Population Aging and Trends in the Provision of Work-Place Training

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and

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July 11, 2008

This study investigates whether the incidence and distribution of work-place training has changed as the German workforce commenced its demographic aging process. As the lifespan in productive employment lengthens human capital investments for older workers become increasingly worthwhile. Using data taken from two different German population surveys we describe recent trends in the development of human capital investments and apply decomposition procedures to the probability of receiving training. Ceteris paribus the shift in the population age distribution by itself would have lead to a decline in training participation over the considered period from the mid 1990s to 2004. However, decomposition analyses yield that behavioral changes are behind the observed increase in training particularly among older workers. This is confirmed by multivariate regressions on pooled annual data: the increase in training probabilities over time is highest among older workers.

JEL Classification: J24, J10, M53

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

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We gratefully acknowledge financial support of the RatSWD / BMBF Germany and the Hans-Frisch-Stiftung.

1. Introduction

In many demographically aging European societies institutional changes cause workers to stay active longer and retire later. This study investigates the development of human capital investments when a workforce both ages and stays in employment longer. In this situation the returns to investments in human capital go up and human capital investments should intensify.

In West Germany the average retirement age rose by about two years between 1980 and 2005 and by one year between 2000 and 2006 alone (DRV 2006, Hoffmann 2007, see Figure 1). As the generosity of the unemployment insurance for older workers declines, the minimum legal retirement age increases, and options for early labor force exit are abolished, these developments will gain momentum. When workers stay in the labor force longer, it pays more to train and to invest in their productivity. We know from existing studies that the participation of workers in training programs is described by a concave age profile, with rapidly declining training probabilities at older ages (cf. Bassanini et al. 2005, Pischke 2001, OECD 1999). As predicted by human capital theory we hypothesize that the negative age gradient of the training incidence flattens as workers become more likely to work at older ages. To test this hypothesis we study whether the incidence of training has increased for workers across the age distribution 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 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. Bellmann and Leber (2008 and studies cited there) use firm data to study the role of training in companies' human resource policies towards older workers. One 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-sections 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.

We analyze data from two different datasets to derive robust and reliable results. One is the German *Mikrozensus* for the years between 1996 and 2004, the other is the German Socioeconomic Panel where we consider the years 1993, 2000, and 2004 (SOEP Group 2001). After describing our samples and the measures of training incidence we first investigate the overall trend. We then 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). Finally, we apply multivariate regression analyses to study the trends in the provision of training and their heterogeneity across workers' age groups.

Our key findings are, first, that most of the increase in the overall training propensity in recent years falls disproportionately on older workers, whose propensity to receive training increases significantly faster over time than that of younger workers. Second, observed changes in the age structure are not the driving force behind the expansion in training. Instead, behavioral changes in the provision of training seem to matter. We speculate that rising returns to continued training might affect these changes in training behavior.

2. Data and Descriptive Evidence

When it comes to the analysis of the developments of work-place training in Germany it is useful to apply data from more than one source. This avoids conclusions that are based on evidence that is idiosyncratic to one specific data set. After all, questions and definitions vary between surveys and occasionally even over time.[1]

As a first data source we use 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 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.[2] The wording of the question was changed repeatedly between surveys. Our analysis compares the training propensity for the years 1996 and 2004, when individuals were asked about their participation in training for professional purposes over the course of the last year. 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 who worked at least 35 hours per week.[3] We observe 52,445 and 48,904 workers for 1996 and 2004, respectively.

In addition, we look at the evidence as provided by the German Socioeconomic Panel (SOEP, SOEP Group 2001). The SOEP is a household panel which has been administered annually since 1984. It asked the exact same question on training participation in 1993, 2000, and 2004. Again we select a sample of full-time workers, aged 25-65 yielding about 20,000 observations over the three years. The question on training is

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[1] For the same reason Puhani and Sonderhof (2008) in their analyses of training provision apply data from various sources.

[2] 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.

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

framed more broadly than in the Mikrozensus and asks for any training over the last three calendar years, be it vocational courses, conferences, conventions, or other.

A first glance at overall sample means indicates rising training participation in both datasets. In the case of the Mikrozensus average training rates rose from 8.7 percent in 1996 to 16.9 percent in 2004. For the SOEP, which considers a much broader measure of training, training participation rates went up from a higher average of 29.3 in 1993 to 34.8 percent in 2004. Figure 2 describes these developments by worker age groups, both for the Mikrozensus (Figure 2a) as well as the SOEP sample (Figure 2b).

