human capital theory. To test this hypothesis we investigate whether the incidence of training has increased for older workers in recent years.

This issue has not been addressed in the literature on training and continued education so far. Most studies in this literature focus on the individual and firm level determinants of training and on training's returns for both sides of the labor market. Among many others, Zwick (2005) analyses the effect of training for companies and Büchel and Pannenberg (2004) or Pischke (2001) looked at the recipients of human capital investments. The only contribution which is close in interest to ours is the study by Shields (1998) on changes in employer-funded training in the United Kingdom. He uses three cross-section datasets of the U.K. Labour Force Survey to study the changes in the determinants of the probability of receiving training between 1984 and 1994. He applies a decomposition analysis in the spirit of Oaxaca-Blinder and confirms the key relevance of age, education, and industry for the probability of receiving training. Over the time of his data the relevance of prior education increased and the age profile flattened, which is what we expect for Germany as well.

In our analysis we apply data from the German *Mikrozensus* of 1996 and 2004. After describing our sample and the measures of training incidence we first investigate the overall trend. We decompose the observed change in training intensity in order to distinguish the effects of developments in the population age structure from changes in age-specific training probabilities. In a second step we perform a regression based decomposition analysis, similar to that performed by Shields (1998).

Our key findings are first that most of the increase in the overall training propensity between 1996 and 2004 falls disproportionately on older workers and second that changes in the characteristics of workers and their employments are not the driving force of the expansion in continued education. Instead, behavioral changes in the provision of training matter. The rising returns to continued training might be the determinants of these changes in training behavior.

2. Data and Descriptive Evidence

Our analysis is based on data from the German *Mikrozensus*, which surveys the residents of one percent of all German dwellings. The key advantage of this dataset is its size. It covers annual samples of over 800,000 individual observations. A disadvantage of the data for our analysis of continued training relates to the way information on training participation has been gathered. Since 1996 a random 45 percent of the full sample has been asked about training activities.[1] The wording of the question was changed repeatedly between surveys. Our analysis compares the training propensity for the years 1996 and 2004, when individuals

[1] Up until 1990 everybody was asked, from 1991 through 1995 the question was answered on a voluntary basis, and since 1996 only 45 percent of the sample is required to answer the question.

were asked about their participation in training for professional purposes over the course of the last year (see Appendix for details). In our sample we consider individuals aged 25 through 65 who have been employed as blue or white collar workers or as civil servants over the course of the last calendar year and worked at least 35 hours per week.[2] Thus, we observe 52,445 and 48,904 workers for 1996 and 2004, respectively.

Figure 1 describes the incidence of training for both years by age group. While the overall shift in the propensity to participate in continued education may at least in part be due to the changed wording of the question, the graph confirms the importance of age for participation in continued education: for both years the age gradient is clearly negative. To render the age profiles comparable we provide normalized data for the year 2004 where all age group-specific probabilities are adjusted by the constant ratio of the overall 1996 probability of training (8.7 percent) relative to the overall 2004 probability (16.9 percent). The normalized line yields first evidence for a flatter age-profile in 2004 than in 1996.

Since we are interested in the relationship between age and training over time we next ask, to what degree the increase in the training propensity was affected by overall population aging and what role shifts in the age-specific training propensity played.

3. Algebraic Decomposition of Changes in Training

We decompose the change in the observed probability of training between 1996 and 2004. The probability of training in the population at time t, $P_t(tr)$, can be described as the weighted sum of age-specific training probabilities:

$$P_t(tr) = \sum_{a=25}^{65} \left[P_t(tr|Age_a) \cdot P_t(Age_a) \right] \quad (1)$$

[2] Apprentices, military personnel, family helpers, and the self-employed are not included in our sample.