In both cases we see a clearly negative age gradient in the provision of training as well as rising overall training incidence over time. To compare the age profiles for the two years we normalized the 2004 data adjusting all age group-specific probabilities by the constant ratio of the overall training probability in the first year relative to that observed in 2004. In consequence, the average training probability of the entire population is then identical in the 1990s data and in the normalized data for 2004. The (dashed) normalized lines yield first evidence regarding the age-specific shift in the training incidence: comparing them to the lines for the 1990s, we see in both datasets a decline in the relative training probability of the young and an increase in the relative training probability of older workers. In both cases the age-profile is flatter in 2004.

3. Algebraic Decomposition of Changes in Training

Since we are interested in the relationship between age and training over time we investigate, to what degree the increase in the training propensity was affected by overall population aging and whether shifts in the age-specific training propensity played a role. We decompose the change in the observed probability of training between early and late observations, again using both datasets. 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:

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

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

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

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:

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

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 older age groups than for others.

The decomposition results for the two datasets are summarized in Table 1. In the case of the Mikrozensus we obtain a gross increase in the training probability of 8.18 percentage points over the considered period. This increase results mostly from an 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 training probabilities. Applying the decomposition of equation (3) yields that most of this change is due to an increase in the average training probability. The average shift reaches 8.29 points. The sum of the specific age effects (δ) is small at only 0.21. However, this hides substantial differences across age groups which are depicted in Figure 3(a): the change for most age groups up through age 44 was zero or negative. It is the older workers aged 45-59 who experienced most of the increase in their training probability.

The decomposition results for the SOEP data are very similar in nature. The gross increase in training probabilities amounts to 5.52 percentage points (see Table 1). Confirming the results for the Mikrozensus above changes in the population age structure alone would have caused a decline in training probabilities. The observed increase is mostly due to average changes in training propensities. Again, age-specific training probabilities (δ) increased for those aged 45 and above and declined for younger workers, as depicted in Figure 3(b). These findings agree with the hypothesis of increasing training probabilities for older workers over time.

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 in sum increased substantially over time. Now, 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 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 first and last observed data years in both surveys. The descriptive statistics on the individual and employment characteristics as well as the marginal effects of the independent variables for the two datasets are presented in Tables 2a and 2b. 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 and in both datasets, workers aged and educational attainment was higher in 2004 than in the 1990s. Also, the share of white collar workers increased. The estimates of the marginal effects of these characteristics indicate 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 shifted ceteris paribus from age 32.4 in 1996 to age 36.9 in 2004 for the Mikrozensus and from 27.4 in 1993 to 28.6 in 2004 for the SOEP, confirming our expectations in the setting of an aging workforce. The marginal effects of sex, nationality, and a university degree increased in absolute value between the two surveys' pairs of years, which is similar to the results Shields (1998) found for the United Kingdom. The same holds for the significant firm size indicators suggesting that the sensitivity of training to its determinants may have increased over time. The pseudo R^2 value for the two Mikrozensus regressions is 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. The pseudo R^2 for the SOEP regressions is higher at about 19 and 12 percent.

As a second step we apply a decomposition procedure 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 use the procedure developed by Fairlie (1999, 2005) for bivariate dependent variables. The effect of changes in parameters (α) and covariates (X) are distinguished using equation (4):

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

$\overline{P}(\alpha_{04}, X_{04})$ 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. 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 (or 1993 for the SOEP data), 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. 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

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

Again, this expression can be evaluated either using the estimates for 2004 (as in equation (5)) or for 1996 (1993 for the SOEP), or for the pooled sample. Each group k of covariates 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 1998).[4] The problem of matching observations on X^k from different years is solved using a procedure akin to propensity score matching (c.f. Fairlie 2005). The standard errors are calculated using the delta method. We apply the Stata 10 algorithm "fairlie" provided by Jann (2006).

The results of our analysis are summarized in Table 3a for the Mikrozensus and 3b for the SOEP. For the Mikrozensus, we start with a raw difference in training probabilities of 8.18 percentage points between 1996 and 2004. 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 3a). This implies that most of the observed change in training cannot be explained by changes in the covariate values over time. This is very different for the case of the SOEP data. Here close

[4] 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 neither the case for the probit estimator nor in the standard case where the predicted values are calculated based on average covariate values.

to the entire difference of 5.5 percentage points in training probabilities over time follows changes in characteristics independent of whether the parameters are based on regressions for the early year, the late year, or pooled data. We suspect that this difference between the two datasets is due to the fact that the wording of the question was not changed and that the measured change in training probabilities is smaller in the case of the SOEP. In the case of the Mikrozensus about 90 percent of the difference in training probabilities over time must be explained by either a change in employee and employer behaviors, by changes in the survey design, or by other "unexplained" factors.

When we investigate the main factors behind the effect of covariate changes we obtain the results presented in the bottom parts of Tables 3a and 3b: the sample age changed a lot over time, however, it would have caused a *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 and the distribution of the workforce between blue and white collar workers, and civil servants.

5. Multivariate Analysis of the Change in Training Probabilities over Time

In this section we take a closer look at the changing correlation patterns behind the incidence of training. We explain the probability of individual training applying a pooled regression model to a complete set of annual data for the years between 1996 and 2004 in the case of the Mikrozensus and for the years 1993, 2000 and 2004 for the SOEP, to capture the developments in the overall training probabilities as well as age group specific changes over time.

The developments of the training probability for different age groups are modeled by interacting a linear time trend with age group indicators. As the design of the questionnaire slightly changed over the years, we use individual year dummies instead of a linear time trend to control for the overall time effect. This flexibly accounts for changes in answering behavior and captures the general trend in training probabilities.

The estimation results are presented in Table 4. The Mikrozensus time dummies are generally highly statistically significant and capture differences in the wording of the question over time as well as the overall trend. The small and insignificant year effects in the SOEP regression suggest that there are hardly any general differences in the annual outcomes. This is plausible in view of the exact identical wording of the question, even though one might have expected a reflection of an overall time trend.

The age group indicators confirm the negative relationship between training probability and age that we found earlier. The older workers are, the less likely they participate in training measures. For those aged 50 and above the differences to the reference group of the 25-29 year olds are statistically highly significant even in the smaller SOEP sample.

Our main interest focuses on the interaction effects between age group indicators and time trend. In the case of the Mikrozensus sample most coefficients of the interaction effects are statistically significantly different from zero and yield a clear pattern of increasing training participation over time for all age groups between age 30 and 59. Similarly, the interaction effects for the SOEP sample are all positive with larger effects for the age groups above age 50. However, the effects based on the SOEP data are neither individually nor jointly significant.

To visualize these changes over time, we predicted the age group specific training probabilities at every point in time for the full sample and calculated the year- and age group-specific average training propensities. The results are depicted in Figure 4a for the Mikrozensus and 4b for the SOEP. The graphs represent the difference in training probabilities for individuals in the age group 25 to 29 and in the older age groups. The overall result is rather unambiguous: in almost all age groups this difference declined over time, which means that the (ceteris paribus) age gradient in the provision of training flattened out over time. This holds for all age groups in the Mikrozensus except for those aged 60 through 65 and it holds for all age groups in the SOEP. The results are close to identical when quadratic instead of linear trend effects are considered.

Therefore, even if the level of training for older workers remains below that for younger workers throughout the observation period over time the training propensity increases most clearly for older workers. We can only speculate that this rising training propensity for older workers reflects that firms increasingly invest in older workers, because they can be expected to remain in the labor force longer than in the past.

6. Conclusions

The objective of the analyses was to test whether the probability of receiving training increased for older workers in recent years. We apply data from two separate surveys and find both, an increase in overall training probabilities as well as shifts in the age-specific training incidence particularly for older workers. The overall increase in the incidence of training is not due to a change in the population age structure but came about through adjustments in conditional training probabilities. The analysis corroborates that older workers benefited from a disproportionate increase in their training incidence in recent years. From the point of view of human capital theory, postponement of retirement increases the returns to investments and should positively affect training probabilities. This is confirmed by our estimation results. Apparently, firms adjust the provision of training opportunities to the expected returns. As the population and workforce aging process will continue we can expect to see continued shifts in the age distribution of training provision.