In consequence, the change in overall training propensities between 1996 and 2004 can be the result of both, a change in age-specific training propensities as well as in the population age distribution. This is clarified by the following decomposition:

$$\begin{aligned}
\Delta P(tr) &= P_{04}(tr) - P_{96}(tr) \\
&= \sum_{a=25}^{65} \left[P_{04}(tr|Age_a) \cdot P_{04}(Age_a)\right] - \sum_{a=25}^{65} \left[P_{96}(tr|Age_a) \cdot P_{96}(Age_a)\right] \\
&= \sum_{a=25}^{65} \left[P_{04}(tr|Age_a) - P_{96}(tr|Age_a)\right] P_{04}(Age_a) - \sum_{a=25}^{65} P_{96}(tr|Age_a)\left[P_{96}(Age_a) - P_{04}(Age_a)\right] \\
&= \sum_{a=25}^{65} \left[\Delta P(tr|Age_a) \cdot P_{04}(Age_a)\right] + \sum_{a=25}^{65} \left[\Delta P(Age_a) \cdot P_{96}(tr|Age_a)\right] \\
&= \quad \textit{shift effect} \quad + \quad \textit{age structure effect}
\end{aligned} \tag{2}$$

We label the first part of this expression the "shift effect" because it reflects the share in *$\Delta P(tr)$* that is independent of changes in the population age structure and due only to shifts in age-specific training probabilities. In contrast the second part, labeled "age structure effect", measures the part of the total change, *$\Delta P(tr)$,* that is due to changes in the population age structure and independent of behavioral changes.

We can decompose the "shift effect" further, to describe the changes in training probabilities for specific age groups:

$$\begin{aligned}
shift &= \sum \left[\Delta P(tr|Age_a) \cdot P_{04}(Age_a)\right] \\
&= \overline{\Delta P(tr|Age_a)} + \sum \left\{\left[\Delta P(tr|Age_a) - \overline{\Delta P(tr|Age_a)}\right] \cdot P_{04}(Age_a)\right\} \\
&= \overline{\Delta P(tr|Age_a)} + \sum \delta_a
\end{aligned} \tag{3}$$

where $\overline{\Delta P(tr|Age_a)} = \frac{1}{65-25} \sum_{a=25}^{65} \left[\Delta P(tr|Age_a)\right]$ describes the average shift of age-specific training probabilities over time. It would also capture the effects of a change in the wording of the question for average training probabilities. The second term of the equation sums the weighted "specific age effects", δ, for all age years *a*. If the training propensities had changed in exactly the same manner for all age years, then all specific age effects, δ, were zero. If, however, particularly older workers receive more training than before, we would expect larger "specific age effects" δ for these age groups than for others.

For the aggregate sample we obtain a gross increase in the training probability of 8.18 percentage points over the considered period. This increase results mostly from a 8.50 point shift effect. The age structure effect is negative at -0.32, indicating that population aging by itself would have reduced the overall training probability. The vast shift effect reflects a considerable change in age-specific training probabilities. Applying the decomposition of equation (3) yields that most of this change is due to an overall increase in age-specific training probabilities: the average shift reaches 8.29 points. The sum of the specific age effects is small at only 0.21. However, this hides substantial differences across age-groups which are depicted in Figure 2: the weighted change for most age-groups up through age 44 was zero or negative. It is the older workers above age 45 who experienced most of the increase in their training probability. This result agrees with our hypothesis.

4. Regression-Based Decomposition

The above decomposition yielded that most of the increase in training probabilities was not due to a shift in the population age structure but to a change in age-specific training probabilities, which went up substantially between 1996 and 2004. In this section we choose a different approach to study the increase in training propensities. Instead of differentiating only the effects of a changed population *age structure* from changes in behavior we look at the changes of *all* potentially relevant determinants of training and evaluate whether changes in their values or alternatively in their association with the incidence of training are behind the developments.