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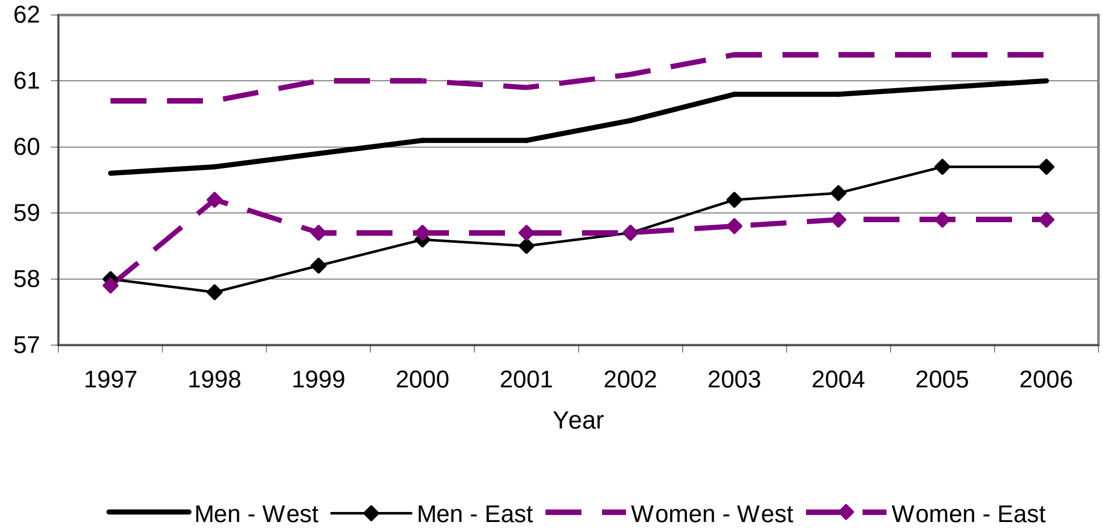
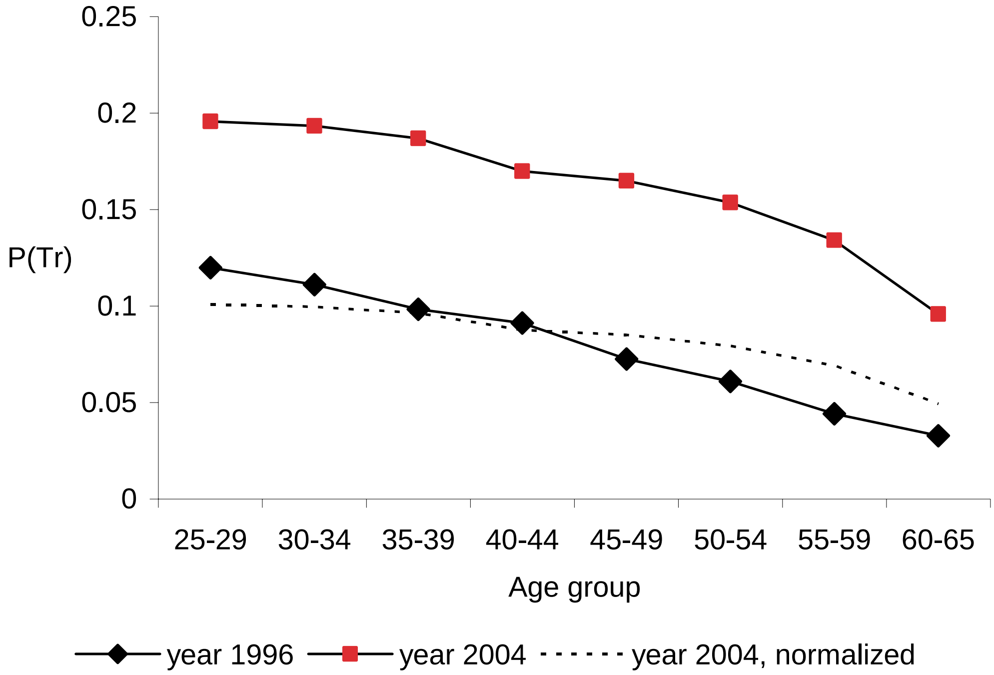
Figure 1 Average Age at Retirement over Time by Sex and Region



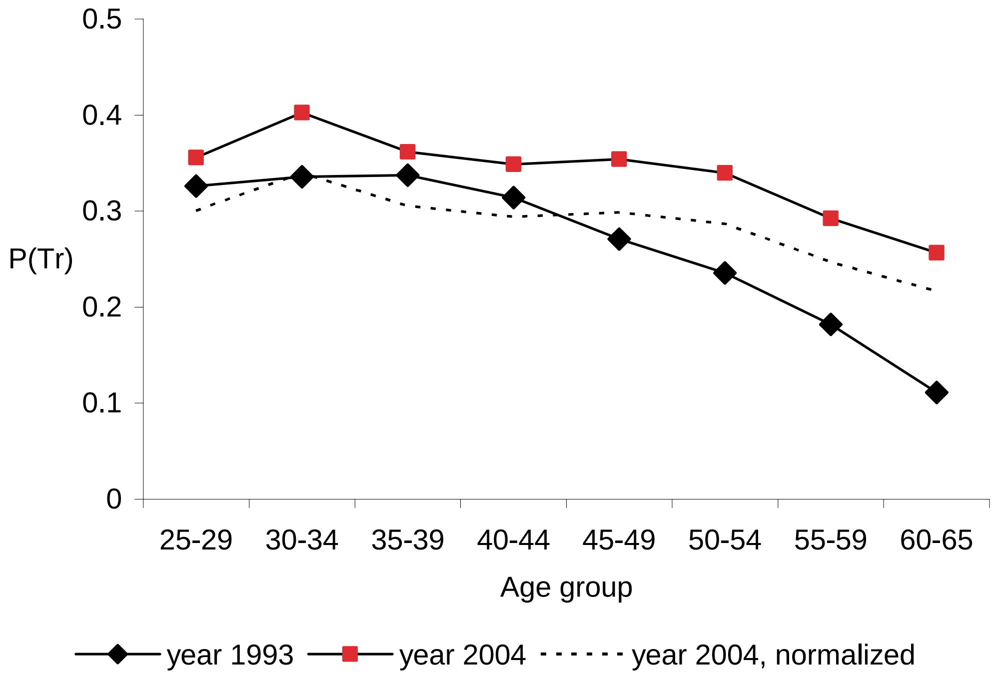
Source: Deutsche Rentenversicherung (2007)

Figure 2 Training Incidence by Age Group and Year

(a) Mikrozensus



(b) SOEP

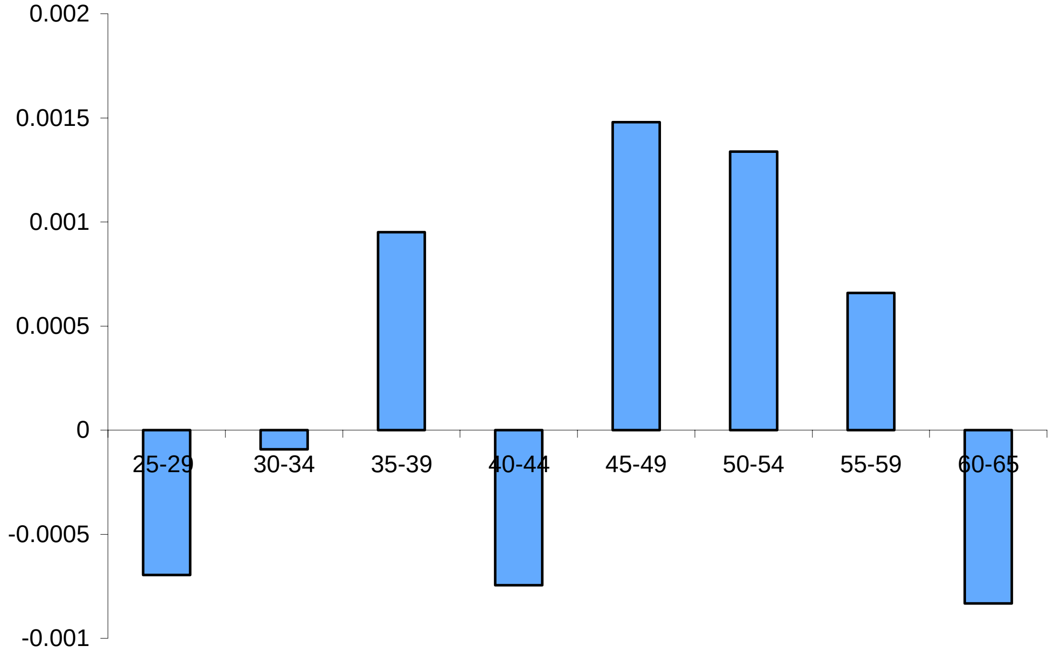


Note: The normalized line for 2004 scales the entries for 2004 such that the 2004 average training probability is equal to that of the earlier year.

Source: Own calculations based on German Mikrozensus 1996 and 2004, SOEP 1993 and 2004.