As a first step we provide probit estimates for the probability of individual training, separately for the two data years. The descriptive statistics on the individual and employment characteristics as well as the marginal effects of the independent variables are presented in Table 1. A comparison of the mean values of the covariates for the two years indicates that the characteristics of the sample have changed over time. On average, workers aged and educational attainment was higher in 2004 then in 1996. Also, the share of blue collar workers declined and that of white collar workers increased. The estimates of the marginal effects of these characteristics indicate some substantial shifts in the variables' correlations with the probability of receiving training over time. The age effect is estimated as a second order polynomial and therefore difficult to interpret. Based on the coefficient estimates we calculate that the highest probability of receiving training moved ceteris paribus from age 32.4 in 1996 to age 36.9 in 2004, confirming our premonitions. The marginal effects of sex, nationality, and education increased in absolute value between the two surveys, which is similar to the results Shield (1998) found for the United Kingdom. The same holds for the blue- and white collar worker effects and for the significant firm size indicators. This suggests that the sensitivity of training to its determinants may have increased over time. It is noteworthy that the pseudo R^2 value of the two regressions was relatively low at 9.4 and 10.7 percent for 1996 and 2004, respectively: only a small fraction of the overall changes in the training probability is subject to the systematic impact of the considered determinants.

As a second step we now apply a version of the Oaxaca-Blinder decomposition to quantify the relative impact of changes in the values of explanatory variables and of changes in their effects for the overall development of training propensities over time. We apply the procedure developed by Fairlie (1999, 2005) to translate the Oaxaca-Blinder decomposition to a situation with a bivariate dependent variable. Fundamentally, the effect of changes in parameters (α) and covariates (X) are distinguished using equation (4):

$$\begin{aligned} \Delta P(tr) &= \left\{ \overline{P}(\alpha_{04}, X_{04}) - \overline{P}(\alpha_{96}, X_{04}) \right\} + \left\{ \overline{P}(\alpha_{96}, X_{04}) - \overline{P}(\alpha_{96}, X_{96}) \right\} \\ &= \quad \text{parameter effect} \quad + \quad \text{characteristics effect} \end{aligned} \tag{4}$$

$\overline{P}(\alpha_{04}, X_{04})$ represents the average predicted probability of receiving training, where every worker's characteristics (X) are as observed in 2004 and the parameters (α) of the probit estimation for 2004 are applied. The first term ("parameter effect") considers the differential in average training probabilities that results when using the 2004 characteristics with both the

2004 and the 1996 parameter vector. However, we focus on the second term, the characteristics effect, which evaluates the effect on training probabilities when the parameter vector α is held constant, e.g. at the 1996 level, and individual training probabilities are calculated using different sets of characteristics. This second term indicates the extent to which the change in training probabilities over time can be attributed to changes in worker characteristics. Instead of using the parameter vector as of 1996, as in equation (4), the characteristics effect can also be evaluated at the 2004 set of parameters α, or at those from a pooled regression, yielding different results. Below, we present the results of all three approaches. An interesting option within this framework of analysis is to decompose the characteristics effect further and to measure the extent to which certain groups of covariates explain the total characteristics effect. To measure the effect of the group of covariates X_k we evaluate

$$\overline{P}\left(\alpha_{04}^{k} X_{04}^{k} + \alpha_{04}^{\neg k} X_{04}^{\neg k}\right) - \overline{P}\left(\alpha_{04}^{k} X_{96}^{k} + \alpha_{04}^{\neg k} X_{04}^{\neg k}\right). \tag{5}$$

Again, this expression can be evaluated either using the estimates for 2004 (as in equation (5)) or for 1996, or for the pooled sample. Each group of covariates k can be evaluated separately and their individual contributions add up to the total "characteristics effect" as in equation (4). The distinguishing feature of the Fairlie approach is that the average of individual predictions is calculated instead of a prediction at average covariate values, which is usually done (see e.g. Shields 1999).[3] The problem of matching observations on X^k from different years is solved using a procedure akin to propensity score matching (c.f. Failie 2005). The standard errors are calculated using the delta method. We apply the Stata9 algorithm "fairlie" provided by Jann (2006).

The results of our analysis are summarized in Table 2. Again, we start with a raw difference in training probabilities of 8.18 percentage points between 1996 and 2004.

[3] In a logit model estimated with a constant the average of the predicted values exactly matches the sample average, i.e. equation (4) holds exactly. This is not the case for the probit estimator nor in the standard case were the predicted values are calculated based on average covariate values.