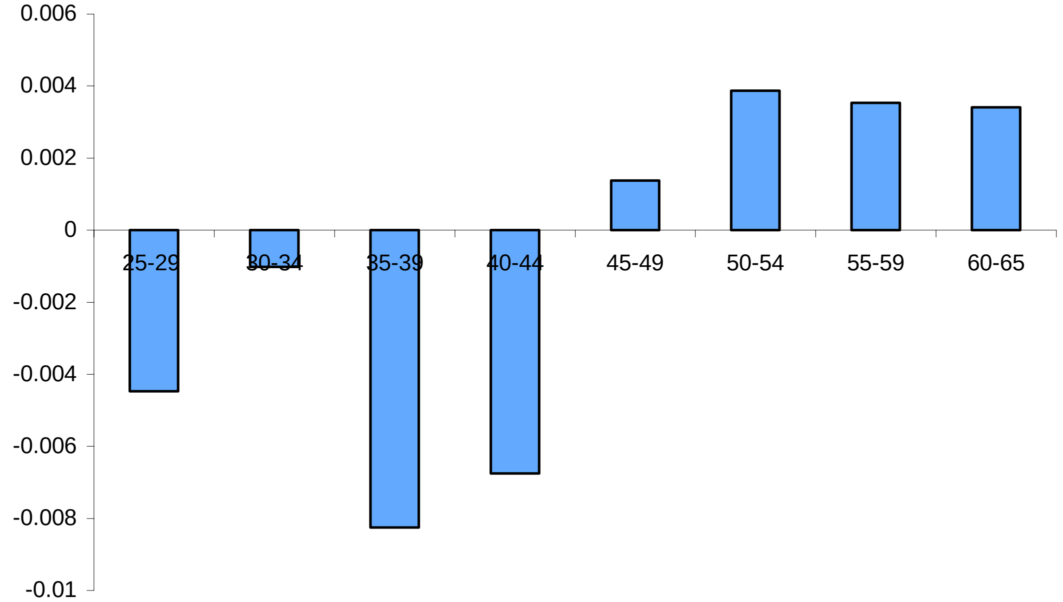
Figure 3 Age-specific Change in the Conditional Training Probability (delta)

(a) Mikrozensus



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

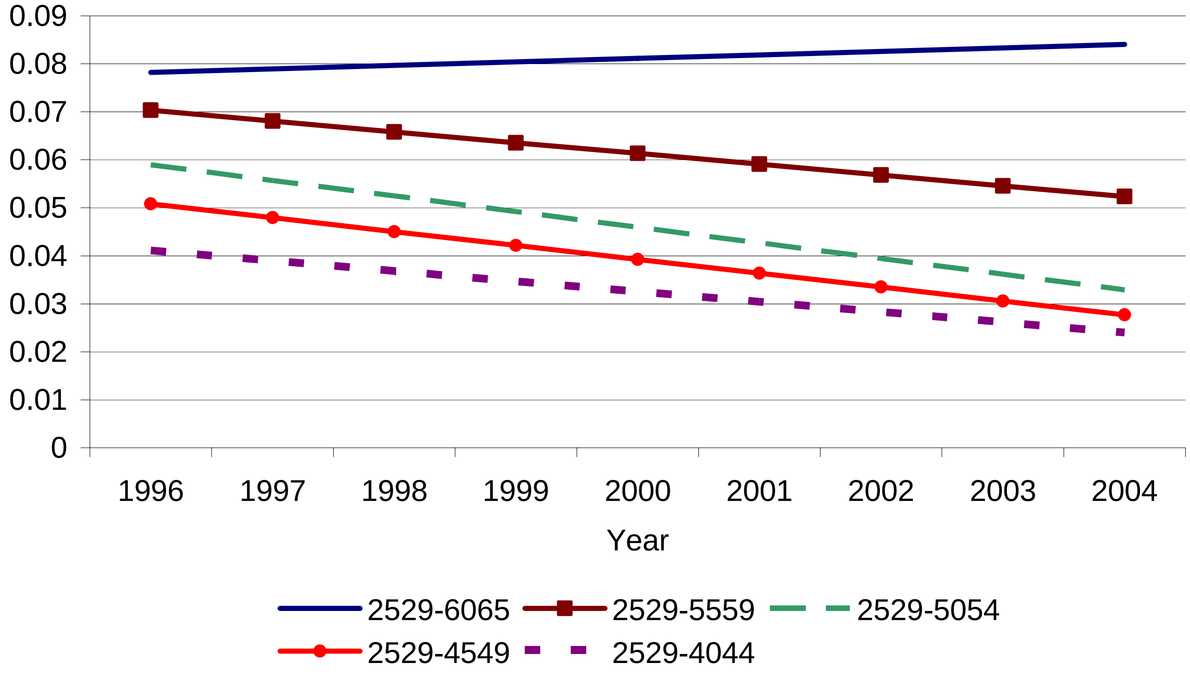
(b) SOEP



Source: Own calculations based on German Socioeconomic Panel 1993 and 2004.

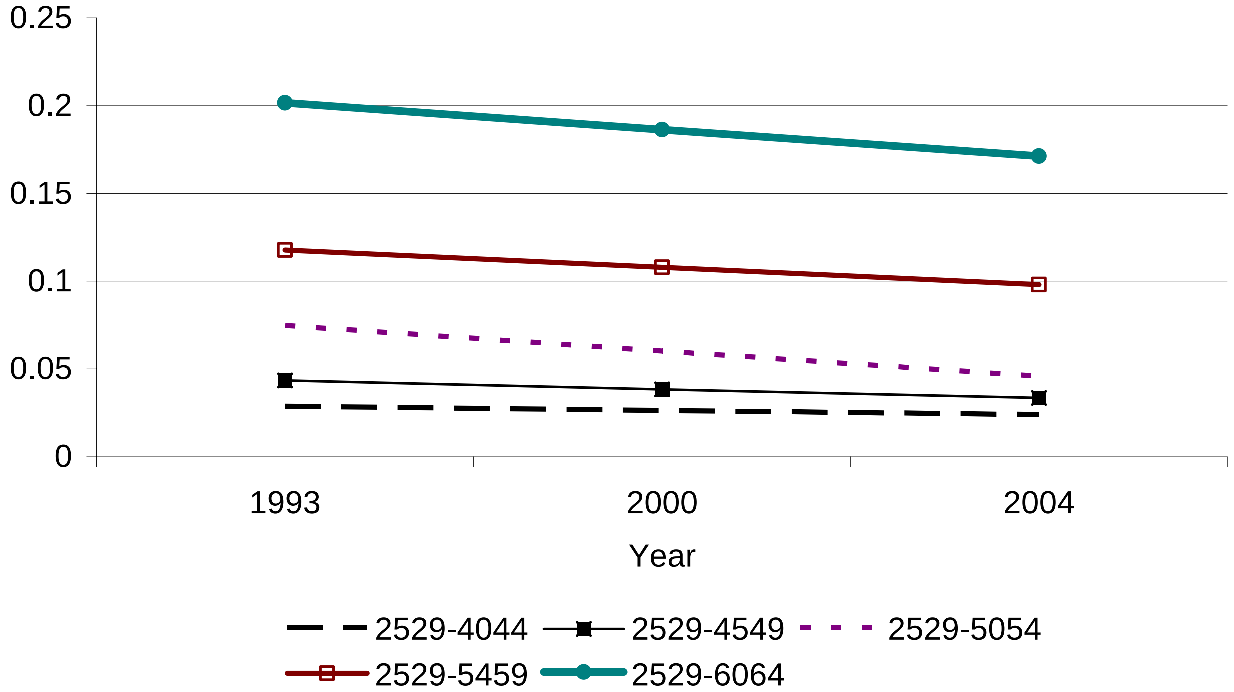
Figure 4 Difference in Predicted Training Probability of Younger (25-29) and Older Workers (in percentage points)

(a) Mikrozensus



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

(b) SOEP



Source: Own calculations based on German Socioeconomic Panel 1993, 2000, and 2004.

Table 1 Results of the age structure decomposition

	Total Change	Shift-Effect			Age-structure
		Total =	Average +	Specific-Age	
Mikrozensus	8.18	8.50			-0.32
			8.29	0.21	
SOEP	5.52	6.65			-1.13
			7.48	-0.83	

Source: Own calculations using Mikrozensus and SOEP Data.

Table 2 Data description and marginal effects in probit estimation of the probability of reporting training for the early and late samples

(a) Mikrozensus

	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
Number of obs.			52,445	48,904

(b) SOEP

	Mean (Std. dev.) 1993	Mean (Std. dev.) 2004	M.E. Probit 1993	M.E. Probit 2004
Age	40.515	43.011	0.028	0.028*
	(10.010)	(9.809)	(1.45)	(1.90)
Age squared / 100	17.416	19.461	-0.051*	-0.049**
	(8.368)	(8.562)	(2.16)	(2.95)
Sex (male=1)	0.666	0.674	0.171**	0.191**
			(3.46)	(5.08)
Marital status (married=1)	0.585	0.666	-0.050	0.041
			(0.99)	(1.08)
Marital status (missing=1)	0.186	-	-0.448*	-
			(1.87)	
Nationality (German=1)	0.806	0.923	0.143	0.214**
			(0.66)	(2.80)
Hauptschule	0.352	0.250	ref.	ref.
Mittlere Reife	0.311	0.344	0.261**	0.132**
			(4.76)	(2.76)
FH-Reife	0.030	0.063	0.358**	0.255**
			(3.16)	(3.48)
Abitur	0.133	0.244	0.444**	0.224**
			(6.50)	(4.17)
Polytechn. Oberschule (DDR)	-	-	-	-
University degree	0.005	0.007	-0.178	-0.090
			(0.70)	(0.49)
Schooling missing	0.169	0.091	-0.222*	-0.143*
			(2.02)	(1.90)
Civil servant	0.485	0.331	ref.	ref.
White collar worker	0.448	0.562	0.792**	0.666**
			(14.32)	(14.23)
Blue collar worker	0.067	0.107	0.801**	0.779**
			(7.96)	(10.19)
Firmsize 1-10 workers	0.182	0.182	ref.	ref.
Firmsize 11-19 workers	0.285	0.311	0.008	0.080
			(0.12)	(1.58)
Firmsize 20-49 workers	0.261	0.245	0.086	0.240**
			(1.28)	(4.42)
Firmsize more than 50 workers	0.261	0.255	0.307**	0.399**
			(4.49)	(7.31)
Firmsize unknown	0.010	0.007	0.131	-0.810**
			(0.63)	(3.06)
Pseudo R-squared			0.1894	0.1196
Number of observations			5,125	7,177

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.