Depending on which set of base parameters we use, between 6.3 and 12 percent of this percentage increase is due to changes in the characteristics of the observed sample (see row 3 of Table 2). This implies that most of the change cannot be explained by changes in the covariate values over time. When we investigate the main factors behind the effect of covariate changes we obtain the results presented in the bottom part of Table 2: the sample age changed a lot over time, however, it would have caused a massive *decline* in probabilities rather than the observed increase. Instead, just about all the other significant characteristic effects help explain the increase in training probabilities. The largest effect derives from the increase in the workforce's education which by itself accounts for at least 70 percent of the total characteristics effect (which however accounts for only 6-12 percent of the total increase in training). Important other contributors are the distribution of the workforce between blue and white collar workers, and civil servants, where the latter have the highest probability of receiving training, and the distribution of workers across regions.

Overall, however, we can explain only a small portion of the changes in training probabilities by looking at worker characteristics. This leaves about 90 percent of the difference to be explained by either behavioral changes among employees and employers, by changes in the survey design, or by other "unexplained" factors.

5. Conclusions

The objective of the analyses was to test whether the probability of receiving training increased for older German workers in recent years. We find both, a general increase in training probabilities – which in part may be due to changes in the survey instrument – as well as shifts in the age-specific training incidence, which is unlikely to be affected by the wording of the survey question. The overall increase in the incidence of training is not due to a change in the population age structure. It was mostly a general increase in training probabilities which benefited older workers most, as hypothesized. Regression based decomposition analysis confirms that most of the change over time cannot be explained by changes in worker or employment characteristics. The overall training incidence would have declined in the aging workforce, had it not been for adjustments in conditional training probabilities. The analysis corroborates that older workers benefited from a disproportionate increase in their training incidence in recent years, which is likely to be influenced by increasing returns to human capital investments.