Table 3 Results of Regression Decomposition

(a) Mikrozensus

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	-5.40%	**	-9.44%	**	-5.16%	**
Sex	0.57%	**	0.73%	**	0.61%	**
Marital Status	1.05%	**	1.87%	**	2.07%	**
Nationality	0.16%	**	0.13%	**	0.13%	**
Education	8.39%	**	5.82%	**	8.53%	**
Region of Residence	3.28%	**	2.77%	**	2.82%	**
Blue / White Collar / Civil Servant	4.43%	**	2.92%	**	2.92%	**
Firmsize	-0.01%		0.14%		0.04%	
Industry	-0.68%	*	1.35%	**	0.07%	

(b) SOEP

Percentage point difference to be explained: 0.055						
Decomposition base:	1993		2004		Pooled	
Share of total difference explained:	108.26%		92.07%		109.77%	
Explained effect due to:						
Age	-26.40%		-25.32%	**	-25.86%	**
Sex	2.12%	**	2.89%	**	2.63%	**
Marital Status	20.35%	**	0.76%		24.49%	**
Nationality	2.71%	**	8.91%	**	3.08%	**
Education	47.76%	**	25.19%	**	34.11%	**
Region of Residence	-8.90%	*	-3.24%		-7.10%	
Blue / White Collar / Civil Servant	66.14%	*	57.70%	**	62.39%	**
Firmsize	1.63%		5.30%	**	3.16%	**
Industry	2.94%	**	19.80%	**	12.81%	**

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

Table 4 Least Squares Coefficient Estimates of the Probability of Training (Pooled Annual Data)

	MZ	SOEP
MZ: year = 1996	ref.	-
MZ: year = 1997	0.008**	-
	(4.60)	
MZ: year = 1998	0.005*	-
	(2.30)	
MZ: year = 1999	-0.030**	-
	(13.46)	
MZ: year = 2000	-0.031**	-
	(11.63)	
MZ: year = 2001	-0.032**	-
	(10.15)	
MZ: year = 2002	-0.036**	-
	(9.74)	
MZ: year = 2003	0.072**	-
	(16.56)	
MZ: year = 2004	0.064**	-
	(13.24)	
SOEP: year = 1993	-	ref.
SOEP: year = 2000	-	0.0001
		(0.01)
SOEP: year = 2004	-	-0.025
		(-1.11)
Agegroup 25-29	ref.	ref.
Agegroup 30-34	-0.013**	-0.036
	(3.41)	(-1.10)
Agegroup 35-39	-0.034**	-0.025
	(8.97)	(-0.77)
Agegroup 40-44	-0.042**	-0.031
	(11.37)	(-0.97)
Agegroup 45-49	-0.051**	-0.048
	(14.00)	(-1.51)
Agegroup 50-54	-0.058**	-0.089**
	(15.57)	(-2.80)
Agegroup 55-59	-0.069**	-0.127**
	(19.09)	(-3.62)
Agegroup 60-65	-0.075**	-0.217**
	(15.57)	(-4.21)
Trend * Agegroup 30-34	-0.000	0.021
	(0.60)	(1.38)
Trend * Agegroup 35-39	0.002**	0.008
	(3.09)	(0.52)
Trend * Agegroup 40-44	0.002**	0.002
	(2.59)	(0.16)
Trend * Agegroup 45-49	0.003**	0.005
	(3.61)	(0.33)
Trend * Agegroup 50-54	0.003**	0.014
	(3.87)	(0.96)
Trend * Agegroup 55-59	0.002**	0.010
	(2.73)	(0.60)
Trend * Agegroup 60-65	-0.001	0.015
	(0.81)	(0.67)
Number of observations	455,285	20,798
R Squared	0.06	0.16

Notes: The columns present the estimated coefficients and in parentheses the t-statistics based on heteroskedasticity-robust standard errors. ** and * indicate statistical significance at the 1 and 5 percent level. Not presented are the effects for 15 federal states, 10 industries, and the above shown personal and job characteristics.