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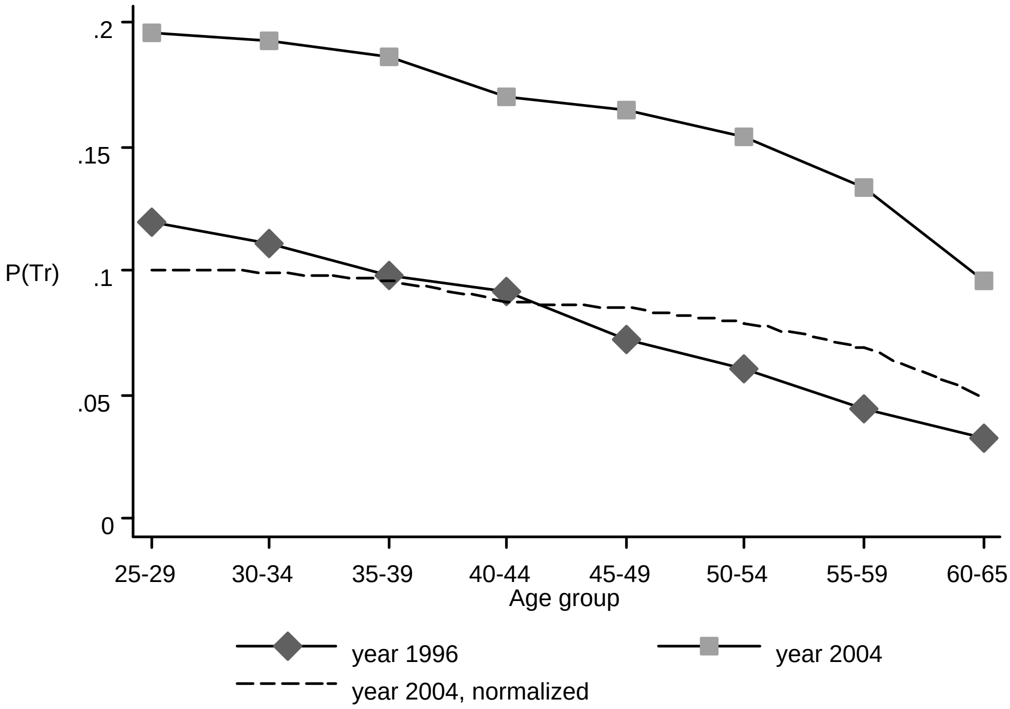
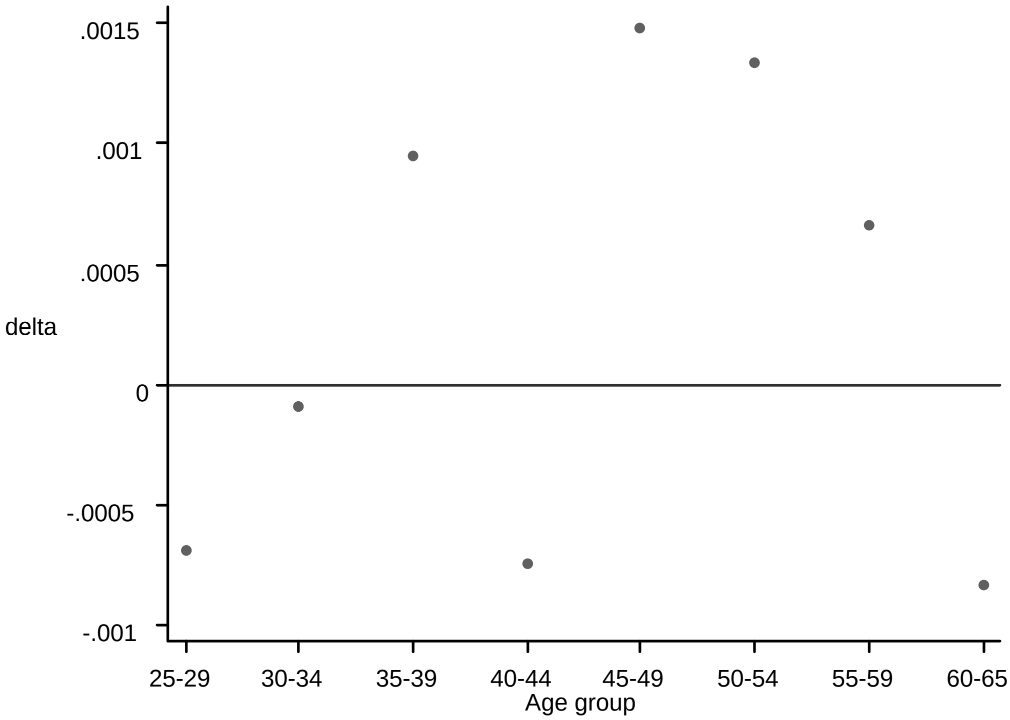
Figure 1 Training Incidence by Age Group and Year



Note: The normalized line for 2004 divides the entries for 2004 by the fixed ratio of the average probability for 1996 over that of 2004.

Source: Own calculations based on German Mikrozensus 1996 and 2004.

Figure 2 Age-specific change in the conditional training probability (δ)



Source: Own calculations based on German Mikrozensus 1996 and 2004.

Table 1 Data description and marginal effects in probit estimation of the probability of reporting training for the samples of 1996 and 2004

	Mean (Std. dev.) 1996	Mean (Std. dev.) 2004	M.E. Probit 1996	M.E. Probit 2004
Age	41.389	42.767	0.002	0.008**
	(10.097)	(42.767)	(1.76)	(5.14)
Age squared / 100	18.150	19.226	-0.005**	-0.012**
	(8.594)	(8.420)	(4.00)	(6.88)
Sex (male=1)	0.673	0.665	0.019**	0.027**
			(7.94)	(7.56)
Marital status (married=1)	0.684	0.636	-0.017**	-0.014**
			(6.84)	(4.01)
Nationality (German=1)	0.948	0.947	0.028**	0.058**
			(5.09)	(7.45)
Hauptschule	0.416	0.323	ref.	ref.
Mittlere Reife	0.176	0.212	0.037**	0.057**
			(10.00)	(10.73)
FH-Reife	0.021	0.038	0.077**	0.085**
			(8.84)	(8.83)
Abitur	0.046	0.074	0.065**	0.075**
			(10.34)	(9.83)
Polytechn. Oberschule (DDR)	0.132	0.123	0.022**	0.027**
			(4.43)	(3.37)
University degree	0.160	0.172	0.060**	0.127**
			(13.96)	(20.09)
Schooling missing	0.050	0.057	0.002	-0.011
			(0.40)	(1.33)
Civil servant	0.090	0.085	ref.	ref.
White collar worker	0.516	0.567	-0.013**	-0.044**
			(3.29)	(7.37)
Blue collar worker	0.394	0.348	-0.059**	-0.147**
			(13.10)	(22.21)
Firmsize 1-10 workers	0.124	0.127	ref.	ref.
Firmsize 11-19 workers	0.096	0.099	-0.003	-0.003
			(0.66)	(0.43)
Firmsize 20-49 workers	0.138	0.138	0.012**	0.020**
			(2.67)	(3.00)
Firmsize more than 50 workers	0.634	0.622	0.020**	0.026**
			(5.48)	(5.04)
Firmsize unknown	0.008	0.013	-0.002	-0.028
			(0.17)	(1.86)
Pseudo R-squared			0.0944	0.1066

Notes: The columns entitled M.E. represent marginal effects, absolute values of z-statistic are presented in parentheses. ** and * indicate statistical significance at the 1 and 5 percent level. Not presented are the marginal effects for 15 federal states and 10 industries. The estimation for 1996 was estimated on a sample of 52,445 observations, that for 2004 used 48,904 observations.

Table 2 Results of Regression Decomposition

Total percentage point difference to be explained: 0.0818			
Decomposition base:	1996	2004	Pooled
Share of total difference explained:	11.8 %	6.3 %	12.0 %
Explained effect due to:			
Age	-45.9 % **	-150.2 % **	-42.9 % **
Sex	4.8 % **	11.6 % **	5.1 % **
Marital Status	8.9 % **	29.8 % **	17.2 % **
Nationality	1.3 % **	2.0 % **	1.0 % **
Education	71.2 % **	92.6 % **	70.9 % **
Region of Residence	27.9 % **	44.1 % **	23.4 % **
Blue / White Collar / Civil Servant	37.6 % **	46.4 % **	24.3 % **
Firmsize	-0.1 %	2.3 %	0.3 %
Industry	-5.8 % *	21.5 % **	0.6 %

Note: ** and * indicate statistical significance at the 1 and 5 percent level. The standard errors were obtained using the delta method.

Appendix – Wording of questions and coding of the indicator

We coded the training participation indicator based on these questions of the surveys:

1996

Question EF 293: *Do you currently participate in vocational training, continued education or re-training, or did you do so within the last four weeks?*
If answer is No, question EF 294 is asked: *Have you since the end of April 1995 participated in vocational training, continued education, or re-training?*

The indicator was coded Yes if either question EF 293 or question EF 294 were answered positively.

2004

Question EF 275: *Have you participated in one or several general or vocational trainings, be it a course, a seminar, a conference, or private instruction, since the end of March of 2003 or are you currently participating?*
If answer is Yes, question EF 276 is asked: *What was the purpose of this training?* (Answer options: professional / private.)

The indicator was coded Yes if, both, question EF 275 was answered positive and the answer to question EF276 was "professional".

Original German language wording of the questions:

1996

EF 293: *Nehmen Sie gegenwärtig an einer beruflichen Ausbildung, Fortbildung oder Umschulung teil, oder haben Sie an einer solchen in den letzten vier Wochen teilgenommen?*
EF 294: *Haben Sie seit Ende April 1995 an einer beruflichen Ausbildung, Fortbildung oder Umschulung teilgenommen?*

2004

EF 275: *Haben Sie seit Ende März 2003 an einer oder mehreren Lehrveranstaltung(en) der allgemeinen oder beruflichen Weiterbildung in Form von Kursen, Seminaren, Tagungen oder Privatunterricht teilgenommen oder nehmen Sie gegenwärtig teil?*
EF 276: *Was ist (oder war) der Zweck dieser Lehrveranstaltung)? (Beruflich / Privat)*